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The Impact of Industrial Parks on Local Labor Markets: Evidence from Ethiopia

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Abstract

Over the past decade, the Ethiopian government has pursued industrial parks (IPs) as a central instrument of industrialization and export-oriented growth. This paper examines how the expansion of IPs over the period 2005–2021 has reshaped local labor markets. We combine a new georeferenced dataset on the built-up area of Ethiopian IPs, constructed from historical satellite imagery, with individual-level micro-data from three waves of the Ethiopian National Labor Force Survey. Using a concentric-ring difference-in-differences design, we document a sharp reallocation of labor in wards within 10 km of expanding IPs: workers move out of agriculture – both as unpaid family workers and as own-account workers – into wage work in construction, alongside a smaller increase in manufacturing employment concentrated in textile and apparel (T&A). The reallocation differs markedly by gender: the agriculture-to-construction shift is driven almost entirely by men, while women account for most of the increase in T&A manufacturing employment. We also document a moderate increase in recent in-migration around expanding IPs, although the local reallocation is driven mainly by the non-migrant population. All effects dissipate rapidly beyond 10 km, underscoring that the effects of IP policy are geographically concentrated.

JEL classification: J23, J24, J30, J80, O14, O17, O19, P33

Keywords: Ethiopia, Industrial Parks, FDI, Labor markets, Structural change, Informality

1. Introduction

The Ethiopian government has identified industrialization as a means to transform the economy and reduce poverty while creating jobs for its rapidly growing population (World Bank, 2019). One of the key policy instruments for Ethiopia's structural transformation has been the development of industrial parks (IPs) (Tang, 2022). The establishment of the Eastern Industrial Zone (IZ), Ethiopia's first industrial park, in 2007 marked the beginning of the development and expansion of IPs in Ethiopia (Giannecchini & Taylor, 2018). Since then, 21 more IPs have been established or planned with the primary objective of attracting foreign firms in labor-intensive and export-oriented light manufacturing, particularly in the textile and apparel (T&A) sector. Through a concerted effort by the government and various agencies, even global brands such as H&M and PVH have been attracted to IPs. This has contributed to a massive increase in FDI inflows, which tripled from $1.3 billion in 2013 to $4.3 billion in 2021 (UNCTAD, 2022),[1] the period in which most of Ethiopia's IPs were established. As the attracted FDI firms mainly produce for global markets, exports of T&A more than tripled over the same period, from $38.7 million in 2013 to $143 million in 2021 (ITC, 2024).[2]

Despite this macroeconomic success, working conditions in Ethiopia's emerging export-oriented T&A sector, which is mainly located in the IPs, have been the subject of much debate. Indeed, recent empirical studies have shown that factory work in the T&A sector is often poorly paid and associated with adverse health outcomes, resulting in high turnover and industrial conflict between employers and workers (Blattman & Dercon, 2018; Chu & Fafchamps, 2022; Oya & Schaefer, 2021). However, there is a lack of systematic empirical evidence for Ethiopia on the broader local impacts – beyond the creation and quality of factory work – of integration into global markets through the establishment of IPs. Yet, such evidence is essential for a more complete understanding of their economic impact (Moretti, 2010). For example, recent evidence from low- and middle-income countries in Asia suggests that place-based IP policies can play a key role in inducing productivity-enhancing structural change – that is, the reallocation of workers from the traditional agricultural sector to the modern services and manufacturing sectors – and may thus

[1] Ethiopia became the largest recipient of FDI in Africa among landlocked developing countries, with its total stock of FDI rising to $31.6 billion in 2021, accounting for about 31.8 percent of the country's GDP in 2021 (UNCTAD, 2022).
[2] Here, T&A exports refer to the export of apparel and clothing accessories, both knitted or crocheted and non-knitted or non-crocheted, classified under Harmonized System codes 61 and 62.

lead to broad improvements in incomes and working conditions (Brussevich, 2023; Gallé et al., 2024; Hyun & Ravi, 2018; Tafese et al., 2025; Zhao & Qu, 2023).

This paper addresses this gap by examining the spatial impact of IP expansion on local labor markets in Ethiopia. To do so, we combine georeferenced data on IPs, compiled from historical satellite imagery, with rich micro-level data on Ethiopian individuals from three waves of the nationally representative National Labor Force Survey (NLFS) for the period 2005-2021. Specifically, following the methodology of Tafese et al. (2025), we use historical satellite imagery from Google Earth Pro to identify the location of Ethiopian IPs and construct a continuous measure of IP exposure based on changes in the built-up area of IPs over time.[3] We then combine this measure with individual-level NLFS data at the level of the ward (also known as kebeles), the lowest administrative unit in Ethiopia.

Using a concentric ring approach, we estimate the spatial impact of IP expansion on individuals in 10 km distance bins around IPs up to 30 km. To identify the causal effect of an increase in the built-up area of IPs on local employment, we use a difference-in-differences (DiD) framework that compares changes in the labor market outcomes of individuals living in close proximity to expanding IPs with changes in outcomes of individuals from the same district (also known as woredas), Ethiopia's second lowest administrative unit, living further away from expanding IPs. We address the main identification concern of non-parallel trends in outcomes of places with and without expanding IPs by including a number of fixed effects, such as district fixed effects, which control for time-invariant confounders, and district-year fixed effects, which capture shocks that are common to all individuals in the same district in the same year. In addition, we test whether wards at different distances from IPs had different pre-treatment trends before the IP establishment by running placebo regressions using the pre-treatment waves of our NLFS data going back to 2005, well before any IPs were planned. Our results for most outcome variables are robust to various extensions using alternative samples, treatments, and outcomes, as well as accounting for migration.

We have three sets of results. First, we document a sharp reallocation of labor in wards within 10 km of expanding IPs: workers move out of agriculture – both as unpaid family workers and own-account workers – into wage work in construction, alongside a smaller increase in manufacturing

[3] In constructing their IP exposure measure from the built-up area in IPs, Tafese et al. (2025) exploit the fact that changes in the area covered by built-up area are a very good predictor of changes in economic activity over time, as has been shown by Bilicka and Seidel (2022).

employment concentrated in textile and apparel. Services employment is unaffected. Second, this reallocation differs markedly by gender. The shift from agriculture into construction is driven almost entirely by men, with a much smaller construction increase among women. Manufacturing employment rises for both groups, but somewhat more strongly for women, largely due to expansion in T&A. Men also see a moderate increase in services employment – driven by elementary services – whereas women do not. Third, we document moderate IP-induced in-migration, almost all of it occurring in the five years preceding the survey. The sectoral reallocation, however, is driven mainly by the local non-migrant population, although recent migrants do account for part of the manufacturing effect. All three patterns are robust to alternative treatment measures, alternative samples, and placebo-augmented specifications.

Our work contributes to three strands of the literature. First, we contribute to a growing body of work that examines the economic impact of place-based policies, particularly Special Economic Zones (SEZs),[4] in developing countries. While existing studies have almost exclusively focused on the impact of place-based policies in Asian economies, we are, to the best of our knowledge, the first to provide rigorous micro-level quantitative evidence for an African country.[5] Our findings complement the evidence on these Asian countries well, particularly with respect to structural changes in employment in exposed locations. Consistent with the evidence on Cambodia (Brussevich, 2023), China (Zhao & Qu, 2023), India (Gallé et al., 2024; Hyun & Ravi, 2018),[6] and Vietnam (Tafese et al., 2025), we find a large decline in agricultural employment in 'treated' locations around expanding IPs in Ethiopia. For manufacturing and services, the literature is more mixed. Similar to the evidence from India and Vietnam, we find a shift towards manufacturing employment in treated locations in Ethiopia, but this shift is more moderate than in the other two countries. In contrast to all other studies, we find the strongest shift towards construction. Additionally, similar to the evidence from Vietnam, we find no impact on employment in services, diverging from the findings in Cambodia and India.

[4] SEZs are usually defined as clearly demarcated areas with a regulatory regime that is distinct from the rest of the economy (Lay & Tafese, 2020). Industrial parks are one type of SEZ that is prominent in Ethiopia, but others such as high-tech, free-trade or economic zones may be more important in other countries.
[5] An exception to this is the study by Abagna et al. (2025) who don't focus on an a single country but on Africa as a whole and use data from the from the Demographic and Health Surveys to examine the impact of SEZs on household wealth.
[6] While Gallé et al. (2024) and Hyun and Ravi (2018) document shifts in employment from agriculture to manufacturing and services, Alkon (2018) and Görg and Mulyukova (2024) mostly find no such reallocation effects. However, the two former studies are arguably better suited for such reallocation analyzes, as they incorporate data on informal production and employment from different data sources into their analyzes.

Second, we contribute to a recent wave of studies focusing on the local impact of investment and trade liberalization on economic outcomes in Ethiopia.[7] Focusing on the impact of greenfield FDI, Abebe et al. (2022) find positive employment spillovers in local manufacturing firms due to the opening of FDI projects.[8] This is partly confirmed in another study by Crescenzi and Limodio (2021), which focuses specifically on Chinese greenfield FDI. They find that employment in local manufacturing firms expands in up- and downstream sectors, while it contracts in local firms in the same sector because of increased competition. While the results of these studies are broadly consistent with the moderate increase in manufacturing employment in treated locations that we find, we also capture shifts across sectors using our individual-level labor market data. Our approach is thus closely related to that of Giovannetti et al. (2022) who also focus on local labor market outcomes from the same individual-level NLFS, but analyze the impact of Ethiopia's trade liberalization in the late 1990s and early 2000s. Similar to our findings, the authors find only small shifts to manufacturing in districts with larger reductions in output tariffs, but unlike us they find the largest shift from agriculture to services, especially for women.[9]

Third, our findings complement a related literature on the working conditions and welfare effects of factory work in Ethiopia's export-oriented T&A sector, much of which is concentrated in the IPs (Abebe et al., 2020, 2024; Blattman & Dercon, 2018; Blattman et al., 2022; Chu & Fafchamps, 2022; Oya & Schaefer, 2021).[10] While that literature focuses on the experience of workers inside IP factories, we look outward at the surrounding labor markets and document a broader reallocation of employment – from agriculture to construction and, more modestly, to manufacturing – in places exposed to expanding IPs. The two perspectives speak to different margins of the same phenomenon and are best read together.

The rest of the paper is organised as follows. Section 2 describes the policy background and presents the characteristics of IPs in Ethiopia. Section 3 presents the data and summary statistics.

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[7] For the sake of brevity, we limit the discussion to the Ethiopian context, although a related, rapidly growing literature has emerged focusing on the impact of FDI projects in Africa more generally (Hoekman et al., 2025; Hoekman & Sanfilippo, 2023; Lakemann et al., 2025; Mendola et al., 2024).

[8] Abebe et al. (2022) focus only on 12 FDI openings between 2004 and 2010, while we consider much larger "shocks" to local labor markets that the establishment of IPs represents.

[9] In another study, Ngoma (2025) focuses specifically on the import side and finds that increases in Chinese imports of intermediate inputs increase employment in manufacturing.

[10] Specifically, Chu & Fafchamps (2022) and Oya & Schaefer (2021) document high turnover and industrial conflict in IPs; Abebe et al. (2020) and Blattman & Dercon (2018) find short-term negative health effects of factory work, while longer-run follow-ups (Abebe et al., 2024; Blattman et al., 2022) find these effects fade and that factory pay is not systematically higher than alternative income-generating opportunities.

Section 4 discusses the empirical strategy. Section 5 presents the empirical findings. Section 6 performs robustness checks and extensions. Finally, Section 7 concludes the paper.

2. Policy Background

Over the past decade, the Ethiopian government has pursued the establishment of IPs as a cornerstone of its economic transformation and industrialization strategy. Based on various public sources, we have identified 22 IPs across the country, of which 15 are public and 7 are private (see Table 1).[11] Every region of Ethiopia has at least one IP, although most of these IPs are located in the central provinces of Oromiya and Amhara, and in the capital, Addis Ababa. Ethiopia's first two IPs, the private Eastern IZ and the public Bole Lemi IP, were established in 2007 and 2014 respectively.[12] All other IPs were established after 2016. To date, 20 IPs have been opened and 2 are still in the planning stage.

Table 1: Ethiopia's IPs

Industrial park name	Region	Year of opening	Ownership
Adama IP	Oromiya	2018	Public
Arerti IP	Amhara	2019	Private
Baeker IAIP	Tigray	To be opened	Public
Bahir Dar IP	Amhara	2020	Public
Bole Lemi IP	Addis Ababa	2014	Public
BulBula IAIP	Oromiya	2021	Public
Bure IAIP	Amhara	2021	Public
DBL IP	Tigray	2021	Private
Debre Birhan IP	Amhara	2019	Public
Dire Dawa IP	Dire Dawa	2018	Public
Eastern IZ	Oromiya	2007	Private
George Shoe IP	Oromiya	2017	Private
Hawassa IP	SNNP	2016	Public
Huajian IP	Addis Ababa	2018	Private
Jimma IP	Oromiya	2019	Public
Kilinto IP	Addis Ababa	2019	Public
Kombolcha IP	Amhara	2017	Public
Mekelle IP	Tigray	2017	Public
Semera IP	Afar	2021	Public
Velocity IP	Tigray	2018	Private
Woda IP	Oromiya	To be opened	Private
Yirgalem IAIP	SNNP	2021	Public

Note: The table shows all operational and planned Ethiopian IPs as of 2022. It

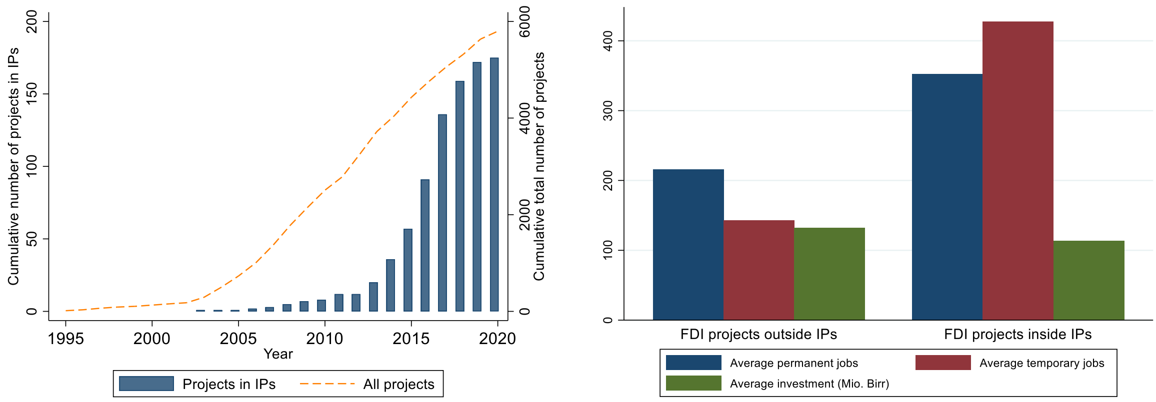
[11] We identified the Ethiopian IPs and their characteristics as of 2022 from various sources from Ethiopian agencies such as the Industrial Parks Development Corporation (IPDC), and cross-validated this with various other public sources including multilateral development organizations such as the World Bank (2022).

[12] The Bole Lemi IP was established by the IPDC in two phases, while the Eastern IZ was established by the Chinese Qiyuan Group. More broadly, most of the private and public IPs in Ethiopia have been established by Chinese state-owned construction companies. Furthermore, officials from the Chinese government and private companies have played a pivotal role in supporting the development of Ethiopia's legal and institutional framework for IP management. See Tang (2022) for details on the development of IPs in Ethiopia and the role played by China.

draws on official Ethiopian agency documents, especially IPDC sources, and is cross-validated with public sources such as the World Bank (2022).

Ethiopia's IPs are populated almost entirely by foreign firms, as those located in IPs are generally required to export their entire output in order to benefit from the preferential tax and customs regimes of IPs (ILO & IFC, 2023).[13] Using project-level data from the Ethiopian Investment Commission (EIC), the left panel of Figure 1 shows that the cumulative number of licensed foreign investment projects located in IPs increased sharply in the early 2010s, rising from eight in 2010 to 178 in 2021[14] – about a decade after foreign investment inflows to Ethiopia began to increase more broadly. As shown in the right panel, FDI projects inside IPs also generate substantially more employment on average than those outside, both permanent jobs (354 vs. 216) and temporary jobs (427 vs. 143). This reflects the concentration of IP-based FDI in manufacturing: 92 percent of FDI projects in IPs are in manufacturing, compared to 62 percent outside IPs. Furthermore, within manufacturing, more than half of FDI projects in IPs are in labor-intensive T&A, compared with around 12 percent outside IPs.

Figure 1: Licensed Foreign Investment Projects in Ethiopia



Notes: Author's own compilation, based on project-level foreign investment data from the EIC. Both operational and (pre-) implementation projects are included. The left panel includes all foreign investment projects. The right panel includes only projects from the period 2013–2019 for which project-level data on investment and job creation are available.

The promotion and development of IPs is guided by Ethiopia's five-year Growth and Transformation Plans (GTP),[15] with three agencies in particular taking the lead across several policy areas. First, the Ethiopian Investment Board (EIB), which is chaired by the Prime Minister and

[13] Another limiting factor for most local firms is that sheds in the IP can generally only be rented in foreign currency.
[14] This includes both operational projects (57 percent) and (pre-) implementation projects (43 percent). We infer whether a foreign investment project is located within an IP from information on the zone in which it is located. While this information is not available for each project, the timing of the establishment of the IPs inferred in this way appears to be consistent with other public sources.
[15] In particular, the GTP II, which was launched in 2015 with the aim of transforming Ethiopia into a lower-middle-income economy by 2025, has placed greater emphasis on the development of IPs across the country (National Planning Commission, 2016).

comprises senior ministers from other key ministries, oversees Ethiopia's investment promotion and IP policy, including the provision of incentives to investors, the removal of policy and regulatory barriers to investment, and the designation of new IPs. Second, the EIB-supervised EIC focuses on the day-to-day operations of foreign investment promotion, such as advising the government on improving the investment climate and administering investment and work permits related to the IPs.[16] Third, the Industrial Parks Development Corporation (IPDC), a for-profit state-owned enterprise (SOE), is tasked with developing and managing the public IPs,[17] including making land available to potential private developers and providing infrastructure and services to investors.

In summary, the Ethiopian government has placed emphasis on creating an institutional structure that promotes strong inter-ministerial/interagency cooperation for investment promotion and IP development, which is centrally coordinated by the Prime Minister's Office. This appears to have supported attracting foreign investors to Ethiopia, in contrast to other African countries such as Kenya, Nigeria and Tanzania, where limited high-level government support and institutional linkages have hindered this (Rodríguez-Pose et al., 2022).

3. Data

We use two main data sources to examine the impact of IPs on local labor markets in Ethiopia. First, we use IP exposure (at different distances) as our treatment variable, which we measure as the total built-up area of IPs. We construct this variable from a unique dataset of geographically-referenced Ethiopian IPs using historical, high-quality Google Earth Pro satellite imagery. This imagery is available on a regular basis – mostly annually or even more frequently – since the late 2000s, and thus for the entire period of the expansion of Ethiopia's IPs. Second, we obtain our individual-level labor market outcomes from three waves of the nationally representative NLFS. The NLFS survey waves are from 2005, 2013, and 2021, covering the period before, during, and after the expansion of IPs, providing an ideal setting to study the local impact of the expansion of IPs on workers. In the following, we explain how we construct our treatment variable, IP exposure,

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[16] Ethiopia was quick to recognize the importance of FDI for the country's economic and social development, and therefore integrated FDI attraction into its development policies as early as during the imperial regime from the early 1950s to 1974 (Gebreeyesus et al., 2022). However, the rise of the Derg regime in 1975 led to a hiatus in foreign investment promotion as the regime adopted a state-led socialist and command economic system and nationalized many private businesses (Newman, 2016). It was only after the Ethiopian People's Revolutionary Democratic Front came to power in 1991 that various liberalization measures such as privatization, trade and investment opening, and market deregulation were again implemented (Gebreeyesus et al., 2022).

[17] Ethiopia's four public integrated agro-industrial parks, which focus on agro-processing, are developed by the regional IPDC in each region. Private IPs are developed by private foreign, mostly Chinese, investors.

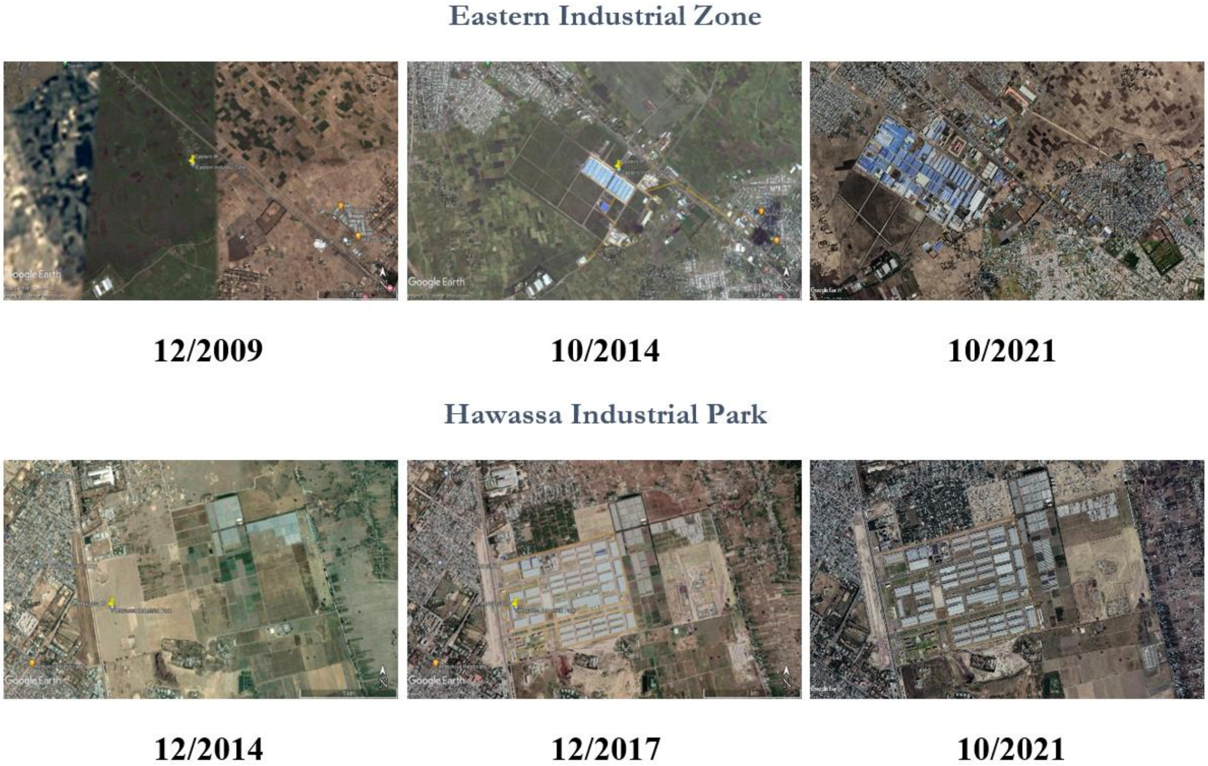
from Google Earth Pro satellite imagery (Section 3.1), present our main labor market outcome variables from the NLFS (Section 3.2), and describe how we combine our treatment and outcome data and present pre-treatment summary statistics (Section 3.3).

3.1 Measuring IP exposure

We construct our main treatment variable of IP exposure from the actual built-up area of IPs that is covered by structures such as factories and sheds using historical Google Earth Pro satellite imagery, closely following Tafese et al. (2025). We measure changes in the built structures of an IP over time by drawing polygons around the factories and sheds within its well-defined boundaries in all years for which satellite imagery is available. We follow this procedure for each IP to construct our continuous IP exposure variable. As Ethiopia's IPs have only recently been established, high-quality imagery is available almost every year – and several times a year for recent years – which also allows us to identify the start of construction for each IP.

Figure 2 shows as an example the expansion and our mapping of Ethiopia's two largest IPs, namely the Eastern IZ and the Hawassa IP. For both IPs, the leftmost satellite image shows the demarcated IP boundaries in the year just before construction began, when there were no built structures – 12/2009 for Eastern IZ and 12/2014 for Hawassa IP. In these earliest images, the built-up area for both IPs is 0 hectares (ha). The rightmost image shows both IPs in the last year of our study period, 2021. By this time, both IPs had expanded significantly, with the Eastern IZ covering a built-up area of 263 ha and the Hawassa IP 113 ha. The middle image shows each IP at an intermediate point, when the IPs had already begun to expand, although not to the extent seen in the last year of the study period.

Figure 2: The Expansion of Ethiopia's Two Biggest Industrial Parks



Notes: The satellite imagery is from Google Earth Pro. The figure shows the expansion of the Eastern IZ and Hawassa IP over time via satellite imagery.

Table 2 summarizes the expansion of Ethiopia's IPs over our study period, showing the total built-up area for each IP in 2005, 2013 and 2021, the three years in which the NLFS waves were conducted. In the subsequent analysis, we exclude the four integrated agro-industrial parks because of their distinct economic focus and limited operational status, leaving 18 IPs. In 2005, none of these 18 IPs had any built-up area. By 2013, the Eastern IZ and Bole Lemi IP had been established, although the latter's built-up area remained small at 4 ha. By 2021, 16 out of the 18 IPs had some built-up area, averaging 46 ha. Their size varied considerably: 4 IPs had less than 10 ha of built-up area, 8 had between 10 and 50 ha, and 6 had more than 50 ha. Overall, the total built-up area of these IPs increased from 0 ha in 2005 to almost 4000 ha in 2021, with growth accelerating particularly in the second half of the 2010s (Appendix Figure 1).

Table 2: IP Expansion over Time

Industrial park name	Built-up area			Rank in 2021
	2005	2013	2021	
Adama IP	0	0	94	*3*
Arerti IP	0	0	13	*13*
Bahir Dar IP	0	0	13	*12*
Bole Lemi IP	0	4	61	*5*
DBL IP	0	0	7	*16*
Debre Birhan IP	0	0	19	*9*
Dire Dawa IP	0	0	69	*4*
Eastern IZ	0	45	263	*1*
George Shoe IP	0	0	31	*8*
Hawassa IP	0	0	113	*2*
Huajian IP	0	0	14	*11*
Jimma IP	0	0	9	*15*
Kilinto IP	0	0	17	*10*
Kombolcha IP	0	0	58	*6*
Mekelle IP	0	0	34	*7*
Semera IP	0	0	0	*17*
Velocity IP	0	0	12	*14*
Woda IP	0	0	0	*17*

Note: Author's own compilation based on satellite imagery from Google Earth Pro. Total built-up area is measured in hectares and includes all physical structures such as factories and sheds that fall within the boundaries of an IP.

3.2 NLFS outcome data

We use individual-level labor market outcomes from three waves of the NLFS, conducted in 2005, 2013 and 2021. The NLFS is a nationally representative survey conducted by the Ethiopian Central Statistical Agency (CSA) in all urban and rural areas. As a repeated cross-sectional survey,[18] each wave of the NLFS samples 43,000–57,000 new households and between 170,000–240,000 new individuals. Apart from its large sample size, the main advantage of the NLFS, which allows for a careful analysis of local labor market dynamics, is its level of detail. Specifically, the NLFS provides detailed information on individuals' employment for both the last seven days and the last twelve months, including their employment status, their occupation at the 4-digit ISCO level, and the main

[18] The NLFS uses a two-stage stratified sampling design to select EAs (primary sampling unit) and households (secondary sampling unit). The stratification is based on the country's regional states and the two city administrations, as well as on rural and urban areas. The sampling frame from which the EAs are randomly selected is derived from the population and housing censuses. While the general sampling approach is the same across the three survey waves, the specific selection methods and classification criteria have evolved slightly over time. More detailed information on the sampling frames, procedures, and descriptive statistics, can be found in the survey reports provided by the CSA for each wave.

type and sector of employment at the 4-digit ISIC level (see Appendix Table 1 for the sectoral classification). In the baseline regression, we use the employment outcomes for the last seven days as they are generally more complete, and available at a higher level of detail. However, we also check the robustness of our results using the employment outcomes for the last twelve months.[19]

The key to examining the spatial impact of IP expansion is that we geolocate the individuals in the NLFS in as much detail as possible. Although we do not know the exact geocoordinates of individuals for reasons of confidentiality, for each household in the NLFS we know the four administrative units in which it is located, which are, from top to bottom, regions, zones, districts, and wards.[20] By matching the Ethiopian ward codes in the NLFS data to the ward codes in the geospatial Africa GeoPortal dataset,[21] which provides the administrative boundaries of every ward in the country, we can extract geocoordinates at the lowest administrative ward level. However, due to changes in administrative codes over time, we cannot match all ward codes across the two databases and have to manually extract the geocoordinates of many kebeles from the Africa GeoPortal and Google Maps based on their name. Overall, we are able to geolocate 74 percent of the individuals at the ward level across the three NLFS waves.[22]

Finally, we restrict our final regression samples in a number of ways. First, we exclude the Tigray region from the analysis because no endline data could be collected from the region, due to the outbreak of the armed conflict between forces allied to the Ethiopian federal government and the Tigray People's Liberation Front (hereafter Tigray War) in November 2020. Second, we drop those

[19] Earnings data are available only for wage employees, excluding self-employed and own-account workers. Because most Ethiopian workers fall into these latter categories, estimating earnings effects would risk selection bias: wage workers account for only 3 percent of agricultural workers, 35 percent of manufacturing workers, 46 percent of service workers, and 60 percent of construction workers. We therefore do not estimate the effect of IP expansion on earnings.
[20] While Ethiopia is administratively divided into four levels, a basic distinction is made between rural and urban areas. In rural areas, wards are villages, and in urban areas wards are neighborhoods within towns. Towns have their own administrative code below the third district level and above the fourth ward level. As towns are already geographically small units and neighborhoods within towns are often not geolocated, we use the geocoordinates of towns for urban areas. For rural areas, we use the geocoordinates of the actual villages.
[21] To our knowledge, the Africa GeoPortal platform is the only source of geospatial data that includes administrative boundaries at the ward level for Ethiopia. An alternative source, the Humanitarian Data Exchange platform, only contains geospatial data at the district level. This is not detailed enough for our empirical analysis, as it includes district-year fixed effects that would absorb treatment effects if defined at this level.
[22] There are significant differences in the success of extracting ward geocoordinates between waves. It worked best for the 2013 NLFS wave, where we were able to extract ward-level geocoordinates for 95 percent of the NLFS wards, as the ward codes in the NLFS were largely identical to those in the Africa GeoPortal dataset. While the changes in administrative codes from the 2013 wave to the 2021 wave were most significant in the NLFS, we were still able to extract ward level geocoordinates for 85 percent of the NLFS wards in 2021 by searching for their names in the Africa GeoPortal dataset and Google Maps. For 2005, however, we were only able to extract ward-level geocoordinates for 49 percent of the wards because the names of the wards were not provided in the NLFS.

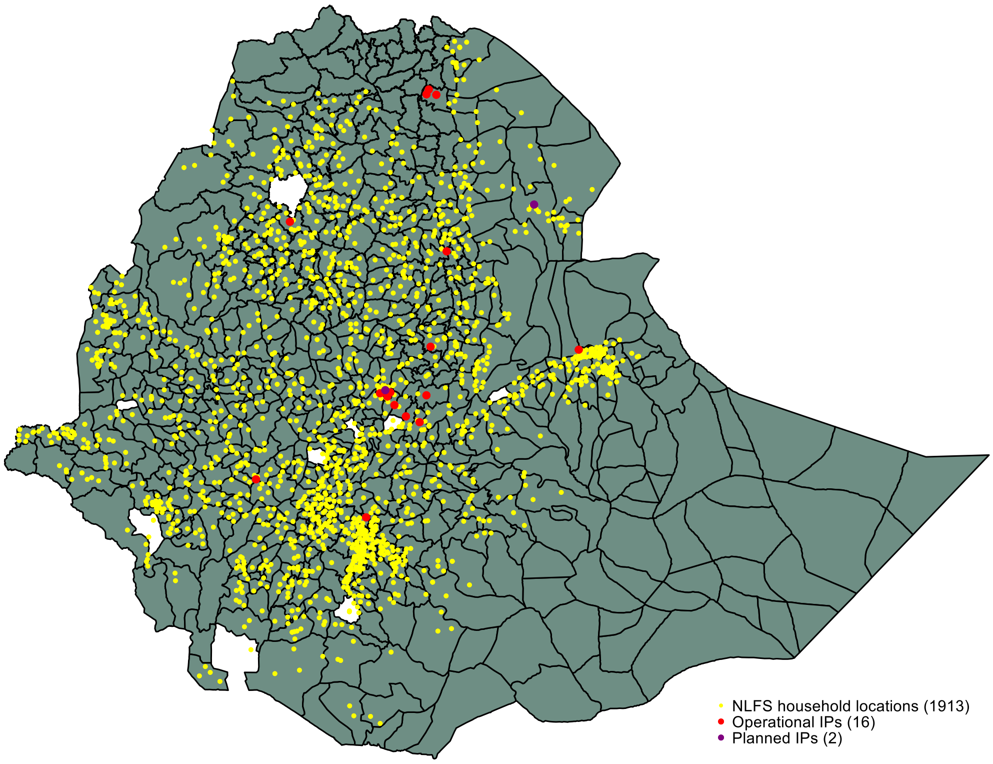
individuals aged 5 or younger for whom no employment information was collected.[23] Third, we drop households that could not be geolocated at the ward-level, which excludes, for example, the Somali region, for which the Africa GeoPortal platform does not provide geocoordinates at the ward level. We thus end up with 385,330 individual-level observations across the three waves of the NLFS.

3.3 Combining IP exposure and NLFS outcome data

We spatially link our measure of IP exposure to the NLFS outcome data using the geocoordinates of the IPs and individuals' home wards. Figure 3 shows on a map of Ethiopia the location of NLFS households (yellow) and the 18 IPs under consideration, distinguishing between those in operation (purple) and those planned (red), as well as administrative district boundaries. In total, there are 1,913 unique household locations at the ward level. Most districts have multiple household locations, and in particular IPs tend to be surrounded by multiple household locations (at varying distances), as they are often located in peri-urban areas on the outskirts of towns and cities. Note that there are no NLFS households in the northern Tigray region and the south-eastern Somali region, as we had to exclude both due to missing data for the reasons mentioned above.

[23] We include children under the legal working age of 15 in Ethiopia because it is not uncommon for them to work, especially in rural areas, where 47 percent of them work compared to 8 percent in urban areas (in the pooled sample). However, our results are robust when we consider only the working-age population aged 15-65.

Figure 3: Location of NLFS Households and IPs in Ethiopia



Note: Author's own compilation based on (i) district-level administrative boundaries from the Africa GeoPortal platform, (ii) the geocoordinates of NLFS households at the ward-level from three waves of the NLFS, and (iii) the geocoordinates of IPs from Google Earth Pro.

We now examine the pre-treatment characteristics by proximity to IPs. To do this, we calculate the distance between IPs and individuals in our sample in 10 km distance bins around IPs based on the geocoordinates of IPs and individuals' home wards.[24] Table 3 shows the pre-treatment characteristics of individuals in 10 km distance bins[25] for the first two NLFS waves, 2005 and 2013, which was before the expansion of most IPs in Ethiopia (see Table 2). The table shows strong differences in the characteristics of wards across distance bins. In terms of the geography and demographics, wards closer to IPs are on average more densely populated, especially those within 20 km of IPs, and individuals living very close to IPs, within 10 km, are much more likely to live in urban wards. In addition, individuals living closer to IPs are on average older and more educated. In terms of employment characteristics, wards closer to IPs have significantly higher proportions of wage employment and significantly lower proportions of own-account and unpaid family work. Correspondingly, the share of employment in private enterprises and the public sector is higher in

[24] Households may fall into more than one distance bin as there is some concentration of IPs, particularly in and around Addis Ababa and Mekelle. For example, a household in the southern part of Addis may fall into a distance bin for the Kilinto IP and for the Bole Lemi IP.

[25] We define distance bins at 10 km rather than smaller distances such as 5 km in order to have a sufficient number of treated observations in each bin.

wards close to IPs, while the share of employment in households is lower. Similarly, the share of employment in manufacturing, services and construction is higher near IPs and lower in agriculture.

Table 3: Pre-Treatment Location Characteristics

	0-10km	10-20km	20-30km	>30km	N
Geography and demographics					
Share of individuals in sample	0,21	0,16	0,09	0,71	254558
Share of individuals in urban ward	0,97	0,38	0,56	0,39	254558
Mean age	28,6	25,4	25,9	25,4	254558
Literacy share	0,84	0,52	0,57	0,49	254518
Employment shares					
Type of work					
Wage work	0,61	0,16	0,24	0,13	151761
Own-account work	0,30	0,41	0,37	0,39	151761
Unpaid family work	0,06	0,41	0,38	0,47	151761
Employer organization					
Household business	0,44	0,84	0,78	0,87	151761
Private enterprise	0,29	0,07	0,10	0,04	151761
Public sector	0,22	0,06	0,09	0,07	151761
Sector					
Agriculture	0,07	0,59	0,49	0,64	151784
Manufacturing	0,16	0,06	0,07	0,06	151784
Services	0,67	0,30	0,40	0,28	151784
Construction	0,10	0,05	0,05	0,03	151784

Note: Author's own compilation based on the 2005 and 2013 NLFS waves. The distance between IPs and individuals is calculated based on the geocoordinates of IPs and individuals' home wards.

4. Empirical Strategy

4.1 Concentric ring approach

We capture the spatial impact of IP expansion in a concentric ring approach using three continuous treatment variables, one for each 10 km distance bin up to a radius of 30 km around an IP. Each treatment variable captures the total built-up IP area to which an individual *i* living in ward *w* falling within the corresponding distance bin *b* is exposed. Formally, the three treatment variables are defined as $\sum_{b=1}^{3} IP\_exposure_{wt[b_w=b]}$, where $b_w = 1$ denotes wards falling within the 0-10 km distance bin, $b_w = 2$ indicates wards falling within the 10-20 km distance bin, and $b_w = 3$, denotes wards falling within the 20-30 km distance bin. $IP\_exposure_{wt}$ is the same for all individuals in the same ward, but varies over time with changes in the total built-up IP area.

Thus, in our concentric ring approach, individuals living more than 30 km away from all IPs are in the control group in all years. Similarly, individuals living within 30 km of a planned IP that has not yet been established are in the control group for that year.[26] Our treatment threshold of 30 km is chosen based on evidence from similar studies, which have shown that the impacts of place-based policies tend to be highly geographically concentrated, with little or no spillovers to neighboring places (Abagna et al., 2025; Gallé et al., 2024; Görg & Mulyukova, 2024; Lu et al., 2019; Tafese et al., 2025). In the Ethiopian context, characterized by low incomes, transport costs are likely to be an even greater constraint on commuting, making spillovers even less likely than in the context of the above studies.

4.2 Baseline specification

To estimate the spatial impact of IP expansion on our individual-level labor market outcomes, we pool the three NLFS waves from 2005, 2013, and 2021 and adopt a DiD design, which we implement using the following two-way fixed effects (TWFE) regression specification:

$$y_{iwdt} = \beta_0 + \sum_{b=1}^{3} \beta_b \, IP\_exposure_{wt[b_w=b]} + \beta_4 IX_{iwdt} + \beta_5 IY_{wd} + \gamma_t + \gamma_d + \gamma_{dt} + \varepsilon_{idt} \quad (1)$$

where y_{iwdt} is the outcome of interest for individual *i* living in ward *w* in district *d* at time *t*. As explained above, $\sum_{b=1}^{3} IP\_exposure_{wt[b_w=b]}$ are our three treatment variables and $\beta_1, \beta_2,$ and β_3 therefore the main coefficients of interest, which capture the effect of an increase in IP built-up area on individuals within 0-10 km, 10-20 km, and 20-30 km of an IP, respectively. We measure IP exposure in 10 ha, which is about twice the median built-up area of IPs in 2021 (see Table 2).

IX_{iwdt} is a vector of time-varying individual-level controls, including an individual's age, a male dummy, and a categorical variable for an individual's highest educational attainment. IY_{wd} is a vector of time-invariant ward-level controls, including three dummy indicators for the 0-10 km, 10-20 km, and 20-30 km distance bins around established IPs that capture whether an individual is in one (or more) of the three treatment groups, and a rural dummy that captures whether the ward is in a rural area (i.e., it is a village) or an urban area (i.e., it is a town).

We also include γ_t year fixed effects, γ_d district fixed effects, γ_{dt} district-year fixed effects. We include district fixed effects even though our treatment varies at the ward-level because most districts are consistently available across all three NLFS survey waves, whereas wards tend to

[26] For example, an individual living in a ward that does not live within 30 km of an IP will have a treatment value of 0 ha in all years. Similarly, an individual living within 10 km of an IP whose built-up area increases from 0 ha in 2013 to 50 ha in 2021, will have a treatment value for the 0-10 km distance bin of 0 ha in 2013 and 50 ha in 2021.

change between survey waves.[27] While the district fixed effects control for time-invariant differences in the characteristics of districts, such as their size and geographical location, the district-year fixed effects capture shocks that are common to all individuals in the same district in a given year. Importantly, the district-year fixed effects also capture shocks that may be correlated with baseline district characteristics.[28] Finally, ε_{idt} is the error term, which is clustered at the district level.[29]

4.3 Identification

Equation (1) identifies the spatial impact of IPs from the correlation in the changes in outcome variables of individuals living in wards that are (more) exposed to IPs and comparable individuals living in comparable wards, in terms of baseline individual- and ward-level characteristics, that are (less or) unexposed to IPs in the same district. The main threat to the identification of the causal parameters of interest β_1, β_2, and β_3 is a violation of the assumption of parallel trends. This would be the case if IPs were systematically established in places whose trends in (labor market) outcomes would have differed from those of places without IPs in the absence of the intervention. Although the selection of sites for IPs is based on a distributional approach, with each region in Ethiopia receiving an IP, within regions selected sites may be on different outcome trend paths than unselected sites – indeed, this is likely, as the accessibility to regional airports, railways and roads is an important selection criterion.

We test for non-parallel trends – i.e., whether wards that are (more) exposed to IPs and those that are (less or) not exposed to IPs had different pre-treatment trends before the establishment of IPs – by running a series of placebo regressions. Our NLFS data are well suited to this, as we have two pre-treatment waves,[30] with the earliest wave from 2005, well before any IPs were planned, let alone established. We implement our placebo regressions by interacting the final treatment exposure in each distance bin with year dummies for 2005, 2013, and 2021, closely following Lu et al. (2019). Econometrically, we replace the treatment variables in our baseline specification (1) with the

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[27] While 88 percent of districts are available in at least two waves, this is only the case for 15 percent of wards. Including ward fixed effects would therefore identify the impact of IPs from only the small subset of wards available in at least two waves.

[28] This is similar to Gallé et al. (2024) who, in their setting where treatment varies at the district level, include interactions of baseline district characteristics with year fixed effects to account for shocks that may be correlated with pre-treatment differences between treated and control districts.

[29] We cluster at the district-level rather than the ward-level – even though treatment varies at the ward level – because districts, unlike wards, are stable over time. In this way, we not only account for within-district correlation of errors, but also for district-level shocks over time. In fact, when we cluster at the ward level, standard errors are lower and therefore underestimated than when we cluster at the district level. The results are available upon request.

[30] Note that a few individuals near the partially established Eastern IZ and Bole Lemi IP were already exposed in 2013.

following terms: $\sum_{b=1}^{3} IP\_exposure_{w2021[b_w=b]}$ X γ_t. Thus, in our concentric ring approach with separate treatment effects for the 0-10 km, 10-20 km, and 20-30 km distance bins, we include a total of nine interaction terms in the placebo regressions, three interactions for each year. As a result, those individuals living within 30 km of an IP that had been established by 2021, receive a placebo treatment in the pre-treatment years 2005 and 2013, when no IP was established (except for Eastern IZ and Bole Lemi in 2013).

Finally, note that our empirical strategy implicitly accounts for two remaining identification assumptions that must hold for the identification of our causal parameters β_1, β_2, and β_3 (see Roth et al. (2023) for a recent review). First, by capturing potential spillover effects on individuals in wards up to 30 km away from IPs in our concentric ring framework, we ensure that the stable unit treatment value assumption (SUTVA) is unlikely to be violated. Indeed, in line with previous evidence on the spatial effects of place-based policies, we also find that the effects are most concentrated in the vicinity of IPs within 10 km, and dissipate rapidly with increasing distance from IPs. Second, although the establishment and expansion of IPs in Ethiopia was "staggered" (i.e., there was variation in the timing of treatment) we use a design that is closer to the classical two-by-two DiD approach, with essentially only a single post-treatment period, which ensures that the assumption of homogeneous treatment effects is not required for causal identification.[31]

5. Results

We first examine the impact of IP expansion on structural changes in employment (Section 5.1). We then explore the differential impact of IP expansion for men and women (Section 5.2) and assess the role of migration (Section 5.3). Finally, we run placebo regressions to test for non-parallel trends in outcomes between locations that are (more) exposed and (less or) not exposed to IPs (Section 5.4).

5.1 Structural changes in employment

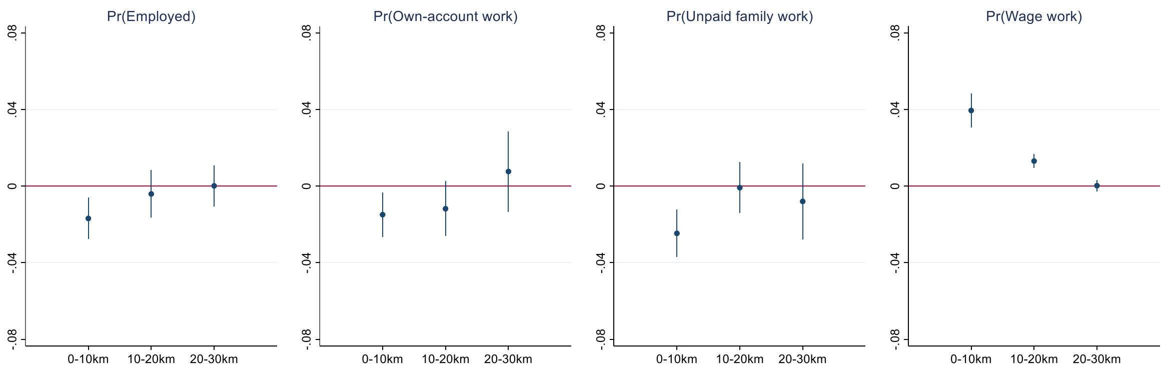
We analyze the impact of IP expansion on structural changes in employment using labor market outcome data on the type and sector of employment of individuals. We present the results of estimating specification (1) in Figure 4 and Figure 5, using separate box plots for the different outcome variables. The coefficients β_1, β_2, and β_3 are shown as blue dots in the box plots and

[31] Although some individuals were exposed to the partially established Eastern IZ and Bole Lemi IP in 2013, excluding these individuals does not change our results, suggesting that there is no violation of the assumption of homogeneous treatment effects. The results are available upon request.

represent the effect of a 10 ha increase in built-up area in the 0-10 km, 10-20 km, and 20-30 km distance bins respectively, with blue vertical lines indicating 95 percent confidence intervals.

Figure 4 shows that there is a statistically highly significant (at the 1 percent level) 1.7 p.p. decrease in the probability of employment (in the last seven days) for every 10 ha increase in the built-up area of IPs within 10 km of expanding IPs. Given the placebo evidence discussed below, we interpret this result cautiously and focus on the reallocation margins conditional on employment. For these employed individuals, we find large and significant (at the 5 percent level or below) changes in the characteristics of employment around expanding IPs: each 10 ha increase in the built-up area of IPs is associated with a 1.5 p.p. and 2.5 p.p. decrease in own-account and unpaid family work, respectively, and a 3.9 p.p. increase in wage work within 10 km of expanding IPs. Except for the moderate effect on the probability of wage work in the 10-20 km distance bin, all effects dissipate and become insignificant beyond 10 km from expanding IPs. Consistent with these changes in employment type, Appendix Figure 2 shows a 3.9 p.p. decrease in employment in household businesses and a 3.2 p.p. increase in the employment in private enterprises within 10 km of expanding IPs.

Figure 4: Spatial Impact of IP Exposure on Type of Employment

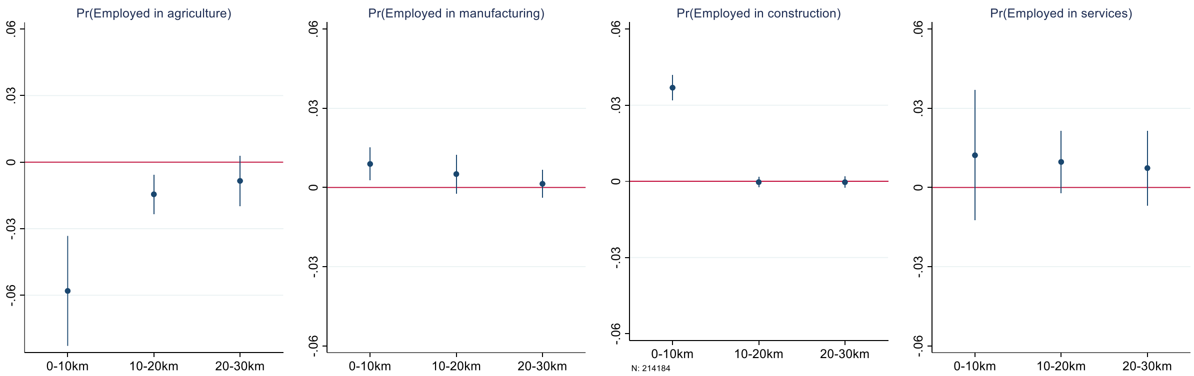


Note: Each plot shows the regression results of estimating specification (1). The leftmost plot uses as the dependent variable a dummy indicator for whether an individual has worked in the last seven days, and the other three plots use dummy indicators for the type of employment of individuals. The first plot includes all surveyed individuals, while the three other plots include only individuals in employment. The blue dots indicate the coefficient estimates of β_1 to β_3, representing the effect of a 10 ha increase in built-up area in the corresponding 10 km distance bin, and the blue vertical lines indicate 95 percent confidence intervals. N=384,879 for this leftmost plot and N=214,161 for the three other plots.

Looking at sectoral changes in employment, Figure 5 shows a large and statistically highly significant (at the 1 percent level) shift in employment from agriculture to construction within 10 km of expanding IPs, with the former decreasing by 5.8 p.p. (or 85 percent) and the latter increasing by 3.7 p.p. (or 32 percent). We also see a modest 0.9 p.p. (or 6 percent) but statistically highly significant (at the 1 percent level) increase in manufacturing employment within 10 km of expanding IPs, which, as might be expected, is entirely driven by textile manufacturing (Appendix

Figure 3). Employment in services, on the other hand, is not affected by the expansion of IPs. Consistent with these sectoral shifts, we document a strong movement away from farm work toward construction-site work, and more modest increases in factory- and home-based work near expanding IPs (Appendix Figure 4). One interpretation of this pattern is that the strongest local employment effects capture, at least in part, the construction phase of park development and related infrastructure, rather than only longer-run factory employment inside the parks. The comparatively smaller increase in manufacturing employment, concentrated in T&A, is in line with this reading.

Figure 5: Spatial Impact of IP Exposure on Sector of Employment



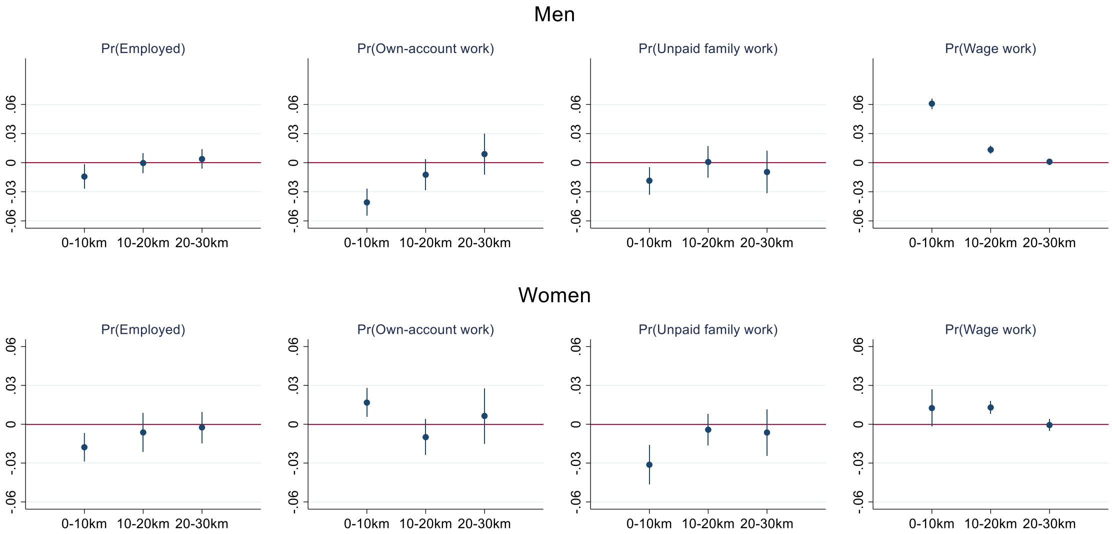
Note: Each plot shows the regression results of estimating specification (1), using as the dependent variable dummy indicators for the sector of employment of individuals. Only individuals in employment are considered. The sectoral classifications follow ISIC Revision 4 codes (see Appendix Table 1). The blue dots indicate the coefficient estimates of β_1 to β_3, representing the effect of a 10 ha increase in built-up area in the corresponding 10 km distance bin, and the blue vertical lines indicate 95 percent confidence intervals. N=214,184 for all four plots.

5.2 Gendered impacts

Gender is perhaps the most important dimension along which the impact of place-based policies can vary. Evidence from India, China, and Vietnam shows that women benefit disproportionately from SEZ policies and the induced structural shifts from agriculture to non-agricultural employment, particularly manufacturing (Tafese et al., 2025; Zhao & Qu, 2023). Ethiopia may follow a similar pattern: both NLFS microdata and specially designed surveys on industrial work (Oya & Schaefer, 2021) show that women dominate the export-oriented T&A sector, much of which is concentrated in IPs. To test whether the labor-market effects of IP expansion differ by gender, we estimate equation (1) separately for men and women.

Figure 6 shows that the IP-induced shifts in the type of employment differ markedly between men and women. Both groups see a decrease in the overall probability of employment within 10 km of expanding IPs, slightly more pronounced for women. Beyond this, however, the patterns diverge. Both groups move out of unpaid family work – again more strongly for women – but they reallocate to different types of employment: men move primarily into wage work, while women move into a combination of own-account work and, to a more moderate extent, wage work. The strong aggregate increase in wage work documented earlier is therefore mainly a male phenomenon.

Figure 6: Spatial Impact of IP Exposure on Type of Employment by Gender



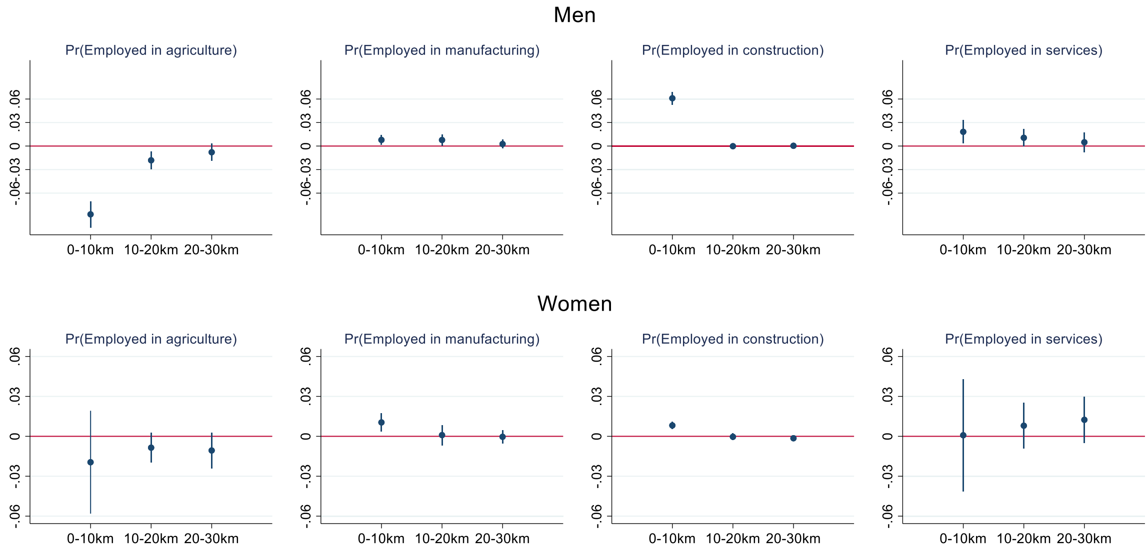
Note: Each plot shows the regression results of estimating specification (1) with interaction terms between the three treatment variables and a male dummy. The leftmost plot uses as the dependent variable a dummy indicator for whether an individual has worked in the last seven days, and the other three plots use dummy indicators for the type of employment of individuals. The first plot includes all surveyed individuals, while the three other plots include only individuals in employment. The blue dots indicate the coefficient estimates of β_1 to β_3, representing the effect of a 10 ha increase in built-up area in the corresponding 10 km distance bin, and the blue vertical lines indicate 95 percent confidence intervals. N=384,879 for the leftmost plot and N=214,161 for the three other plots.

The same broad pattern emerges for sectoral employment (see Figure 7): reallocation across sectors is generally stronger for men than for women. The shift from agriculture to construction is driven almost entirely by men; for women, the decline in agricultural employment is not statistically significant, and the increase in construction employment is much smaller. Manufacturing employment expands for both groups within 10 km of expanding IPs, with a somewhat larger increase for women. Consistent with the studies cited above, around two-thirds of the rise in female manufacturing employment is accounted for by the T&A sector[32]; for men, the manufacturing increase is spread more evenly across subsectors. We also find a moderate increase in services employment for men – driven by elementary services[33] – but not for women.

[32] Textile manufacturing alone accounts for almost half of the increase in female manufacturing employment within 10 km of expanding IPs. Results are available upon request.

[33] These elementary services comprise cleaners and helpers, food-preparation assistants, refuse workers, and street and related elementary services workers.

Figure 7: Spatial Impact of IP Exposure on Sector of Employment by Gender



Note: Each plot shows the regression results of estimating specification (1) with interaction terms between the three treatment variables and a male dummy, using as the dependent variable dummy indicators for the sector of employment of individuals. Only individuals in employment are considered. The sectoral classifications follow ISIC Revision 4 codes (see Appendix Table 1). The blue dots indicate the coefficient estimates of β_1 to β_3, representing the effect of a 10 ha increase in built-up area in the corresponding 10 km distance bin, and the blue vertical lines indicate 95 percent confidence intervals. N=214,184 for all four plots.

5.3 Migration

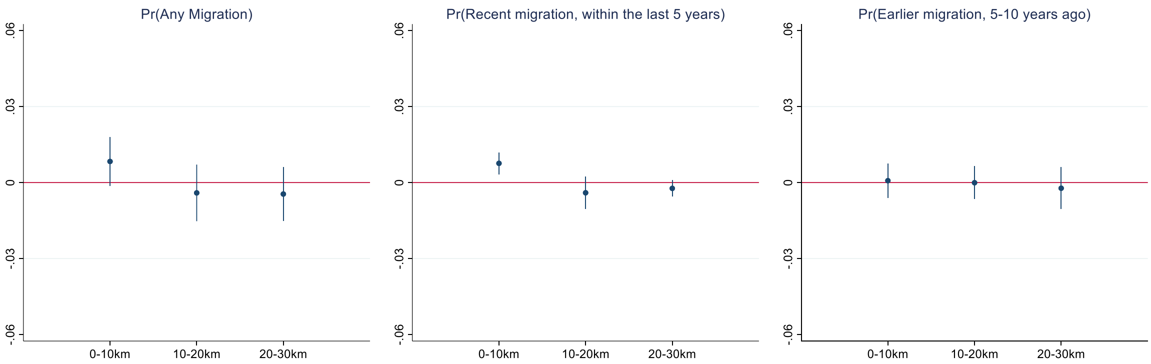
Previous evidence from specially designed surveys of workers in IPs suggests that a significant proportion, and in some cases the majority, of the workers in Ethiopian IPs are recent migrants (Abebe et al., 2024; Hardy et al., 2024; Meyer et al., 2021). This is also reflected in our nationally representative NLFS data, which show that migrants who have moved to their current residence within the last 10 years are overrepresented among workers employed in the export-oriented T&A sector, typically concentrated in IPs.[34] Beyond T&A manufacturing, our data show that migrants are also overrepresented in construction and services, and underrepresented in agriculture. Taking migration into account is therefore important to assess whether the IP-induced changes in the employment that we have documented were primarily driven by migration to locations near expanding IPs.

Figure 8 shows that the expansion of IPs does indeed lead to a moderate 0.8 p.p. (or 5 percent) increase in migration within 10 km of expanding IPs (significant at the 10 percent level). This effect is almost entirely driven by recent migration within the five years before the survey (significant at

[34] While migrants make up 18 percent of the total sample, they account for 28 percent of workers in the T&A sector (ISIC rev. 4 2-digit codes 13 to 15) and 29 percent of the stationary plant and machine operators (ISCO rev. 08 2-digit code 81).

the 1 percent level). Such recent migration is consistent with potential direct and indirect job creation around expanding IPs.

Figure 8: Spatial Impact of IP Exposure on Migration



Note: Each plot shows the regression results of estimating specification (1), using dummies for the migration status as the dependent variable. Individuals are considered to be migrants if they have moved to their current place of residence within the last ten years. The blue dots indicate the coefficients estimates of β_1 to β_3, representing the effect of a 10 ha increase in built-up area in the corresponding 10 km distance bin, and the blue vertical lines indicate 95 percent confidence intervals. N=384,878 for all three plots.

To assess the role of migration in the IP-induced sectoral reallocation, Table 4 compares local effects estimated with migrants included (columns 1–4) and excluded (columns 5–8). The two sets of estimates are broadly similar, suggesting that the increased migration is not the main driver of employment changes. The largest relative difference appears in manufacturing, where the estimated effect falls by about one-third when the sample is restricted to non-migrants (column 2 vs. column 6). This is in line with evidence that many workers in Ethiopian IPs are migrants. By contrast, the larger shifts out of agriculture and into construction are driven mainly by the local non-migrant population.

Table 4: Spatial Impact of IP Exposure with and without Migrants

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Local effects, incl. migrants				**Local effects, excl. migrants**			
	Pr(Employed in agriculture)	Pr(Employed in manufacturing)	Pr(Employed in construction)	Pr(Employed in services)	Pr(Employed in agriculture)	Pr(Employed in manufacturing)	Pr(Employed in construction)	Pr(Employed in services)
IP exposure 0-10km	-0.057***	0.009***	0.037***	0.011	-0.056***	0.006***	0.035***	0.015
	(0.013)	(0.003)	(0.002)	(0.013)	(0.012)	(0.001)	(0.002)	(0.012)
IP exposure 10-20km	-0.014***	0.005	-0.000	0.009	-0.018***	0.001	-0.000	0.017***
	(0.004)	(0.004)	(0.001)	(0.006)	(0.005)	(0.002)	(0.001)	(0.005)
IP exposure 20-30km	-0.009	0.001	-0.000	0.008	-0.011*	-0.001	-0.001	0.013**
	(0.006)	(0.003)	(0.001)	(0.007)	(0.006)	(0.001)	(0.001)	(0.006)
Observations	214.184	214.184	214.184	214.184	176.483	176.483	176.483	176.483
R-squared	0,600	0,089	0,085	0,420	0,590	0,100	0,089	0,420
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ward controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Notes: The reported results are based on estimating the district-level specification (1). Columns 1-4 include the full sample. Columns 5–8 exclude migrants from the full sample. In addition, only individuals in employment are considered. Standard errors are reported in parentheses, clustered at district level. ***p < 0.01, **p < 0.05, *p < 0.1.

5.4 Placebo regressions

As discussed in Section 4.3, the main threat to identifying a causal effect of IP expansion is a violation of the assumption of parallel trends. We analyze trends in pre-treatment outcomes (i.e., before the establishment of IPs) in wards that were later (more) exposed to IPs compared to those that were (less or) not exposed to IPs. To do this, we regress our main outcomes on nine terms that interact the 'final' total IP built-up area in 2021 with survey year dummies from 2005, 2013, and 2021. In the absence of differential trends in pre-treatment outcomes between treated and untreated wards, the coefficients on the placebo interaction terms with the year dummies for 2005 and 2013 should be statistically insignificant or economically small, as no IPs had been established at that time.

There are two main findings from our placebo regressions, which we report in Table 5. First, there are no significant differential trends in most pre-treatment outcomes, as the coefficients on most of the placebo interaction terms with the year dummies for 2005 and 2013 are either statistically insignificant or economically small (below 0.01 p.p.). However, column 1 (probability of being employed) is a notable exception, as the placebo interaction terms are sometimes highly statistically and economically significant. Second, the actual treatment interaction terms with the year dummy for 2021 are very similar in magnitude and statistical significance to our baseline effects for most outcomes. In particular, the similar coefficients on the treatment interaction terms with the year dummy for 2021 for the 0-10 km distance bin reinforce our baseline findings. The effects of IP expansion on the probability of being employed, which cancel each other out within the 0-10 km and 10-20 km distance bins, are again the exception. In summary, the placebo regressions support our baseline findings of a significant impact of IP expansion on the type and sector of employment, but suggest that the estimated effect on the probability of being employed should be interpreted with caution due to its sensitivity to specification.

Table 5: Placebo Regressions

	(1) Pr(Employed)	(2) Pr(Own-account work)	(3) Pr(Unpaid family work)	(4) Pr(Wage work)	(5) Pr(Employed in agriculture)	(6) Pr(Employed in manufacturing)	(7) Pr(Employed in construction)	(8) Pr(Employed in services)
IP exposure 0-10km X year2005	0.010*	0.002	-0.000	-0.001	-0.000	0.007***	-0.001	-0.006
	(0.006)	(0.006)	(0.006)	(0.003)	(0.009)	(0.003)	(0.003)	(0.008)
IP exposure 10-20km X year2005	0.025***	-0.006	0.008	-0.002	0.008	0.005**	0.002	-0.015*
	(0.007)	(0.006)	(0.006)	(0.004)	(0.008)	(0.002)	(0.003)	(0.008)
IP exposure 20-30km X year2005	-0.001	-0.003	0.004	-0.002	-0.002	0.002**	-0.002	0.002
	(0.005)	(0.004)	(0.006)	(0.002)	(0.005)	(0.001)	(0.002)	(0.003)
IP exposure 0-10km X year2013	0.005	-0.004	0.006	-0.000	0.012	0.006	0.001	-0.019
	(0.011)	(0.009)	(0.007)	(0.006)	(0.013)	(0.005)	(0.004)	(0.013)
IP exposure 10-20km X year2013	0.026***	0.003	0.000	-0.004	-0.007	0.005*	0.003	-0.002
	(0.007)	(0.007)	(0.007)	(0.005)	(0.008)	(0.003)	(0.004)	(0.010)
IP exposure 20-30km X year2013	-0.008	0.001	-0.004	0.001	-0.010	0.006***	0.000	0.004
	(0.006)	(0.003)	(0.006)	(0.004)	(0.008)	(0.002)	(0.002)	(0.007)
IP exposure 0-10km X year2021	-0.011*	-0.015*	-0.024***	0.039***	-0.054***	0.013***	0.037***	0.004
	(0.006)	(0.008)	(0.009)	(0.005)	(0.016)	(0.003)	(0.003)	(0.015)
IP exposure 10-20km X year2021	0.010**	-0.012	0.000	0.011***	-0.015**	0.008**	0.001	0.006
	(0.005)	(0.009)	(0.009)	(0.003)	(0.007)	(0.004)	(0.003)	(0.009)
IP exposure 20-30km X year2021	-0.002	0.007	-0.008	0.001	-0.012	0.003	-0.001	0.009
	(0.005)	(0.011)	(0.011)	(0.002)	(0.009)	(0.002)	(0.002)	(0.009)
Observations	384.879	214.161	214.161	214.161	214.184	214.184	214.184	214.184
R-squared	0,230	0,280	0,470	0,450	0,600	0,089	0,085	0,420
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ward controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Notes: The reported results are based on estimating the district-level specification (1). Column 1 includes all surveyed individuals and columns 2-8 include only individuals in employment. Standard errors are reported in parentheses, clustered at district level. ***p < 0.01, **p < 0.05, *p < 0.1.

6. Robustness

In this section, we perform various robustness checks using alternative outcome variables, treatment variables, and samples. Due to space limitations, we focus only on the indicators for the type and sector of employment of individuals, for which robust effects are also documented in our baseline and placebo regressions.

6.1 Alternative outcomes

We re-run specification (1) with alternative outcomes to test the sensitivity of our results to two recent adverse shocks to the Ethiopian economy and in particular to its export-oriented T&A manufacturing sector (ILO & IFC, 2023). First, the outbreak of the COVID-19 pandemic in March 2020 has led to significant order cancellations by global buyers sourcing from (foreign) suppliers in the Ethiopian IPs (Mengistu et al., 2020)[35] and to massive layoffs of workers, particularly women and migrants, in some IPs (Hardy et al., 2024; Meyer et al., 2021). The second shock came with the outbreak of the Tigray War in November 2020, which led to the closure of all factories in IPs in Tigray, which we exclude from our empirical analysis. As a result of this war, Ethiopia lost its status

[35] 68 percent of export-oriented firms reported a decline in sales in a phone-survey in mid-2020.

as a beneficiary of the African Growth and Opportunity Act (AGOA)[36] on January 1st, 2022 (i.e., after the 2021 wave of the NLFs had been implemented). With the vast majority of Ethiopian T&A exports going to the US market (e.g., 73 percent in 2021), the loss of AGOA status led to significant order cancellations, factory closures, and job losses in Ethiopian IPs (ILO & IFC, 2023; Reuters, 2021).

Because of these shocks, one concern is that our 2021 NLFS outcome data reflect the economic realities in Ethiopia at an idiosyncratic point in time that was heavily influenced by one of these two shocks. We therefore re-run specification (1) using as outcomes individuals' employment in the last twelve months rather than in the last 7 days (i.e., including the period prior to the outbreak of the Tigray War and even the outbreak of the COVID-19 pandemic).[37] Appendix Table 2 shows that using employment outcomes referring to the last 12 months, instead of the last 7 days, produces results very similar to our baseline, although sometimes slightly smaller (especially for agriculture, which becomes insignificant).[38]

6.2 Alternative treatment variables

We test the robustness of our novel treatment measure by using two alternative measures of IP exposure that we derive from the EIC project-level foreign investment data referred to in Section 2. Specifically, we use the cumulative investment and job creation – including both permanent and temporary jobs – in each IP in the survey years as our alternative measures of IP exposure.[39] Similar to the large differences in the built-up area across IPs (see Table 2), there are also significant differences in cumulative investment and job creation across IPs (see Appendix Figure 5).[40] Moreover, changes in cumulative investment and job creation in IPs over time are strongly

[36] Under AGOA, firms based in Ethiopia were able to export apparel and footwear products duty-free to the US market, by far the largest destination for Ethiopian T&A exports.
[37] The 2021 NLFS wave was conducted from January 25th, 2021 to February 25th, 2021 (i.e., the outcome variables referring to the last twelve months cover the period January/February 2020-January/February 2021).
[38] In addition, only 0.2 percent of individuals in our sample in the NLFS 2021 wave report that they did not work (in the last seven days) due to the outbreak of the pandemic, suggesting that it had little impact on employment status and patterns at the time of the survey.
[39] As detailed project-level foreign investment data are not available after 2019, we take the total investment and total job creation up to 2019 as our IP exposure in 2021, the year of the last NLFS wave. As the number of foreign investment projects in IPs has slowed down recently, the alternative measures should still capture most of the total capital investment and job creation between 2013 and 2021. For 2005, we set the values for both IP measures to 0, as there had been no IPs in that year. Finally, several IPs (Asosa, Aysha, Bahir Dar, Bishoftu, DBL, Velocity, and Woda) had no approved foreign investment projects by 2019 according to the EIC data, so there are fewer individuals exposed to IPs in the regressions using the alternative treatment variables.
[40] Four IPs – Adama IP, Bole Lemi IP, Eastern IZ, and Hawassa IP – account for the majority of capital investment and job creation in foreign investment projects between 2013 and 2021.

correlated with changes in their total built-up area, as shown by very strong correlations of 0.93 and 0.69.

The Appendix Table 3 and Appendix Table 4 show the regression results using exposure to cumulative investment and job creation in IPs within the 0-10 km, 10-20 km, and 20-30 km distance bins as the treatment variables. We apply the hyperbolic sine transformation to both sets of treatment variables to account for the highly skewed distributions of cumulative investment and job creation and the many zero values. Using these alternative treatment variables produces very similar results to our baseline specification in terms of the pattern and magnitude of the estimated effects.[41] Only the effect on manufacturing employment is no longer statistically significant when cumulative investment and job creation are used as treatment variables. Overall, the results strengthen our confidence in using the built-up area of IPs as a proxy for IP activity in our baseline specification, as it produces very similar results to using these alternative proxies.[42]

6.3 Alternative samples

Finally, we test the sensitivity of our baseline results using different samples to estimate the impact of IP expansion. First, following Abagna et al. (2025), we use a restricted sample that only includes individuals who are ultimately exposed to an IP in 2021 (i.e., the treatment group). This ensures that our estimated effects are only identified from variations in the degree of exposure to an IP, reducing concerns about the treatment endogeneity and non-parallel trends. Second, we use a restricted sample that excludes Addis Ababa, where almost a quarter of individuals in the pooled sample live within 10 km of an established IP, compared to about 6 percent in other regions of Ethiopia. This tests whether our baseline results are driven by Addis Ababa specifically, or whether they hold more broadly across the country.

[41] For large values, as is the case in our context for cumulative investment and job creation, the coefficients on the sine-transformed variables are interpreted as log-transformed variables. For example, the coefficient of -0.047 in column 1 in Appendix Table 3 tells us that a 1% increase in cumulative investment decreases the probability of own-account work by 0.00047 percentage points. This represents a significant economic impact, with foreign investment increasing substantially between 2005 and 2021.

[42] We still prefer to use actual built-up area as a proxy for economic activity in IPs in our baseline specification because it is superior to the cumulative investment and job creation measures due to several shortcomings in the project-level foreign investment data from which they are derived. First, although the data include the date of approval of investment projects, we do not know exactly when they became operational and, for projects in the (pre-)implementation phase, whether they became operational at all. Second, the project-level investment data are likely to miss some foreign investment projects in IPs, as we infer whether a project is in an IP or not from a single variable that is not clearly defined and has many missing values. Third, project-level investment and job creation figures are likely to capture only initial greenfield investment and job creation, but not follow-on investment and job creation. In contrast, our measure of IP built-up area captures all three aspects.

The regression results of estimating restricted samples using only the treatment group and excluding Addis Ababa are shown in Appendix Table 5 and Appendix Table 6 respectively. Both tables show that using the restricted samples produces very similar results to the baseline effects. Notably, including only the treatment group shows even stronger effects than in the baseline regressions, reflected in an even larger shift out of agriculture and a much larger shift into manufacturing alongside construction (Appendix Table 5).

7. Conclusion

Ethiopia has been one of the fastest globalizers in Africa over the past two decades. This has been reflected in significant growth in FDI inflows and exports over this period. A key element in attracting foreign investors and generating export growth, particularly in the light manufacturing T&A sector, has been the establishment and expansion of more than 20 IPs across the country. As a result, Ethiopia's IP program and the working conditions in the new industrial jobs in these IPs have recently attracted considerable policy and academic attention.

This paper adds another facet to this growing body of evidence by examining the spatial impact of IP expansion on local labor markets in Ethiopia. To do so, we combine individual-level labor market data from the 2005, 2013, and 2021 NLFS waves at the lowest administrative level in Ethiopia with a continuous measure of IP exposure based on changes in the built-up area of IPs over time, which we construct from historical satellite imagery. We then use a concentric ring approach and a DiD design to estimate the impact of IP exposure within 10 km distance bins up to 30 km around expanding IPs.

We find that the expansion of IPs significantly reallocates the local employment landscape, which is highly concentrated in locations within 10 km of IPs. This is reflected in large and statistically highly significant shifts from own-account work and unpaid family work to wage work, and from employment in agriculture to employment in construction. We also document a moderate shift towards employment in manufacturing near expanding IPs, which is primarily driven by T&A manufacturing, but no significant impact on employment in services. These shifts are consistent with the findings of Giovannetti et al. (2022), who also find a large employment shift out of agriculture and a moderate shift to manufacturing in places more exposed to trade liberalization. However, unlike us, the authors find a large employment shift to services, while we find a large shift to construction. We also show that these employment shifts differ markedly by gender: the agriculture-to-construction shift is driven almost entirely by men, while manufacturing employment rises for both men and women, somewhat more strongly for women and largely through T&A. In addition, we document moderate in-migration around expanding IPs, concentrated among recent migrants, but show that the observed sectoral reallocation is driven mainly by the local non-migrant population, although part of the increase in manufacturing employment appears to be attributable to migrants.

We account for the potential endogeneity of our treatment by including a rich set of district-level fixed effects in our baseline specification, controlling for time-invariant confounders and time-varying shocks. We also test for non-parallel trends in labor market outcomes of places with and without expanding IPs – the main identification concern – by running a series of placebo regressions. We find no differential pre-trends for the type-of-employment and sector-of-employment outcomes, but the placebos do flag pre-trends for the overall probability of employment, which we therefore treat as descriptive rather than causal. Our main reallocation results are robust to alternative outcome variables, treatment variables, and samples.

Our findings are consistent with evidence from Asia (Brussevich, 2023; Gallé et al., 2024; Hyun & Ravi, 2018; Tafese et al., 2025; Zhao & Qu, 2023), showing that place-based industrial policies in Ethiopia are inducing structural change by shifting employment from agriculture to modern sectors of the economy. However, despite being designed to promote manufacturing-led industrialization, Ethiopia's IPs have so far had only a modest impact on manufacturing employment, with moderate gains concentrated in T&A and little expansion elsewhere. The largest local effect – on construction – likely reflects in part the construction phase of the parks themselves and supporting infrastructure, rather than only steady-state factory hiring. This contrasts with India and Vietnam (Hyun & Ravi, 2018; Tafese et al., 2025), where IPs have contributed significantly to the manufacturing expansion and productivity-enhancing structural transformation.

It is also well-known from other contexts such as Vietnam that the expansion of IPs can lead to significant earnings gains, even beyond (foreign) manufacturing (Tafese et al., 2025), which we cannot analyze for Ethiopia due to the lack of earnings data for own-account and unpaid family workers. Future research should therefore examine broader welfare effects at the household level to better understand the socio-economic impact of industrialization in Ethiopia. Ultimately, it is still too early to judge whether Ethiopia's IP program has been a success or a failure. However, achieving deeper and more widespread benefits from GVC integration will likely require diversification beyond T&A into other manufacturing subsectors.

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Data Availability Statement

The IP data that we constructed from Google Earth Pro satellite imagery on which this article is based are available in the online supplementary material. Specifically, we provide access to the polygons for each IP in the KML file 'Ethiopia IP Polygons' and to the built-up area over time for each IP in the STATA file 'Ethiopia IP Built-up Areas'. The NLFS data from the CSA cannot be made publicly available due to contractual restrictions, as it is subject to their data access policy.

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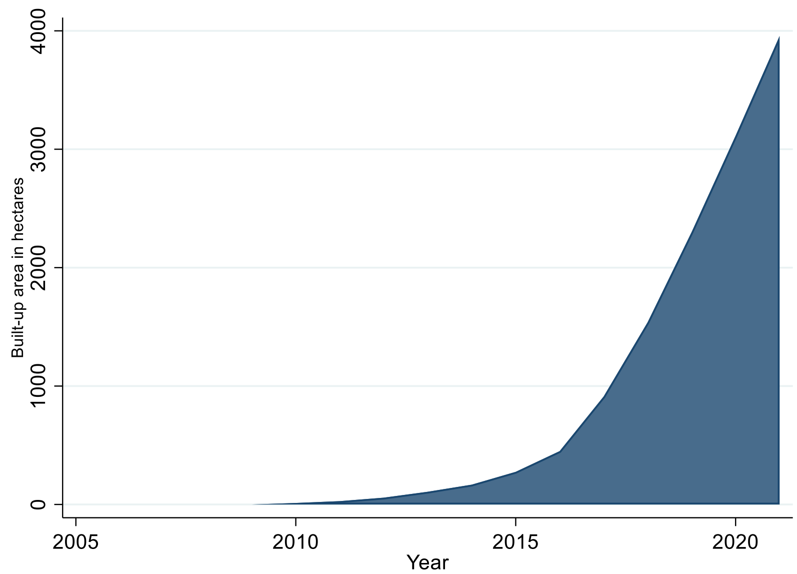
A Appendix

A.1 IPs and FDI in Ethiopia

Appendix Figure 1: Total IP Built-up Area of Ethiopia's IPs over Time



Notes: Author's own compilation based on satellite imagery from Google Earth Pro. Total built-up area is measured in hectares and includes all physical structures such as factories and sheds that fall within the boundaries of an IP.

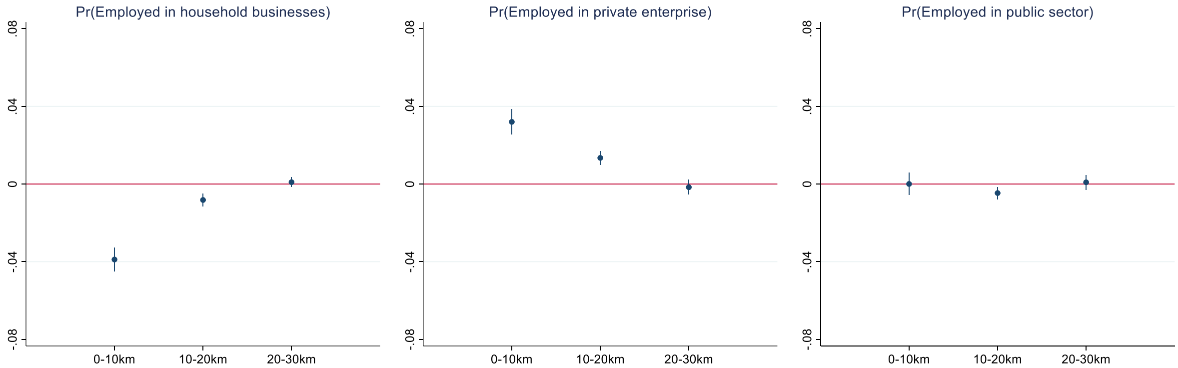
A.2 Additional main and robustness results

Appendix Table 1: Sectoral Classification

Sector used in Analysis	ISIC Section	ISIC Section Description
Agriculture	A	Agriculture, forestry and fishing
Manufacturing	C	Manufacturing
Construction	B	Mining and quarrying
	D	Electricity, gas, steam and air conditioning supply
	F	Construction
Services	E, G-U	Services

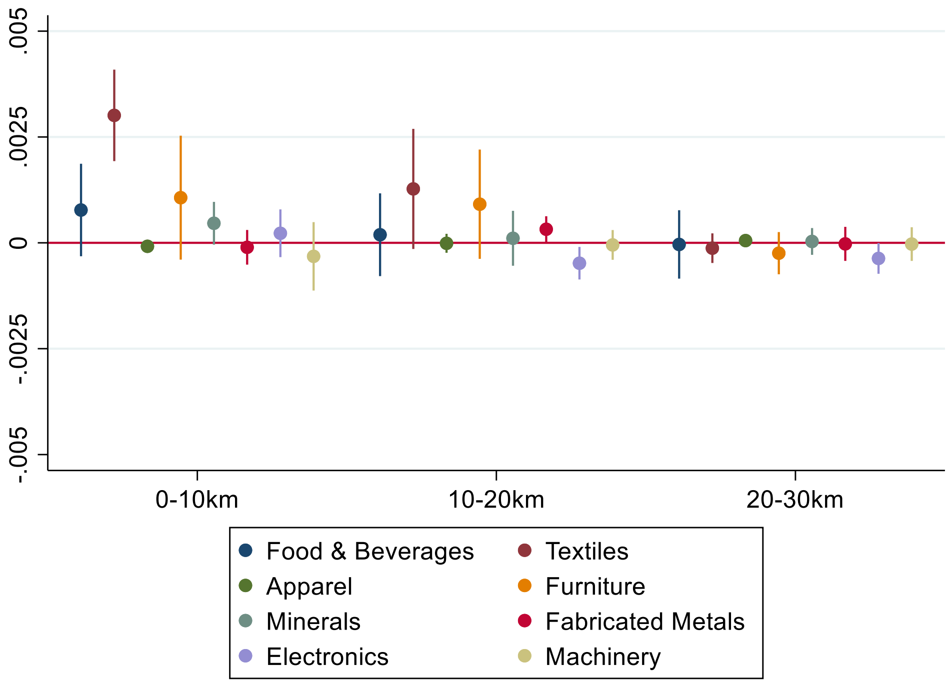
Notes: The sectoral classifications follow ISIC Revision 4.

Appendix Figure 2: Spatial Impact of IP Exposure on Type of Employer Firm



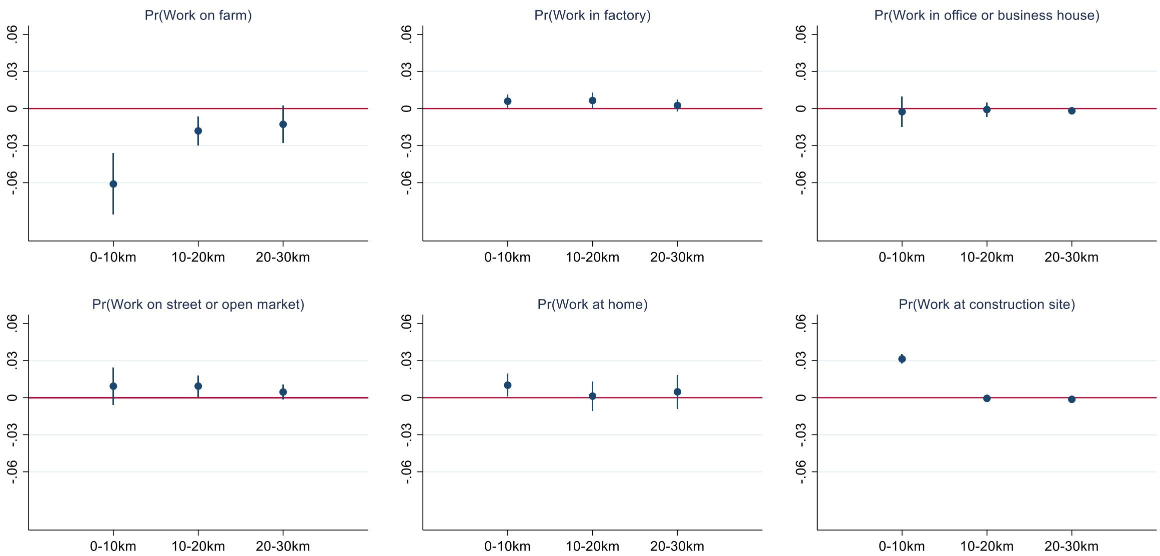
Note: Each plot shows the regression results of estimating specification (1), using as the dependent variable a dummy indicator for the type of employer firm of an individual. The blue dots indicate the coefficient estimates of β_1 to β_3 representing the effect of a 10 ha increase in built-up area in the corresponding 10 km distance bin, and the blue vertical lines indicate 95% confidence intervals. N=214,161 for all three plots.

Appendix Figure 3: Spatial Impact of a 10 ha Increase in IP Built-up Area on Employment in Manufacturing Subsectors



Notes: The reported results are based on estimating specification (1) using as the dependent variable a dummy indicator for the main 2-digit manufacturing subsectors. The sectoral classifications follow ISIC Revision 4 codes. Only individuals in employment are considered and are classified according to the 2-digit code of the firm in which they are employed. Divisions 10 and 11 are classified in Food & Beverages; division 13 in Textiles; division 14 in Apparel; divisions 16, 17, and 31 in Furniture; division 23 in Minerals; division 24 and 25 in Fabricated Metals; divisions 26 and 27 in Electronics; and division 28 in Machinery. Standard errors are reported in parentheses, clustered at district level. ***p < 0.01, **p < 0.05, *p < 0.1.

Appendix Figure 4: Spatial Impact of IP Expansion on Place of Work



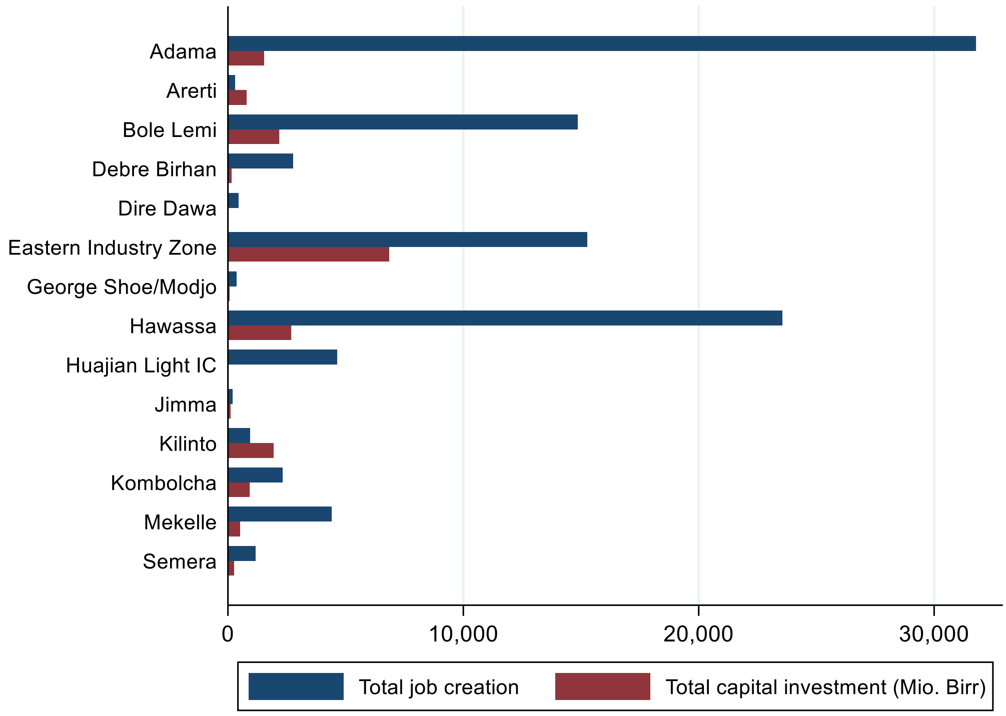
Note: Each plot shows the regression results of estimating specification (1), using as the dependent variable a dummy indicator for an individual's place of work. The blue dots indicate the coefficients β_1 to β_3 representing the effect of a 10 ha increase in built-up area in the corresponding 10 km distance bin, and the blue vertical lines indicate 95% confidence intervals. N=208,648 for all five plots.

Appendix Table 2: Spatial Impact of IP Expansion on Type and Sector of Employment in the Last 12 Months

	(1) Pr(Own-account work)	(2) Pr(Unpaid family work)	(3) Pr(Wage work)	(4) Pr(Employed in agriculture)	(5) Pr(Employed in manufacturing)	(6) Pr(Employed in construction)	(7) Pr(Employed in services)
IP exposure 0-10km	-0.013**	-0.020***	0.034***	-0.022	0.007**	0.029***	-0.008
	(0.006)	(0.008)	(0.007)	(0.017)	(0.003)	(0.003)	(0.017)
IP exposure 10-20km	-0.015**	-0.001	0.016***	-0.010*	0.008**	0.001	0.001
	(0.007)	(0.006)	(0.003)	(0.006)	(0.004)	(0.001)	(0.007)
IP exposure 20-30km	0.007	-0.009	0.002	-0.011*	0.004	0.000	0.007
	(0.010)	(0.009)	(0.002)	(0.005)	(0.003)	(0.001)	(0.007)
Observations	209.065	209.065	209.065	169.632	169.632	211.580	169.632
R-squared	0,270	0,460	0,450	0,600	0,073	0,082	0,440
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ward controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The reported results are based on estimating the district-level specification (1). The outcome variables refer to the type and sector of employment of individuals in the last 12 months. Only individuals in employment are considered. Standard errors are reported in parentheses, clustered at district level. ***p < 0.01, **p < 0.05, *p < 0.1.

Appendix Figure 5: Cumulative Job Creation and Capital Investment by IP, 2013–2019



Note: Author's own compilation, based on project-level foreign investment data from the EIC. Both operational and (pre-) implementation projects are included. We focus on the period 2013–2019 because project-level foreign investment data is not available other periods.

Appendix Table 3: Spatial Impact of Total IP Investment on Type and Sector of Employment

	(1) Pr(Own-account work)	(2) Pr(Unpaid family work)	(3) Pr(Wage work)	(4) Pr(Employed in agriculture)	(5) Pr(Employed in manufacturing)	(6) Pr(Employed in construction)	(7) Pr(Employed in services)
IP investment 0-10km	-0.047***	0.013	0.034***	-0.042**	0.007	0.028**	0.006
	(0.006)	(0.017)	(0.013)	(0.020)	(0.011)	(0.012)	(0.013)
IP investment 10-20km	-0.012	-0.008	0.021***	-0.020*	0.003	0.004	0.013
	(0.018)	(0.016)	(0.007)	(0.011)	(0.004)	(0.008)	(0.012)
IP investment 20-30km	0.017	-0.018	0.002	-0.011	-0.001	0.001	0.011
	(0.022)	(0.021)	(0.006)	(0.011)	(0.003)	(0.004)	(0.012)
Observations	214.161	214.161	214.161	214.184	214.184	214.184	214.184
R-squared	0,280	0,470	0,450	0,600	0,089	0,084	0,420
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ward controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The reported results are based on estimating the district-level specification (1). The treatment variables capture the cumulative IP investment within the three distance bins to which an individual is exposed during the period 2013–2019. We apply the hyperbolic sine transformation to the treatment variables to account for their highly skewed distributions and the large number of zero values. Only individuals in employment are considered. Standard errors are reported in parentheses, clustered at district level. ***p < 0.01, **p < 0.05, *p < 0.1.

Appendix Table 4: Spatial Impact of Total IP Job Creation on Type and Sector of Employment

	(1) Pr(Own-account work)	(2) Pr(Unpaid family work)	(3) Pr(Wage work)	(4) Pr(Employed in agriculture)	(5) Pr(Employed in manufacturing)	(6) Pr(Employed in construction)	(7) Pr(Employed in services)
IP job creation 0-10km	-0.028***	-0.001	0.029***	-0.038***	0.004	0.026***	0.008
	(0.009)	(0.017)	(0.008)	(0.014)	(0.005)	(0.008)	(0.009)
IP job creation 10-20km	-0.012	-0.003	0.015***	-0.014**	0.001	0.002	0.011**
	(0.008)	(0.007)	(0.004)	(0.006)	(0.002)	(0.004)	(0.005)
IP job creation 20-30km	0.012	-0.013	0.001	-0.009	-0.001	0.000	0.009
	(0.013)	(0.012)	(0.004)	(0.007)	(0.002)	(0.002)	(0.007)
Observations	214.161	214.161	214.161	214.184	214.184	214.184	214.184
R-squared	0,280	0,470	0,450	0,600	0,089	0,084	0,420
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ward controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The reported results are based on estimating the district-level specification (1). The treatment variables capture the total IP job creation within the three distance bins to which an individual is exposed. We apply the hyperbolic sine transformation to the treatment variables to account for their highly skewed distributions and the large number of zero values. Only individuals in employment are considered. Standard errors are reported in parentheses, clustered at district level. ***p < 0.01, **p < 0.05, *p < 0.1.

Appendix Table 5: Spatial Impact of IP Exposure on Type and Sector of Employment, Treatment Group Only

	(1) Pr(Own-account work)	(2) Pr(Unpaid family work)	(3) Pr(Wage work)	(4) Pr(Employed in agriculture)	(5) Pr(Employed in manufacturing)	(6) Pr(Employed in construction)	(7) Pr(Employed in services)
IP exposure 0-10km	-0.023**	-0.032**	0.053***	-0.074***	0.021***	0.040***	0.012
	(0.011)	(0.014)	(0.010)	(0.014)	(0.005)	(0.007)	(0.009)
IP exposure 10-20km	-0.021***	0.004	0.016	-0.017	0.016***	-0.000	0.001
	(0.006)	(0.014)	(0.012)	(0.015)	(0.005)	(0.007)	(0.006)
IP exposure 20-30km	-0.003	-0.006	0.008	-0.012	0.011***	0.000	0.001
	(0.002)	(0.009)	(0.007)	(0.010)	(0.003)	(0.005)	(0.003)
Observations	53.514	53.514	53.514	53.516	53.516	53.516	53.516
R-squared	0,160	0,430	0,320	0,620	0,063	0,055	0,270
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ward controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The reported results are based on estimating the district-level specification (1). The sample is restricted to individuals who are ultimately exposed to an IP in 2021 (i.e., the treatment group). In addition, only individuals in employment are considered. Standard errors are reported in parentheses, clustered at district level. ***p < 0.01, **p < 0.05, *p < 0.1.

Appendix Table 6: Spatial Impact of IP Exposure on Type and Sector of Employment, Excluding Addis Ababa

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Pr(Own-account work)	Pr(Unpaid family work)	Pr(Wage work)	Pr(Employed in agriculture)	Pr(Employed in manufacturing)	Pr(Employed in construction)	Pr(Employed in services)
IP exposure 0-10km	-0.015**	-0.026***	0.040***	-0.057***	0.009***	0.037***	0.011
	(0.006)	(0.006)	(0.004)	(0.012)	(0.003)	(0.003)	(0.012)
IP exposure 10-20km	-0.012	-0.001	0.013***	-0.014***	0.005	-0.000	0.009
	(0.007)	(0.007)	(0.002)	(0.004)	(0.004)	(0.001)	(0.006)
IP exposure 20-30km	0.008	-0.008	0.000	-0.009	0.001	-0.000	0.007
	(0.011)	(0.010)	(0.001)	(0.006)	(0.003)	(0.001)	(0.007)
Observations	198.670	198.670	198.670	198.693	198.693	198.693	198.693
R-squared	0,290	0,460	0,440	0,580	0,088	0,086	0,430
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ward controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Notes: The reported results are based on estimating the district-level specification (1). The sample is restricted to individuals living outside of Addis Ababa. In addition, only individuals in employment are considered. Standard errors are reported in parentheses, clustered at district level. ***p < 0.01, **p < 0.05, *p < 0.1.

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