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) aimed at establishing industrial clusters in Italy in the 1960s and 1970s. 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 employment. We document a stark rise in knowledge-intensive services, which contribute significantly to the long-lasting employment effects of PBIP. Cost-benefit analysis indicates that the policy generated net gains in the long run.

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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 PBIPs among economists and policymakers. While government intervention can correct market failures and foster long-run development, it can 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 remains unclear. In addition, these programs 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 persisting well after the end of the program.

The IDAs were launched in 1960 as part of a broader regional policy called *Extraordinary Intervention in the Mezzogiorno* (EIM). The EIM was introduced by the government to stimulate economic development in Southern Italy through infrastructure building and in-

[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 (Alessandrini et al., 2019) and the United Kingdom (Fai, 2018).

vestment grants 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 (hence a lower cost of capital) for firms located in an IDA and financed additional infrastructures. IDA expenses totalled roughly €88 billion, or 0.5 percent of national GDP each year between 1960 and the end of the program in the late 1970s.

The market failure that cluster policies such as the IDAs aim to address are agglomeration economies. As predicted by a simple spatial model, place-based intervention would raise the density of economic agents in the targeted area. In the presence of knowledge spillovers and thick market externalities, higher proximity between agents boosts local productivity. Then, the cluster keeps attracting workers and firms even after subsidies cease and until local prices grow high enough. Because agents do not fully internalize these positive externalities, government subsidies have an efficiency justification (Duranton and Puga, 2004; Moretti, 2011).

A first test of the presence of agglomeration economies (and hence of the success of the intervention) 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 data for the population of private firms since the 1990s.

Valid identification requires isolating exogenous variation in IDA status, which is challenging for PBIPs due to their selective nature. The criteria set by the government in the late 1950s to establish IDAs offer a unique source of spatial variation. An IDA had to be centered around a large city and included neighboring municipalities. The key requirement was that municipalities bordering the center had to be part of the IDA. This resulted in a "minimum" IDA border traced by municipalities contiguous to the 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 this "contiguity rule" in a fuzzy regression discontinuity (RD) design where the running variable is the distance of a municipality from the minimum IDA border and IDA status is the binary treatment. The identifying assumption is that only IDA status changes discontinuously and that areas within and outside of the border are otherwise similar. There are indeed no systematic imbalances in lagged outcomes and other relevant covariates at the RD 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 orthogonal to municipalities' characteristics. To account for unobserved factors, we also rely on a difference-in-discontinuities design that allows for confounding discontinuities at the cutoff as long as they are constant over time – 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. The rise in local employment is, at least in part, driven by higher labor force participation of residents. The novel evidence of *increasing* effects of PBIP after termination stands 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, 2022). This demands further investigation into the sources of persistence.

Such stark persistence originates from sectors not directly targeted by the policy. By decomposing the baseline effect across sectors, we find that manufacturing – the only subsidized sector – drove most of the growth in employment density 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 source of larger agglomeration in IDAs in the long run.

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). After the end of the program, however, we 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.

These findings are confirmed using an alternative empirical strategy. Exploiting again the contiguity rule described earlier, we compare over time municipalities bordering IDA centers to a new control group: municipalities bordering "placebo centers" in the Center-North of Italy (outside of the EIM jurisdiction). This approach 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 spillovers (Allen and Arkolakis, 2023). In a related exercise, we explicitly estimate the spatial spillovers of the IDA policy by comparing 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 evidence of small displacement effects in manufacturing employment while IDAs were in place, but not in the long run.

These structural transformations towards skilled jobs are primarily a result of the *type* of manufacturing stimulated in the IDAs. We estimate a larger share of manufacturing industries with high technology intensity 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 (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. A second channel is increased demand for high-skill business services such as consulting, human resources and legal activities. Granular industry data confirm that these jobs (and firms) are indeed more widespread 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 long-run positive 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.

Cost-benefit analysis shows that the benefits entailed by the program outweigh the costs. We first calculate a long-term cost per job created of about $30,000, comparable to other regional policies examined in the literature (Criscuolo et al., 2019; Siegloch et al., 2022). We then make a more comprehensive assessment following the approach of Busso et al. (2013). We compute the net surplus accruing to workers, firms and landlords in the form of wages, profits and housing rents, respectively. In contrast to existing studies, we focus on the surplus generated by the policy only *after* its termination. We find that the present discounted value of the net gains produced between 1991 and 2011 at least compensate for the policy's total costs. These calculations suggest that the IDA program led to a net surplus, assuming that it produced gains also while it was in place or after 2011.

In the last part of the paper, we provide first evidence that the long-run impact of place-based intervention depends on the initial conditions in the targeted locations. We reach this conclusion by comparing 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 not dissimilar to that observed for the IDAs. However, employment in services – especially KIS – did not respond to the intervention. There are also no effects on the share of high-technology manufacturing, nor on education and wages.

Comparing these two experiences is instructive. The IDAs were high-potential poles explicitly chosen as future clusters; in contrast, areas around the EIM border had less favorable geography and low density of employment and firms before the policy. Albeit suggestive, these findings illustrate 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 growing body of research on industrial policies, which despite their broad diffusion remain under-studied in empirical work (Juhász et al., 2023). Recent papers analyzing historical programs have uncovered causal estimates of 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 complements the existing evidence by illustrating how industrial policy shapes the transition towards manufacturing and eventually into advanced services. Specifically, this is the first study providing a detailed account of the dynamic response of the services sector, which is typically not the 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), a growing literature has 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 scant literature on the long-run effects of cluster policies (Garin and Rothbaum, 2022; Giorcelli and Li, 2022; Heblich et al., 2022) by documenting persistence and offering new insights on the underlying mechanisms. Our work clearly illustrates how the services sector contributes to persistent effects through local multipliers and agglomeration economies. We also identify the policy-driven stimulus to high-technology industries as a key factor. Last, we note that initial conditions matter, and that one of the stated goals 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 impact on labor markets (Moretti, 2012; Autor and Dorn, 2013; Charles et al., 2019; Gagliardi et al., 2023; Helm et al., 2023). If leading to specialization of economic activity and production in a limited set of industries, industrial interventions might undermine long-run develop-

[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).

ment when manufacturing districts must adjust to technological shifts (Barba Navaretti and Markovic, 2021).[3] In contrast, we show that PBIP has expedited structural change in the targeted areas, which transitioned into diversified poles integrating high-skill manufacturing and services.[4] The novel evidence we provide on the ability of PBIP to incentivize high-skill jobs resonates with Rodrik and Stantcheva (2021), who advocate the creation of "good jobs" (and of firms demanding them) as the main target of industrial policy going forward.

Fourth, our results add to the existing 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 spillovers of PBIP across different classes of services, better assessing how these programs shape the structure of the economy. This study also provides the first *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 novel causal evidence on the EIM – the most ambitious regional program in Italy's history (Felice and Lepore, 2017). Recent studies in political economy (Colussi et al., 2020; Buscemi and Romani, 2022) consistently report a null economic impact of the EIM in the long term. Among these, Albanese et al. (2023) find that EIM transfers led to a transition out of agriculture towards industry, halted the growth of services and did not raise local employment in the long run. We show instead that the intervention has successfully promoted development in a few targeted areas of Southern Italy – the IDAs. Our results also relate to Cerrato (2024), which focuses on the aggregate welfare consequences of the EIM and documents net gains in national industrial production. Our analysis examines more in depth a specific dimension of the EIM – the IDAs – and goes beyond the direct impact on manufacturing, unveiling the effects of the program on other areas of the economy and unpacking the sources of persistence.

[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. Resonating findings are obtained in Kim et al. (2021) 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 knowledge intensive services. Our paper highlights the role that government policy can play in this process.

The paper is organized as follows. Section 2 provides an overview of the policy; Section 3 describes the data sources; Section 4 outlines the identification strategy; Section 5 presents the baseline results; Section 6 explores the underlying mechanisms; Section 7 conducts cost-benefit analysis; Section 8 further discusses our findings. The last Section concludes.

2 Historical background

The North-South economic divide has been a recurring theme in Italy's policy debate, particularly so in the aftermath of World War II when this gap was at its peak. An ambitious regional policy called *Extraordinary Intervention in the Mezzogiorno* (EIM) was put in place by the central government in 1950 to jump-start development in an area covering 40 percent of Italy's surface (Law n. 646/1950).[5] The program had an initial lifespan of ten years, which was then prolonged several times until 1992. The government mandated the intervention to a state-owned agency called *Cassa per il Mezzogiorno* (Cassa).

At its onset, the main goal of the EIM was to accelerate structural transformation by enhancing agricultural productivity and promoting a shift to manufacturing. To achieve this, the Cassa financed infrastructure interventions (mostly in transportation and water supply) during its first decade of activity (see Appendix A.1 for details on the functioning of the EIM). A new phase of the EIM began in the late 1950s, when the program was extended both in time and scope and its focus shifted markedly towards industrial policy to support businesses in Southern regions and attract investments.[6]

To pursue its new mandate, the Cassa conceded capital and interest grants to firms located in its jurisdiction. The eligible investments were those for building new plants, enlarging existing ones, purchasing machinery and performing generic works such as connections to energy and transport services. The following 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.

[5] GDP per capita in the South was roughly half of that if 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.

[6] In the policymaker's words, entrepreneurs located in the South (or willing to locate there) needed to be compensated "*for the natural inferiority of the Mezzogiorno relative to other areas, with its subsequent costs and risks*" (See Cassa's Annual Report, 1957-58 and Laws n. 634/1957 and n. 555/1959).

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 as suitable for industrial agglomeration, with the goal of "*clearly directing the location choices of economic agents*" and "*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*. The consortium submitted a development plan for the area to the Cassa, outlining the proposed investments and reporting information about the included municipalities. Each IDA was centered around a provincial capital and extended to more municipalities surrounding the center, subject to a minimum population threshold (200,000 people as of 1958). Other requirements were related to the geological properties of the area (e.g., low seismicity) and to the presence of basic infrastructure.

Subject to the government's approval of the plan, the Cassa could subsidize the expenses borne by each consortium in its IDA.[7] In addition, the investment grants for individual firms in the EIM area were more generous for firms located in IDAs, which thus faced even lower cost of capital than other EIM firms. 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 IDA firms.[8]

The IDA program was effectively in place for almost two decades from 1960 until the late 1970s, when investment grants for IDA firms were equalized to those for other firms in the EIM region. EIM transfers continued also through the 1980s, but with no distinction between IDAs and other EIM municipalities. The EIM was terminated by 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).

[7]These included connections to transport and energy services, the construction of plants and houses for workers and their families, and the provision of professional training classes. The original subsidy rate for these expenses was 50 percent, which rose to 85 percent in 1961.

[8]The Cassa was pursuing two separate industrial policy goals. The first ("*industrial concentration*") was to establish large industrial clusters (the IDAs). The second ("*industrial diffusion*") was to favor industrial development in peripheral regions by supporting small firms in municipalities with limited industrial activity.

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 information on the universe of Cassa's interventions from the ASET database, which stores recently digitized records of the agency's activities since its inception in 1950.[9] Records for roughly 110,000 firm subsidies are available and collate information on the grant's amount, year, sector and municipality. The data also include about 75,000 infrastructure projects reporting the financial resources allocated as well as the year, location and type of infrastructure.

Panel (a) in Figure 1 shows total EIM expenses (excluding concessional loans) by year, scaled by the total population in the EIM region in 1951. The program only performed infrastructure works during its first decade (the 1950s). A strong industrial push then began in the 1960s with a massive rise in firm investment subsidies.[10] Panel (b) shows that most EIM expenses were concentrated in IDA municipalities, in particular during the peak in the 1960s and 1970s. Especially for IDAs, firm grants went disproportionately to capital intensive industries such as chemical, metallurgy and transport manufacturing.[11]

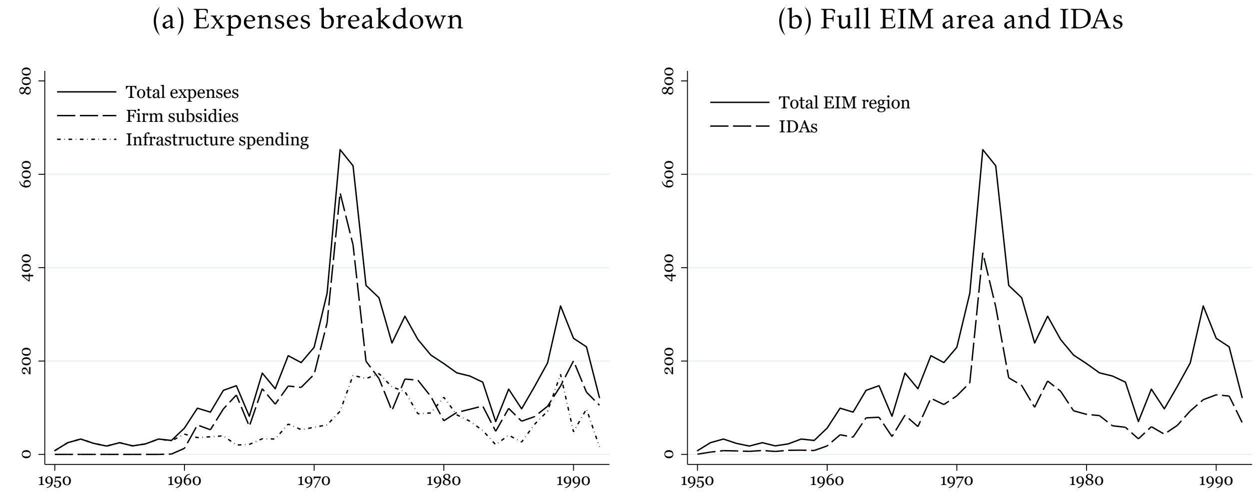
The ASET archives also provide a list of the IDAs, along with all the included municipalities, which we digitize and plot in Figure 2. A total of 14 IDAs comprising 328 municipalities have been established throughout Southern Italy during the 1960s. These are indicated on the map by the yellow regions surrounding the brown IDA centers. 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 (these differences do not change much if excluding IDA centers). IDA municipalities absorbed more than half of the overall EIM expenses (cumulative €165 billion), despite covering about one

[9] The ASET (Archives for the Regional Economic Development) project, launched in 2013, was set up to catalogue and preserve the archives and balance sheets of the Cassa.

[10] Law n. 853/1971 boosted the Cassa's spending by raising both the agency's financial endowment and the maximum proportion of firm investment that could be financed by a grant.

[11] We describe the ASET data and provide more detail about the Cassa's interventions in Appendix A.1.

Figure 1. EIM expenses



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

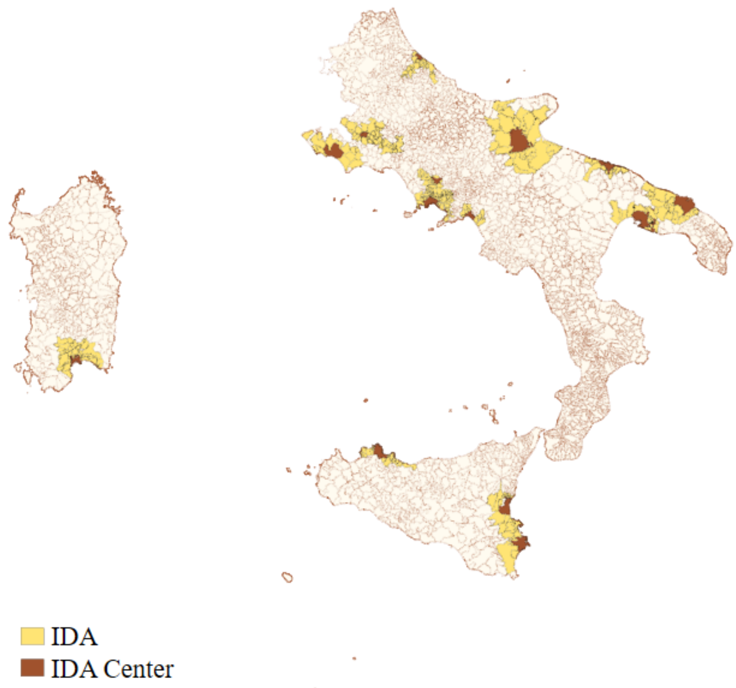
tenth of the surface of the entire EIM region and hosting one third of its population.

Industrial censuses. The main outcome variable of the paper (employment density) is computed using the number of workers per municipality reported in decennial industrial censuses spanning six decades (1951 to 2011, including an intermediate census in 1996), sourced from the Italian statistical institute (Istat). The data allow us to reconstruct employment and establishment counts 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 prior to the policy, which is essential for identification purposes.[12] We thus reconstruct the evolution of employment (and the number of establishments) across municipalities long before the start of the EIM by manually 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 detailed

[12]While the EIM was inaugurated in 1950, actual intervention 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



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.

information on firm employment counts, 6-digit sector, location, workforce composition and average wage paid. Importantly, the granular sector-level information will allow us to distinguish manufacturing activities by technological intensity and service activities by knowledge 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. Importantly, we collapse this 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 describe this data source more in 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 geographical 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 (OMI) at the Italian Tax Office (house prices) and AIDA PA (municipality balance sheets and spending information).

4 Identification strategy

The selective nature of PBIPs such as the IDAs makes identification of causal effects challenging. The locations targeted by these programs are not randomly picked but tend to differ from other areas in many dimensions, potentially unobserved and likely correlated with future economic outcomes. IDA municipalities were positively selected, as their choice was explicitly informed by their agglomeration potential. As a necessary condition for eligibility, the government imposed that the candidate area showed a "*propensity for industrial concentration*" (Ministerial Circular n. 21354/1959). Many years before the start of the program, IDA municipalities featured a larger density of workers and establishments relative to other EIM municipalities (Table 1). They were also more densely populated, their residents were more educated and less likely to work in agriculture, and their geography was more suited to industrialization.

These traits make IDA municipalities uncomparable to other municipalities in Southern Italy. Performing a causal evaluation of the IDA program 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 large city (a provincial capital) and then included municipalities in its surroundings up to a minimum population threshold.[13] 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.

The government imposition that all municipalities bordering the center be automatically included in the IDA can be exploited for identification. The outer boundaries of the con-

[13]The consortium could add more municipalities not farther than 25 km from the IDA center, a limit set by the government to avoid the mechanic inclusion of municipalities until the population requirements were met. This limit was by and large respected, and 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

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.

tiguous municipalities trace a "minimum" IDA border $\mathcal{J}$ that separates two regions within ($\mathbb{W}$) and outside ($\mathbb{O}$) this boundary. Figure 3 Panel a) provides an illustration. 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.

Negative values of the distance δ_m are assigned to municipalities in region $\mathbb{W}$, that is, the IDA centers and its bordering neighbors. To identify these municipalities, we define the binary instrument $W_m = \mathbb{1}[\ell_m \in \mathbb{W}] = \mathbb{1}[\delta_m \leq 0]$. Let also IDA_m be a treatment indicator taking value of one if municipality m belongs to any of the 14 IDAs. To the extent that the probability of belonging to an IDA changes discontinuously at the cutoff $\mathcal{J}$, the distance metric δ_m can be used as running variable in a fuzzy RD setting where IDA_m is the treatment variable 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 pose restrictions on the choice of the bandwidth. Within the minimum IDA border, there are only 14 IDA centers and 137 bordering municipalities. The limited sample size requires picking a bandwidth wide enough to include all these municipalities, equivalent to 16 km. We then adopt a symmetric bandwidth of 16 km outside of the minimum IDA border, although results are robust to the choice of different bandwidths, as showed later.

This identification strategy rests on three main assumptions:

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

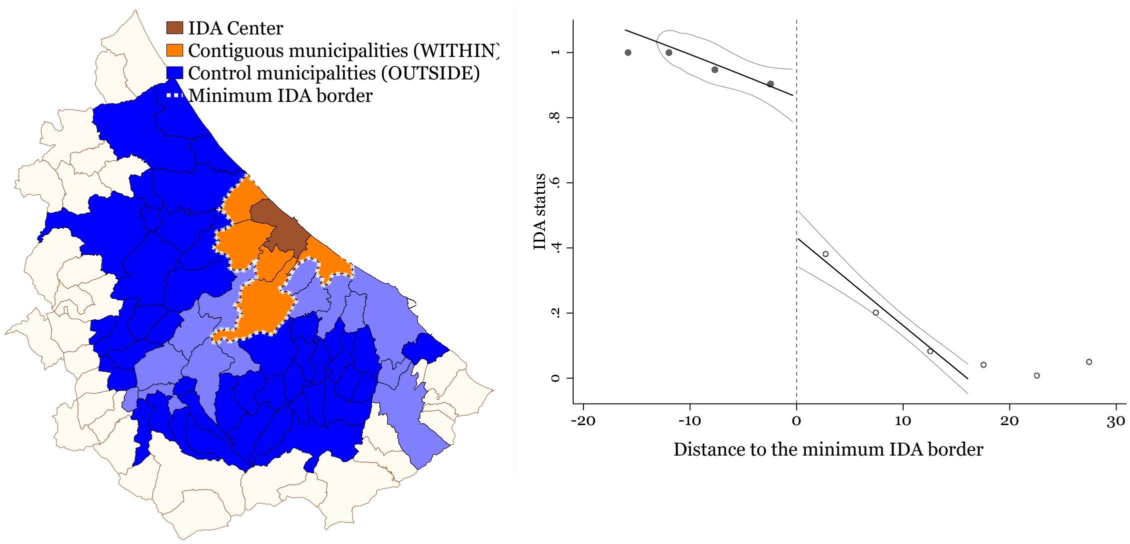
Assumption A1 essentially requires that there is a first stage. To illustrate the idea, Figure 3 Panel b) plots the probability that municipality m belongs to an IDA as a function of the running variable (distance to the minimum IDA border), $Pr(IDA_m = 1 \mid \delta_m)$.[14] A neat drop in IDA status is detected at the boundary, which provides graphical evidence in favor of Assumption A1. IDA status is very close to one within the RD cutoff and drops to about 50 percentage points right outside of it.[15]

[14] 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 do not change when these two IDAs are included.

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

Figure 3. The minimum IDA border

(a) Illustration (b) IDAs – First stage



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 15 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.

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.

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

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

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 $Y_m = Y_m(0) + IDA_m \cdot (Y_m(1) - Y_m(0))$. Assumption A2 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 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 most likely satisfied in our analysis. 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 no 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.

Appendix Figure B1.1 shows RD plots for many other pre-determined covariates and confirms 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.[16] To address concerns about unobserved confounders jumping at 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.

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. Assumption A3 requires that there is no municipality that would belong to an IDA if and only if it was not contiguous to the IDA center. 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 ($IDA_m(\delta_m) = W_m$).

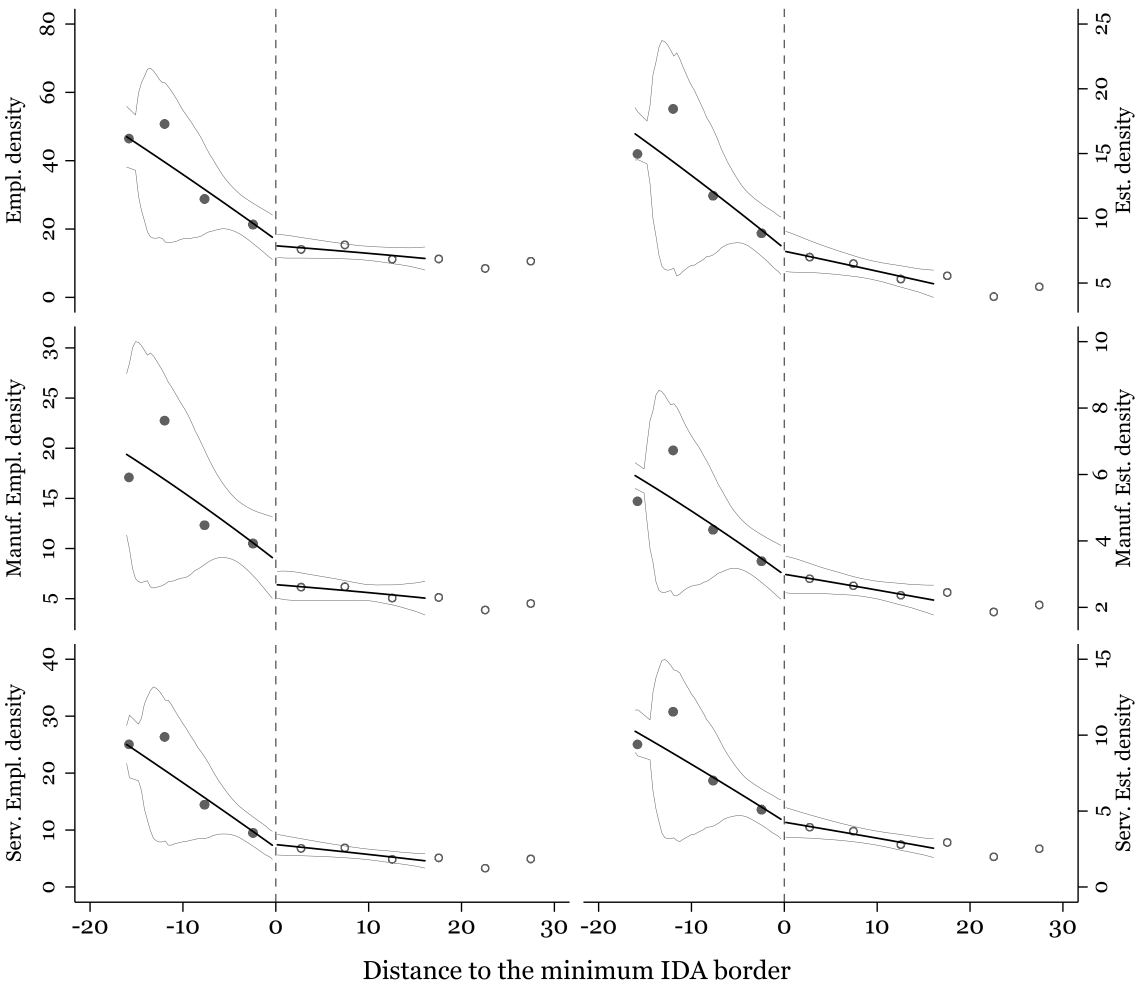
Proposition 1. *Under A1, A2 and A3 the fuzzy RD estimand $\beta = \pi/\vartheta$ identifies the local average treatment effect (LATE) for the sub-population of compliers.*

Proof. See Appendix B.2.

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) spanning one century. This allows us to 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:

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

Figure 4. Balancing at the minimum IDA border, 1951



Number of workers and establishments are 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.

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

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 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.[17]

Other identification strategies. The paper leverages two more designs. First, we will again exploit the contiguity rule and focus on provincial capitals in the Center-North of Italy, which would have most likely been candidate IDA centers had they been part of the EIM region. In turn, municipalities bordering these cities can be used as an alternative control group in an event-study design. This source of variation will also be used to estimate the displacement effects of the IDA program, and will inspire a triple differences approach (Appendix B.3). Second, we will compare our main results to those derived from a spatial RD design at the border separating the EIM jurisdiction from the rest of Italy (Appendix B.4).

5 Results

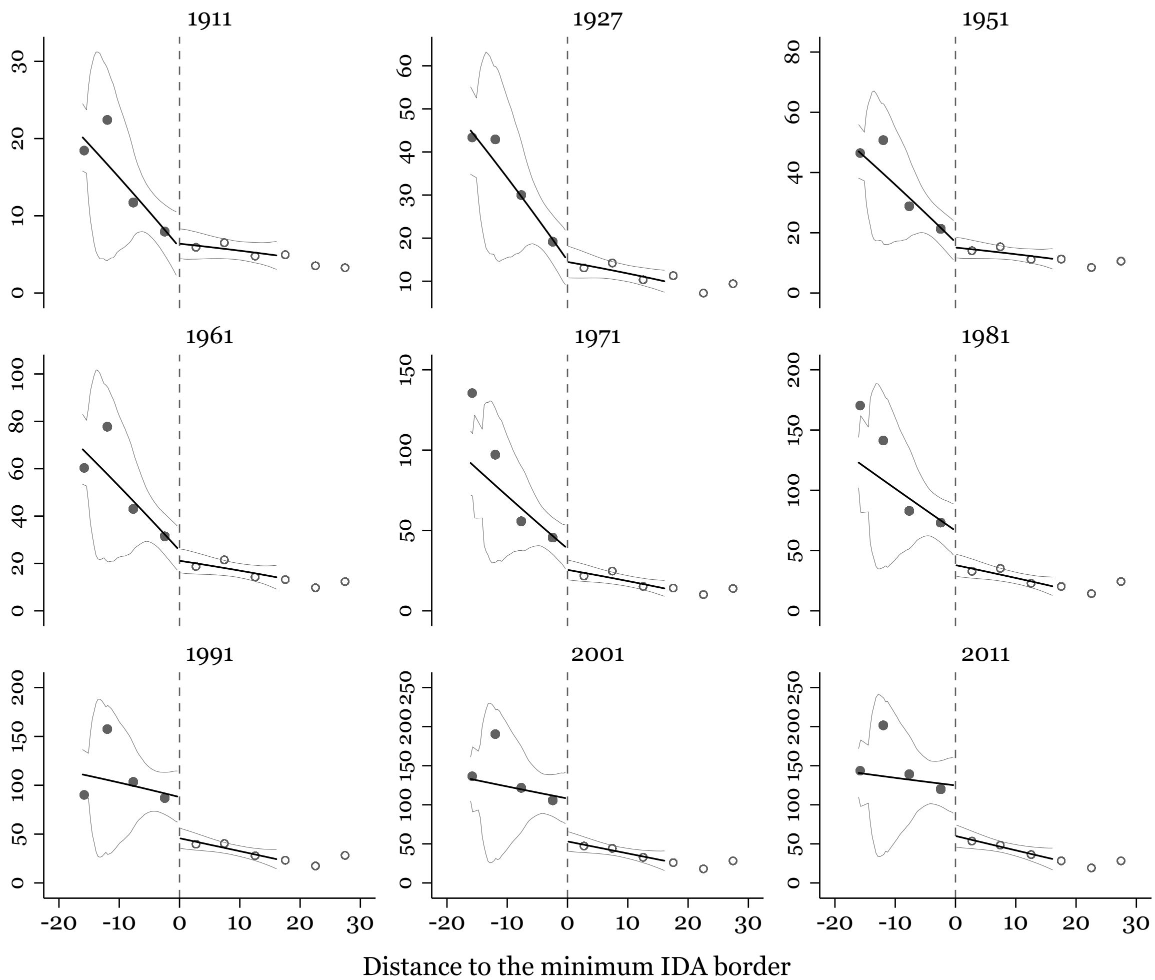
How has the IDA policy affected local employment? Viewed through the lens of a simple model of spatial equilibrium, which we develop in Appendix C.1, a place-based policy that alters the relative cost of capital across locations is expected to shift up the (relative) labor demand curve and, in turn, raise employment in the targeted area.[18] 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 above) but also in the previ-

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

[18] The same effect would arise in response to other IDA measures, such as infrastructure works and training classes for workers, that would raise local productivity (Kline and Moretti, 2014b).

Figure 5. Employment density



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.

ous decades (1911 and 1927), which lends more evidence in favor of 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 C2.1.

Baseline estimates. Table 3 shows the baseline regression estimates for employment density separately for 1991 (right 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). Column (2) reports the 2-SLS estimates for the LATE, which is estimated at 111 workers per km^2 in 1991 and 161 workers per km^2 in 2011. Column (3) replaces IDA status with EIM funding per municipality resident (as of 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 weak first stage.

Robustness tests. The baseline estimates are robust to several checks, presented in the Appendix. Table C2.2 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 moderately 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 C2.3 and C2.4 show that results are robust when allowing for spatial correlation in standard errors (Conley, 1999), or conducting local randomization inference (Cattaneo et al., 2016). Table C2.5 shows that results do not change if including two IDAs (Napoli and Caserta), which are excluded in the baseline analysis because of the short distance (about 25 km) between the two centers. Figure C2.2 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 C2.6 presents non-parametric estimates obtained through the algorithm proposed in Calonico et al. (2014).

[19] Appendix Table C2.1 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.

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

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

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 is allowed to differ within and outside of the cutoff. This procedure delivers indeed quite a narrow bandwidth within the cutoff (6-7 km), effectively 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 C2.3 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 instructive as it helps assessing whether the baseline estimates incorporate spatial spillovers. It is indeed possible that the positive effects we find 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. The effect does decline 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 (as already clear from the RD plots in Figure 5).

In fact, the strong persistence we observe could hardly originate solely from displacement of economic activity. While spatial spillovers should be expected during the policy years, they should not be large (as control municipalities still had access to EIM subsidies) and are unlikely to persist in the very long run.[20] We confirm these points below, using a control group located far away from treated units – in fact, outside of the EIM area.

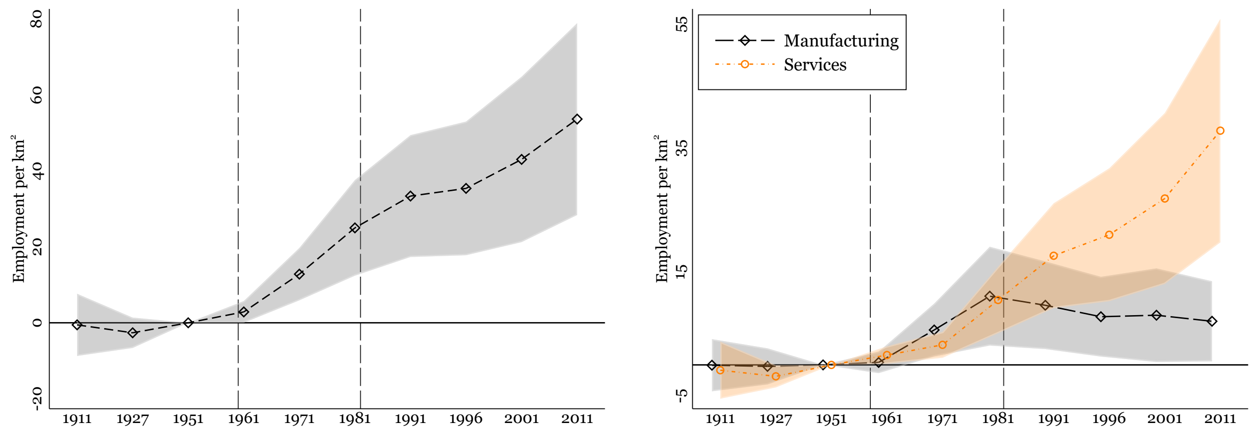
Difference-in-discontinuities. Figure 6 Panel (a) shows our most robust estimates – the ρ_j coefficients of the Diff-in-Disc design in Equation 2. First, we find evidence in favor of parallel trends, as there is no difference in employment density between treated and control municipalities in 1911 and 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 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.

Manufacturing versus services. How does this stark persistence originate? To better inspect our results, we decompose employment density between manufacturing and services and show the corresponding coefficient estimates in Figure 6 Panel (b). The rising agglomeration during the policy years is driven in large part 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

[20] Data available from 1991 onwards show that migration and relocation rates did not differ significantly at the cutoff (Table C2.7), though we observe higher resident population in 1991 and 2011 (Table C2.8). The (reduced-form) effect on population density hovers around 40 percent, not far from the 50 percent effect on employment density (which reflects the municipality of work). This suggests that our results are not driven by commuting of workers into treated areas. Last, Table C2.9 shows that the employment effect of the policy came, at least in part, from increasing aggregate employment in treated areas, as the employment rate and labor market participation rose and the unemployment rate decreased during the 1970s and 1980s.

Figure 6. Difference-in-discontinuities

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



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.

EIM see a substantial increase in agglomeration in the services sector, which is at the basis of the persistent effect of the policy.[21]

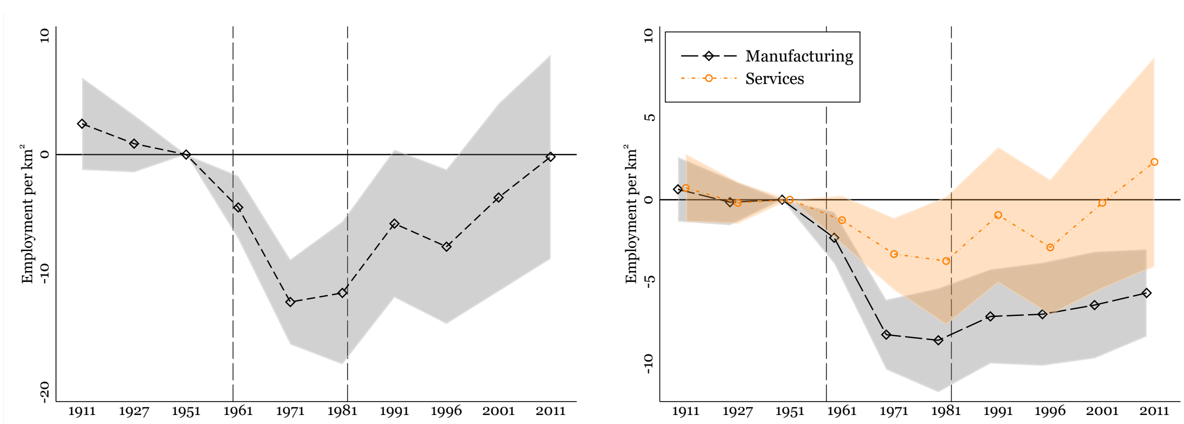
Alternative identification. We now conduct an additional analysis again exploiting the contiguity rule. We consider provincial capitals in the Center-North of Italy, which would have likely been IDA centers had they been part of the EIM region (to ease exposition, we refer to them as "placebo centers"; see Appendix B.3 for details). We leverage this source of variation in three ways. First, 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 C2.9 and C2.10. 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 is useful for two main reasons. 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.

[21] Figure C2.4 reports the Diff-in-Disc results for firm density. Figures C2.5-C2.8 and Table C2.10 show the RD plots and the cross-sectional fuzzy RD estimates separately by manufacturing and services.

Estimating spatial spillovers. This design allows us to go one step further and directly estimate spatial spillovers. In a second exercise, we run the same event study as above but use 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 consider their counterpart: 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 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 a shift of economic activity around the cutoff. These displacement effects are largely concentrated in manufacturing, and are instead barely noticeable in the non-targeted services sector. Most importantly, they tend to disappear in the long term. In 2011, we observe no spillover of the IDA policy to nearby areas. The persistent effect of PBIP is therefore not driven by continued displacement of economic activity.[22]

Figure 7. Estimating the spatial spillovers of the IDA program

(a) Employment density (b) Manufacturing versus services



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.

[22]The results for firm density are similar, and showed in Figure C2.11.

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 baseline Diff-in-Disc of Equation 2. We show the estimates in Appendix Figures C2.12 and C2.13. Although less precisely estimated, most likely as a result of the more demanding specification, the event study coefficients are very similar to those in the main findings at around 50 workers per km^2 in 2011.

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 lesser 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 effects on services employment should occur mostly in non-tradables such as retail and hospitality. The (relative) slow stabilization in manufacturing employment, likely due to the end of subsidies and also reflecting the structural decline of industry starting in the 1980s, implies that multiplier effects cannot fully explain the continued response in services.

Instead, the enduring growth of the services sector after the end of PBIP is in line 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.

Non-tradables versus KIS. We now test the above predictions by decomposing the effect on services. As noted, the contemporaneous 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.[23]

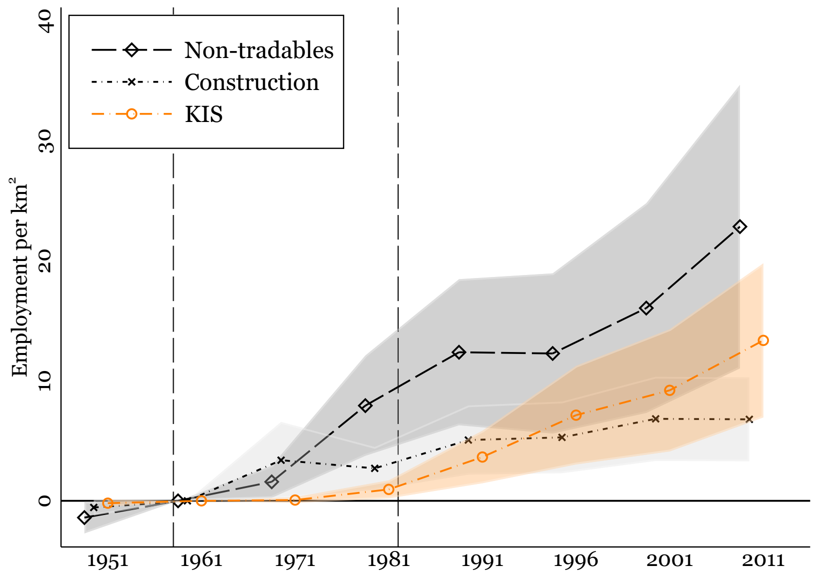
As noted above, these pecuniary externalities can account for the contemporaneous rise in services but cannot by themselves explain our persistent effects. Assuming a multiplier of one also after 1981, higher manufacturing employment in treated areas after the end of the policy would account for 50 percent of the increase in services employment in 1991 and 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.[24] To zoom into these developments we 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 for details). We replicate the baseline municipality-level fuzzy RD design and show results in Table D1, which reports coefficient estimates separately for the shares of KIS and other services in 1991 and 2011. 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.

[23] 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).

[24] 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 low, at 2-3 workers per km^2. The results for firm density, showed in Appendix Figure D1, are similar. We also observe continued agglomeration in non-tradable services. This result could be driven either by contemporaneous local multiplier effects (from either 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.

Figure 8. Employment density – Sectoral breakdown



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.

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 EIM, 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 pool of specialized, high-skilled workers in the local labor market. Second, by providing demand for business services such as consulting, legal and information technology.[25]

Both channels seem to be at play. Figure D4 plots the share of cumulative KIS hires (job-to-job) from high-technology manufacturing between 1991 and 2011.[26] 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

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

[26] 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.

hard without input-output linkages between firms. 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.

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.[27] The IDA policy also stimulated human capital accumulation and workers' skills 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? 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.[28] For manufacturing and KIS firms, we estimate a positive long-run effect on labor productivity, investment and sales. Manufacturing firms also exhibit higher profits per worker. Finally, Figure D5 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. Precisely identifying the market failure tackled by government policy is challenging, as market failures are rarely observed directly. Our evidence suggests

[27] 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.

[28] 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 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

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

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.[29] Second, sectoral specialization within manufacturing measured with the Krugman Specialization Index (Krugman, 1992) has *decreased* following the policy, suggesting that subsidies did not benefit targeted industries exclusively. Third, we rule out an alternative channel of persistence related to continued public investment in the 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, which was introduced right at the end of the EIM. We find no meaningful discontinuity in any of these

[29] As in Lang et al. (2022), we also find that PBIP has not promoted equality, as evidenced by the higher Gini coefficient. In fact, the policy does not seem to have improved equality not only within municipalities but also between them. Figure D6 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.

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

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

variables, which points to agglomeration economies as the main source of persistence (Garin and Rothbaum, 2022; von Ehrlich and Seidel, 2018).

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 reduced-form 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 taxation of 50 percent.[30] Using the long-run Diff-in-Disc estimate delivers a very 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).[31]

Cost-benefit analysis. We then move beyond cost-per-job estimates and conduct a back-of-the-envelope analysis of the cost-effectiveness 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 the benefits of the policy, we proceed in five steps: i) for each of the outcomes of interest (wage bill, firm profits and housing rents), we calculate the observed amount each year from 1991 to 2011; 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 that would have obtained 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 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 in the two decades after 1991, with

[30] 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 immigration while they were in place as we find significant differences in current population. We therefore impose a 50 percent deadweight loss as in Criscuolo et al. (2019) and Siegloch et al. (2022).

[31] 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).

most of the benefits accruing to workers (€52 billion) and firms (€33 billion).[32] Total IDA expenses can be directly computed in the ASET data and amount to €88 billion. The gains generated by the 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 example of PBIP? How can these interventions 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 each IDA region is above or below the median of the following six variables: mean elevation, slope, cumulative EIM subsidies per capita, 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. Figure F1 shows the resulting Diff-in-Disc coefficients.

We measure slightly better employment effects in IDAs with more favorable geographical traits and higher share of services at the onset of the policy. The most striking differences occur however when splitting the sample based on the incidence of high-technology manufacturing in 1991 and education levels in 1951. Places where the policy stimulated high-technology industries more, and places with larger initial human capital endowment, are also those where the policy had a larger employment impact in the long term.[33] Still, some persistence in the effect of the IDA policy remains visible across all these heterogeneity cuts. Admittedly, our set-up is not 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 at the EIM border.

[32] 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.

[33] 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.

The EIM border. As summarized in Appendix B.4 and detailed in Albanese et al. (2023), the northern boundary separating the EIM area from the rest of Italy gives rise to a spatial RD design that compares municipalities south of the border, which were subsidized by the Cassa, to municipalities 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).[34] Areas north and south of the border were on parallel trends before the beginning of the policy. A positive effect emerged starting in the 1970s, albeit not statistically significant. The coefficient peaked at the end of the EIM in 1991 but eventually declined, suggesting lack of persistence in the impact of the intervention at the EIM border.

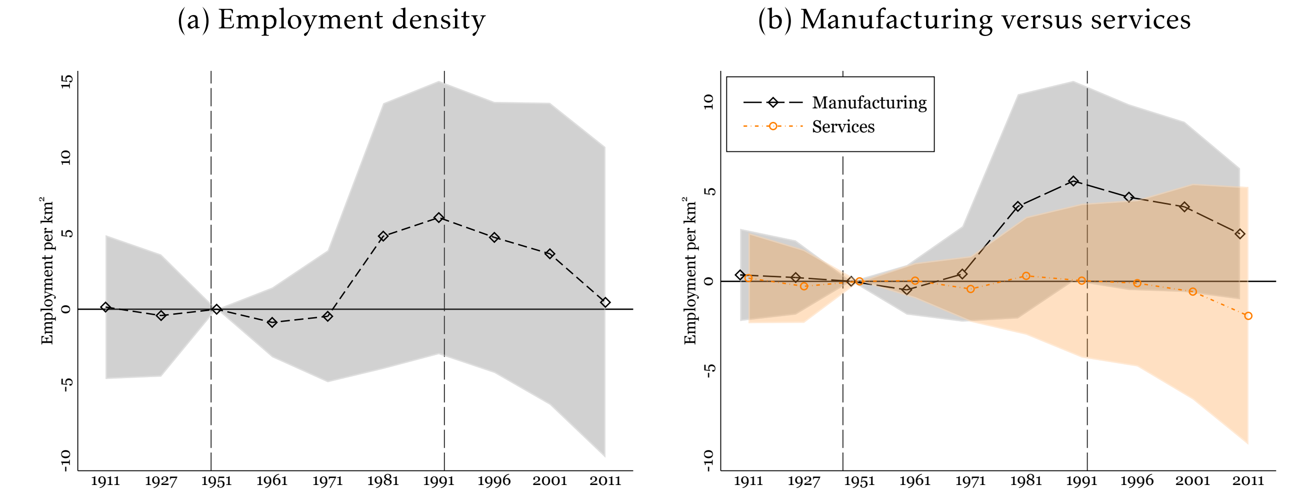
Panel (b) breaks down the effect on employment density into manufacturing and services. Similarly to what was found for IDAs, manufacturing employment rose during the policy years but stabilized as the incentives terminated. However, services did not respond to government subsidies, thus not contributing to long-run agglomeration as instead observed in the case of IDAs. We also observe no effect on firm density (Figure F8).

The results listed in the previous sections tend not to hold at the EIM border (Appendix F). There is no differential incidence of KIS workers and firms south of the border, nor any effect on the share of high-technology manufacturing.[35] Wages are significantly higher south of the border in 1991, but exclusively for manufacturing and other 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 other services and not in KIS (as observed for the IDAs). Last, we find no effects on local incomes and even negative long-run effects on house prices.

[34] We show raw RD plots at the border in Appendix F, Figures F2 to F7. The regression function is smooth in the decades before the EIM, supporting the continuity assumption also in this RD design. A positive discontinuity emerges in the 1970s and then more clearly in the 1980s and 1990s. As the policy ended, however, the jump at the cutoff becomes barely noticeable. We report cross-sectional RD regression estimates for 1991 and 2011 in Appendix Tables F1 and F2.

[35] EIM firm subsidies at the border went disproportionately towards 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



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.

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.[36] 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. 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 as large for IDAs. Places south of the border had instead less favorable geography, a larger share of people employed 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 less suitable to the formation of local clusters. This evidence, albeit 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.[37]

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

[37]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.

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, several 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.

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A Appendix A: 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 Cassa was in charge of planning, execution and monitoring of initiatives in four domains (agriculture, drains and aqueducts, transport and tourism development) subject to the government's allocation of the overall endowment 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 of the infrastructure. Often, both the formulation and execution of the initiatives were performed directly by the Cassa.

Firm 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, importantly, the projected 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. 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.

The ASET data. The ASET archives record detailed 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. 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

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

Raw amounts in € million (2011 prices). Per capita amounts in € (2011 prices) per 1951 inhabitant in the Cassa's region. Amounts computed only from geo-coded interventions available in the ASET database.

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 shows the breakdown of 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 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.

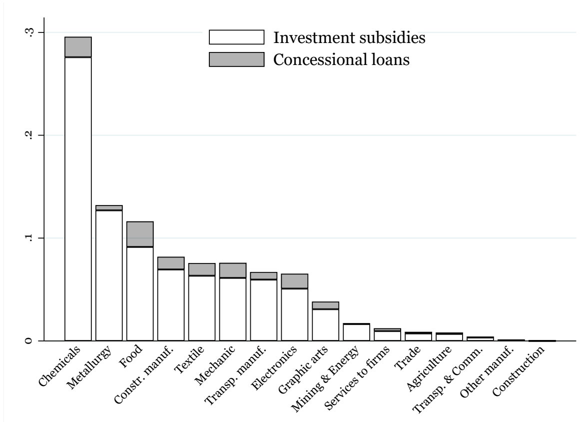
Last, Figure A1.2 plots the spatial distribution of EIM expenses across the roughly 3,000 municipalities in the EIM area, separately by expenditure item. The EIM jurisdiction included ten regions: Abruzzo, Basilicata, Calabria, Campania, Lazio, Marche, Molise, Apulia, Sardinia and Sicily. The territories of all these regions, except for Lazio and Marche, traditionally define the Italian South.[38] While firm subsidies are largely concentrated in the IDAs, infrastructure spending is most pronounced in the internal areas.[39]

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

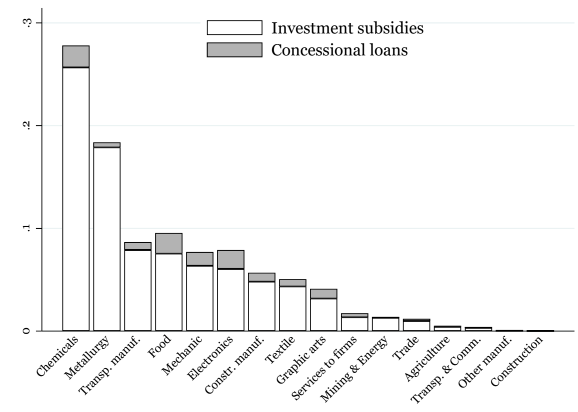
[39] The 14 IDA centers were Latina, Frosinone, Caserta, Napoli, Salerno, Pescara, Foggia, Bari, Taranto, Brindisi, Palermo, Catania, Siracusa and Cagliari. IDAs do not include the so-called *Industrialization Nuclei* – less extensive areas whereby a small number of firms could take advantage of local raw materials and a specialized workforce.

Appendix Figure A1.1. Incentives to firms – breakdown

(a) Full EIM area



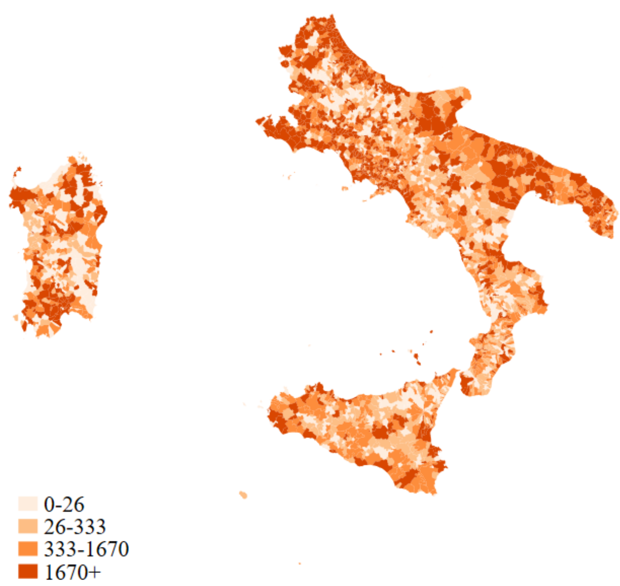
(b) IDAs



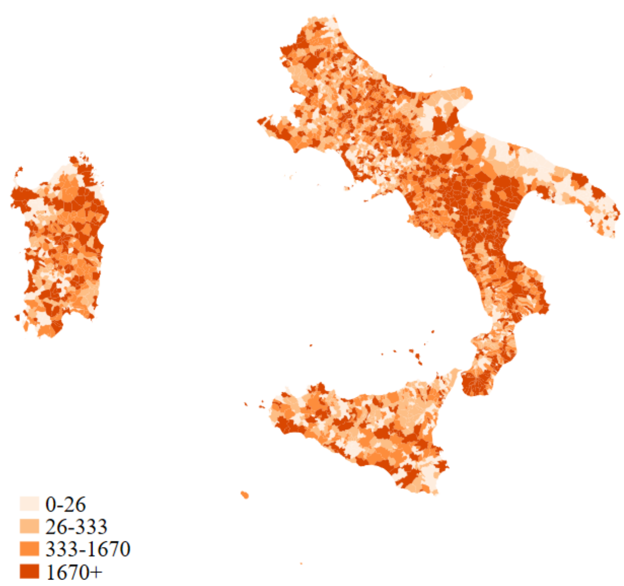
Sector breakdown of firm investment subsidies and concessional loans. Panel (a) includes all EIM municipalities. Panel (b) includes IDAs only.

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

(a) Firm subsidies



(b) Infrastructure expenses



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 manually digitizing the 1911 and 1927 industrial censuses, available only in pdf format at the Istat historical archives. We match post-World War II censuses with the historical censuses using municipality names. To account 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).[40]

We exploit the within-manufacturing sectoral breakdown to compute a measure of sectoral concentration – the Krugman Specialization Index (KSI) – following Krugman (1992):

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

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

[40]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.

advanced regions of the North (Lombardy, Veneto and Piemonte), as well as smaller 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.

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)

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.[41]

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, linked with the identifiers of firms where they work. 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). Through the firm identifiers, we merge the worker- and firm-level administrative data to gather information on the sector of

[41] 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

employment and the municipality where the firm is located.

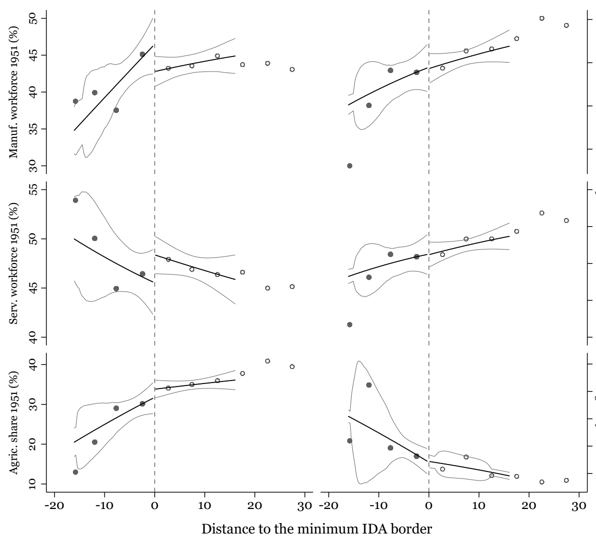
The data record all labor market transitions of workers included in the sample. Therefore, they can be used to compute hiring at the municipality level, as discussed in Section 6 and showed for example in Figure D4. We define hirings in a given year t as the municipality-level sum of non-employment to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

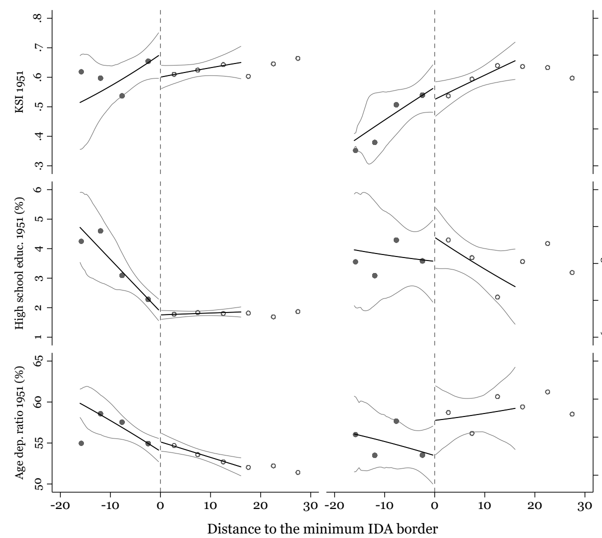
B.1 Appendix B1

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

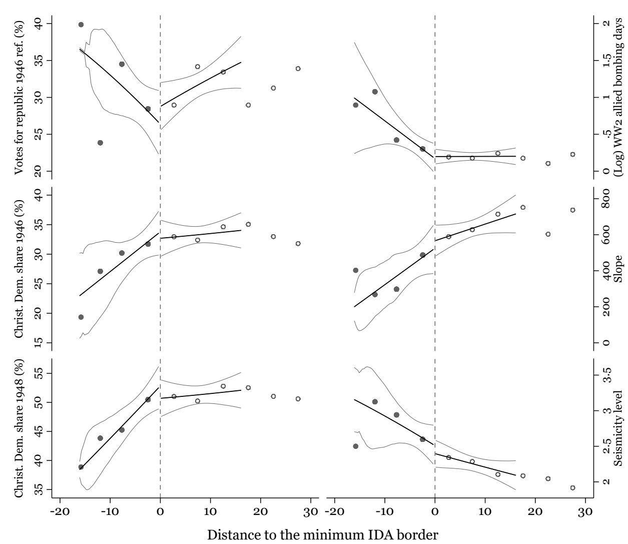
(a)



(b)



(c)



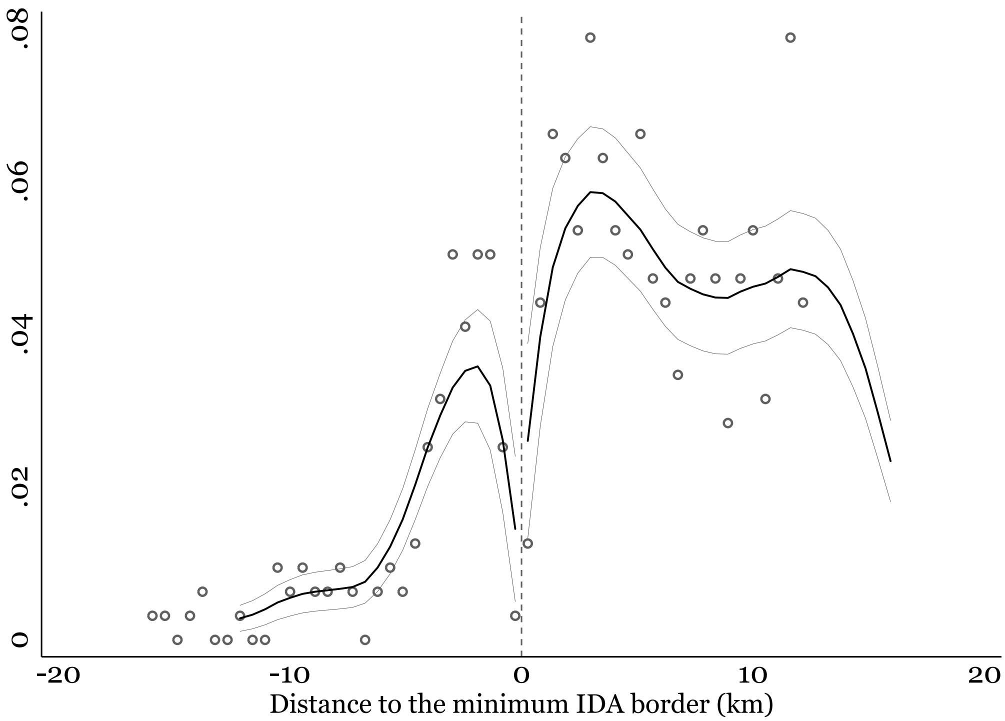
Panel (a): "Manuf. workforce" and "Serv. workforce" are the shares of manufacturing and services workers in the 1951 industrial census. "Agric. share" computed as the number of agriculture workers per 100 residents aged at least 15. "Empl. rate" is the ratio of employed people to total residents aged 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	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

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



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

B.2 Appendix B2

Proof of Proposition 1. 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 (Imbens and Lemieux, 2008; Hahn et al., 2001):

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

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

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:

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

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:

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

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

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 (instead of A2 in the main text) 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.[42] 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.

[42] 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: Alternative identification strategy

In this strategy we again exploit the exogenous imposition that municipalities bordering IDA centers be automatically included in IDAs and compare these with municipalities bordering provincial capitals in the Center-North of Italy, which would have likely been IDA centers if they were part of the program's jurisdiction. To ease exposition, we will refer to provincial capitals in the Center-North 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).

Simple event study. In a first approach, we pool together the 120 municipalities bordering IDA centers (in orange) and the 243 municipalities bordering placebo centers (in grey). 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 empirically verify the parallel trends assumption:

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

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 can also be exploited to investigate possible spillover effects of the IDA policy to the control group in the baseline identification strategy. Specifically, 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.[43]

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. Let W_m be an indicator denoting municipalities border-

[43] 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).

ing either IDA centers or placebo centers (the union of the orange and grey municipalities). 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:

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

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:

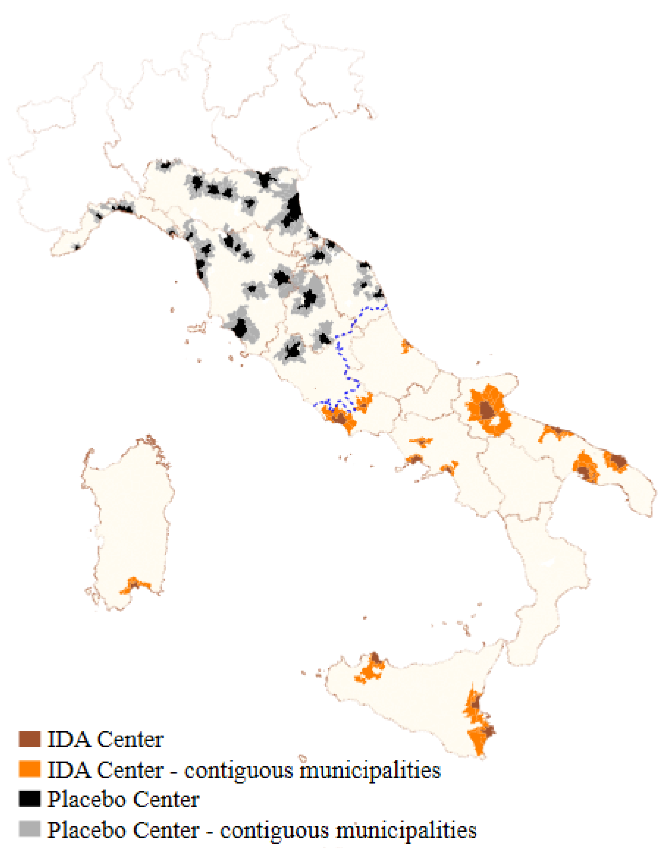
$$\rho = \underbrace{\{(E[Y_m \mid T_m = 1,\ W_m = 1,\ P = 1] - E[Y_m \mid T_m = 1, W_m = 1,\ P = 0]) - (E[Y_m \mid T_m = 0,\ W_m = 1,\ P = 1] - E[Y_m \mid T_m = 0, W_m = 1,\ P = 0])\}}_{\text{"Within" effect}}$$

$$-$$

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

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



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.[44] 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. Panel (b) of Figure B4.1 plots Cassa's expenses around the border, clearly showing a stark jump equivalent to roughly 15,000 euros per capita.[45]

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, lending further credibility to this strategy.

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

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

[45] 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.

the EIM border.[46] 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 when considering in the proof of Appendix B.2 that a sharp RD design is a special case of fuzzy RD with perfect compliance: $\lim_{\iota_m \to 0^-} Pr(B_m = 1 \mid \iota_m) - \lim_{\iota_m \to 0^+} Pr(B_m = 1 \mid \iota_m) = 1$.

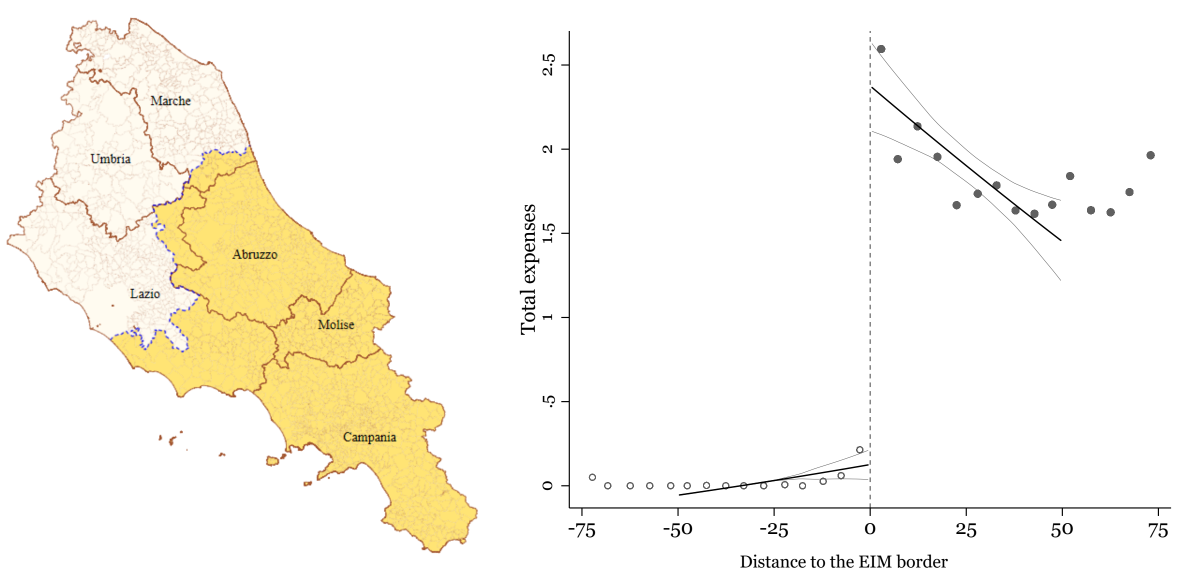
To further improve on internal validity, we can again specify a dynamic version of Equation B4.1 in the form of a Diff-in-Disc design:

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

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



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.

[46] 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.

C Appendix C

C.1 Appendix C1: Theory

We sketch here a simple spatial equilibrium model drawing on Kline (2010) and Kline and Moretti (2014b). The model describes the direct effect on employment of a place-based policy that changes the relative cost of capital across locations. We consider two cities indexed by $j \in \{A, B\}$ and workers making location decisions.

Workers. There is a continuum of workers (each indexed by i) of measure one. Location decisions between the two cities are free. Each worker inelastically supplies one unit of labor (every worker is employed) and demands one unit of housing. For worker i, the utility of locating in city j is:

$$u_{ij} = w_j - r_j + A_j + \epsilon_{ij} = \bar{u}_j + \epsilon_{ij} \tag{C1.1}$$

where w_j is the local wage, r_j is the rental rate of housing, A_j are amenities in city j and the (mean zero) error term ϵ_{ij} denotes worker i's preferences for city j.[47] The systematic component $\bar{u}_j$ denotes utility of residence in city j that is independent of a worker's idiosyncratic taste. Worker i locates in city A (and not in city B) if $u_{iA} \geq u_{iB}$, or $\epsilon_{iB} - \epsilon_{iA} \leq \bar{u}_A - \bar{u}_B$. The measure of workers locating in city A is thus:

$$L_A = G(\bar{u}_A - \bar{u}_B) \tag{C1.2}$$

where $G(\cdot)$ is the cdf of $\epsilon_{iB} - \epsilon_{iA}$.

Firms. Firms produce a single good Y with a constant returns to scale Cobb Douglas production function $Y_j = X_j L_j^{\alpha} K_j^{1-\alpha}$, where L_j and K_j denote production inputs (labor and capital) and X_j denotes productivity in city j. Firms sell their product on the international market at price one and make zero profits. The marginal cost of capital ρ is constant across cities, but each city applies a capital subsidy τ_j. Firms choose inputs to equate marginal revenue

[47] Because there are no barriers to worker movement, without idiosyncratic tastes for location workers will be perfectly mobile and any benefit of place-based subsidies will capitalize into housing rents (Bartik, 2020).

products to marginal costs:

$$w_j = \alpha \frac{Y_j}{L_j}; \qquad\qquad \rho(1-\tau_j) = (1-\alpha)\frac{Y_j}{K_j};$$

Combining these leads to the inverse local demand equation:

$$\ln w_j = M + \frac{1}{\alpha}\ln\ X_j - \frac{1-\alpha}{\alpha}\ln\ \rho(1-\tau_j) \tag{C1.3}$$

where $M \equiv \ln\alpha + \frac{(1-\alpha)}{\alpha}\ln(1-\alpha)$ is a constant term. Labor demand is flat in wage-employment space and wages in city j depend positively on local productivity and negatively on the local cost of capital.

Housing market. The marginal cost of producing an additional unit of housing is denoted by $r_j = r(L_j)$, with $r(\cdot)$ increasing in local population due to the fixed availability of land.

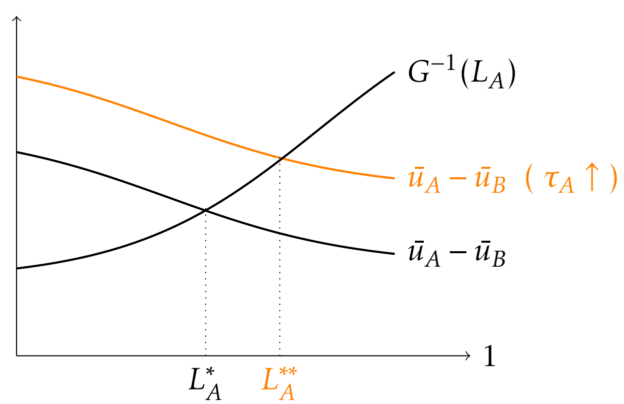
Equilibrium. Combining C1.2 with C1.3 and the housing supply equation leads to the equilibrium condition:

$$G^{-1}(L_A) = \frac{e^M}{\rho^{\frac{(1-\alpha)}{\alpha}}}\left[\frac{X_A^{\frac{1}{\alpha}}}{(1-\tau_A)^{\frac{(1-\alpha)}{\alpha}}} - \frac{X_B^{\frac{1}{\alpha}}}{(1-\tau_B)^{\frac{(1-\alpha)}{\alpha}}}\right] + A_A - A_B - (r(L_A) - r(1-L_A)) \tag{C1.4}$$

The left-hand side can be interpreted as a relative supply curve to city A, defining the taste of a marginal worker for city B relative to city A. As L_A rises, the relative taste for city B increases and the curve slopes up. The right-hand side is instead the relative demand curve (the difference in real wages across the two cities minus the difference in amenities). As L_A rises, real wages in city A decrease relative to city B and the willingness to pay to work in A goes down. At equilibrium, the marginal worker is indifferent between the two cities. Figure C1.1 shows the two curves in black and depicts the model's equilibrium city size L_A^*.

The effect of PBIP. Consider now a place-based subsidy that alters the relative cost of capital across the two cities by increasing the capital subsidy in city A. From C1.3, we obtain that an increase in τ_A raises the wage paid in city A by $dw_A/d\tau_A = w_A(1-\alpha)/\alpha(1-\tau_A)$. The policy pushes the relative demand curve up (the orange line in Figure C1.1) and leads to a larger equilibrium share of workers in city A, L_A^{**}. A similar conclusion obtains if the policy increases local productivity X_A, through for example investment in infrastructure.[48] Notably, the model imposes that any increase in employment in city A occurs through out-migration from city B. In the data, we test whether the policy had any effect on local labor market participation and unemployment. In the presence of agglomeration economies in production, $X_j = X(L_j)$, the relative demand curve might become upward sloping in some segments and multiple equilibria arise. In this setting, large enough government intervention might push the economy in a developed equilibrium in the long run (Kline, 2010).

Appendix Figure C1.1. The employment effects of PBIP

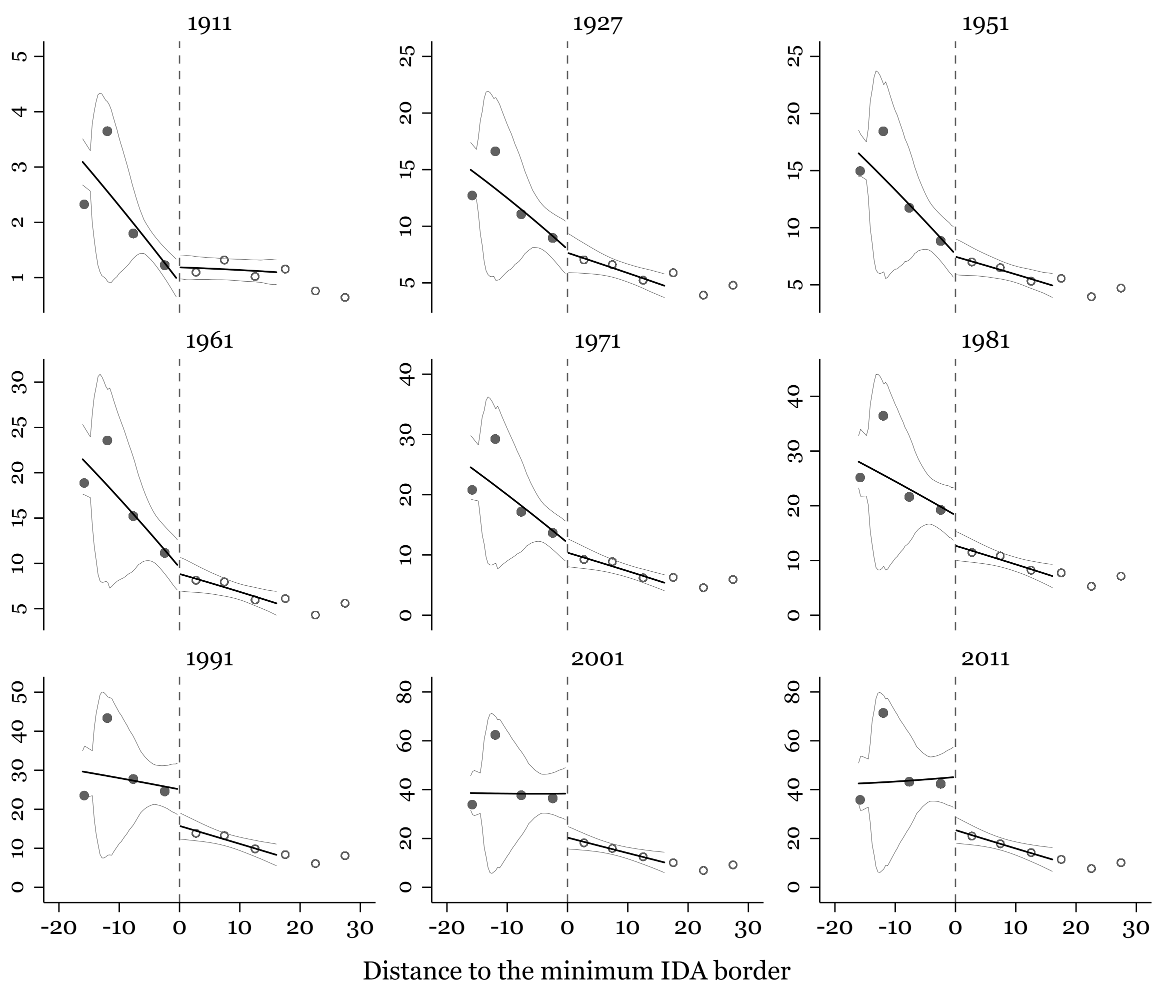


The graph shows the spatial equilibrium of the model described in Appendix C.1. The black demand and supply curves denote the initial equilibrium. The orange demand curve is the one resulting from an increase in the capital subsidy in city A. See Kline (2010), Kline and Moretti (2014b) and text for details.

[48]Here we do not make any parametric assumption on the shape of the $G(\cdot)$ and $r(\cdot)$ functions and we do not explicitly derive the effects on employment. These would depend on workers' preferences for location, which determine worker mobility, and on the local elasticity of housing supply. See Kline and Moretti (2014b) for a more detailed analysis.

C.2 Appendix C2: Results

Appendix Figure C2.1. Establishment density



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 C2.1. 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

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 C2.2. 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

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 C2.3. Employment and establishment density – Conley standard errors

	Employment per km^2 1991	Employment per km^2 2011	Establishments per km^2 1991	Establishments per km^2 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

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 C2.4. 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

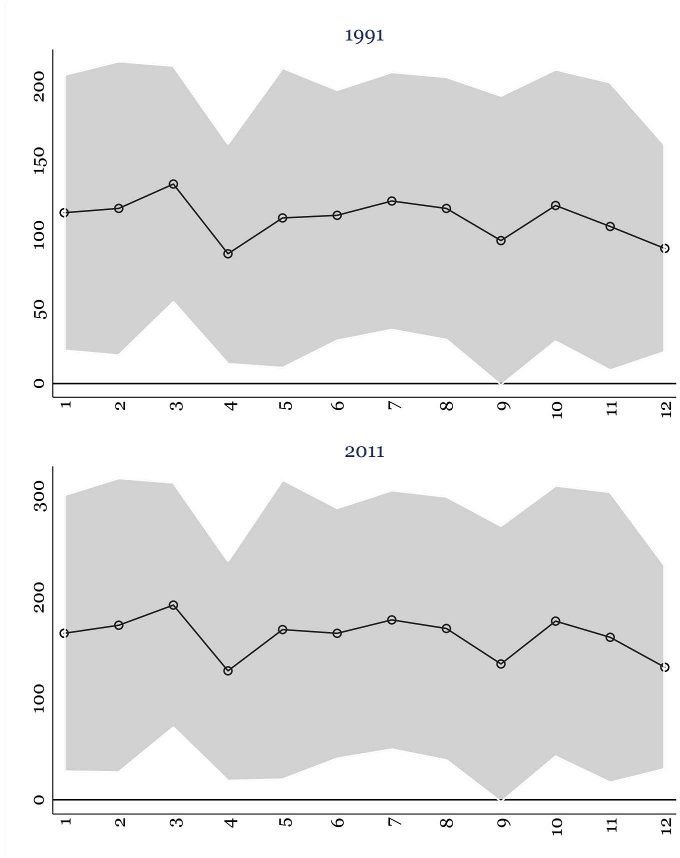
Estimation output for the fuzzy RD desing using local randomization inference as proposed in Cattaneo et al. (2016), with 1,000 replications, uniform kernel and without specifying a polynomial for the outcome transformation model – see the *rdrandinf* command in Cattaneo et al. (2016). The window-selection 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 C2.5. 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

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 C2.2. Employment density – Exclude individual IDAs



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.

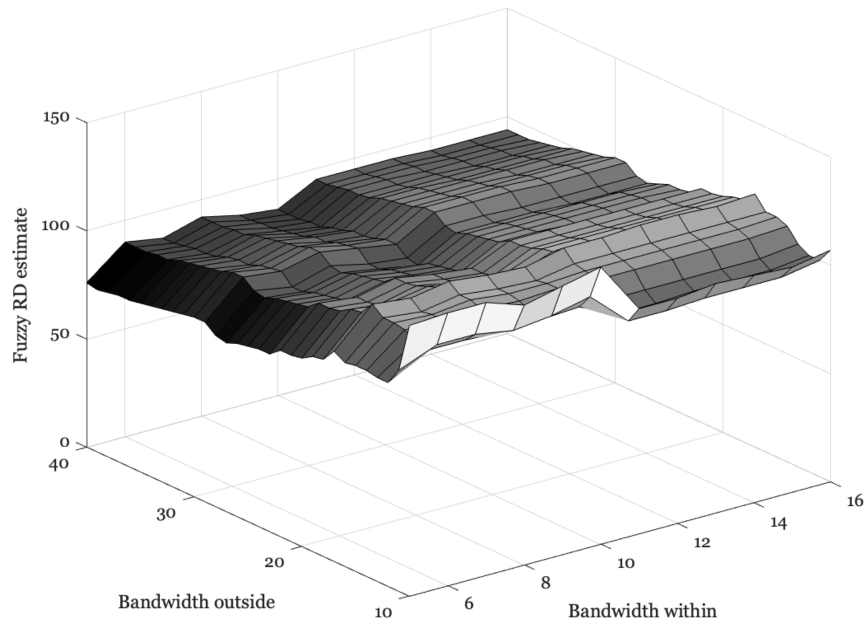
Appendix Table C2.6. Employment density – Non-parametric fuzzy RD estimates

	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

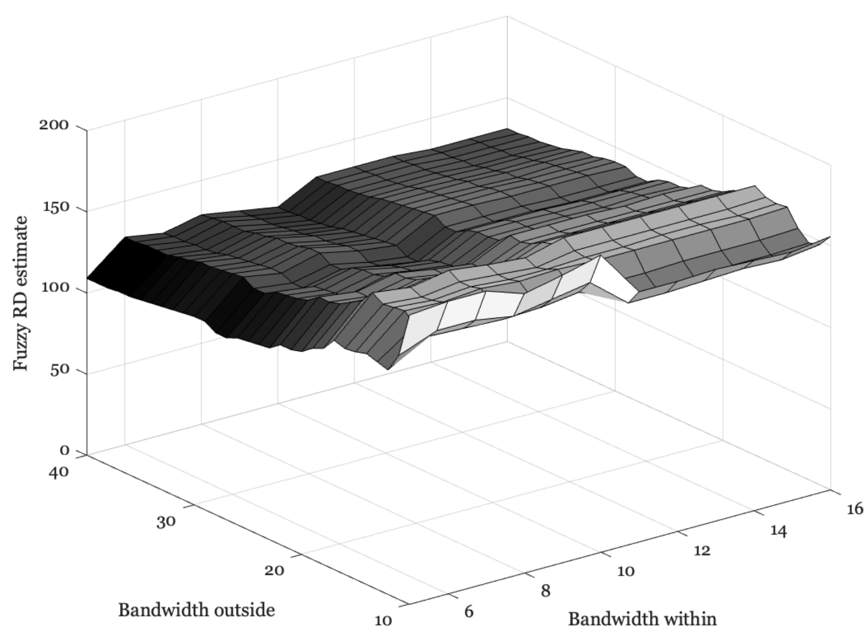
Fuzzy RD estimates obtained using the non-parametric estimation and robust bias-corrected inference method proposed by Calonico et al. (2014). The optimal bandwidth is computed by minimizing the Mean Squared Error separately left and right of the cutoff. Observations are weighted using a triangular kernel. 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 C2.3. Employment density – robustness to bandwidth choice

(a) 1991



(b) 2011



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

Appendix Table C2.7. 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

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 C2.8. (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

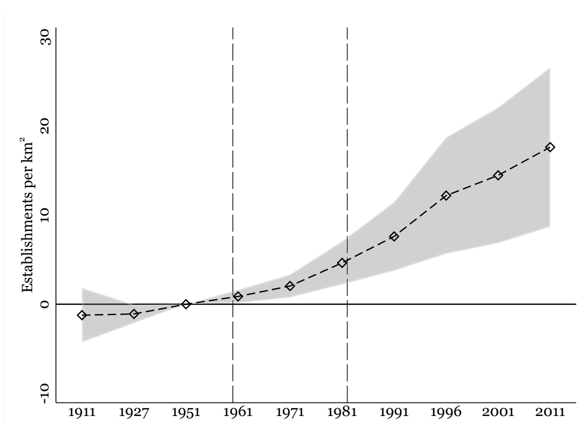
Replication of Table 3, Columns (1)-(2). Outcomes defined as the logarithm of the number of workers per km^2 and of the number of residents per km^2. Standard errors clustered by IDA region in parentheses. See text for details. * p<0.10, ** p<0.05, *** p<0.01

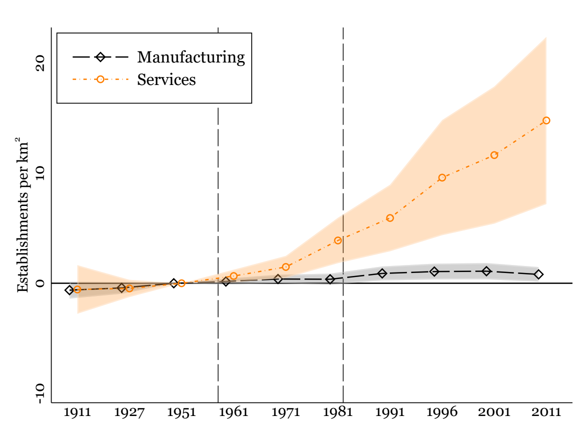
Appendix Table C2.9. Employment and participation rate – Fuzzy RD estimates

	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

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

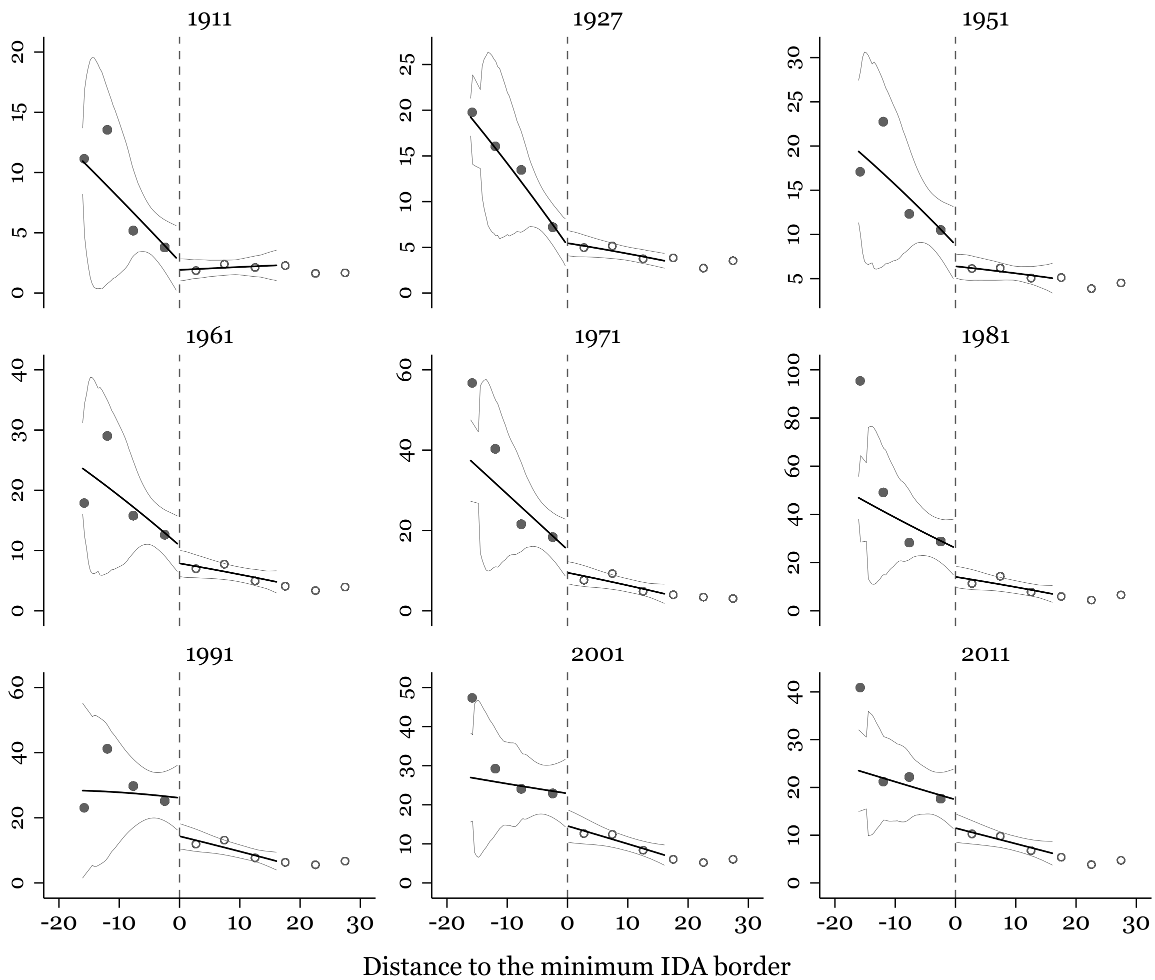
Appendix Figure C2.4. Establishment density – Diff-in-Disc





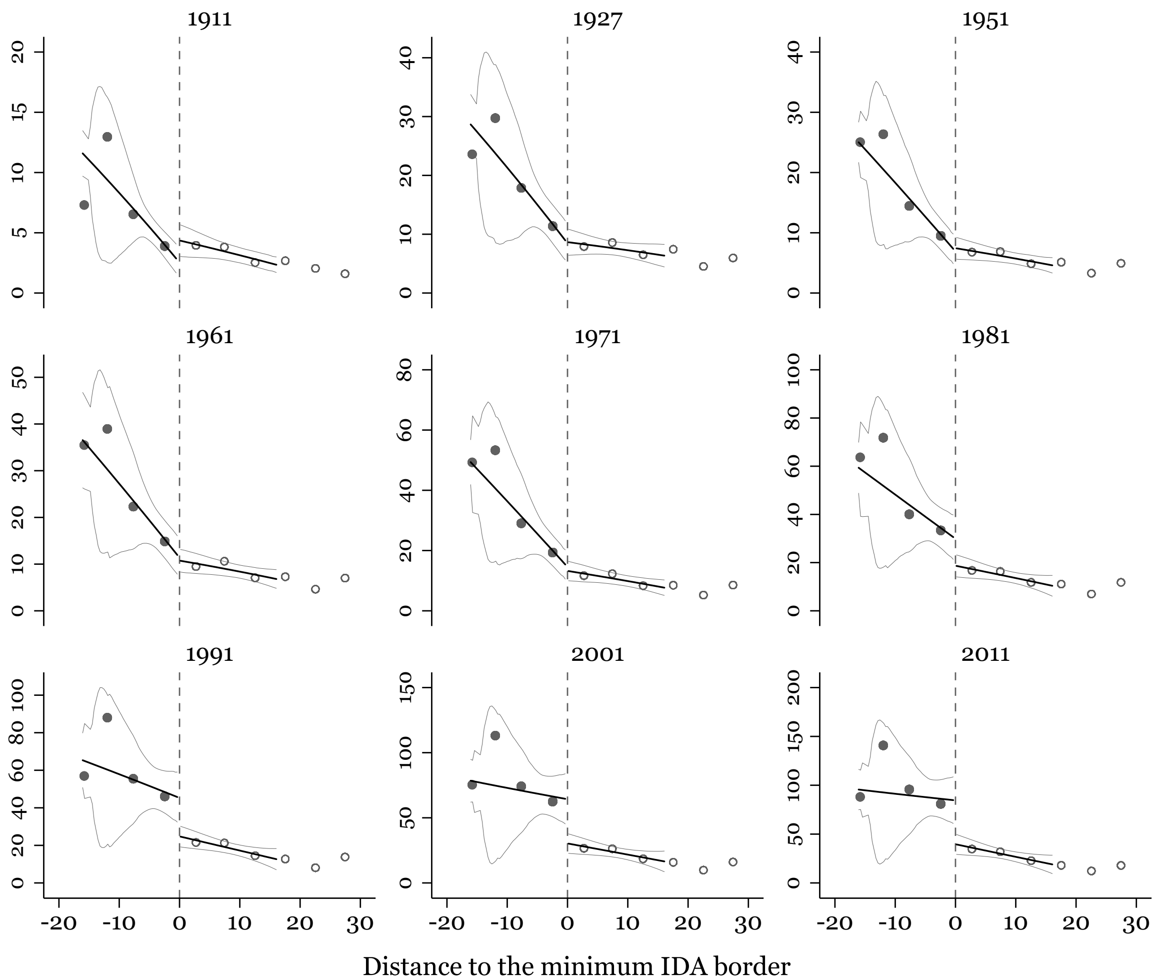
Coefficient estimates for Equation 2. Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the IDAs. See text for details.

Appendix Figure C2.5. Manufacturing employment density



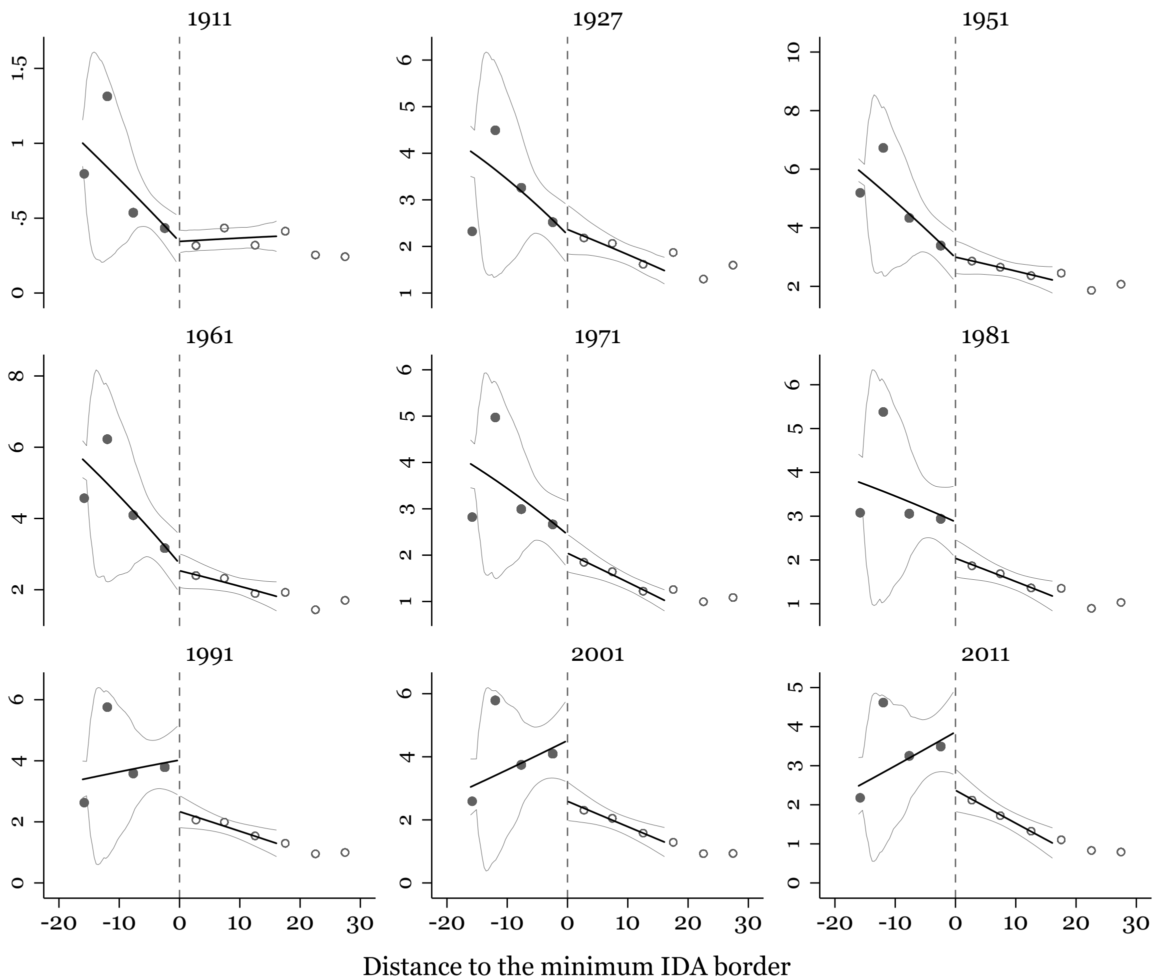
Negative distance denotes municipalities within the minimum IDA border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately at either side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

Appendix Figure C2.6. Services employment density



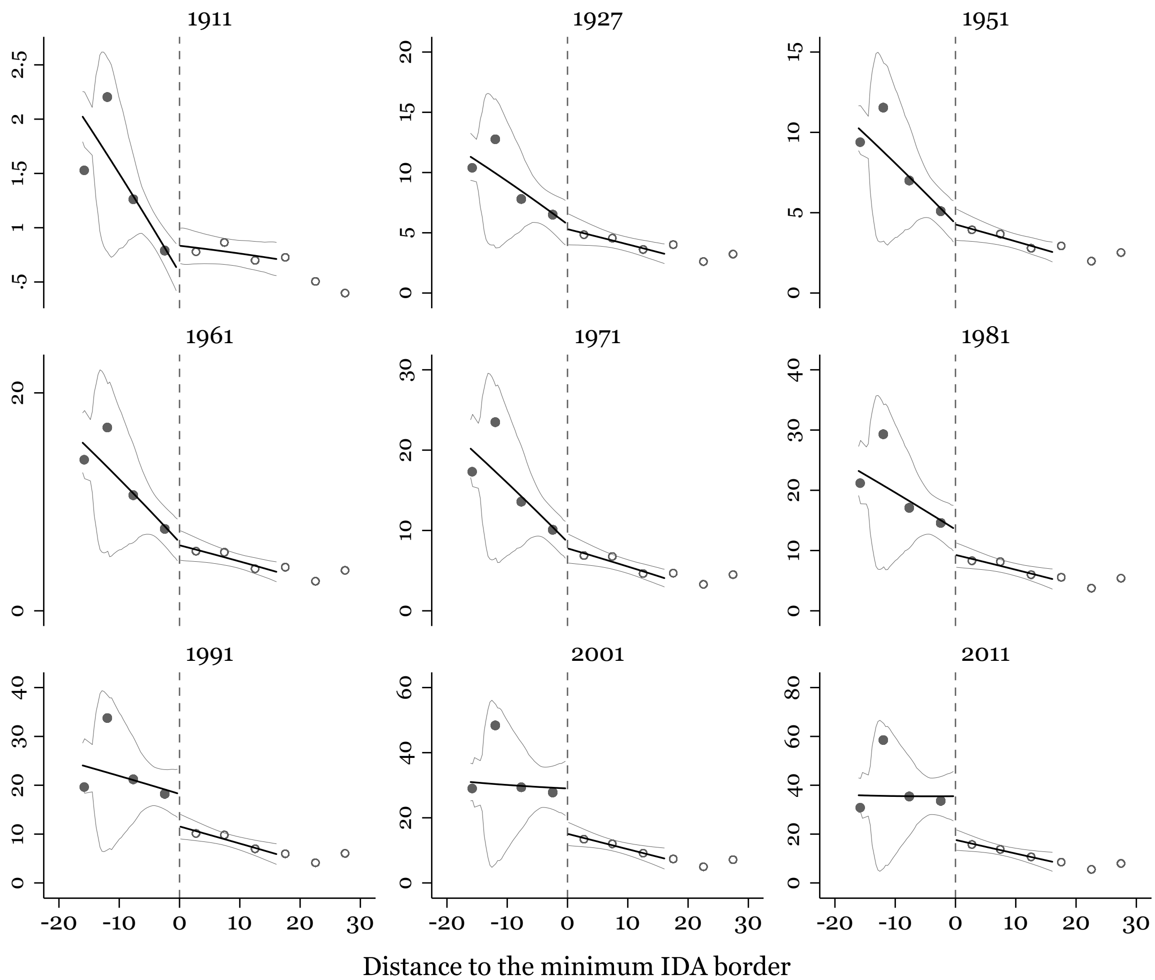
Negative distance denotes municipalities within the minimum IDA border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately at either side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

Appendix Figure C2.7. Manufacturing establishment density



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 C2.8. Services establishment density



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.

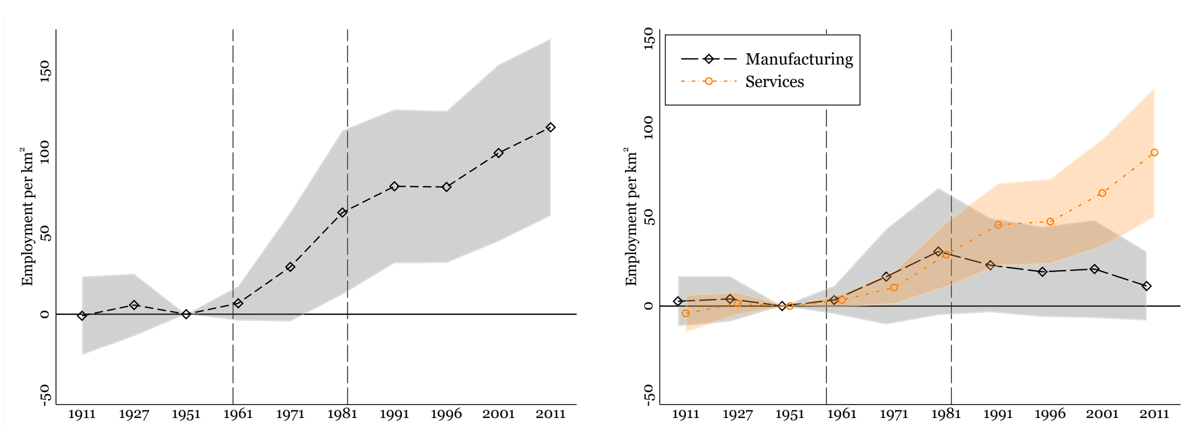
Appendix Table C2.10. Manufacturing and services densities – Fuzzy RD estimates

	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

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

Appendix Figure C2.9. Event study using Center-North (within) – Empl. density

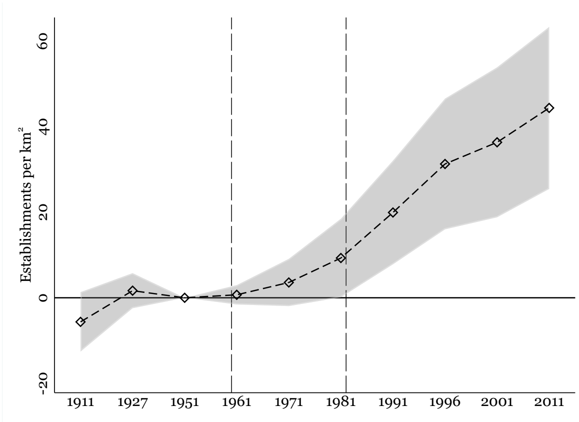
(a) Employment density (b) Manufacturing versus services



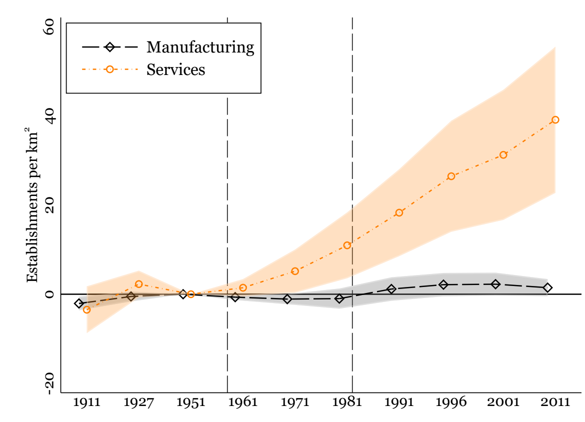
Coefficient estimates for Equation B3.1. Sample restricted to municipalities within the minimum IDA border excluding IDA centers (treatment group) and municipalities bordering placebo centers (control group). Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the IDAs. See text for details.

Appendix Figure C2.10. Event study using Center-North (within) – Est. density

(a) Establishment density



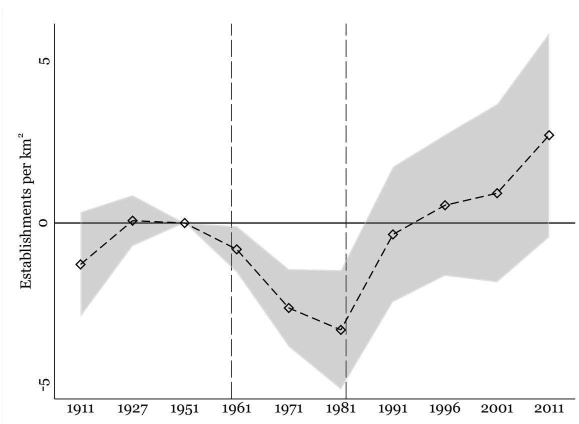
(b) Manufacturing versus services



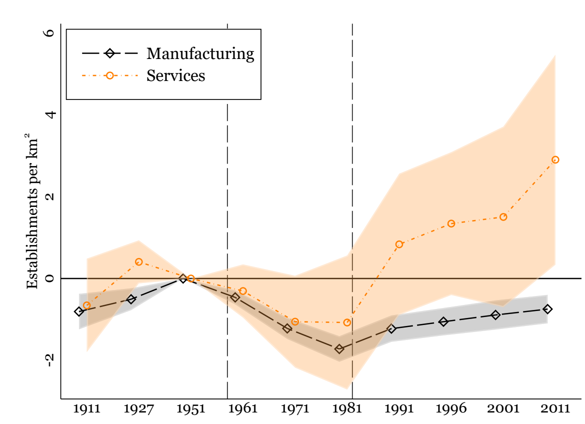
Coefficient estimates for Equation B3.1. Sample restricted to municipalities within the minimum IDA border excluding IDA centers (treatment group) and municipalities bordering placebo centers (control group). Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the IDAs. See text for details.

Appendix Figure C2.11. Event study using Center-North (outside) – Est. density

(a) Establishment density



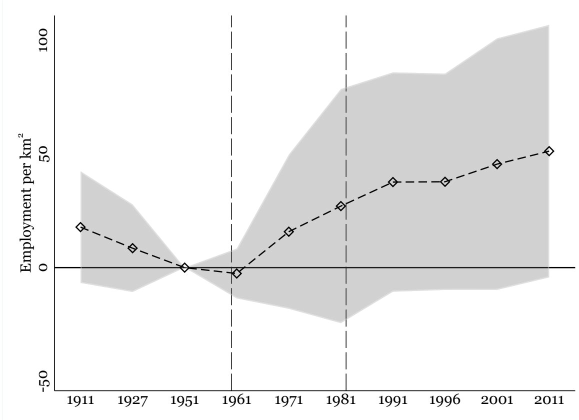
(b) Manufacturing versus services



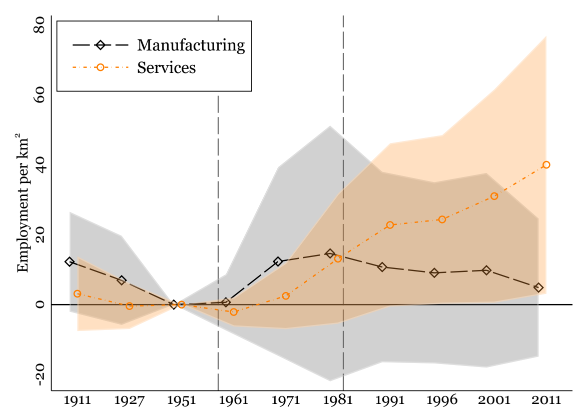
Coefficient estimates for Equation B3.1. Sample restricted to municipalities up to 16 km outside of the minimum IDA border (treatment group) and municipalities up to 16 km outside of the placebo border traced by municipalities bordering placebo centers (control group). The treatment group excludes IDA 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 C2.12. Triple differences – Empl. density

(a) Employment density



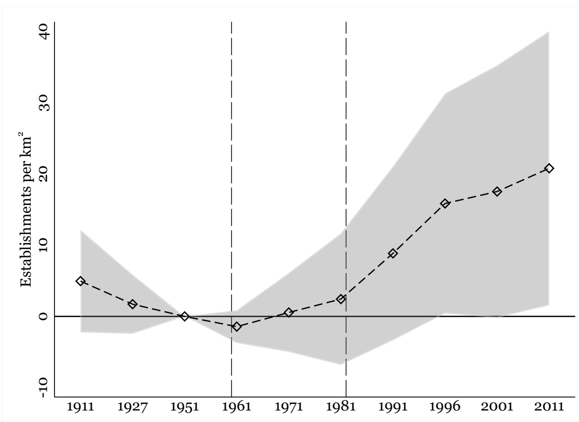
(b) Manufacturing versus services



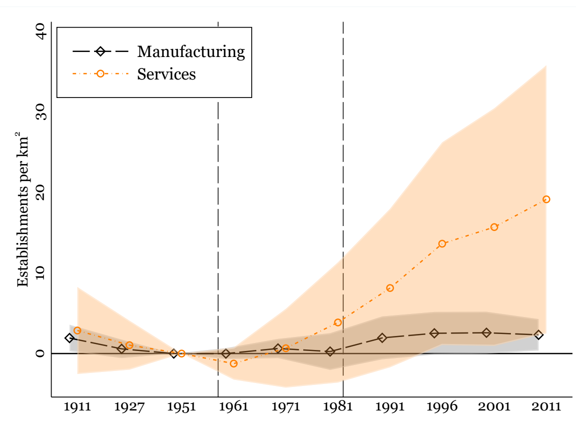
Coefficient estimates for Equation B3.2. Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the IDAs. See text for details.

Appendix Figure C2.13. Triple differences – Est. density

(a) Establishment density



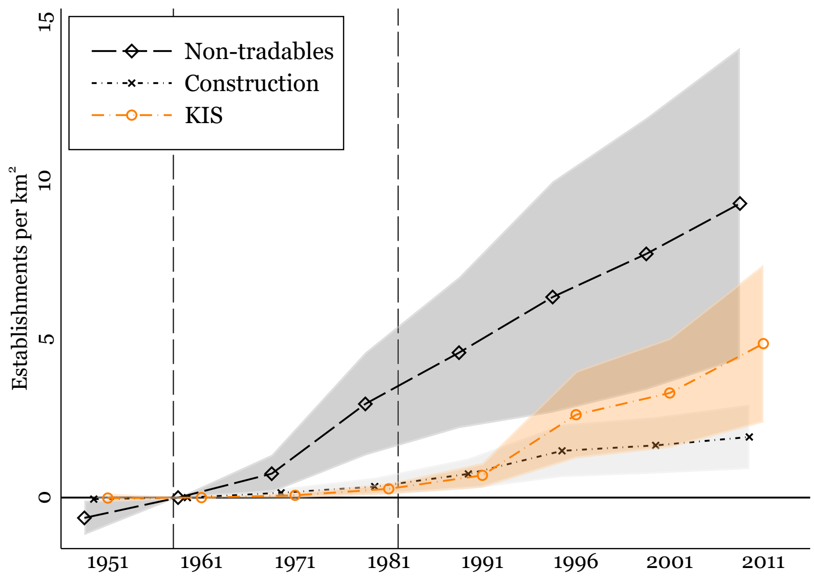
(b) Manufacturing versus services



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

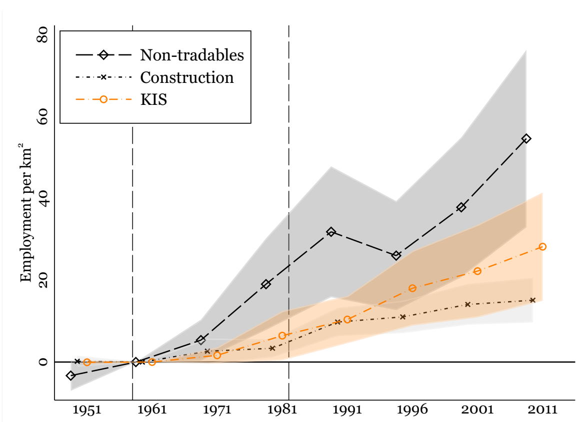
Appendix Figure D1. Establishment density – Services breakdown



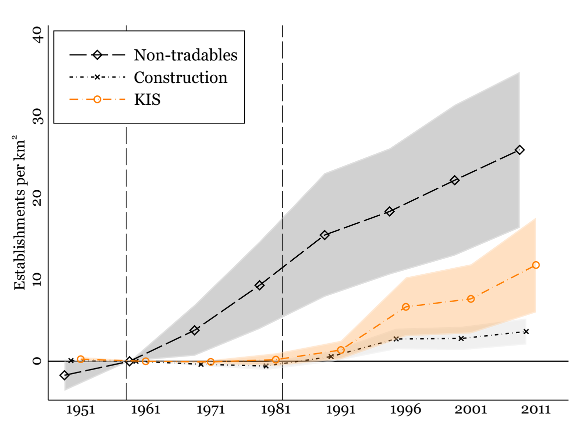
Coefficient estimates for Equation 2. Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the IDAs. "Non-tradables" include wholesale and retail trade, hotels and restaurants and other 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



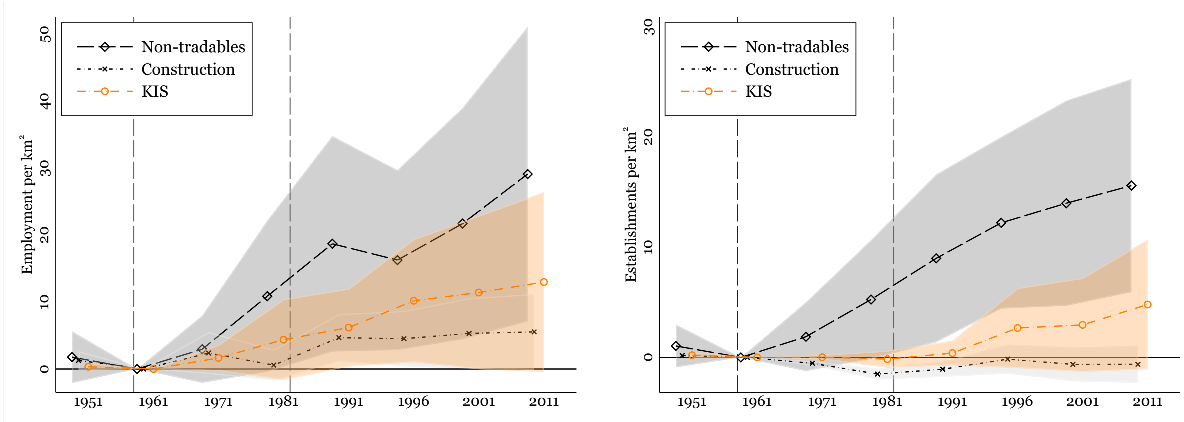
(b) Establishment density



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

(a) Employment density (b) Establishment density



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

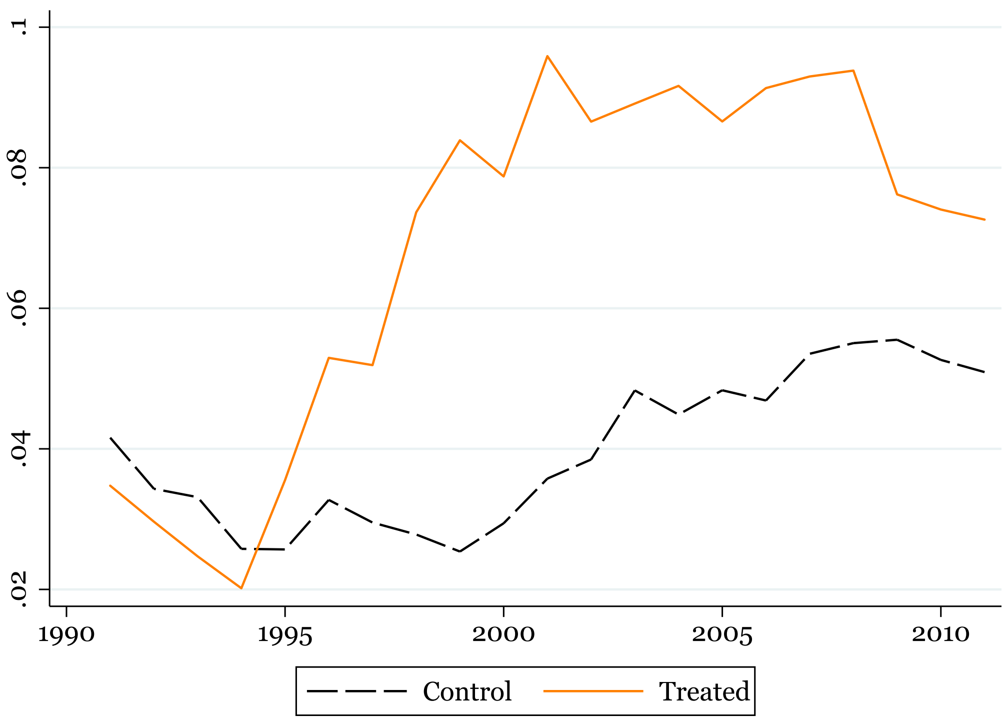
Replication of Table 3, Column (2). The outcomes are the share of employment and establishments in KIS and other services. The shares are obtained from social security data on the universe of Italian firms and the KIS classification is obtained from Eurostat/OECD. See Appendix A.3 and text for details.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

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



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. "KIS" (knowledge-intensive services) include communication, finance and insurance and services to firms. The shares are computed for municipalities included in the baseline estimation sample. Treated municipalities are those bordering IDA centers. 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

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

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

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

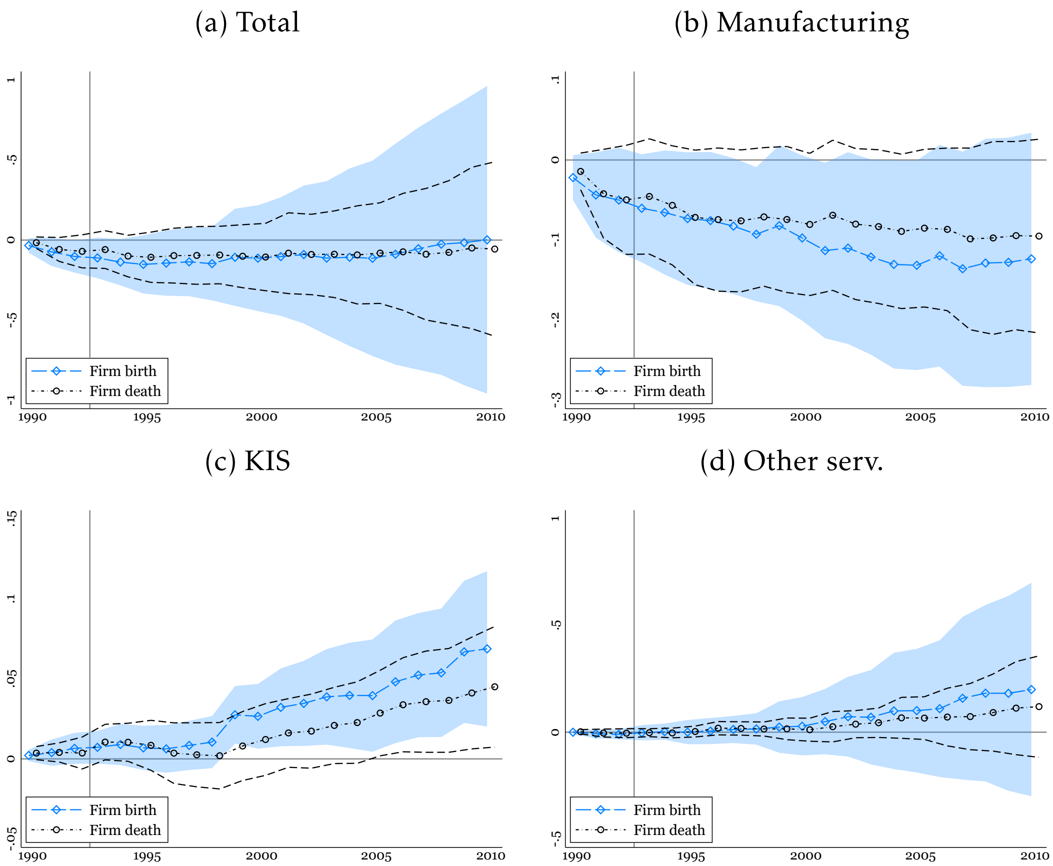
Replication of Table 3, Column (2). Outcomes are computed as the share of firms in each tertile of the distribution of firm size and wage paid. Tertiles are derived on the universe of the Italian firms each year. See Appendix A.3 and text for details. * p<0.10, ** p<0.05, *** p<0.01

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

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 D5. Firm dynamics – Fuzzy RD estimates



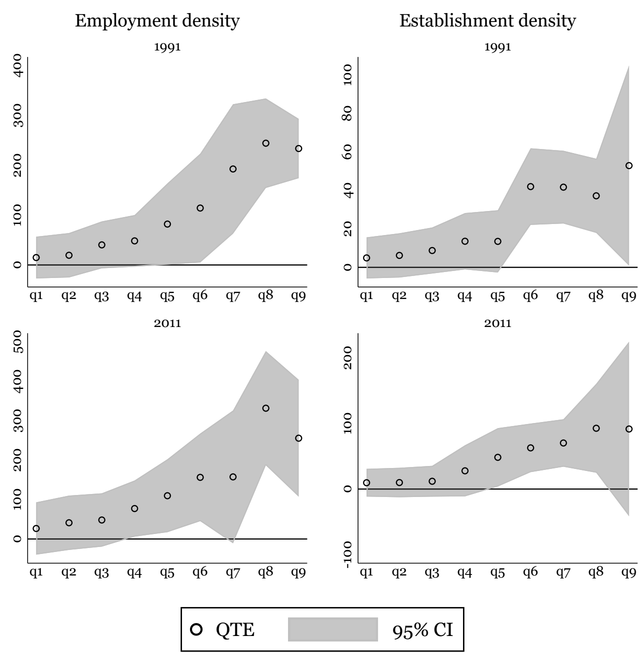
Coefficient estimates for the fuzzy RD model of Equations 1a and 1b. The shaded areas denote 95 percent confidence intervals. The vertical line marks the end of the EIM. Firm birth and death rates computed as the cumulative number of firm births and deaths every year since 1990, as a share of the total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

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 D6. Quantile treatment effects



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

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 dead-weight loss of taxation 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 C2.9 Panel (a): 115.44 workers per km^2) and *iii*) the triple differences (Figure C2.12 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 reduced-form estimates, which builds on the study of US Empowerment Zones in Busso et al. (2013).[49] 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 (very large) costs. We break down total surplus into three components: wage gains for workers, corporate profits for firms and rental gains for landlords.[50] 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 sourced 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 municipal-

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

[50]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.

ity.[51]

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 of rental prices in € /squared meter in a municipality, which we then multiply by the total building area in the municipality to obtain the flow.[52] We compute annual flows in 2004 and 2011, which we then linearly interpolate for the other years.

We then compute the effect of the policy on each of these outcomes in the post-IDA years ($\hat{\pi}_j$). 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 $counterfactual_{jy} = observed_{jy}/(1+\hat{\pi}_j)$. In turn, the net benefit is 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

[51] 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.

[52] 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.

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 log 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

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

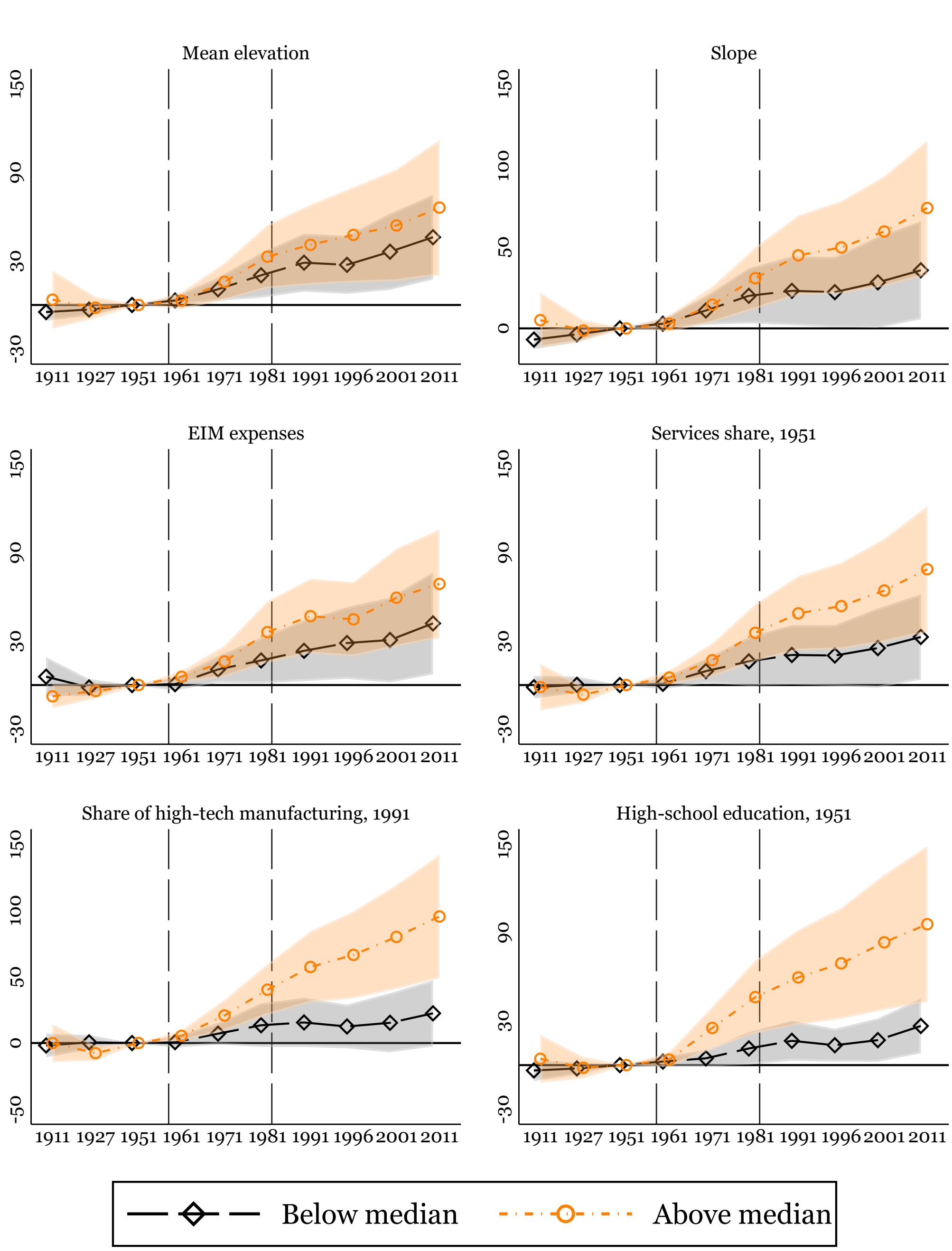
Appendix Table E2. Benefits of the IDA policy

	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

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.

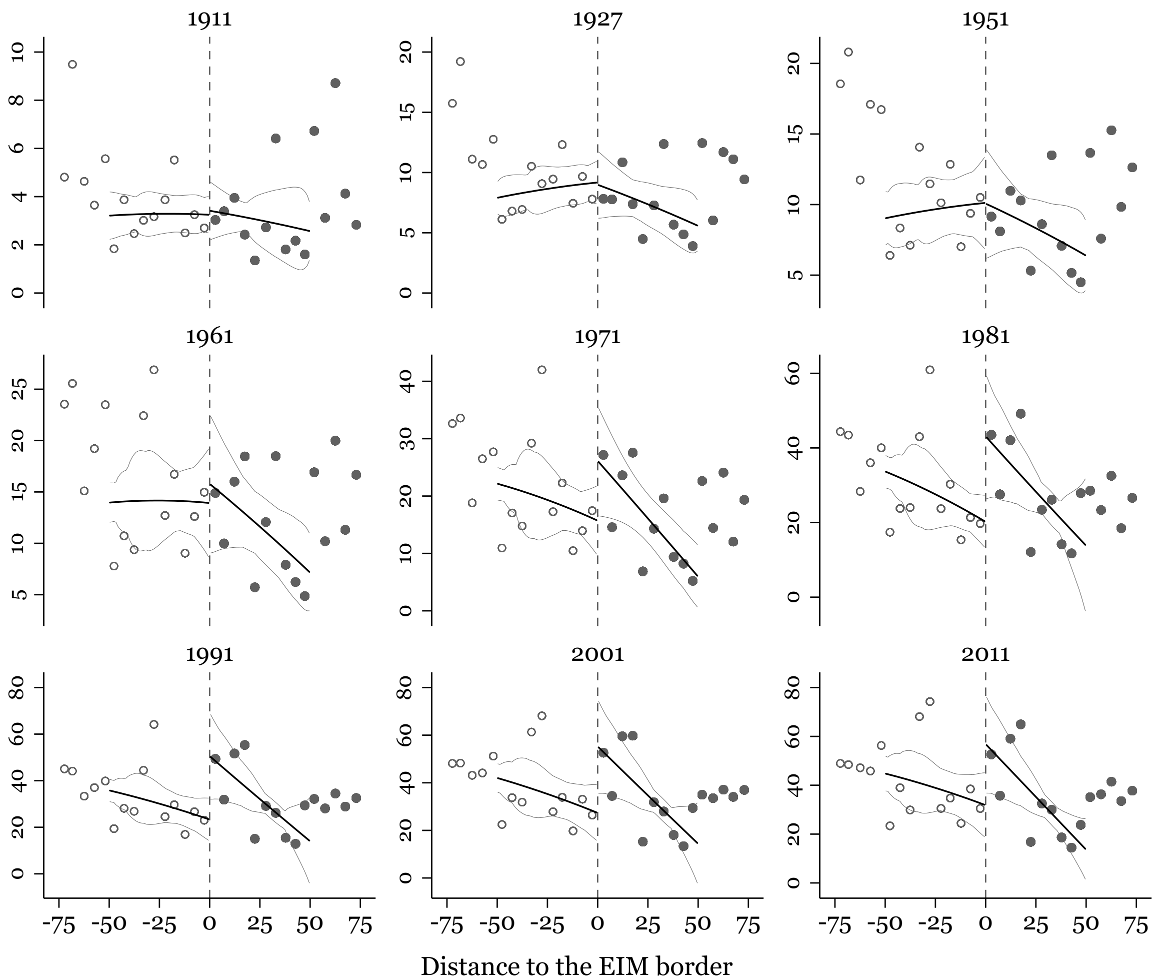
F Appendix F

Appendix Figure F1. Employment density – Heterogeneity



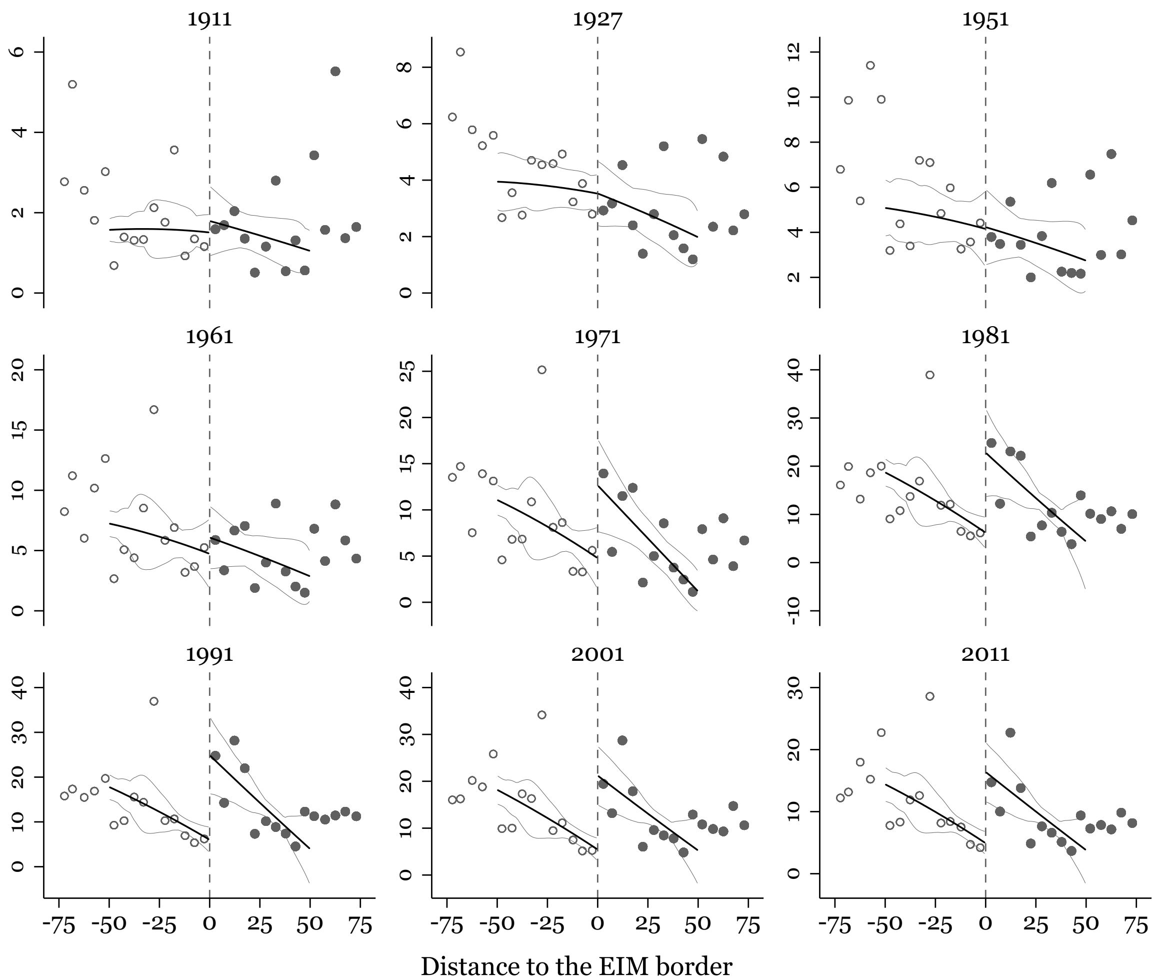
Coefficient estimates for Equation 2. EIM expenses measured in euros (2011 prices) per 1951 inhabitant, cumulated between 1950 and 1992. For each of the six variables, we compute the mean within each IDA region using only municipalities bordering the IDA center. Share of high-technology manufacturing 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



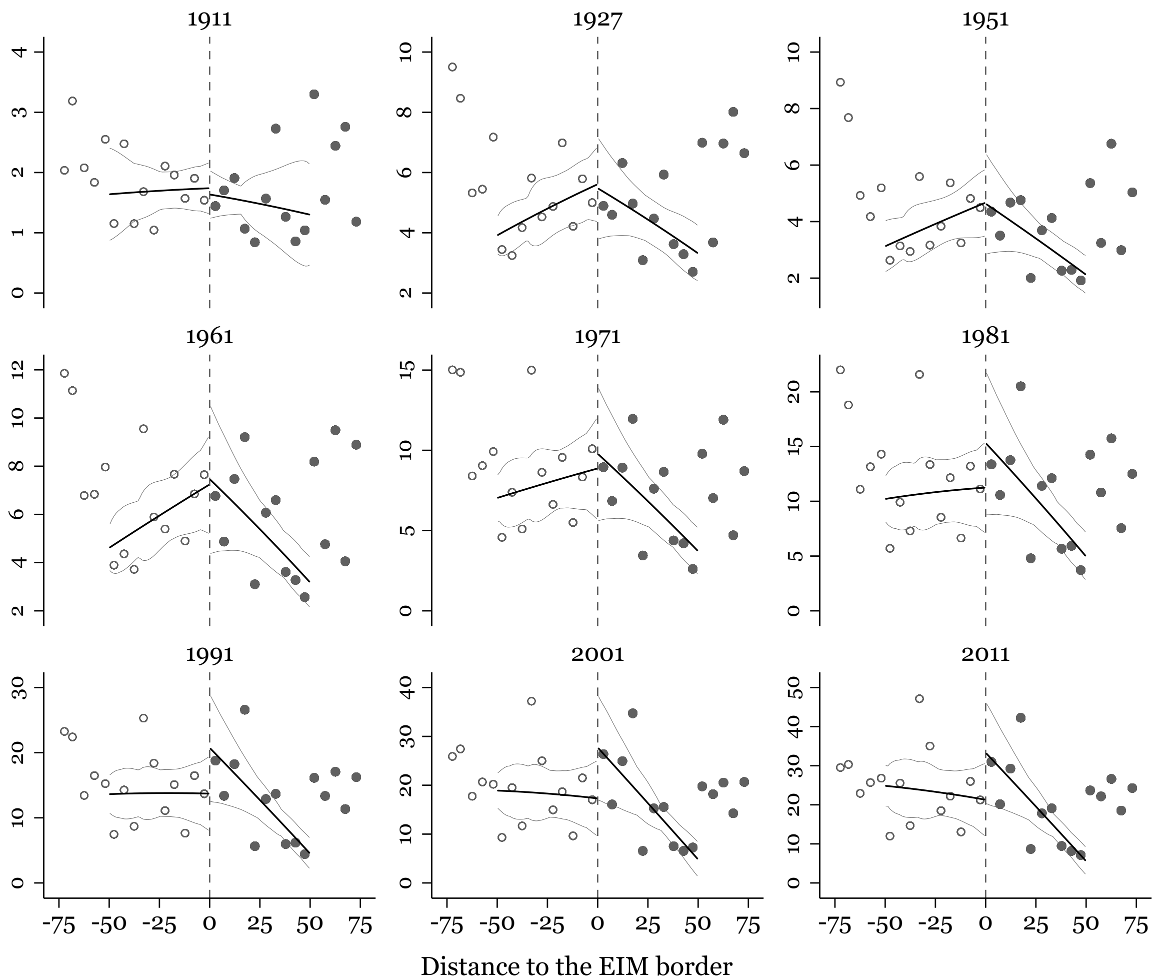
Negative distance denotes municipalities north of the EIM border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately north and south of the 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



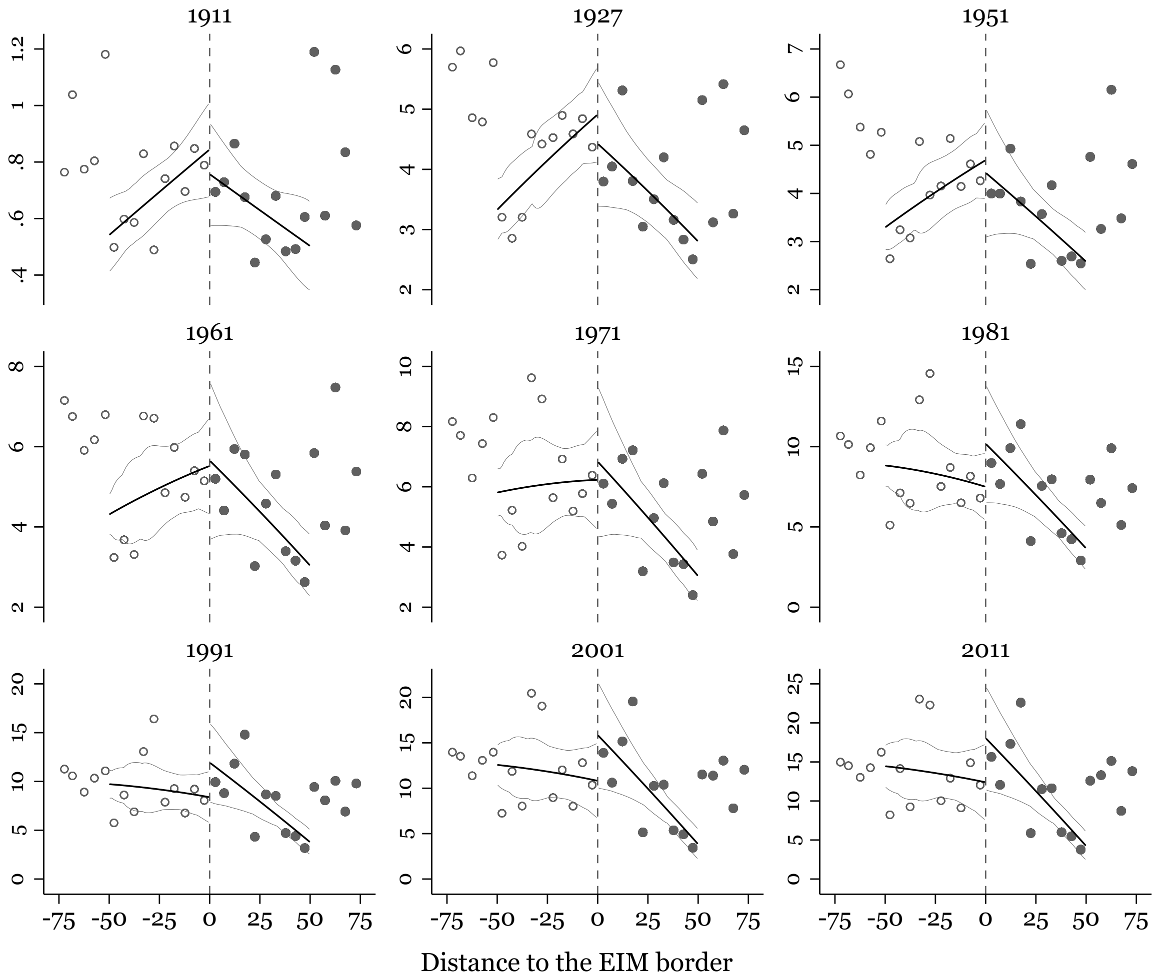
Negative distance denotes municipalities north of the EIM border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately north and south of the 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



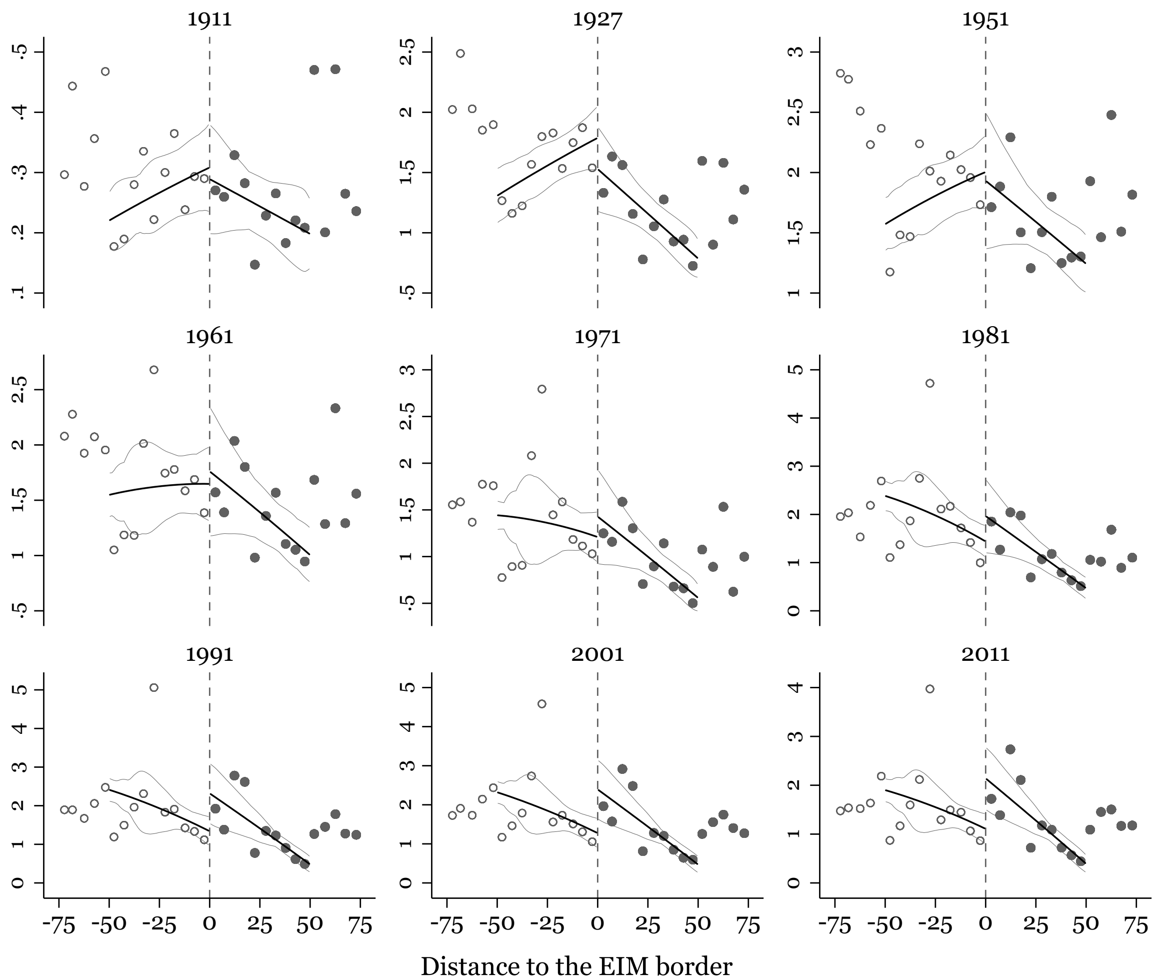
Negative distance denotes municipalities north of the EIM border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately north and south of the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

Appendix Figure F5. Establishment density



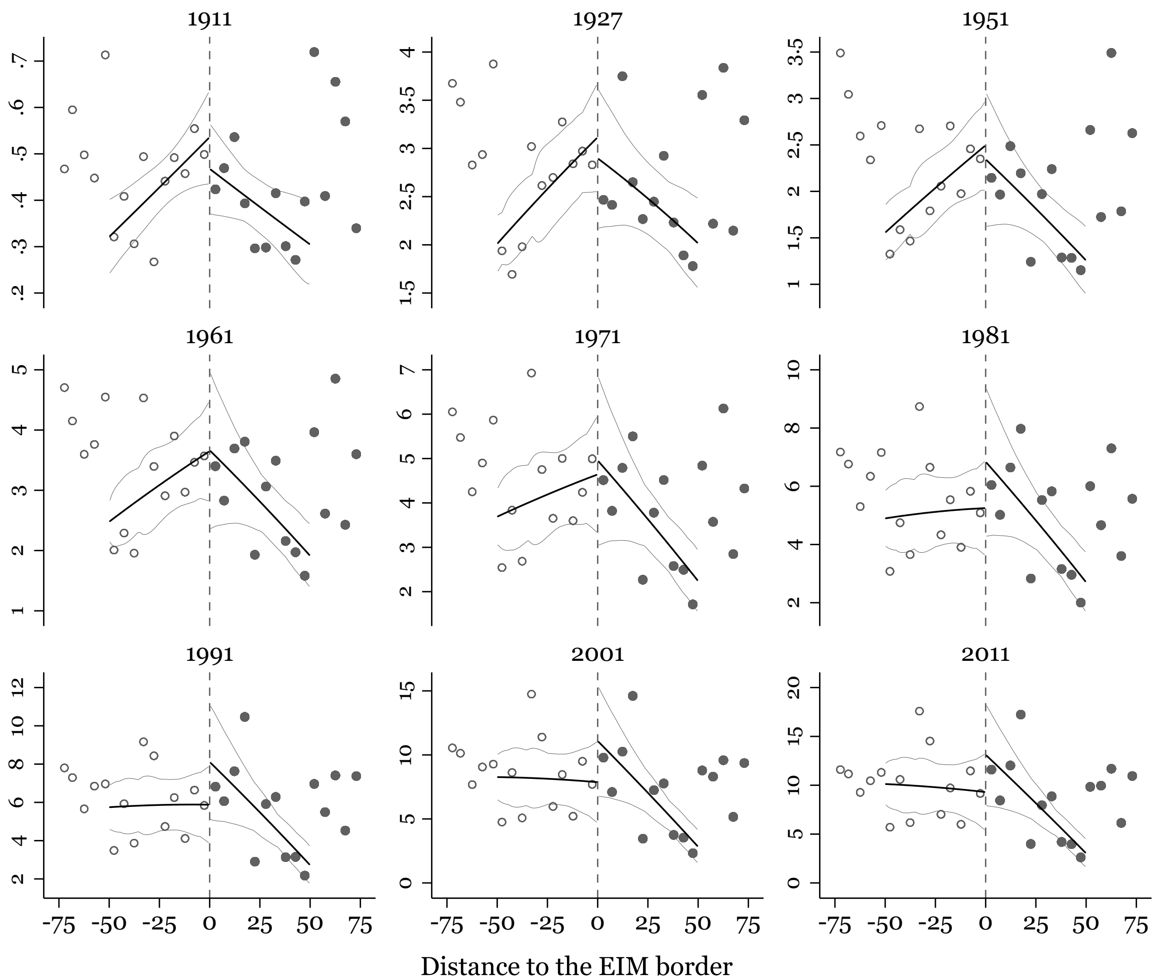
Negative distance denotes municipalities north of the EIM border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately north and south of the 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



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



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

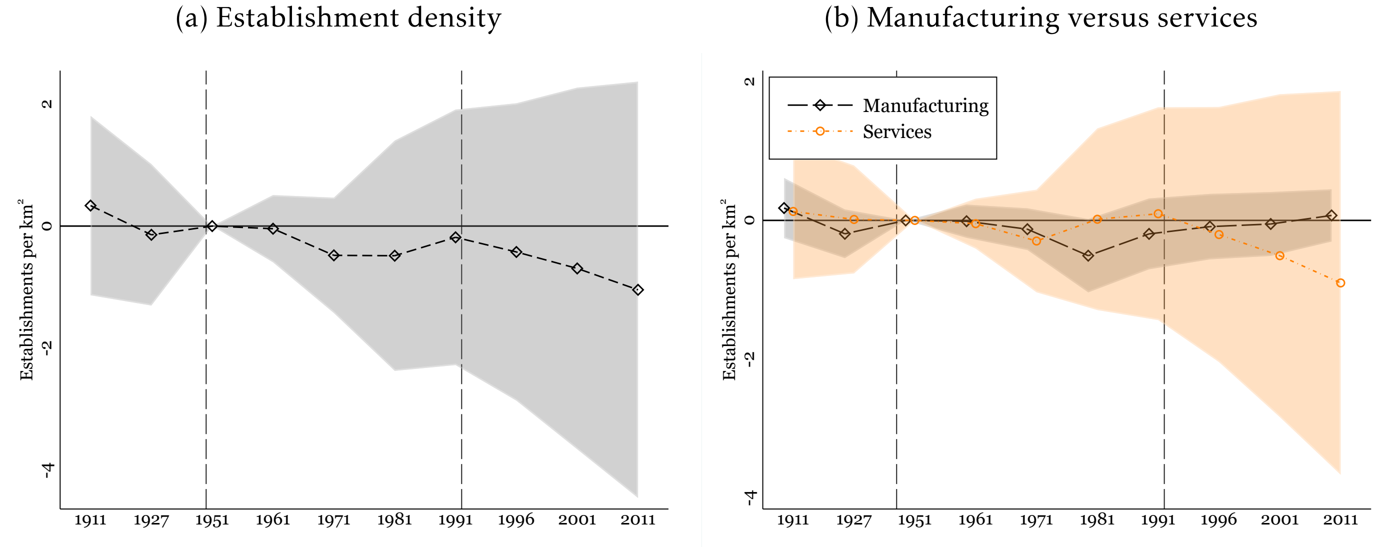
Coefficient estimates from Equation B4.1 separately for employment density and establishment density. All regressions are estimated over a 50-km symmetric bandwidth around the EIM border and control for a linear polynomial in the distance to the border and border segment effects. Standard errors allow 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

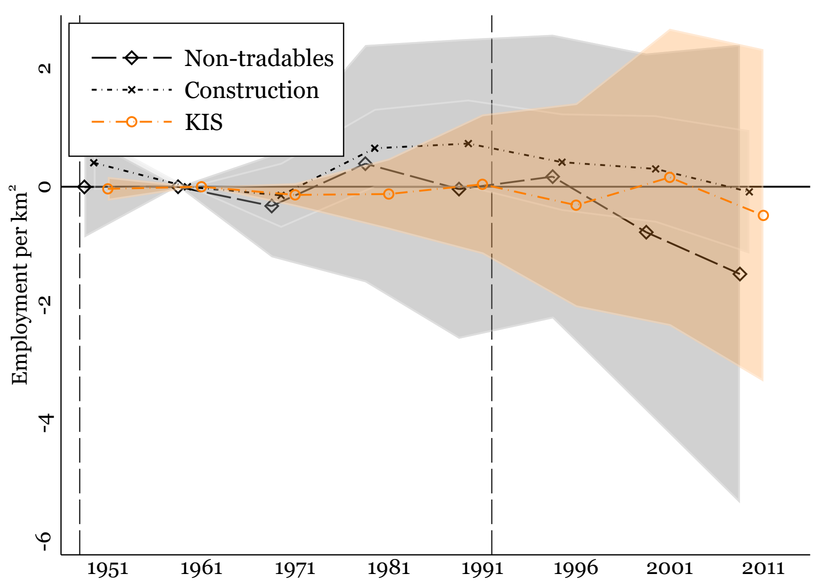
Coefficient estimates from Equation B4.1 separately for employment density and establishment density. All regressions are estimated over a 50-km symmetric bandwidth around the EIM border and control for a linear polynomial in the distance to the border and border segment effects. Standard errors allow 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



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



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

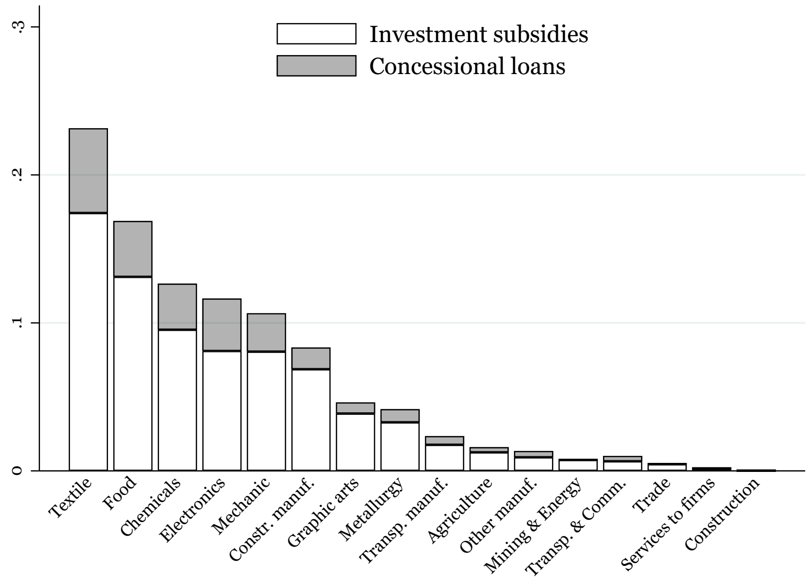
Coefficient estimates from Equation B4.1. All regressions are estimated over a 50-km symmetric bandwidth around the EIM border and control for a linear polynomial in the distance to the border and border segment effects. Standard errors allow for spatial correlation (Conley, 1999). The outcomes are the 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

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



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

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

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

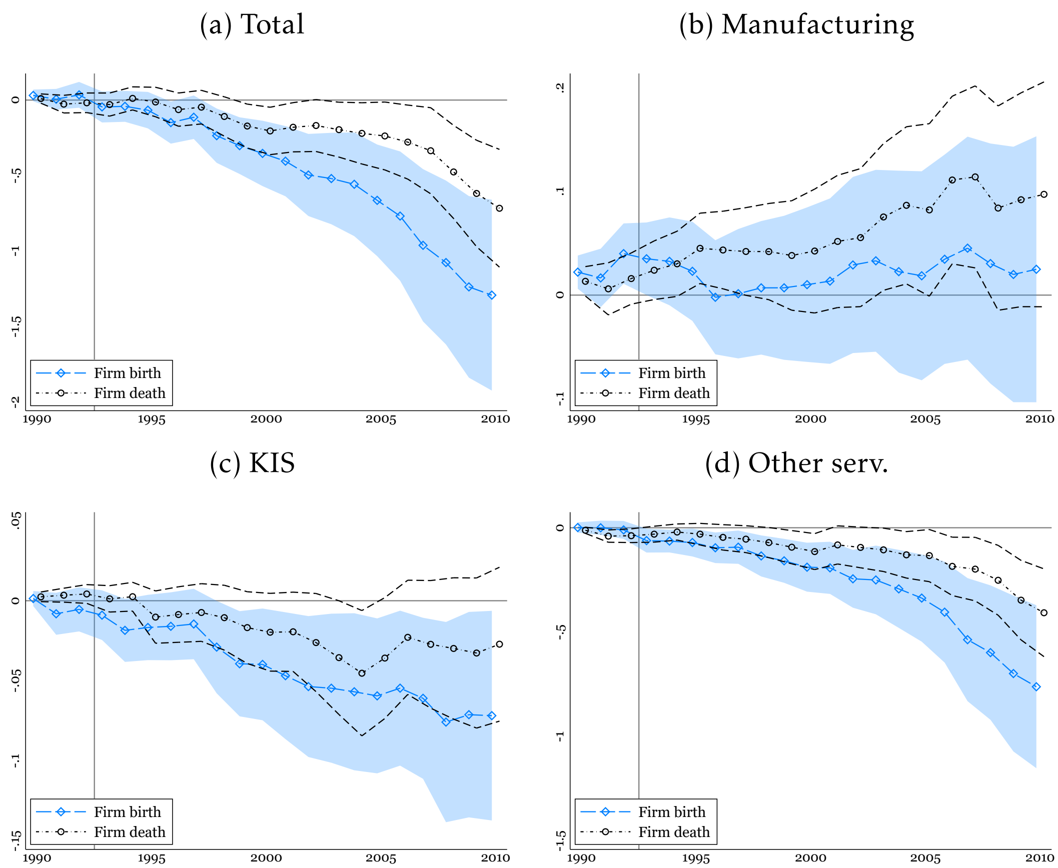
Coefficient estimates from Equation B4.1. All regressions are estimated over a 50-km symmetric bandwidth around the EIM border and control for a linear polynomial in the distance to the border and border segment effects. Standard errors allow for spatial correlation (Conley, 1999). Outcomes are computed 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

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



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

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)
Share of high-tech manuf. (%, 1951)	5.11	5.21
	(5.50)	(2.94)
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

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. "Share of high-tech manuf." is the share of manufacturing workers employed in chemical and mechanics in 1951. "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 common 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 apply away from the IDA centers? Angrist and Rokkanen (2015) devise a method to extrapolate RD treatment effects to inframarginal units, leveraging the availability of additional predictors of the outcome other than the running variable. Conditional on a vector of these covariates (henceforth, "CIA covariates"), there is mean independence between the outcome and the running variable – a Conditional Independence Assumption (CIA). To obtain the CIA covariates, we exploit the data-driven algorithm in Palomba (2023).[53] Specifically, we feed the following list of potential baseline predictors of the outcome (employment density in 2011): geographical characteristics (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 as CIA covariates slope, mean elevation, seismicity and population density in 1951. Conditional on these, the correlation between employment density and distance to the cutoff breaks, as showed in Columns (1) and (2) of Table G1.[54] These 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 reduced-form RD estimate of 60 workers per km^2 in 2011.

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

[54] 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).

Other compliance groups. An added limitation to external validity in fuzzy RD designs is that the estimated LATE refers to complier units (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-takers and never-takers. They show that this condition implies exogeneity of treatment participation, which can be falsified using a joint test of restrictions. Namely, one should test equality of average outcome between always-takers and treated compliers, and never-takers and control compliers. Bertanha and Imbens (2020) propose a joint formal test of these restrictions, which we perform within the baseline 16-km bandwidth using employment density in 2011 as outcome.[55] 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. Most 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.

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

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)*

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