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Alisha Weber
UNIDO
University of Göttingen
Università di Firenze

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Table of Contents

1. Introduction

Ethiopia is experiencing rapid population growth, with a current population of over 100 million projected to reach 210 million by 2060 (World Bank, 2019). This surge poses a significant challenge as the country must create sufficient employment opportunities. To address this issue, in the Growth and Transformation Plan (GTP) the Ethiopian government has identified industrialisation as a means to transform the economy and reduce poverty while generating jobs (Weldesilassie et al., 2017; World Bank, 2019). The development of IPs is set as a national strategy for structural transformation (Tang, 2022). With the establishment of the Eastern Industrial Zone (EIZ) in 2007, Ethiopia's first special economic zone (SEZ), the collaboration between China and Ethiopia in the development and management of SEZs was initiated (Giannecchini & Taylor, 2018). Since then, IPs have been key policy instruments for elevating structural economic transformation by attracting foreign direct investment (FDI) in the labour-intensive and export-led manufacturing sector (Geiger & Moller, 2015; Weldesilassie et al., 2017). The increasing proliferation of IPs in developing nations is a trend that holds significant potential for local economic structures and social outcomes. Despite their growing prominence, however, the broader impacts of these IPs on labour markets, household dynamics, and food security are yet to be comprehensively understood. This paper seeks to illuminate these dynamics in Ethiopia, given its recent ambitious industrialisation efforts, including the construction of several IPs across the country.

Through a detailed exploration of nationally representative Living Standards Measurement Study (LSMS) survey data, this study focuses on several critical aspects. First, it analyses how individuals' exposure to IPs influences labour market outcomes, particularly in terms of wages, employment likelihood, and the allocation of time spent on paid work, agricultural activities, and household labour. A special focus is put on the gender dimension to be able to distinguish the impact of IPs on both men and women. It then delves into the consequences for food security, both actual and perceived food insecurity. Again, gender-differentiated outcomes are analysed. Finally, the spillover effects on non-farm enterprises are examined, exploring impacts on revenue, costs, and profit as well as their total household income share.

In the quest to comprehend the multifaceted impacts of these IPs, this study draws inspiration from the method pioneered by Tafese et al. (2023). Their approach involves leveraging historical satellite imagery to delineate the built-up area of SEZs over time, providing a measure of SEZ exposure. Similarly, the spatial data used for the analysis in this study is computed by using satellite imagery to draw polygons around the factory sheds of IPs for each year. Thereby, the area covered by any IP in Ethiopia in each year is obtained. The exploited household survey data and non-farm enterprise survey data that contains the outcome variables of interest is provided in the World Bank LSMS data.

Furthermore, the methodology by Tafese et al. (2023) is adapted by employing a distance-based cutoff: A Staggered Difference-in-Difference (DiD) framework is employed in which the built-up IP area in 100-hectare units within a 20 km radius is used as the treatment variable and different labour market, socioeconomic, food security, and non-firm enterprise outcomes are the respective independent variables. Thereby, the impact of IP exposure is identified from the correlation between the change in the average outcome of interest of individuals and non-farm enterprises and the change in the total built-up IP area. In additional robustness checks, the distance threshold is reduced to 15 km and 10 km.

The main sectors represented in Ethiopia's IPs are apparel and textiles, leather, agro-processing, pharmaceuticals, and chemicals, with the highest share in apparel and textiles. The goal is to build on the country's agricultural base and transition towards new manufacturing activities that will employ young and semi-skilled workers (Geiger & Moller, 2015). Typically, the textile and clothing industry in Ethiopia offers employment opportunities to young, unskilled workers with lower educational qualifications, of whom the majority are women (ILO, 2022). According to the Industrial Parks Development Corporation, a public enterprise that has developed and is currently operating 12 IPs in Ethiopia, around 75 thousand jobs have been created in only the public IPs. However, according to ILO (2022), IP garment manufacturing operations in Ethiopia face severe skill shortages in high-skilled and management positions. Therefore, instead of hiring locally, garment enterprises hire expatriates to work in management and design. Most local employees work in the field of sewing and stitching, which requires low-skill labour, and has a high turnover rate due to low wages and difficult working conditions (Blattman & Dercon, 2018). Hence, it is important to investigate not only job creation but also factors such as wages and working hours to observe whether enterprises benefit only from low-cost manual labour and create few higher-skilled jobs for the local population. In this paper, a special focus is placed on the gender dimension, since it is expected that the labour market effects on women will be particularly strong due to women representing the majority of workers in the textile and garment sector (ILO, 2022).

The findings suggest a potentially transformative effect of IPs on local economic landscapes and households. Particularly, IPs influence labour market outcomes significantly, suggesting an increase in paid work and a decrease in agricultural activities for men, with a similar but lesser impact on women. Despite this apparent shift from agriculture to wage labour, the results suggest that IPs do not jeopardize food security. Instead, proximity to IPs is associated with decreased food insecurity. Additionally, IPs demonstrate a substantial positive impact on local non-farm enterprises in terms of increased revenue and profit as well as decreased costs. However, the impact of IPs on employment and wages is complex, necessitating further research, particularly regarding gender disparities and job quality.

This paper contributes to the understanding of these dynamics, by employing advanced statistical analyses and robustness checks to strengthen the robustness of the findings. It aims to contribute valuable insights to the ongoing discourse on industrialisation and its impacts on local economies and households, particularly in the context of developing countries.

This paper begins by reviewing the current literature on relevant topics, setting the stage for a detailed background analysis of FDI in Ethiopia, Ethiopia's IP policy and administrative structure, and the status of food security in the country. This is followed by a comprehensive data section, which explains the variables used in the analysis and provides descriptive statistics. Subsequently, the focus shifts to the empirical strategy, providing a foundation for the results section. The results are then thoroughly examined in the following discussion. Finally, the paper closes with some concluding remarks.

2. Literature Review

This paper relates to several strands of literature. Primarily, it adds depth to the body of work examining the performance of SEZs and IPs, encompassing aspects such as job creation and the gender-differentiated impacts they bear. Beyond this, it contributes to the scarce empirical evidence on the developmental, especially labour market, impacts of IPs in particular, and FDI in general. Here, it delves into the effects and possible spillover implications of these investments.

Furthermore, it adds to the increasing number of studies that are exploring the broader labour market implications of SEZs and FDI, as well as to a more comprehensive understanding of the IP landscape in Ethiopia. Besides, the paper relates to the labour market effects of economic integration in economies characterised by substantial informal employment. Finally, the gender lens of this paper enables it to make a significant contribution to the discourse on gender inequalities in Ethiopia.

Studies evaluating the performance of SEZs, including their direct employment generation and gender-differentiated impacts, generally report mixed evidence with substantial variation across different nations. Illustrating this, Farole (2011) finds that SEZs in Latin American and Caribbean countries, like Honduras and the Dominican Republic, have shown a job creation rate more than quadruple that of SEZs in African countries such as Ghana and Kenya. According to Farole (2011), the success of SEZs in Africa is closely linked to the competitiveness of the national economy and the national investment climate. Additionally, SEZs with proximate access to large consumer markets, suppliers, and labour tend to be more successful. Challenges faced by SEZs in Africa include inadequate infrastructure, limited access to finance, weak institutional capacity, and poor governance. Besides, there are concerns about the quality and sustainability of employment generated by SEZs. Specifically, SEZs may generate low-quality jobs with poor working conditions and limited opportunities for skill development. Furthermore, SEZs may be vulnerable to external shocks and not sustainable in the long term.

SEZs have created an important avenue for women to enter the formal economy at better wages than in agriculture and domestic service, which are their main alternative occupations. Farole (2011) summarises the findings of several studies, finding that firms located inside SEZs employ more women than firms in the rest of the country. However, there are concerns regarding gender-differentiated impacts. Women tend to be concentrated in low-skilled, low-paid positions and may face discrimination and harassment in the workplace. Additionally, women may not benefit as much from the links and spillovers with domestic firms, which can limit their opportunities for skill development and career advancement. Against this background, the paper aims to explore these gender-specific impacts within the context of Ethiopia. The goal is to enhance our understanding of how IP strategies can be structured and executed to ensure widespread benefits across genders.

In a separate study, Frick et al. (2019) employed nightlight data as a proxy to measure for SEZ performance, along with an extensive set of SEZ policy variables and characteristics across numerous countries. Their findings suggest three primary observations: first, sustaining growth within SEZs is challenging over time; second, SEZ policies often struggle to facilitate technological upgrading or value addition; and third, the size of an SEZ plays a crucial role, with larger zones demonstrating higher growth potential. In line with the findings of Farole (2011), they also highlight the importance of the country- and regional-specific context in determining the performance of SEZs. SEZs situated in areas with relatively lower wealth levels but within a convenient distance from the country's largest city and easily accessible to the world's main developed markets have shown the most vigorous economic growth. Furthermore, countries with a history of established industrialisation tend to provide a more advantageous environment for SEZs. Thus, considerable disparities can exist in the success rates of SEZs based on their specific economic and geographic contexts. On the contrary, efforts to drive economic growth in SEZs through schemes like incentive packages, ownership models, and management structures, have generally demonstrated a limited impact. Additionally, corporate tax breaks, a common feature of most SEZ policies, have had a minimal role in enhancing zone dynamism, with their effectiveness largely confined to more developed countries. Hence, according to Frick et al. (2019), the effectiveness of elements such as tax relief, the presence of an autonomous zone regulator, or non-fiscal advantages like a national one-stop-shop, is more context-specific than previously assumed. This paper contributes to the literature by employing a rather novel approach pioneered by Tafese et al. (2023) in the context of Vietnam as a proxy for SEZ performance in Ethiopia. Instead of using nightlight data, alterations in the firm's occupied area are used, which explains a higher share (29 % and 80 %, respectively) of changes in firm turnover (Bilicka & Seidel, 2022).

Most studies suggest that SEZs effectively attract FDI, serving as a valuable tool to increase FDI inflows. Wang (2013), for instance, examines whether SEZs increase FDI inflows by exploiting differences in the timing of SEZ creation across municipalities in China. In his analysis, he compares changes between municipalities establishing SEZs in earlier and in later rounds, as well as between municipalities with multiple SEZs and only one SEZ. His findings reveal that SEZs have a significant impact on FDI inflows, increasing per capita FDI by 21.7% and the growth rate of FDI by 6.9 percentage points on average. Furthermore, he finds that the SEZ program neither crowds in nor crowds out domestic investment.

This paper is connected to the growing body of research on FDI and its associated effects in less developed countries. The working paper by Hoekman et al. (2023) employs a dataset comprised of over 40 million individual-level observations. This data is cross-referenced with information about the existence of greenfield projects within roughly 2500 subnational geographical units between the years 1987 and 2019. The results suggest a correlation between the launch of these projects and an upswing in job creation, a shift of the workforce to advanced industries, and towards jobs demanding higher skills. Further geospatial analyses from Hoekman et al. (2023) connect the emergence of greenfield projects with changes in the performance of domestic companies exploiting data from the World Bank's Enterprise Survey. Their results indicate beneficial horizontal and inter-industry linkages.

In a related study focused on China, Lu et al. (2019) examine the latest round of China's SEZs. They used firm census data covering a four-year period (from 2004 to 2008) and assessed how firms' performance changed (including the entering and exiting of firms) in SEZ-exposed villages compared with those in non-exposed villages. At the village scale, they observed that SEZs had a positive impact on employment (an approximate increase of 30%), production, capital, and the total number of firms. Furthermore, their analysis suggests that the changes were driven more by the entry and exit of firms rather than by the effects on incumbents or relocations. Finally, they found that capital-intensive industries saw larger positive effects compared to those that are labour-intensive. This result provides important insights for Ethiopia since the majority of

Ethiopian SEZs are focused on the textile and apparel industry which is typically considered a labour-intensive industry. This is because the production processes in this industry often require a large amount of manual labour for tasks such as spinning, weaving, and garment-making. Interestingly, contrary to the studies by Frick et al. (2019) and Farole (2011), they discovered that factors like market potential and transportation network access did not significantly enhance the effects of the program. To verify their DiD findings, they did a robustness check employing a boundary discontinuity design.

Adding to this, Gorg & Mulyukova (2022) analyse the impact of SEZs in India, exploiting variations in time and location of their implementation. The study employs geocoded data at the firm level and the geographical location of SEZs using a concentric ring approach for their analysis. Thus, using available data on the size of the SEZ, spatial rings around the centroid are created. Thereby, they can approximate firms inside a SEZ and create distance bands, each with a 5 km radius until 15 km outside a SEZ, which allows for the estimation of the spatial extent of any potential spillovers stemming from SEZs. The findings reveal that after accounting for initial selection bias, the implementation of SEZs has resulted in negative productivity growth for firms located within the SEZs. Additionally, no evidence of positive spillover effects to the surrounding areas was found. However, when the analysis was narrowed down to only commercial SEZs, the negative productivity impact disappeared. This suggests that governmental interference might have a role in the performance of these zones. In terms of zone size, the study found that larger-than-average SEZs showed strong positive growth in productivity for firms located within these zones. This suggests that the size of SEZs has a substantial influence on their performance and supports the approach of using the spatial size of IPs as a proxy for their performance in this paper. Gorg & Mulyukova (2022) conclude that the inefficiencies in the SEZ program could be attributed to a specific characteristic of the Indian SEZ policy design. Specifically, the option for SEZs to be single-firm entities may invite political interference and rent-seeking behaviour, more so than in larger SEZs hosting multiple firms.

An increasing number of studies are exploring the broader labour market implications of SEZs and FDI in general, employing more advanced identification strategies to ascertain the causal effects of SEZs. Tafese et al. (2023) have significantly advanced our understanding of the local labour-market impacts of SEZs, particularly in the context of Vietnam. Their methodological innovation involves utilising historical satellite imagery to track the built-up area of SEZs over time, presenting a continuous measure of SEZ exposure. This approach, offering a more dynamic understanding of the temporal evolution of SEZs, has been influential in unravelling the intricate effects of these zones on employment patterns, wages, and the quality of employment. Covering a seven-year period from 2013 to 2019, the analysis utilises entropy balancing weights to enhance comparability between treatment and control districts in a DiD design. Notably, their findings indicate a shift in employment from agriculture and services to manufacturing, with positive spillovers to workers in domestic firms and considerable heterogeneity in effects across gender, education, and age. The effects are particularly pronounced for women and individuals with lower to medium levels of education. This pioneering work serves as a valuable precedent for the exploration of the impacts of IPs in Ethiopia, with adaptations to suit the unique context of the Ethiopian industrial landscape. Furthermore, Hyun & Ravi (2018) analysed India's SEZ initiative, initiated in 2005, which received an annual investment equivalent to roughly 0.5% of India's GDP until 2015. They employed a DiD methodology, contrasting changes in productivity and employment from 2005 to 2010 between regions with at least one SEZ ("treated" regions) and regions without an SEZ ("control" regions). To ensure a comparison between similar regions, they selected "control" regions that were qualified to run a SEZ but had not yet implemented one. Their findings reveal that after five years, average labour productivity in formal sector manufacturing firms in SEZ districts increased by 24% compared to control regions. Formal production increased by 46%, employment by 18%, and investment in plants and machinery by 37%. These gains resulted in a 14% increase in formal sector wages. Lastly, they noted a systemic transition in SEZ regions towards a more formal economy, indicated by a 50% decrease in total informal production in SEZ districts and a 24% decrease in total informal employment, limited to manufacturing and not observed in the services sector. Adding to this, the above mentioned study by Wang (2013) also relates to the labour market impacts of SEZs. In his country-level analysis of Chinese SEZs, he finds that the average wage of workers increased by 8% while the cost of living in municipalities with SEZs increases by 5%.

In an attempt to address the question of whether multinational enterprises affect local labour opportunities, Mendola et al. (2021) use the geolocalised Demographic and Health Surveys (DHS) data and combine it with information on multinationals' (MNE) affiliates across Sub-Saharan Africa. They discover that individuals living in a 5 km radius of an MNE affiliate have a 3 % higher probability of employment, which seems to be primarily driven by domestic SME affiliates. When distinguishing between on-farm and off-farm employment, being close to an MNE affiliate correlates with a 2.35% decrease in the likelihood of on-farm employment, but a 5.3% increase in off-farm employment. However, the type of MNE activity matters. Proximity to domestic MNEs affiliates is associated with a 5.4% increase in the likelihood of on-farm employment, while proximity to foreign MNEs is associated with a 4.5% decrease. The opposite effects are observed for off-farm employment. The likelihood of off-farm employment increases by 6.7% for those close to a foreign MNE affiliate, suggesting that foreign MNEs have a positive effect in reallocating local workers from on-farm to off-farm jobs. Lastly, they find that the average job quality rises around foreign MNE affiliates.

Recent research delves into the employment outcomes of greenfield FDI in Ethiopia. Abebe et al. (2022) investigate the impact of sizable greenfield ventures in Ethiopia's manufacturing industry. For this, they use a DiD approach and analyse firm census data on employment, and administrative data on greenfield projects. Defining control districts as those districts where a project has been licensed but operational activities have not yet commenced, they find that in districts with large greenfield investments employment in domestic firms increased. This increase amounted to 24 percent or approximately 20 new employees per firm on average. Furthermore, in districts where newly opened greenfield projects are located, local plant establishment increased by 47 percent. Specifically focusing on Chinese FDI, Crescenzi & Limodio (2021) investigate the effects of FDI in Ethiopian districts, differentiating between the effects on domestic firms in the same industry and those in upstream and downstream industries. They combine a detailed dataset at firm and district-level with a natural experiment inducing exogenous variation in district-sector Chinese FDI by exploiting sector-specific export tax changes in China to show the effects of Chinese FDI on local growth, domestic investment, and competition with domestic firms. The study finds that there are positive impacts on employment for domestic firms in supplier and buyer industries, while there are negative effects on employment for domestic firms in the same sector. However, after a span of 6-12 years, positive net effects on local growth can be observed.

While both studies focus solely on the impact of FDI, this paper expands on this focus by exploring the role of IPs. This unique angle, combined with the use of household-level data, allows for a more nuanced analysis of labour market outcomes across various groups, including distinctions by gender, ethnicity, or socioeconomic status. Furthermore, household-level data often contains more detailed and granular information about individuals and their work. This can include the types of jobs they have, the hours they work, their income, and the conditions of their employment.

In the Policy Research Working Paper Series, Monga (2011) discusses the potential benefits of cluster-based industrial parks (CBIPs) for developing countries and provides a strategic roadmap to development practitioners and policymakers on how to effectively implement a CBIP approach to industrial development. CBIPs are designed to promote clustering of firms in related industries, i.e., to create IPs in which the located firms have a common focus. According to Monga (2011) African and other developing countries can reap substantial economic and social benefits from CBIPs, from fostering intra-industry knowledge spillovers, efficient supply chains and economies of scale, to establishing both forward and backward linkages. Furthermore, CBIPs can generate manufacturing jobs and absorb large segments of the low-skill labour force, promote skill, industrial, and technological upgrading, improve the economy's endowment structure, and move towards higher-value activities. However, these advantages can only be fully realised if all other obstacles, such as those resulting in increased factor costs, have been effectively addressed. The obstacles that CBIPs may face include a lack of political will or support, inadequate infrastructure, insufficient financing, weak institutional capacity, and resistance from local communities or businesses. Additionally, there may be challenges related to attracting and retaining skilled labour, ensuring compliance with environmental and labour standards, and managing potential negative externalities such as pollution or congestion. Even well-designed CBIPs can only succeed if they are backed by strong political commitment from the highest levels of governments to improve the business environment. Almost all of Ethiopia's IPs are focused on a specific industry, e.g., Hawassa IP is focused on textile and apparel while Kilinto IP is specialised on the pharmaceutical sector. These examples offer tangible instances of how Ethiopia is implementing the CBIP approach and allows for an analysis of the varied impacts of IPs across different sectors. However, Monga (2011) also urges us to acknowledge the potential constraints that may affect the effectiveness of CBIPs. This paper echoes this premise, arguing that the success of these parks is interlinked with the broader economic environment and policy landscape. It delves into the diverse impacts of IPs across different sectors, thereby contributing to a richer and more nuanced understanding of the role of CBIPs in influencing local communities and labour market outcomes in Ethiopia, while prompting a broader reflection on the enabling conditions needed for these parks to thrive.

Adding to a more comprehensive understanding of the IP landscape in Ethiopia, several studies examine the performance of single Ethiopian IPs in case studies. For example, Giannecchini & Taylor (2018) present a case study of the EIZ. The study is based on primary research involving interviews with investors, zone developers and operators, regulatory authorities, government officials, and other vital stakeholders, carried out in both Beijing and Ethiopia. The analysis of the EIZ focuses on its potential on developmental and structural transformation in Ethiopia, the current challenges it faces, and the possible benefits for all stakeholders. The authors conclude that poor information circulation, risk aversion, and an unfavourable environment for contract enforcement and investment protection have led to personalised business relationships, remarkably low productivity, and the chase for opportunistic profits in frequently disordered markets. They also state that the local population – providing cheap labour – mainly if not solely benefits through additional employment generation, while benefits such as spillovers, technology, and knowledge transfer are yet to be seen. Furthermore, Tang (2022) compares how Ethiopia and

Vietnam have learned from China and Taiwan's SEZ policies through case studies, including 53 interviews with key stakeholders. Based on the existing theories on policy transfer, Tang (2022) develops a three-stage SEZ policy adoption framework for developing or transitioning countries and selects the EIZ – first SEZ of the country – and Hawassa IP – established in 2016 and flagship state-run IP – for the case studies. According to Tang (2022), the presence of China in Ethiopia's SEZ development process has been substantial, with China providing lessons on both macro-level SEZ planning and micro-level construction skills, influencing administrative restructuring, and enabling large-scale transfer of China's SEZ experiences to Ethiopia, all while Chinese companies established a majority of the private SEZs and constructed most of Ethiopia's federal IPs. Ethiopian elites believed that the government's leading role was a key factor in the success of China's SEZs and developed state-owned SEZs like Bole Lemi and Hawassa IP, which struggled to sustain operations and effectively transfer SEZ management practices from China, respectively. Tang (2022) argues that this was largely due to the lack of local autonomy reflected by the Hawassa administration not being able to make necessary purchases or implement policy reforms. The study concludes that even though the Ethiopian government implemented various policies such as tax incentives, infrastructure investments, and streamlined customs procedures, delays in infrastructure development and difficulties in attracting foreign investors remain challenges.

These case studies offer an in-depth understanding of the unique economic, social, and political dynamics shaping the performance and outcomes of specific IPs, such as the EIZ and the Hawassa IP. Notably, they illuminate the central role of international influence and collaboration, particularly with China, in shaping Ethiopia's approach to IP development. Furthermore, the studies uncover specific issues that hinder optimal IP operation and provide an understanding of how benefits from these IPs trickle down to local populations, primarily through employment generation, while other potential advantages like technology transfer and knowledge spillovers remain largely unrealised. However, while case studies provide rich detail about specific instances, they are often less able to deliver generalisable conclusions about the broader population of IPs in Ethiopia. This is where my paper contributes: I employ a quasi-experimental research design to generate more generalisable evidence about the impact of IPs in Ethiopia. This design allows for a more comprehensive analysis that accounts for various factors across different IPs, including time-varying elements and region-specific characteristics, that could influence IP performance. My study thus complements the existing case study research by providing a wider lens on IP operation and impact in Ethiopia. Ultimately, through synthesising findings from detailed case studies and broad quasi-experimental research, a more comprehensive understanding of Ethiopia's IP landscape, its challenges, and its potentials for spurring economic transformation can be derived.

This paper relates to the literature on the labour market effects of economic integration in economies characterised by a high share of informal employment. Ethiopia, being one of Africa's rapidly urbanising countries, faces significant challenges, with unemployment standing as a key issue in its urban centres. According to Kibret (2014), Ethiopia's job creation efforts have struggled to keep pace with the growth of the labour force, particularly concerning for new entrants into the labour market. Even though unemployment rates in urban areas show a declining trend, they remain high, especially among women and the youth, and vary significantly across different urban regions. Informal sectors, engaging about a third of the total employed individuals, play a significant role in Ethiopia's urban economy, thereby providing employment to a substantial portion of the growing urban labour force. Despite several policies and strategies for employment generation introduced by the government, both public and private sectors' capacity to create jobs is hampered by various factors, including privatisation, high tax rates, and inadequate finance, credit, and infrastructure (Kibret, 2014).

Lastly, this paper will contribute to the existing literature on gender inequalities in Ethiopia. Despite efforts to reduce the gender gap in areas such as education, employment, income, and political as well as economic participation, large inequalities continue to persist in Ethiopia (Abegaz & Nene, 2023). In 2016, Ethiopia ranked 100 out of 115 countries with a gender gap index of 0.66, according to the World Economic Forum. In their study on gender wage and productivity gaps in the manufacturing sector in Ethiopia, Abegaz & Nene (2023) use firm-level data and investigate gender wage differentials between skilled and unskilled workers after controlling for factors affecting average wages. Their findings exhibit a significant gender wage gap, with a gross gender wage gap of 49 % and an unconditional within firm gap of 39 %. This indicates that a segregation of women workers into low-wage corporations accounts for about 10% of the gender wage gap. Controlling for average productivity reduces the magnitude of the wage gap but does not eliminate it. Interestingly, neither firm characteristics such as exporting status, capital per employee, firm size (measured by the logarithm of number of workers), and firm age have an impact with the exception that foreign-owned firms seem to have a lower gender wage gap. This finding is especially relevant for this paper, since IPs are characterised by attracting FDI and majorly incorporating foreign-owned firms (Crescenzi & Limodio, 2021; Tang, 2022). The examination of gender inequalities in Ethiopia provides a valuable and necessary perspective to the broader investigation of labour market impacts of IPs. Gender is an integral aspect of labour market dynamics, and understanding its role in the context of IPs will contribute to a more comprehensive understanding of the impact of FDI and IPs on structural change in Ethiopia.

The main sectors represented in Ethiopia's IPs are apparel and textiles, leather, agro-processing, pharmaceuticals, and chemicals, with the highest share in apparel and textiles. The goal is to build on the country's agricultural base and transition towards new manufacturing activities that will employ young and semi-skilled workers (Geiger & Moller, 2015). Typically, the textile and clothing industry in Ethiopia offers employment opportunities to young, unskilled workers with lower educational qualifications, of whom the majority are women (ILO, 2022). According to the IPDC, a public enterprise that developed and is currently operating 12 IPs in Ethiopia, around 75 thousand jobs have been created in only the public IPs. However, according to ILO (2022), IP garment manufacturing operations in Ethiopia face a severe skill shortage in high-skilled and management positions. Therefore, garment enterprises, instead of hiring locally, hire expatriates to work in management and design. Most local employees work in the field of sewing and stitching, which requires low-skill labour and has a high turnover rate due to low wages and difficult working conditions (Blattman & Dercon, 2018). If high-skilled jobs are mostly taken up by expatriates and local women are primarily employed in low-skilled jobs, this could exacerbate gender inequalities in the long term. Investigating whether IPs provide pathways for women to move into higher-skilled roles over time is therefore crucial.

Methodically, the paper relates to Tafese et al. (2023) as well as to a recent paper by Bilicka & Seidel (2022), where they investigate the potential of remote sensing nightlight data as a predictor of economic activity for smaller spatial units such as firms. They examined the world's 18 leading car manufacturers, matching the spatial footprints of their production sites with nightlight and firm financial data. Their findings suggest that nightlight data could explain a substantial 80% of the variation in firm turnover between factories. Yet, when it came to temporal variations in firm turnover, nightlight data only accounted for 29% of the change. Of particular relevance is their additional finding: alterations in the spatial area of factories predicted changes in turnover with a higher degree of accuracy (80%) than changes in light intensity. These results support the use of historical images of IPs' built-up areas over time as proxies for firm activity in IPs.

All in all, the literature demonstrates a broad consensus that IPs and SEZs can contribute to promoting economic growth and development (Farole, 2011; Frick et al., 2019; UNCTAD, 2019). However, IPs are no guarantee for higher FDI inflows or GVC participation. In fact, the performance of many zones remains below expectations (UNCTAD, 2019). Their effectiveness varies significantly and much depends on specific circumstances, such as site location, access to sufficient pools of labour, infrastructure, institutional capacity, and the investment climate (Monga, 2011; UNCTAD, 2019). Furthermore, research suggests that SEZs' efficacy in job creation and income growth has been mixed (Farole, 2011).

Besides, the literature acknowledges Ethiopia's labour market challenges and gender disparities, particularly in wages (Abegaz & Nene, 2023). However, the intersection of these issues within the context of IPs is not sufficiently explored. This paper makes a significant contribution, examining how IPs affect gender and labour dynamics and whether they exacerbate or alleviate existing inequalities. While the literature underscores the potential benefits and challenges of CBIPs, a gap remains in evaluating the specific policies and strategies used to implement them. The paper addresses this by evaluating the strategic choice of the Ethiopian government in shaping the country's IP landscape mainly through CBIPs.

Additionally, most of the existing literature focuses either on the micro-level (specific case studies) or on the macro-level (national or international trends). Studies focusing on individual case studies to analyse the performance of specific IPs in Ethiopia provide useful insights into unique economic, social, and political dynamics shaping IPs' performance but lack generalisability (Giannecchini & Taylor, 2018; Tang, 2022). This paper bridges this divide by applying a quasi-experimental design that links the impacts on individual IPs to the broader socio-economic context of Ethiopia. Methodologically, the strength of this paper lies in adopting a pioneering approach, initially introduced by Tafese et al. (2023). Unlike existing studies that often employ a binary approach indicating the mere existence of an IP or rely on the extrapolation of night light data (Frick et al., 2019; Hyun & Ravi, 2018) this approach uses historical satellite images to capture the actual built-up area of IPs as a proxy for their performance and exposure.. Changes in the spatial area explain a much higher share of the variation in firm turnover across time than light intensity and a binary approach ignores the variation of the sizable IP growth over time (Bilicka & Seidel, 2022).

In summary, this paper can contribute substantially to the existing literature by providing a more generalised understanding of IPs' impact in Ethiopia, evaluating the effectiveness of policy implementation, and delving deeper into the intersectionality of labour dynamics, gender disparities, and IP operation. These findings can fill gaps in the current body of research and provide practical implications for policy-making and IP management in developing economies, such as Ethiopia.

3. Background

In this chapter background information regarding FDI in Ethiopia, the IP policy and administrative structure as well as the status of food security in Ethiopia is summarised.

3.1 Foreign Direct Investment in Ethiopia

FDI is commonly regarded as a catalyst for economic growth and can accelerate industrialisation and structural transformation especially in developing nations (Li & Tanna, 2019). According to Gebreeyesus et al. (2022) Ethiopia acknowledged early on that FDI contributed to the economic and social development of countries in East and Southeast Asia, and therefore integrated FDI attraction into its development policy during the Imperial regime. In this period, which spanned from early 1950s to 1974, industrial policies can be characterised as favouring import substitution and being private sector led. FDI was seen as the primary driver of industrial growth and gained high priority. This resulted in a strong FDI presence, with roughly 65% of medium and large-scale manufacturing firms being foreign-owned or operated by the end of the regime (Chole, 1995; Gebreeyesus et al., 2022). However, the rise of the Derg regime in 1975 led to a disruption in foreign investment promotion as the regime adopted a socialist and command economic system, nationalising many privately-owned businesses. While also favouring import substitution, the industrial policies during the Derg regime, which spanned until 1991, are characterised as being state-led (Gebreeyesus, 2013; Newman, 2016).

As outlined by Gebreeyesus et al. (2022), when the Ethiopian People's Revolutionary Democratic Front came to power in 1991, they implemented various liberalisation measures including privatisation, trade opening, market deregulation as well as revisions to investment and labour laws. The Ethiopian Industrial Development Strategy formulated in 2003 emphasises the crucial role of domestic investors, but at the same time recognises the potential of FDI in filling the gap of capital, technology, and managerial experience in local firms.

In recent years Ethiopia's industrialisation strategy, which receives top-level support, particularly from the Prime Minister, places a significant emphasis on attracting FDI. The nation's investment policies have undergone multiple revisions to facilitate FDI influx and create a more FDI-friendly environment (Zhang et al., 2018).

Largely driven by a well-structured SEZ policy, dynamic investment promotion strategies, and robust governmental backing, FDI increased from USD 1.3 billion in 2013 to USD 4.3 billion in 2021 (Figure 1) (UNCTAD, 2022). Similarly, the total stock of FDI increased from USD 4,206 billion in 2010 to USD 31,596 billion in 2021, which equals around 31.8% of the country's GDP (Figure 2). Ethiopia, being a central hub for China's Belt and Road Initiative, experienced a major increase in Chinese investments, tripling in 2021 compared to 2020. Thereby, Ethiopia became the largest landlocked developing country (LLDC) FDI recipient in Africa (UNCTAD, 2022).

Figure 1: FDI inflows in billion USD in Ethiopia, Source: UNCTAD (2016, 2022)

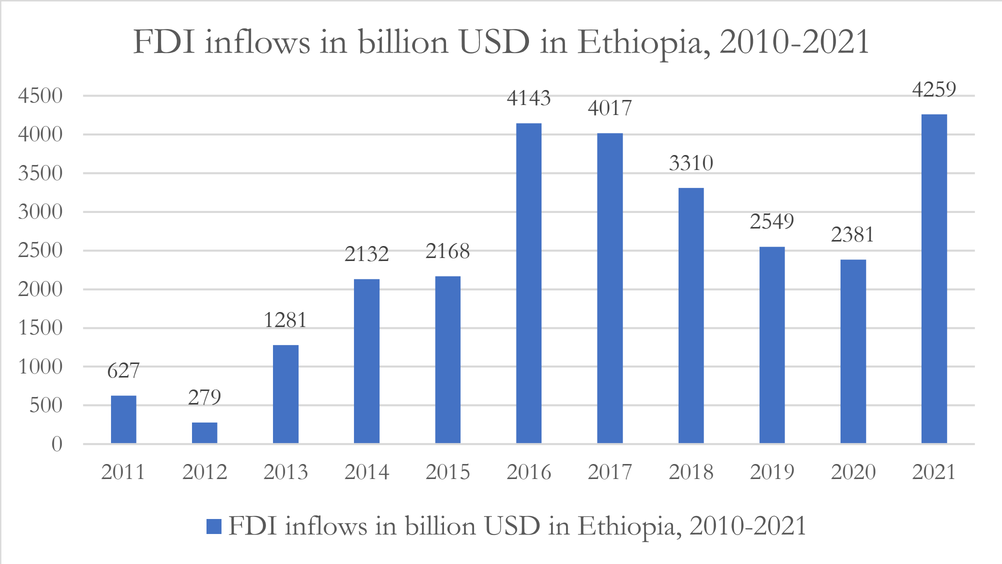
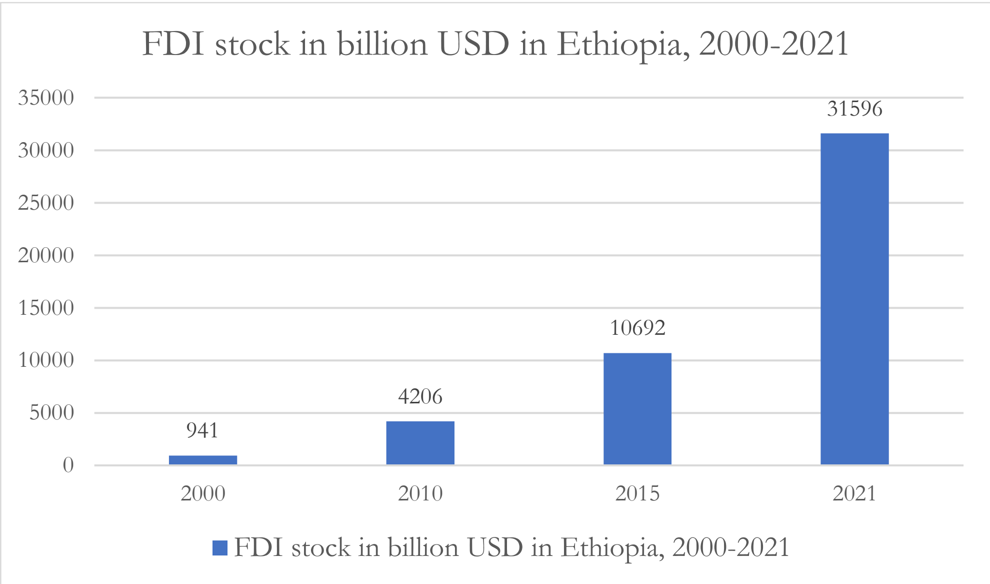


Figure 2: FDI stock in billion USD in Ethiopia, Source: UNCTAD (2016, 2022)



With a particular focus on the manufacturing industry, Ethiopia is strategically directing FDI towards specific sectors such as textile and clothing, leather goods, agro-processing, and pharmaceuticals and chemicals. The goal is to capitalise on the country's agricultural base and pivot towards new, labour-intensive manufacturing activities that can employ the young and semi-skilled workforce in large numbers (Zhang et al., 2018).

Despite its considerable potential in light manufacturing, Ethiopia faces significant challenges including limited access to land, inadequate infrastructure, trade logistics issues, customs regulations, and a skills deficit (Zhang et al., 2018). FDI is viewed as a solution to alleviate these constraints, with IPs expected to play a crucial role. In this regard, Ethiopia prefers IPs as a gateway to FDI because they have the advantage of lowering entry and operational costs (Mihretu & Llobet, 2017).

3.2 Ethiopia's IP Policy and Administrative Structure

Tang (2022) defines IPs in Ethiopia as an 'area with distinct boundary designed by the appropriate organ to develop comprehensive, integrated, multiple or selected functions of industries and includes special economic zones, technology parks, export processing zones, agro-processing zone, free trade zones and the like designated by the Investment Board'. SEZs are defined as 'geographically delimited areas within which governments facilitate industrial activity through fiscal and regulatory incentives and infrastructure support'. In Ethiopia, they are typically referred to as IPs, however in literature they are also referred to as SEZs, which is why in the following "IP" and "SEZ" will be used interchangeably.

In 2010 Ethiopia's first Growth and Transformation Plan (GTP I), a medium-term strategic framework for the five-year period from 2010 to 2015, was launched. There, the long-term goal to become a middle-income country by 2025 has been defined. In particular, its vision is 'to become a country where democratic rule, good-governance and social justice reigns, upon the involvement and free will of its peoples; and once extricating itself from poverty and becomes a middle-income economy' (Federal Democratic Republic of Ethiopia, 2010). The plan is focused on fostering and sustaining broad-based economic growth through different sectors, such as the agricultural and industrial sector. In this framework, also the promotion and support of the development of industrial zones is specified in order to create opportunity for integrated industrial development. It is aimed that this will lead to efficiency gains, reduction of investment requirements, employment generation, improved income, and economic growth.

Following the completion of GTP I, in 2015 Ethiopia launched the Ethiopia's Growth and Transformation Plan II (GTP II) for the five-year period from 2015 to 2020. In the GTP II, the long-term goal has been adjusted to becoming a lower middle-income country by 2025. At the core of GTP II lie the expansion of industrial development with a primary focus on light manufacturing, a significant shift in export development and the modernisation in the development of the agriculture sector (Federal Democratic Republic of Ethiopia, 2016). Although the significance of IPs was already highlighted in GTP I, in GTP II a greater emphasis is put on developing several IPs throughout the country. According to the Federal Democratic Republic of Ethiopia (2016) IPs are expected to promote export processing and to create a conducive environment for boosting investments in the manufacturing sector. Besides, the implementation of comprehensive measures is planned. These include tackling financial constraints via regional lease financing institutions and the Development Bank of Ethiopia, addressing the marketing and financial challenges of Small and Medium Enterprises (SMEs), and resolving SMEs' market access issues by fostering connections with local industries.

Ethiopia's strategy towards SEZs encompasses various policy areas like trade, investment promotion, labour, and environmental policies, which according to Farole (2011) is crucial for the effective development and implementation of SEZs. The Ethiopian government has placed great emphasis on the creation of an institutional structure that fosters smooth inter-agency cooperation, particularly between entities dealing with investment promotion and the SEZ policy (Rodríguez-Pose et al., 2022). Three entities are involved with SEZs: the Ethiopian Investment Board (EIB), the Ethiopian Investment Commission (EIC) and the Industrial Parks Development Corporation (IPDC).

According to Zhang et al. (2018), the EIB was established to oversee the comprehensive investment promotion strategy and SEZ policy. The EIB is chaired by the Prime Minister and includes senior ministers from key agencies that play direct or indirect roles in investment decisions. Representatives from, among others, foreign affairs, industry finance, agriculture, the national bank, and the City of Addis Ababa also sit on the board. The board's primary role is to guide overall investment and IP policy in Ethiopia. It provides incentives to investors, addresses policy and regulatory hurdles to investment, designates new IPs, and opens up new investment areas for FDI. This arrangement signifies a shift, as the promotion and retention of FDI, previously considered a mere technical issue of a government agency, now sits at the government's core agenda.

Based on the information of IAIP (2023), the EIC is an autonomous government body, established in 1992, with the primary role of promoting private, especially foreign, direct investment. Overseen by the EIB, which is chaired by the Prime Minister, the Commission is led by a commissioner who is also a member of the EIB. Functions of the EIC focus on day-to-day operational aspects. These include, among others, the promotion of investment opportunities specifically to foreign investors and administering permits related to the IPs, reaching from investment permits to work permits. Furthermore, the EIC gives policy recommendations to the government on how to create an appealing investment climate for investors.

In addition, as outlined by Zhang et al. (2018) the IPDC was established in 2014 and modelled after Singapore's JTC Corporation. This state-owned, profit-driven corporation is tasked with developing and managing IPs, as well as functioning as a land bank to provide land to potential private developers. The aim is to create shared infrastructure and services in industrial facilities in order to help businesses cut down on operational costs and boost efficiency. In collaboration with private developers, the IPDC is set to spur the growth of existing industries and stimulate new ones by developing new industrial land and spaces.

Notably, Rodríguez-Pose et al. (2022) states that Ethiopia's institutional arrangement is distinctive in the sense that both the EIB and the EIC share responsibility for the investment promotion and the development and implementation of the IP strategy. This model underscores the interconnectedness of these two functions and the need for synchronising investment promotion efforts with SEZ programs. Another distinctive feature mentioned is the direct involvement of the prime minister's office, which co-ordinates activities across different agencies and thereby sends a strong signal to potential investors about the governments support for the SEZ strategy. For example, survey results show that almost half of the investors chose Ethiopia due to the government's strong support, with 75% of firms acknowledging they were actively approached by the government. Additionally, the inclusion of senior representatives from various ministries on the EIB board facilitates effective collaboration between different institutions and at the same time ensures policy coherence (Akileswaran et al., 2020; Rodríguez-Pose et al., 2022).

In summary, Ethiopia's approach to SEZ development, intertwines SEZ policies with investment promotion efforts and involves robust institutional collaboration. This strategy stands in contrast to that of other African countries like Kenya, Nigeria, and Tanzania, where a lack of formal institutional links has impeded a coordinated approach to SEZ development (Rodríguez-Pose et al., 2022).

3.3 Food Security in Ethiopia

The definition for food security agreed upon at the 1996 World Food Summit (FAO, 1996) states "food security exists when all people, at all times, have physical and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life."

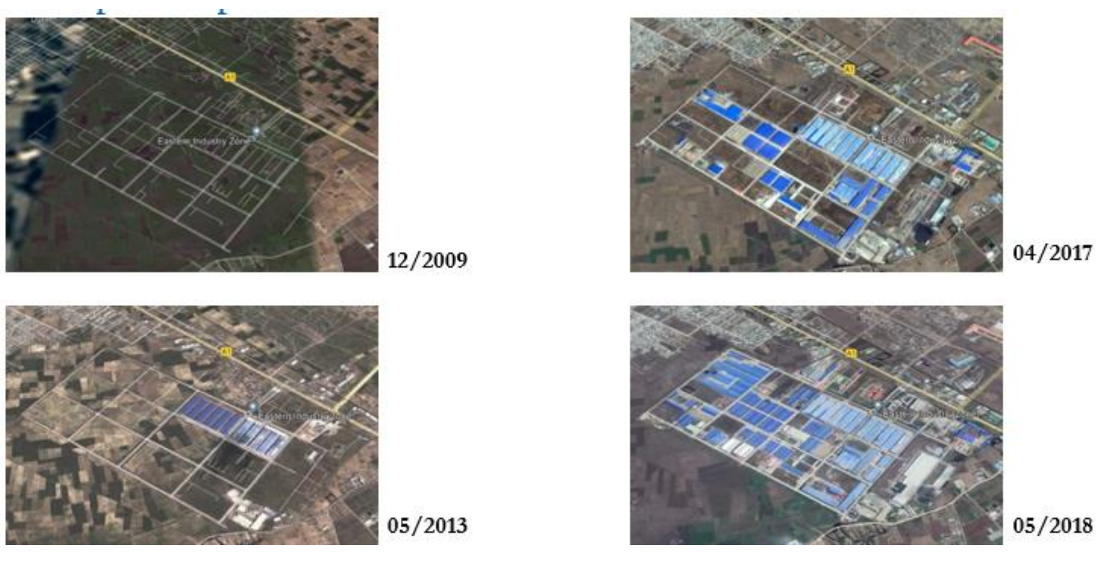
According to Abebaw et al. (2010) The Ethiopian economy is heavily reliant on the agricultural sector, a major player in labour force employment (85%), gross domestic product (around 50%), and foreign exchange earnings (90%) in any given year. In 2021 Ethiopia had the highest number of inhabitants facing food insecurity, around 16.9 million, among the countries in East Africa (Statista, 2021). In the period between 2019 and 2021, the prevalence of severe or moderate food insecurity in the total population amounted 56.2 %, which translates into 64.7 million people (FAOSTAT, 2023). According to FAO (2023) an estimated 20.1 million people require urgent food aid in Ethiopia. This pressing situation would primarily stem from the lasting effects of conflict in the northern regions, drought in the south, coupled with substantial macroeconomic issues and sporadic intercommunal violence nationwide (Abebaw et al., 2010; FAO, 2023). Historically, Ethiopia's agricultural sector has also struggled with the aftereffects of misguided policies, characterised by excessive market regulation and enforced quota deliveries by farmers at sub-market prices which combined with persistent droughts and outdated agricultural practices, has led to prevalent food insecurity in Ethiopia already in the past (Abebaw et al., 2010; Devereux, 2000).

Previously, the response to food insecurity has heavily relied on food aid and concessional food imports (Little, 2008). Despite these efforts, food insecurity persists, and is a pressing concern, with an estimated 24.9 % of the population, around 28.6 million people, living undernourished between 2019 and 2021 (FAOSTAT, 2023).

4. Data

Historical satellite images from Google Earth are used to trace the evolution of the built-up area of IPs over the period from 2007 to 2022. Building on the foundation laid by Tafese et al. (2023), this approach provides continuous data, enabling a detailed examination of the changes in the infrastructure of IPs. Through data provided by the IPDC and additional web research, 26 IPs in 10 regions in Ethiopia could be identified and mapped. In Figure 3, the expansion of the IP EIZ in the Oromiya region between 2009 and 2019 can be observed. As the size and number of factory sheds varies substantially over the years, using only a binary approach for the development of IPs is no accurate measure.

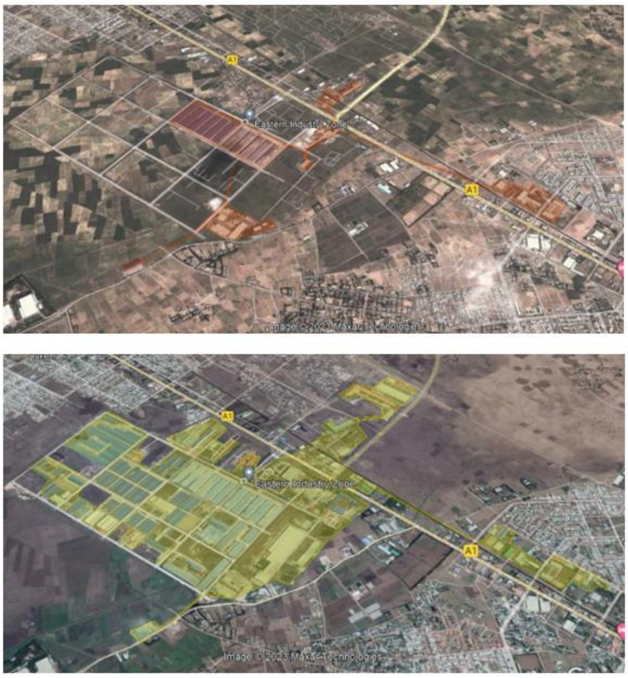
Figure 3: Expansion of IP EIZ



In particular, each year a polygon is drawn around the factory sheds to identify the exact size of the IP per year and thereby the growth over the years. The drawing of the polygons was done in the software Google Earth Pro. There an Ethiopia folder was constructed, that contains a separate Google Earth place for each region of Ethiopia in which an IP is currently located or planned. For each IP, a folder named after the IP and located within the according region is set up. Then a placemark is put in the centre of the IP to obtain the exact latitude and longitude. First, the zero polygon containing a null area is created for the last image before construction began. The main reason for the creation of the zero polygon is to later be able to decipher how much time lies between the first image containing an IP and the last image without an IP in order to confine the initial build up period as exact as possible. The beginning of construction can be attributed to the timeframe between the last image without any visible construction (zero polygon) and the first image with visible construction. In Ethiopia, for each IP an image in the year before its first construction on satellite images is available. This means that the first existence of any IP can be attributed within the period of a specific year. The years in which zero polygons are identified, i.e., the last image without any construction, range from 2009 to 2022, while most occur between 2015 and 2017 (14 out of 26) (see Appendix Table 11).

The aim is to capture only the area of the actual factory sheds as precisely as possible. With these data, a yearly measure of exposure to IPs is constructed. In Figure 4 the polygons that were drawn for the EIZ in 2013 (orange) and 2018 (yellow) can be observed. For the majority of IPs, the first sheds were visible between 2015 and 2018 (15 out of 26), i.e., construction had initiated (see Appendix Table 12). Still, there are 5 IPs for which no sheds are visible on recent satellite imagery, i.e., the construction has not yet begun.

Figure 4*: Polygons of EIZ in 2013 and 2018*



A recent study by Bilicka and Seidel (2022) revealed that alterations in the factory's area occupied explain a higher share of the changes in firm turnover (around 80%) compared to changes in the night light identified through satellite imagery (29%). These results support the choice of using changes in the overall built-up IP area as a proxy for changes in economic activity instead of alternative measures such as night light data.

The IP exposure measure is linked to the Ethiopian Socioeconomic Survey (ESS) and Ethiopian Rural Socioeconomic Survey (ERSS) household-level data - a joint collaborative project between the Central Statistics Agency of Ethiopia (CSA) and the World Bank LSMS.

The ESS1 (2011/12) comprises 4,000 households in rural areas and small towns, whereas in the ESS2 and ESS3 (2013/14, 2015/16) the sample was expanded to include 1,500 urban households to ensure nationally representative estimates. While the first three waves form a panel, the most recent ESS4 wave (2018/19) is the beginning of a new panel, not a follow-up, that includes further enumeration areas (7,527 households) and is also representative of regions as well as rural and urban areas (World Bank, 2023). All waves collect multi-topic household-level data. The household questionnaire is split into 15 sections that entail questions on household roster, education, health, time use and labour, food and food aggregate, non-food expenditure, food security, shocks, housing, assets, non-farm enterprise, other income, assistance, credit and contact information. In the analysis, besides the household roster, primarily the sections on labour and time use, education, food security, health and non-farm enterprises will be used.

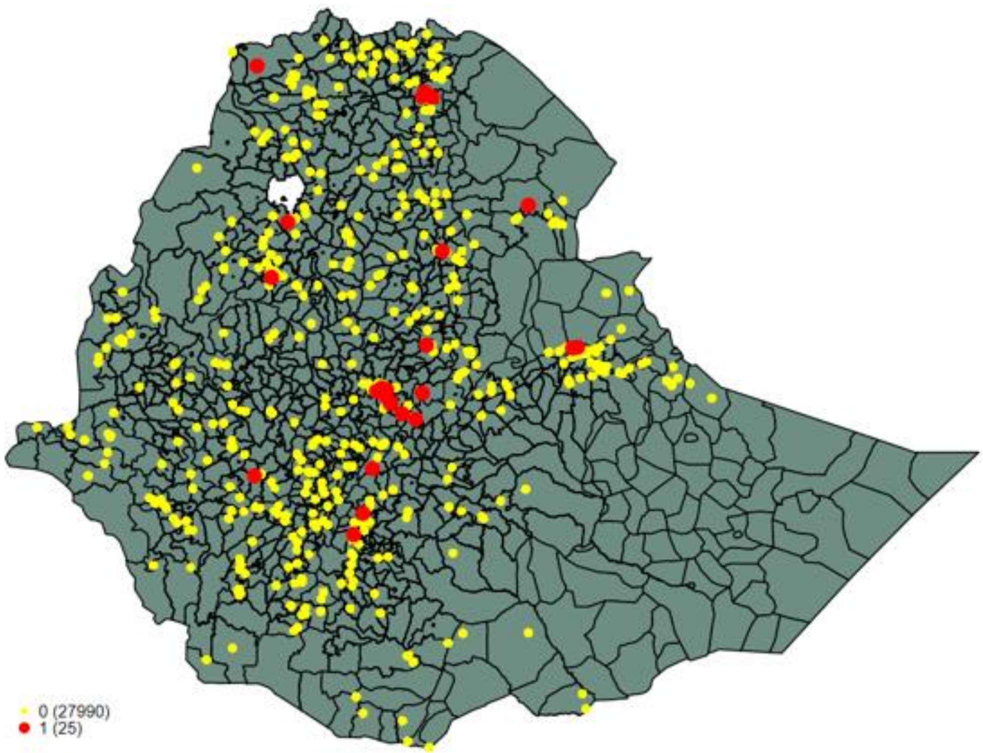
The ESS employed a two-stage probability sampling approach in its consecutive waves. In the previous waves (ESS1, ESS2 and ESS3), the first stage involved selecting enumeration areas (EAs) using simple random sampling (SRS) from the sample of Agricultural Sample Survey (AgSS) EAs. These EAs were chosen based on a probability proportional to the size of the population (PPS). In the rural and small-town areas, 290 and 43 EAs respectively were selected from the AgSS EAs. Additionally, 100 EAs were selected for ESS2 and included in the ESS1 sample. The second stage of this wave involved selecting households in each EA for interview. In rural EAs, a total of 12 households were sampled, with 10 randomly selected from the sample of 30 AgSS households, which were households involved in farming or livestock activities. Additionally, 2 households were randomly selected from all other households in the rural EA (those not engaged in agriculture or livestock).

In the most recent wave, ESS4, the first stage of sampling in rural areas involved using SRS to select EAs from the sample for the 2018 AgSS EAs. For urban areas, EAs were chosen directly from the urban EAs within each region using PPS systematically. Once the sample EAs were selected, they were classified as urban or rural using power allocation. The second stage was to use systematic random sampling to select households to be surveyed in each EA. From the rural EAs, 10 agricultural households and 2 non-agricultural households were selected. For urban areas, a total of 15 households were selected per EA regardless of the households' economic activity.

The approach for both waves ensured a representative sample across rural, small town, and urban areas, with proportional allocation and systematic random sampling as key techniques. However, the specific selection methods and classification criteria slightly evolved from the previous waves to the recent one, allowing for an updated and accurate representation of the Ethiopian population.

The ESS data are linked to the IP data based on distance between the longitude and latitude of the households and the IPs. In Figure 5 the location of the IPs (red) and the households (yellow) is visible. For each IP a variable is generated that measures the distance to each household. However, to maintain the confidentiality of sample households modified enumeration-area-level (EA) coordinates are provided by World Bank (2023) as part of the household-geovariable table instead of the exact household coordinates. These modified coordinates are generated by applying a random offset within a specified range to the average EA value. The method employed for coordinate modification relies on the random shift of EA central point coordinates (or the mean of household GPS positions per EA) within a pre-determined range based on whether the area is urban or rural. In smaller towns and urban zones, the coordinates are altered within a range of 0-2 km. In contrast, rural areas, where the population is more spread out and the risk of data exposure might be greater, a shift range of 0-5 km is applied. Further, a 0-10 km shift range is implemented for 1% of EAs, effectively broadening the established range for all points to 10 km, albeit only introducing a minimal level of noise. The shifted points are limited at the zone-level which ensures that they remain within the correct zone for spatial associations or overlays based on the point's location within a polygon. These coordinates are EA-level representative and adhere to confirmed accuracy boundaries.

Figure 5: Ethiopia Household Observations & IPs



Notes: Map of Ethiopia with yellow representing households surveyed in LSMS and red representing IPs.

5. Method

In this section, the data treatment of all variables that are included in the analysis is described and descriptive statistics are provided. Thereafter, the empirical strategy is outlined.

5.1 Data Treatment & Descriptives

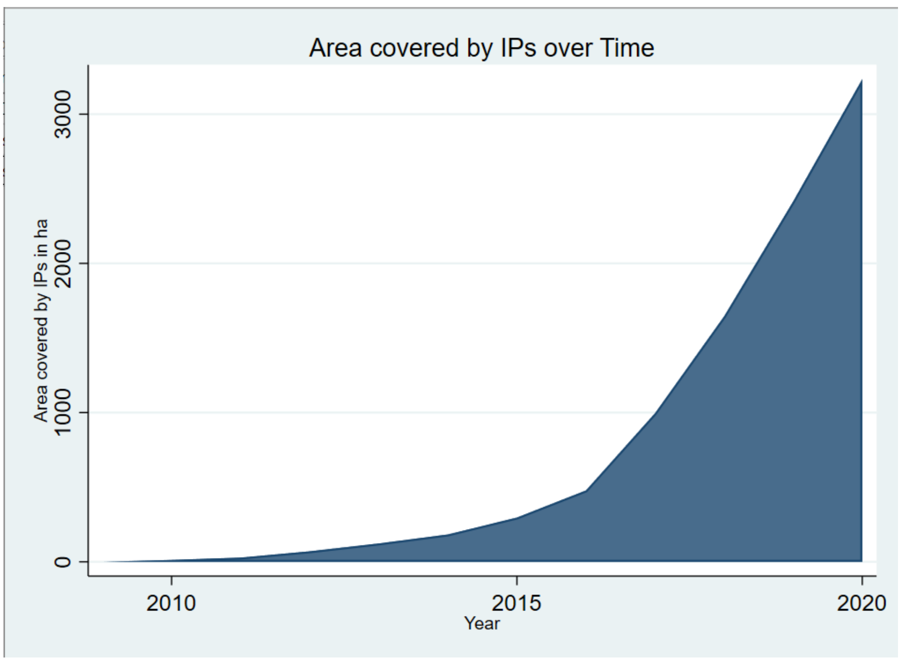
In the following, each variable included in the analysis will be described in detail. The considered outcomes of interest on the household level are wage, time spent on paid labour, time spent on household agricultural activities, time spent on household labour, employment status, perceived food insecurity, and food insecurity. As control variables sex, attendance of school, highest grade achieved, education of mother, and rural vs. urban location are included in the different analyses. Furthermore, for non-farm enterprises the outcomes of interest are revenue, costs, profit, and the share contributed to the household income. Distance to the nearest population centre and rural vs. urban serve as control variables.

5.1.1 Industrial Park Growth

Firstly, the treatment variable contains the information of the aggregated area in 100-hectares of the built-up IP area within a 20 km distance threshold for each individual. This means that if individuals are exposed to more than one IP, their occupied area is aggregated to capture the total IP exposure. If individuals are not exposed to any IP within a 20 km radius, then the treatment variable is zero. In all four waves, 66,531 individuals are included in the analysis of which 10,523 (15.82 %) are exposed to an IP that occupies an area larger than zero and 56,008 (84.18 %) are not exposed to an IP. In robustness checks, the threshold is narrowed down to 15 km and 10 km, which translates into considering 9,417 (14.15 %) and 8,557 (12.86 %) as treated individuals, respectively.

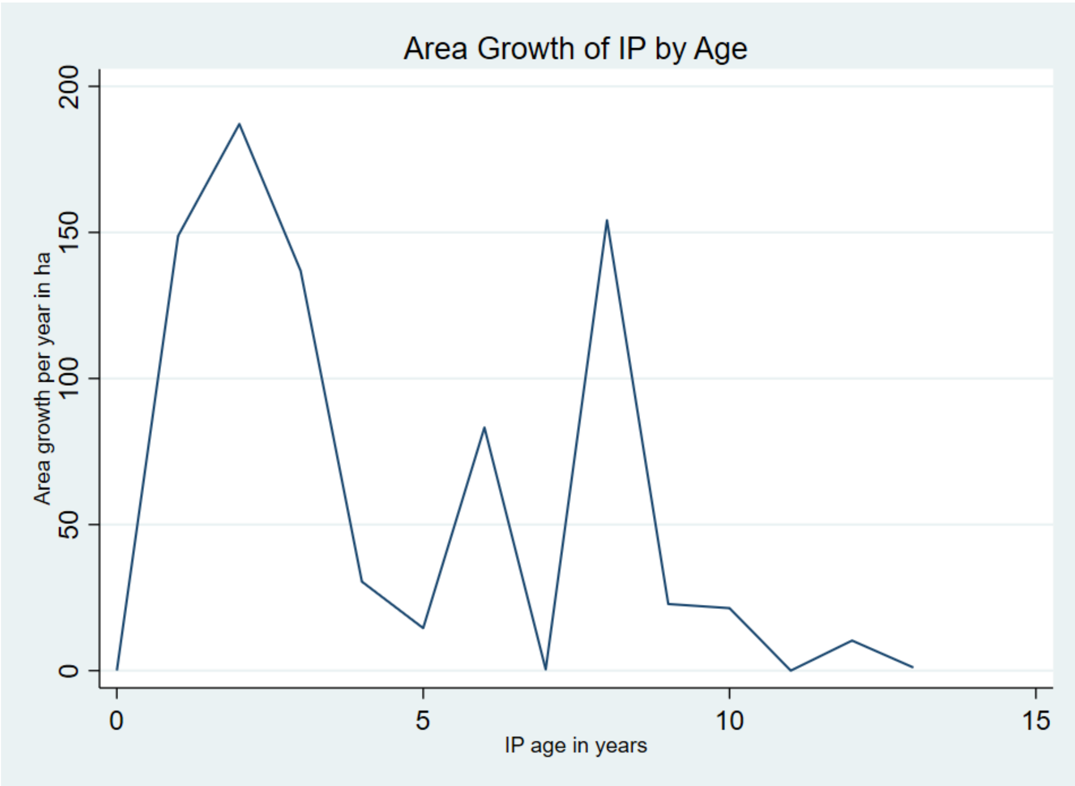
In Figure 6, the total area covered by IPs in Ethiopia over time is exhibited. The area grew from almost zero in 2010, to over 3000 hectares in 2020. The built-up area increased strongly especially in the years between 2016 and 2020.

Figure 6: Area covered by IPs over Time



When observing the area growth by age, i.e., the years since the first construction of the IP, it is visible that IPs seem to majorly grow in the first four years of existence (Figure 7). However, this is misleading since most IPs construction began in the years 2015/2016. Hence, the age of the majority of IPs is not more than four to five years. Keeping this in mind, one can also see peaks of area growth between 5 and 10 years after construction, implying that IP area grows substantially over longer periods of time. This supports the framework of not using a binary approach for IP exposure, but instead using the built-up IP area in 100-hectares as the treatment variable. The mean of the treatment variable amounts to 60.28 hectares while the median is 48.7 hectares. The largest IP in Ethiopia in 2020 was the EIZ with 263.78 hectares.

Figure 7: Area Growth of IP by Age



5.1.2 Labour Market Outcomes

In the subsequent section, the construction of the wage variables is explained in detail. Within the LSMS survey, the individuals could report their wages for timeframes ranging from hour to year. Hence, there is the need to adjust the wage data to a standardised value that captures the wage over the same amount of time. Using the information on how many months per year, weeks per month and hours per week the individuals reported to have worked in the last 12 months, a wage variable that contains the total wage of the last 12 months has been constructed.

In Table 13 (see Appendix) the different occupation categories that an individual's response could fall under when asked about their occupation over the past 12 months are listed, with each category accompanied by its corresponding occupation code. Individuals had to describe their main job over the last 12 months and the interviewer classified the occupation codes accordingly. Similarly, for the industry information, individuals described what kind of trade or business their main job over the last 12 months is connected with (main product or service) and the interviewers classified the industry codes. In Table 14 (see Appendix) the different industries that the employer of the interviewed individuals could be classified in are listed. With around 25 %, the majority of wage workers were employed in (sales and services) elementary occupations (Group 9), followed by 19 % (physical, mathematical and engineering science) professionals (Group 2) and 17 % service, shop and market sales workers as well as related workers (Group 5).

To identify outliers, the interquartile range (IQR) method as specified by Vinutha et al. (2018) is used. There, outliers are defined as any value that falls below Q1 - 1.5 IQR or above Q3 + 1.5 IQR, where Q1 is the first quartile (25th percentile), Q3 is the third quartile (75th percentile), and the IQR is the difference between Q3 and Q1. Before excluding outliers with the IQR strategy, the mean total wage for Group 5 was 100,076 BIRR for the last 12 months, which is substantially higher than the mean total wage reported by Group 2 (52,630 BIRR) and Group 9 (18,782 BIRR). This result is surprising since one would expect that, on average, shop and market sales workers would have lower mean wages than professionals. However, the median of group 5 is with 13,500 BIRR substantially lower. This indicates the presence of strong outliers within this group. After adjusting for outliers, 68 out of 1,022 observations (around 7 %) from group 5 were excluded and the mean total wage for group 5 drops to 11,200 BIRR and the median amounts 12,000 BIRR. When taking a closer look at these reported wages, there has probably been an error in the reporting. For example, someone reported earning 20,000 BIRR per day working in a private household. This would be more than the total mean average wage in the last 12 months for the majority of occupation categories. Furthermore, after excluding outliers, for all occupation groups the total mean wage amounts to 20,325 BIRR compared to 45,692 BIRR beforehand. The median drops to 15,000 BIRR, compared to 17,000, respectively. Using the GDP per capita in the local currency unit only for the four years of the LSMS waves (2012, 2014, 2016, 2019), an average GDP per capita value is calculated that equals 14,034 BIRR per year (World Bank, 2021). The consistency of the survey wages - after excluding outliers - with the average GDP per capita for the respective years strengthens the confidence in excluding outliers with the IQR strategy.

As the reported wage structures vary greatly depending on the timeframe they are reported for, an additional variable that contains the information on monthly wages only for individuals that reported their wage per month is constructed. Typically, the employment type is different for workers that get paid on, for example, a monthly vs. a daily basis.

For both, the total wage and the monthly wage variable, the log transformation is computed after adding a constant of "1" to ensure that no zeros will be excluded through the log transformation. By logarithmising the variables, the impact of outliers is reduced. Since the wage distributions are often right-skewed, with a long right tail due to a small number of individuals with very high wages. Taking the logarithm can help to normalise the distribution, making it more symmetrical and hence suitable for statistical analysis.

The time spent on paid labour is identified by asking the individuals how many hours they have spent in the last seven days doing any work for a wage, salary, commission, or any payment in kind, excluding temporary work. If individuals did not participate in such activities, zero is recorded and otherwise the number of hours worked are recorded. While around 89 % reported to have worked zero hours on paid labour, around 11 % spent on average 43.05 hours on paid labour, ranging from one hour to 106 hours, with a median of 41 hours per week.

Similarly, to obtain the information on time spent on household agricultural activities, individuals are asked how many hours in the last seven days they spend on household agricultural activities (including livestock and fishing-related activities) whether for sale or for household use. Around half of the respondents (51.06 %) reported to have not spent time on household agricultural activities, while the other half (48.94 %) reported to have spent between one and 100 hours. From the latter, the mean hours reported spent on household agricultural activities per week are 23.97 hours and the median is 21 hours.

To obtain the employment status, individuals are asked whether at any time over the last 12 months, they were employed in any kind of job, including part-time labour, for wage, salary, commission, or any payment in kind, for anyone who is not a member of their household (excluding temporary work). Individuals could reply with either yes or no. Out of the 51,697 individuals from whom a reply is available, 92.33 % (47,732) reported to not have been employed while 7.67 % (3,965) reported employment and 1,348 of those 7.67 % were exposed to an IP.

5.1.3 Food Security Outcomes

Besides labour market outcomes, also the effect of IP exposure on food security is analysed. More specifically, two variables are considered to measure the impact of built-up IP area on food security. Firstly, respondents had to answer whether they were worried about their household not having enough food in the past seven days. This dummy variable takes the value one if they were worried and zero otherwise and is labelled as "perceived food insecurity" in the following. Furthermore, the information on whether respondents were faced with a situation of not having enough food to feed the household in the last 12 months, is included in the analysis and labelled as "food insecurity". This dummy variable takes the value one if the individuals were faced with a situation of food insecurity and zero otherwise. Interestingly, more respondents reported food insecurity (22.27 %) than perceived food insecurity (16.72 %).

5.1.4 Non-Farm Enterprise Outcomes

The information on non-farm enterprises is based on a household questionnaire, where either the head of the household or the most knowledgeable member would provide the answers for the household. According to the World Bank (2023) "a household non-farm enterprise is an organised commercial activity and/or a commercial establishment that is owned and managed by household members. It can be very informal and have no hired labour or formal registration. For instance, non-agricultural, one-man operations providing goods/services for various different non-household members/groups, i.e., working independently on their own account, must be classified as non-farm enterprises." From this part of the questionnaire, information on the kind of enterprise, to whom it primarily sells its products, the average monthly sales, the average monthly costs as well as the share of total household cash income that came from this enterprise are used in the analysis.

In the separate analysis on the impact of exposure to IPs on non-farm enterprises, four main outcome variables are included. In the survey, firms had to report their average monthly sales and their average monthly costs in the last 12 months for the months in which the business was operating. Using this information, a third variable "profit" is constructed that deducts the average monthly costs from the average monthly revenue to get a better insight into the actual profits of those firms. For all three variables the IQR method as specified by Vinutha et al. (2018) is used to identify outliers. To be able to take the log of the cost and revenue variable, a constant of "1" is added. Thereby, no zero values exist that would be eliminated through taking the log.

After accounting for outliers, the average monthly sales range from 0 to 8425 BIRR, with a mean of 1615.45 BIRR and a median of 877.5 BIRR. Similarly, the monthly costs range from 0 to a reported maximum of 7350 BIRR. While the mean monthly costs amount 1124.02 BIRR, the median costs, 400 BIRR, are much smaller.

Since the profit variable takes negative values when the average monthly costs are larger than the average monthly revenues, the variable is transformed by adding a constant of "1225" – adding one to the largest negative profit to ensure that neither negative values nor zeros occur in the data. Additionally, to ensure the robustness of the results after such a transformation, another profit variable is created by taking the absolute value of profit, performing the log transformation and then reinstating the sign. The largest observed profit amounts to 2150 BIRR, with a mean of 414.16 BIRR and a median of around 260 BIRR.

Furthermore, the variable "income share" is included which exhibits the share of total household income that the non-farm enterprise contributes. It is an ordinal variable that ranges from 1 to 5, with 1 being classified as contributing "almost none", 2 "around 25 %", 3 "around 50 %", 4 "around 75 %" and 5 "all". In the last wave of LSMS, the households could report the exact percentage share instead of the ordinal category. For the consistency in the variable the observations from the latest wave were classified accordingly: almost none if the contribution was equal to or less than 15 %, around 25 % if it was between 16 and 35 %, around half if the contribution was between 36 and 55 %, around 75 % if it was between 56 and 85 % and all if the contribution to total household income was above 85 %. In total, the information is available for 6,737 households of whom 1,274 are exposed to an IP. Out of all reported income shares, around 25 % reported that the business contributed almost nothing to the total household income and around 15 % reported the entire household income is made up of the revenue of the non-farm business, while for the majority (32 %) it contributed around 25 %.

5.1.5 Control Variables

In the following, the control variables included in the separate analyses will be described. The variable sex is coded "0" if the individual is female and "1" if the individual is male. Furthermore, the variable rural contains the information about whether the household lives in a rural or urban location and is coded "1" for rural and "2" for urban. The information about whether individuals attended school or not is exhibited by the variable attendance school and is "1" if they attended school and "2" if they never attended school. The highest grade achieved can range from kindergarten education to level 4 education for both the individuals reporting for themselves but also for the highest level of their mother's education. Lastly, the variable distance to population centre measures the distance in km to the nearest population centre with more than 20,000 inhabitants.

5.2 Empirical Strategy

The impact of IP exposure is identified from the correlation between the *change* in the average outcome of interest of individuals and the *change* in total built-up IP area. Specifically, in order to investigate the impact of IP exposure on the population, the following Staggered Difference-in-Difference (DiD) framework is used:

$$y_{iwt} = \beta_0 + \beta_1 IP_{it} + \beta_2 IP_{it}\ X\ Male_{iw} + \beta_3 IX_{iwt} + \gamma_t + \gamma_w + \varepsilon_{iwt} \qquad (1)$$

Where y_{iwt} is the outcome of interest – time spent on paid labour, time spent on agricultural activities, time spent on household work, employment status, wage, food insecurity and perceived food insecurity – for individual i in woreda w at time t. IP_{it} is the built-up area of IPs in 100-hectares, which is used as measure of individual i's IP exposure at time t. Individuals are considered to be exposed to IPs if they live within a span of 20 km around any IP. This exposure limit has been chosen based on Lu et al. (2019) who document micro-level evidence about the impact of China's SEZ. They use a concentric ring analysis to estimate the magnitude of any SEZ spillovers on the adjacent area with a cutoff at 20 km. Similarly, in their analysis of the influence of Indian SEZs, Hyun & Ravi (2018) restrict their analysis to an area at most 15 km away from the closest SEZ.

To estimate the heterogeneous effects of IP exposure on men and women, the term $IP_{it}\ X\ Male_{iw}$ is introduced, which is an interaction between the IP exposure measure and a dummy variable that takes the value 1 if the individual is male and 0 if the individual is female. IX_{iwt} is a vector of individual-level time-varying controls in woreda w. In the labour market analysis, the included controls are the individual's gender, age, and education. γ_t and γ_w are year and woreda fixed effects, and ε_{iwt} is the idiosyncratic error term clustered at the woreda level.

Besides labour market outcomes, also the effect of IP exposure on food insecurity and perceived food insecurity is analysed. The same model as described above is used for these analyses. However, the vector of control variables includes the mother's education, the distance to the nearest population centre and whether the household is located in a rural or an urban location. These variables were chosen as controls, since they are believed to impact (perceived) food security according to literature (Abebaw et al., 2010).

In a separate analysis the impact of exposure to IPs on non-farm enterprises is examined. The information on non-farm enterprises is available at the household-level, where one household can own multiple non-farm enterprises. To investigate the impact of IP exposure on the non-agricultural businesses, the following Staggered Difference-in-Difference (DiD) framework is used:

$$y_{hwt} = \beta_0 + \beta_1 IP_{ht} + \beta_2 IX_{hwt} + \gamma_t + \gamma_w + \varepsilon_{hwt} \quad (2)$$

Where y_{hwt} is the outcome of interest – average monthly revenue, costs and profits as well as income share – for household h in woreda w at time t. IP_{ht} is the built-up area of IPs in 100 hectare units, which is used as measure of households' IP exposure at time t. Households are considered to be exposed to IPs, if they live within a span of 20 km around any IP. In a robustness check, this span is reduced to 10 km. With the variable IX_{hwt} it is controlled for whether the household h in woreda w at time t lives in a rural or urban location. γ_t and γ_w are year and woreda fixed effects, and ε_{hwt} is the idiosyncratic error term clustered at the woreda level.

Even though, the analyses are done at the level of IP exposure, the standard errors are clustered at the woreda-level and woreda fixed effects are introduced. This choice has been made based on the structure of woredas in Ethiopia. Often, the group of individuals being exposed to the same IP live in different woredas. Clustering at the woreda-level assumes that individuals within the same woreda are more likely to have similar unobserved characteristics or experience similar shocks, and therefore their error terms are more likely to be correlated. Given that woredas can be rural or urban and individuals exposed to the same IP can live in an urban woreda, e.g., the city centre, or a rather rural woreda, outside the city, it is likely to assume that individuals have similar unobserved characteristics based on the woreda they live in. For example, urban woredas are typically equipped with better infrastructure, while rural woredas sometimes even lack basic infrastructure such as paved roads, which impacts access to IPs as well as other socioeconomic characteristics. In fact, almost 2,500 individuals exposed to an IP live in rural locations, while over 8,000 individuals live in urban locations. For example, 1,040 individuals are exposed to the Hawassa IP over the years, of whom 259 individuals reside in rural locations and 781 reside in urban locations.

The staggered DiD relies on the exogeneity assumption: The identification strategy produces valid estimates under the condition that the treatment rollout over time is exogenous to relevant third variables. That is, conditional on all included covariates and fixed effects, the creation of new and growth of existing IPs is independent of other unobserved factors influencing the socioeconomic conditions considered (Rude, 2020). According to the IPDC the selection of the location of the IPs is primarily based on a distributional approach: each region in Ethiopia receives one IP. As a second condition the location selection depends on the linkage to regional airports, railway, and roads. Additionally, under the parallel trends assumptions, in order to establish a causal relationship between IP exposure and the outcome variable of interest, the outcome variable of interest for the treatment and the control group would have followed parallel trends in the absence of treatment. As an additional robustness check, the conditional parallel trends assumption as outlined by Callaway & Sant'Anna (2021) is conducted, where only areas in which an IP is planned, but not yet constructed, are used as the control group. As a further robustness check, it is also tested whether the results hold under different definitions of exposure. The alternative exposure measures for the robustness checks are defined as being exposed to an IP if the distance from an individual is less than 10 km and less than 15 km to an IP.

6. Results

In the analysis, the intricate dynamics of how the exposure to IPs in Ethiopia shapes labour market outcomes and influences household economics is unveiled, shedding light on both the gender-differentiated impacts and the broader socioeconomic spillovers. The findings unravel a complex narrative, demonstrating how proximity to these economic hubs alters employment patterns, work hours allocation, household responsibilities, and food security. In addition to these direct impacts, also the indirect consequences on non-farm enterprises are investigated, exploring shifts in revenue, profitability, costs, and their role in contributing to household income. Each layer of analysis presents a piece of a larger puzzle, providing a better understanding of how these industrial developments are reshaping social and economic structures in Ethiopia. In the following, a summary of these findings is presented.

In examining the effect of IPs on labour dynamics, a core facet of the analysis focuses on the allocation of labour hours among paid work, household agricultural activities, and domestic chores. This perspective offers critical insights into how the introduction of IPs can lead to profound shifts in everyday labour practices and roles within the affected communities.

Drawing from the analysis, a tangible impact is apparent with each 100-hectare increase in built-up IP area within a 20 km radius. Specifically, such an increase leads to an additional 3.66 hours, on average, worked per week for paid labour, holding all other variables constant (Table 1, column 1). This result, which is statistically significant at the 1% level, indicates a positive relationship between the growth of IPs in the local area and the time individuals devote to paid work. Interestingly, as the definition of IP exposure is modified to include only individuals residing within a 15 km or 10 km radius from an IP it is observed that the effect on the hours worked for paid labour increases consistently. Specifically, for each 100-hectare increment in built-up IP area within a 15 km radius, an individual, on average, is expected to work an extra 5.81 hours per week in return for a wage (column 2). This effect intensifies even further with the 10 km exposure threshold, resulting in an additional 6.13 hours worked per week (column 3). Both these effects are statistically significant ($p < 0.01$). This evidence implies that the proximity to an IP plays a crucial role in influencing its impact. In this context, closer proximity to an IP corresponds to an increase in the hours spent on paid work.

Table 1: Hours Spent on Paid Labour at 20 km, 15 km and 10 km Threshold

Hours Spent on Paid Labour			
	(1)	(2)	(3)
	20 km IP	15 km IP	10 km IP
IP exposure 20 km	3.658**		
	(1.150)		
IP exposure 15 km		5.806***	
		(1.038)	
IP exposure 10 km			6.126***
			(1.351)
Sex	1.780***	1.780***	1.787***
	(0.262)	(0.262)	(0.262)
Age	0.105***	0.104***	0.104***
	(0.0138)	(0.0138)	(0.0139)
Attended School	-10.63**	-10.65**	-10.65**
	(3.441)	(3.441)	(3.440)
Highest Grade	0.142***	0.143***	0.143***
	(0.0211)	(0.0211)	(0.0211)
Constant	12.11***	11.93***	11.94***
	(3.330)	(3.330)	(3.326)
Observations	22991	22991	22991

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Notes: Coefficient estimates are obtained from OLS estimation. The dependent variable equals individuals' hours spent on paid labour in the last week. The independent variables equal the built-up IP area in 100-hectatare units.

Contrarily, the hours spent on household agricultural labour decrease by 8.39 hours per week, on average, if the built-up IP area within a 20 km radius increases by 100 hectare ($p = 0.028$) (Table 2, column 1). This result suggests a negative association between the built-up area of IPs within proximity and the hours an individual spends in agricultural labour, implying a shift from agricultural labour to paid labour as industrial areas expand. Again, when the threshold of exposure is reduced, the effect becomes stronger: a 100 hectare increase of built-up IP area within a 15 (10) km radius, is associated with individuals spending, on average, 15.46 (14.16) fewer hours per week on household agricultural labour, holding all other variables constant ($p < 0.01$)

(columns 2 and 3). These results further strengthen the inference that the expansion of IP areas is associated with a decrease in hours spent on agricultural work, and that this association is more pronounced when considering individuals closer to IPs (i.e., within a 10 or 15 km radius). The changes in the coefficients for the exposure to IP area with an exposure limit of 10 and 15 km compared to the original treatment variable suggest that the impact of IP expansion on agricultural labour might be more localised, with stronger effects observed within closer proximities. This is consistent with a narrative of rural workers transitioning from agricultural labour to industrial labour as opportunities become available closer to their homes.

In Table 3 the regression results of the analysis on gender-differentiated impacts including the interaction term between treatment and sex are shown. At a cutoff level of 20 km, women's working hours neither in paid labour nor in household agriculture are significantly affected by the exposure to IPs. Instead, the effect is only apparent for men. On average, men spend 4.87 hours more per week on paid labour and 9.82 hours less on household agricultural labour when exposed to the build-up of a 100-hectare IP (columns 1 and 2). However, when moving closer to the IP also a significant effect on women can be observed: Women spend, on average, 3.53 and 3.71 hours more on paid labour when exposed to an IP within 15 km and 10 km, respectively (columns 3 and 5). This effect is even stronger for men, expected to spend, on average, 7.01 and 7.58 hours more on paid labour per week. Especially the time spent on household agricultural labour is impacted by the build-up of an IP in close proximity. Women spend, on average, 12.74 and 11.53 hours less on agricultural activities when exposed to an IP within 15 km or 10 km, respectively (columns 4 and 6). Again, the observed effect is even stronger for men, spending 16.98 and 15.88 hours less on household agricultural labour.

Table 2: Hours Spent on Household Agricultural Labour at 20 km, 15 km and 10 km Threshold

Hours Spent on Household Agricultural Labour			
	(1)	(2)	(3)
	20 km IP	15 km IP	10 km IP
IP exposure 20 km	-8.394*		
	(3.807)		
IP exposure 15 km		-15.46***	
		(1.863)	
IP exposure 10 km			-14.16***
			(1.806)
Sex	3.950***	3.954***	3.923***
	(0.302)	(0.302)	(0.305)
Age	0.0773***	0.0790***	0.0797***
	(0.0119)	(0.0118)	(0.0118)
Attended School	3.584*	3.564*	3.531*
	(1.734)	(1.733)	(1.734)
Highest Grade	-0.0793***	-0.0797***	-0.0797***
	(0.0135)	(0.0134)	(0.0134)
Constant	3293	3.834*	3.634*
	(1.746)	(1.716)	(1.705)
Observations	23762	23762	23762

Standard errors in parentheses

* p<0.05, ** p<0.01, *** p<0.001

Notes: Coefficient estimates are obtained from OLS estimation. The dependent variable equals individuals' hours spent on household agricultural labour in the last week. The independent variables equal the built-up IP area in 100-hectatare units and interaction terms between the individuals' gender and the built-up IP area are included.

These results suggest that proximity to IPs has a significant influence on the allocation of labour hours between paid work and household agricultural work, with this effect differing between men and women. Initially, within a 20 km radius of an IP, only men seem to be affected, increasing their hours of paid work and decreasing their time spent on household agricultural labour. This effect could be due to the attraction of better or more stable income opportunities within these IPs compared to household agriculture. Men, traditionally considered primary earners, may be more likely to shift towards these new opportunities. This dynamic can also be related to gender roles, societal norms, or labour market structures that might privilege men's access to paid labour opportunities in IPs.

However, moving closer to the IP (within a 15 km or 10 km radius), the effect starts to become noticeable for women as well. Women increase their time in paid labour and decrease their time in household agricultural work, albeit to a lesser extent than men. The stronger effect for men might be due to several reasons, such as the nature of jobs available in the IPs, societal norms around gender roles, women's dual burden of work and home responsibilities, and other gender-related barriers to work.

The significant reduction in hours spent on household agricultural activities for both men and women in proximity to IPs could imply a shift in the local economy from agricultural to industrial activities. This might be due to the economic opportunities IPs bring, altering the local labour market and drawing workers into industrial jobs. It's important to consider, however, whether this shift is beneficial for these workers in the long run, particularly given the potentially precarious nature of jobs within IPs, as well as implications for food security and rural livelihoods if household agricultural activities decrease.

These patterns indicate the importance of considering gender dynamics when planning and assessing the impact of IPs. For instance, if women are increasing their time in paid labour, who is taking over the household duties they traditionally handle? Is this leading to an increased burden on women, or are household roles being renegotiated? Understanding these dynamics could provide insights for policy to ensure IPs promote inclusive and sustainable development.

Trying to answer these questions, a regression analysis of the reported hours spent on household activities is conducted (Table 4). The results exhibit that within a 20 km radius to the build-up of a 100-hectare IP, the hours spent on household activities decrease more for women (-3.54) than they do for men (-1.56) (column 1). Both results are significant at the 1% level. Interestingly, moving closer to the IP (10 km threshold), the time spent on household activities still decreases for women (-1.17) but increases for men (+1.18) (column 3). However, this effect is only significant for men ($p < 0.01$).

Within a 20 km radius of an IP, both women and men reduce their time spent on household activities, with women's reduction being more than twice that of men. This could indicate that the increased opportunities for paid work, perhaps due to the IP, are enticing both genders away from household labour, but that this effect is stronger for women. This could potentially be explained by a substitution effect: women are substituting some of their traditional household labour for the new paid work opportunities. The fact that the reduction is larger for women suggests a higher elasticity in their allocation of time between household and paid labour activities as compared to men, possibly due to traditionally spending more time on household duties.

However, as moving closer to the IP (within a 10 km radius), an intriguing divergence appears: while women continue to decrease their time spent on household activities, men actually increase theirs. It could be that as women gain more opportunities for paid work close to the IP, men may be compensating for the reduction in women's household labour by increasing their own contribution. The fact that this effect is significant for men indicates a notable shift in the gendered division of labour within households close to the IPs, with men taking on a larger share of household duties than prior to the existence of the IP. This shift implies a broader social transformation within these communities. It is also plausible that, as men's and women's work shift towards the IPs, household work previously considered 'women's work' becomes redefined as 'shared work'. These findings suggest that the influence of IPs on local economies might not just transform work outside the home but also work within the home.

However, it is important to note that the observed shifts in time allocation might also bring about new challenges and tensions, particularly if the increase in paid labour leads to a 'double burden' for women (if they still do the majority of household work) or if men face stigma or resistance for taking on more 'feminine' household tasks. Further research could help to illuminate these dynamics and their implications for gender relations and wellbeing in these communities.

Table 3: Hours Spent on Paid Labour and Agricultural Activities at 20 km, 15 km, and 10 km Threshold– Gender-Differentiated Outcomes

Hours Spent on Paid Labour and Household Agricultural Activites - Gender-Differentiated Impact

	(1)	(2)	(3)	(4)	(5)	(6)
	20 km IP - Paid Labour	20 km IP - Agriculture	15 km IP - Paid Labour	15 km IP - Agriculture	10 km IP - Paid Labour	10 km IP - Agriculture
IP exposure 20 km	1.510	-5.943				
	(1.281)	(3.784)				
Interaction 20 km * Sex	3.360***	-3.873***				
	(0.887)	(0.843)				
IP exposure 15 km			3.530**	-12.74***		
			(1.183)	(1.933)		
Interaction 15 km * Sex			3.476***	-4.241***		
			(0.948)	(1.001)		
IP exposure 10 km					3.712**	-11.53***
					(1.395)	(1.846)
Interaction 10 km * Sex					3.863***	-4.351***
					(1.012)	(1.135)
Sex	1.321***	4.387***	1.352***	4.377***	1.337***	4.328***
	(0.246)	(0.303)	(0.247)	(0.301)	(0.247)	(0.304)
Age	0.105***	0.0760***	0.105***	0.0775***	0.105***	0.0785***
	(0.0140)	(0.0120)	(0.0140)	(0.0119)	(0.0140)	(0.0119)
Attended School	-10.63**	3.575*	-10.64**	3.535*	-10.61**	3.469*
	(3.436)	(1.728)	(3.434)	(1.727)	(3.430)	(1.729)
Highest Grade	0.142***	-0.0785***	0.142***	-0.0788***	0.142***	-0.0785***
	(0.0211)	(0.0134)	(0.0211)	(0.0134)	(0.0210)	(0.0134)
Constant	12.41***	3028	12.21***	3.594*	12.20***	3.437*
	(3.310)	(1.732)	(3.308)	(1.704)	(3.300)	(1.695)
Observations	22991	23762	22991	23762	22991	23762

Standard errors in parentheses

* p<0.05, ** p<0.01, *** p<0.001

Notes: Coefficient estimates are obtained from OLS estimation. The dependent variables equal individuals' hours spent on paid labour and household agricultural labour in the last week. The independent variables equal the built-up IP area in 100-hectatare units and interaction terms between the individuals' gender and the built-up IP area are included

Table 4: Household Labour at 20 km, 15 km, and 10 km Threshold– Gender Differentiated Impacts

Household Labour - Gender-Differentiated Impacts

	(1) 20 km IP	(2) 15 km IP	(3) 10 km IP
IP exposure 20 km	-3.537**		
	(1.188)		
Interaction 20 km * Sex	1.977**		
	(0.674)		
IP exposure 15 km		-1.415	
		(1.698)	
Interaction 15 km * Sex		1.926**	
		(0.731)	
IP exposure 10 km			-1.174
			(2.068)
Interaction 10 km * Sex			2.349**
			(0.742)
Sex	-0.289	-0.258	-0.289
	(0.305)	(0.302)	(0.299)
Age	0.140***	0.140***	0.140***
	(0.0122)	(0.0122)	(0.0123)
Attended School	0.293	0.357	0.380
	(2.721)	(2.721)	(2.721)
Highest Grade	-0.0285*	-0.0293*	-0.0296*
	(0.0126)	(0.0126)	(0.0126)
Constant	3453	3128	3082
	-2797	-2798	-2800
Observations	22424	22424	22424

Standard errors in parentheses

* p<0.05, ** p<0.01, *** p<0.001

Notes: Coefficient estimates are obtained from OLS estimation. The dependent variable equals individuals' hours spent on household labour in the last week. The independent variables equal the built-up IP area in 100-hectatare units and interaction terms between the individuals' gender and the built-up IP area are included.

When observing the employment rates within the last 12 months, the likelihood of being employed when exposed to an IP seems to only significantly increase for men (Table 5). In particular, being exposed to the build-up of a 100-hectare IP is associated with a 13.28 percentage point increase in men's likelihood of being employed (column 1). This positive relationship between IP exposure and employment for men holds when only including individuals closer to the IP (columns 2 and 3). These additional findings on employment rates reinforce the observed patterns. The significant increase in likelihood of employment for men when exposed to IPs indicates that the industrial developments are primarily benefiting men in terms of job opportunities. This could further contribute to the shift from household agricultural activities to paid work, particularly for men.

However, the absence of a significant effect on women's employment likelihood suggests that women are not gaining paid employment opportunities from the IP to the same extent as men. This effect might be influenced by a variety of factors, including the nature of the jobs available in the IPs, societal norms around gender roles, and the presence of gender-related barriers to work. If the jobs offered by the IPs are traditionally male-dominated or require skills more commonly possessed by men, this could lead to an increased likelihood of employment for men.

What is observed is that while the likelihood of employment for women does not seem to change significantly when exposed to an IP, the hours spent on paid labour increase while the hours spent on agricultural activities and household labour decrease. This could indicate that only women who were already engaged in paid labour increase their working hours which would explain why an increase in hours spent on paid labour, but no significant change in overall employment likelihood for women can be observed. This dynamic could be occurring if the IPs are presenting opportunities for overtime or additional shifts for women who are already employed. Furthermore, it could be that already employed women shift from their previous occupation to an employment within an IP and their working hours increase. Besides, it could also be that domestic firms competing with firms inside the IPs or suppliers and buyers have an increased workload through the presence of the IP and therefore employees within proximity to IPs are required to work more hours. Lastly, also demand spillovers through, for example, an increased presence of workers around the IP that consume in the local shops can lead to an increased workload.

These results underscore the importance of implementing gender-inclusive policies and practices in the planning and operation of IPs. Efforts could be made to ensure that the jobs created by IPs are accessible and beneficial to both men and women, such as by providing training opportunities for women, implementing family-friendly work policies, and actively promoting gender equality within the workplaces in the IPs. In addition, further research could explore the quality and nature of the jobs that men and women are taking up in and around the IP, as well as the broader impacts on household dynamics and community wellbeing.

Table 5: Employment at 20 km, 15 km, and 10 km Threshold – Gender-Differentiated Impacts

Employment - Gender-Differentiated Impacts	(1) 20 km IP	(2) 15 km IP	(3) 10 km IP
IP exposure 20 km	0.0661		
	(0.0523)		
Interaction 20 km * Sex	0.0667***		
	(0.0195)		
IP exposure 15 km		0.0521	
		(0.0795)	
Interaction 15 km * Sex		0.0701***	
		(0.0208)	
IP exposure 10 km			0.0236
			(0.0717)
Interaction 10 km * Sex			0.0769***
			(0.0221)
Sex	0.0378***	0.0381***	0.0379***
	(0.00548)	(0.00542)	(0.00541)
Age	0.00319***	0.00320***	0.00320***
	(0.000293)	(0.000293)	(0.000293)
Attended School	-0.398***	-0.399***	-0.399***
	(0.0613)	(0.0614)	(0.0614)
Highest Grade	0.00404***	0.00405***	0.00405***
	(0.000409)	(0.000411)	(0.000411)
Constant	0.353***	0.356***	0.359***
	(0.0592)	(0.0594)	(0.0593)
Observations	28965	28965	28965

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Notes: Coefficient estimates are obtained from OLS estimation. The dependent variable is a binary indicator for individuals' employment status equalling 1 if an individual has been employed in the past 12 months, 0 otherwise. The independent variables equal the built-up IP area in 100-hectatare units and interaction terms between individuals' gender and built-up IP area are included.

For the wages of individuals exposed to IPs the results are mixed. In Table 6 the effect of exposure to IPs on the total wages and on only monthly reported wages is shown. While the effect on men's monthly reported wages within a 20 km distance from an IP seems to be positive, it decreases steadily with proximity to the IP. Even though this effect is significant for men ($p < 0.01$), when observing the total wage changes, the effect is neither clearly negative nor positive and varies greatly with proximity. For women, no significant effect on monthly nor total wages can be observed.

Since these results do not exhibit any clear effect of exposure to IPs on wages, it remains challenging to formulate a definitive interpretation. These results indicate that the impact of IPs on wages is complex and not straightforward. IPs often bring a mix of jobs into the local labour market, ranging from high-skilled to low-skilled jobs. The observed variability in wage effects could potentially reflect the diverse nature of jobs created in these IPs. The variability in wage effects could also be related to supply and demand dynamics. For example, if an IP increases the demand for labour but there is an ample supply of workers, then the increased competition could potentially dampen any positive wage effects.

Women may primarily be getting low-paid, precarious jobs in the IPs, which could explain why there's no significant wage effect observed for them. Lastly, the variability in wage effects could potentially be due to measurement issues. For example, the total wages measure might include various types of income including income from less formal jobs while the monthly wage might be reported for rather formal jobs, which could introduce variability into the findings. Also, if there's a high degree of informality in the local labour market, this could complicate the measurement of wages. While these results don't allow for a clear interpretation of the impact of IPs on wages, they do highlight the complexity of this issue. Further research might be needed to better understand these dynamics, such as qualitative studies to explore the nature of jobs created in IPs and the barriers workers face in accessing these jobs. Moreover, these findings underscore the importance of considering gender and spatial dynamics in the assessment of IPs' impact on local labour markets.

Table 6: Total Wages and Monthly Reported Wages at the 20 km, 15 km, and 10 km Threshold – Gender Differentiated Outcomes

Wages - Gender-Differentiated Impacts

	(1)	(2)	(3)	(4)	(5)	(6)
	20 km IP - Monthly Wages	20 km IP - All Wages	15 km IP - Monthly Wages	15 km IP - All Wages	10 km IP - Monthly Wages	10 km IP - All Wages
IP exposure 20 km	0.173	-0.0828				
	(0.209)	(0.183)				
Interaction 20 km * Sex	0.114**	0.140				
	(0.0407)	(0.0787)				
IP exposure 15 km			-0.0963	-0.298		
			(0.180)	(0.295)		
Interaction 15 km * Sex			0.114**	0.146		
			(0.0414)	(0.0784)		
IP exposure 10 km					-0.146	0.144
					(0.286)	(0.271)
Interaction 10 km * Sex					0.124**	0.165*
					(0.0431)	(0.0793)
Sex	0.317***	0.269***	0.318***	0.269***	0.315***	0.265***
	(0.0289)	(0.0447)	(0.0284)	(0.0442)	(0.0282)	(0.0440)
Age	0.0164***	0.0218***	0.0164***	0.0218***	0.0164***	0.0217***
	(0.00223)	(0.00258)	(0.00221)	(0.00258)	(0.00221)	(0.00260)
Attended School	-3.283***	-3.252***	-3.281***	-3.250***	-3.280***	-3.252***
	(0.321)	(0.279)	(0.321)	(0.279)	(0.322)	(0.279)
Highest Grade	0.0316***	0.0331***	0.0316***	0.0330***	0.0316***	0.0330***
	(0.00257)	(0.00267)	(0.00257)	(0.00267)	(0.00257)	(0.00265)
Constant	9.362***	11.30***	9.433***	11.35***	9.445***	11.25***
	(0.270)	(0.231)	(0.273)	(0.245)	(0.279)	(0.229)
Observations	4576	4887	4576	4887	4576	4887

Standard errors in parentheses

* p<0.05, ** p<0.01, *** p<0.001

Notes:
Coefficient estimates are obtained from OLS estimation. The dependent variables equal individuals' logarithmised total wages and logartihmised monthly reported wages. The independent variables equal the built-up IP area in 100-hectatare units and interaction terms between the individuals' gender and the built-up IP area are included.

When assessing the control variables across all regressions, a consistent pattern is apparent. Educational attainment exhibits a positive correlation with hours spent on paid labour, the likelihood of employment, and wage levels. Contrastingly, it is inversely related to the hours dedicated to agricultural labour and household labour. Similarly, progressing to higher grades is associated with more hours allocated to paid labour, a rise in the likelihood of employment and higher wages as well as less hours spent on agricultural activities and household work. Consistent with the gender-differentiated analysis, being male translates into more time allocated to both paid and agricultural work and less time for household chores, alongside an increased likelihood of employment and higher wages. Lastly, age appears to have a positive influence on all observed outcomes of interest, indicating the potential value of experience in labour market outcomes.

Alongside labour market outcomes, food security is also a key consideration in this analysis. With the observed decrease in hours spent on household agricultural work for both men and women, the ensuing impact on food security deserves further attention. While this reduction in agricultural labour could imply compromised food security, it is also possible that the potential shift towards industrialisation might enhance overall welfare levels and hence bolster food security. To this end, IP exposure within a 20 km radius exhibits a promising, albeit statistically insignificant, trend: A 100 hectare increase in the built-up IP area corresponds to a 6.57 percentage point decrease in the likelihood of experiencing food insecurity ($p = 0.212$) (Table 7, column 1). However, this pattern strengthens with closer proximity: within a 15 km and 10 km radius the probability of experiencing food insecurity decreases by 14.96 and 27.64 percentage points respectively, on average, and is statistically significant at the 1% level (columns 2 and 3). Importantly, this effect does not appear to significantly differ between men and women when considering the interaction between treatment and sex.

Table 7: Food Insecurity at 20 km, 15 km and 10 km Threshold

Food Insecurity	(1) 20 km IP	(2) 15 km IP	(3) 10 km IP
IP exposure 20 km	-0.0657 (0.0526)		
IP exposure 15 km		-0.150*** (0.0380)	
IP exposure 10 km			-0.276*** (0.0725)
Distance Population Center	-0.0000920 (0.000555)	-0.000143 (0.000541)	-0.000213 (0.000525)
Rural vs. Urban	-0.0825*** (0.0232)	-0.0802*** (0.0232)	-0.0719** (0.0243)
Education Mother	0.000230** (0.0000863)	0.000228** (0.0000860)	0.000217* (0.0000858)
Constant	0.317*** (0.0369)	0.324*** (0.0362)	0.327*** (0.0382)
Observations	50126	50126	50126

Standard errors in parentheses

* p<0.05, ** p<0.01, *** p<0.001

Notes: Coefficient estimates are obtained from OLS estimation. The dependent variable is a binary indicator equalling 1 if an individual has reported food insecurity within the past 12 months, 0 otherwise. The independent variables equal the built-up IP area in 100-hectatare units.

In addition to the actual occurrence of food insecurity, the perceived food insecurity is included as an additional measure for food security (Table 8). In the perceived food insecurity, a similar pattern can be observed: an increase of 100-hectare built-up IP area at the 20 km threshold is associated with a decrease in the likelihood of worrying about the households' food security by 10.2 percentage points, on average (column 1). Again, this effect intensifies with proximity to the IP, reducing perceived food insecurity by 16.3 percentage points with a 15 km threshold. When controlling for the gender-differentiated impact, the magnitude of the effect is similar for both men and women, but the significance level is higher for women ($p < 0.05$) than it is for men ($p < 0.1$ at 20 and 15 km threshold, $p > 0.15$ at 10 km threshold) (see Appendix Table 15). The consistent signs and similar magnitudes of the control variables across both regressions suggest that the model is reliable and that the relationships between the control variables and the outcomes of interest (food security and perceived food insecurity) are consistent, which strengthens the confidence in the results and the validity of the control variables. Interestingly, one deviation emerges in the context of urban versus rural household location: residing in urban areas appears to be positively correlated with perceived food insecurity, yet inversely associated with actual instances of food insecurity. This discrepancy deserves further exploration, potentially indicating a disparity between perceptions and reality of food security among urban households.

These findings suggest a positive relationship between the establishment of IPs and local food security. The reduction in household agricultural labour due to IP exposure might initially raise concerns about the capacity of households to secure their own food. However, these fears do not seem to manifest in the data, with food security apparently improving with closer proximity to IPs. This might be due to the income effect: the establishment of IPs could provide new income opportunities, allowing households to purchase food even if they are spending less time in agricultural production. This could also explain why the worry about food security decreases with IP exposure. However, while this pattern is encouraging, it's also important to interpret these findings in context. Food security is a multifaceted issue that can be influenced by a multitude of factors, including the prices and availability of food in the local market, and broader socioeconomic conditions. Future research could delve further into these dynamics to better understand the specific mechanisms through which IPs impact food security. Moreover, the impact on nutritional quality of the diet, an aspect of food security not captured in this study, could be a valuable area for further exploration.

Table 8: Perceived Food Insecurity at 20 km, 15 km, and 10 km Threshold

Perceived Food Insecurity			
	(1)	(2)	(3)
	20 km IP	15 km IP	10 km IP
IP exposure 20 km	-0.102**		
	(0.0381)		
IP exposure 15 km		-0.163***	
		(0.0215)	
IP exposure 10 km			-0.153***
			(0.0347)
Distance Population	-0.000749*	-0.000787*	-0.000778*
Center	(0.000339)	(0.000347)	(0.000341)
Rural vs. Urban	0.0381	0.0399*	0.0422*
	(0.0203)	(0.0202)	(0.0205)
Education Mother	0.000333***	0.000333***	0.000330***
	(0.0000844)	(0.0000843)	(0.0000840)
Constant	0.124***	0.128***	0.122***
	(0.0307)	(0.0301)	(0.0298)
Observations	50192	50192	50192

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Notes: Coefficient estimates are obtained from OLS estimation. The dependent variable is a binary indicator equalling 1 if an individual has reported being concerned regarding food insecurity within the past week, 0 otherwise. The independent variables equal the built-up IP area in 100-hectatare units.

To measure for spillover effects, the analysis employed a fixed effects regression model to estimate the effect of exposure to the built-up area of an IP (measured in 100 hectares within a span of 20 km) on several outcomes of non-farm enterprises. Specifically, the monthly revenue, costs, profit (all measured in BIRR and logarithmised) and income share that the non-farm enterprise contributes to the household income were taken into account. Controlling for rural vs. urban locations and accounting for year and woreda fixed effects, the model did not find a statistically significant impact of treatment on the income share that the firm contributes to the household income when applying the exposure measure threshold of 20 km. This means that it cannot confidently be asserted that the observed effect is not due to random chance. Since the 95 % confidence interval for the treatment effect ranges from negative to positive values, one cannot even conclude whether exposure to IP has a positive, negative or null effect on the share of household income contribution. However, the effect on revenue, costs and profit is positive and statistically significant. In Table 9, the regression results are shown. A 100-hectare increase in built-up IP area within a 20 km radius is associated with a 44.36 % increase in revenue (p = 0.00), a 77.31 % decrease in costs (p = 0.01) and a 12.76 % increase in profits (p = 0.01), on average. This suggests that the spillover effects of IPs on local non-farm enterprises are sizeable. When observing the effects in a linear instead of a log model, the results stay consistent. Furthermore, when transforming the profit variable through taking the log transformation of the absolute value of profit and then reinstating the sign, the observed effect is even larger. The results are in line with the findings by Hoekman et al. (2023), finding that FDI is associated with an increase in productivity and sales for firms exposed to the demand of FDI firms.

Table 9: Non-Farm Enterprises at 20 km Threshold

Non-Farm Enterprises	(1)	(2)	(3)	(4)
	Income Share	Revenue	Costs	Profit
SEZ-exposure 20 km	0.0206	0.444***	-0.773*	0.128*
	(0.0934)	(0.0634)	(0.303)	(0.0497)
Rural	0.858***	0.563***	0.870***	0.0417
	(0.124)	(0.137)	(0.225)	(0.0422)
Constant	1.298***	5.380***	4.141***	7.248***
	(0.187)	(0.202)	(0.332)	(0.0593)
Observations	6696	4711	5557	4475

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Notes: Coefficient estimates are obtained from OLS estimation. The dependent variables are household's non-farm enterprise income share of total household income (ordinal category ranging from 1 - almost nothing – to 5 – all), revenue (logarithmised), costs (logarithmised) and profits (logarithmised) within last 12 months. The independent variables equal the built-up IP area in 100-hectatare units.

However, when moving to the robustness check, an interesting shift in the results can be observed. Narrowing down the IP exposure threshold from 20 km to 10 km, exhibits a significant influence on the observed impact of IPs on non-farm enterprises. In Table 10 the regression results with the 10 km cutoff radius are shown. In column (2) and (3) it can be observed that a 100-hectare increase in the IP area is associated with a 206.33 % increase in the monthly revenue and a 98.48 % decrease in the monthly costs of non-farm enterprises, on average. This translates into a positive effect on the firm profit: A 100-hectare increase in the built-up IP area is associated with a 34.33 % increase in the monthly profit (column 4). Furthermore, an increase in exposure to a 100-hectare IP area is associated with an approximate 0.489 increase in the ordinal category (ranging from 1 to 5) of the enterprises' contribution to household income. For instance, if the income from a non-farm enterprise in an area without any IP contributes to the total household income in terms of the ordinal category 2 (translates into around 25%), the build-up of a 100-hectare IP is associated with an increase to the ordinal categorical value of 2.489, i.e., moving up almost half a category. This suggests that exposure to an IP within a 10 km radius is associated with an increase in the share of non-farm enterprises' income contributing to the total household income. All effects are significant at the 1 % level. Furthermore, the control for whether enterprises are located in rural or urban areas reveals a consistent positive correlation across all outcomes of interest. This suggests that being situated in an urban location is associated with higher revenue and costs as well as a higher share contributed to total household income for non-farm enterprises.

Table 10: Non-Farm Enterprises at 10 km Threshold

Non-Farm Enterprises

	(1) Income Share	(2) Revenue	(3) Costs	(4) Profit
SEZ-exposure 10 km	0.489***	2.063***	-0.985***	0.343***
	(0.127)	(0.302)	(0.166)	(0.0628)
Rural	0.855***	0.553***	0.874***	0.0393
	(0.123)	(0.139)	(0.226)	(0.0416)
Constant	1.256***	5.286***	4.138***	7.240***
	(0.186)	(0.207)	(0.333)	(0.0581)
Observations	6696	4711	5557	4475

Standard errors in parentheses

* p<0.05, ** p<0.01, *** p<0.001

Notes: Coefficient estimates are obtained from OLS estimation. The dependent variables are household's non-farm enterprise income share of total household income (ordinal category ranging from 1 - almost nothing – to 5 – all), revenue (logarithmised), costs (logarithmised) and profits (logarithmised) within last 12 months. The independent variables equal the built-up IP area in 100-hectatare units.

Overall, these results suggest that the presence of an IP has a substantial impact on non-farm enterprises, especially within close proximity to the IPs (10 km). This impact seems to downsize with a larger radius of 20 km, suggesting that geographical proximity plays a crucial role in the transmission of potential economic spillovers. There are several possible explanations for these results. Firstly, the positive results could be due to agglomeration economies, referring to the benefits that firms obtain by locating near each other (Hoekman et al., 2023; Lu et al., 2019; Monga, 2011). Proximity to an IP often means better access to infrastructure like roads, electricity, and telecommunications. Non-farm enterprises closer to the IP could leverage these to improve their operations, hence enhancing their profits and revenue and reducing their costs. Secondly, IPs can foster innovation and knowledge sharing due to the concentration of businesses. Non-farm enterprises within proximity could benefit from these knowledge spillovers, allowing them to adopt new techniques or technologies, thereby improving their performance (Monga, 2011). Furthermore, IPs often create dense networks of suppliers and customers (Crescenzi & Limodio, 2021; Monga, 2011). Businesses within close proximity can more easily become part of this network, either supplying the firms within the IP or using the outputs of these firms as inputs for their own business. This interconnectedness can lead to increased business opportunities and hence better financial performance. When observing the industries of the firms around the 10 km of the IPs, this could especially be the case for the 10.02 % of the firms in manufacturing and the 13.18 % in transport and storage. However, the major group (38.14 %) of firms are in the industry of wholesale and retail trade as well as repair of vehicles (group 7). These enterprises are more likely to benefit from demand spillovers. For example, the employees working in the IP and in the firms supplying it might spend their wages on local goods and services, creating additional demand for non-farm enterprises located nearby. As for why the impacts were larger closer to the IP, the closer the non-farm enterprises are to the IP, the more likely they are to benefit from agglomeration economies, hence, the greater the impact on their revenue and costs. As the distance from the IP increases, so too might the transaction costs associated with interacting with the IP (such as transport costs, communication costs, etc.). These higher transaction costs could partially negate the benefits of proximity to the IP for enterprises located 20 km away.

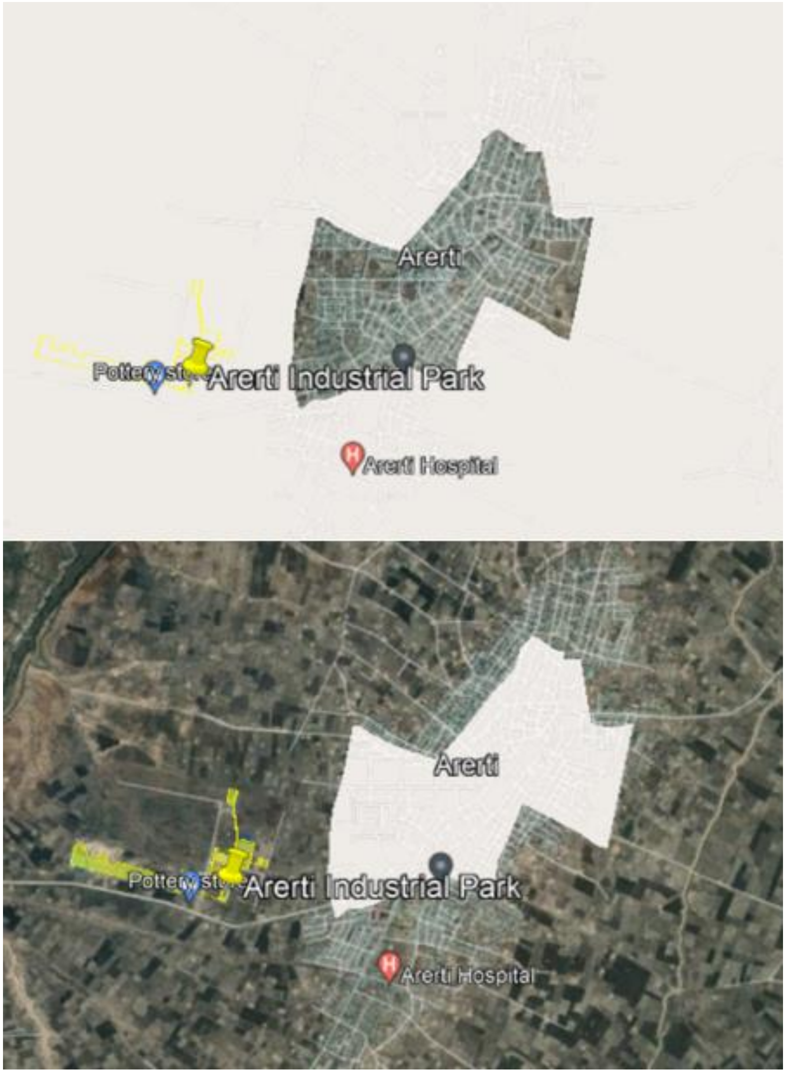
Several placebo regressions are run to test for the validity of the results. For the placebo regressions the health section of the LSMS data is exploited assuming that the presence of IPs should not have a significant impact on health outcomes and medical visits. The outcomes of interest used are whether the individual received any medical assistance and the number of health visits in the last 12 months, recent health problems and the number of absent days due to illness. The exposure to IPs does not show any significant effect in any of the regressions. These placebo regressions further strengthen the credibility of the results. Specifically, if the presence of IPs had a broad and indiscriminate impact on all facets of life, one might expect to see significant effects in areas like health outcomes and medical visits. But the absence of such effects in the placebo tests suggests that the estimated effects in the labour market are not simply artifacts of broad societal or economic shifts accompanying the introduction of IPs. Instead, these labour market effects are more likely to be genuine responses to the direct influences of IPs, strengthening the credibility of the findings.

7. Discussion

Most academic papers that conduct an empirical analysis of the impact of FDI or IPs in Ethiopia, such as Crescenzi & Limodio (2021) or Abebe et al. (2022), study the effects at the woreda-level (district-level). Initially, the idea was to also conduct the analysis at the woreda-level and consider individuals as treated that live in a woreda containing at least one built-up IP. However, after a closer analysis of the woreda structure in Ethiopia, it became clear that this geographical unit of analysis would not accurately capture the treated individuals. In most cases it would actually exclude the individual that have most likely been treated, i.e., affected by the build-up of IPs. In Ethiopia it is frequently the case that the outskirts of a city are classified as another woreda than the city itself. Mostly, IPs are located just outside the city centre and therefore falling into a different woreda than the city. However, when observing the landscapes around IPs on satellite images, one can observe that residential areas are rarely in proximity to the IPs. Instead, the closest residential area is typically located in the city. A visual example is demonstrated in Figure 8, where Arerti IP, located in the Amhara region, is pictured. In the upper image, the woreda Minjar Shenkora is coloured in white, while the Arerti town district is the area within that is not coloured. The yellow placemark identifies the location of the Arerti IP that is located just outside the Arerti town woreda. In the bottom image the Arerti town district is coloured in white. The visible area around the Arerti town woreda is the Minjar Shenkora woreda, in which the Arerti IP is located in. There, it is observable that the IP is mainly surrounded by fallow land. Hence, only using the Minjar Shenkora woreda as the unit of analysis might not include individuals living closest to the IP. Instead, it would exclude all the individuals living in the Arerti town woreda even though they might have been affected by the built-up of the Arerti IP. The geographic structure is similar for the IPs in Bahir Dar, Asosa, Bishoftu, Dukem, Yirgalem, Bure and Semera.

The selection of the geographical unit of analysis bears substantial implications for the validity of the findings. Specifically, the woreda-level unit of analysis may inadvertently exclude a critical group from the study. This exclusion could lead to biased or misleading results, as the omitted group might even be the group most likely to be impacted by the treatment. Therefore, to enhance the accuracy, robustness, and representativeness of the analysis, it is crucial to reconsider the geographical unit of analysis in order to better capture the treated individuals. By choosing to include all individuals within a 20 km radius of the IP, it is ensured that also the individuals in the close-by town woreda are included in the analysis.

Figure 8: Woredas Arerti IP



Notes: Above Minjar Shenkora woreda in white, below Arerti town woreda in white

The modification of the coordinates in the ESS data could potentially pose an issue to the analysis since the coordinate modification introduces a degree of uncertainty about the exact location of households. This uncertainty is relatively small in urban areas, with a maximum offset of 2 km, but it can be larger in rural areas, where the maximum offset is up to 5 km. In a small proportion of cases (1% of EAs), the maximum offset can be as large as 10 km. Thus, for households that are near the 20 km cutoff, the coordinate modification could potentially misclassify some households, causing them to fall either within or outside of the 20 km exposure boundary erroneously. For example, if a household is actually 19 km from an IP but the offset is 2 km, it would appear to be

21 km away, outside the exposure cutoff. Conversely, if a household is 21 km away, but the offset is -2 km, it would appear to be 19 km away and thus within the exposure cutoff. While this level of noise may not significantly impact overall trends and conclusions, especially with the sample size being relatively large, it could introduce some level of measurement error, particularly at the boundaries of the exposure cutoff. To deal with this issue, robustness checks are introduced that use an exposure threshold of 10 and 15 km. These robustness checks show that the effect of exposure to IP actually becomes stronger with vicinity and provide additional reassurance in the validity of the findings.

One drawback of the analysis, however, is that the exogeneity assumption, i.e., that the treatment rollout over time is exogenous to relevant third variables, cannot be tested. Conditional on all included covariates and fixed effects, the creation of new and growth of existing IPs should be independent of other unobserved factors influencing the socioeconomic conditions considered (Rude, 2020). Thus, the treatment needs to be exogenous to satisfy the parallel trends assumption, i.e., requires that the average outcomes of the treated individuals with IP exposure and individuals in the control group with no IP exposure would have followed “parallel trends” in the absence of treatment. If IPs were systematically allocated and established around individuals and non-farm enterprises, whose trends in the observed outcomes differed from those without IPs this assumption would be violated. However, the selection of the IPs is not random and instead is based on a distributional approach: each region in Ethiopia receives one IP. While this approach would not pose significant challenges for the analysis, the second step in which the exact location of the IPs is determined raises concerns: the exact location selection depends, among others, on the linkage to regional airports, railway, and roads. It is likely to assume that individuals’ labour market outcomes and socioeconomic conditions in such well-connected locations might be influenced by these unobserved factors. The woreda structure typically differs among woredas, with urban woredas having, among others, better infrastructure while rural woredas often lack sufficient infrastructure such as paved roads. By introducing woreda fixed effects and controlling for rural vs. urban locations this difference might be minimised. However, there could be time-varying factors at the woreda level that affect both outcome variables and the rollout of treatment. To further test for this assumption, a regression could be run, in which the built-up area of IPs is the outcome variable, and several pre-treatment covariates such as access to infrastructure could be introduced as potential explanatory variables. Alternatively, they could be used as control variables in the main analysis. While the data used in this paper does not contain such variables, an additional dataset containing this information could be included in the analysis of future research.

To address these identification challenges, robustness checks as outlined by Callaway & Sant'Anna (2021) addressing the conditional parallel trends assumption are conducted where only individuals living in areas in which an IP is planned, but not yet constructed, are used as the control group. This method reduces the sample size substantially to 12,487 individuals. As well as that, the treatment group is with 10,523 individuals amounting to around 84 % of the sample substantially larger than the control group which contains only 1,964 individuals equalling around 16 % of the sample. The majority of the observed effects are in line with previously identified trends. In particular, the time allocated to paid labour increases for both men and women while the time spent on agricultural activities decreases for both men and women when exposed to IPs (see Appendix, Table 16). The likelihood of employment increases, interestingly especially for women (see Appendix, Table 17). The food insecurity and perceived food insecurity decreases with vicinity to an IP, while this effect is again especially strong for women (see Appendix, Table 18). In contrast to previous findings, the hours spent on household labour seem to increase with exposure to IPs (see Appendix, Table 16). Furthermore, wage levels seem to decrease at 20 and 15 km threshold levels while they increase sizably and significantly with 58.35 percent at the 10 km threshold (see Appendix, Table 19). Overall, these results strengthen the confidence in previous findings and further highlight the importance of proximity to the IP, with individuals on average experiencing greater benefits at the 10 km threshold than the 20 km threshold.

8. Conclusion

The aim of this paper is to shed light on the impact of IPs on the local population in Ethiopia by examining labour market, socioeconomic and food security outcomes as well as indirect spillovers on non-farm enterprises. Using a Staggered DiD framework with year and woreda fixed effects, clustered at the woreda-level the causal relationship is analysed. A special focus is put on the gender-dynamics of the outcomes, trying to identify whether the impact differs among men and women by employing an interaction term between gender and treatment. Furthermore, a rather novel approach using the actual built-up area of IPs by obtaining the data through satellite imagery from Google Earth Pro is used to proxy for the exposure intensity to IPs. Viewing satellite imagery, the importance of using an alternative to a binary approach becomes obvious: the IPs grow substantially over time. Therefore, the impact on outcomes such as job creation or income effects also varies significantly depending on the actual size of those areas. In the first year of existence, the IPs are frequently still very small with on average 11 hectares. However, in their final stage observed in this analysis, they occupy an average of 58 hectares per IP, with the largest IP amounting to around 264 hectares. Hence, using a binary approach would not account for this considerable variation in size over time. Additionally, recent research has shown that a spatial approach explains more of the variation in firm-turnover than the frequently used alternative approach employing nighlight data (Bilicka & Seidel, 2022).

The analysis touches upon several dimensions, starting with the allocation of time between paid labour, household agricultural activities and household work. The introduction of IPs significantly influences labour dynamics within a 20 km radius, primarily affecting men, leading to an increase in their hours of paid work and a decrease in their time spent on agricultural labour. As the threshold is reduced to a 15 km or 10 km radius, a similar impact becomes noticeable for women, albeit to a lesser extent. This shift from agricultural to industrial work could indicate a transformation in the local economy, raising questions around the long-term benefits in terms of food security and supply. The differential effect on men and women suggests the importance of considering gender dynamics in the planning and evaluation of IPs. Lastly, the reduction in time spent on household activities especially for women hints at a broader social transformation within communities surrounding IPs, with the gendered division of labour within households appearing to be redefined.

Besides, exposure to IPs significantly increases men's likelihood of employment, a shift that supports the transition from agricultural activities to paid work. This employment effect, however, does not seem to extend to women, according to the main analysis. Yet, women already engaged in paid work appear to increase their working hours, suggesting IPs could be providing opportunities for overtime or additional shifts. Furthermore, in a subsequent robustness check, using only individuals that will be treated in the future but are not treated yet as a control group, especially women’s likelihood of employment seems to be positively affected by the exposure to IPs. This finding underscores the need for further research to fully understand the impact of IPs on women's employment opportunities. Similarly, the effect of IPs on wages is complex and inconclusive. While exposure to IPs is associated with an increase in men's reported monthly wages, this effect seems to diminish with closer proximity. For women, no significant wage effect is observed, further emphasising the need for more in-depth investigation into the quality of jobs created by IPs.

Given that the majority of IPs in Ethiopia are specialised in the textile and apparel sector – a sector known for high turnover rates, low wages, and difficult working conditions – it is likely that these factors are contributing to the mixed findings for wages and likelihood of employment (Blattman & Dercon, 2018). At the same time, the textile and clothing sector typically offers employment opportunities to young, unskilled women (ILO, 2022). While this would match the increase in women’s employment likelihood observed in the robustness check, such a trend cannot be observed in the main analysis. However, the low wages paid in this sector could explain the mixed findings for women's wages. These mixed findings underscore the importance of further research into the quality of jobs IPs create, especially for women, and their broader impacts on household dynamics and community well-being.

To measure for other socioeconomic impacts of the exposure to IPs, food security outcomes are observed. The findings suggest that exposure to IPs within a 20 km radius is associated with a decrease in food insecurity, and that this effect strengthens with closer proximity. A similar pattern emerges in perceived food insecurity, with the likelihood of being concerned about food security decreasing with IP exposure. Importantly, this positive impact does not significantly differ between men and women. Intriguingly, urban households show a discrepancy, having a positive correlation with perceived food insecurity but an inverse association with actual instances of food insecurity. The observed reduction in agricultural labour due to IP exposure does not appear to compromise food security, potentially due to new income opportunities allowing households to purchase food. However, food security is complex and influenced by various factors, necessitating further research to understand the specific mechanisms through which IPs impact food security and the nutritional quality of diets. Supported by UNIDO, four Integrated Agro Industrial Parks are developed by the Government of Ethiopia with the aim to achieve overall agricultural transformation of the country (IAIP, 2023). This could potentially further contribute to enhancing food security. The actual impact of these IPs on food security could be studied in future research.

Interestingly, the study found significant spillover effects from IPs on non-farm enterprises, especially within close proximity (10 km). Exposure to IPs was associated with a substantial increase in monthly revenue and profit, alongside a significant decrease in costs. The effects were less pronounced at a 20 km radius, indicating the crucial role of geographical proximity in economic spillovers. Importantly, proximity to an IP was also linked with an increased contribution of non-farm enterprise income to overall household income. These results might be attributed to demand spillovers or agglomeration economies, where businesses located near each other benefit from shared infrastructure, innovation, and knowledge, along with the establishment of dense supplier and customer networks. However, the greater the distance from the IP, the higher the transaction costs, which could offset the benefits of proximity for enterprises located further away. These findings suggest that IPs can have a substantial positive impact on local non-farm enterprises, particularly those in close proximity.

Placebo regressions and robustness checks further validate the study's findings about the positive impact of IPs. The absence of significant effects on health outcomes and medical visits in placebo regressions suggests that the identified labour market impacts are likely direct responses to IPs, rather than broad societal shifts. Robustness checks using a smaller control group of areas where

IPs are planned but not yet built also confirmed earlier trends. However, unlike previous results, hours spent on household labour seemed to increase, and wage levels showed varied effects based on proximity to the IP.

Within this year, a new wave of LSMS data will be released, which would allow including more recent data in the analysis. Currently, the last available survey data covers a period up until 2019, but the satellite imagery is typically available until 2022, depending on the exact location. In future research, the newest survey wave could be added to the existing data and allow for an analysis that includes recently constructed IPs such as the Integrated Agro Industrial Parks.

Overall, the impact of IPs on the local population in Ethiopia seems to be positive, increasing likelihood of employment, a shift in time allocation from agriculture to paid labour while simultaneously enhancing food security. However, wages do not seem to be significantly impacted, which leads to questions about the quality of employment that is generated through IPs. Further research should focus on evaluating the quality of employment. Furthermore, overall men seem to benefit more from the IPs than women. This highlights the importance of implementing gender-inclusive policies. To ensure that the jobs created by IPs are accessible and beneficial to both men and women, provision of training opportunities for women, the implementation of family-friendly work policies, and active promotion of gender equality within the workplaces could be enhanced.

9. References

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10. Appendix

Table 11: Zero Polygons

Year	2009	2012	2013	2015	2016	2017	2018	2019	2020	2021	2022	Total
Number IPs	1	1	1	4	5	5	1	2	3	1	2	26

Table 12: Year First Construction Visible

Year	2010	2013	2015	2016	2017	2018	2019	2020	No Construction	Total
Number IPs	1	2	2	3	5	5	2	1	5	26

Table 13: Occupation Codes

Code	Description
01	Legislators, Senior Government Officials and Managers
02	Professionals/ Physical, Mathematical and Engineering Science Professionals
03	Technicians and Associate Professionals/ Physical and Engineering Science Associate Professionals
04	Clerks, Office clerks
05	Service Workers and Shop and Market Sales Workers/ Personal and Protective Service workers, Travel attendants and related workers
06	Skilled Agricultural and Fishery Workers Market-Oriented Skilled Agricultural and Fishery Workers
07	Craft And Related Trades Workers, Extraction and Building Trades Workers
08	Plant and Machine Operators and Assemblers, Stationary-Plant and Related Operators
09	Elementary Occupations, Sales and Services Elementary Occupations
10	Army/ Member of the Armed Forces

Table 14: Industry Code

01	Agriculture, Hunting, Forestry and Production of Related Products and Services
02	Fishing, Fish Farms and Service Activities Incidental to Fishing
03	Mining and Quarrying
04	Manufacturing
05	Electricity, Gas, Steam and Hot Water Supply
06	Construction, Site Preparation, Land Clearing
07	Wholesale and Retail Trade, Repair of Vehicles, Personal and Household Goods/ Sale, Maintenance and Repair of Motor Vehicles and Motorcycles; Retail, Sale of Automotive Fuel
08	Hotels and Restaurants/ Hotels (With Hotel Rooms); Camping Sites and Other Provision of Short-Stay Accommodation
09	Transport, Storage and Communications/ Land Transport – People and Merchandise
10	Financial Intermediation (Except Insurance and Pension Funding)
11	Real Estate, Renting and Business Activities
12	Public Administration and Defense, Compulsory Social Security
13	Education
14	Health and Social Work
15	Other Social, Cultural, Personal and Household Activities Including Sewage and Refuse Disposal, Sanitation, and Similar Activities
16	Private Households with Employed Persons
17	Extra-Territorial Organisations and Bodies including International Organisations and NGOs

Table 15: Perceived Food Insecurity at 20 km, 15 km, and 10 km Threshold – Gender Differentiated Impact

Perceived Food Insecurity - Gender-Differentiated Impact			
	(1) 20 km IP	(2) 15 km IP	(3) 10 km IP
IP exposure 20 km	-0.0966* (0.0377)		
Interaction 20 km * Sex	-0.0105 (0.00611)		
IP exposure 15 km		-0.158*** (0.0216)	
Interaction 15 km * Sex		-0.0113 (0.00664)	
IP exposure 10 km			-0.148*** (0.0350)
Interaction 10 km * Sex			-0.0101 (0.00710)
Distance Population Cen	-0.000748* (0.000339)	-0.000787* (0.000347)	-0.000778* (0.000341)
Rural vs. Urban	0.0381 (0.0203)	0.0398* (0.0202)	0.0421* (0.0205)
Education Mother	0.000332*** (0.0000845)	0.000332*** (0.0000844)	0.000329*** (0.0000842)
Constant	0.124*** (0.0307)	0.128*** (0.0301)	0.122*** (0.0298)
Observations	50192	50192	50192

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Notes: Coefficient estimates are obtained from OLS estimation. The dependent variable is a binary indicator equalling 1 if an individual has reported being concerned regarding food insecurity within the past week, 0 otherwise. The independent variables equal the built-up IP area in 100-hectatare units and interaction terms between individuals' gender and built-up IP area are included.

Table 16: Robustness Check Hours Spent on Paid Labour, Household Agricultural Activities and Household Work at 20 km, 15 km, and 10 km Threshold

Hours Spent on Paid Labour, Household Agricultural Activities and Household Work

	(1) 20 km IP - Paid Labour	(2) 20 km IP - Agriculture	(3) 20 km IP - Household Work	(4) 15 km IP - Paid Labour	(5) 15 km IP - Agriculture	(6) 15 km IP - Household Work	(7) 10 km IP - Paid Labour	(8) 10 km IP - Agriculture	(9) 10 km IP - Household Work
IP exposure 20 km	1.755	-11.50***	1826						
	(3.092)	(2.003)	(2.344)						
IP exposure 15 km				3663	-13.52***	3230			
				(2.261)	(2.024)	(1.721)			
IP exposure 10 km							5.105*	-10.76	3099
							(2.093)	(5.571)	(1.722)
Sex	3.728***	1.438**	1.680*	3.723***	1.448**	1.675*	3.742***	1.357**	1.690*
	(0.555)	(0.445)	(0.668)	(0.556)	(0.450)	(0.668)	(0.551)	(0.429)	(0.665)
Age	0.126***	0.0281*	0.155***	0.126***	0.0292*	0.155***	0.125**	0.0307*	0.154***
	(0.0368)	(0.0123)	(0.0289)	(0.0369)	(0.0124)	(0.0291)	(0.0371)	(0.0129)	(0.0292)
Attended School	1332	1458	2178	1373	1369	2212	1439	1279	2231
	(6.811)	(1.544)	(5.529)	(6.809)	(1.541)	(5.530)	(6.806)	(1.537)	(5.531)
Highest Grade	0.0905*	-0.0175	-0.0279	0.0900*	-0.0164	-0.0283	0.0892*	-0.0156	-0.0285
	(0.0399)	(0.0154)	(0.0280)	(0.0398)	(0.0149)	(0.0280)	(0.0395)	(0.0145)	(0.0280)
Constant	5917	6.326***	0.137	5113	6.578***	-0.407	4555	5066	-0.259
	(6.692)	(1.594)	(5.926)	(6.593)	(1.564)	(5.848)	(6.574)	(2.566)	(5.838)
Observations	5948	5120	5402	5948	5120	5402	5948	5120	5402

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Notes: Coefficient estimates are obtained from OLS estimation. The dependent variables equal individuals' hours spent on paid labour, household agricultural labour and household labour in the last week. The independent variables equal the built-up IP area in 100-hectatare units.

Table 17: Robustness Check Employment at 20 km, 15 km, and 10 km Threshold – Gender Differentiated Outcomes

Employment - Gender-Differentiated Outcomes

	(1) 20 km IP	(2) 15 km IP	(3) 10 km IP
IP exposure 20 km	0.182***		
	(0.0514)		
Interaction 20 km * Sex	0.0156		
	(0.0256)		
IP exposure 15 km		0.151***	
		(0.0377)	
Interaction 15 km * Sex		0.0206	
		(0.0257)	
IP exposure 10 km			0.0787
			(0.0498)
Interaction 10 km * Sex			0.0276
			(0.0272)
Sex	0.0799***	0.0783***	0.0765***
	(0.0152)	(0.0142)	(0.0141)
Age	0.00374***	0.00374***	0.00374***
	(0.000701)	(0.000702)	(0.000703)
Attended School	-0.211*	-0.211*	-0.210*
	(0.103)	(0.103)	(0.103)
Highest Grade	0.00308***	0.00307***	0.00306***
	(0.000698)	(0.000697)	(0.000696)
Constant	0.123	0.145	0.180
	(0.104)	(0.102)	(0.101)
Observations	7284	7284	7284

Standard errors in parentheses

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Notes: Coefficient estimates are obtained from OLS estimation. The dependent variable is a binary indicator equalling 1 if an individual has reported food insecurity within the past 12 months, 0 otherwise. The independent variables equal the built-up IP area in 100-hectatare units and interaction terms between individuals' gender and built-up IP area are included.

Table 18: Food Insecurity and Perceived Food Insecurity at 20 km, 15 km, and 10 km Threshold – Gender-Differentiated Outcomes

Food Insecurity and Perceived Food Insecurity - Gender-Differentiated Outcomes

	(1) 20 km IP - Food Insecurity	(2) 20 km IP - Perceived Food Insecurity	(3) 15 km IP - Food Insecurity	(4) 15 km IP - Perceived Food Insecurity	(5) 10 km IP - Food Insecurity	(6) 10 km IP - Perceived Food Insecurity
IP exposure 20 km	-0.0915	-0.197***				
	(0.132)	(0.0478)				
Interaction 20 km * Sex	0.00338	-0.0106				
	(0.00616)	(0.00630)				
IP exposure 15 km			-0.145	-0.202***		
			(0.105)	(0.0338)		
Interaction 15 km * Sex			0.00380	-0.0108		
			(0.00651)	(0.00683)		
IP exposure 10 km					-0.0965*	-0.413***
					(0.0428)	(0.0957)
Interaction 10 km * Sex					-0.00935	0.00568
					(0.00720)	(0.00434)
Distance Population Center	0.0122***	0.00692*	0.0106**	0.00487	0.00572	0.00542
	(0.00357)	(0.00287)	(0.00342)	(0.00300)	(0.00314)	(0.00310)
Rural vs. Urban	-0.0195	0.0432	-0.0281	0.0287	0.0520*	0.0343
	(0.0209)	(0.0252)	(0.0200)	(0.0258)	(0.0222)	(0.0203)
Education Mother	0.000337**	0.000605***	0.000341**	0.000609***	0.000601***	0.000332*
	(0.000127)	(0.000126)	(0.000128)	(0.000126)	(0.000126)	(0.000128)
Constant	0.107	0.0917	0.153	0.125	0.0240	0.191*
	(0.0926)	(0.0672)	(0.0817)	(0.0675)	(0.0658)	(0.0742)
Observations	10954	10958	10954	10958	10958	10954

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Notes: Coefficient estimates are obtained from OLS estimation. The dependent variables are binary indicator equalling 1 if an individual has reported food insecurity within the past 12 months or was concerned about food insecurity within the past week, 0 otherwise. The independent variables equal the built-up IP area in 100-hectatare units and interaction terms between the individuals' gender and the built-up IP area are included

Table 19: Robustness Check Total Wages at 20 km, 15 km, and 10 km Threshold

Total Wages			
	(1)	(2)	(3)
	20 km IP	15 km IP	10 km IP
IP exposure 20 km	-1.945**		
	(0.593)		
IP exposure 15 km		-1.198***	
		(0.118)	
IP exposure 10 km			0.583**
			(0.213)
Sex	0.379***	0.379***	0.379***
	(0.0546)	(0.0547)	(0.0548)
Age	0.0218***	0.0219***	0.0218***
	(0.00408)	(0.00409)	(0.00407)
Attended School	-2.876***	-2.891***	-2.870***
	(0.376)	(0.380)	(0.373)
Highest Grade	0.0289***	0.0290***	0.0287***
	(0.00333)	(0.00339)	(0.00327)
Constant	12.19***	11.75***	10.80***
	(0.454)	(0.299)	(0.304)
Observations	2272,00	2272,00	2272

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Notes: Coefficient estimates are obtained from OLS estimation. The dependent variables equal individuals' logarithmised total wages. The independent variables equal the built-up IP area in 100-hectatare units.

Table 20: Descriptive Statistics for Variables in Individual-Level Analysis

Descriptive Statistics - Individuals

	(1)	(2)	(3)	(4)	(5)
Variables	Obs	Mean	Std. Dev.	Min	Max
Hours Paid Labour	40503	4.735	15.058	0	106
Hours Agriculture	43926	11732	17.071	0	100
Hours Household Labour	40159	5.76	15.574	0	108
Employment	51697	.077	.266	0	1
Total Wage (log)	5772	9365	1.31	0	11.27
Monthly Reported Wage (log)	5172	7.42	.987	2996	11.695
Food Insecurity	66229	.223	.416	0	1
Perceived Food Insecurity	66346	.167	.373	0	1
Sex	64626	.482	.5	0	1
Rural vs. Urban	66391	1329	.47	1	2
Attendance School	56343	1422	.494	1	2
Highest Grade	32589	11817	12.581	0	99
Education Mother	50498	84.321	32.391	0	99
Distance Population Center	66105	33.054	33.683	0	285.1

Table 21: Descriptive Statistics for Variables in Household-Level Analysis

Descriptive Statistics - Non-Farm Enterprises

	(1)	(2)	(3)	(4)	(5)
Variables	Obs	Mean	Std. Dev.	Min	Max
Total Household Income Share	6737	2586	1356	1	5
Monthly Sales (log)	4776	6254	1569	0	8902
Monthly Costs (log)	5610	5331	23774	0	8903
Monthly Profit (log)	4540	7318	.489	0	8124
Rural vs. Urban	30540	1388	.487	1	2

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