The Impact of Refugee Camps on the Labour Market Outcomes in Rwanda

by

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Abstract

The paper estimates the labour market outcomes in Rwanda exposed to refugee camps inside the country by using Two-way Fixed Effect Difference and Difference method. This study uses DHS survey data merged with GIS data to locate the geographic location of the respondents relative to camps. I created a 15 km buffer zone around the camps as treatment group against the control group who are located over 25 km from the nearest camp. I conducted the quantitative analysis for both genders separately to measure the impacts on males and females. I conducted the event study analysis to test the parallel trends assumption and measure the dynamic treatment effects. The result of the study indicates that forced immigration did not significantly impact employment in Rwanda and its major industries.

Keywords: Refugee impacts, Regional migration, forced migration, labour market, Refugee-host dynamics, Agricultural employment

Contents

1 Introduction

In recent years, immigration-related issues have been on top of the headlines in the media. While the impacts of immigration on the developed countries have received the most attention through research, the same issue is never explored to a similar extent on the low-income countries. According to the United Nations High Commissioner for Refugees 2024, 122.6 million people are forcibly displaced, out of which over 32 million people are refugees who are under UNHCR's mandate[1]. This figure is more than doubled in the last decade due to the rise of global political tensions. This increase prompts attention from the international community to support forcibly displaced people with humanitarian aid. While the importance of supporting these target groups is undeniable, it is also important to evaluate their impact on the host countries.

Although immigration can refer to both voluntary and forced displacement of people, I primarily focus on the impacts of 'forced' immigration on a low-income country. The term forced migrant or refugee, refers to someone who is forced to flee their home due to persecution, war, or violence (United Nations High Commissioner for Refugees, 2023). Historically, most research have focused on the impact of refugee influx on industrialized and middle-income countries, while little attention has been directed to low-income countries. This is important because the economic structure of low-income countries is different than middle and high-income countries, as low-income countries are primarily focused on agricultural industries. As a result, we should expect that the following impacts of refugee influx would be different than what other papers have concluded on more developed countries.

Economists are looking for the impact of refugee influxes on host communities across various domains. Previous studies have focused on the broader impact of forced immigration on host communities such as child nutrition, child health, and housing availability, while other studies have focused on the impacts of refugees on the labour market dy-

[1] United Nations High Commissioner for Refugees. (n.d.). Figures at a glance.

namics. The purpose of this paper is to evaluate the impacts of refugees living in the settlement camps on the local labour market and its top industries in a low-income country. While most of the existing literature is focused on high-income and middle-income countries like Turkey and Jordan, this paper is seeking to expand the area to low-income countries. As far as I am aware, there has been one study on Kagera region located in Tanzania by Jean-François Maystadt and Philip Verwimp (2014) which examines the impact of forced immigration on the labour market following the Burundian (1993) and Rwandan (1994) crises. The results of the paper found that farmers and skilled workers benefited from cheap labor and increased opportunities in aid-related activities. On the other hand, some low-skill job particularly in agriculture faced a decline in wages due to higher competition for jobs.

Rwanda is the selected low-income country for this study due to its distinctive geography, socioeconomic structure and immigration laws. The portion of refugees to the overall population is very large in this country due to its relatively smaller overall population. Moreover, Rwanda has open-door policy towards immigration, and refugees have the right of free movement and work which would lead to distinctive outcomes for the economy of its class. This is the opposite of Tanzania in which refugees are not allowed to leave the camps to a certain distance, and they have no right to work as immigrants. Furthermore, Rwanda is located in a more conflict-prone zone that shares borders with countries like DRC and Burundi. As a result, refugees are often coming from countries with similar culture and background which impacts their integration to Rwanda's economy.

For this study, I used two main data sources for my analysis. Firstly, I used the Demographic and Health Surveys (DHS) for the years 2005, 2010, 2014, and 2019. This dataset provides detailed information about the household characteristics, employment, and geographic location of the household in the survey which can be compared to camp locations. This will be useful for proximity-based analysis of the refugee impact on the local population. Secondly, I used data from UNHCR and other public websites for camp location and the years of operation. This enables to identify treatment areas by designing a buffer zone around the camp locations and their activity timelines. Finally, combining both datasets based on geographic locations and operational years will allow for localized impacts of refugee camps on the labour market in Rwanda.

To evaluate the impact of forced immigration on Rwanda's labour market and top industries, we leverage the geographic and temporal data on camp locations combined with labor market outcomes from the DHS surveys. The difference-in-difference (DiD) methodology is well suited for our purpose given the the existing constraints on data availability and the lack of a panel data structure. This method allows us to compare the labour market outcomes before and after camp openings in regions around the camps.

I analyzed the impacts of refugee camps on the employment rate in Rwanda and its top industries by the number of people employed in those industries for both genders. The results of the study suggest that refugee camps did not significantly impact the labour market outcomes over the duration of this study.

Following this section, section 2 discusses the context of the study, about Rwanda's economy and demographic structure, and immigration laws impacting refugee rights and livelihoods in this country. Section 3 provides a literature review of relevant works on the topic and identifies the gap that this paper is aiming to address. Section 4 provides a more detailed explanation of data sources and discusses the assembly of data and statistics description. Section 5 explains the methodology used for the estimation with the underlying assumptions of the model. This section also discusses the limitation associated with the approach in this study. Section 6 presents the empirical results of analysing trends, agricultural labour, and other important findings. At last, Section 7 summarizes the work that has been done throughout the paper and discusses the findings of this study and its policy implications. This section will propose directions for future research on the topic.

2 Context

Rwanda is a landlocked country located in central Africa that, according to the World Bank,[2] is considered a low-income country. The country has a relatively small population which means that medium and large-scale immigration can have a noticeable impact on the labour market in this country. About 60 percent of the total population are younger people under 25 years old[3] which reflect the level of competitiveness of its labour market. This implies that refugees must participate in higher competition to find jobs.

Rwanda is not considered an urbanized country since more than 70 percent of the total population are living in rural areas who are mainly active in the agricultural (National Institution of Statistics of Rwanda). Most urban populations are living in the capital city of Kigali which serves as the economic hub for the country.

Rwanda's Gross Domestic Product (GDP) has grown at an average rate of more than 7 percent in the last two decades (Figure 5). Although the total size of the economy (GDP) is relatively small, the country has almost the same GDP per capita as its neighbours (Figure 4). Despite the rapid economic growth, according to the World Bank 2022, agriculture is still the primary industry in the country which employs around 56 percent[4] of the workforce.

Rwanda is generally considered an immigration friendly country and as of October 2024, over 134,000 refugees and asylum seekers are living in Rwanda (Figure 2)[5] who are registered with UNHCR (United Nations High Commissioner for Refugees, 2024). Most of the refugee population in Rwanda are coming from two neighboring nations, Democratic Republic of Congo and Burundi account for more than 99 percent of all refugees and asylum seekers in Rwanda who are mostly hosted in Mahama camp, located

[2] World Bank. (2024). *World Development Indicators*

[3] United Nations, Department of Economic and Social Affairs, Population Division. (2023). World Population Prospects 2022.

[4] World Bank. (2024). Employment in agriculture (perecntage of total employment).

[5] United Nations High Commissioner for Refugees (UNHCR). (2024). Rwanda country profile: Refugees and asylum seekers in Rwanda.

in the eastern part of Rwanda.

Most refugees are not living in urban areas, but they are mostly located in designated camp which enables them to have access to humanitarian aid, healthcare services and education. Rwanda has seen two major refugee influx over the years. The first refugee influxes happened in 2015, following the coup attempt and ethnic tensions in Burundi (Figure 2). In 2020, an increase in violence over natural resources in eastern Democratic Republic of the Congo resulted in a huge refugee influx to Rwanda. In this study, the survey timeline starts at 2005 and goes to 2020, and during this time period three camps opened to host the refugee population (Mahama, Kigeme, and Mogombwa camps opened in 2015, 2012 and 2014 respectively). Gihembe camp closed in 2021 which falls out of the timeline of available survey data for this study (Table 2). The remaining three camps, namely Kiziba and Gihembe were open prior to the study period.

According to the UN Refugee Agency, the refugee population in Rwanda enjoys more open immigration regulation in comparison with other countries. Official refugees in Rwanda can receive refugee ID which gives them the right to work in the country. refugees living outside the camps have access to community-Based health insurance, like a citizen and other foreigners[6]. Rwanda also grants freedom of movement to refugees which enables them to leave the camps and seek out jobs in other areas to find better opportunities. However, health and education and other humanitarian assistance are only available within the designated camp areas in Rwanda. To fund the humanitarian assistance, Rwanda relies on foreign aid from developed nations to support its refugee programs which means the availability of health care and education for refugees relies on financial aid from other countries.

[6]Government of Rwanda. (2014). Act 13TER of 2014

Figure 1: Comparison of Refugee Camps in Rwanda for 2015 and 2024

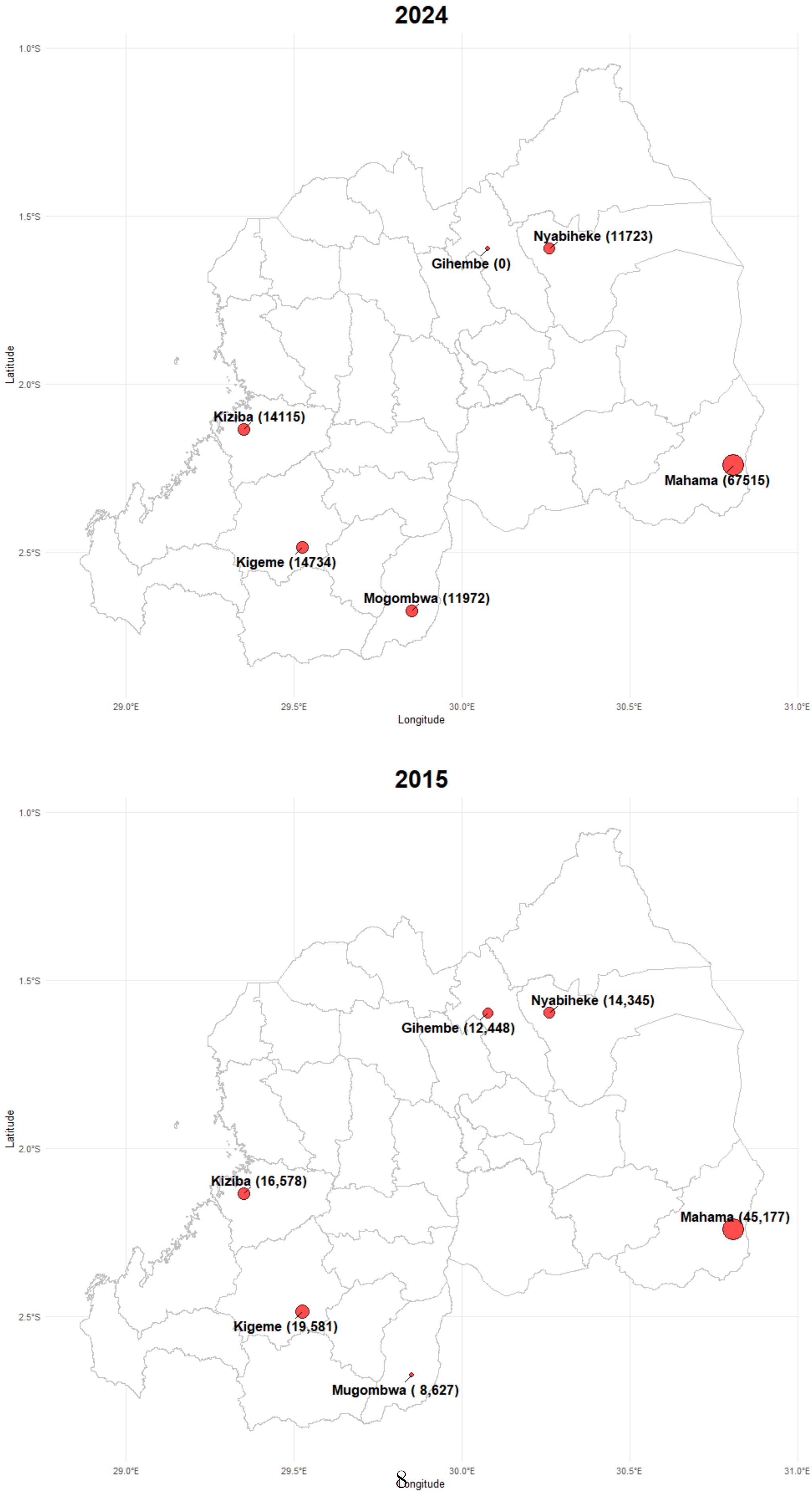
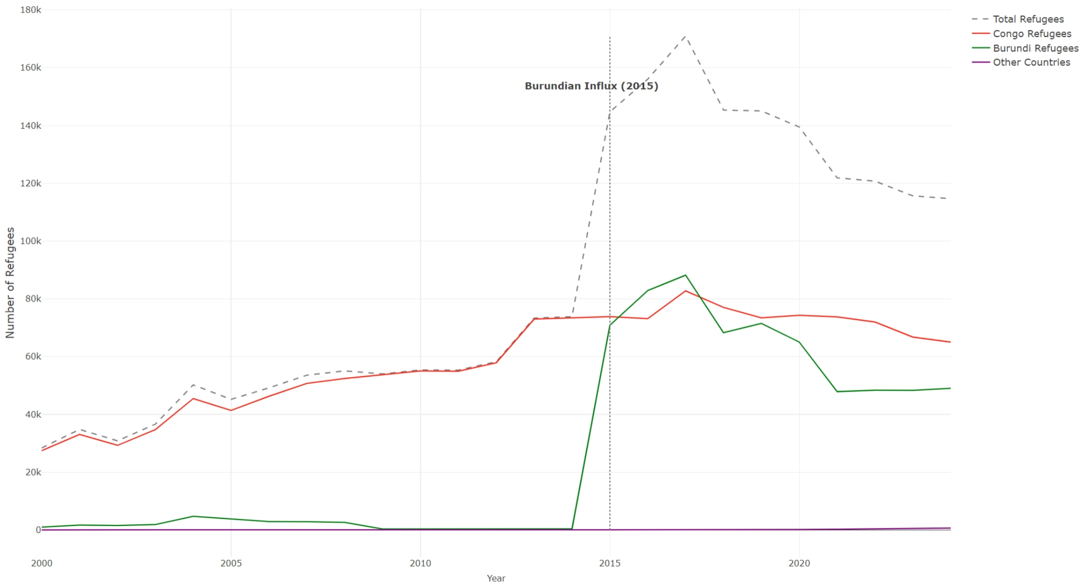


Figure 2: Number of Refugees in Rwanda



Source: authors' calculations based on available data in UNHCR Data Portal (2024).

3 Literature Review

The subject of the impact of forced immigration on labour market is not entirely new. The Mariel boatlift in 1980 which saw 125,000 Cuban refugees fleeing to Florida attracted lots of attention among the research community. Nobel Prize winner David Card studies the impact of the Mariel Boatlift on the Miami labor market in 1990, focusing on wage and unemployment rates among less-skilled workers. His findings suggested that in spite of a 7 percent increase in labour supply, there was no significant adverse impact on the wages and unemployment rate among non-Cuban workers. His findings contradicted the popular belief that immigration led to more competition for jobs and a lower employment rate for the native population. Later, George J. Borjas offered a re-examination of the impacts of the 1980 Mariel boatlift. He criticized Card's methodology and his control groups for failing to focus on specifically low-skilled native workers. His approach was different than Card's, by excluding teenagers and recent immigrants from the sample and just focusing on male worker aged 25 to 59. He also created a synthetic control group via weighted combinations of similar cities that matched Miami pre-Boatlift trends in both wages and employment. His results contradicted Card's paper as he found a 10 to 30 percent reduction in the wages of low-skilled workers in Miami. This sparked a debate over immigration's economic effects and methodologies used in labour economics.

Although these studies provided a great foundation for other research, the study on the impact of forced immigration on low-income countries has been limited. Most studies have focused on middle-income countries with high Syrian and Venezuelan refugees. For middle-income countries, a study done by Doruk Cengiz and Hasan Tekgüç (2022) is related to our topic which analyses the impact of mass Syrian refugees on the Turkish economy and labour force from 2012 to 2015. The study finds no adverse impact on the employment of low-skill Turkish workers, while there has been a minor temporary decline in the wages of this group. On the other hand, high-skill Turkish workers experienced higher wages and employment outcomes. Another study done by Rafael Alfena Zago (2024) focuses on the impact of Venezuelan refugees on the Brazilian labour market. The study finds that native monthly earnings have improved slightly due to greater demand from refugees, while the employment competition for native low-skill workers has also increased.

For the context of low-income country, the closest work to our paper is from Maystadt and Verwimp (2014). The study focuses on the impact of sudden refugee influx to Kagera region located in Tanzania followed by coup attempt and assassination of Burundian president, Melchior Ndadaye in 1993 and Rwanda's genocide in 1994. Following these events and mass migrations to Tanzania, Kagera region hosted about 700,000 refugees. The writers use difference and difference method to estimate how proximity to camps impact the welfare of host population.

Maystadt and Verwimp findings suggest that the impact of refugees on the region is not uniform, but it varies substantially among different groups and occupations in the local community. Households engaged in subsistence agriculture benefited from an increase in demand and an ample new labour force. This led to a substantial increase in the harvest of some agricultural products. On the other hand, low-skilled workers faced more competition, and the wages were reduced significantly. The study highlights the complexity of impacts on the labour market in the host country.

Moreover, the study also points to improvement of roads and other infrastructure and healthcare facilities which created positive externality on local communities living closer to camps. However, increase in competition has led to more environmental degradation which put more pressure on locals as firewood is the main sources of fuel for cooking which led to disproportionate negative impact on women.

The academic literature has highly focused on middle-income countries such as Turkey, Jordan, and Colombia. This study aims to examine the impact of refugees on a low-income country with specific focus on top industries. Although Maystadt and Verwimp (2014) seems to be like the closest paper to this topic due to both countries' similarities, it doesn't help with the case of Rwanda. Rwanda's immigration laws are fairly open and place no restriction on refugee movement or right to work which is the opposite of Tanzania's refugee immigration laws. Furthermore, the case of Rwanda is not compatible with previous studies focused on middle-income countries such as Turkey and Colombia, since unlike Rwanda, there are no concentrated campsites in these countries.

4 Data

Unfortunately, there is no comprehensive country-based panel dataset for Rwanda to measure the impact of refugee camps on host communities. I created a dataset using publicly available Demographic and Health Survey Data (DHS) which is a globally recognized initiative that provides data for low- and middle-income countries. DHS data covers key demographics and contains a wide range of topics which includes socioeconomic information such as education, wealth index and employment. Furthermore, the availability of geospatial data in Demographic and Health Survey Data is useful to measure the proximity to camps. I constructed a repeated cross-sectional data for the years 2005, 2010, 2014, and 2019 since DHS survey results are not available on an annual basis for Rwanda.

Demographic and Health Surveys (DHS) are comprehensive, but it is important to mention that there are some limitations in the survey that are particularly relevant to this study. Firstly, the DHS survey omits institutionalized populations, including refugees in camps. While the exclusion of refugees from the DHS survey seems like it would create a gap in the study, but it would instead help us to focus specifically on the local population impacted by the refugee influx which is the main purpose of this paper. As a result, this limitation with the DHS survey serves as an advantage for our paper since this would eliminate biased results that might be created by having both refugees and local respondents in the survey. Secondly, I use geospatial data to measure distance to camps, but the geospatial data in DHS survey is randomly displaced to protect respondent confidentiality. While random displacement is essential for confidentiality, this jittering introduces random error into our analysis since I use proximity to refugee camps as a variable in our analysis. For this study, I designed a 15 km buffer zone around the camps, and this jittering can cause misclassification of the clusters relative to camp locations. For example, clusters that are displaced outside the buffer zone might inaccurately appear unaffected by refugee camps, while clusters displaced inside the buffer might inaccurately appear impacted.

To combat the issue of random displacement of cluster locations, I introduced neutral areas further around the 15 km buffer zone by an additional 10 km. This donuts shaped neutral area would effectively prevent the displacement of clusters from the buffer zone (treated) to outside the buffer zone (control group) due to random displacements. The reason for using a 10 km neutral area is due to the nature of the jittering in DHS data. DHS cluster location randomly jittered, up 2 km in urban areas and up to 5 km in rural area to protect the confidentiality of the respondents[7]. The advantage of using a neutral zone is to reduce or eliminate the random measurement error which would impact the results. The disadvantage of using using neutral zone is sacrificing the sample size for better accuracy, but since I have a relatively large sample size, this would not be an issue.

[7]United Nations High Commissioner for Refugees. (2023). Efficient circulation networks for refugee and host community integration

The information about camp locations and their years of operation was gathered from publicly available sources. This information is essential for identifying the location of camps with respect to clusters for assessing the impact on local populations living closer to camps. The geographic location of camps was obtained from the United Nations Refugee Agency in People of Concern maps which are available online for public access. The maps provide centroid locations of camps which offers a precise yet generalized representation of camp locations. While centroid locations are accurate, it does not account for the full geographic extent of camp boundaries where the economic interaction with the local population might occur. Data on the years of operation of camps were gathered through internet research including reports from international agencies and humanitarian organizations. This dataset includes the years of opening to closure of each camp which enables the creation of a timeline for event study analysis.

For preparing the dataset for the study, I also used Geographic Information System (GIS) which is available in the DHS dataset for each annual survey. The DHS dataset includes household districts and subdistricts and the associated approximate location of each respondent which is used to calculate the linear distance of respondents to the location of the nearest camp which I used to classify the treated and control groups according to distance to the closest camp.

Table 1 contains the summary statistics of the DHS dataset used in this study in different categories. Most of the respondents to the survey were female since historically DHS survey is focused on health topics traditionally associated with women such as reproductive health, fertility, child nutrition and so on. As a result, the target has been deliberately focused on female respondents aged 15 to 49. For this reason, I provided information for both genders separately to address the issue of disproportionate gender-based survey. The table also provides information about the characteristics of the respondents for both treated and control groups according to their living distance to camps. The table suggests that some characteristics such as age, years of education, and wealth index do not vary by proximity to camp locations. The information in the descriptive table also supports the general belief that women in low-income countries are more engaged in agricultural activities than men. On the other hand, we can see that people living closer to camps are more engaged in the agricultural industry which is reasonable since most camps are located in rural areas that host communities with lower wealth index.

Table 1: Summary Statistics by Distance to Closest Camp and Treatment Status

Variables	**Whole Sample**		**Treated (within 15 km)**		**Control (>25 km)**	
	Obs.	Mean	Obs.	Mean	Obs.	Mean
			Overall			
Age	77002	29.23	8605	29.34	53907	29.16
Sex	77002	0.68	8605	0.68	53907	0.69
Yrs. Education	77002	4.02	8605	4.02	53907	4.01
Rural	77002	0.77	8605	0.78	53907	0.73
Wealth Index	77002	3.14	8605	2.78	53907	3.29
Agriculture	61532	0.66	7115	0.73	42416	0.61
			Male			
Age	23879	30.56	2694	30.83	16679	30.54
Sex	23879	0	2694	0	16679	0
Yrs. Education	23879	4.01	2694	4.03	16679	4.02
Rural	23879	0.77	2694	0.83	16679	0.72
Wealth Index	23879	3.24	2694	2.87	16679	3.31
Agriculture	19838	0.54	2306	0.61	13864	0.50
			Female			
Age	53123	28.63	5911	28.65	37228	28.55
Sex	53123	1	5911	1	37228	1
Yrs. Education	53123	4.07	5911	4.01	37228	4.13
Rural	53123	0.77	5911	0.82	37228	0.73
Wealth Index	53123	3.1	5911	2.74	37228	3.33
Agriculture	41694	0.72	4809	0.78	28552	0.67

Source: Authors' calculations based on DHS datasets used in this study.

Table 2: Operation Year of Camps in Rwanda

Camp	**Open Year**	**Close Year**
Mahama	2015	Still Open
Kigeme	2012	Still Open
Kiziba	1996	Still Open
Nyabiheke	2005	Still Open
Gihembe	1997	2021
Mugombwa	2014	Still Open

Source: Data is gathered through documents of UNHCR.

5 Methods

5.1 Spatial Difference-in-Differences (DID) within 15 km Buffer Zone

To estimate the impact of forced immigration on labour market in Rwanda, we utilize two-way fixed effects difference-in-differences regression. Given our topic, there are some advantages of using this model. This method allows us to account for the time-invariant differences since districts and sub-districts are naturally different from each other. Secondly, the model considers the time-specific shocks which might affect the entire areas all at once, such as economic recession. The baseline regression follows the specification in the equation below:

$$Y_{it} = \beta_0 + \beta_1 \cdot Camp_{it} + \gamma X_{it} + \alpha_i + \lambda_t + \epsilon_{it}$$

Where Y_{it} is the labour market outcome of individual i in DHS cluster at the time $_t$. The $Camp_{it}$ is a binary variable indicating the presence of camps within 15 km of the respondents' location at given time t. In other words, if the respondent was located closer than 15 km of an active camp, it would be considered as a treated group in the model. The control group in the model are respondents living farther away from 25 km radius from the refugee camp location, whether active or not. One can imagine a donuts-shape area between 15 km to 25 km around the camps is excluded from the model. As a result, the coefficient β_1 would indicate the average treatment effect of living close to refugee camp on the probability of employment. The vector X_{it} captures are control variables or individual characteristics in the model which are age, years of education, level of wealth, number of household members or family size, and place of residency which can be rural or urban.

I used two fixed effects in the model. The variable α_i is the subdistrict fixed effect to capture the geographic time invariant characteristics in the model. The second variable λ_t is time fixed effect which indicates the years that the DHS surveys were conducted in 2005, 2010, 2014, and 2019. The error term ϵ_{it} captures all unobserved factors which can impact employment in the model.

The treatment is defined based on the proximity of the household cluster location to the nearest camp within 15 km. The distance of 15 km is ideal for the context and method used in this study given already existing papers related to this topic[8]. Individuals within 15 km buffer zone are in treatment group. The parallel trends assumption is crucial to ensure the validity of the Difference-in-Differences (DID) method in this paper. This assumption states that in the absence of treatment, the difference between the treatment (individuals within 15 km of camps) and the control group (individuals farther away from 25 km to the nearest refugee camps) is constant over time. I assume that the parallel trend assumption in the model holds, and to test the assumption I conducted event study in the next section.

One of the most important concerns about the two-way fixed effects difference-in-differences model is the issue of heterogeneous treatment timing. I consider an individual as treated according to the proximity to the camp in the year in which the camp is opened within 15 km and will remain treated as long as the camp is active during all years, while others remain untreated. The issue is that the model will not just compare the treated with the control group, but it often compares groups treated earlier to groups treated later which would result in mixing the treatment effects across time. The issue was mentioned in the Goodman-Bacon (2021) paper which shows that TWFE DID estimates can be biased if the treatment effects vary over time. In other words, the results might be biased because the impact of refugee camps can be lessened over time as the local economy adapts during a longer period. This means that by mixing the short-term and long-term impact of the refugee camps, the result might be biased which would lead to misleading estimations of the labour market outcome.

[8]Common distance used in similar studies and environmental degradation papers. See Reference section

I acknowledge that existence of random measurement error can impact the results on the labour market outcomes. DHS cluster location has been randomly jittered, up to 2 km in urban areas and up to 5 km in rural area[9], to protect the confidentiality of the respondents. This will obscure the exact location and would lead to misclassification of treatment and control group. I considered a 10 km neutral zone around the buffer zones to reduce the measurement error. Furthermore, due to the seasonality of the farming activity, the survey might be conducted at different times of the year which is another potential measurement error. These measurement errors can impact the result which would make it harder to find significant effects, even if they exist. I encourage readers to account these limitations in the interpretation of the results.

5.2 Event Study

The impacts of refugee camps on the employment rate can vary over time. Most low-skill refugees engage in agricultural activities which impacts the labour supply. Furthermore, the presence of refugees also increases the demand for products. As a result, the impacts are on supply and demand side which might be lessened over a longer period of time. To evaluate the impacts of refugee camps, I constructed the equation below to estimate an event study for the model.

$$Y_{it} = \alpha_i + \lambda_t + \sum_{s \neq -1} \beta_s \cdot D_i \cdot 1[RelTime_s] + X_{it}\gamma + \epsilon_{it}$$

In the equation above, Y_{it} is the binary indicator of employment rate for individual i sampled in year t. α_i is captures the geographic location of the participants in the survey as the fixed effect. λ_t uses DHS survey year as time fixed effect which aims to captures time specific shocks through all sub-districts. $1[RelTime_s]$ is a set of binary indicators for each of the relevant time period($RelTime_0$ is excluded). The indicators reflect the treatment impact for respondents living within 15 km of the nearest camp at each time

[9]Measure DHS. (2019). Protecting the Privacy of DHS Survey Respondents: Displacement of GPS Data.

period s. In other words, D_i is binary variable which equal to one if the individual lives within 15 km of camps, whereas $1[RelTime_s]$ would be equal to one if the observation corresponds to relative time period s. β_s is the coefficient of interest which represents the effect of proximity to camps at relative time s. Additionally, I controlled for X_{it} which is a vector of individual controls which includes the place of residency (urban or rural), household size, years of education and wealth index. Since the impacts are different on both genders, I have different sets of regressions for male and female respondents separately.

The event study analysis would help us to assess the validity of the parallel trends assumption which is necessary for casual inference of the model used in this paper (Angrist and Pischke, 2009). For parallel assumption to hold, there should not be a significant difference between treated and untreated groups in pretreatment period. If there are significant differences between these two groups prior to the treatment year then the assumption is violated. I reported the results of event study analysis for overall employment and for agricultural sector outcomes separately in different figures in the Appendix section of this paper.

The results show that there are no clear upward or downward trends in the pre-treatment period which reflects that both treatment and control group followed a similar trend prior to the camp establishment. We observed some fluctuations which are not consistent or statistically robust to show any pre-existing trends. The results might reflect that camp openings slightly boosted the employment in the agricultural sector in post-treatment era (long term). Overall, the results of the event study support the parallel trends assumption since the pre-treatment coefficients are not significant and close to zero.

I acknowledge that there are certain limitations to any results from event study analysis. The event study in this paper assumes homogeneous effects among all participants in the survey which might not be correct in our analysis. In such scenario, the study event coefficient might be impacted by treatment effect and other relative time periods (Sun and Abraham, 2020). Furthermore, movement of people inside and outside the buffer can cause spillover effects since labour reallocation is not accounted for in the model due to data limitation. The reader should be cautious when drawing conclusions from the results of the event study in this paper.

6 Results

Table 3 reports the results for labour market outcomes. This table focuses on the impact of refugee camps on employment rate for both genders. The preliminary results suggest an increase of 0.044 of male employment in the treatment group but it is not statistically significant. The lack of satisfying significance level reveals no impact on the male employment rate within the treatment group. For female respondents, the coefficient is smaller at 0.006 and the lack of statistically significant outcome implies no measurable impact on this group same as male respondents. The age of respondents seems to have a small impact on the employment participation rate which is not far from the expectations. Most of the respondents to the survey are among people aged 15 to 49 and as a result, older people are more likely to have job, but the impact seems to be small since the coefficient is 0.009 for the age variable.

The number of household members seems to have a reverse impact on male and female participation rates in the labour market. This could be due to the case that in larger family, members of the families support each other in which case we see reduction in the participation in the labour market. It should be noted that this variable does not necessarily target the head of the household but instead it targets any family members, so the results of this variable are not far from expectations.

Table 4 reports the results in the agricultural sector. The results of the assessment of impact on this sector is almost similar to impacts on employment rate in table 3. The results indicate that camp establishments has no significant impact on agricultural sector employment rate for both genders. On the other hand, wealth index shows negative coefficient for both genders which reflects that individuals with higher wealth are less likely to be active in agricultural sector. The respondents in rural areas are also more likely to participate in this sector for both genders given the results, which is not far from expectations.

Table 5 reports the results on the construction sector. This is another chosen industry to be examined in this study given the large number of people employed in this sector. The results show no measurable impacts on the construction sector for both genders since the results are almost insignificant at all levels. I have also replicated the model for mining sector and presented the results in table 6. The results for mining sector are also insignificant at all levels.

Table 3: Impact of Camps on **Overall Employment** Rate by Gender

Variable	**Male (Clustered)**	**Female (Clustered)**
Treatment	0.044 (0.055)	0.006 (0.030)
Age of respondents	0.009** (0.001)	0.013** (0.001)
Education level	0.007 (0.004)	0.008* (0.002)
Wealth index	-0.003 (0.008)	-0.027* (0.006)
Number of household members	-0.017** (0.002)	-0.013** (0.002)
Place of residency (Rural)	-0.028 (0.029)	0.021 (0.019)
Observations	17,015	36,792
Fixed Effects	DHSYEAR, Subdistrict	DHSYEAR, Subdistrict
Standard Errors	Clustered (DHSYEAR)	Clustered (DHSYEAR)
RMSE	0.325	0.385
Adj. R^2	0.231	0.171
Within R^2	0.103	0.107

Source: Authors' calculations based on DHS datasets used in this study.
The stars reflect significance level based on P-values:
*** Significant at the 0.01 percent level.
** Significant at the 0.1 percent level.
* Significant at the 1 percent level.

Table 4: Impact of Camps on **Agricultural Sector** Employment Rate by Gender

Variable	**Male (Clustered)**	**Female (Clustered)**
Treatment	0.016 (0.080)	0.017 (0.036)
Age of household member	0.006** (0.001)	0.005* (0.001)
Highest year of education	-0.001 (0.002)	0.002 (0.001)
Wealth index numeric	-0.062* (0.016)	-0.062* (0.019)
Number of household members	0.002 (0.004)	-0.002 (0.005)
Place of residency (Rural)	0.176* (0.051)	0.208* (0.037)
Observations	14,143	28,068
Fixed Effects	DHSYEAR, Subdistrict	DHSYEAR, Subdistrict
Standard Errors	Clustered (DHSYEAR)	Clustered (DHSYEAR)
RMSE	0.407	0.368
Adj. R^2	0.321	0.392
Within R^2	0.069	0.082

Source: Authors' calculations based on DHS datasets used in this study.
The stars reflect significance level based on P-values:
*** Significant at the 0.01 percent level.
** Significant at the 0.1 percent level.
* Significant at the 1 percent level.

Table 5: Impact of Camps on **Construction Sector** Employment Rate by Gender

Variable	**Male (Clustered)**	**Female (Clustered)**
Treatment	-0.023 (0.015)	0.012 (0.021)
Age of household member	0.001 (0.000)	-0.000 (0.000)
Highest year of education	0.001 (0.003)	-0.000 (0.000)
Wealth index numeric	-0.001 (0.004)	-0.001 (0.000)
Number of household members	-0.000 (0.001)	-0.001. (0.000)
Place of residency (Rural)	-0.016 (0.016)	-0.006 (0.004)
Observations	14,143	28,068
Fixed Effects	DHSYEAR, Subdistrict	DHSYEAR, Subdistrict
Standard Errors	Clustered (DHSYEAR)	Clustered (DHSYEAR)
RMSE	0.276	0.117
Adj. R^2	0.036	0.019
Within R^2	0.002	0.001

Source: Authors' calculations based on DHS datasets used in this study.
The stars reflect significance level based on P-values:
*** Significant at the 0.01 percent level.
** Significant at the 0.1 percent level.
* Significant at the 1 percent level.

Table 6: Impact of Camps on **Mining Sector** Employment Rate by Gender

Variable	**Male (Clustered)**	**Female (Clustered)**
Treatment	0.002 (0.009)	0.009 (0.011)
Age of household member	-0.001 (0.001)	-0.000 (0.000)
Highest year of education	-0.001 (0.001)	0.000 (0.000)
Wealth index numeric	-0.007 (0.005)	-0.001 (0.001)
Number of household members	-0.000 (0.001)	-0.000* (0.000)
Place of residency (Rural)	-0.015 (0.010)	-0.001 (0.003)
Observations	14,143	28,068
Fixed Effects	DHSYEAR, Subdistrict	DHSYEAR, Subdistrict
Standard Errors	Clustered (DHSYEAR)	Clustered (DHSYEAR)
RMSE	0.181	0.095
Adj. R^2	0.048	0.026
Within R^2	0.004	0.001

Source: Authors' calculations based on DHS datasets used in this study.
The stars reflect significance level based on P-values:
*** Significant at the 0.01 percent level.
** Significant at the 0.1 percent level.
* Significant at the 1 percent level.

7 Conclusion

The topic of forced immigration and its impact on the host countries has always been a point of focus for most nations around the world. However, the focus of most academic research is on high-income and middle-income countries. This study aims to fill the gap in the existing research on forced immigration in a low-income country, Rwanda in this study, especially since considerable portion of global refugees are living in low-income countries. The previous limited studies on the similar topic on low-income countries do not apply to the case of Rwanda due to more welcoming immigration laws and the right to work for refugees. Furthermore, the geographic location of the country which is located in conflict-prone zone, and its distinctive cultural background turn it into valuable case for examining the topic.

To measure the impacts of forced immigration on Rwanda's labour market, I used the DHS dataset to quantify the impacts on host communities living closer to camps. In carrying out this study, I utilized Two-way Fixed Effect Difference and Difference empirical strategy and tried to interpret the results extracted from the method. The focus of the study is on employment outcomes and Rwanda's top industries based on the number of people employed in each industry which are the agricultural, construction and mining sectors.

The results indicate that refugee camps did not have a measurable impact on Rwanda's labour market and its top industries. I also employed event study analysis as part of the method to evaluate differences in trends between the treated and comparison groups both before and after the treatment. The result of the event study showed that the parallel trend assumption holds for this study.

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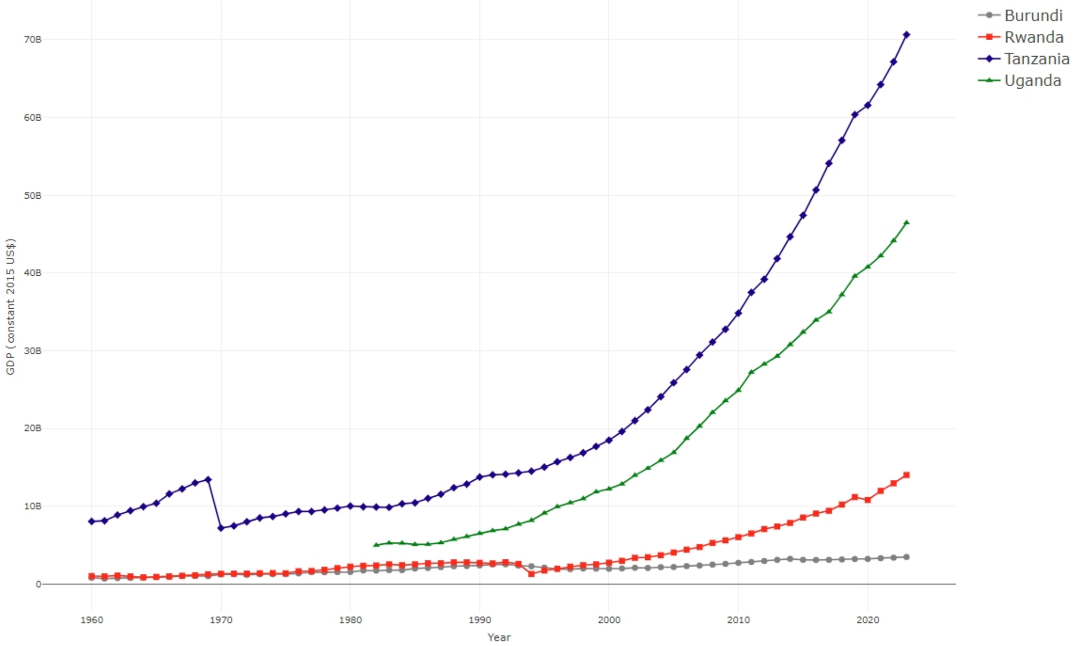
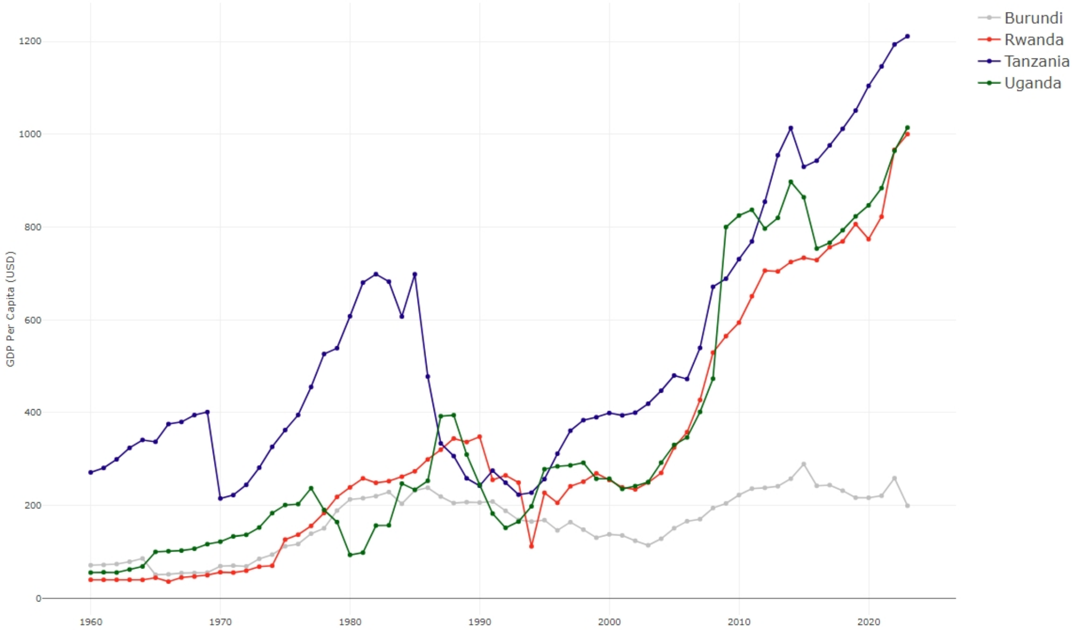
Appendix

Figure 3: GDP of Rwanda and its neighbors



Authors' calculations based on available data in World Bank (2024).

Figure 4: GDP Per Capita of Rwanda and its neighbors

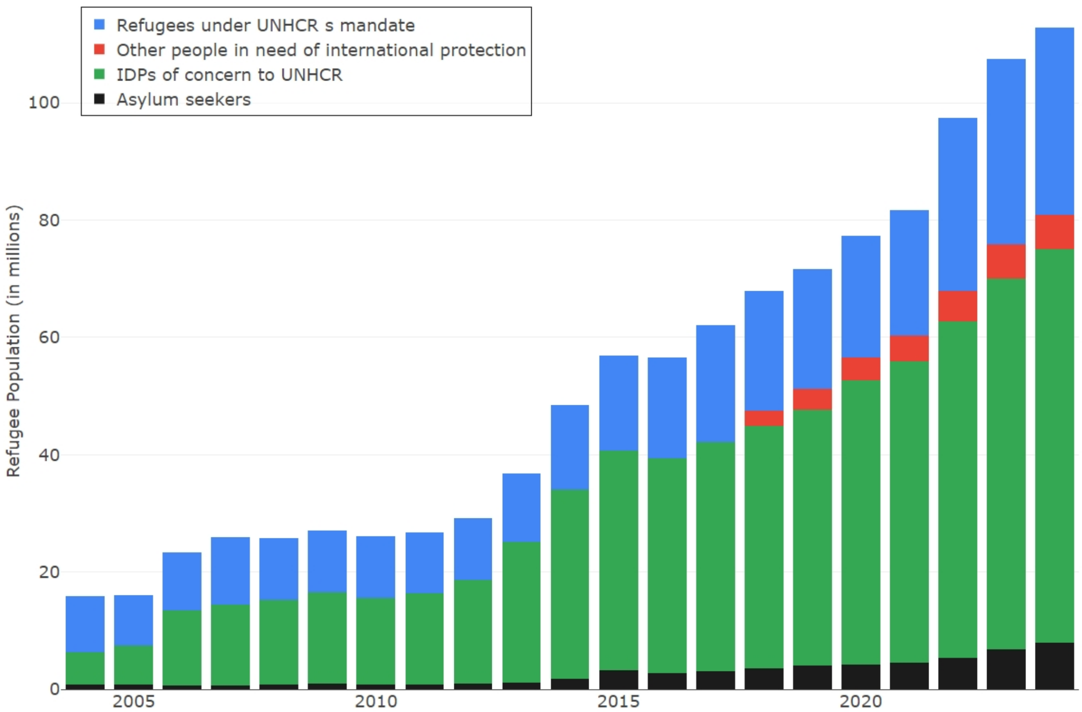


Authors' calculations based on available data in World Bank (2024).

Figure 5: Rwanda's Annual GDP Growth

Source: authors' calculations based on available data in World Bank (2024).

Figure 6: Total number of Global Refugees in Different Categories



Source: authors' calculations based on available data in UNHCR Data Portal (2024).

Figure 7: Plots of event study analysis for overall employment outcome for male in the first graph and for female in the second graph.

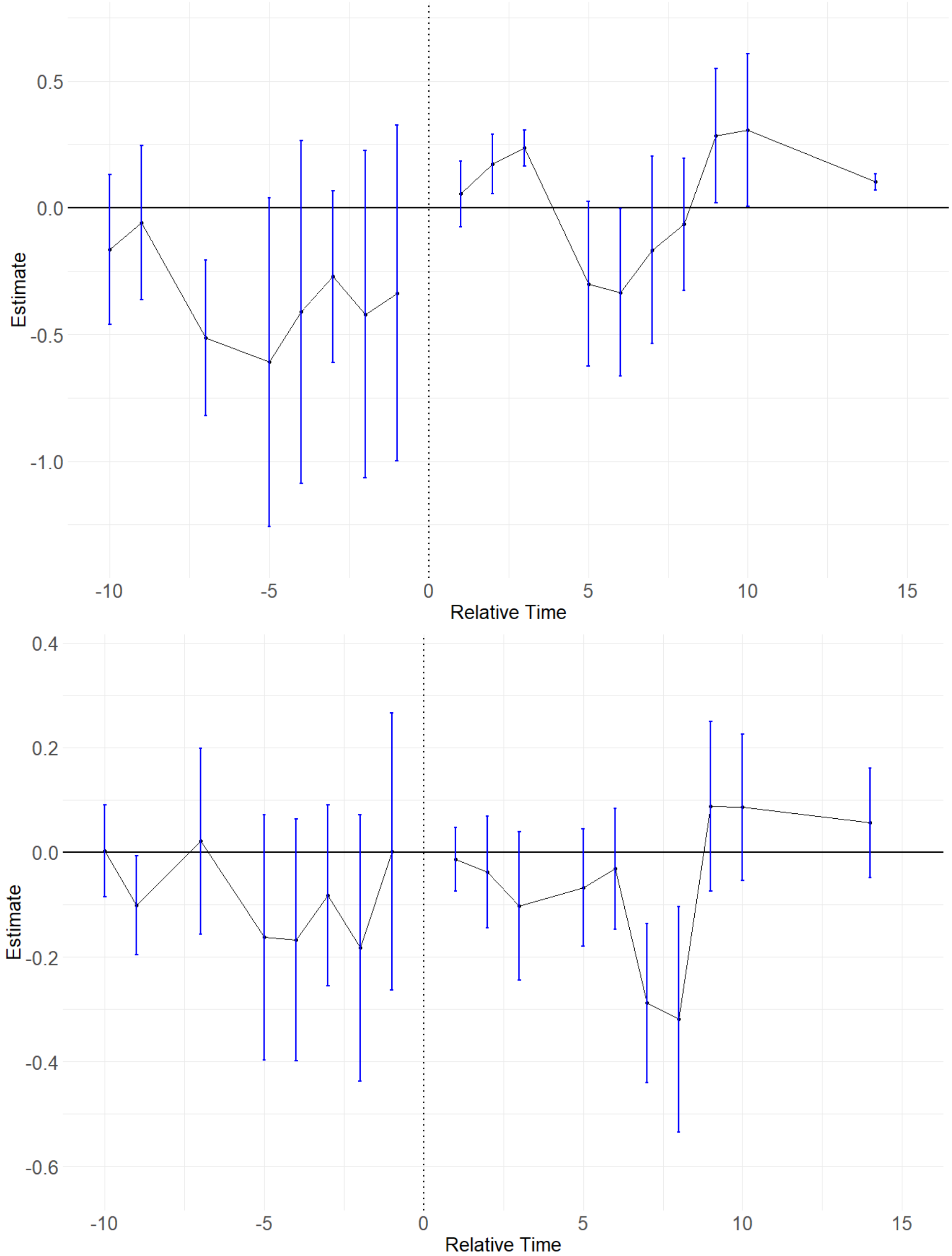


Figure 8: Plots of event study analysis for agricultural sector for male in the first graph and for female in the second graph.