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

Lorenzo Incoronato Salvatore Lattanzio

Abstract

This paper studies a place-based industrial policy (PBIP) aiming to establish industrial clusters in Italy in the 1960s-70s. Combining historical archives spanning one century with administrative data and leveraging exogenous variation in government intervention, we investigate both the immediate effects of PBIP and its long-term implications for local development. We document agglomeration of workers and firms in the targeted areas persisting well after the end of the policy. By promoting high-technology manufacturing, PBIP favored demand for business services and the emergence of a skilled local workforce. Over time, this produced a spillover from manufacturing – the only sector targeted by the program – to services, especially in knowledge-intensive jobs. Accordingly, we estimate higher local wages, human capital, and house prices in the long run. We provide suggestive evidence that these persistent effects may depend on the initial conditions of targeted locations.

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

*Incoronato: CSEF–University of Naples Federico II, CESifo, CReAM and Rockwool Foundation Berlin (lorenzo.incoronato@unina.it); Lattanzio: Directorate General for Economics, Statistics and Research, Bank of Italy, and Dondena Centre for Research on Social Dynamics and Public Policy (salvatore.lattanzio@bancaditalia.it). We are grateful to Monica Andini, Tito Boeri, Kirill Borusyak, Courtney Brell, David Card, Emanuele Ciani, Fabrizio Colella, Lucas Conwell, Julian Costas-Fernandez, Leonardo D'Amico, Christian Dustmann, Emanuele Felice, Giovanni Gallipoli, Ines Helm, Jonas Hjort, Réka Juhász, Patrick Kline, Hyejin Ku, Thomas Lemieux, Attila Lindner, Paolo Pinotti, Imran Rasul, Lucrezia Reichlin, Kilian Rieder, Uta Schönberg, Michel Serafinelli, Gabriel Ulyssea, Eliana Viviano, and to audiences at NBER Summer Institute 2024, UCL, UBC, IIES Stockholm, LMU, Bocconi, CSEF–Federico II, Tor Vergata, Católica Lisbon, EBRD, IZA/OECD, CESifo, CEPR-Bank of Spain, CReAM Workshop on Regional Inequality, Milan Labour Lunch, and FBK-Irvapp for their comments and suggestions. The views expressed in this article are those of the authors and are not the responsibility of the Bank of Italy or the Eurosystem.

1. Introduction

In recent decades, advanced economies have witnessed rising spatial inequality as "left-behind" industrial districts struggled to adapt to technical change and globalization. In response to this trend, place-based industrial policies (PBIPs) seeking to bolster local manufacturing and establish industrial clusters have gained traction (Porter, 2000; Kline and Moretti, 2014b).[1] Despite their rising popularity, little is known about the persistent effects of PBIPs on local development. Leveraging a century's worth of data, this paper studies a historical program to assess whether PBIPs benefit the targeted locations in the long run, exploring the sources of persistence, their spillover effects and cost-effectiveness.

There is intense debate on these programs among economists. While government intervention can correct market failures and foster local development, it may also lead to inefficiencies and misallocation, yielding – at best – only temporary benefits (Rodrik, 2019; Heblich et al., 2022). In addition, PBIPs might not only impact the targeted industries and locations but produce spillovers to the rest of the economy. Shedding light on these issues requires examining the effects 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., 2024).

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

The IDAs were launched in 1960 as part of a broader regional policy called *Extraordinary Intervention in the Mezzogiorno* (EIM). The EIM was introduced by the Italian govern-

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

ment to stimulate development in southern regions through infrastructure building and investment subsidies to manufacturing firms. The IDAs were groups of municipalities *within* the EIM jurisdiction identified as suitable hosts for industrial clusters. To direct firms and workers towards IDAs, the government set a higher subsidy rate on investments (hence a lower cost of capital) for firms located in an IDA and financed additional infrastructures. IDA expenses totalled roughly €90 billion, or 0.5 percent of national GDP each year between 1960 and the end of the program in the late 1970s.

We first explore whether the policy raised economic activity in the targeted clusters. To do so, we reconstruct the number of workers and establishments across municipalities over one hundred years – 1911 to 2011 – by digitizing historical censuses. We then scale these by the municipality's area to build our main outcomes. 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 with rich administrative micro data for the population of private firms (and a matched random sample of workers) since 1990.

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

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

We estimate a positive effect on local employment density emerging while IDAs were in place and continuing to grow afterwards. We measure a discontinuity of about 40 workers per square kilometer (km^2) (50 percent of a standard deviation) at the end of the policy. In 2011 – almost four decades after peak funding in IDAs – the effect is still large at 60 workers per km^2 (60 percent of a standard deviation). We find similar results for firm density. This long-lasting impact reflects – at least in part – higher labor force participation and lower unemployment of residents, and we do not observe continued migration into the treated areas. This evidence of *increasing* effects of PBIP after its termination stands somewhat in contrast with previous findings on industrial cluster policies, which indicate employment effects that are, at best, positive but fading over time (Garin and Rothbaum, 2024).

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

These spillovers to services raise key questions. Why did non-targeted sectors respond to industrial policy? How can the effect on services be so persistent? To answer, we further decompose the response of services. While IDAs were in place, the rise of employment and firm density in services occurred exclusively for non-tradables (e.g., retail, hospitality), in line with local multipliers (Moretti, 2010). Starting in the 1980s, however, we also document steep growth of knowledge-intensive services (KIS, e.g., information technology, business services). This suggests the development of a skilled local workforce, with possible knowledge spillovers and broader structural change in the targeted areas.

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

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

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

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

These findings suggest the diffusion of "good jobs" (Rodrik and Stantcheva, 2021) in IDAs. Accordingly, the effect on local wages and tax incomes 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 higher house prices. Firms in IDAs – especially in KIS – are more productive and tend to invest more than control firms in the long run. Last, we find small changes in municipal spending and other government transfers in the decades after the policy, which suggests that our persistent effects have not been driven by continued public investment in IDAs (von Ehrlich and Seidel, 2018).

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

In the last part of the paper we conduct heterogeneity analysis and show how the impact of PBIP may depend on the characteristics of the targeted locations. We first compare IDAs with each other and find that IDAs with higher initial (1951) human capital are those where the effects are largest. We then contrast the 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. (2024). For manufacturing employment, we estimate a positive but fading effect qualitatively similar to that observed for the IDAs. However, services – especially KIS – did not respond to the intervention. There are also no effects on high-technology manufacturing, nor on education and wages. While suggestive, this exercise highlights the role of local initial conditions. While IDAs were high-potential poles suitable to future agglomeration, areas around the EIM border had less favorable geography and low density of workers and firms before the policy.

Related literature and contributions. This paper first relates to the growing body of work on industrial policy (Juhász et al., 2024). Recent studies of historical programs have uncovered the effects of industrial policy on local development and structural change (Juhász, 2018; Hanlon, 2020; Mitrunen, 2020; Choi and Levchenko, 2021; Giorcelli and Li, 2022; Kantor and Whalley, 2022; Lane, 2022). Our work adds to the existing evidence by illustrating how these interventions can shape the transition towards manufacturing and eventually into skilled services. We also provide a first detailed account of the dynamic response of the services sector, which is not the typical target of industrial policy.

Second, we contribute to the ongoing debate on place-based policies (Kline and Moretti, 2014b; Neumark and Simpson, 2015; von Ehrlich and Overman, 2020) and their long-run implications (Kline and Moretti, 2014a). Specifically, our focus is on firm 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). We complement the nascent literature on the long-run effects of cluster policies (Giorcelli and Li, 2022; Heblich et al., 2022; Garin and Rothbaum, 2024) by offering new insights on the mechanisms underlying persistence. Our work describes how the services sector contributes to persistent effects through local multipliers and the development of high-technology industries. We also characterize how the long-run impact of PBIP may depend on the initial conditions of the targeted locations.

Third, our findings speak to the literature analyzing the manufacturing decline and its consequences (Charles et al., 2019; Gagliardi et al., 2023; Helm et al., 2023). If leading to specialization in a limited set of industries, cluster policy may undermine local development as manufacturing districts must adjust to technological shifts (Barba Navaretti and Markovic, 2021).[2] Instead, we show that PBIP may favor the transition of targeted areas into development poles integrating high-skill manufacturing and services and promoting "good jobs" (as well as firms demanding them) (Rodrik and Stantcheva, 2021).[3]

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

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

Fourth, our results add to the evidence on local multipliers (Moretti, 2010) and, more broadly, on the spillovers of (place-based) industrial policies to non-targeted sectors and locations (Greenstone et al., 2010; Atalay et al., 2022; Giorcelli and Li, 2022; Lane, 2022; Siegloch et al., 2022). We are the first to break down the effects of PBIP across different classes of services, shedding more light on how these programs may shape the structure of the economy. We also provide new *dynamic* estimates of the spillover effects of place-based policy to nearby locations, showing displacement of economic activity away from non-targeted areas during the intervention, but much less so in the long run.

Last, this paper produces new evidence on the EIM – the most ambitious regional program in Italy's history (Felice and Lepore, 2017). Recent studies (Colussi et al., 2020; Buscemi and Romani, 2022) consistently report a null impact of the policy. Among these, Albanese et al. (2024) find that EIM transfers led to a transition out of agriculture into industry but did not raise employment in the long run. We show instead that the EIM promoted development in a few select clusters. Studying the aggregate implications of the EIM, Cerrato (2024) indeed finds gains in national industrial production. We instead examine more in depth a prominent facet of the EIM (the IDAs) and go beyond direct impacts on manufacturing, using administrative micro data to unveil the effects of the program on other areas of the economy and to identify possible sources of persistence.

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

2. Background

The EIM. In the aftermath of World War II, the gap between Southern Italy and the rest of the country was at its peak. In 1950, a regional policy called *Extraordinary Intervention in the Mezzogiorno* (EIM) was put in place (and financed) by the central government to jump-start development in the South – roughly 40 percent of Italy's surface (Law n.

646/1950).[4] The EIM had an initial lifespan of ten years, then prolonged several times until 1992, and was run by a state-owned agency called *Cassa per il Mezzogiorno* (Cassa).

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

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

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

An IDA was created upon initiative of a group of local authorities (municipalities and provinces) called a *consortium*, which submitted a development plan to the government. The plan outlined the proposed investments and a list of municipalities to be included in the IDA. For each candidate municipality, the consortium had to report information on economic, demographic and geographic characteristics. The choice to include the

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

individual municipalities proposed by the consortium, and to ratify the creation of the IDA, rested with the government. A total of 14 IDAs were created – see Section 3.[5]

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

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

The IDA program was de-facto in place from 1960 until the late 1970s, when grants for IDA firms were equalized to those for other EIM firms. Transfers continued also through the 1980s, but with no distinction between IDAs and other EIM areas. The EIM ended with Law n. 488/1992, which introduced a new set of firm subsidies that also covered depressed areas in the Center-North (Bronzini and de Blasio, 2006; Cerqua and Pellegrini, 2014; Cingano et al., 2022).

3. Data

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

[5] We do not observe the initial proposals from consortia, but only the final list of municipalities included in each IDA as approved by the government.

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

Panel (a) in Figure 1 shows total EIM expenses by year, scaled by the total population in the EIM region in 1951. The Cassa only performed infrastructure works during its first decade (the 1950s). A strong industrial push began in the 1960s with a massive rise in firm subsidies. Most expenses were concentrated in IDAs, especially during the peak in the 1960s and 1970s (Panel (b)). Investment grants went disproportionately to capital intensive industries such as chemical, metallurgy and transport manufacturing – see Appendix A.1.

The ASET archives also record a list of the IDAs and the included municipalities, which we digitize and plot in Figure 2. A total of 14 IDAs comprising 328 municipalities had been established throughout Southern Italy. These are indicated by the yellow regions surrounding the brown IDA centers (the main cities of the South). On average, IDA municipalities received EIM funding of around €10,000 (cumulated between 1950 and 1992 and measured in 2011 prices) per 1951 resident, twice as much as other EIM municipalities (the number does not change much if excluding IDA centers). IDAs absorbed more than half of the overall EIM expenses (cumulative €165 billion), despite covering one tenth of the surface of the entire EIM region and hosting one third of its population.[7]

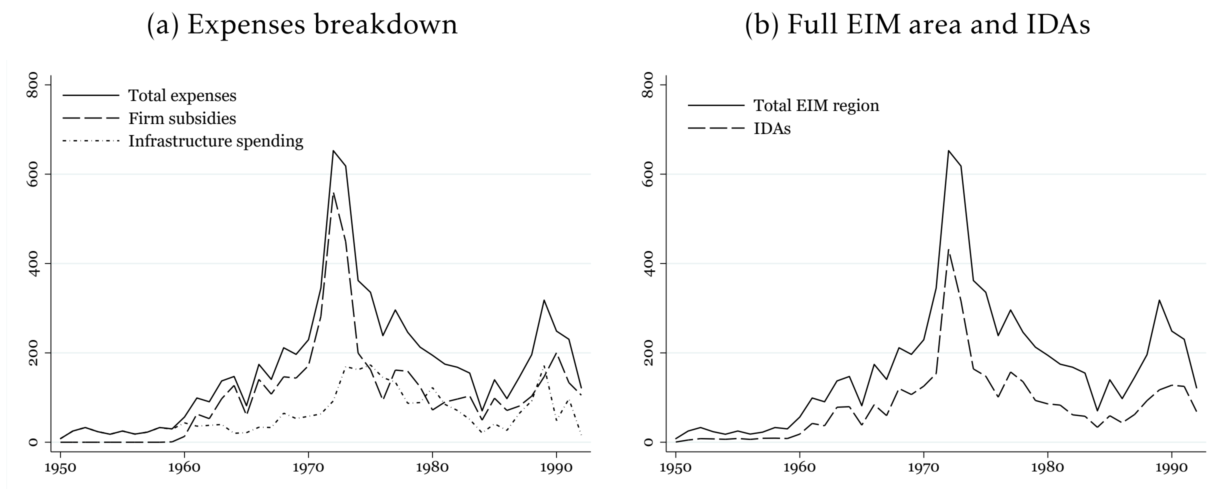
Industrial censuses. To build our main outcomes, we collect data on the number of workers and establishments per municipality from decennial industrial censuses spanning six decades (1951 to 2011, including an intermediate census in 1996), sourced from the Italian statistical institute (Istat).[8] The data report employment and establishment

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

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

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

Figure 1. EIM expenses



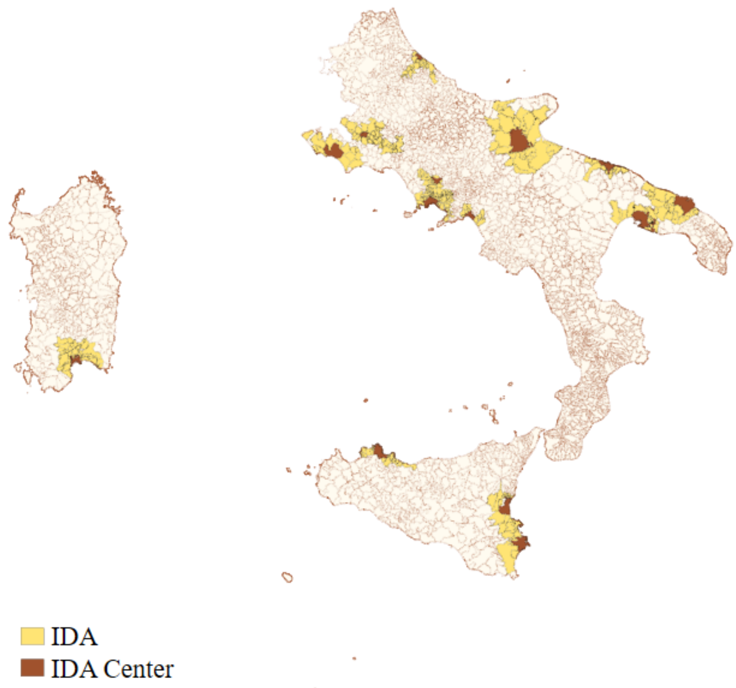
Notes: Flow EIM expenses in € (2011 prices) scaled by total population in the EIM region in 1951. Loans to firms are excluded.

counts in the private sector, separately for manufacturing and services (the terms "firm" and "establishment" are used interchangeably throughout the paper). The availability of data well after the end of the policy enables us to tackle key questions on its long-run effects. However, only the 1951 census allows us to evaluate the balancing properties of the outcome before the policy, which is essential for identification purposes.[9] We thus reconstruct municipality-level employment and number of establishments long before the start of the EIM by hand-digitizing the 1911 and 1927 industrial censuses, available in the historical archives of Istat (see Appendix A.2 for details).

Social security. The third main data source of the paper is the administrative archive on the population of Italian firms in the non-agricultural private sector from social security records (INPS), available at the Bank of Italy. The data start in 1990 and include information on firm employment counts, 6-digit sector, location, workforce composition and average wages. Importantly, the granular sector-level information allows 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

[9] EIM interventions began in the early 1950s and involved infrastructure works only. The Cassa's industrial policy (including the IDA program) started in the 1960s (Figure 1).

Figure 2. The Industrial Development Areas (IDAs)



Notes: The full map shows the entire EIM jurisdiction. IDAs are denoted in brown/yellow. 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.

for incorporated limited liability companies and report detailed balance sheet information. Last, we obtain matched employer-employee data by merging the firm dataset with a 7 percent random sample of Italian workers. We collapse the data at a more aggregate level of analysis (the municipality) as we cannot match the establishment-level subsidy data with the administrative records. We provide more detail in Appendix A.3.

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

4. Identification strategy

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

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

This "contiguity rule" – all municipalities bordering the center are automatically included in the IDA – can be exploited for identification. Figure 3 Panel (a) provides an illustration. The outer boundaries of the contiguous municipalities trace a "minimum" IDA border – the dashed white line in the map – separating municipalities in a within-cutoff region (the IDA center in brown and the contiguous municipalities in orange) and a outside-cutoff region (in blue). The outside-cutoff region may include both municipalities that are part of the IDA (in light blue) and municipalities that are not (in dark blue).[10] Below, we clarify how we choose the specific extension of the outside-cutoff region in our estimation.

Our analysis exploits the contiguity rule in a simple way. Let δ_m denote the geodesic

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

Table 1. IDA municipalities – descriptive statistics

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

Notes: Sample restricted to the EIM region. Employment and establishments (total and manufacturing) are sourced from the 1951 industrial census. "Agriculture share" computed as the number of agriculture workers per 100 residents aged at least 15. “High school education” is 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.

distance between the centroid of a municipality m and the minimum border of the closest IDA. Negative values of δ_m are assigned to municipalities in the within-cutoff region, that is, the IDA center and its bordering neighbors. The binary instrument $W_m = \mathbb{1}[\delta_m \leq 0]$ identifies municipalities in the within-cutoff region. Let also IDA_m be a treatment indicator taking value of one if municipality m belongs to any of the 14 IDAs depicted in Figure 2. To the extent that the probability of belonging to an IDA changes discontinuously at the minimum IDA border, the distance metric δ_m can be used as running variable in a fuzzy RD setting where IDA_m is the treatment variable, W_m is the instrument and Y_m is the outcome:

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

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

Equation 1a is the first-stage regression and Equation 1b is the reduced form. $\varphi(\delta_m)$ 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 bandwidth's choice. Within the minimum IDA border, there are only 14 IDA centers and 137 contiguous municipalities. The small sample size requires picking a bandwidth wide enough to include all these municipalities, which is equivalent to 16 km. We then adopt a symmetric bandwidth of 16 km also outside of the minimum IDA border, although – as showed later – results are robust to choosing different bandwidths.[11]

This identification strategy rests on three main assumptions, which we here describe intuitively while leaving a more formal treatment to Appendix B. First, IDA status must discontinuously jump at the minimum IDA border – a first stage assumption. To illustrate the idea, Figure 3 Panel (b) plots the probability that a municipality m belongs to an IDA as a function of the distance to the minimum IDA border, $Pr(IDA_m = 1 \mid \delta_m)$.[12] There is a neat drop in IDA status at the cutoff, confirming a strong first stage. IDA status is very close to one within the RD cutoff and drops to about 50 percent right outside of it.[13]

Table 2 shows the estimation output of the first-stage Equation 1a. The drop in IDA status of Figure 3(b) is quantified at 39 percentage points, and associated with lower

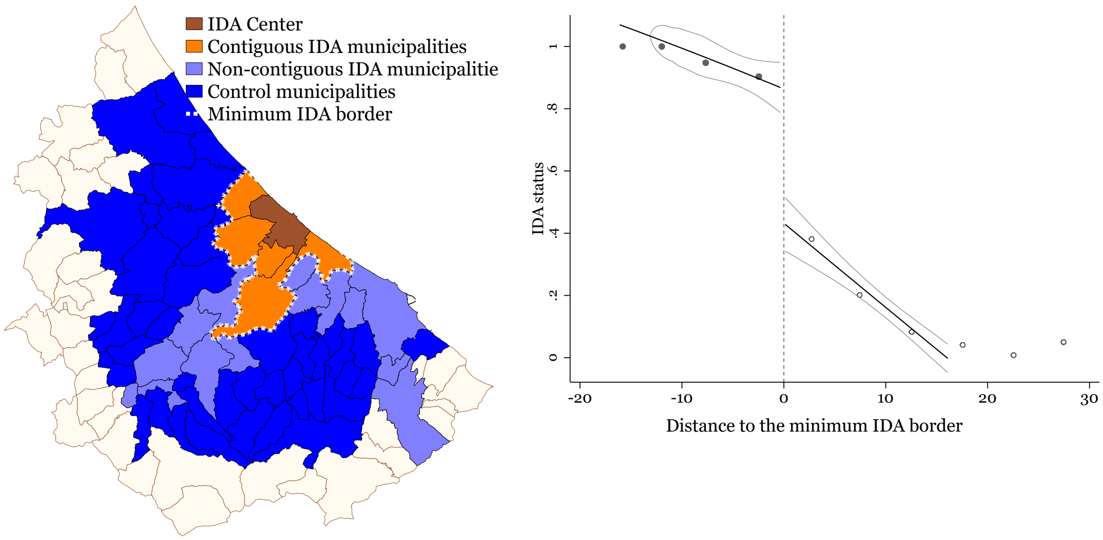
[11] Admittedly, our RD design suffers from limited variation in the running variable within the cutoff (corresponding to the IDA centers and contiguous municipalities). We will show that results still hold when using a longitudinal design that does not rely on controlling for distance to the cutoff,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

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

[13] 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



Notes: Panel (a) shows the minimum IDA border for one of the IDAs (Pescara). The IDA center (the Pescara municipality) 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 13 for an explanation of the non-unitary treatment probability within the cutoff. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately at each side of the border using a symmetric 16-km bandwidth. The gray lines are 95 percent confidence intervals.

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 infrastructure expenses from the Cassa and not those borne by the IDA's consortium.

The second assumption is that potential outcomes are continuous at the cutoff. The continuity assumption requires relevant factors other than IDA status not to jump at the minimum IDA border, thus enabling to causally attribute any observed change in outcomes to the IDA treatment. While the assumption is not testable, we argue that it is likely satisfied. The contiguity rule, which gives rise to the minimum IDA border, is an arbitrary choice of the government. While potential outcomes are certainly related to the distance to a large city (the IDA center), there are less reasons to expect discontinuous jumps in such relationship. To confirm this, we look for discontinuities in lagged outcomes at the cutoff. Figure 4 shows RD plots for employment and firm density in 1951 (a decade before the introduction of the IDAs). Unsurprisingly, agglomeration in 1951 was

Table 2. IDAs – First stage

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

Notes: Estimation output of Equation 1a using a 16-km symmetric bandwidth around the minimum IDA border. The specification controls for a linear polynomial in the distance to the border and for IDA region effects. EIM expenses measured in thousand € (2011 prices) per 1951 resident, winsorized at 1 and 99 percent. Standard errors clustered by IDA region in parentheses.

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.

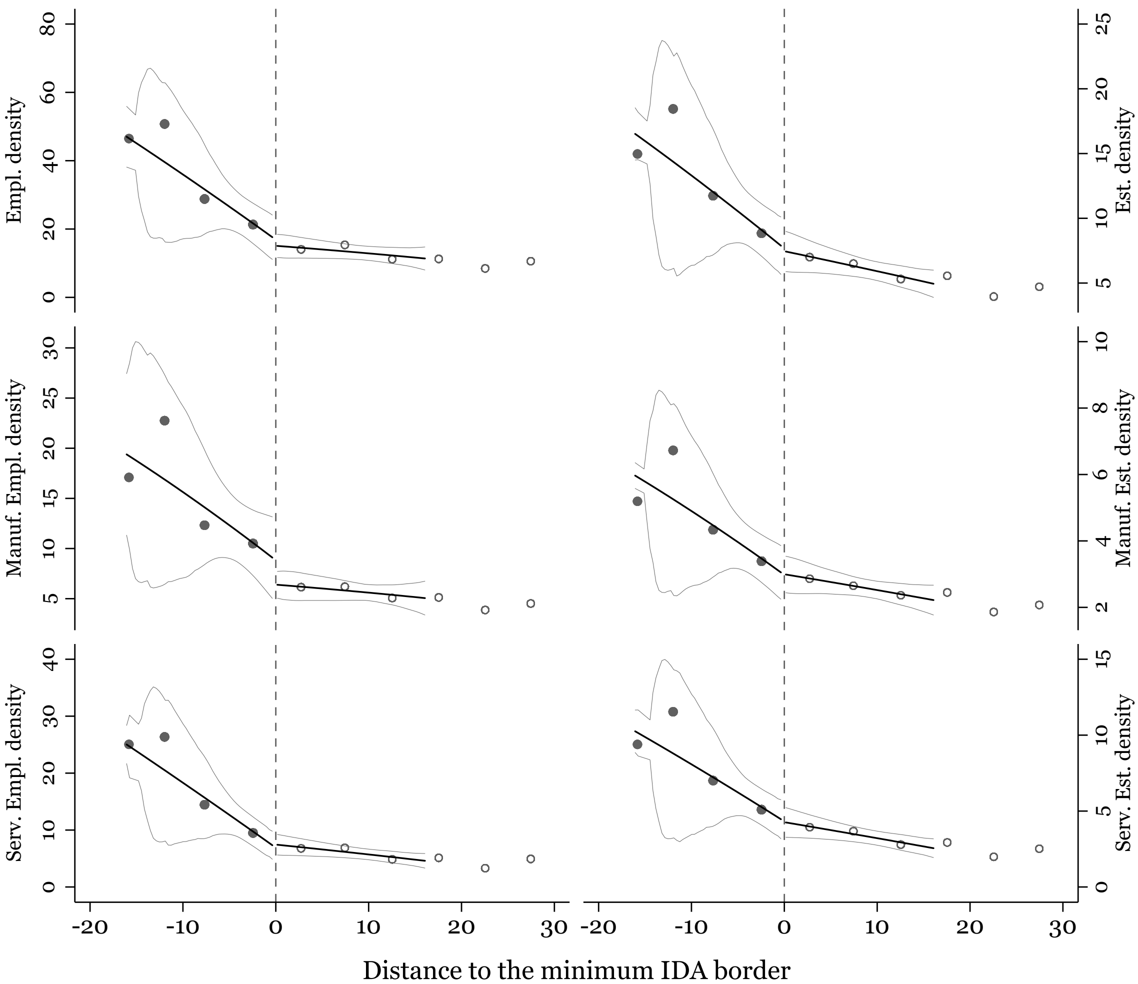
Appendix Figure B1.1 shows RD plots for many other variables. There are no discontinuities in labor market and demographic characteristics such as employment rate, population density, education and population age and gender composition. There is also balancing in geographical traits and, importantly, in voting outcomes before the policy (measured as the votes share for the incumbent government party). The lack of a discontinuity in electoral preferences reassures that IDA inclusion was not driven by political considerations.[14] To address concerns about unobserved confounders at the cutoff, we will test our results under an alternative identification design that, again exploiting the contiguity rule, uses municipalities bordering provincial capitals in the Center-North of Italy as new control group.

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

This empirical approach does not exploit the longitudinal dimension of our data. In

[14]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, arguably implying small differences in Marshall Plan funding (Gagliarducci et al., 2020; Bianchi and Giorcelli, 2023).

Figure 4. Balancing at the minimum IDA border, 1951



Notes: Number of workers and establishments sourced from the 1951 industrial census. Negative distance denotes municipalities within the minimum IDA border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately at each side of the border using a symmetric 16-km bandwidth. The gray lines are 95 percent confidence intervals.

fact, we observe the main outcomes (employment and firm density) at ten points in time (1911, 1927, 1951, 1961, 1971, 1981, 1991, 1996, 2001 and 2011) over one century. We can then corroborate our identification by accounting for unobserved, time-invariant municipality characteristics. The regression form is a difference-in-discontinuities (Diff-in-Disc) design – a dynamic specification of the reduced-form Equation 1b:

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

$Y_{m,t}$ is the outcome for municipality m and census year t, μ_m are municipality effects and σ_t are census year effects. The specification tracks municipalities contiguous to IDA centers over time (excluding the centers themselves) and compares them to municipalities up to 16 km away from the minimum IDA border. The coefficients of interest ρ_j capture the difference in outcomes between municipalities within and outside of the cutoff in census year j relative to the baseline difference in 1951, which is normalized to zero. Valid identification no longer requires continuity of potential outcomes at the cutoff, but hinges on the weaker assumption that outcomes in municipalities bordering IDA centers would have behaved similarly to municipalities right outside of the cutoff in the absence of the policy. An indirect test of this parallel trends assumption is provided by the coefficients ρ_{1911} and ρ_{1927}, which should be undistinguishable from zero.[15]

Placebo centers. Our empirical design is not immune to threats. The estimated effects may incorporate (positive or negative) spillovers to control municipalities, which being very close to IDAs may themselves be affected by the policy. There may also be differential trends between municipalities contiguous to IDA centers and those further away, due, for example, to urban growth stemming from the centers. We propose an alternative design to rebut these concerns. Namely, we focus on placebo centers – provincial capitals in the Center-North of Italy that would have likely been candidate IDA centers had they been part of the EIM region. In turn, again exploiting the contiguity rule, municipalities bordering placebo centers can be used as new control group and compared over time to municipalities bordering IDA centers. By using locations far away from IDAs as control, this exercise rules out strong spatial spillovers to the control group. Placebo centers are also used to directly estimate these spatial spillovers, by comparing the control group in the baseline design (municipalities just outside of the minimum IDA border) to their counterpart in the Center-North around placebo centers. Last, we run a triple differences specification that compares the evolution of outcomes around IDA centers (as per Equation 2) versus around placebo centers, subtracting any differential trend at the cutoff driven by, say, urban growth. Appendix B.3 describes these designs more in detail.

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

The EIM border. In Section 8 we compare our results for IDAs to those derived from a spatial RD design at the border separating the EIM jurisdiction from the rest of Italy (Albanese et al., 2024), discussed in Appendix B.4. This exercise will be useful to understand how the effects of government transfers depend on the initial conditions of subsidized areas, as it will contrast high-potential locations (the IDAs) to regions with low initial agglomeration (around the EIM border).

5. Results

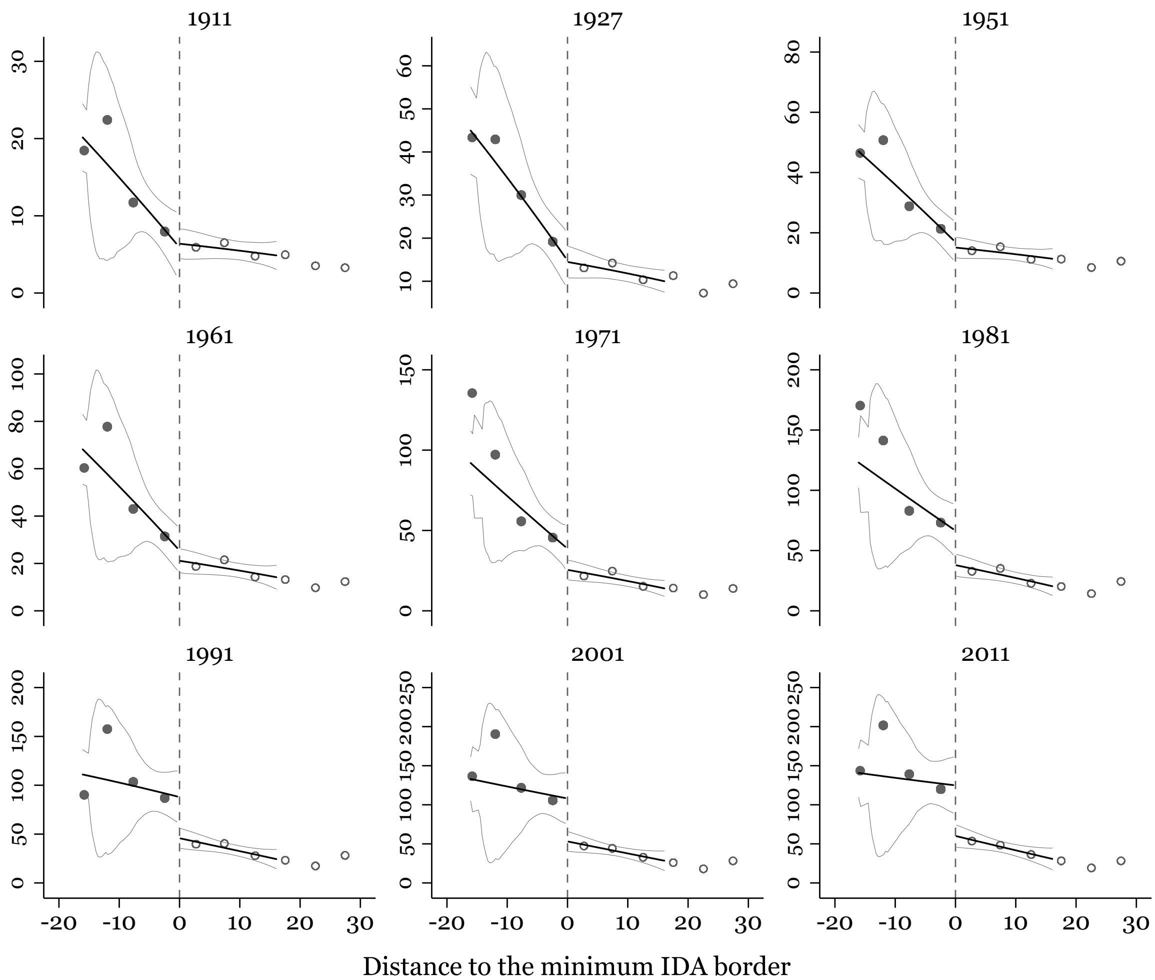
How has the IDA policy affected local employment? Viewed through the lens of a simple model of spatial equilibrium (Kline and Moretti, 2014b), a place-based policy that alters the cost of capital across locations shifts the (relative) labor demand curve up and raises employment in the targeted area.[16] To test this prediction, we first provide graphical evidence by plotting employment density around the minimum IDA border, then show regression estimates to quantify the discontinuities.

Graphical evidence. Figure 5 shows RD plots for employment density around the minimum IDA border in each census year. There is no tangible difference in agglomeration at the cutoff not only at the onset of the EIM in 1951 (as showed in Figure 4) but also in the previous decades (1911 and 1927), which further supports the continuity assumption. Starting in the 1970s a positive discontinuity emerges at the cutoff, as agglomeration increased in municipalities bordering IDA centers relative to those immediately outside of the cutoff. The jump at the border remains visible at the end of subsidies in 1991 and, importantly, also in the following decades. We document a very similar pattern for firm density, as showed in Appendix Figure C1.[17]

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

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

Figure 5. Employment density



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

Baseline estimates. Table 3 shows the baseline regression estimates for employment density separately for 1991 (at the end of the intervention) and 2011 (the latest period we observe).[18] 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

[18] Appendix Table C1 shows results for firm density. Although 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. Also, we show the effect in 1991 rather than in 1981 to preserve consistency with the results (showed later) from social security data, which are not available before 1990. That said, results for 1981 and 1991 are very similar.

Table 3. Employment density – Baseline

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

Notes: Column (1) shows the estimation output of Equation 1b. Column (2) reports the fuzzy RD estimates, see Equations 1a and 1b. 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.

rises to about 63 workers per km^2 (60 percent of a standard deviation). These effects are equivalent to 51 log points in 1991 and 55 log points in 2011 and are comparable in magnitude to those in von Ehrlich and Seidel (2018) (Table C7). Column (2) reports 2-SLS estimates for the LATE, which is estimated at 111 workers per km^2 in 1991 and 161 workers per km^2 in 2011. Column (3) replaces IDA status with EIM funding per municipality resident in 1951 as treatment variable. A rise in subsidies of €1000 (2011 prices) per 1951 resident (about 13 percent of the mean, see Table 2) leads to 7.2 more workers per km^2 in 1991 and 10.3 more in 2011. We interpret these estimates with more caution in light of the weaker first stage.[19]

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

Robustness tests. The baseline estimates are robust to several checks, showed in Appendix C. Table C2 reports robustness tests to i) more flexible polynomial specifications of the RD control function; ii) excluding IDA centers from the sample; iii) controlling for distance to the IDA center; iv) excluding IDA region effects from the specification. The estimated discontinuity declines but remains large and significant when using a quadratic or cubic RD polynomial and when excluding IDA centers. The effect stays roughly unchanged in magnitude and significance when controlling for the distance to the IDA center or excluding IDA region dummies. Tables C3 and C4 show that results hold when allowing for spatial correlation in standard errors (Conley, 1999), or conducting local randomization inference (Cattaneo et al., 2016). Table C5 confirms that results do not change if including two IDAs (Napoli and Caserta) that are excluded in the baseline analysis because of the short distance between the two centers. Figure C2 shows that the RD coefficient remains stable as we replicate the baseline estimation excluding one IDA region at a time, confirming that results are not driven by a specific IDA. Last, Table C6 presents non-parametric estimates obtained following Calonico et al. (2014). We weigh each municipality using a triangular kernel function giving more weight to places close to the cutoff. We also compute an MSE-optimal bandwidth that can differ within and outside of the cutoff. This procedure delivers indeed quite a narrow bandwidth within the cutoff (6-7 km), focusing only on the contiguous municipalities. The RD coefficient rises in magnitude but is less precisely estimated – most likely because of the small number of observations within the cutoff.

Bandwidth choice and spillovers. Figure C3 shows the LATE estimate obtained over a range of bandwidths around the cutoff, both in 1991 and 2011. Deriving our effects on a varying sample is a first assessment of whether the baseline estimates incorporate spatial spillovers. Positive coefficients may reflect displacement of workers and firms from control areas close to the cutoff. If driven by such displacement, estimates should shrink when using a broader control group farther away from the cutoff. Indeed, the effect declines as more and more municipalities are added to the sample outside of the border, but

not satisfied and we may be overestimating the intensive margin effect.

the impact of the policy remains stable overall. This suggests that displacement effects, albeit present, are likely of limited magnitude. We address these issues more in detail in the next paragraphs.

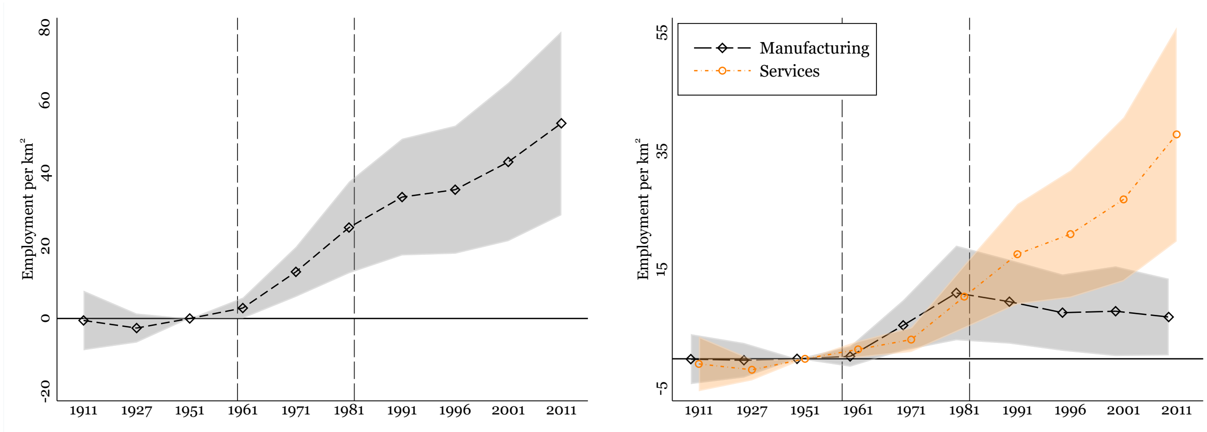
Population, migration, participation. Our employment measure is based on the municipality of work. Results may thus reflect workers commuting around the cutoff. Table C7 shows however that the effect on population density (based instead on the municipality of residence) is not far from that on employment density, suggesting that worker commuting is not a key driver of our results. A more concrete possibility is that the policy led to migration into IDAs. Data available starting in 1991 show no significant difference in migration rates at the cutoff in 1991 and 2011 – see Table C8 (we also find no effect on commuting, consistent with the effects on population in Table C7). Migration into IDAs might have been higher during the policy years, in response to the subsidies. We unfortunately lack municipality-level migration data before 1991 to directly test it, and will explore possible migration into IDAs using the alternative design discussed at the end of this Section. For now, we notice that the strong persistence we observe could hardly originate solely from migration from untreated areas. While displacement effects should be expected during the policy years (as confirmed in Cerrato (2024) using province-level data), they should not be too large (as non-IDA municipalities still had access to EIM subsidies) and are unlikely to persist in the long run. Indeed, Table C9 shows that the policy also led to the creation of new jobs in treated areas, as the employment rate and labor market participation of residents rose and the unemployment rate decreased during the 1970s and 1980s.[20]

Difference-in-discontinuities. Figure 6(a) shows the estimated ρ_j coefficients from the Diff-in-Disc design in Equation 2. First, we find evidence of parallel trends, as there is no difference in employment density between treated and control municipalities in 1911 and 1927 relative to the difference in 1951 (which, as showed in Figure 5, is very close to

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

Figure 6. Difference-in-discontinuities

(a) Employment density (b) Manufacturing versus services



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

zero itself). We then observe a steady increase in the Diff-in-Disc coefficient during the policy years, reaching about 30 workers per km^2 at the end of the intervention. The effect continues to rise in the ensuing decades and is close to 50 workers per km^2 in 2011.

Manufacturing versus services. How does such stark persistence originate? We decompose employment density between manufacturing and services and show the coefficient estimates in Figure 6(b). The rising agglomeration during the 1960s is driven largely by manufacturing employment and, to a smaller extent, services. The manufacturing boost stabilizes towards the end of the policy in the 1980s and moderately declines afterwards. In contrast, the decades after the end of the EIM see a substantial increase in agglomeration in the services sector, which is at the basis of the persistent effect of the policy.[21]

Placebo centers. We now test whether results hold with the alternative approach using placebo centers – provincial capitals in the Center-North of Italy that would have likely been IDA centers had they been part of the EIM region (see Section 4 and Appendix B.3 for details). We leverage this source of variation in three ways. In the first exercise, we run a simple event study analysis comparing treated municipalities bordering IDA centers

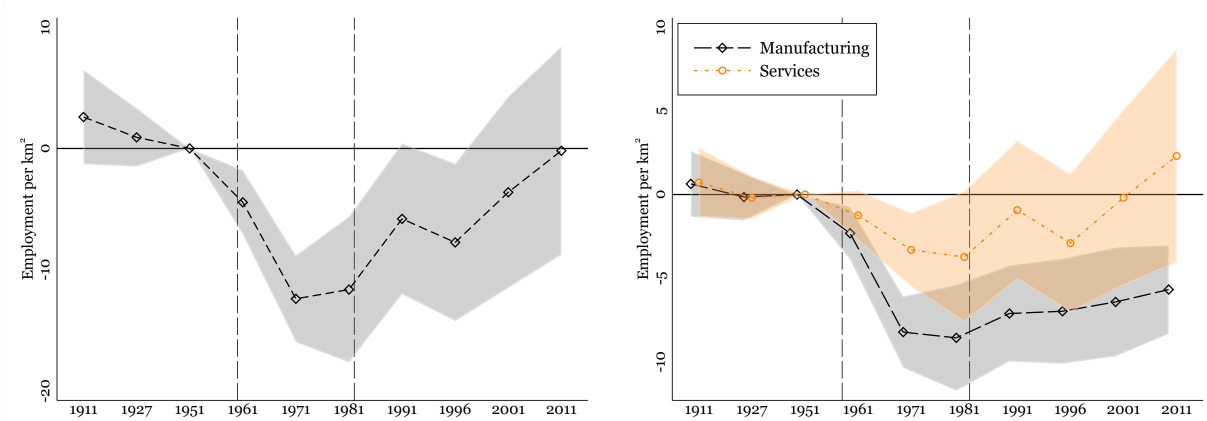
[21] Figure C4 reports the Diff-in-Disc results for firm density. Figures C5-C8 and Table C10 show the RD plots and the cross-sectional fuzzy RD estimates separately by manufacturing and services.

with control municipalities bordering placebo centers before and after the institution of the IDAs (Equation B3.1), and plot the coefficients in Figures C9 and C10. The two groups are on parallel trends before the policy. Once the IDAs are introduced, economic density increases in the treated areas and the long-term effect is largely concentrated in services, in line with the main results. While these coefficients cannot be directly compared to the baseline Diff-in-Disc estimates, the choice of a new control group away from the IDAs addresses two main issues. First, it makes spatial spillovers to control units unlikely. Second, it suffers less from concerns that control municipalities are not part of IDAs because of unobserved reasons.

Estimating spatial spillovers. In a second exercise, we aim to directly estimate spatial spillovers. We run the same event study as above but consider municipalities up to 16 km outside of the minimum IDA border (the control group in the baseline RD design) as treatment group. As new control group, we take their counterpart in the Center-North: municipalities up to 16 km outside of the "placebo" boundary traced by municipalities bordering placebo centers. This set-up enables us to investigate possible displacement effects to areas right outside of the minimum IDA border. Figure 7(a) shows the results. We document a negative effect on employment density outside of the minimum IDA border while IDAs were in place, suggesting some displacement as a result of the policy. During the 1970s, these spillovers reached about 10 workers per km^2, vis-à-vis a baseline effect of 30 workers per km^2 in 1981 (Figure 6). According to these estimates, roughly one third of the effect of IDAs while they were in place reflects an employment shift around the cut-off. These displacement effects are largely concentrated in manufacturing, while they are barely noticeable in the services sector (Figure 7(b)). Most importantly, they tend to fade in the long term. By 2011, we observe little spillovers of the IDA policy, although manufacturing employment is still lower in nearby areas. Overall, however, the persistent effect of PBIP does not appear to be driven solely by continued displacement of economic activity (the results for firm density are similar, and showed in Figure C11).

Figure 7. Estimating the spatial spillovers of the IDA program

(a) Employment density (b) Manufacturing versus services



Notes: Coefficient estimates for Equation B3.1. Sample restricted to municipalities up to 16 km outside of the minimum IDA border (treatment group) and municipalities up to 16 km outside of the placebo border traced by municipalities bordering placebo centers (control group). The treatment group excludes IDA municipalities. Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the IDAs.

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

6. Mechanisms

Our results indicate persistence in the effects of PBIP and highlight clear sectoral patterns. We document an immediate response of manufacturing (the only recipient of subsidies) and, to a lower extent, services, during the policy years. As the intervention ceases, the effect on manufacturing stabilizes but employment in services continues to grow. How can the rise in services – not the main target of the policy – be rationalized?

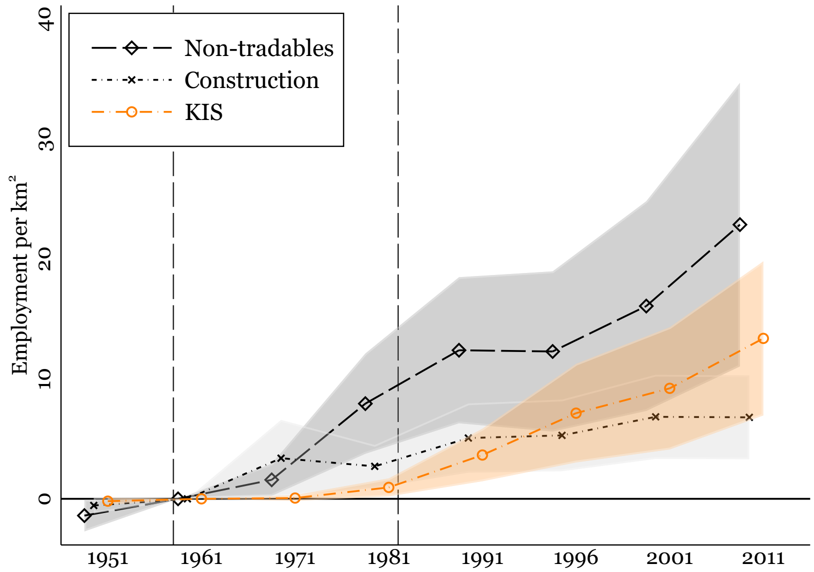
The rise in services while IDAs were in place is most likely a result of multiplier effects, as the stimulus to local manufacturing boosts demand for local goods and services (Moretti, 2010). This implies that the contemporaneous effect on services employment should have occurred mostly in non-tradables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

Instead, the enduring growth of the services sector after the end of the policy 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 these predictions by decomposing the effect on services. As discussed, the immediate impact on services employment while IDAs were in place is 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.[22] As noted above, these pecuniary externalities can account for the contemporaneous rise in services but cannot by themselves explain our persistent effects. Assuming a multiplier of one also after 1981, higher manufacturing employment in treated areas after the end of the policy would account for 50 percent of the increase in services employment in 1991 and only 20 percent in 2011.

[22] 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.

Figure 8. Employment density – Sectoral breakdown



Notes: Coefficient estimates for Equation 2. Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the IDAs. "Non-tradables": wholesale and retail trade, hotels and restaurants and other. "KIS": communication, finance and insurance and services to firms. We cannot perform this breakdown within services for the 1911 and 1927 historical censuses.

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 of KIS in treated areas.[23] 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). We replicate the baseline fuzzy RD design (Table 3) and show results in Table D1, which reports coefficient estimates separately for the shares of KIS and other services in 1991 and 2011 (the firm data are available only starting in 1990). IDA status leads to a 8 percentage points larger share of workers and 6 percentage points larger share of firms in KIS. The effects are economically large and persist well after the end of the policy.

[23]The lack of effects on KIS while IDAs were in place is not surprising: mean KIS employment density in the 1960s-70s in our sample was still very 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, which could be driven by multiplier effects (from manufacturing or KIS), or by endogenous agglomeration in urban amenities (Leonardi and Moretti, 2022). These results are confirmed with the alternative approach using placebo centers (Appendix Figures D2 and D3).

The role of high-technology manufacturing. Did the policy affect the *composition* of manufacturing? Can this explain the rise of KIS? We inspect this in Table D2, where we distinguish between high- and low-technology manufacturing industries using the Eurostat/OECD classification. At the end of the policy, treated municipalities had a larger share of workers and firms in high-technology manufacturing than control ones. The stimulus to high-technology industries might have contributed to the subsequent development of KIS in two ways. First, by establishing a local pool of specialized, high-skill workers – a thick labor market externality. Second, by creating demand for business services such as consulting, legal and information technology – a local demand multiplier.[24]

Both channels seem to be at play. To study the first one, Figure D4 plots the cumulative share of new hires (job-to-job) in KIS from high-technology manufacturing between 1991 and 2011.[25] 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. Assessing the second channel is harder. National input-output tables confirm that high-technology manufacturing industries' demand for skilled services is twice as large than for low-technology industries (Figure D5). While we cannot observe input-output linkages at the municipality level to directly assess this channel, we leverage granular sector information in the administrative data. In Appendix Table D3, 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

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

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

Table 4. (Log) wages – Fuzzy RD estimates

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

Notes: Fuzzy RD estimates, see Equations 1a and 1b. 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 for details.

about 27 percent.[26] We also find higher human capital and skills among the resident population in the long term (Table 5). The share of high-school educated is 10-11 percentage points larger in 1991 and 2011, and the share of young people with a university degree is 5 and 9 points larger in 1991 and 2011, respectively. We also estimate a large positive effect (10-11 percentage points) on the share of high-skilled occupations (managers and professionals), at the expenses of low-skilled ones (routine jobs).

Firms. How did the policy affect firms? Table D5 shows a prevalence of large and high-paying firms in IDAs in 1991 and 2011. Table D6 shows results for balance sheet outcomes in 2011.[27] For manufacturing and KIS firms, we estimate positive long-run effects on labor productivity, investment and sales. Manufacturing firms also earn higher profits per worker. Last, Figure D6 shows year-by-year estimates of the fuzzy RD coefficient when using cumulative firm entry and exit rates (starting in 1990) as outcome. While

[26] Table D4 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.

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

Table 5. Education and occupations – Fuzzy RD estimates

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

Notes: Fuzzy RD estimates, see Equations 1a and 1b. "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 9). "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).

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.

Assessing persistence. Our evidence so far is consistent, in principle, with the presence of agglomeration economies.[28] Admittedly, our empirical design based on local spatial variation is not well suited to identify such externalities. Still, additional findings showed in Tables D7 and D8 at least do not exclude the presence of agglomeration economies. First, we document sizable long-term effects on local incomes and house prices.[29] Second,

[28] Following government intervention, the targeted areas witness an increase in economic density. In the presence of knowledge spillovers or thick market externalities, higher proximity between agents boosts local productivity. Then, the cluster keeps attracting workers and firms even after subsidies cease and until local prices grow high enough. Government subsidies that internalize these externalities have an efficiency justification (Duranton and Puga, 2004; Moretti, 2011).

[29] We also find that PBIP raised local inequality, as evidenced by the higher Gini coefficient. On a similar note, Figure D7 reports quantile treatment effects estimated following Frandsen et al. (2012), showing higher effects on employment and firm density at higher deciles of the distribution.

sectoral specialization within manufacturing measured with the Krugman Specialization Index (Krugman, 1992) has *decreased* following the policy, suggesting that the benefits of subsidies extended beyond the targeted industries. Third, we rule out (some) other possible sources of persistence linked to continued public investment in treated areas after the end of the policy. We test this by estimating our fuzzy RD model for municipal expenditures sourced from municipality balance sheets between 2000 and 2010, broken down into different items. We add two more outcomes: the cumulative EU structural funds received between 2007 and 2013 and the total subsidies within Law n. 488/1992, introduced right after the EIM. We find no discontinuity in any of these outcomes. That said, we cannot rule out that other local policies and regulations (that we do not account for) explain, at least in part, our persistent effects.[30]

7. Cost-benefit analysis

While our findings highlight a positive impact of the policy, whether these benefits outweigh the costs remains to be addressed. We now use our estimates to inform a cost-benefit analysis of the IDA program. Appendix E provides more detail.

Cost per job. We begin by calculating the cost per job. While relatively straightforward, this measure provides an easy way to compare policies with each other. We first use the empirical estimates of Table 3, Column (3), suggesting that an increase in EIM funding of €1,000 per 1951 resident leads to 10.3 more workers per km^2 in 2011. For the average municipality in the estimation sample, these estimates translate in a cost per job of €17,989 or $25,048 (2011 prices), which rises to $37,571 assuming a deadweight loss of 50 percent.[31] Using the long-run Diff-in-Disc estimates (Figure 6(a)) delivers a similar cost per job of $21,716 ($32,575 including deadweight loss), which remains roughly stable when substituting the estimates from our alternative identification strategies (Figure

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

[31] For a similar analysis see Freedman (2012). The magnitude of the deadweight loss largely depends on the effect of place-based policy on location decisions (Busso et al., 2013). While we estimate no migration effects in the long run, our results suggest that the IDAs induced migration while they were in place (Section 5). We therefore impose a 50 percent deadweight loss as in Criscuolo et al. (2019) and Siegloch et al. (2022).

C9(a) and C12(a)). The cost per job of the IDA policy falls not far from 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).[32]

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

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

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

[33]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.

8. Discussion and further implications

The last part of our analysis explores how the long-run effects of PBIP may depend on the characteristics of the targeted areas, and especially their initial conditions.

Heterogeneity. We explore possible heterogeneity across IDAs, asking whether persistence is linked to specific local characteristics. We split the group of 12 IDA regions in our sample into two sub-groups based on whether a region is above or below the median, for the following variables: elevation, slope, cumulative EIM subsidies, services share in 1951, share of high-technology manufacturing in 1991 and high-school education in 1951. We then conduct analysis separately for IDAs above and below the median. Figure F1 shows the Diff-in-Disc coefficients.

We measure no significant difference in employment effects between IDAs based on their geographical traits or EIM funding. A larger share of services at the onset of the policy seems to lead to higher long-run effects, but the difference between the estimated coefficients is small. The most striking differential effects are found when splitting the sample of IDAs based on the incidence of high-technology manufacturing in 1991 (clearly an outcome of the policy) and education levels in 1951. IDAs where the policy stimulated high-technology industries more, and IDAs with larger initial human capital endowment, are also those where the policy had a larger employment impact in the long term.[34] Still, some persistence in the effect of the policy remains visible across all heterogeneity cuts. Our set-up is admittedly not best suited to heterogeneity analysis because of the relatively small sample size and the RD design. To further investigate heterogeneous results, we conduct our analysis in other areas of Southern Italy, which also received EIM subsidies.

The EIM border. As summarized in Appendix B.4 and detailed in Albanese et al. (2024), the northern border separating the EIM region from the rest of Italy gives rise to a spatial RD design that compares areas south of the border, which were subsidized by the Cassa,

[34] 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.

to areas north of it. For sake of brevity, Figure 9 shows the most robust estimates from a Diff-in-Disc design run at the EIM border (Equation B4.2).[35] Panel (a) shows the estimates for employment density. Areas north and south of the border were on parallel trends before the beginning of the policy. A positive effect emerges starting in the 1970s, albeit not statistically significant. The coefficient peaks at the end of the EIM in 1991 but eventually declines, showing no persistent impact of the intervention. Panel (b) breaks down the effect between manufacturing and services. Similarly to IDAs, manufacturing employment rises during the policy years but stabilizes as the incentives terminate. However, in stark contrast with the case of IDAs, services *do not* respond to subsidies.

The results listed in Section 6 do not hold at the EIM border (Appendix F). The share of workers and firms in KIS and high-technology manufacturing is unaffected.[36] Wages are higher south of the border in 1991, but only in manufacturing and non-tradable services. By 2011, the wage effect has disappeared. We find no 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 only for manufacturing and non-tradables and not in KIS. Last, we find no effects on local incomes and even negative long-run effects on house prices.

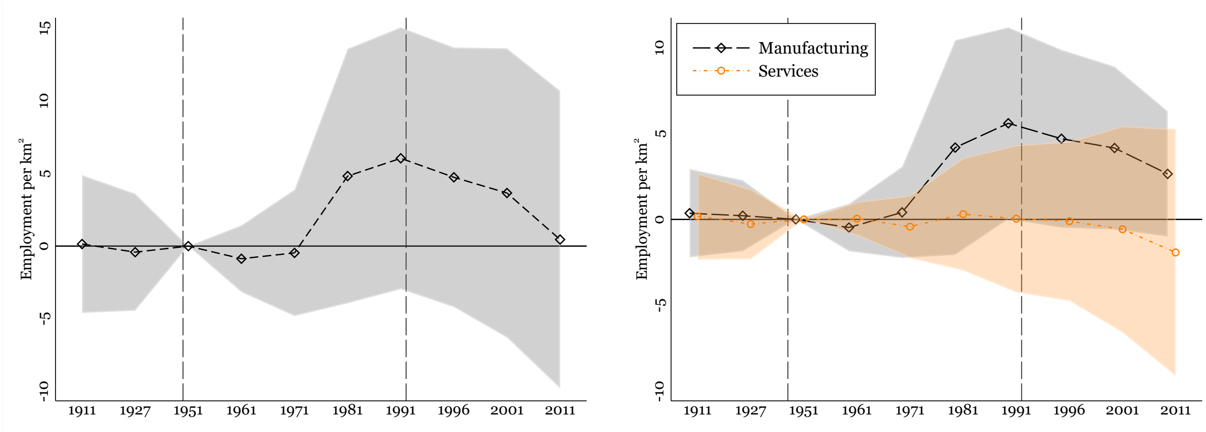
Initial conditions. While government intervention led to broad and persistent results in IDAs, its effects at the EIM border were concentrated in the targeted sectors (manufacturing) and dissipated shortly after the end of subsidies. These opposite findings may depend on different local initial conditions. Table F10 provides suggestive evidence in this regard, comparing municipalities bordering IDA centers to municipalities south of the EIM border. The two groups do not differ much in the amount of per capita funding from the Cassa. There are however substantial differences in pre-existing (1951) agglomeration of workers and firms and population density, which were about three times larger

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

[36]EIM firm subsidies at the border went mostly to low-technology industries such as textiles and food (Figure F10), as opposed to more advanced industries in the case of IDAs (Figure A1.1).

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

(a) Employment density (b) Manufacturing versus services



Notes: Coefficient estimates for Equation B4.2. Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the EIM.

in IDAs. Places south of the EIM border had instead much less favorable geography, a larger share of workers in agriculture and slightly less educated population before the policy. Put differently, while IDAs were explicitly selected as hubs for future agglomeration, areas around the EIM border were more peripheral and, arguably, less suitable to the formation of local clusters.[37]

9. Conclusion

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

[37] While we stress the role of initial conditions, another possible explanation for these findings lies in the role of expectations. In models with multiple steady states, agents' expectations that a community will be in a developed equilibrium can become self-fulfilling (Kline, 2010). The policymaker committed to establishing local hubs in IDAs, while there was no such explicit commitment for the areas around the EIM border.

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

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

References

Abowd, John, Francis Kramarz, and David Margolis, "High Wage Workers and High Wage Firms," *Econometrica*, 1999, *67* (2), 251–334. 32, 51, 82

Albanese, Giuseppe, Guido de Blasio, and Lorenzo Incoronato, "Government Transfers and Votes for State Intervention," *American Economic Journal: Economic Policy*, August 2024, *16* (3), 451–80. 6, 8, 21, 36, 61

Alessandrini, Michele, Pietro Celotti, Erich Dallhammer, Helene Gorny, Andrea Gramillano, Bernd Schuh, Chiara Zingaretti, Maria Toptsidou, and Mailin Gaupp-Berghausen, *Implementing a place-based approach to EU industrial policy strategy*, European Committee of the Regions, 2019. 2

Allen, Treb and Costas Arkolakis, "Economic Activity across Space: A Supply and Demand Approach," *Journal of Economic Perspectives*, 2023, *37* (2), 3–28. 5

Atalay, Enghin, Ali Hortaçsu, Mustafa Runyun, Chad Syverson, and Mehmet Fatih Ulu, "Micro- and Macroeconomic Impacts of a Place-Based Industrial Policy," *Working Paper*, 2022. 8

Bartik, Timothy, Brian Asquith, and Kathleen Bolter, "The Chips and Science Act Offers Funding for Place-Based Policies Unparalleled in U.S. History," 2022. 2

Bianchi, Nicola and Michela Giorcelli, "Reconstruction Aid, Public Infrastructure, and Economic Development: The Case of the Marshall Plan in Italy," *The Journal of Economic History*, 2023, *83* (2), 501–537. 18

Bronzini, Raffaello and Guido de Blasio, "Evaluating the impact of investment incentives: The case of Italy's Law 488/1992," *Journal of Urban Economics*, 2006, *60* (2), 327–349. 10

Buscemi, Tancredi and Giulia Romani, "The Political Economy of Regional Development: Evidence from the Cassa per il Mezzogiorno," Working Papers 2022:18, Department of Economics, University of Venice "Ca' Foscari" 2022. 8

Busso, Matias, Jesse Gregory, and Patrick Kline, "Assessing the Incidence and Efficiency of a Prominent Place Based Policy," *American Economic Review*, 2013, *103* (2), 897–947. 6, 34, 35, 87

Calonico, Sebastian, Matias Cattaneo, and Rocio Titiunik, "Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs," *Econometrica*, 2014, *82*, 2295–2326. 24, 62, 67

Cattaneo, Matias, Rocio Titiunik, and Gonzalo Vazquez-Bare, "Inference in regression discontinuity designs under local randomization," *Stata Journal*, 2016, *16* (2), 331–367. 24, 66

Cerqua, Augusto and Guido Pellegrini, "Do subsidies to private capital boost firms' growth? A multiple regression discontinuity design approach," *Journal of Public Economics*, 2014, *109* (C), 114–126. 10, 35

Cerrato, Andrea, "How Big Is the Big Push? The Macroeconomic Effects of a Large-Scale Regional Development Program," *Working Paper*, 2024. 8, 25

Charles, Kerwin Kofi, Erik Hurst, and Mariel Schwartz, "The Transformation of Manufacturing and the Decline in US Employment," *NBER Macroeconomics Annual*, 2019, *33* (1), 307 – 372. 7

Chaurey, Ritam, "Location-based tax incentives: Evidence from India," *Journal of Public Economics*, 2017, *156* (C), 101–120. 35

Choi, Jaedo and Andrei Levchenko, "The Long-Term Effects of Industrial Policy," CEPR Discussion Papers 16534, Centre for Economic Policy Research 2021. 7

Cingano, Federico, Filippo Palomba, Paolo Pinotti, and Enrico Rettore, "Making Subsidies Work: Rules vs. Discretion," CEPR Discussion Papers 17004, Centre for Economic Policy Research 2022. 7, 10, 35

Colussi, Tommaso, Giampaolo Lecce, Marco Manacorda, and Massimiliano Gaetano Onorato, "The Politics and Economics of Government Aid: Evidence from the Italian Cassa per il Mezzogiorno," *Working Paper*, 2020. 8

Conley, Timothy, "GMM estimation with cross sectional dependence," *Journal of Econometrics*, 1999, *92* (1), 1–45. 24, 62, 65, 97, 99, 100, 101, 102, 103

Criscuolo, Chiara, Ralf Martin, Henry Overman, and John van Reenen, "Some Causal Effects of an Industrial Policy," *American Economic Review*, 2019, *109* (1), 48–85. 6, 7, 34, 35

De Philippis, Marta, Andrea Locatelli, Giulio Papini, and Roberto Torrini, "Italian economic growth and the North-South gap: Historical trends and future projections in light of the recent demographic scenarios," Questioni di Economia e Finanza (Occasional Papers) 683, Bank of Italy 2022. 9

Duranton, Gilles and Diego Puga, "Micro-foundations of urban agglomeration economies," in J. V. Henderson and J. F. Thisse, eds., *Handbook of Regional and Urban Economics*, 1 ed., Vol. 4, Elsevier, 2004, chapter 48, pp. 2063–2117. 33

Fai, Felicia, "Place-Based Perspectives on the UK Industrial Strategy," IPR Policy Brief, Institute for Policy Research, University of Bath 2018. 2

Falck, Oliver, Stephan Heblich, and Stefan Kipar, "Industrial innovation: Direct evidence from a cluster-oriented policy," *Regional Science and Urban Economics*, 2010, *40* (6), 574–582. 7

Felice, Emanuele and Amedeo Lepore, "State intervention and economic growth in Southern Italy: the rise and fall of the 'Cassa per il Mezzogiorno' (1950-1986)," *Business history*, 2017, *59* (3), 319–341. 8

Frandsen, Brigham R., Markus Frölich, and Blaise Melly, "Quantile treatment effects in the regression discontinuity design," *Journal of Econometrics*, 2012, *168* (2), 382–395. 33, 85

Freedman, Matthew, "Teaching new markets old tricks: The effects of subsidized investment on low-income neighborhoods," *Journal of Public Economics*, 2012, *96* (11), 1000–1014. 34

Gagliardi, Luisa, Enrico Moretti, and Michel Serafinelli, "The World's Rust Belts: The Heterogeneous Effects of Deindustrialization on 1,993 Cities in Six Countries," *Working Paper*, 2023. 7, 36

Gagliarducci, Stefano, Massimiliano Onorato, Francesco Sobbrio, and Guido Tabellini, "War of the Waves: Radio and Resistance during World War II," *American Economic Journal: Applied Economics*, 2020, *12* (4), 1–38. 18, 52

Garin, Andrew and Jonathan Rothbaum, "The Long-Run Impacts of Public Industrial Investment on Local Development and Economic Mobility: Evidence from World War II," NBER Working Papers 32265, National Bureau of Economic Research 2024. 4, 7

Giorcelli, Michela and Bo Li, "Technology Transfer and Early Industrial Development: Evidence from the Sino-Soviet Alliance," CEPR Discussion Papers 16980, Centre for Economic Policy Research 2022. 7, 8

Greenstone, Michael, Richard Hornbeck, and Enrico Moretti, "Identifying Agglomeration Spillovers: Evidence from Winners and Losers of Large Plant Openings," *Journal of Political Economy*, 2010, *118* (3), 536–598. 8

Grembi, Veronica, Tommaso Nannicini, and Ugo Troiano, "Do Fiscal Rules Matter?," *American Economic Journal: Applied Economics*, 2016, *8* (3), 1–30. 54

Hahn, Jinyong, Petra Todd, and Wilbert van der Klaauw, "Identification and Estimation of Treatment Effects with a Regression-Discontinuity Design," *Econometrica*, 2001, *69* (1), 201–09. 54, 55

Hanlon, Walker, "The Persistent Effect of Temporary Input Cost Advantages in Shipbuilding, 1850 to 1911," *Journal of the European Economic Association*, 2020, *18* (6), 3173–3209. 5, 7

Heblich, Stephan, Marlon Seror, Hao Xu, and Yanos Zylberberg, "Industrial Clusters in the Long Run: Evidence from Million-Rouble Plants in China," Working Paper 30744, National Bureau of Economic Research December 2022. 2, 7

Helm, Ines, Alice Kügler, and Uta Schönberg, "Displacement Effects in Manufacturing and Structural Change," IZA Discussion Papers 16344, Institute of Labor Economics (IZA) 2023. 7

Imbens, Guido and Thomas Lemieux, "Regression discontinuity designs: A guide to practice," *Journal of Econometrics*, 2008, *142* (2), 615–635. 54

Juhász, Réka, "Temporary Protection and Technology Adoption: Evidence from the Napoleonic Blockade," *American Economic Review*, 2018, *108* (11), 3339–76. 7

_ , Nathan Lane, and Dani Rodrik, "The New Economics of Industrial Policy," *Annual Review of Economics*, 2024. 2, 7

Kantor, Shawn and Alexander Whalley, "Moonshot: Public R&D and Growth," *Working Paper*, 2022. 7

Kim, Minho, Munseob Lee, and Yongseok Shin, "The Plant-Level View of an Industrial Policy: The Korean Heavy Industry Drive of 1973," Working Paper 29252, National Bureau of Economic Research 2021. 7

Kline, Patrick, "Place Based Policies, Heterogeneity, and Agglomeration," *American Economic Review*, 2010, *100* (2), 383–87. 38

__ **and Enrico Moretti**, " Local Economic Development, Agglomeration Economies, and the Big Push: 100 Years of Evidence from the Tennessee Valley Authority," *The Quarterly Journal of Economics*, 2014, *129* (1), 275–331. 7

__ **and** __ , "People, Places, and Public Policy: Some Simple Welfare Economics of Local Economic Development Programs," *Annual Review of Economics*, 2014, *6* (1), 629–662. 2, 7, 21

Krugman, Paul, *Geography and Trade*, 1 ed., Vol. 1, The MIT Press, 1992. 34, 49

Lane, Nathaniel, "Manufacturing Revolutions: Industrial Policy and Industrialization in South Korea," EconStor Preprints, ZBW - Leibniz Information Centre for Economics 2022. 7, 8

Lapoint, Cameron and Shogo Sakabe, "Place-Based Policies and the Geography of Corporate Investment," *Working Paper*, 2022. 7, 35, 88

Leonardi, Marco and Enrico Moretti, "The Agglomeration of Urban Amenities: Evidence from Milan Restaurants," CEPR Discussion Papers 16937, Centre for Economic Policy Research 2022. 30

Lu, Yi, Jin Wang, and Lianming Zhu, "Place-Based Policies, Creation, and Agglomeration Economies: Evidence from China's Economic Zone Program," *American Economic Journal: Economic Policy*, 2019, *11* (3), 325–60. 7, 35, 88

Meyersson, Erik, "Islamic Rule and the Empowerment of the Poor and Pious," *Econometrica*, 2014, *82* (1), 229–269.

Millán-Quijano, Jaime, "Fuzzy difference in discontinuities," *Applied Economics Letters*, 2020, *27* (19), 1552–1555. 20, 54, 56

Mitrunen, Matti, "Industrial Policy, Structural Change and Intergenerational Mobility: Evidence from the Finnish War Reparations," *Working Paper*, 2020. 7

Moretti, Enrico, "Local Multipliers," *American Economic Review*, 2010, *100* (2), 373–77. 4, 8, 29, 31

__ , "Local Labor Markets," in O. Ashenfelter and D. Card, eds., *Handbook of Labor Economics*, 1 ed., Vol. 4B, Elsevier, 2011, chapter 14, pp. 1237–1313. 33

Navaretti, Giorgio Barba and Borislav Markovic, "Place-based policies and the foundations of productivity in the private sector," *OECD-EC high-level expert workshop Productivity Policy for Places*, 2021. 7

Neumark, David and Helen Simpson, "Chapter 18 - Place-Based Policies," in Gilles Duranton, J. Vernon Henderson, and William C. Strange, eds., *Handbook of Regional and Urban Economics*, Vol. 5 of *Handbook of Regional and Urban Economics*, Elsevier, 2015, pp. 1197–1287. 7

Porter, Michael E., "Location, Competition, and Economic Development: Local Clusters in a Global Economy," *Economic Development Quarterly*, 2000, *14* (1), 15–34. 2

Rodrik, Dani, "Where Are We in the Economics of Industrial Policies?," *Frontiers of Economics in China*, 2019, *14* (3), 329–335. 2

__ , "An Industrial Policy for Good Jobs," Technical Report, The Hamilton Project, Brookings 2022. 39

__ **and Stefanie Stantcheva**, "Fixing capitalism's good jobs problem," *Oxford Review of Economic Policy*, 2021, *37* (4), 824–837. 6, 7, 39

Siegloch, Sebastian, Nils Wehrhöfer, and Tobias Etzel, "Spillover, Efficiency and Equity Effects of Regional Firm Subsidies," ECONtribute Discussion Papers Series 210, University of Bonn and University of Cologne 2022. 6, 8, 34, 35

von Ehrlich, Maximilian and Henry G. Overman, "Place-Based Policies and Spatial Disparities across European Cities," *Journal of Economic Perspectives*, 2020, *34* (3), 128–49. 7

__ **and Tobias Seidel**, "The Persistent Effects of Place-Based Policy: Evidence from the West-German Zonenrandgebiet," *American Economic Journal: Economic Policy*, 2018, *10* (4), 344–74. 6, 23

A. Appendix A: Background and Data

A.1. Appendix A1: The EIM subsidies

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

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

Firm grants. Starting in 1960, the focus of the EIM shifted towards industrial policy, stimulating public and private investment in the South. The main policy item was firm investment grants. Grant applications were submitted by firms to special credit institutions in charge of investigating the proposed investment (including estimated job creation). The applications were then forwarded to the Cassa, which decided on the outcome and the amount of the subsidy (we only observe successful applications in the data). The specific allocation criteria changed several times over the course of the EIM.[38] During the 1960s-70s, the key inputs for the subsidy rate were firm size, sector and location. More precisely, small firms, firms in heavy industries, and firms located in IDAs could obtain a higher subsidy rate on their investment (up to 6.5 percentage points higher, separately for each of these three criteria). The maximum subsidy rate, originally set at 20 percent, has been periodically increased and reached 45 percent by 1971. Firms could apply for concessional loans, too. The sum of grants and loans conceded by the Cassa to a single firm could not exceed 85 percent of the total investment by the firm.

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

The IDAs. The establishment process for IDAs is described in Section 2. Here we clarify how investment grants differed for IDA firms. Firms in IDAs were entitled to larger subsidies from the Cassa in two ways. First, the subsidy rate on investments was up to 6.5 percentage points higher for IDA firms than for other EIM firms, as mentioned above. Second, all IDA firms could access grants regardless of size, while there where limits to both firm size (up to 500 workers, investment below €1.5 million) and municipality size (up to 75,000 people) elsewhere in the EIM region.[39] These size limits were removed in 1967. Subsidy rates were equalized between IDA and non-IDA firms in the late 1970s.

The *Industrialization Nuclei*. Together with the IDAs, the government also introduced the so-called *Industrialization Nuclei* to favor "*minor concentration*" (see footnote 39). The Nuclei were less extensive areas (usually just one municipality) where a small number of firms could take advantage of local materials and a specialized workforce. The contiguity rule, which inspires our identification strategy, did not apply to the Nuclei. The 79 municipalities included in Nuclei are dropped from our analysis and estimation sample.

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

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

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

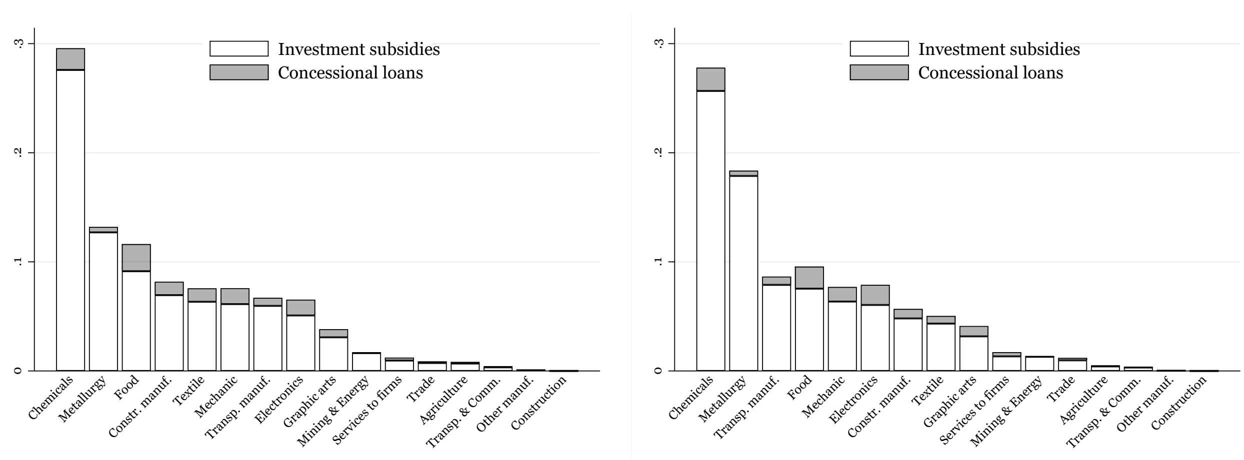
	Total expenses		Infrastructure spending		Firm subsidies	
	Amount	Per capita	Amount	Per capita	Amount	Per capita
1950-1959	5,309	236.4	5,290	235.5	19	0.8
1960-1969	29,990	1,335.2	8,607	383.2	21,382	952.0
1970-1979	79,439	3,536.9	26,368	1,174.0	53,071	2,362.9
1980-1989	37,270	1,659.4	16,781	747.2	20,489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

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

Appendix Figure A1.1. Incentives to firms – breakdown

(a) Full EIM area

(b) IDAs



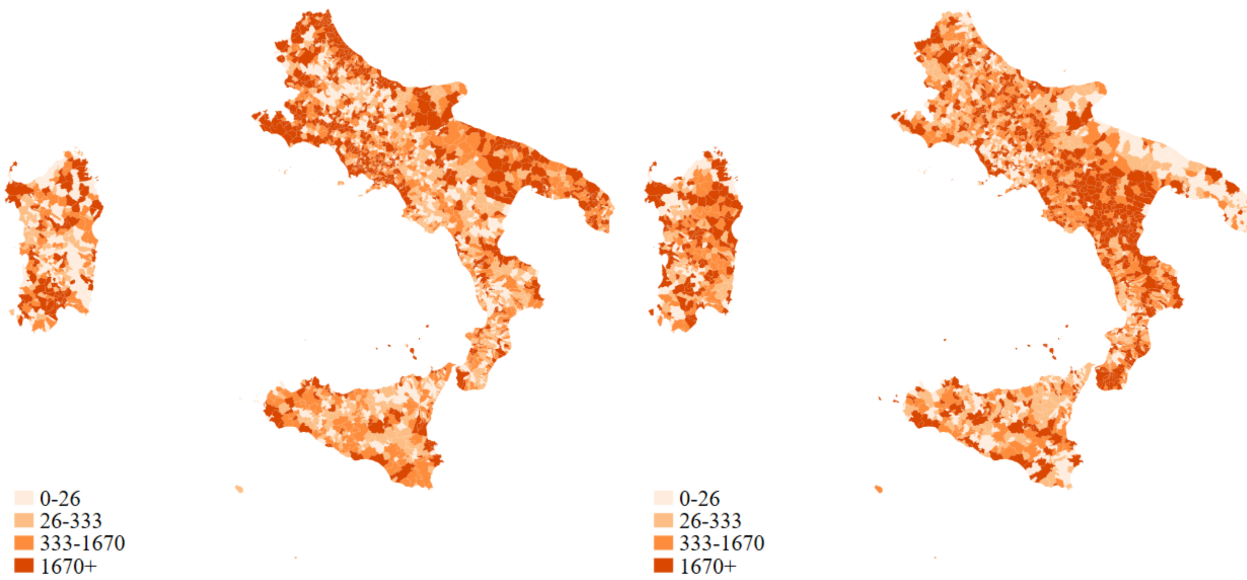
Notes: Sector breakdown of firm investment subsidies and concessional loans. Panel (a) includes all EIM municipalities. Panel (b) includes IDAs only.

Figure A1.1 breaks down firm 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 to 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 loans are relatively limited. Also, the share of subsidies to services firms is negligible.

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

(a) Firm subsidies

(b) Infrastructure expenses



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

Last, Figure A1.2 plots the 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.[40] While firm subsidies are largely concentrated in the IDAs, infrastructure spending is most pronounced in the internal areas.

A.2. Appendix A2: Industrial censuses

We collect data on the number of workers and establishments by sector across Italian municipalities from decennial industrial censuses between 1951 and 2011 (including an intermediate census in 1996), sourced from the Istat website. We complement the data by hand-digitizing the 1911 and 1927 industrial censuses, available only in pdf format in the Istat historical archives. We match post-World War II censuses with the historical censuses using municipality names. To correct for municipality name changes, annexations and mergers we rely on a database reporting all administrative changes since Italy's

[40]The EIM region also included some small islands of Tuscany, which we drop from the sample.

unification in 1861 (www.elesh.it). We exclude municipalities in the 1911 and/or the 1927 census that are then split into two or more municipalities in the post-War censuses.

Table A2.1 shows descriptives for employment and firm density (computed as number of workers and establishments per km^2) across census years, separately for the EIM area, the IDAs and the rest of Italy. The data also report a broad sector breakdown between manufacturing (food, textile, wood, metallurgy, mechanic, mineral, chemical, rubber, plastic and others), construction, mining, energy and services (wholesale and retail trade, hotels and restaurants, transport, communications, finance and insurance, firm services and other services).[41]

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

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

Where $y^s_{m,t}$ is the number of manufacturing workers in municipality m, census year t and sector s, $y_{m,t}$ is the total number of manufacturing workers in municipality m and census year t, y^s_t is the number of manufacturing workers in the reference group in census year t and sector s and y_t is the total number of manufacturing workers in the reference group in census year t. The index provides a simple measure of sectoral specialization in municipality m relative to a reference group, which we set here as all Italian regions except for the more advanced regions of the North (Lombardy, Veneto and Piemonte) and the small regions close to the Alps (Valle d'Aosta, Friuli Venezia Giulia and Trentino Alto Adige) – areas with likely uncomparable industrial structure to that of the EIM regions.

A.3. Appendix A3: Administrative social security 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

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

Appendix Table A2.1. Industrial census – descriptive statistics

	1911	1927	1951	1961	1971	1981	1991	1996	2001	2011
					Panel (a): Employment density					
EIM area										
Mean	5.70	12.39	13.81	18.18	21.27	31.11	35.35	34.31	40.45	43.91
S.D.	(14.73)	(26.11)	(31.55)	(46.85)	(59.39)	(80.52)	(85.55)	(86.50)	(99.42)	(104.39)
IDAs										
Mean	14.71	31.41	37.91	54.78	73.23	108.09	120.73	122.96	143.14	157.13
S.D.	(29.09)	(50.76)	(63.18)	(95.19)	(127.52)	(166.01)	(172.40)	(177.77)	(200.31)	(207.71)
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)
IDAs										
Mean	1.77	12.23	12.75	16.44	19.33	25.71	31.61	39.40	45.06	51.74
S.D.	(2.18)	(13.86)	(15.08)	(20.10)	(24.62)	(32.81)	(39.13)	(50.01)	(57.83)	(64.64)
Rest of Italy										
Mean	1.18	6.51	6.65	8.42	10.68	15.09	16.50	18.05	21.12	22.71
S.D.	(1.39)	(7.29)	(8.46)	(11.85)	(15.67)	(22.10)	(24.57)	(28.59)	(33.72)	(36.41)

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

earnings, the 6-digit sector (based on Eurostat's NACE Rev. 2 groups) and the municipality. Using firm tax identifiers, we match this dataset with balance sheet information from the Cerved group, available for limited liability corporations since 1995. The Cerved data report detailed income statements including firm sales, value added, profits and investment. We narrow our focus to firms in the non-agricultural private sector and exclude NACE codes 1 to 3, 84 to 88 and 97 to 99, corresponding to agriculture, public sector and families as employers. This selection is standard for the Italian data, as these industries are only partially represented in the social security archives. The detailed sector information allows us to 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.[42]

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

The data record all labor market transitions of the included workers. They can thus be used to compute hiring at the municipality level, as discussed in Section 6. We define hires 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 we estimate a two-way fixed effects regression in years 1990-2010 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. Estimation 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.

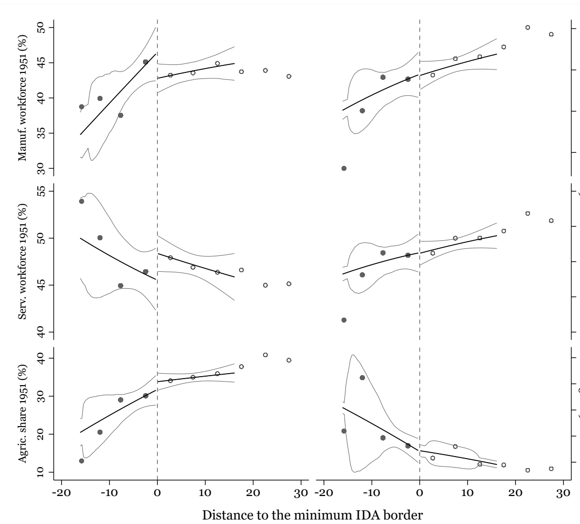
[42]See https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Knowledge-intensive_services_(KIS) and https://www.oecd.org/sti/ind/48350231.pdf

B. Appendix B: Identification

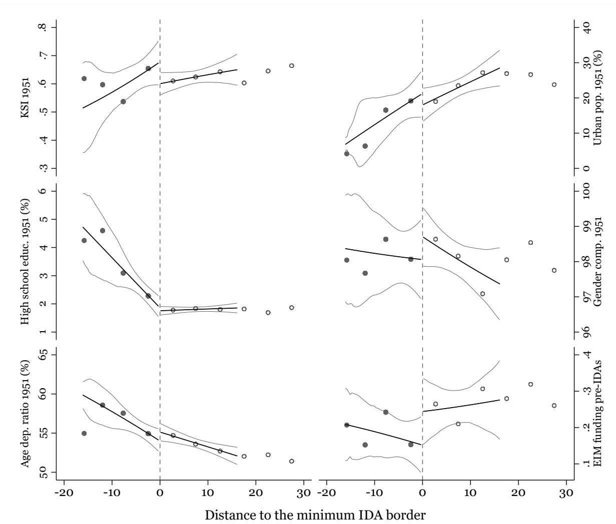
B.1. Appendix B1

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

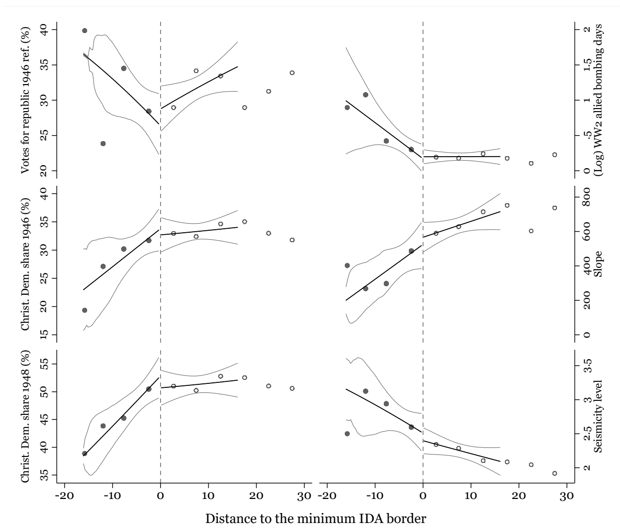
(a)



(b)



(c)



Notes: Panel (a): "Manuf. workforce" and "Serv. workforce" are the shares of manufacturing and services workers in the 1951 industrial census. "Agric. share" computed as the number of agriculture workers per 100 residents aged at least 15. "Empl. rate" is the ratio of employed people to total residents aged 15 years and older. "Part. rate" is the ratio of the resident working population to the resident population of the same age group. "Pop. density" is 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 each side of the border using a symmetric 16-km bandwidth. The gray lines are 95 percent confidence intervals. Appendix Table B1.1 shows the corresponding coefficient estimates.

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

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

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

(c)	KSI	High school	Age dep.	Urban pop.	Gender	Pre-IDA exp.
RD Estimate	0.06	0.57	-0.85	2.52	-0.58	-0.06
	(0.05)	(0.23)	(0.54)	(3.90)	(0.59)	(0.07)
Mean	0.63	1.97	54.05	21.95	98.05	0.24
S.D.	0.26	1.20	5.95	25.05	4.78	0.46
Observations	587	563	563	537	563	563
R^2	0.12	0.17	0.46	0.63	0.25	0.07

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

Notes: All outcomes as of 1951, unless noted otherwise. Estimation output of Equation 1b using a 16-km symmetric bandwidth around the minimum IDA border. The specification controls for a linear polynomial in the distance from the border and IDA region effects. Standard errors clustered by IDA region in parentheses. See Figure 4 and Figure B1.1 for details.

B.2. Appendix B2

Main identification. Here, we describe more formally the main identification strategy of the paper, which is sketched intuitively in Section 4. The outer boundaries of the municipalities contiguous to the IDA center trace a "minimum" IDA border $\mathcal{J}$ that separates two regions within ($\mathbb{W}$) and outside ($\mathbb{O}$) this boundary. Let the centroid of municipality m be denoted by the latitude-longitude pair $\ell_m = (l_{x,m}, l_{y,m})$. Let also $\delta_m \equiv d(\ell_m, \mathcal{J})$ denote the geodesic distance between municipality m's centroid and the minimum border of the closest IDA, with negative values of δ_m assigned to municipalities in region $\mathbb{W}$. The binary instrument $W_m = \mathbb{1}[\ell_m \in \mathbb{W}] = \mathbb{1}[\delta_m \leq 0]$ identifies these municipalities. Let also IDA_m be a treatment indicator. This identification strategy rests on three main assumptions:

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

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

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

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

$IDA_m(\delta_m)$ denotes potential treatment selection as a function of the running variable. Three municipality types are therefore allowed to exist in the proximity of the cutoff: always-takers ($IDA_m(\delta_m) = 1$), never-takers ($IDA_m(\delta_m) = 0$) and compliers ($IDA_m(\delta_m) = W_m$). Under Assumptions A1, A2 and A3, the fuzzy RD estimand $\beta = \pi/\vartheta$ identifies the average causal effect for compliers at the cutoff – a standard result in the RD literature (Hahn et al., 2001; Imbens and Lemieux, 2008).

(Fuzzy) Difference in discontinuities. We discuss identification for the Diff-in-Disc design introduced at the end of Section 4, drawing on 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 (an IDA center) and depends solely on the running variable δ_m and not on the time period. IDA_m^p denotes IDA status and is equal to zero for all municipalities at $p = 0$. After the introduction of the policy, imperfect compliance is such that IDA status jumps discontinuously (but not sharply) at the cutoff (Assumption 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 design in that it allows bordering a large city (the IDA center) to affect the outcome independently of IDA status (the treatment of interest). To show this, we posit a new continuity assumption implying that, once accounting for IDA treatment and for contiguity to an IDA center, no other relevant factors jump at the minimum IDA border.

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

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

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

where θ denotes municipality types, so that $\theta = \theta_A$ if $IDA_m(\delta_m) = 1$ (always-takers),

$\theta = \theta_N$ if $IDA_m(\delta_m) = 0$ (never-takers) and $\theta = \theta_C$ if $IDA_m(\delta_m) = W_m$ (compliers). The cross-sectional reduced-form estimator identifies not only the treatment effect of interest (that of IDA status, on the first row), but also 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.[43] 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.

B.3. Appendix B3: Placebo centers

Our alternative design exploits provincial capitals in the Center-North of Italy, which would have likely been IDA centers had they been part of the EIM region. We refer to these as "placebo centers". Figure B3.1 provides an illustration. Placebo centers are in black and their bordering municipalities are in grey. For comparability purposes, we exclude the industrialized regions in the North of Italy (Lombardy, Veneto and Piemonte), and smaller regions close to the Alps. We leverage this source of variation in three ways.

[43] 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.

Simple event study. In a first approach, we pool together the 120 municipalities bordering IDA centers (in orange in Figure B3.1) and the 243 municipalities bordering placebo centers (in grey in Figure B3.1). We compare these two groups before and after the institution of IDAs in a simple event study design. Let T_m be a treatment indicator denoting municipalities in the EIM area (those bordering IDA centers) and let $P = \mathbb{1}[year \geq 1960]$ be the time indicator defined above. Define 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 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:

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

Under the standard assumption:

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

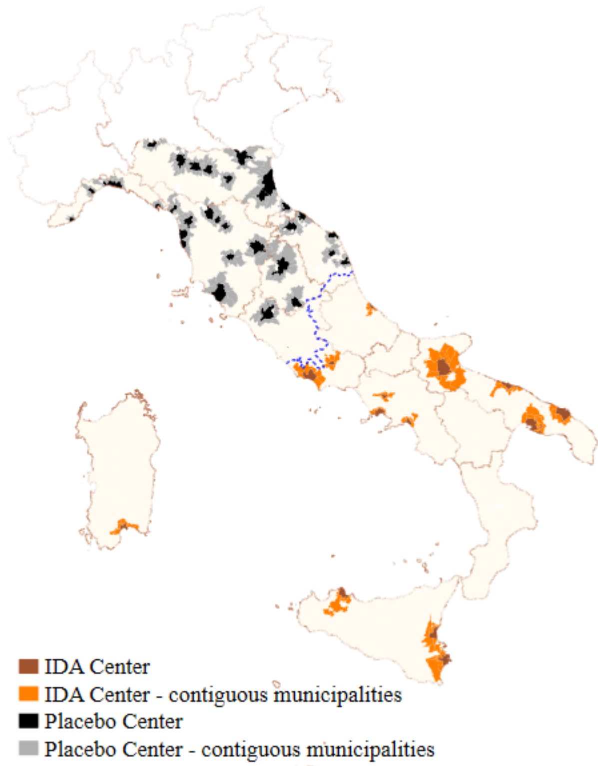
the DID coefficient identifies the causal effect of interest.

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

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

Where $Y_{m,t}$ is the outcome of interest for municipality m and census year t, μ_m are munic-

Appendix Figure B3.1. Alternative identification – graphical illustration



Notes: Municipalities bordering IDA centers are 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.

ipality 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. The ρ_{1911} and ρ_{1927} coefficients provide a test of the parallel trends assumption.

Testing for displacement. This source of variation is also exploited to investigate possible spillover effects of the IDA policy to the control group in the baseline identification strategy. Namely, we use municipalities up to 16 km outside of the "placebo" boundary traced by municipalities bordering placebo centers as a counterfactual for municipalities up to 16 km outside of the minimum IDA border (the control group in the baseline design). We estimate the same specification of Equation B3.1, where again $T_m = 1$ for municipalities in the EIM area.[44]

[44] To identify spillover effects, the treatment group of this design excludes municipalities outside of the minimum IDA border that were part of the IDA (the always-takers, in light blue in Figure 3 Panel (a)).

Triple differences. In a last approach, we estimate an unified model that pools together municipalities (i) bordering IDA centers; ii) bordering placebo centers; and iii) up to 16 km away from the first two groups. The resulting sample comprises 1478 municipalities, 622 of which are in the EIM area (these are used in the baseline analysis, see Section 4). Let W_m be an indicator denoting municipalities bordering either IDA centers or placebo centers (the union of the orange and grey municipalities in Figure B3.1). Let also T_m be the indicator denoting municipalities in the EIM area, defined above, and $P = \mathbb{1}[year \geq 1960]$. The observed outcome can again be defined as a function of potential outcomes $Y_m = Y_m(1) \cdot T_m \cdot W_m \cdot P + Y_m(0) \cdot (1 - T_m \cdot W_m \cdot P)$. The causal effect of interest is now $E[Y_m(1) - Y_m(0) \mid T_m = 1,\ W_m = 1,\ P = 1]$. The fully saturated model is:

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

The triple DID coefficient ρ now identifies:

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

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 the Diff-in-Disc design comparing municipalities within and outside of the minimum IDA border, and the event study comparing municipalities bordering IDA centers to municipalities bordering placebo centers. Identification now requires that any differential trend in the control outcome is the same across the two groups, so that it would cancel out when taking the triple difference.

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 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 in 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, we obtain the following – where the "within" difference is identified by the event study in B3.1, while the "outside" difference estimates possible spillovers of the IDA policy to nearby areas:

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

B.4. Appendix B4: The EIM border

Our last identification strategy exploits the discontinuity at the northern boundary of the EIM jurisdiction.[45] When the EIM began in 1950, the policymaker had to separate the area of intervention from the rest of Italy, splitting the country in two halves. This border was set above the traditional boundaries of the Southern Italian regions and extended into Central Italy (Figure B4.1(a)). The border was set in 1950 and the EIM area remained since unchanged until the termination of the policy in 1992. Figure B4.1(b) plots Cassa's expenses around the border, clearly showing a stark jump equivalent to roughly 15,000 euros per capita.

As described in Albanese et al. (2024), the RD continuity assumption likely holds at the border. Inspection of the parliamentary discussions that led to the drawing of the border reveals that this choice was informed by technical details related to the execution of infrastructure projects, without much consideration of the economic conditions of those areas. In addition, the border does not systematically coincide with regional boundaries, nor does it matter for other policies realized before, during or after the EIM. Balancing tests in Albanese et al. (2024) reveal no large discontinuity in pre-determined municipality characteristics.

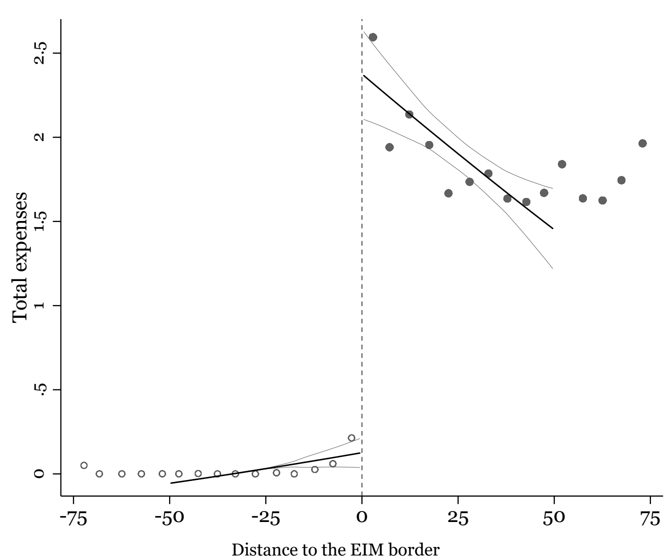
We specify a sharp RD design that uses distance to the border ι_m as running variable and $B_m = \mathbb{1}[\iota_m \geq 0]$ as treatment indicator:

[45] More details on the EIM border and its suitability as a RD cutoff are in Albanese et al. (2024).

Appendix Figure B4.1. The EIM border

(a) The border

(b) Total EIM expenses



Notes: Panel (a) shows the EIM border as the dashed blue line. Panel (b) shows (log) total EIM expenses in thousand € (2011 prices) per 1951 resident, cumulated between 1950 and 1992. Negative distance denotes municipalities north of the EIM border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately north and south of the border using a 50-km symmetric bandwidth. The gray lines are 95 percent confidence intervals. 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.

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

Where Y_m is the outcome of interest, λ_b are border-segment fixed effects denoting the segment of the border closest to municipality m and $\varphi(\iota_m)$ is a linear polynomial. We use a baseline bandwidth of 50 km north and south of the border.[46] Standard errors allow for arbitrary correlation across space following Conley (1999).

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

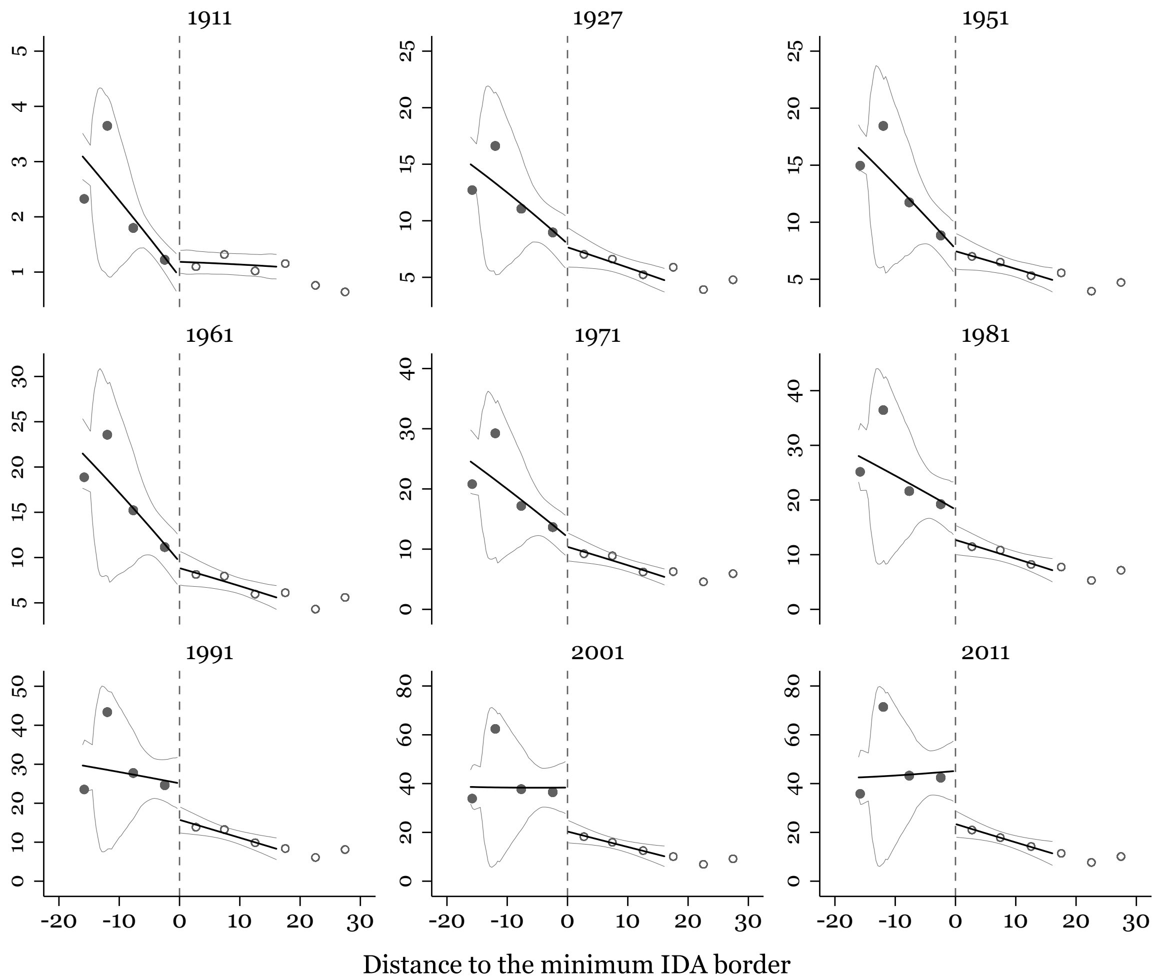
$$Y_{m,t} = \mu_m + \sigma_t + \sum_{j \neq 1951} \rho_j \cdot \mathbb{1}[t = j] \cdot B_m + \epsilon_{m,t} \tag{B4.2}$$

Where notation is as in Equation 2. We use a 50-km symmetric bandwidth around the border and cluster standard errors by municipality.

[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: Results

Appendix Figure C1. Establishment density



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

Appendix Table C1. Establishment density – Baseline

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

Notes: Column (1) shows the estimation output of Equation 1b. Column (2) reports the fuzzy RD estimates. Column (3) replaces IDA status with EIM subsidies as treatment variable. See Table 3 for details.

Appendix Table C2. Employment density – Robustness tests

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

Notes: Fuzzy RD estimates, see Equations 1a and 1b, 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.

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

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

Notes: Fuzzy RD estimates, see Equations 1a and 1b. Standard errors allow for spatial correlation (Conley, 1999).

Appendix Table C4. Employment and firm density – Randomization inference

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

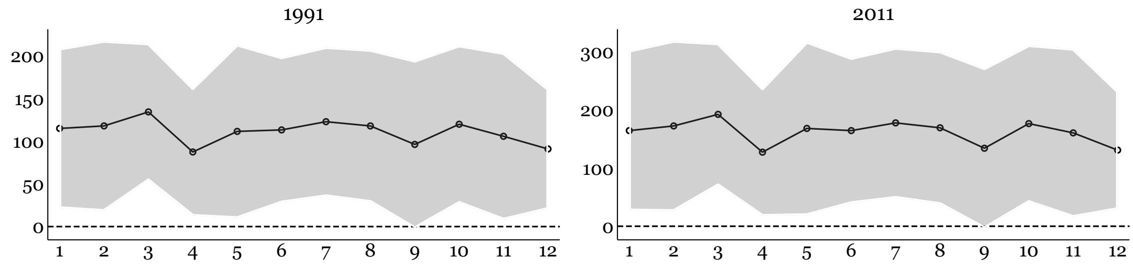
Notes: Estimation output for the fuzzy RD desing using local randomization inference as proposed in Cattaneo et al. (2016), with 1,000 replications, uniform kernel and without specifying a polynomial for the outcome transformation model – see the *rdrandinf* command in Cattaneo et al. (2016). The window-selection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

Appendix Table C5. Employment density – All IDAs

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

Notes: Fuzzy RD estimates, see Equations 1a and 1b, 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.

Appendix Figure C2. Employment density – Exclude individual IDAs



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

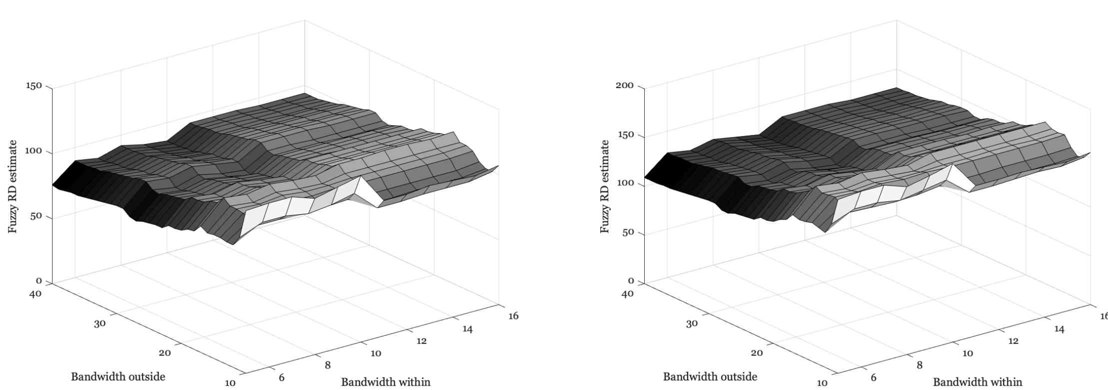
Appendix Table C6. Employment density – Non-parametric fuzzy RD estimates

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

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

Appendix Figure C3. Employment density – robustness to bandwidth choice

(a) 1991 (b) 2011



Notes: Estimates of the fuzzy RD coefficient from Equations 1a and 1b using varying bandwidths around the RD cutoff.

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

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

Notes: Fuzzy RD estimates, see Equations 1a and 1b. 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.

Appendix Table C8. Migration and relocation – Fuzzy RD estimates

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

Notes: Fuzzy RD estimates, see Equations 1a and 1b. "Net migration": net inflow of immigrants into the municipality as a share of resident population. "Mobil.": share of resident population who travel daily for work or study outside the municipality to the resident population aged up to 64. "Mobil. work": share of resident population commuting daily for work outside the municipality to resident population commuting daily for work within the municipality.

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

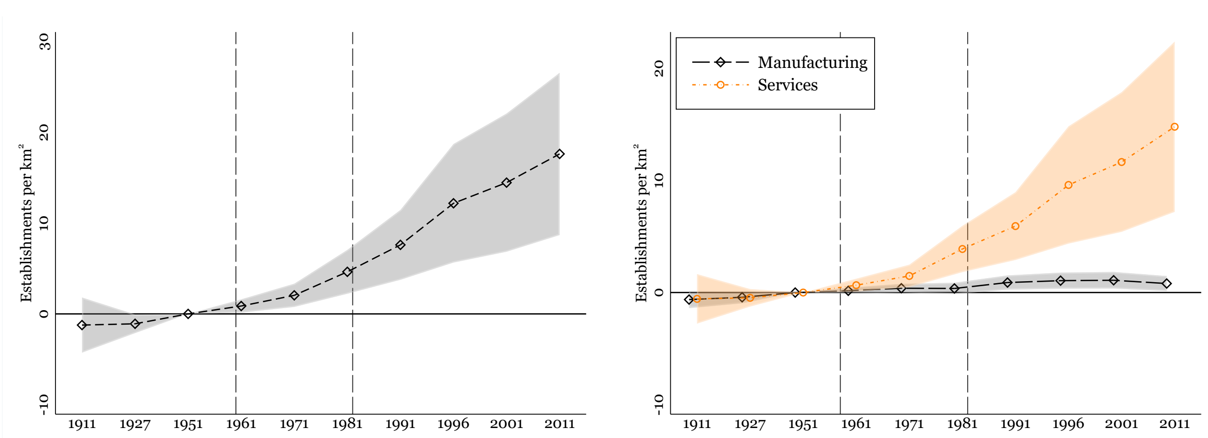
	1981	1991	2011
	Employment rate		
RD Estimate	4.75	3.97	1.90
	(1.60)	(1.69)	(1.31)
Mean around the border	36.23	33.88	38.33
Standard deviation	5.78	5.68	4.66
Observations	581	587	587
	Participation rate		
RD Estimate	3.45	3.40	3.09
	(1.26)	(1.17)	(1.32)
Mean around the border	46.91	47.21	46.13
Standard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

Notes: Fuzzy RD estimates, see Equations 1a and 1b. "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.

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

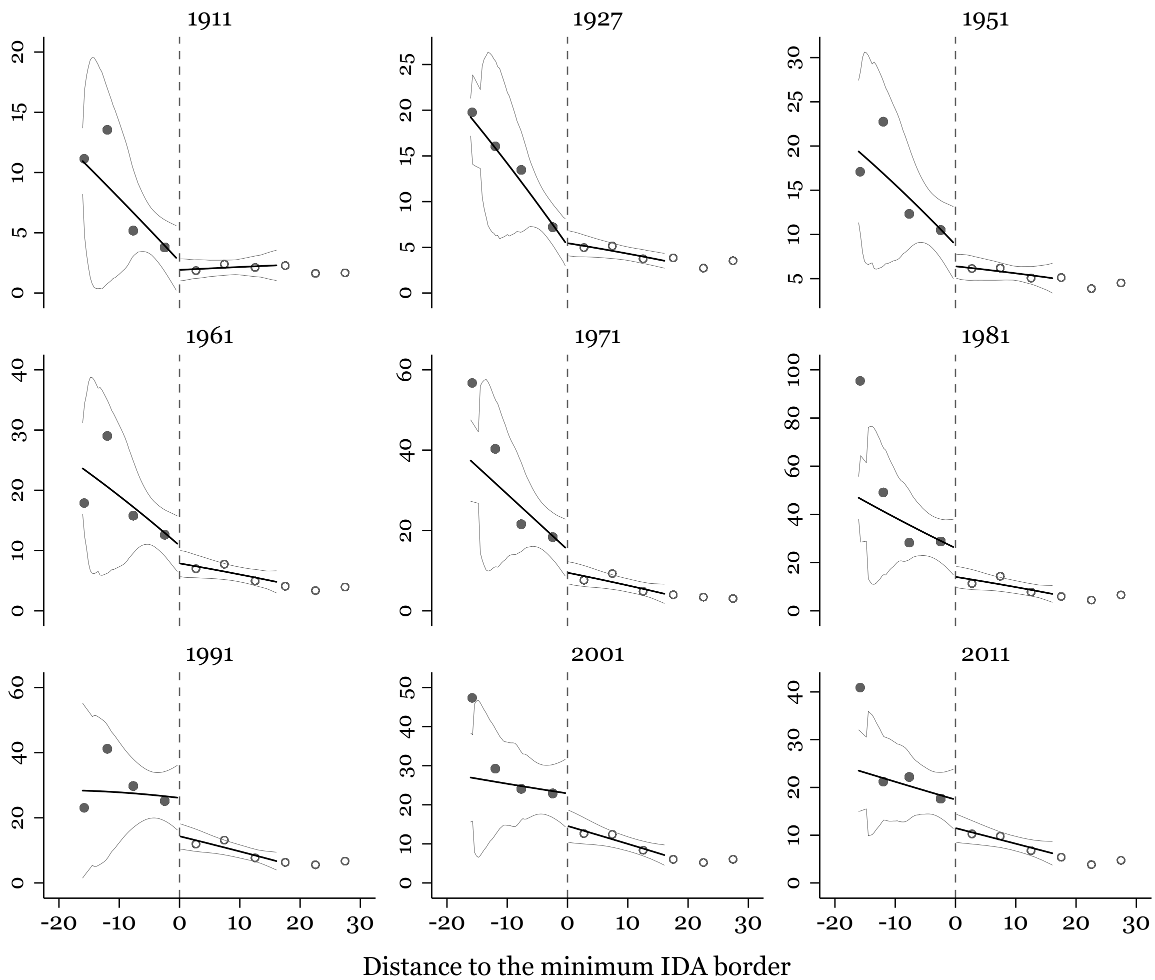
(a) Establishment density

(b) Manufacturing versus services



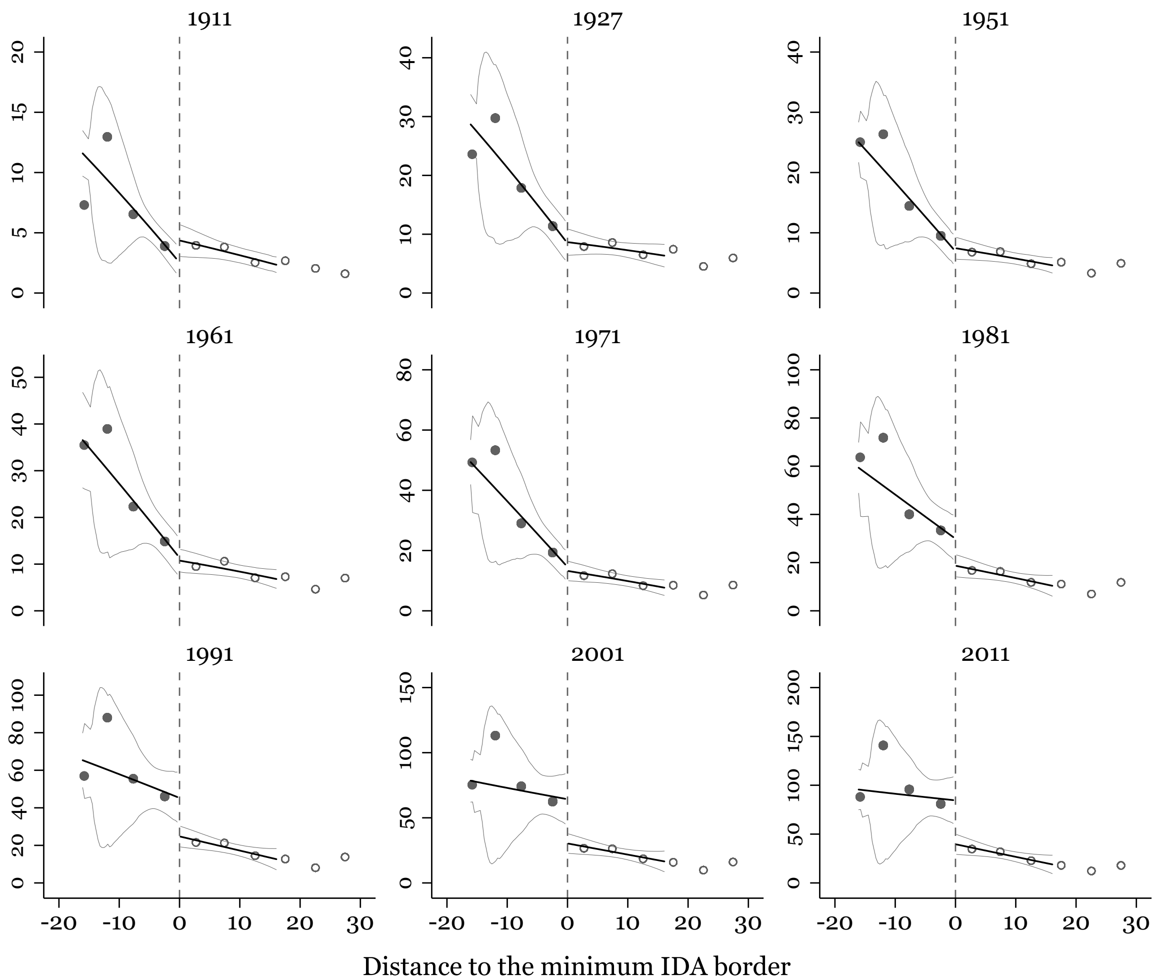
Notes: Coefficient estimates for Equation 2. Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the IDAs.

Appendix Figure C5. Manufacturing employment density



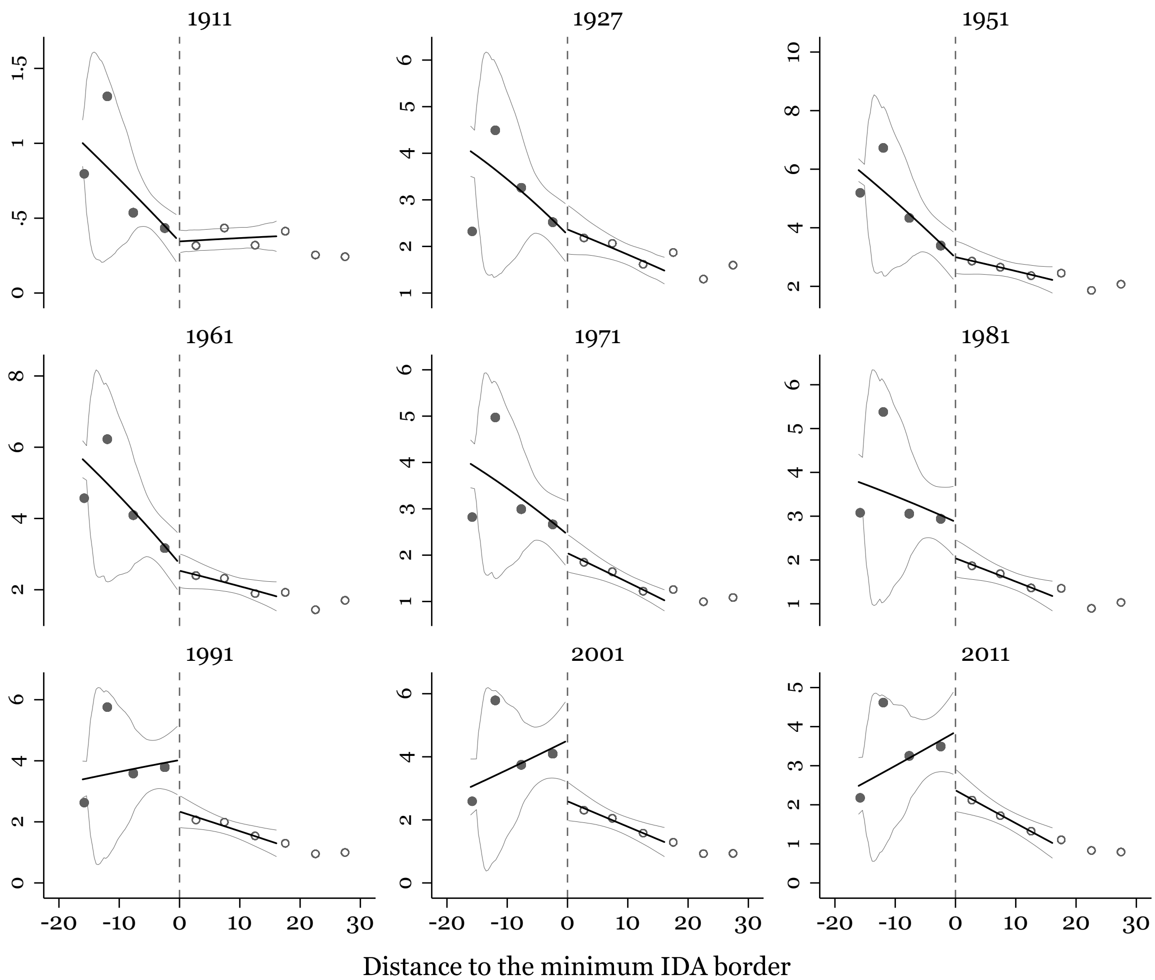
Notes: Negative distance denotes municipalities within the minimum IDA border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately at each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

Appendix Figure C6. Services employment density



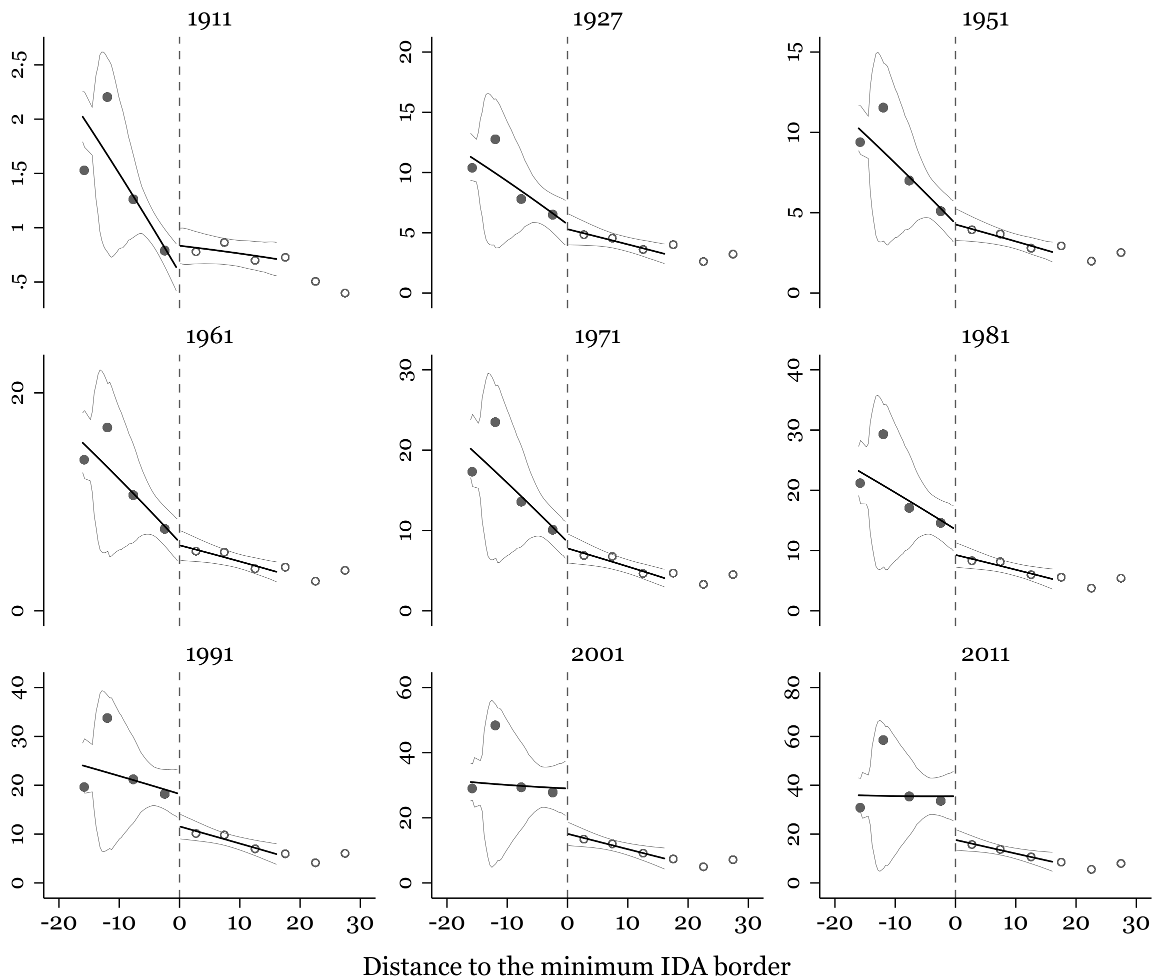
Notes: Negative distance denotes municipalities within the minimum IDA border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately at each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

Appendix Figure C7. Manufacturing establishment density



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

Appendix Figure C8. Services establishment density



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

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

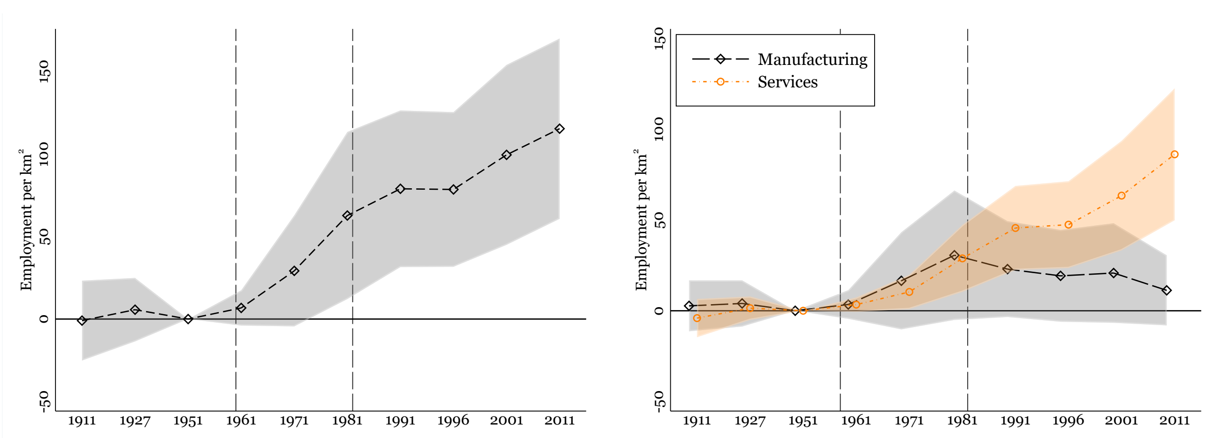
	Employment density		Establishment density	
	Manufacturing	Services	Manufacturing	Services
	Contemporaneous effect (1991)			
RD Estimate	28.27	57.40	3.69	17.76
	(14.08)	(23.17)	(1.61)	(8.32)
Mean around the border	14.06	25.45	2.26	11.10
Standard deviation	26.80	43.14	3.30	16.90
Observations	586	586	586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

Notes: Fuzzy RD estimates, see Equations 1a and 1b for details.

Appendix Figure C9. Placebo centers (within) – Empl. density

(a) Employment density

(b) Manufacturing versus services

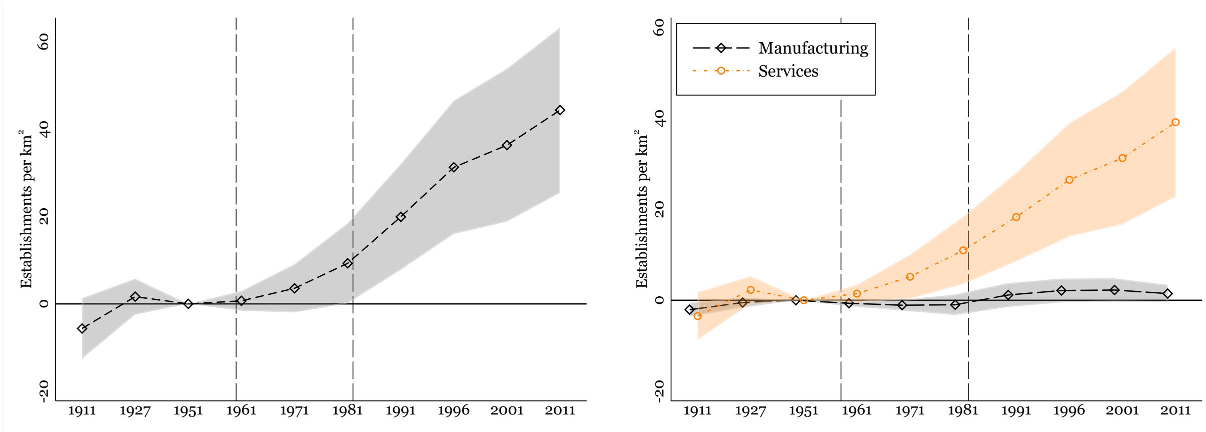


Notes: Coefficient estimates for Equation B3.1. Sample restricted to municipalities within the minimum IDA border excluding IDA centers (treatment group) and municipalities bordering placebo centers (control group). Standard errors clustered at the municipality level. The shaded areas denote 95 percent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

Appendix Figure C10. Placebo centers (within) – Est. density

(a) Establishment density

(b) Manufacturing versus services

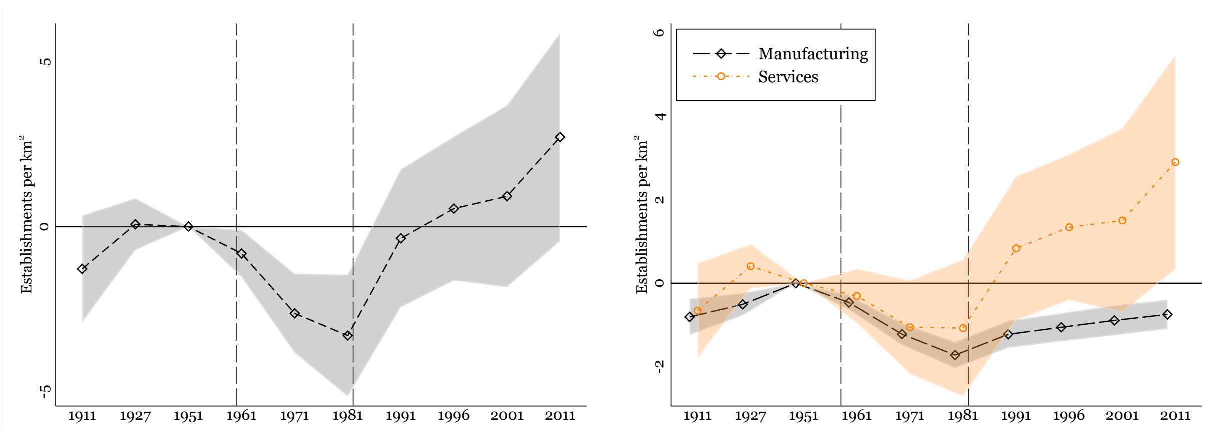


Notes: Coefficient estimates for Equation B3.1. Sample restricted to municipalities within the minimum IDA border excluding IDA centers (treatment group) and municipalities bordering placebo centers (control group). Standard errors clustered at the municipality level. The shaded areas denote 95 percent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

Appendix Figure C11. Placebo centers (outside) – Est. density

(a) Establishment density

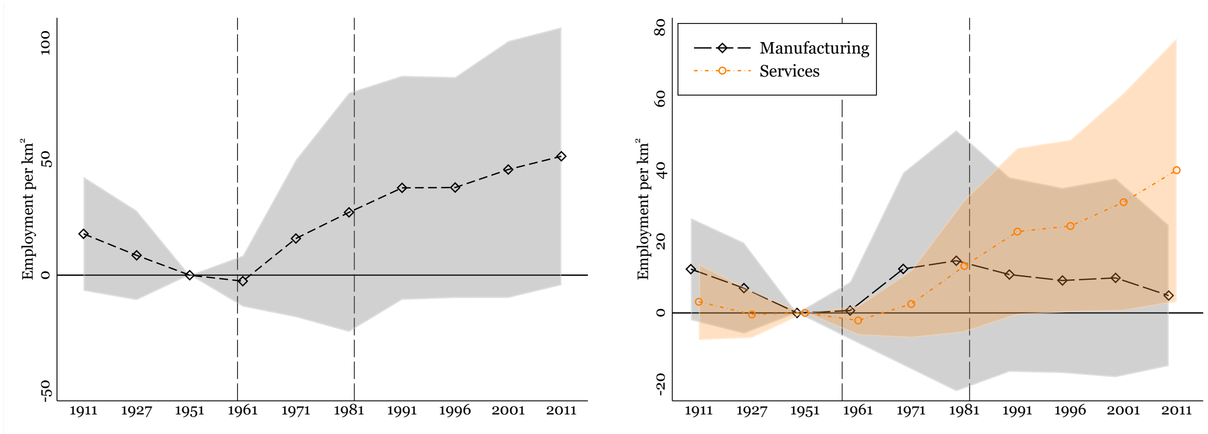
(b) Manufacturing versus services



Notes: Coefficient estimates for Equation B3.1. Sample restricted to municipalities up to 16 km outside of the minimum IDA border (treatment group) and municipalities up to 16 km outside of the placebo border traced by municipalities bordering placebo centers (control group). The treatment group excludes IDA municipalities. Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the IDAs.

Appendix Figure C12. Triple differences – Empl. density

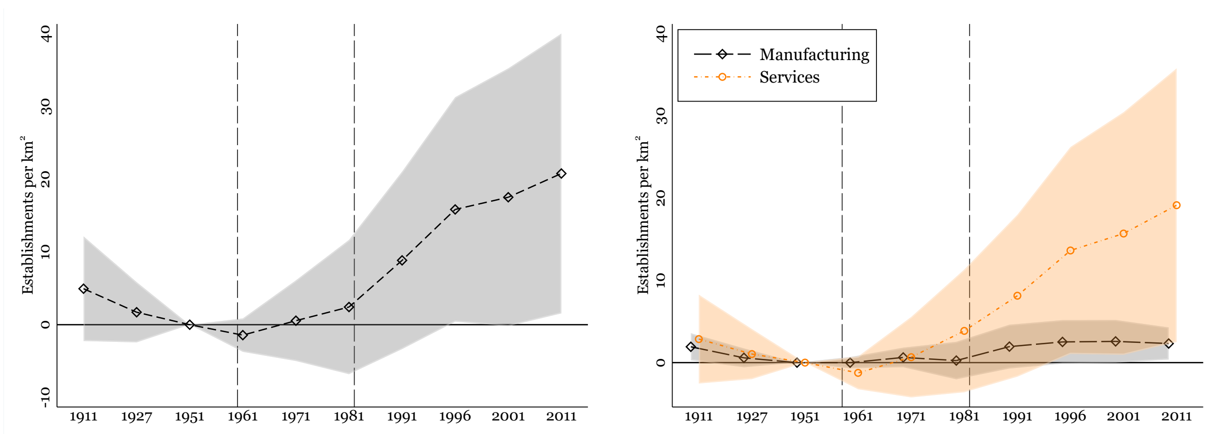
(a) Employment density (b) Manufacturing versus services



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

Appendix Figure C13. Triple differences – Est. density

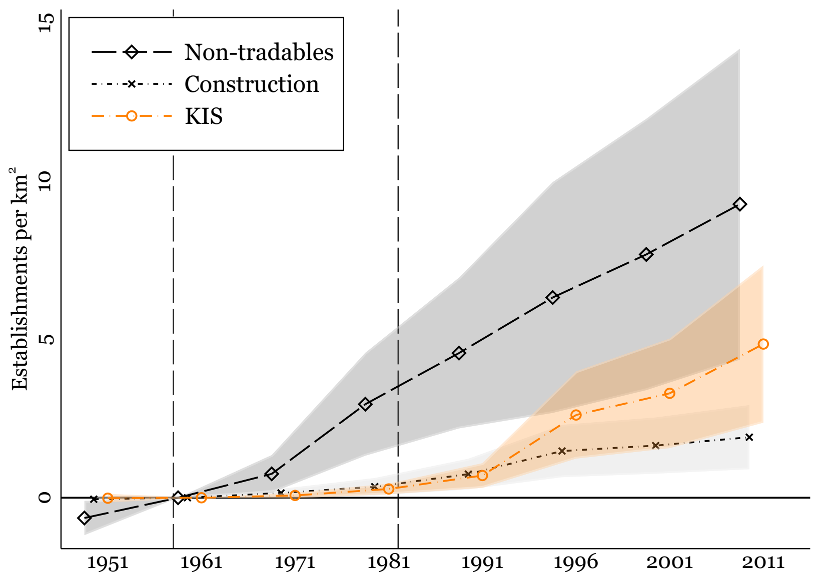
(a) Establishment density (b) Manufacturing versus services



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

D. Appendix D: Mechanisms

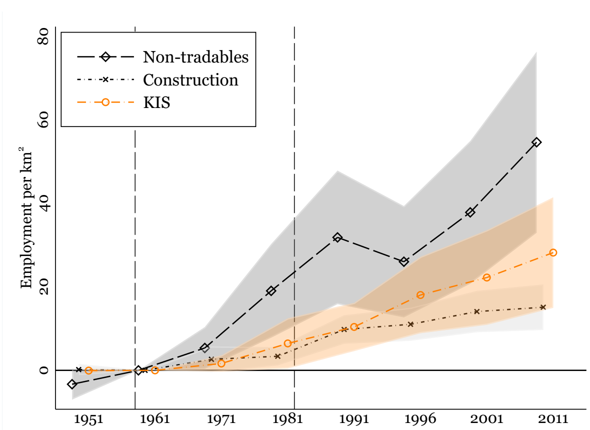
Appendix Figure D1. Establishment density – Services breakdown



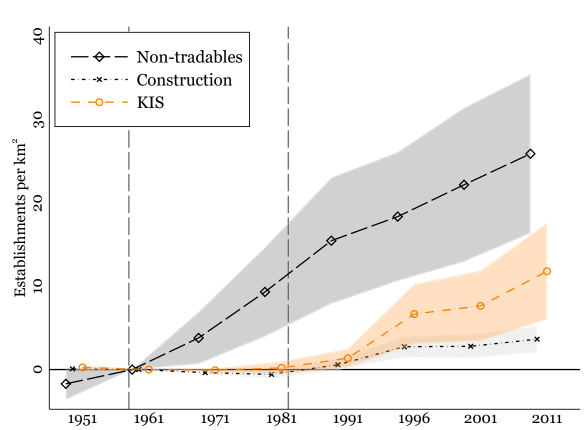
Notes: Coefficient estimates for Equation 2. Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the IDAs. "Non-tradables" include wholesale and retail trade, hotels and restaurants and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

Appendix Figure D2. Placebo centers (within) – Services breakdown

(a) Employment density



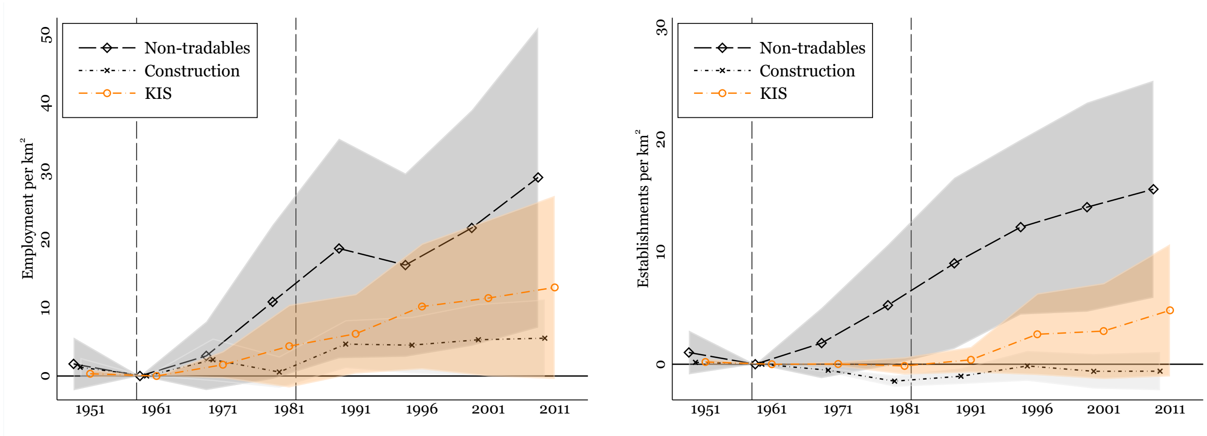
(b) Establishment density



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

Appendix Figure D3. Triple differences – Services breakdown

(a) Employment density (b) Establishment density



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

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

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

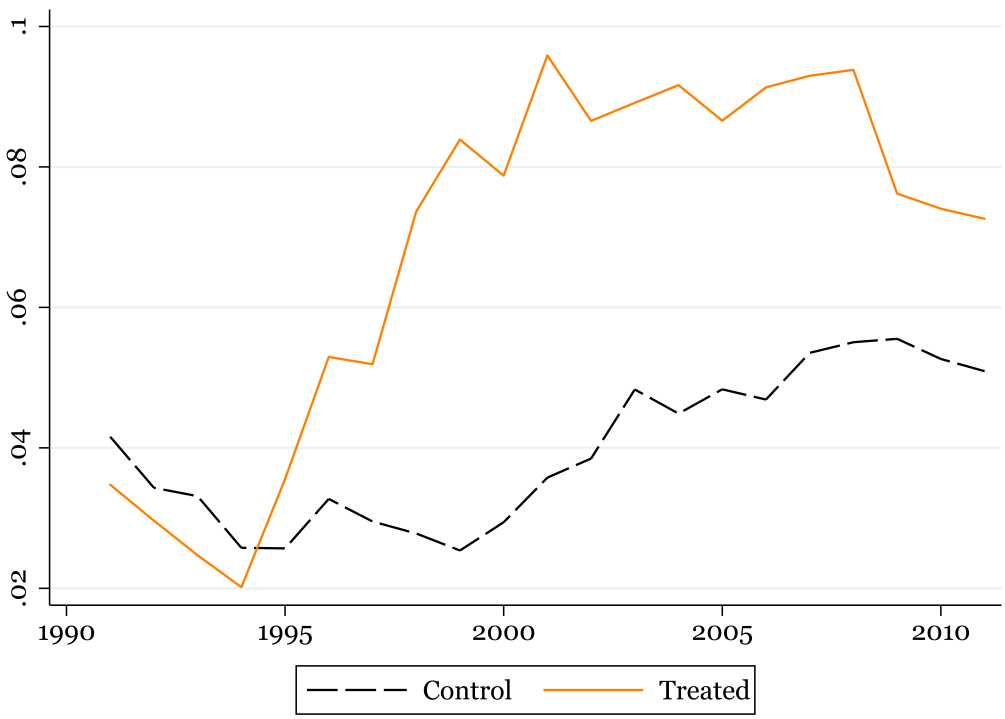
Notes: Fuzzy RD estimates, see Equations 1a and 1b. The outcomes are the share of employment and establishments in KIS and other services. The shares are obtained from social security data on the universe of Italian firms in the private sector and the KIS classification is obtained from Eurostat/OECD. See Appendix A.3 for details.

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

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

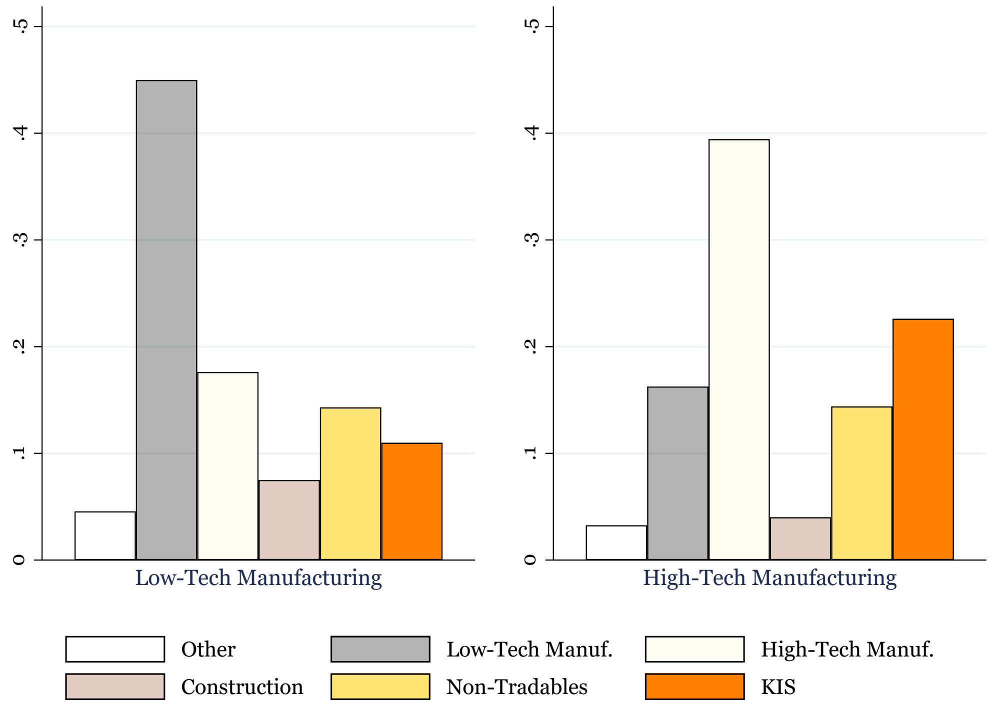
Notes: Fuzzy RD estimates, see Equations 1a and 1b. The outcomes are the share of employment across manufacturing sub-sectors, grouped by technological intensity. The shares are obtained from social security data on the universe of Italian firms and the technology classification is obtained from Eurostat/OECD. See Appendix A.3 for details.

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



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

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



Notes: The chart shows the breakdown of inputs demanded by low-technology and high-technology manufacturing industries, respectively, for 2020. Each bar is computed as the average across industries. The KIS classification and the manufacturing technology intensity classification are obtained from Eurostat/OECD.

Appendix Table D3. Shares within services – Fuzzy RD estimates

	RD Estimate	S.E.	Mean	S.D.
	Employment shares			
Other human resources provision	3.17	(1.76)	0.31	3.82
Maintenance and repair of motor vehicles	2.49	(0.66)	4.31	7.14
Computer programming, consultancy and related activities	1.60	(0.66)	0.91	2.53
Other 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	-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	-2.91	(1.06)	3.28	4.82
	Firm shares			
Reinsurance	0.79	(0.49)	0.66	1.80
Management consultancy activities	0.68	(0.30)	0.44	1.01
Data processing, hosting and related activities; web portals	0.66	(0.41)	0.52	1.29
Sports activities	0.64	(0.36)	0.39	1.61
Legal activities	0.55	(0.28)	0.75	1.13
Other professional, scientific and technical activities n.e.c.	0.47	(0.19)	0.33	0.99
Support activities for transportation	0.44	(0.17)	0.73	1.47
Buying and selling of own real estate	0.41	(0.20)	0.15	0.63
Retail trade not in stores, stalls or markets	0.26	(0.09)	0.16	0.52
Other postal and courier activities	0.14	(0.08)	0.06	0.24
Wholesale of information and communication equipment	0.11	(0.06)	0.12	0.39
Market research and public opinion polling	0.11	(0.06)	0.04	0.21
Fund management activities	0.03	(0.01)	0.01	0.06
Translation and interpretation activities	0.01	(0.00)	0.00	0.01
Wholesale and retail trade and repair of motor vehicles	-0.04	(0.02)	0.01	0.05
Retail sale in non-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	-4.15	(1.19)	5.38	4.57

Notes: Fuzzy RD estimates, see Equations 1a and 1b. Regressions run for employment and 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.

Appendix Table D4. Worker AKM effects – Fuzzy RD estimates (2011)

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

Notes: Fuzzy RD estimates, see Equations 1a and 1b. 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 for details.

Appendix Table D5. Firm size and wage distribution – Fuzzy RD estimates

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

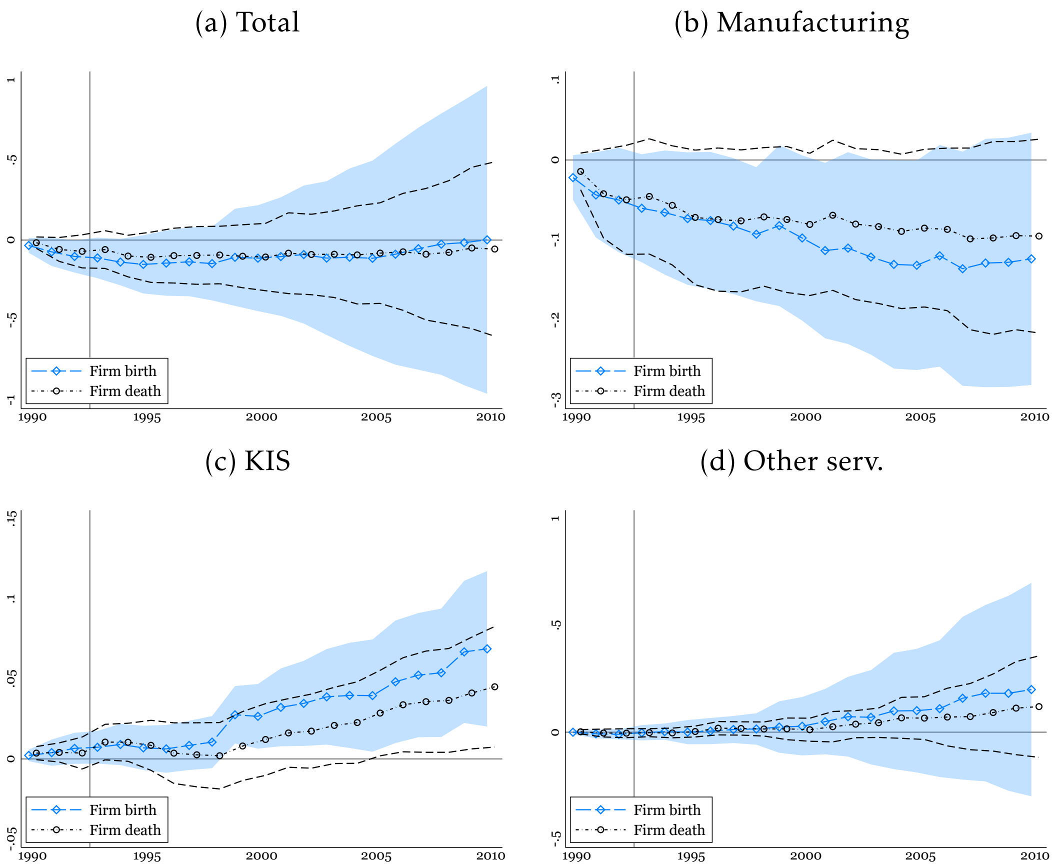
Notes: Fuzzy RD estimates, see Equations 1a and 1b. Outcomes are computed as the share of firms in each tertile of the distribution of firm size and wage paid. Tertiles are derived on the universe of the Italian firms each year. See Appendix A.3 for details.

Appendix Table D6. Balance sheet outcomes, 2011 – Fuzzy RD estimates

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

Notes: Fuzzy RD estimates, see Equations 1a and 1b. All outcomes are as of 2011 and expressed in natural logarithm, scaled by total firm workforce. See Appendix A.3 for details.

Appendix Figure D6. Firm dynamics – Fuzzy RD estimates



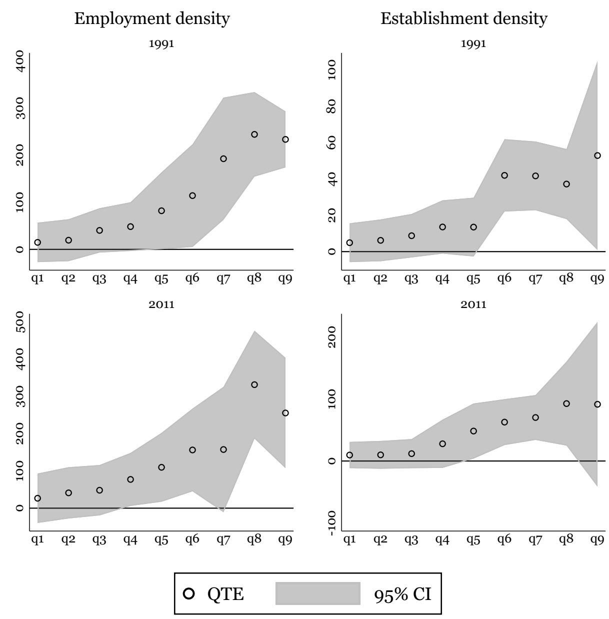
Notes: Coefficient estimates for the fuzzy RD model of Equations 1a and 1b. The shaded areas denote 95 percent confidence intervals. The vertical line marks the end of the EIM. Firm birth and death rates computed as the cumulative number of firm births and deaths every year since 1990, as a share of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

Appendix Table D7. Other outcomes – Fuzzy RD estimates

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

Notes: Fuzzy RD estimates, see Equations 1a and 1b. "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).

Appendix Figure D7. Quantile treatment effects



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

Appendix Table D8. Other expenditures – Fuzzy RD estimates

a)	Total	Admin.	Educ.	Viabil.	Territ.
RD Estimate	-0.10	-0.06	-0.25	-0.11	-0.02
	(0.12)	(0.14)	(0.14)	(0.21)	(0.16)
Mean around the border	9.43	8.18	6.84	7.21	8.09
Standard deviation	0.41	0.39	0.43	0.65	0.58
Observations	587	587	587	587	587
b)	Social	Just. & pol.	Cult. & sport	L. 488/1992	EU Funds
RD Estimate	0.11	0.21	-0.19	0.91	0.15
	(0.16)	(0.20)	(0.22)	(1.24)	(0.30)
Mean around the border	6.90	6.15	6.37	4.45	6.46
Standard deviation	0.54	0.41	0.75	4.34	1.24
Observations	587	587	587	587	544

Notes: Fuzzy RD estimates, see Equations 1a and 1b. 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. "Admin." measures spending in administrative services; "Educ." in education and childcare services; "Viabil." in viability, urban planning and infrastructure; "Territ." in environmental services (e.g., waste collection and recycling); "Social" in social services; "Just. & pol." in justice and local police; "Cult. & sport" in cultural and recreational services. "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).

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

As alternative, we use the more robust 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(a): 53.64 workers per km^2), *ii*) the design using municipalities bordering provincial capitals in the Center-North as controls (Figure C9(a): 115.44 workers per km^2) and *iii*) the triple differences (Figure C12(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, very similar to the €5,720 jump reported in Table 2 Column (2) for the full sample. For design *ii*), which compares municipalities bordering IDA centers to those bordering provincial capitals in the Center-North, we simply take the average EIM funding for the former group (€11,520 per 1951 resident). We then multiply these average cost measures by the average 1951 population in the estimation sample (8287.16, 9900.70 and 7650.64) to obtain total EIM funding in the average municipality: €48,040,678 for design *i*), €114,058,387 for design *ii*) and €44,350,743 for design *iii*). Putting everything together, we estimate a cost per job of €15,596 ($21,716) for design *i*), €14,675 ($20,433) for design *ii*) and €16,294 ($22,687) for design *iii*). Assuming a 50 percent deadweight loss, the final estimates of the cost per jobs are similar to the baseline ones: $32,575 for design *i*), $30,650 for design *ii*) and $34,031 for design *iii*).

Cost-benefit analysis. We now describe the cost-benefit analysis based on our estimates, which builds on the study of US Empowerment Zones in Busso et al. (2013). 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. We break down total surplus into three components: wage gains for workers, corporate profits for firms, and rental gains for landlords.[47] For each of these components, we compute the flow each year between 1991 and 2011. Specifically:

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

2. Corporate profits: income statements from Cerved are available only for incorporated firms. In addition, the Cerved data start in 1995 and coverage is not very large until the 2000s. For these reasons, we impute firm profits for all incorporated firms using the fitted value of a regression of firm profits on total wages and employment, controlling for year and province dummies. This procedure sets to zero profits of all non-incorporated firms, thus underestimating total profits in a municipality.[48]

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

[48]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.

3. Housing rents: we unfortunately have data on house prices and rents only for 2004 and 2011. We use information on rental prices in € /squared meter in a municipality, which we then multiply by the total building area in the municipality to obtain the flow.[49] We compute annual flows in 2004 and 2011, which we then linearly interpolate for the other years.

We then compute the effect of the policy on each of these outcomes in the post-IDA years ($\hat{\pi}_j$) (Table E1). For the wage bill and firm profits, we run a cross-sectional specification of Equation 1b at the minimum IDA border on the pooled sample of years between 1991 and 2011, controlling for year effects. This produces a unique (reduced-form) estimate of the effect of IDAs after their termination. Estimating the coefficient year by year and then averaging the effect across years delivers almost identical results. For housing rents, we estimate Equation 1b separately for 2004 and 2011 and then compute the average of the two coefficients.

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

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

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

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

Notes: For wages and profits, we estimate Equation 1b on the pooled sample 1991-2011 and include year effects. For rents, we run Equation 1b separately for 2004 and 2011. Standard errors clustered by IDA region.

Appendix Table E2. Benefits of the IDA policy

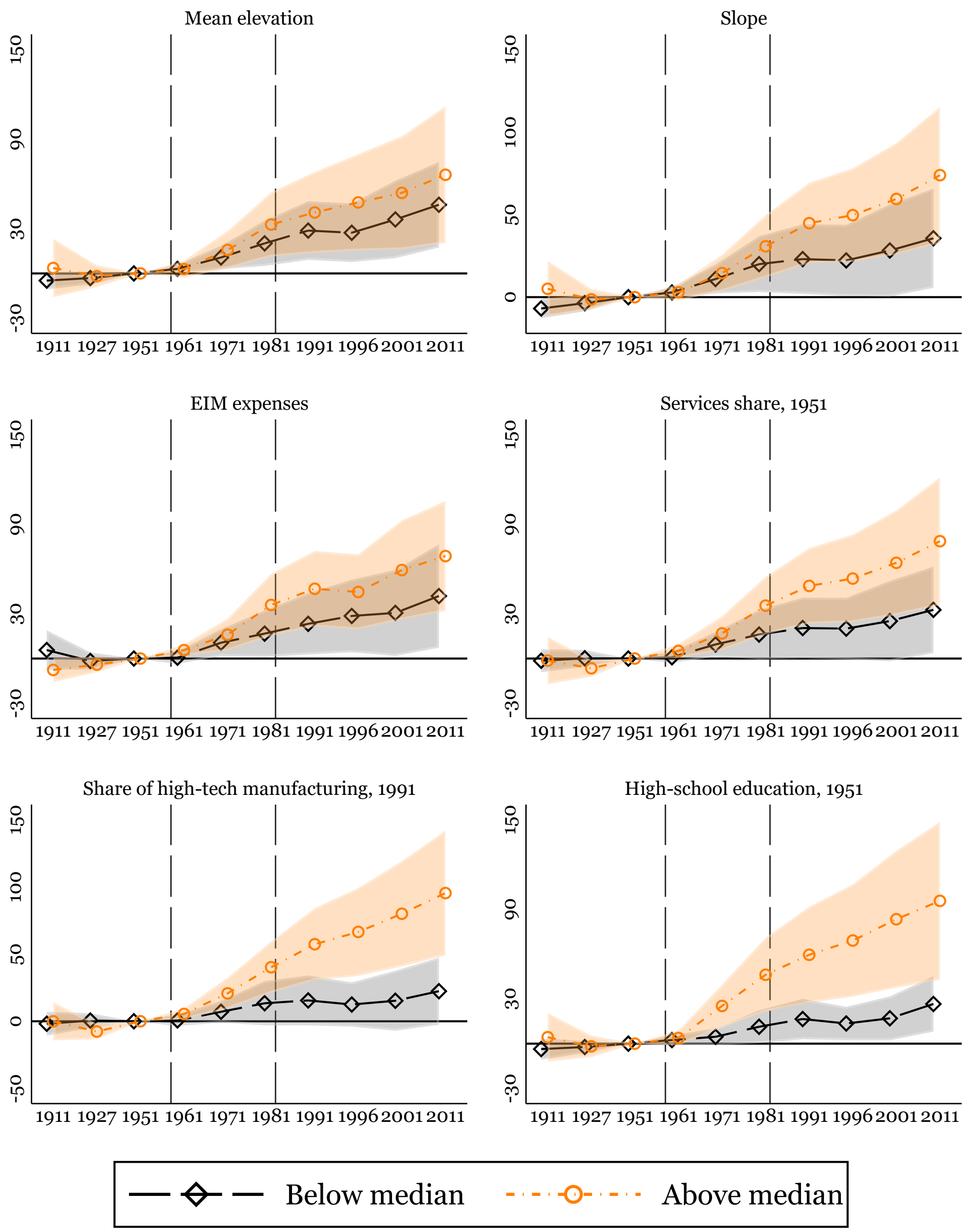
	Observed (€bn)	$\hat{\pi}_j$	Counterfactual (€bn)	Benefit (€bn)	PDV benefits (€bn)
Wage bill	237.16	0.70	118.07	119.09	52.06
Firm profits	118.68	0.97	44.80	73.88	32.66
Housing rents	20.63	0.19	17.12	3.50	1.21
Total	376.46		179.99	196.47	85.93

Notes: All amounts are cumulated between 1991 and 2011 and measured in billion € (2011 prices). Counterfactual amount 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.

This analysis comes with some caveats. On the one hand, the total costs of the IDA policy are likely larger than €88 billion as they also include expenses from 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 D7. In logarithmic terms, we estimate a positive effect of 18 percent on house prices in 2011. This results in further €10 billion accruing to landlords, which do not feature in our baseline calculations. All considered, our conclusion that the 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.

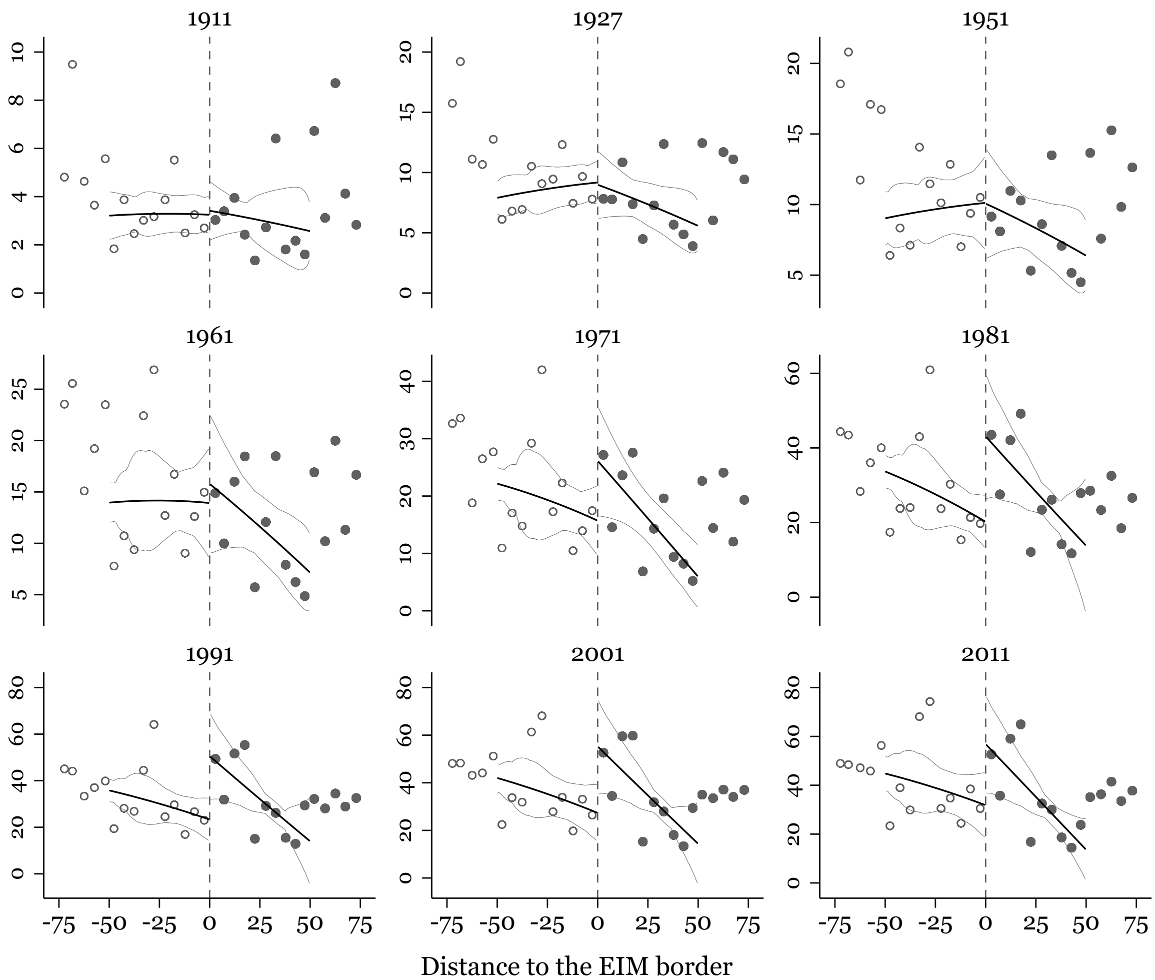
F. Appendix F

Appendix Figure F1. Employment density – Heterogeneity



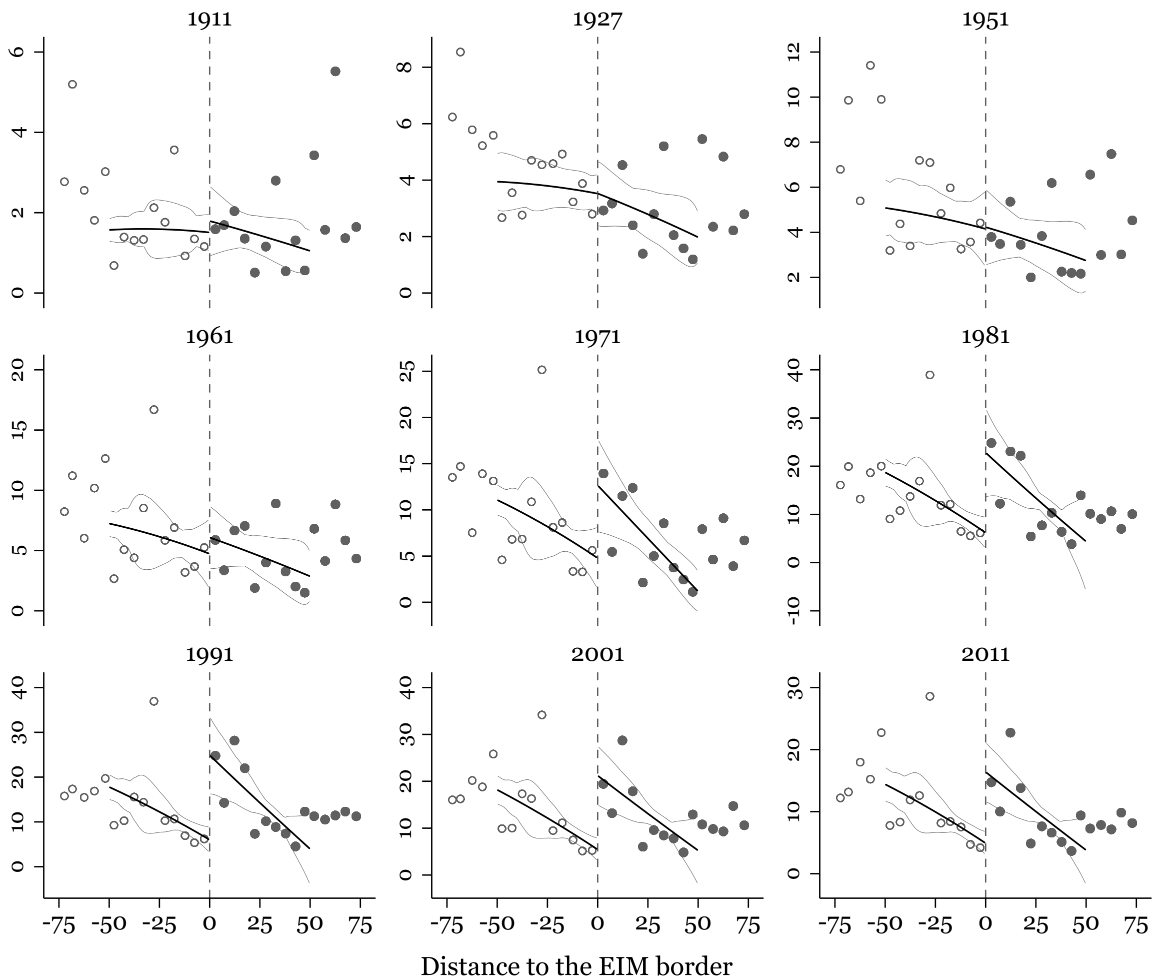
Notes: Coefficient estimates for Equation 2. EIM expenses measured in euros (2011 prices) per 1951 inhabitant, cumulated between 1950 and 1992. Share of high-technology manufacturing computed according to the Eurostat/OECD classification. For each of the six variables, we compute the mean within each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

Appendix Figure F2. Employment density



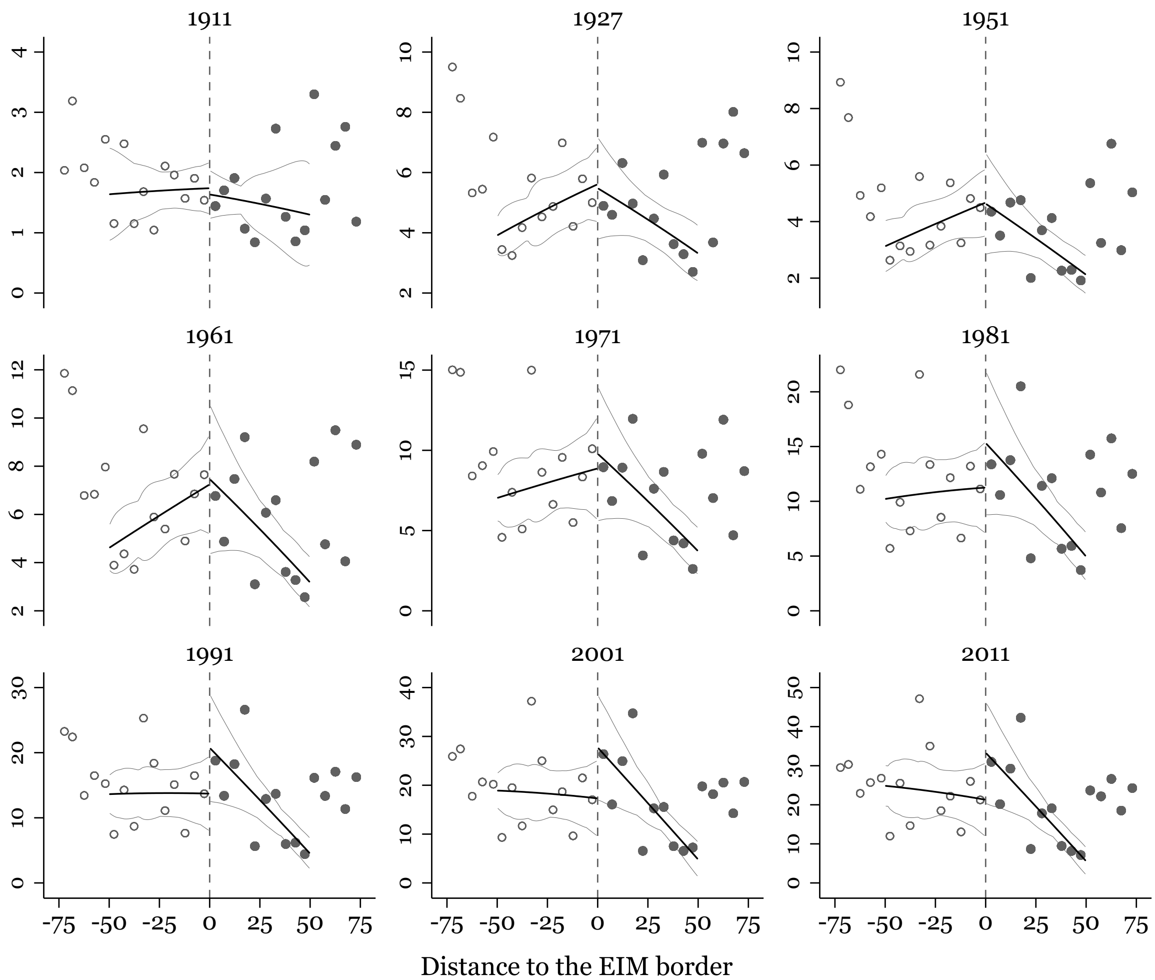
Notes: Negative distance denotes municipalities north of the EIM border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately north and south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

Appendix Figure F3. Manufacturing employment density



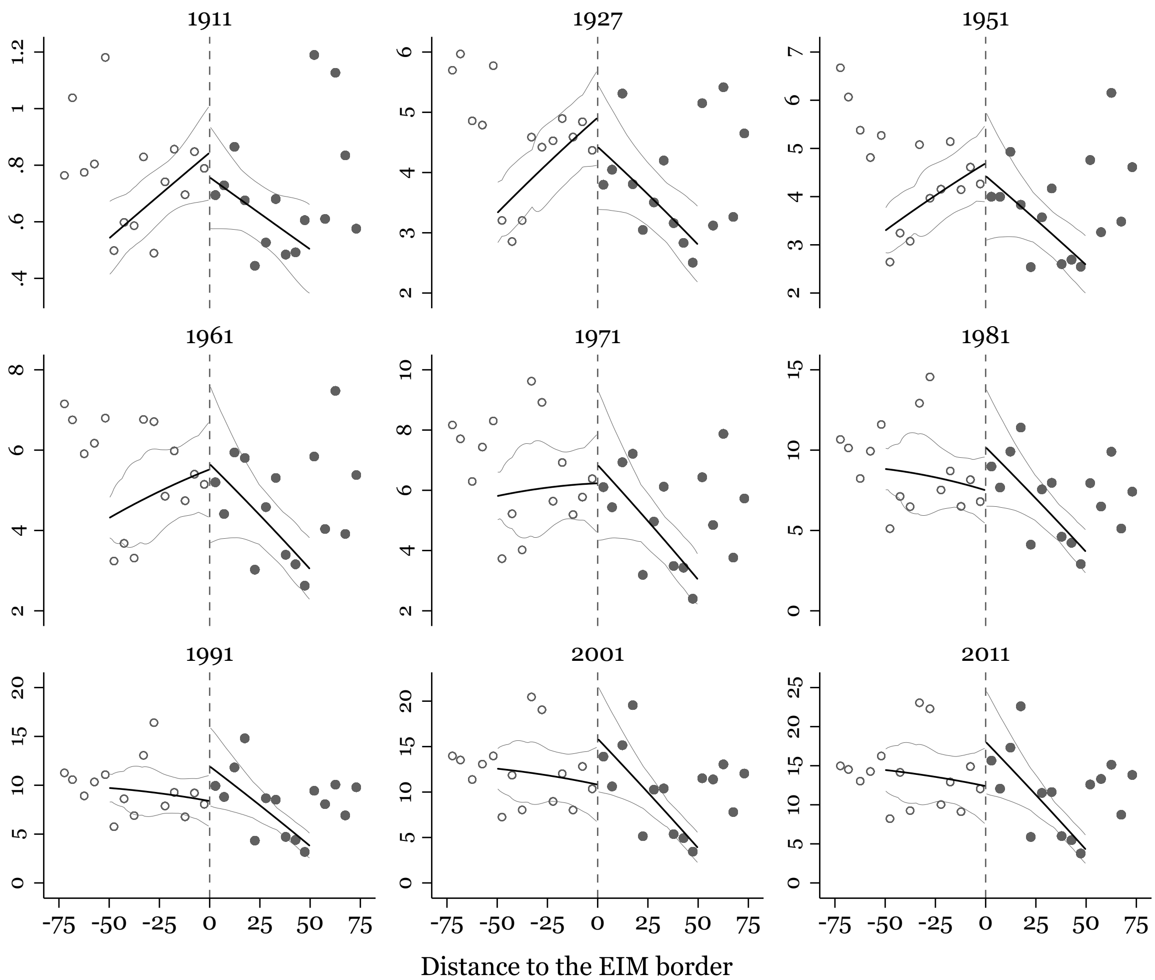
Notes: Negative distance denotes municipalities north of the EIM border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately north and south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

Appendix Figure F4. Services employment density



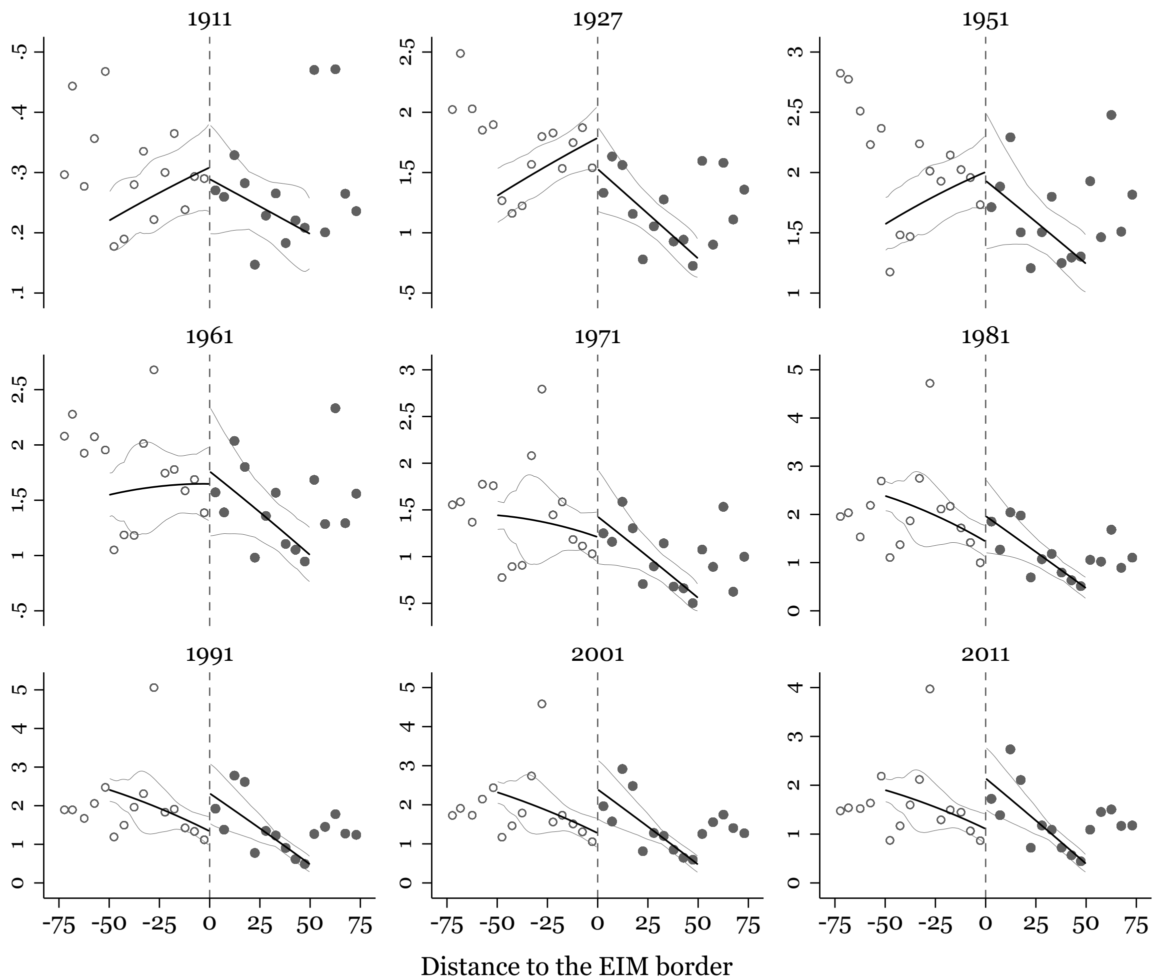
Notes: Negative distance denotes municipalities north of the EIM border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately north and south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

Appendix Figure F5. Establishment density



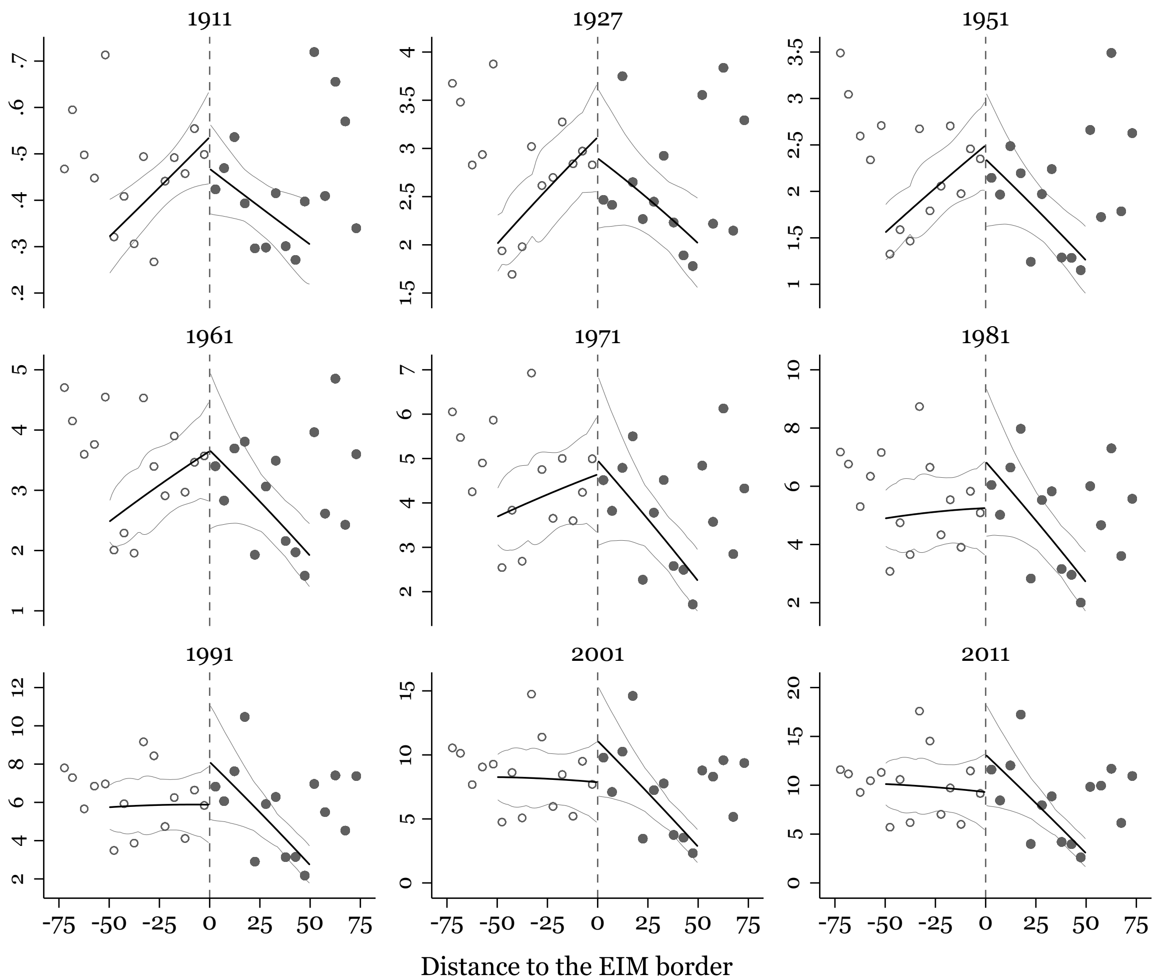
Notes: Negative distance denotes municipalities north of the EIM border. The dots are binned means of the outcome computed within disjoint, evenly-spaced 5-km bins of the running variable. The solid black line is a linear polynomial of the outcome on the running variable, fit separately north and south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

Appendix Figure F6. Manufacturing establishment density



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

Appendix Figure F7. Services establishment density



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

Appendix Table F1. RD estimates – EIM border

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

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

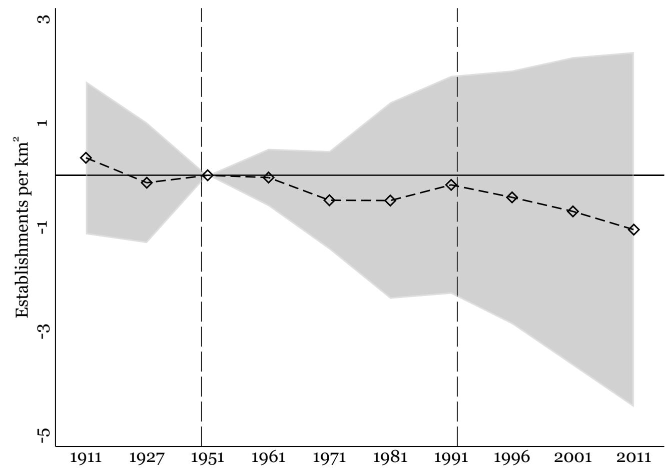
Appendix Table F2. Manufacturing and services densities – EIM border

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

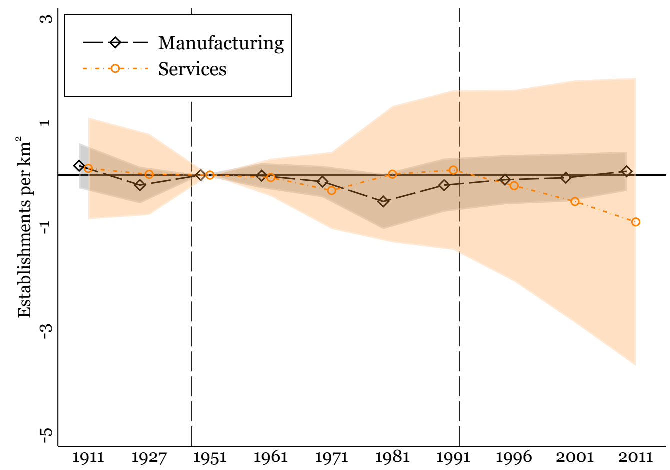
Notes: Coefficient estimates from Equation B4.1 separately for employment density and establishment density. All regressions are estimated over a 50-km symmetric bandwidth around the EIM border and control for a linear polynomial in the distance to the border and border segment effects. Standard errors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

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

(a) Establishment density

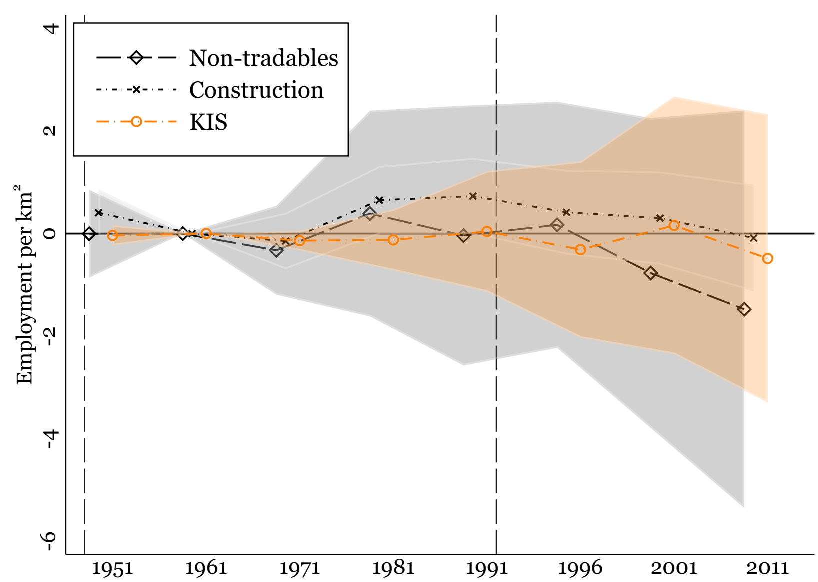


(b) Manufacturing versus services



Notes: Coefficient estimates for Equation B4.2. Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the EIM.

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



Notes: Coefficient estimates for Equation B4.2. Standard errors clustered at the municipality level. The shaded areas denote 95 percent confidence intervals. The dashed vertical lines mark the beginning and the end of the EIM. "Non-tradables" include wholesale and retail trade, hotels and restaurants and other. KIS include communication, finance and insurance and services to firms.

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

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

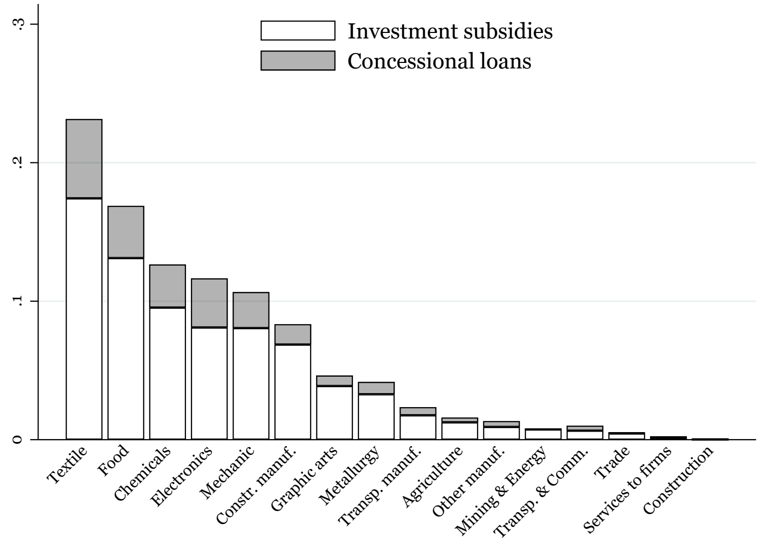
Notes: Coefficient estimates from Equation B4.1. All regressions are estimated over a 50-km symmetric bandwidth around the EIM border and control for a linear polynomial in the distance to the border and border segment effects. Standard errors allow for spatial correlation (Conley, 1999). The outcomes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

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

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

Notes: Coefficient estimates from Equation B4.1. All regressions are estimated over a 50-km symmetric bandwidth around the EIM border and control for a linear polynomial in the distance to the border and border segment effects. Standard errors allow for spatial correlation (Conley, 1999). The outcomes are the share of employment across manufacturing sub-sectors, grouped by technological intensity. The shares are obtained from social security data on the universe of Italian firms and the technology classification is obtained from Eurostat/OECD. See Appendix A.3 for details.

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



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

Appendix Table F5. (Log) wages – EIM border

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

Notes: Coefficient estimates from Equation B4.1. All regressions are estimated over a 50-km symmetric bandwidth around the EIM border and control for a linear polynomial in the distance to the border and border segment effects. Standard errors allow for spatial correlation (Conley, 1999). Outcome computed as the natural logarithm of the average monthly wage paid by the firm, then averaged across firms in a municipality. See Appendix A.3 for details.

Appendix Table F6. Education and occupations – EIM border

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

Notes: Coefficient estimates from Equation B4.1. All regressions are estimated over a 50-km symmetric bandwidth around the EIM border and control for a linear polynomial in the distance to the border and border segment effects. Standard errors allow for spatial correlation (Conley, 1999). Outcomes are defined in Table 5.

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

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

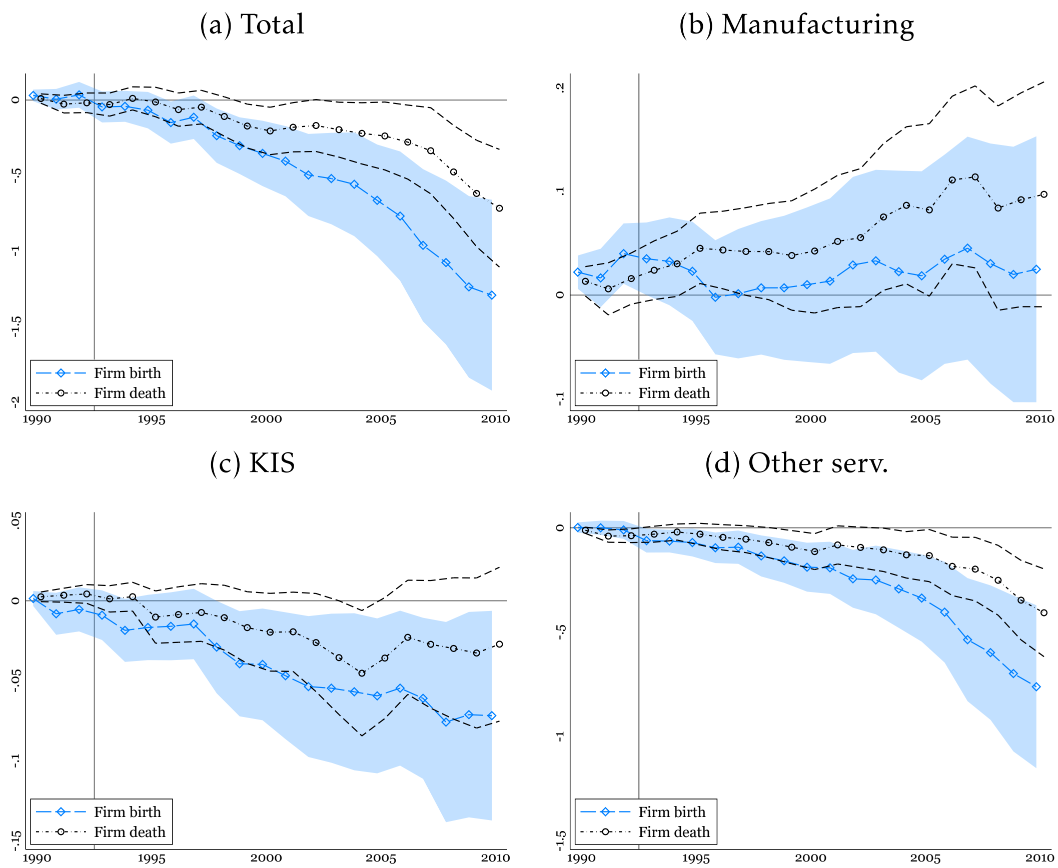
Notes: Coefficient estimates from Equation B4.1. All regressions are estimated over a 50-km symmetric bandwidth around the EIM border and control for a linear polynomial in the distance to the border and border segment effects. Standard errors allow for spatial correlation (Conley, 1999). Outcomes are defined in Table D5.

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

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

Notes: Coefficient estimates from Equation B4.1. All regressions are estimated over a 50-km symmetric bandwidth around the EIM border and control for a linear polynomial in the distance to the border and border segment effects. Standard errors allow for spatial correlation (Conley, 1999). Outcomes defined in Table D6.

Appendix Figure F11. Firm dynamics – EIM border



Notes: Estimates of Equation B4.1 using a 50-km bandwidth and controlling for a linear polynomial in distance to the border and for border segment effects. Standard errors computed using Conley (1999). Shaded areas are 95 percent confidence intervals. The vertical line marks the end of the EIM. Firm birth/death rates computed as the cumulative number of firm births/deaths every year since 1990, as a share of the total number of firms in the municipality in 1990.

Appendix Table F9. Other outcomes – EIM border

	Housing value	Rents	Tax income	Gini coeff.	Krugman Index
RD Estimate	-153.68	-0.57	-0.02	0.01	0.02
	(67.86)	(0.26)	(0.02)	(0.00)	(0.06)
Mean around the border	1106.11	4.14	9.18	0.37	1.06
Standard deviation	511.06	2.01	0.15	0.04	0.43
Observations	584	522	586	587	586

Notes: Estimates for 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). Outcomes defined in Table D7.

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

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

Notes: Column (1) restricts the sample to municipalities bordering IDA centers and Column (2) to municipalities 50 km south of the EIM border. The sample excludes municipalities 50 km south of the EIM border that belong to IDAs. Firm subsidies and infrastructure spending measured in thousand 2011 euros per 1951 resident, winsorized at 1 and 99 percent. Employment and establishments (total and manufacturing) are sourced from the 1951 industrial census. "Agriculture share" computed as the number of agriculture workers per 100 residents aged at least 15. “High school education” denotes the share of people aged at least 6 with high school education or more. "Mean elevation" and "Slope" measured in meters. "Seismicity" is a categorical variable ranging from 1 "High seismicity" to 4 "Very low seismicity". Standard deviations in parentheses.