The Legacy of Conflict: Aggregate Evidence from Sierra Leone

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Abstract

This paper studies the general equilibrium impact of civil war in Sierra Leone. I first use an instrumental variable (IV) strategy and geographic conflict variation to estimate reduced-form effects. I show that civil war leads to affected areas having a higher share of workers in agriculture, fewer educated workers and lower worker income. In order to explicitly take into account general equilibrium effects such as selective migration in response to the war, I then develop an economic geography model. The model sheds light on different mechanisms through which conflict affects aggregate income: Changes in education, firm productivity and individual productivity have both direct effects on income and indirect effects by changing the allocation of labor across sectors and locations. Changes in amenities also affect the spatial allocation of labor. Next, while education outcomes are observed, I structurally estimate all unobserved parameters. In particular, I leverage the structure of the model along with observed income information and migration flows to identify firm productivities, amenities and average individual productivities. Finally, I use the model to perform counterfactual simulations. Aggregate income in Sierra Leone is estimated to be 32% lower today as a result of the civil war. Importantly, firm productivity losses can explain most of the decrease while human capital reductions alone can only account for a small part of the effect. Selective migration in response to the war also seems to play an important role and implies that local reduced-form effects are misleading when trying to estimate aggregate effects.

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1. Introduction

Violent conflict is still a major global challenge with devastating consequences. In the last decade, civil war plagued about a fifth of all countries worldwide with a global death toll of almost 900,000 people.[1] What is more, extreme poverty is increasingly concentrated in countries affected by conflict. By 2030, two third of the world's extreme poor are projected to live in fragile and conflict-affected situations (World Bank, 2020). While studying the causes and consequences of conflict has become a major field of inquiry within economics over the last few decades,[2] there is still a major gap in our understanding of the impact of war on the economy in two dimensions. First, while a growing literature documents the economic impact of conflict on affected places, we have little evidence on the *aggregate* consequences in the long run. Investigating the aggregate impact on an economy requires taking into account general equilibrium effects. By its very nature, within-country analyses that compares more and less conflict affected places fail to account for such effects. Second, analyses that investigate mechanisms of how conflict affects livelihoods have largely focused on the human capital channel. In particular, structural labor market and firm activity effects have received little attention. This is not surprising given how commonly education and health outcomes are observed in surveys while there is often a lack of data on firms.

This paper seeks to make advances on both fronts by providing a general equilibrium analysis of the 1991-2002 civil war in Sierra Leone. Specifically, I ask two questions. First, what is the long-run effect of the civil war on aggregate income? Second, what are the potential drivers of aggregate income losses? The main original contribution of the paper is to develop and structurally estimate a general equilibrium model of the impact of conflict. I find that civil war strongly reduces human capital and firm productivity in the non-agricultural sector. This has both direct implications for aggregate income and indirect ones by changing the sector composition of workers and the labor allocation across space. Taken together, aggregate income is 31.6% lower today as a result of the war that ended almost twenty years ago. While having received the most attention in the literature as a mechanism, the human capital reduction can only account for about a tenth of the effect. By contrast, firm productivity losses can explain more than half the reduction.

This paper has two parts. The first part is a reduced-form analysis of the effect of conflict. This analysis shows that conflict alters the economy in major ways and motivates key elements of the general equilibrium model I develop and estimate in a second part. Drawing mainly on household survey data from 2018, I observe workers' income, sector choice and education. I measure conflict intensity as the average victimization households experience within a chiefdom.[3] Since conflict is not randomly placed I use

[1] This is according to UCDP data from Pettersson & Öberg (2020).
[2] Blattman & Miguel (2010) provide an excellent review of the literature.
[3] Chiefdoms are the lowest level of administration in Sierra Leone. There are 159 chiefdoms in the country of which sufficient information is observed in 151 that are used in the analysis.

distance to the Liberian border as an instrument. As a result of Liberian involvement in the beginning of the war, distance to the border strongly predicts conflict intensity. At the same time, Sierra Leonean trade with Liberia was negligible before the war. Chiefdoms close to and far from the border within small districts are comparable on various pre-war observables. Thus, the instrument creates exogenous variation of conflict within districts. A placebo test on education effects for people above school age when the war started confirms exogeneity.

The reduced-form analysis establishes large income differences between more and less affected chiefdoms. However, spatial income differences do not necessarily reflect *aggregate* income effects. In general equilibrium, people move. Therefore, spatial income differences capture both the direct effect of conflict and the reallocation of labor.

One purpose of the general equilibrium model I develop in this paper is to address this issue. The general equilibrium structure allows me to estimate aggregate income effects. Another purpose is to provide a theoretical framework and estimation of the underlying mechanisms. Importantly, I can include mechanisms that are not directly observed in the data but which I can identify in a structural estimation of the model. The basic setup is an economic geography model with 151 locations reflecting the chiefdoms of Sierra Leone. To capture population movement and a sector shift in response to the war, the model features labor mobility across these locations and two sectors, agriculture and non-agriculture. Individuals are heterogeneous in individual productivities for each destination and sector as well as exogenous education realizations. In a Roy (1951) fashion, this gives rise to worker sorting into a destination and sector. Locations differ in amenities such as local public goods and services and firm-level productivities in each sector.

Conflict is assumed to affect four sets of parameters with both direct and indirect implications for aggregate income: (i) (observed) education, (ii) (unobserved) firm-level productivities, (iv) (unobserved) individual productivities and (iii) (unobserved) amenities. Structural estimation identifies the model parameters. In particular, I use observed incomes and migration flows to estimate firm and individual productivities as well as location amenities. To estimate the causal impact of conflict on these parameters, I use the same IV strategy as before. With these estimates in hand, I perform counterfactual simulations which estimate the aggregate income effect of conflict. The simulations take into account general equilibrium changes.

A key result emerging from the reduced-form analysis is that workers living in chiefdoms hit by conflict experience substantial income losses, even twenty years after the end of the war. Moving from a low conflict intensity chiefdom (at the 25^{th} percentile of the conflict distribution) to a high conflict intensity chiefdom (at the 75^{th} percentile) leads to a drop in income by 38%. A look at the sector allocation of workers reveals an important driver behind this income loss: reverse structural transformation. Workers are 23 percentage points more likely to work in the lower paying agricultural sector in high conflict chiefdoms as opposed to low conflict chiefdoms.

The general equilibrium model highlights how conflict affects income and sector allocation. Education, firm productivity, individual productivity and amenities can change in response to conflict. This has direct effects in the locations affected and indirect effects in general equilibrium when people move and market wages change. Increasing conflict by one standard deviation leads to a reduction of the share of primary school educated people by 6.9 percentage points. Returns to education are estimated to be higher in non-agriculture than in agriculture which implies that education losses harm the non-agricultural sector more and can lead to a sector shift into agriculture. Lower human capital also directly decreases income in both sectors. As for firm productivities, I show that conflict affects the sectors differentially. While there is no effect on agricultural firm productivity, non-agricultural firm productivity reduces by 28.4% per standard deviation of conflict. Naturally, a firm-level productivity loss in non-agriculture is also consistent with the sector shift into agricultural work and income losses in non-agriculture. Average individual productivities decrease by 12.2% per standard deviation of conflict, but only among the uneducated. This reduces income of workers born in chiefdoms affected by conflict.

Beyond these direct effects, education losses, non-agricultural firm productivity reductions and a decrease in individual productivity among the uneducated have important general equilibrium implications. People move in response to these changes. Workers are assumed to be mobile subject to a migration cost that is specific to their level of education and their sector of work. Three forces governing how migration changes are worth highlighting. First, the sector shift leads to changed relative wages between the sectors in affected locations which has an impact on the composition of in- and out-migrants. Second, lower non-agricultural firm productivity in chiefdoms hit by conflict generally encourages non-agricultural workers to leave those locations. Third, the composition of migrants changes in response to lower education in affected chiefdoms since migration cost is higher for uneducated workers than for educated workers in agriculture. The composition of stayers in conflict affected chiefdoms will therefore consist of more uneducated agricultural workers which tend to have low productivity.

Since amenities are not sector-specific and are a component of utility but not of income, any amenity changes would only result in aggregate income effects through general equilibrium effects of worker movement. However, the estimated effect of conflict on amenities is small and insignificant. In the long run, amenities seem to remain unaffected by the civil war.

General equilibrium effects imply that the observed sector allocation and income difference between more and less affected chiefdoms by conflict reflects not only the direct effect of conflict but also selective migration. In particular, the changes in the spatial allocation of labor in response to the war described above would suggest a positive selection of migrants out of high conflict chiefdoms. Therefore, the spatial divergence in income may overstate the aggregate income effect. To address this issue, I use the model to simulate counterfactual scenarios that reverse conflict and all general equilibrium effects associated with it. In the first simulation, I consider a full reversal of the war. In this scenario, the education, non-agricultural firm productivity and individual productivity loss among the uneducated are reverted. A second set of simulations serves to assess the quantitative importance of the channels. I revert the effect on the three sets of parameters separately.

The first scenario estimates an aggregate income loss of 31.6% in the Sierra Leonean economy today relative to a simulated peace economy. The aggregate share of agricultural workers is 20.8 percentage points higher than it would be in the absence of war. An effect of conflict on non-agricultural firm productivity alone would lead to an aggregate income reduction by 17.8%. By contrast, an effect on average individual productivity among the uneducated or on education only would lead to an aggregate income reduction by 10.5% or 3.7%, respectively. Therefore, firm productivity losses seem to be the most important driver of the civil war impact on the Sierra Leonean economy.

While the estimate on the full war effect is large, it is still substantially lower than what the reduced-form evidence on spatial divergence suggests. If we were to take the reduced-form estimate and calculate a country-wide weighted average by conflict intensity and chiefdom population we would arrive at a 46% aggregate income loss. This suggests that general equilibrium forces such as selective migration play a major role in generating spatial income differences between more and less affected chiefdoms by conflict.

This paper makes two main contributions. First, it provides estimates of the long-run aggregate income effect of civil war that explicitly take into account general equilibrium forces. While early cross-country macro studies (Alesina & Perotti, 1996; Barro, 1991; Collier, 1999) show a clear negative link between conflict and aggregate economic performance, establishing causality from these correlations is difficult.[4] A great number of institutional and economic differences between war-torn countries and countries at peace may drive the result. On the other hand, micro-empirical within-country studies that compare more and less affected households or locations such as Miguel & Roland (2011), Besley & Reynal-Querol (2014), Serneels & Verpoorten (2015) and Abadie & Gardeazabal (2003) are similar in nature to my reduced-form analysis.[5] As Blattman & Miguel (2010) note, even with a solid identification strategy, this approach cannot account for general equilibrium effects. I combine the best of both worlds. Using a within-country identification strategy in combination with a general equilibrium model allows me to estimate aggregate effects that can causally be attributed to the civil war. To the best of my knowledge, this is the first paper to estimate a general equilibrium model in the study of conflict.[6]

[4] Cerra & Saxena (2008) is similar to these analyses but broader in scope since it considers not only civil war but also financial crises. The authors estimate impulse response functions using a panel of many countries over several decades.

[5] Abadie & Gardeazabal (2003) use regional GDP data as opposed to household-level data and provide an aggregate effect analysis at the regional level. However, the concern around general equilibrium effects still applies. Factor mobility and price changes in general equilibrium imply that the estimates may capture mere spatial divergence between the Basque region and other regions to some extent and may not be informative about aggregate effects at the country level.

[6] Dal Bó & Dal Bó (2011) use a general equilibrium model in their analysis of conflict. However, their

The model I develop is an economic geography model that draws on Bryan & Morten (2019), Hsieh et al. (2019) and Eaton & Kortum (2002).[7] In particular, civil war typically leads to the reallocation of labor across space with important general equilibrium implications. This concerns not only the size of population movement but also the selection. Indeed, Davis & Weinstein (2002) and Brakman et al. (2004) find that city growth is unaffected by bombing intensity. However, this does not speak to the selection of migrants. In this study, I also find that the number of migrants is unaffected by conflict but the selection of migrants seems to play a major role in accounting for spatial differences in income as a result of the war.[8]

The second contribution of this paper is to shed light on a channel of the impact of conflict that has received little attention so far: reverse structural transformation, in particular as fuelled by decreases in non-agricultural firm productivity. This can capture a variety of elements that could be affected by war such as market access or electricity connection. My model features labor as the only input into production. Immobile physical capital would enter the model in the same way as firm-level productivity. Therefore, reductions in the latter could also capture physical capital reductions such as the destruction of local buildings or machines. Only few studies consider firm or sector allocation outcomes and these are typically short-run analyses (Bozzoli et al., 2012; Camacho & Rodriguez, 2013; Collier & Duponchel, 2013). By contrast, the literature on human capital effects of conflicts is large.[9] Indeed, this paper also demonstrates evidence on human capital losses as a result of the war. But their role in explaining persistent aggregate income effects is shown to be limited. Depending on which factors are the main drivers behind persistent consequences of conflict for economic welfare, the implications for post-war policy differ greatly. My analysis suggests that restoring firm productivity deserves greater policy focus.

The remainder of the paper is organized as follows. Section 2 provides a brief overview of the Sierra Leonean civil war that motivates it as an empirical setting. Section 3 discusses the empirical design of this study and section 4 presents reduced-form results. In section 5, I develop the model and discuss its estimation strategy in section 6. Section 7 presents the results of the model estimation, followed by the presentation and discussion of counterfactual simulations in section 8. Finally, section 9 concludes.

paper is about the causes of conflict and not about the general equilibrium consequences of it. It is also purely theoretical. They do not make use of data, let alone carry out structural estimation. While their model finds empirical application in Dube & Vargas (2013), the estimates are an investigation of two specific reduced-form mechanisms that are directly observed in the data. My approach estimates and simulates full general equilibria. This allows both for aggregate effect estimation and a quantitative assessment of mechanisms that are not directly observed in the data.

[7]The model also has similarities with elements in Allen & Arkolakis (2014), Redding (2016) and Lagakos & Waugh (2013).

[8]This result is also in line with other papers that highlight the importance of selective migration in explaining spatial income differences such as Young (2013).

[9]Focusing on civil war and long-run outcomes at least 10 years after the end of war, these include Akbulut-Yuksel (2014); Akresh & De Walque (2011); Galdo (2013); La Mattina (2018); Leon (2012); Saing & Kazianga (2020).

2. The Civil War in Sierra Leone

Sierra Leone suffered an atrocious civil war between 1991 and 2002 that caused some 70,000 casualties, displacement of roughly half the population and left many people injured, maimed and raped (UNDP, 2006). While the war was extremely brutal, the country has experienced a long period of sustained peace since it ended in early 2002. This provides an ideal setting to investigate long-run effects of the war today.

The civil war started as an insurgency by the Revolutionary United Front (RUF) under Foday Sankoh in 1991 entering the country from Liberia in the southeastern part of the country.[10] The RUF was a small rebel group at the onset of war with the political goal of overthrowing the ruling one-party regime, led by the All People's Congress (APC) party under Joseph Saidu Momoh (Richards, 1996). Their insurgency was supported by the National Patriotic Front for Liberia (NPFL) led by Charles Taylor and involved in the ongoing Liberian civil war. In fact, the RUF had started their fighting activities in Liberia along with the NPFL when the war broke out in the neighboring country in 1989. Foday Sankoh and Charles Taylor had met each other and worked and trained together before. The RUF remained mainly active and the fighting concentrated in the southern parts of Sierra Leone bordering Liberia between 1991 and 1995 until it eventually spread to other parts of the country. This involvement with Liberia means that distance to the Liberian border is highly predictive of conflict intensity and motivates its use as an instrumental variable.

As Richards (1996) argues, political grievances played an important role as a cause of the civil war. In particular young people were discontent with a patrimonial system in which a small group of patrons rules and decides on the allocation of opportunities and transfers arbitrarily. They felt disenfranchised and robbed of education and other opportunities. The RUF's ideological roots lied in an idea of egalitarianism which initially helped in recruiting disenfranchised youth. However, as knowledge of the atrocities committed by the group spread, recruitment by capture became more necessary and common.

One of the atrocious features of the Sierra Leonean civil war was the extreme degree of violence against civilians, in particular all the community looting operations as well as the raping, killing and maiming that characterized the war. Quite tellingly, such operations were called "Operation Pay Yourself" or "Operation No Living Thing". These acts of violence were not only committed by the RUF, but also by the Sierra Leonean Army (SLA) throughout the war, often by so-called "Sobels" who were soldiers by day and rebels by night, taking on an identity under which it was more legitimate and less consequential to engage in these activities. With such violent activities characterizing how households were affected by the war, Sierra Leone provides a unique data environment for the study of conflict. The Sierra Leonean Integrated Household Survey 2011 contains direct information on how households were victimized as a result of the war. This information can

[10]Figure B1 displays the location of Sierra Leone and Liberia in West Africa.

be used as a measure for conflict intensity that captures the effect of the civil war well.

The opportunistic behavior of fighters demonstrates that there was an element of "greed" to the civil war that also became increasingly prevalent in the illicit mining or smuggling of diamonds.[11] The diamond wealth resulting from these activities helped funding the war and provided incentives to prolong it (Keen, 2005; Richards, 2004). Therefore, throughout the war, economic motives became increasingly important in the rebels' decision to engage in fighting.

Another interesting feature is the lack of ethnic or religious divisions as a key driver of war, as Bellows & Miguel (2009) point out. No ethnic group appeared to be disproportionately victimized and there seems to be no evidence that violence against a particular civil community was more pronounced if the community and the fighting group have largely differing ethnicity.

3. Empirical Design

3.1. Data

The main source of data for this study is the Sierra Leonean Integrated Household Survey (IHS) 2011 and 2018 which are general representative individual-level surveys (Statistics Sierra Leone, 2018). I use detailed questions on economic activity in 2018 to construct the following outcome variables. First, as a proxy for worker income, I use household expenditure information on food and non-food items and divide this by the number of working people in a household.[12] The reason for using information on expenditures rather than income directly is that the expenditure data is much more complete and highly likely to be more reliable. It is recorded in weekly visits by enumerators during which households indicate the items they bought and at which price they did so. Such information is significantly easier to remember than providing information on different income sources over the past year in a setting where most workers are subsistence farmers or engage in small business activities without any bookkeeping.

Second, the main sector that individuals work in is constructed according to the ISIC classification (see Figure B2). For all main results, a simple binary distinction between agriculture and non-agriculture (manufacturing and services) is made.

Third, education outcomes are recorded directly. From information on completed grades, I use years of schooling and an indicator for having finished primary education.

Regarding conflict data, the 2011 survey contains a section with a number of questions on the impact of conflict on individuals and households that I make use of. As a conflict

[11] The literature on the causes of conflict broadly distinguishes between economic opportunism and political grievances – coined the "greed" and "grievances" routes to conflict in the seminal work by Collier & Hoeffler (2004).

[12] The division by the number of workers is done to reflect worker income. However, all instrumental variable analyses can be performed on related measures such as total household expenditures or expenditures per adult equivalent. The main findings go through in this robustness exercise as demonstrated in section 4.2.

measure, I follow Bellows & Miguel (2009) in constructing a victimization index. This index is the share of "yes" answers to eight binary questions in the survey that cover how households were affected by the war along the following dimensions: (1) whether the household lost property or assets; (2) whether the house was burnt; (3) whether household members were killed; (4) whether relatives were killed; (5) whether household members lost limbs; (6) whether household members were molested or raped; (7) whether household members were displaced; (8) whether the war had any other effect on the household.[13] Given that the extreme degree of violence against civilians was a feature of the Sierra Leonean civil war, a victimization index seems to be a sensible measure of the intensity of conflict.[14]

For my analysis and in line with Bellows & Miguel (2009), I aggregate the household-level victimization experience at the chiefdom level to construct conflict measures at that level. For ease of interpretation, the measure is standardized. With five chiefdoms missing in the household survey 2018 and three different ones missing in the household survey 2011, I observe 150 chiefdoms in addition to the capital Freetown in 2018. Chiefdoms are the lowest level of administration. At the next higher level, Sierra Leone is administered in 14 districts, the level of my fixed effects in the empirical analysis. The aggregation and subsequent treatment of conflict at the chiefdom level serves to capture potentially large within-chiefdom spillovers of conflict.

Furthermore, the 2018 survey contains detailed information on migration. In particular, the chiefdom of birth as well as the chiefdom of residence and the year of moving are recorded for each individual. This information is crucial when estimating the model. The estimation requires knowledge of both origin and destination for all individuals.

In addition to socio-economic control variables from the IHS data, I use data from Glennerster et al. (2013) for some land characteristics as controls and census data from 1963, 1985 and 2015.[15] I also use geographic information to compute the distance of a chiefdom centroid from the Liberian border which serves as an instrumental variable in my analysis. In order to test whether this instrument correlates with pre-war characteristics, I draw on census data as well as data used in Bellows & Miguel (2009) and Acemoglu et al. (2014). They provide information on economic outcomes before the war, albeit partially incomplete, including education and expenditure in 1989 as well as historic tax and trade variables. Summary statistics for all variables used are provided in Table 1.

[13] Bellows & Miguel (2009) use very similar questions in a survey carried out by the Institutional Reform and Capacity Building Project (IRCBP) to construct their victimization index.

[14] An alternative data source that is used in many recent papers studying conflict is the ACLED dataset. However, this data cannot be used for Sierra Leone since ACLED only covers conflict events from 1997 which would only capture the last few years of the civil war in Sierra Leone.

[15] I only have aggregate information at the chiefdom level for the 1963 and 1985 census and excerpts for the 2015 wave of the census.

Table 1: Summary Statistics

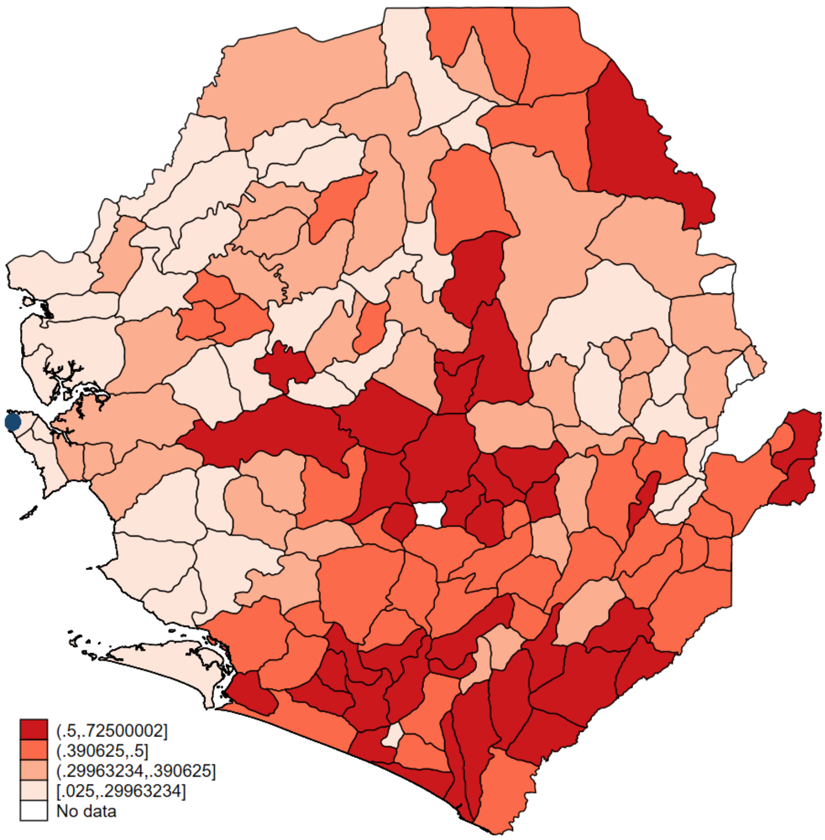
	N	Mean	Std. Dev.
Individual Level			
Female dummy	21407	0.54	0.50
Household size	21407	7.27	3.75
Age	21407	36.5	16.3
Religion is Christianity	21407	0.23	0.42
Religion is Islam	21407	0.76	0.42
Years of schooling	21396	5.19	5.44
Finished primary school	21397	0.47	0.50
Worker Level			
Main sector is agriculture	14482	0.54	0.50
Main sector is manufacturing	14482	0.090	0.29
Main sector is services	14482	0.37	0.48
20 day expenditures per worker (in USD)	14355	60.3	61.9
Chiefdom Level			
Conflict	163	0.21	1.01
Distance to border	166	114.9	80.0
Vector ruggedness measure, (3x3 window)	166	0.37	0.081
Average Elevation (km)	166	0.17	0.15
% of chiefdom w/ slope between 2-8%	166	58.5	14.8
% of chiefdom w/ slope between 8-30%	166	19.8	15.3
% of chiefdom w/ slope between 30-45%	166	3.31	5.04
School attendance 1989	76	0.28	0.20
School enrollment 1989	76	0.30	0.20
Log p.c. expend. 1989	76	7.94	0.68
Log pop. density 1985	159	3.79	0.78
19th Cen. trading route	154	20.0	19.7
Mining permission 1930	154	0.18	0.38
Hut Tax/Area 1900	89	0.94	1.42
Hut Tax/Pop. 1900	88	0.028	0.030
Population 1963	153	13712.0	9961.6

Note – The individual sample consists of all individuals in 2018 who were born before the end of the war in 2001. The worker sample is restricted to the working population. All monetary values are in 2018 USD and the top 1% is truncated.

3.2. Identification Strategy

My main specification to estimate the effect of conflict on outcomes is an instrumental variable (IV) specification using the distance to the Liberian border as an instrument for conflict. Given the interlinkages between the civil wars in Liberia and Sierra Leone and the fact that fighting originated and concentrated in the border area for a long time, distance to the Liberian border is strongly correlated with conflict intensity. As Figure 1 depicts clearly, while fighting spread to most parts of the country throughout the war, the highest conflict levels are experienced by areas bordering Liberia in the Southeast and in the corridor between the border and the capital Freetown in the very West towards which the rebels progressed.

Figure 1: Variation of the Victimization Index



Note – Standardized victimization index for all chiefdoms of Sierra Leone. The south-eastern border on the map is the border with Liberia. The blue dot in the western part of the country marks the capital Freetown. Missing conflict information in three chiefdoms.

My IV-2SLS specification is characterized by the following equations:

$$y_{ic} = \alpha_{district} + \beta\, \widehat{conflict}_c + \mathbf{X_{ic}}'\mu + \epsilon_{ic} \quad \text{(Second Stage)} \tag{1}$$

$$\widehat{conflict}_c = \hat{\alpha}^{FS}_{district} + \hat{\gamma}^{FS} distance_c + \mathbf{X_{ic}}'\hat{\mu}^{FS} \quad \text{(First Stage)} \tag{2}$$

where y_{ic} is the outcome of interest for individual i in chiefdom c, $distance_c$ is the instrument and $\alpha_{district}$ capture district-level fixed effects. The vector of controls includes a set of socio-economic controls as well as characteristics of the land. Importantly, in all specifications, I control for distance to one of the five largest cities in Sierra Leone (Freetown, Bo, Kenema, Koidu, Makeni). These five cities are well known as urban and regional economic centres and the only large cities of the country with a population exceeding 100,000 inhabitants. Controlling for distance to these cities ensures that any potential mechanical relationship between border distance and distance to large cities does not act as a confounder. The underlying reason for a potentially confounding relationship is that economic development can have a highly geographic component. Growth in an area can subsequently lead to economic development around that area (Felkner & Townsend, 2011).[16]

While different regions within Sierra Leone differ not only in their distance to the Liberian border but also in terms of other characteristics that are correlated with economic outcomes, performing the analysis within districts is crucial to satisfy the exclusion restriction. The identification assumption is therefore that, within districts and conditional on the set of control variables used, distance to the Liberian border only affects outcomes after the war through inducing variation in conflict, but not through any other channel.

One potential concern with this assumption is that distance to the Liberian border is naturally related to trade. Even within the same district, chiefdoms that are located closer to the border may have been more active in trading before the war and therefore at a different level of economic development. This would lead to a violation of the identification assumption. However, I argue that such a violation is unlikely to play a major role for three reasons.

First, trade with Liberia is only of negligible size relative to the total trade volumes of Sierra Leone before the war. Exports to Liberia as a share of total exports are less than 0.1% before the war.[17] The main trading partners of Sierra Leone are Europe and the US and trade with these partners would not go through Sierra Leone but rather through their main port in Freetown. Distance to Freetown as one of the major urban centres is controlled for in all specifications.

Second, I provide a test against the hypothesis of trade as a major confounder by excluding chiefdoms directly bordering Liberia and repeating my main IV analysis on worker income as an outcome. To the extent that chiefdoms with a direct border would especially benefit from trade, this should lead to results that differ from the main results on the full sample. However, the results with the restricted sample are very comparable to the main results.

Third, districts are small. Sierra Leone as a whole country is as large in area as the Netherlands and Belgium together and subdivided into 13 rural districts, excluding

[16] In addition, the full set of controls contains the following variables. Socio-economic controls are household head's sex, age, age squared, religion as well as household size. The land characteristics are a vector ruggedness measure, the average elevation in a chiefdom, the share of chiefdom terrain with slope between 2-8%, 8-30% and 30-45%, the share of chiefdom terrain with coarse texture and with medium texture, as well as the share of chiefdom soil with poor drainage and with excessive drainage.

[17] Information from the UN Comtrade Database (United Nations, 2020). The most recent year with information on trade in Sierra Leone before the war started is 1986.

Freetown. The average rural district's area is therefore only 5000 square kilometers. While location likely matters for trade at the country level, it is implausible that it would play an important role within these small districts.

Another concern pertaining in particular to the sector allocation as an outcome of interest may be differences in the quality of the land that are related to the border distance. This is the main reason behind including a variety of land characteristics as a set of control variables in the analysis. In fact, the inclusion of these controls leads to stronger IV results. Therefore, choosing the sparser and more precisely estimated specification without land controls as my preferred specification is a conservative approach which means that the results can be interpreted as a lower bound on the true effect.

Further to these considerations, I also use pre-war characteristics drawing on data used in Bellows & Miguel (2009) and Acemoglu et al. (2014) to test whether distance to the Liberian border has predictive power for economic outcomes before the war within districts. The results are shown in Table 2. Distance to the border within districts has no significant predictive power (at the conventional 5% level) for any outcome. In fact, only one outcome has a significant coefficient at the 10% level which can easily arise by chance when testing nine outcomes. Given these results on observable variables, it seems very unlikely that the instrument is related to post-war outcomes through other unobservable channels.

Considering the first stage, results of a formal test are shown in Table 3.[18] I include Kleibergen-Paap F statistics that allow for the cluster structure of my error term and are still comfortably above the conventional threshold of 10.[19] In addition to these F statistics, I follow Andrews et al. (2019) and report weak-IV robust p-values based on the Anderson-Rubin statistic. For all main results, they are close to the classic p-values and do not change conclusions about inference.

For the analysis of education outcomes, the fact that education is usually obtained during a particular age provides me with additional cohort variation that I can exploit for a placebo test of the identification assumption. I split the sample and run the IV analysis separately for people who were at school age when the war started and those who were already old enough to have finished their education. I use a generous definition of school age with age 30 at the beginning of the war as a cut-off point.[20] If the instruments does not satisfy the exclusion restriction in a way that is relevant for education as an outcome, this should become visible in the analysis of the old cohort. I show that conflict only affects people at school age but there is no effect for the old cohort. This lends further support to the exogeneity of the instrument.

[18] Figure B3 graphically displays the correlation between my standardized conflict measure and distance to the Liberian border within districts.

[19] Note that Kleibergen-Paap F statistics are equivalent to Montiel-Pflueger F statistics in the weak IV test in the just identified case with one endogenous regressor and one instrument.

[20] The results are robust to using different cut-off points, for example anyone aged 18 or older at the beginning of the war.

Table 2: Correlation of Instrument with Pre-war Observables

	(1) School attendance 1989	(2) School enrollment 1989	(3) Log p.c. expend. 1989
Distance to border	0.00140	0.00128	0.00673
	(0.00119)	(0.00126)	(0.00659)
N	76	76	76
R^2	0.511	0.438	0.326
District FE	✓	✓	✓
	(4) Log pop. density 1985	(5) 19th Cen. trading route	(6) Mining permission 1930
Distance to border	0.00401*	-0.0652	0.00109
	(0.00235)	(0.0492)	(0.00128)
N	159	154	154
R^2	0.280	0.571	0.208
District FE	✓	✓	✓
	(7) Hut Tax/Area 1900	(8) Hut Tax/Pop. 1900	(9) Population 1963
Distance to border	0.000485	0.0000284	0.954
	(0.00629)	(0.000140)	(24.33)
N	89	88	153
R^2	0.332	0.416	0.199
District FE	✓	✓	✓

Note – All specifications include district fixed effect. Clustered standard errors at the chiefdom level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: First Stage

	(1) Conflict	(2) Conflict	(3) Conflict	(4) Conflict
Distance to border (km)	-0.0128***	-0.0114***	-0.0120***	-0.0104***
	(0.00264)	(0.00292)	(0.00272)	(0.00292)
Sample	Individuals	Individuals	Workers	Workers
N	21407	21407	14482	14482
R^2	0.738	0.748	0.714	0.728
F (KP)	23.59	15.34	19.47	12.67
Socio-econ. Controls	✓	✓	✓	✓
Land Controls		✓		✓
District FE	✓	✓	✓	✓

Note – Clustered standard errors at the chiefdom level in parentheses. Kleibergen-Paap cluster-robust F statistic reported. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4. Reduced-form Results

4.1. Main Results

Table 4 demonstrates the results of an OLS regression and the IV specification for worker income, as proxied for by expenditures per worker, for different sets of control variables. The effect of conflict is large. Based on the more parsimonious specification in column (3), an additional standard variation of conflict intensity reduces income by 30% twenty years after the end of the war. This means that workers living in chiefdoms that are at the 75$^{\text{th}}$ percentile of the conflict distribution (high conflict intensity) have 38% lower income than households living in chiefdoms at the 25$^{\text{th}}$ percentile of the conflict distribution (low conflict intensity). The results suggest substantially lower livelihoods in more affected chiefdoms as a result of the war.

Two observations that apply to this and further results on economic outcomes are noteworthy. First, the specification including land controls (column 4) delivers a stronger result. This could be the case because of bias when not controlling for land characteristics of the chiefdoms. Considering the first stage results and the large size of the effect even without land controls, however, this could also plausibly reflect the strength of the instrument conditional on the whole set of socio-economic and land controls. The relevant F statistic drops from 19.33 to 12.64 when including land controls. In the spirit of a cautious interpretation of the results, I would therefore consider the specification without land controls as the more reliable one and take it as a more reasonable estimate of the effect of civil war.

Second, the IV results are stronger than the OLS results. The difference between IV and OLS results is consistent with a positive selection into conflict in the sense that conflict takes place in areas that are richer to begin with. In light of the fact that economic considerations played a key role in the rebels' decision to engage in conflict this

Table 4: Expenditures per Worker

	Log household expenditures per worker			
	(1)	(2)	(3)	(4)
Conflict	-0.0674*	-0.0797**	-0.306**	-0.479**
	(0.0348)	(0.0358)	(0.129)	(0.187)
N	14355	14355	14355	14355
R^2	0.356	0.367	0.322	0.282
Estimation Method	OLS	OLS	IV	IV
First Stage F (KP)			19.33	12.64
AR p-value			0.012	0.001
Socio-econ. Controls	✓	✓	✓	✓
Land Controls		✓		✓
District FE	✓	✓	✓	✓

Note – Outcome variable: Log total expenditures per worker. Conflict standardized and instrumented with distance to border. Clustered standard errors at the chiefdom level in parentheses. Kleibergen-Paap cluster-robust F statistic and p-value for weak instrument robust Anderson-Rubin test of $H_0 : \beta = 0$ reported. Stars refer to standard t-tests. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

is plausible.[21] At the individual level, many young people were easily recruited by the rebel movement because engagement in looting communities was economically more attractive than alternative ways to make a living. At the collective level, the rebel movement aimed at controlling and generating revenue from diamond mines as a source of income.[22]

A large sector shift in economic activity may be a key driver of these income effects. The results on the main sector of work are shown in Table 5 (and graphically displayed in Figure B4 for the preferred specification with socio-economic controls only). With a standard deviation increase in conflict intensity, workers are 18.5 percentage points more likely to work in agriculture and correspondingly less likely to engage in non-agricultural activities. This means that workers in high conflict chiefdoms (at the 75th percentile of the conflict distribution) are 23 percentage points more likely to work in agriculture than those in low conflict chiefdoms (25th percentile). The employment share in agriculture in the whole country is 55%. Such increases in areas experiencing more conflict constitute a large shift in the sector allocation. Both the manufacturing and services sector experience a loss of workers.[23] Since pay in the agricultural sector is on average just above one third of what it is in the non-agricultural sector in Sierra Leone, a sector shift into agricultural work can be an important driving force of lower average income.[24]

To the extent that education and the sector of employment are correlated, human capital loss as a result of the war may be the reason for the sector shift. Indeed, the

[21] In their analysis of Rwanda, Justino & Verwimp (2013) also find that richer households were targeted.

[22] This may raise an endogeneity concern if the location of diamond mines at the beginning of the war is correlated with the instrument. Unfortunately, no information on the location of diamond mines in 1991 is available. Using information on their location in 2002 from Bellows & Miguel (2009), however, I can establish that the instrument is uncorrelated with distance to diamond mines in 2002. Furthermore, controlling for distance to diamond mines does not change any results in the IV analysis.

[23] This pattern of results holds up when we consider all individuals, including the unemployed, and not only workers. The results can be found inTable A1.

[24] In 2018, expenditures per worker in 20 days were on average 34 USD for agricultural workers and 91 USD for non-agricultural workers.

Table 5: Sector Allocation

	Work in Agriculture				Work in Non-agriculture			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Conflict	0.0601**	0.0715***	0.185**	0.312***	-0.0601**	-0.0715***	-0.185**	-0.312***
	(0.0236)	(0.0237)	(0.0799)	(0.111)	(0.0236)	(0.0237)	(0.0799)	(0.111)
N	14482	14482	14482	14482	14482	14482	14482	14482
R^2	0.369	0.386	0.347	0.312	0.369	0.386	0.347	0.312
Estimation Method	OLS	OLS	IV	IV	OLS	OLS	IV	IV
First Stage F (KP)			19.47	12.67			19.47	12.67
AR p-value			0.028	0.002			0.028	0.002
Socio-econ. Controls	✓	✓	✓	✓	✓	✓	✓	✓
Land Controls		✓		✓		✓		✓
District FE	✓	✓	✓	✓	✓	✓	✓	✓
	Work in Manufacturing				Work in Services			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Conflict	-0.0152*	-0.0140	-0.0712***	-0.0979***	-0.0449**	-0.0575***	-0.113*	-0.214**
	(0.00907)	(0.00873)	(0.0236)	(0.0362)	(0.0203)	(0.0197)	(0.0638)	(0.0832)
N	14482	14482	14482	14482	14482	14482	14482	14482
R^2	0.0740	0.0769	0.0604	0.0494	0.297	0.314	0.290	0.280
Estimation Method	OLS	OLS	IV	IV	OLS	OLS	IV	IV
First Stage F (KP)			19.47	12.67			19.47	12.67
AR p-value			0.002	0.001			0.090	0.006
Socio-econ. Controls	✓	✓	✓	✓	✓	✓	✓	✓
Land Controls		✓		✓		✓		✓
District FE	✓	✓	✓	✓	✓	✓	✓	✓

Note – Outcome variables: Indicator variables for sector of work. Conflict standardized and instrumented with distance to border. Clustered standard errors at the chiefdom level in parentheses. Kleibergen-Paap cluster-robust F statistic and p-value for weak instrument robust Anderson-Rubin test of $H_0 : \beta = 0$ reported. Stars refer to standard t-tests. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

correlation between education and employment in agriculture is strong. While 68% of workers without primary school education are employed in agriculture, this share drops to 27% for workers who finished primary school.[25] The estimation results of the effect of conflict on education are presented in Table 6 and 7. In the preferred specification in column (3), individuals are 10 percentage points less likely to finish primary school as conflict intensity increases by one standard deviation; or correspondingly 13 percentage points less likely when moving from low conflict to high conflict chiefdoms (25th to 75th percentile). Alternatively measured, individuals lose one year of schooling per standard deviation of conflict (correspondingly 1.2 years as you move from low to high conflict chiefdoms). Relative to the country-wide share of primary educated workers of 47% and an average education of 5.2 years, these are substantial losses.

Table 6: Years of Schooling

	Years of Schooling			
	(1)	(2)	(3)	(4)
Conflict	-0.318**	-0.392**	-0.991*	-1.758***
	(0.156)	(0.163)	(0.537)	(0.660)
N	21396	21396	21396	21396
R^2	0.355	0.363	0.350	0.343
Estimation Method	OLS	OLS	IV	IV
First Stage F (KP)			23.59	15.33
AR p-value			0.065	0.003
Socio-econ. Controls	✓	✓	✓	✓
Land Controls		✓		✓
District FE	✓	✓	✓	✓

Note – Outcome variable: Years of schooling. Conflict standardized and instrumented with distance to border. Clustered standard errors at the chiefdom level in parentheses. Kleibergen-Paap cluster-robust F statistic and p-value for weak instrument robust Anderson-Rubin test of $H_0 : \beta = 0$ reported. Stars refer to standard t-tests. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.2. Identification Tests and Robustness

These results pass an important placebo test for the exogeneity of the instrument and are robust to a number of robustness checks. First, it is reassuring to see that the education effect only materializes for young people who were actually at school age when the war started while there is no significant effect for those old enough to have finished their education by that time. Table A2 demonstrates these results. Columns (1) and (3) present the education effect for individuals at school age when the war starts. The effect is slightly stronger than the main effect for everyone. By contrast, columns (2) and (4)

[25] This correlation can be the result of lower returns to education in agriculture. Differential returns by sector are a key part in the model that generates a correlation between education and sector choice. In line with the given correlation, the structural estimation of the model estimates returns to education in the non-agricultural sector to be substantially larger than returns in agriculture.

Table 7: Primary Education

	Primary Education			
	(1)	(2)	(3)	(4)
Conflict	-0.0317**	-0.0361**	-0.102**	-0.164***
	(0.0137)	(0.0141)	(0.0462)	(0.0580)
N	21397	21397	21397	21397
R^2	0.332	0.339	0.326	0.319
Estimation Method	OLS	OLS	IV	IV
First Stage F (KP)			23.59	15.33
AR p-value			0.031	0.002
Socio-econ. Controls	✓	✓	✓	✓
Land Controls		✓		✓
District FE	✓	✓	✓	✓

Note – Outcome variable: Indicator for having finished primary school. Conflict standardized and instrumented with distance to border. Clustered standard errors at the chiefdom level in parentheses. Kleibergen-Paap cluster-robust F statistic and p-value for weak instrument robust Anderson-Rubin test of $H_0 : \beta = 0$ reported. Stars refer to standard t-tests. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

show the effect for people above school age for both education outcomes. The coefficients are close to zero and insignificant.

Second, the main results on worker expenditures are robust to the exclusion of chiefdoms directly bordering Liberia. Table A3 provides the results for the restricted sample. The effect of conflict is a 33.8% reduction in expenditures per worker as conflict increases by one standard deviation in the preferred specification in column (3). The coefficient is very close to the corresponding effect for all chiefdoms (30.6%) and statistically indistinguishable. Other specifications and OLS results are also very similar. This suggests that trade with Liberia is unlikely to be a threat to identification.

Third, the main results on worker expenditures are robust to using different variations of household expenditures measures. The division by the number of workers is not driving the result. Table A4 and A5 show the results for total household expenditures and total household expenditures per adult equivalent, respectively. While the IV coefficients for both alternative measures are a bit smaller than the ones reported in the main results, they are still sizeable and significant. The reduction is around 17% per standard deviation of conflict increase in both alternative specifications.

Fourth, the results on all outcomes are robust to the exclusion of the capital Freetown. Bellows & Miguel (2009) argue that the capital's local institutions and history are quite different from the rest of the country. However, any such differences do not seem to be driving my results since the outcomes without Freetown are very comparable to my main results with Freetown. Table A6 shows the results on expenditures per worker, employment in agriculture, years of schooling and primary education when the sample excludes the capital Freetown. All OLS and IV coefficients are very close to the ones in the main specifications including Freetown.

4.3. Further Discussion

These reduced-form results suggest that civil war has strong persistent effects on the livelihoods of households that live in affected chiefdoms. A loss of human capital has direct implications for worker income and can be a reason for a shift in the sector of employment to the extent that lower education is correlated with employment in agriculture. Workers are a lot more likely to work in agriculture as a result of their chiefdom being hit by conflict. Since pay in agriculture is lower than in the non-agricultural sector, such a shift is a driving force for lower income in chiefdoms that are more heavily affected by conflict.

The presented estimates identify spatial differences. The results are essentially generated by comparing more and less affected areas by the civil war. If productive resources are reallocated across space as a result of the war, however, spatial differences do not only capture the direct effect of conflict but also the reallocation of resources. In particular, we may be concerned about labor supply changing in locations when people move in response to the war.

The 2011 survey indicates that around 50% of all households were displaced at some point during or after the war. Even considering migration in the long run, migration rates in the 2015 census and 2018 household survey are between 25% and 30%. It is quite plausible that the selection of migrants changes as a result of the war. For example, if more productive non-agricultural workers leave conflict areas during or after the war and stay in less affected areas, my estimate would also capture this type of selective migration. The fact that income is higher in less affected areas after the war is partly due to the changing type of movers to these areas. As a result, spatial income differences would overstate the aggregate income effect of conflict. In order to understand the aggregate income effect, the following part develops a model that explicitly takes into account general equilibrium effects of the war such as selective migration. Structural estimation of the model and counterfactual simulations allow me to estimate the aggregate income effect of the civil war in Sierra Leone.

Further to estimating the aggregate income effect, the development and estimation of the model also allows me to shed light on *unobserved* mechanisms of the effect of war. While education is observed, there are other important determinants of productivity that could be affected by the war and a driver of the sector shift and income effects. A simple quantitative evaluation of the observed effects suggests that education is unlikely to be the only driving force of income effects. Individuals lose on average one year of schooling while the loss in earnings is about 30% of workers' income as conflict increases by one standard deviation in their chiefdom. If education was the only channel leading to income reductions, the returns to education for an additional year of schooling would need to be 30% to generate these findings. This is an order of magnitude larger than the typical estimates ranging between 7% and 9%.[26] In the model, other determinants of

[26]For reviews on worldwide returns to an additional year of schooling, see for example Peet et al. (2015) and Psacharopoulos & Patrinos (2018).

the sector shift and income effects are captured by sector-specific firm productivities and average individual productivities beyond education. Using the structure of the model, I can estimate these objects and evaluate the impact that conflict has on them.

5. Model Theory

The model is a static general equilibrium economic geography model. The basic setup draws on Bryan & Morten (2019) and Hsieh et al. (2019) and contains elements that are similar to other work in quantitative economic geography, in particular Eaton & Kortum (2002), Allen & Arkolakis (2014) and Redding (2016). In order to capture basic characteristics of the Sierra Leonean economy and the key pathways how conflict affects the economy, the model contains the following principal features that are motivated by the reduced-form results.

First, the high migration rate in Sierra Leone with movement potentially responding to conflict motivate an economic geography setup with endogenous location choice. Workers choose locations on the basis of an individual location-specific productivity and subject to migration cost. Furthermore, locations differ in aggregate firm productivities and amenities, both of which can be affected by conflict. In this way, conflict can change the spatial allocation of labor.

Second, the reduced-form results indicate that the sector allocation is an important pathway how conflict affects the economy. Therefore, the model features an agricultural and non-agricultural sector. Workers sort into sectors on the basis of individual sector-specific productivities. Firm productivities are also sector-specific and govern sector choice. A differential effect of conflict on firm productivities by sectors can be one mechanism how conflict affects sector allocation.

Third, education and employment in the non-agricultural sector are highly correlated in Sierra Leone. This could be the result of differing returns to education across sectors. With sector-specific returns to education, an education loss resulting from conflict can have both direct effects on income and indirect effects through a change in the sector composition. To capture this mechanism, the model features education with differential returns by sector.

This structure[27] allows me to lay out both the direct effects of conflict and the indirect effects through a change in the sector composition and spatial allocation of labor. By explicitly taking into account general equilibrium forces, I am able to estimate aggregate income effects when estimating the model in a next step. While the reduced-form results identify spatial income differences, aggregate income effects may be very different if there

[27] The structure of labor mobility under movement cost and destination choice based on individual productivity draws is comparable to the core structure in Bryan & Morten (2019). Conceptually similar to the industries in Hsieh et al. (2019), I have two sectors and sector-specific individual productivity draws. I also introduce human capital with differential returns to education by sector. Relevant to my context, this gives rise to worker sorting across sectors on the basis of both (firm and individual) productivities and education.

is a strong spatial reallocation of labor in response to the war. In addition, estimating unobserved parameters such as firm and average individual productivities as well as amenities using the structure of the model allows me to consider potential mechanisms of a conflict impact on income that are not directly observed in the data.

5.1. Basic setup

Economic environment. The economy consists of 151 locations (chiefdoms) with the set of them denoted by $\mathcal{K}$ and comprises a continuum of individuals indexed by i. They are born in an origin chiefdom $c \in \mathcal{K}$ and can decide to move to destination chiefdom $d \in \mathcal{K}$ where they work in a particular sector $S \in \{A, N\}$, either agriculture or non-agriculture. Movement is costly and differs by sector and education level. Movement cost is denoted by τ^S_{ecd} and enters as a utility cost.

In an Armington (1969) fashion, each location produces a unique agricultural and non-agricultural good that is consumed everywhere. This structure serves as a dispersion force. In order to keep the model as simple as possible, I abstract from trade cost and assume that goods are traded costlessly across space.[28] Locations differ in the firm productivities in each sector A^S_d and amenities a_d.

In the spirit of Roy (1951), workers are heterogeneous in their productivity which is specific to both the sector and the destination they choose to work in (or the sectoral product that is produced in that destination). Workers are also endowed with an exogenous education level e.[29]

Preferences. Individuals have CES preferences over all goods produced in each sector and destination. They consume quantity c^S_{id} of the good produced in sector S and destination d. Their utility is also influenced by amenities in their destination a_d and the cost of moving to that destination and choosing their sector to work in τ^S_{ecd}. The utility function is therefore

$$U^S_{id} = a_d(1 - \tau^S_{ecd}) \left(\sum_d (c^A_{id})^{\frac{\sigma-1}{\sigma}} + (c^N_{id})^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{3}$$

where σ denotes the elasticity of substitution. In line with standard economic geography models, amenities can be thought of to capture elements such as natural beauty, the availability of local public goods and services and the quality of housing. In the particular context of this conflict study, an additional way to think of what amenities capture would

[28] Empirically, a lack of sufficient data on trade between chiefdoms or price differences across chiefdoms also prevent the estimation of a model featuring trade cost. Appendix D.1 outlines briefly what the introduction of trade cost in the model would mean. Section 8.3 discusses the implications for my results.

[29] Education is assumed to be exogenous for the sake of simplicity. Conflict is assumed to affect education directly as an exogenous parameter. However, making education endogenous and considering conflict as a shock to an exogenous education *cost* parameter delivers results that are conceptually equivalent to the model with exogenous education. An extension with endogenous education choice and exogenous education cost is outlined in Appendix D.2.

be the safety of a place. They enter multiplicatively in the utility function.

Like migration cost, they play a key role in workers' location choice. I model migration cost τ^S_{ecd} as the share of income that workers with education e lose when moving from c to d and choosing sector S. Migration cost can be thought of in several ways. One is the actual physical cost of moving away from home. Beyond that and potentially much more importantly, however, this parameter captures the cost of integration into a new community in order to be able to work there. In the Sierra Leonean context, chiefdoms still have traditional chiefdom administrations and strong local governance structures. Traditional chiefs who are members of locally well-known and respected so-called "ruling families" govern many parts of public life. In this context, integration into a new community is an important factor to be able to live and work there.

This cost τ^S_{ecd} is assumed to be both education- and sector-specific. The motivation behind this is threefold. First, this is the most general type of moving cost the model could allow for. I am able to estimate this cost non-parametrically and therefore let the data decide to what extent moving cost may actually differ across sectors and education levels. Second, a growing theoretical and empirical literature suggests that moving cost may differ by education level.[30] Reasons cited here are, for example, a better state of information about opportunities in different places among more educated people or greater availability of valuable job matches. Third, with sector dependence this parameter captures any friction of entering the non-agricultural sector. This may be due to the necessity of moving to a larger town within the same location for non-agricultural employment. This could also embody the fact that non-agricultural work requires connections or fixed investments for people born in rural areas where agricultural work is the default option. Empirically, it turns out that such frictions are quite real. Given the estimated large wage differences between workers in agriculture and non-agriculture (even accounting for selection on individual productivities), such a friction can rationalize the relatively high number of workers in agriculture.

Costless trade of goods results in common prices for each good p^S_d and a common CES price index P for the entire economy across all destinations:

$$P = \left(\sum_d (p^A_d)^{1-\sigma} + (p^N_d)^{1-\sigma} \right)^{\frac{1}{1-\sigma}} \tag{4}$$

Workers supply l^S_{id} effective units of labor in the sector and destination of their choice and are getting paid at the wage rate w^S_d. Their nominal income is therefore $m^S_{id} = w^S_d l^S_{id}$. Standard CES utility maximization results in indirect utility as a linear function of worker income:

$$V^S_{id} = \frac{a_d(1-\tau^S_{ecd})w^S_d l^S_{id}}{P} \tag{5}$$

[30]See, for example, Amior (2015); Kennan & Walker (2011); Wozniak (2010).

Productivities and labor supply. Workers draw individual productivities for each sector and destination z_{id}^S from a Fréchet distribution. The average productivity draw is different for each sector and destination and it also varies by origin and education level. For workers from origin c with education level e, the average productivity draw for sector S and destination d is captured in the scale parameter q_{ecd}^S. Along with independence, this results in the following multivariate distribution from which productivities are drawn:

$$F_{ec}(\mathbf{z}) = \exp\left(-\sum_d \sum_S \left(\frac{z_{id}^S}{q_{ecd}^S}\right)^{-\theta}\right) \tag{6}$$

where $\mathbf{z}$ denotes the vector of productivity draws and the shape parameter θ governs the dispersion of productivities. A high realization of θ means low dispersion, that is, productivities for the goods produced in different destinations are close to each other. One interpretation of this would be a high degree of similarity across products produced in different destinations.

In this formulation, workers from origin c with education e are, on average, the same in the sense that they draw from the same productivity distribution. Let $q_{ecd}^S = \overline{q_{ec}}\epsilon_{ecd}^S$, that is, average productivity draws are made up of a common component $\overline{q_{ec}}$ for all workers from origin chiefdom c with education e and some variation across sectors and destination with mean 1. This common component essentially captures the average individual productivity draw that someone *from* origin c with education e has. While the remaining variation of the scale parameter ϵ_{ecd}^S is assumed to be random, the common component $\overline{q_{ec}}$ may well be a function of chiefdom's characteristics. These are characteristics that shape how productive people will be who are born and grow up in an origin chiefdom c with education e. Differences in the common component $\overline{q_{ec}}$ across origins and education levels therefore capture the idea that some origins have better capabilities to produce high-productivity individuals, e.g., better healthcare, quality of schooling, childcare, etc.

Apart from productivities, workers also differ in the exogenous realization of their education level e which determines human capital in a standard Mincerian way. Let ϕ^S be the sector-specific returns to education. Human capital for workers with education e is exogenous and assumed to be

$$h_e^S = \exp(\phi^S e) \tag{7}$$

Human capital is combined with a worker's productivity draw to determine their effective individual amount of labor supplied in the market:

$$l_{id}^S = h_e^S z_{id}^S \tag{8}$$

Sector and destination choice. Using the expression for labor supply 8 in the indirect utility function 5, we can rewrite indirect utility as

$$V_{id}^S = \frac{v_{ecd}^S z_{id}^S}{P} \tag{9}$$

where $v_{ecd}^S := a_d(1-\tau_{ecd}^S)w_d^S h_e^S$. This essentially captures the wage rate in destination-sector (d,S) adjusted for amenities, movement cost and human capital. From the distribution of productivities, it follows that indirect utility for workers from origin c with education e across sectors and destinations follows a Fréchet distribution with scale parameter $\frac{v_{ecd}^S q_{ecd}^S}{P}$. Based on this distribution, we can characterize workers' sector and destination choice. The probability that a worker with education level e from origin c chooses sector S in destination d is

$$\pi_{ecd}^S := Pr\left[V_{id}^S > V_{id'}^{S'}\ \forall d', S'\right] = \frac{(v_{ecd}^S \epsilon_{ecd}^S)^\theta}{\sum_{d'}\sum_{S'}(v_{ecd'}^{S'}\epsilon_{ecd'}^{S'})^\theta} \tag{10}$$

This equation describes worker sorting behavior. If the adjusted wage rate in a particular chiefdom and sector is high relative to all other chiefdoms and sectors, the chiefdom and sector are attractive to work in.

In a similar way, properties of the Fréchet distribution give rise to the following characterization of the average productivity of workers *choosing* sector S and destination d:

$$E\left[z_i | i \in M_{ecd}^S\right] = (\pi_{ecd}^S)^{-1/\theta} q_{ecd}^S \Gamma\left(\frac{\theta-1}{\theta}\right) \tag{11}$$

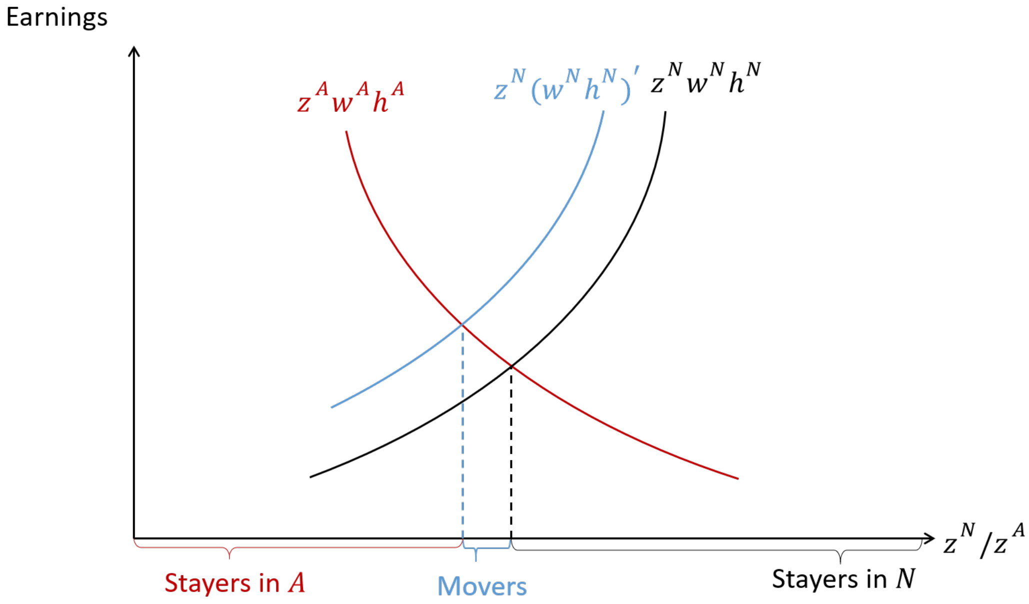
where $\Gamma(\cdot)$ is the Gamma function.[31] Average productivity in a destination-sector (d,S) depends negatively on the share of workers choosing that destination d and sector S. This reflects a selection mechanism. The marginal migrant who chooses to make that move is the one drawn from the leftmost part of the distribution with the lowest productivity. This selection mechanism is displayed graphically for sector choice in Figure 2. The negative relationship between the share of workers choosing (d,S) and average productivity in that destination-sector pair giving rise to this selection mechanism is a result of alignment of comparative and absolute advantage. Graphically, this is represented by the upward sloping curves in the figure. This assumption of alignment is hard-baked into the model by using independent Fréchet draws. Heckman & Honore (1990) refer to this as the standard case and it is intuitively appealing that those workers who have a comparative advantage for working in a particular destination-sector pair would also absolutely perform better there.[32]

This formulation of average productivities is useful to represent the relationship between average income and average productivity:

[31] Derivations of equation 10 and 11 are provided in the Appendix, section C.

[32] Lagakos & Waugh (2013) and Adao (2016) expand on this notion more formally. Lagakos & Waugh (2013) also provide an alternative multivariate characterization of the Fréchet distribution using the Frank copula and arbitrary correlation between productivity draws. This version does *not* automatically generate alignment between comparative and absolute advantage. The aim of their analysis is indeed to allow for different cases and let the data in their global cross-country analysis decide whether they find evidence of such alignment. This turns out to be the case.

Figure 2: Worker Selection



Note – This graph shows the sector choice response within a location as wages change. A higher wage in non-agriculture implies more people choosing to work in this sector. As a result of comparative and absolute advantage being aligned (both curves upward sloping), the average productivity of the movers is lower than that of the stayers in N. Therefore, overall average productivity in that sector must go down.

$$\overline{m_{ecd}^S} = w_d^S h_e^S (\pi_{ecd}^S)^{-1/\theta} q_{ecd}^S \Gamma\left(\frac{\theta-1}{\theta}\right) \tag{12}$$

Since average productivity determines average income in a sector S and destination d for all workers from c with education e, the same negative relationship with the share of workers manifests here. The strength of this negative relationship is governed by the size of $1/\theta$. Lower productivity dispersion (high θ) leads to a small size of $1/\theta$ and therefore little reactivity of average income to the share of workers from c with education e choosing (d, S). This is intuitively appealing. Low productivity dispersion implies that the marginal migrant worker is very similar to previous migrants in terms of their productivity.

Equation 10 and 12 are the key estimating equations to determine parameters of the model. The estimation exploits the fact that migration flows π_{ecd}^S and average incomes $\overline{m_{ecd}^S}$ are observed in the data.

Production. Production is linear in the sole input of production, labor L_d^S. Within sectors and destinations, perfectly competing firms are identical and the representative firm deploys firm-level productivity A_d^S.[33] Therefore, production of the unique good in

[33] The Armington structure gives rise to this productivity term that is specific to the unique good produced in sector S and destination d. An alternative way of modelling, similar to Tombe & Zhu (2019), would have the production of two aggregate final goods in the economy, agricultural and non-agricultural, that are both made up of a continuum of intermediate goods. In each location, any number of varieties of the intermediate good can be produced and traded and all chiefdoms have location- and product-specific productivity draws for the production of intermediate goods. As a result, chiefdoms specialize in the goods that they are most productive at. While conflict is assumed to affect A_d^S in the provided model, it would be a shock to the average productivity draw in the alter-

sector S and destination d is

$$Y_d^S = A_d^S L_d^S \tag{13}$$

Denote the set of workers with education level e from origin c choosing to live in destination d and work in in sector S by M_{ecd}^S. The labor force in a particular sector is the accumulation of individual sector-specific productivities:

$$L_d^S = \sum_c \sum_e \int_{i:i \in M_{ecd}^S} l_{id}^S \, dF_{ec}(z_{id}^S) \tag{14}$$

Firms are paying the wage rate w_d^S per effective unit of labor supplied. Perfect competition among firms within a sector and destination implies that prices equal marginal cost:

$$p_d^S = \frac{w_d^S}{A_d^S} \tag{15}$$

5.2. Equilibrium and Conflict Impact

Market clearing and equilibrium. Market clearing implies that total production equals total consumption for each unique sectoral good in a destination:

$$A_d^S L_d^S = C_d^S = \frac{(p_d^S)^{-\sigma}}{P^{1-\sigma}} GDP \tag{16}$$

where C_d^S denotes total consumption of the good produced in destination d and sector S and GDP denotes GDP or total income in the economy. The second equality comes from CES preferences over all goods.

Using the definition of individual labor supply 8 and the characterization of average productivity in a destination-sector 11, we can reformulate total labor supply in a destination-sector as a function of labor movement across space π_{ecd}^S and exogenous parameters only:

$$L_d^S = \sum_c \sum_e \overline{N_{ec}} (\pi_{ecd}^S)^{1-\frac{1}{\theta}} h_e^S q_{ecd}^S \Gamma \left(\frac{\theta - 1}{\theta} \right) \tag{17}$$

where $\overline{N_{ec}}$ is the birth population in origin c with education level e. Noting that the movement probabilities π_{ecd}^S are itself a function of exogenous parameters and endogenous wage rates w_d^S, substituting equation 15 in for prices and taking the ratio of the market clearing conditions across a sector or destination, the model can be solved as the following system of equations in endogenous destination-sector labor unit wage rates:

$$\left(\frac{w_d^S}{w_f^T} \right)^{\sigma} = \left(\frac{A_d^S}{A_f^T} \right)^{\sigma - 1} \frac{L_f^T}{L_d^S} \quad \forall S, T \in \{A, N\} \; \forall d, f \in \mathcal{K} \tag{18}$$

native setting (e.g. the scale parameter on a Fréchet distribution). Conceptually, all results discussed here would still go through. The Armington structure simply provides a stronger dispersion force such that labor mobility in response to conflict effects would be stronger in the alternative setting.

The impact of conflict. Even though the way conflict affects an economy is a dynamic phenomenon, we can analyze it by considering comparative statics in the provided (primarily) static model that does not explicitly feature time periods. Conflict can be modelled as a change to the fundamental parameters, in response to which people choose destination and sectors of work. This model structure has an implicit timing assumption. The empirical analysis focuses on outcomes in 2018 and is limited to individuals who were born before the end of the war in 2001 (and therefore working-age adults in 2018). Consider 1991 as the initial situation of the economy before the war. The war between 1991 and 2001 affects four sets of parameters: (i) education realizations of those from affected (origin) chiefdoms, (ii) firm productivities in (destination) chiefdoms, (iii) individual productivities of those from affected (origin) chiefdoms, and (iv) amenities in (destination) chiefdoms. As a function of the parameter values in the war economy, individuals decide on destinations and sectors. We observe the post-war equilibrium in 2018. Essentially, we therefore require the moving decision to take place after the shock of the war and after education has realized. This is largely borne out in the data. The median age at migration is 19 years with 79% of the sample moving after the age of 12 which is the typical age of finishing primary school.[34] The median moving year in the observed sample is 2003 with 82% of migrants having moved after the war has started.

The effect of conflict on the four sets of parameters can be thought of in the following way. First, consider the effect on education. The destruction of schools and killings of teachers can plausibly result in individuals losing out on education in their chiefdom of origin. If individuals have a worse realization of education e, this directly translates into lower human capital $h_e^S = \exp(\phi^S e)$. To what extent sector-specific human capital suffers from the education reduction is governed by the returns to education in each sector ϕ^S.

Second, conflict may affect firm-level productivities A_d^S in each sector and destination. In the model, this parameter would essentially capture any sector-specific determinant of productivity. For example, it could entail the destruction of essential infrastructure for production in a sector. It could also capture immobile physical capital. I do not model physical capital here explicitly. To the extent that physical capital is immobile, however, this would enter the model in exactly the same way as A_d^S. Any destruction of physical capital without reconstruction in the long run would therefore be captured by a reduction of A_d^S.

Third, conflict may affect average individual productivity draws $\overline{q_{ec}}$ for people from origin chiefdom c with education e. Conceptually distinct from the effect on firm productivities A_d^S that affect everyone who chooses to work in a particular sector and destination (irrespective of where they are from), the idea of this effect is that it harms all individuals who are born and grow up in a certain origin c and have education e (irrespective of where

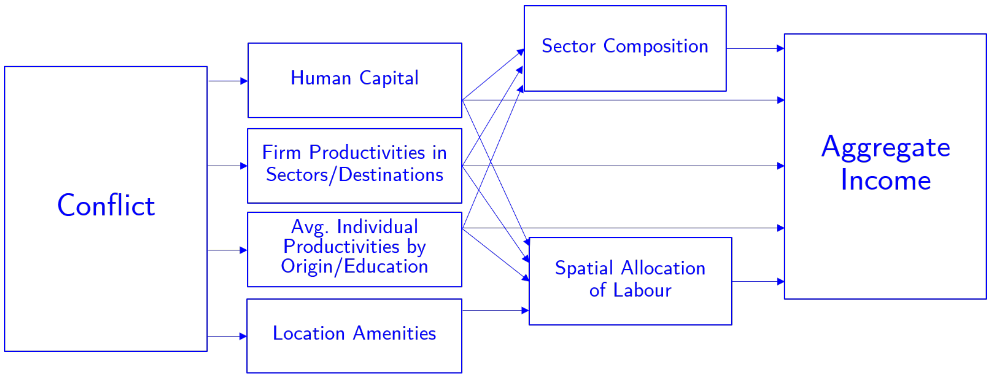
[34] The empirical identification in section 6 considers a simple binary indicator for having obtained primary school education as the education realization e. This keeps the model relatively simple and reflects the fact that primary education is still the main educational qualification for a large part of the population. Less than 10% of the sample have secondary or higher education.

they choose to live and work). A change in $\overline{q_{ec}}$ due to conflict captures any effect that the war has on chiefdom characteristics shaping such origin productivities. This may include an effect on the state of healthcare, in particular for newborns and infants, or the quality of education (given the level of education e which enters the model separately).[35]

Fourth, conflict may have an impact on the amenities of a chiefdom a_d. If fighting leads to the destruction of local public goods or a generally risky environment to live in, this would be captured by the amenities in the model.

Changes to these parameter have direct implications for income of workers and indirect implications by changing the allocation of labor across sectors and space. Figure 3 shows these relationships in a diagram. Provided that σ is large,[36] the market clearing condition 18 reveals that changes to firm-level productivities have a first-order impact on labor unit wage rates. By contrast, changes to education, average individual productivities and amenities only affect wages through the general equilibrium channel by affecting labor supply in each sector and destination. This means that shocks to firm-level productivities have first-order impacts on income as well as sector and destination choice through their direct impact on wage rates.[37]

Figure 3: Key Mechanisms in the Model



Note – This diagram depicts the key mechanisms how conflict affects income both directly and indirectly in the model.

The effect on income is straightforward. Worker income is a direct function of the sector-destination wage rate w_d^S, human capital h_e^S and average individual productivities $\overline{q_{ec}}$. Hence, reductions in education, firm productivities and average individual productivities directly decrease income.

For the effect on sector and destination choice, it is instructive to consider the ratio of π_{ecd}^S across sectors and locations to see how conflict changes the labor allocation across sectors and space:

[35]Indeed, the working-age population considered in 2018 is quite young when the war starts. This is necessary for interpreting changes in $\overline{q_{ec}}$ due to conflict as shocks in early life. The median age of individuals at the start of the war is 6 years with 36% of the sample being born during the war.

[36]As discussed in section 6.3, I set $\sigma = 4$ in the model estimation and discuss the relevant literature that suggests at least such a large value.

[37]The intuition for this positive first-oder impact of A_d^S on w_d^S is straight-forward. Consider an increase in A_d^S. As a result, marginal cost decreases and the price drops. Demand rises and the wage adjusts on the labor market to enable increased production.

$$\frac{\pi^A_{ecd}}{\pi^N_{ecd}} = \left(\frac{w^A_d \exp(\phi^A e)(1-\tau^A_{ecd})\epsilon^A_{ecd}}{w^N_d \exp(\phi^N e)(1-\tau^N_{ecd})\epsilon^N_{ecd}}\right)^\theta \tag{19}$$

$$\frac{\pi^S_{ecd}}{\pi^S_{ecc}} = \left(\frac{a_d w^S_d(1-\tau^S_{ecd})\epsilon^S_{ecd}}{a_c w^S_c(1-\tau^S_{ecc})\epsilon^S_{ecc}}\right)^\theta \tag{20}$$

By equation 19, any changes in firm-level productivities affect sector choice to the extent that one sector is hit harder than the other through the first-order impact of A^S_d on wage rates w^S_d. If non-agricultural firm productivity decreases to a greater extent than agricultural firm productivity, this leads to a decrease in the relative wage w^N_d/w^A_d with the implication that individuals move out of sector N into sector A.

Education has a direct impact on sector choice within a location to the extent that returns to education differ by sector. In particular, if $\phi^N > \phi^A$, workers are more likely to work in agriculture as conflict negatively affects their education since education losses translate into a greater human capital loss in sector N.

A countervailing general equilibrium force that softens this shift in the sector allocation is the wage rate reaction. By the equilibrium condition 18, an increase in non-agricultural workers puts downward pressure on wages in that sector.

Changes in average individual productivities have an impact on sector choice only through such a general equilibrium effect on wage rates to the extent that wage rates across sectors are affected differentially. This is true if average individual productivities are differentially changed by education level since differential returns to education across sectors generate a correlation between education level and sector of employment. In particular, if average individual productivities decrease among the uneducated to a greater extent than among the educated, the agricultural sector that employs relatively more uneducated workers experiences a greater loss in labor supply. This translates into a relative wage increase in agriculture through the equilibrium condition 18 which subsequently leads to a sector shift into agriculture.

Changes in amenities do not have any direct or indirect effect on the sector composition since amenities are not sector-specific but they affect location choice. Equation 20 represents the probability of leaving relative to the probability of staying at home within a given sector S. Considering a conflict effect at origin, as a_c decreases workers are more likely to leave. Similarly, if firm productivities at home go down wage rates w^S_c decrease which encourages leaving.

General equilibrium changes in wage rates in response to education or average individual productivity changes affect the spatial allocation of labor. In particular, if education or average individual productivity decreases, labor supply decreases which puts upward pressure on wage rates and encourages staying. Education losses can also lead to *direct* effects on location choice if moving cost differs by education level. In particular, if moving is more costly for the uneducated, $\tau^S_{0cd} > \tau^S_{1cd}$, a decrease in education encourages more stayers.

Apart from potentially changing the number of movers, the interplay of education, firm productivity, average individual productivity and amenity changes as a result of conflict may also change the composition of movers. How the composition changes depends on the existence and strengths of the effects discussed above. This is, among others, shaped by parameter realizations such as differential returns to education by sector, differential moving cost by education and the extent to which conflict affects the parameters of the model.

6. Model Estimation

This section describes how the parameters of the model and the extent to which they are affected by conflict are estimated. While education outcomes are observed in the data, firm-level productivities, average individual productivities and amenities are not. The structure of the model allows for a recursive estimation strategy in four steps, similar to the estimation strategy used by Bryan & Morten (2019). First, I use a measure of observed income variance to identify the Fréchet shape parameter θ that captures the dispersion of individual productivities. Second, the variation of income across sectors, space and education levels identifies labor unit wage rates w_d^S, returns to education ϕ^S and the common component of the Fréchet scale parameter by origin and education $\overline{q_{ec}}$ which measures average individual productivities. The model definition of average incomes (equation 12) is used as a regression equation in this step. Third, from estimated wage rates in each location and sector w_d^S I can infer firm-level productivities A_d^S using the market clearing conditions. Fourth, I make use of the fact that location and sector choice depend on amenity and wage rate differences across space and sectors as well as migration cost (equation 10). Conditional on estimated wage rates w_d^S, observed migration flows and sector choices identify amenities a_d and migration cost τ_{ecd}^S.

6.1. Step 1: Estimating Productivity Dispersion θ

The Fréchet distribution permits the following expression of moments of average income:

$$\frac{var[m_{ecd}^S]}{\overline{m_{ecd}^S}^2} = \frac{\Gamma(\frac{\theta-2}{\theta})}{\Gamma(\frac{\theta-1}{\theta})^2} - 1 \tag{21}$$

To use this and further relationships from the model in the estimation, I construct a dataset in which the unit of observation is a (c, e, d, S) cell on the migration matrix. Throughout, the education realization is a simple binary variable indicating whether workers have finished primary school or not. For each origin-education pair (151 origin chiefdoms $\times$ 2 education levels), I consider outcomes in each destination-sector pair

(151 destination chiefdoms × 2 sectors).[38]

The left-hand side of equation 21 is the squared coefficient of variation of income. How income varies within a destination-sector for people sharing the same origin and education level identifies the dispersion of individual productivities. The intuition is that this group of workers faces the same wage rates, human capital and average individual productivity and is selected in the same way. Therefore, the only element that can explain how their income varies is variation in their individual productivities.

Using the observed moment on the left-hand side in each (c, e, d, S) cell, I perform a general method-of-moment estimation of θ. For the second moment on the Fréchet distribution to exist, θ needs to exceed 2. In this admissible range of θ values greater than 2, the function has a unique solution.

6.2. Step 2: Estimating Wage Rates w_d^S, Education Returns ϕ^S and Average Individual Productivities $\overline{q_{ec}}$

Taking the logarithm of equation 12 yields the following regression equation:

$$\ln \overline{m_{ecd}^S} = \underbrace{\ln \Gamma\left(\frac{\theta-1}{\theta}\right) w_d^S}_{\text{Destination-sector FE}} - \frac{1}{\theta} \ln \pi_{ecd}^S + (\phi^A - \phi^N)(e \times I^A) + \underbrace{\phi^N e + \ln \overline{q_{ec}}}_{\text{Origin-education FE}} + \ln \epsilon_{ecd}^S \quad (22)$$

where I^A is a dummy variable for the agricultural sector. Average income for workers with origin-education (c, e) who choose destination-sector (d, S) is determined by the wage rate in that destination-sector, their human capital and the average individual productivity draw $q_{ecd}^S = \overline{q_{ec}} \epsilon_{ecd}^S$. The share of workers π_{ecd}^S with origin c and education e who choose destination d and sector S enters as a selection term: The more people make that choice, the lower the average productivity (see discussion above and Figure 2).

Observing π_{ecd}^S and having estimated θ, we can fully control for this selection mechanism by plugging this information into the equation. Taking $\ln \epsilon_{ecd}^S$ with mean 0 as an error term,[39] a regression[40] of $\ln \overline{m_{ecd}^S} + \frac{1}{\theta} \ln \pi_{ecd}^S$ on destination-sector fixed effects, origin-

[38] The 151 chiefdoms consist of 146 observed chiefdoms (5 missing in the 2018 household data, 3 missing in the 2011 household data with conflict information) in all but the Western Region, the four chiefdoms in the Western Rural District and taking the capital Freetown as one chiefdom.

[39] The motivation for taking $\ln \epsilon_{ecd}^S$ as an error term is that this is assumed to be random variation in the average individual productivities, after taking out the origin-education common component $\overline{q_{ec}}$. Conceptually, assuming randomness here is innocuous. If people were particularly productive in some sectors or destinations (across all origins or education levels), the estimation here essentially loads this onto the sector-destination fixed effects which are used in the next step to identify firm productivities A_d^S. Roughly speaking, when observing high income in a particular sector-destination, this means that I cannot disentangle whether this comes from high individual productivity draws for that sector-destination or because firms in that sector-destination are very productive. Taking $\ln \epsilon_{ecd}^S$ as a random error term, the estimation strategy always identifies this as firm productivity. However, conceptually, this distinction does not seem relevant. If all individuals working for firms in a particular sector-destination are particularly productive, this can be interpreted as high firm productivity.

[40] In order to be able to make use of information when $\pi_{ecd}^S = 0$ and deal with potential heteroskedasticity issues introducing bias in this log-specification, I follow Silva & Tenreyro (2006) and make use of Poisson pseudo-maximum likelihood (PPML) estimation for this equation.

education fixed effects and observed education realization times sector choice identifies the wage rates w_d^S, origin-education component of the average individual productivity $\overline{q_{ec}}$, and differential returns to education in the two sectors $\phi^A - \phi^N$.[41] Intuitively, controlling for the selection into a destination and sector, variation in income across space, sector and education levels identifies the wage rates, average individual productivities and returns to education.[42] Using the θ estimates from Step 1, I can recover estimates of w_d^S from the destination-sector fixed effects.

6.3. Step 3: Computing Labor Supply L_d^S and Firm Productivity A_d^S

Using estimates from the previous steps and observed origin populations by education level $\overline{N_{ec}}$ allows me to compute labor supply in each destination and sector as stated in equation 17. Having computed labor supplies and drawing on my w_d^S estimates from Step 2, I only need an estimate of the elasticity of substitution σ to proceed with the identification of firm-level productivities A_d^S. I borrow the value from the literature and set $\sigma = 4$.[43]

With these values in hand, firm-level productivities are identified up to scale in the market clearing conditions 18, restated here for ease of reference:

$$\left(\frac{w_d^S}{w_f^T}\right)^{\sigma} = \left(\frac{A_d^S}{A_f^T}\right)^{\sigma-1} \frac{L_f^T}{L_d^S} \quad \forall S,T \in \{A,N\}\ \forall d,f \in \mathcal{K} \tag{23}$$

I normalize $A^N_{Freetown} \equiv 1$ and can then recover A_d^S for each destination and sector one-by-one. The normalization essentially implies that all values of A_d^S are measured relative to non-agricultural firm productivity in the capital.[44]

[41] With sector-origin fixed effects, I am not able to separately identify ϕ^A, ϕ^N and $\overline{q_{ec}}$. Instead, I can identify $\phi^A - \phi^N$, $\ln \overline{q_{0c}}$ for the uneducated and $\phi^N + \ln \overline{q_{1c}}$ for the educated. For all further estimations and simulations, however, this information suffices since average individual productivities $\overline{q_{ec}}$ and human capital $\exp(\phi^S e)$ only enter jointly in these calculations.

[42] Destination-sector fixed effects and origin-education fixed effects are only identified up to scale relative to each other since origins and destinations are the same locations. As a normalization, I choose the origin-education fixed effect of Freetown to be 0 with the implication that $\exp(\phi^N)\overline{q_{1,Freetown}} = 1$. Therefore, all other origin scale parameter average estimates $\overline{q_{ec}}$ are evaluated relative to the distribution for educated people in the capital.

[43] I follow papers that make use of a similar elasticity of substitution. Bryan & Morten (2019) and Allen & Arkolakis (2014) consider an elasticity of substitution of Armington goods across space within a country but do not have a sector dimension. They use a value of 8 for the elasticity. Hsieh et al. (2019) and Bernard et al. (2003) use values between 3 and 4 for the substitution between goods across industries and countries, respectively. Conceptually, the fact that the good I consider varies across both sectors and space makes it most comparable to the notion of different industries. I therefore choose a value of 4 but discuss robustness of my main results to values of σ between 4 and 8 in section 8.3.

[44] An introduction of trade cost in the classic iceberg format would have an implication for the estimation of A_d^S in this step. This is briefly outlined in Appendix D.1.

6.4. Step 4: Estimating Amenities a_d and Migration Cost τ^S_{ecd}

In order to estimate amenities and movement cost across sectors and destinations, I consider the share of leavers within a sector relative to stayers. This yields the following equations (the logarithm of equation 20):

$$\begin{aligned}\frac{\ln \pi^S_{ecd} - \ln \pi^S_{ecc}}{\theta} &= \ln a_d - \ln a_c + \ln w^S_d - \ln w^S_c \\ &\quad + \ln(1-\tau^S_{ecd}) - \ln(1-\tau^S_{ecc}) + \ln \epsilon^S_{ecd} - \ln \epsilon^S_{ecc}\end{aligned} \tag{24}$$

Using estimated θ, w^S_c and observed migration flows across sectors and destinations π^S_{ecd}, equation 24 identifies amenities up to scale. I treat the whole expression on the bottom involving τ and ϵ as a residual in a regression. The amenities are coefficients on the regressor $I_{d=k} - I_{c=k}$ which is a destination minus an origin dummy variable. Intuitively, controlling for wage rate differences across space, migration flows are governed by amenity differences between locations and migration cost.

Under the assumption of symmetric migration cost, amenity differences and migration cost can be identified separately. In this case, amenity differences shape migration flows asymmetrically while migration cost affects migration flows symmetrically. If amenities in location d are much larger than in location c, few people move from d to c while many people make the opposite move. If migration cost between the two locations is large, few people move both ways.[45]

In the same spirit as before with firm-level productivities, I normalize everything against the capital and set $a_{Freetown} \equiv 1$. For the same reasons as before in step 2, I make use of Poisson pseudo-maximum likelihood (PPML) estimation for this equation.

Using the symmetry assumption of migration cost, adding equation 24 for the flow from c to d and the flow from d to c yields an expression of bi-directional migration flows that is only a function of migration cost, random variation and the already estimated parameter θ:

$$\ln \frac{\pi^S_{ecd}\pi^S_{edc}}{\pi^S_{ecc}\pi^S_{edd}} = 2\theta \ln(1-\tau^S_{ecd}) - \theta \ln(1-\tau^S_{ecc}) - \theta \ln(1-\tau^S_{edd}) + \theta \ln \frac{\epsilon_{ecd}\epsilon_{edc}}{\epsilon_{ecc}\epsilon_{edd}} \tag{25}$$

Focusing on the τ elements, this expression picks up precisely how the symmetric element of migration flows is governed by migration cost. If few people move *both ways* between c and d relative to those who stay at home, this must be driven by high migration cost.

The τ expression on the right hand side uncovers migration cost between two locations relative to the cost of staying at home in both locations. The cost to enter a particular sector at home may be different for agriculture and non-agriculture. In particular, suppose

[45] Asymmetries in migration cost between two locations, that is $\tau^S_{ecd} \neq \tau^S_{edc}$, would be loaded onto the amenity estimate. Since amenities are the same across education levels and sectors within a location while migration cost is education- and sector-specific, the amenity estimate would be a composite of amenities and the average asymmetry in migration cost across education and sectors. This would only affect the interpretation of the estimate, but not any substantial results in counterfactual simulations performed below.

it is costless for people to stay at home and work in agriculture, that is, $\tau^A_{ecc} = 0$. In this case, τ^N_{ecc} captures the cost to enter the non-agricultural sector. This may be driven by the fixed cost to set up a business or the need to move to an urban area (even within the same chiefdom) to engage in non-agricultural work. In order to capture this cost, I use the sector share differential within a location (the logarithm of equation 19):

$$\begin{aligned}\frac{\ln \pi^A_{ecc} - \ln \pi^N_{ecc}}{\theta} &= \ln w^A_c - \ln w^N_c + (\phi^A - \phi^N)e \\ &+ \ln(1-\tau^A_{ecc}) - \ln(1-\tau^N_{ecc}) + \ln \epsilon^A_{ecc} - \ln \epsilon^N_{ecc}\end{aligned} \tag{26}$$

Abstracting again from the ϵ terms and under the assumption $\tau^A_{ecc} = 0$, this equation identifies the cost to enter the non-agricultural sector at home τ^N_{ecc}, given observed movement flows between the sectors, estimated wage rate differences and estimated human capital differences. Intuitively, if we observe few people working in the non-agricultural sector and many people working in agriculture in a given origin chiefdom c, even after controlling for wage and human capital differences between the two sectors, this must be driven by some friction to enter the non-agricultural sector. On average, I estimate a substantial friction. It is estimated to be 0.4, that is, workers have to forgo 40% of their utility to work in non-agriculture.[46] We can use the estimate of τ^N_{ecc} (and τ^N_{edd}) to identify τ^N_{ecd} from the estimate coming out of equation 25.[47]

7. Estimation Results

7.1. Model Parameters and Validation

Table 8 shows the estimated model parameters. The dispersion parameter θ is estimated to be 4.729. In relation to Bryan & Morten (2019) who estimate this object as well, I find parameters that compare plausibly to theirs. Their equivalent estimate of θ is 3.18

[46] Put differently, the difference between wages in agriculture and non-agriculture is much larger than what human capital differences and the sector composition would suggest. In order to discipline the model to predict a relatively low share of workers in non-agriculture given the large wage differences, we need a substantial cost to enter that sector. This cost parameter relates to the literature on the agricultural productivity gap (see for example Gollin et al., 2014; Hicks et al., 2020; Lagakos et al., 2020; Young, 2014). My estimate of a large friction is broadly in line with this literature.

[47] To fix ideas, I have assumed $\tau^A_{ecc} = 1\ \forall c$ and abstracted from the ϵ elements which are random variations with a mean of 1. In fact, what I identify with the described estimation procedure is in its exponentiated form a combination of τ and ϵ terms:

$$\frac{(1-\tau^S_{ecd})\sqrt{\epsilon^S_{ecd}\epsilon^S_{edc}}}{\sqrt{(1-\tau^S_{ecc})(1-\tau^S_{edd})\epsilon^S_{ecc}\epsilon^S_{edd}}} \tag{27}$$

In some sense, assuming $\tau^A_{ecc} = 1\ \forall c$ is just a normalization. The weaker assumption we require is simply that the cost to enter the agricultural sector at home is the same in each location. Setting it to 1 is simply a normalization. While the friction to enter the non-agricultural sector relative to agriculture seems plausible (and empirically real), there is no good reason to believe that there are differential frictions to enter the (default) agricultural sector at home in different chiefdoms. Regarding the ϵ terms, as long as they are random with a mean of 1, our expression above identifies the correct migration cost on average.

for Indonesia and 2.69 for the US. The degree of productivity dispersion this measures can be interpreted as the degree of similarity of goods produced in different locations. It would therefore be expected that less developed countries with a smaller range of varied goods produced would have a smaller degree of dispersion which is reflected in a higher θ realization.

Table 8: Model Parameters

Parameter	Description	Value	Source
θ	Fréchet dispersion	4.729	Estimation
$\phi^N - \phi^A$	Difference in education returns	0.247	Estimation
σ	Elasticity of substitution	4	Literature
A_d^A	Agricultural firm productivity	0.054	Estimation
A_d^N	Non-agricultural firm productivity	0.113	Estimation
a_d	Amenities	0.902	Estimation
$\overline{q_{0c}}$	Avg. individual productivity for uneducated	1.005	Estimation
$\exp(\phi^N)\overline{q_{1c}}$	Avg. individual productivity for educated	1.435	Estimation
τ_{0cd}^A	Migration cost for uneducated in A	0.490	Estimation
τ_{0cd}^N	Migration cost for uneducated in N	0.666	Estimation
τ_{1cd}^A	Migration cost for educated in A	0.406	Estimation
τ_{1cd}^N	Migration cost for educated in N	0.687	Estimation
N_{0c}	Origin population of uneducated	1204	Observed
N_{1c}	Origin population of educated	425	Observed

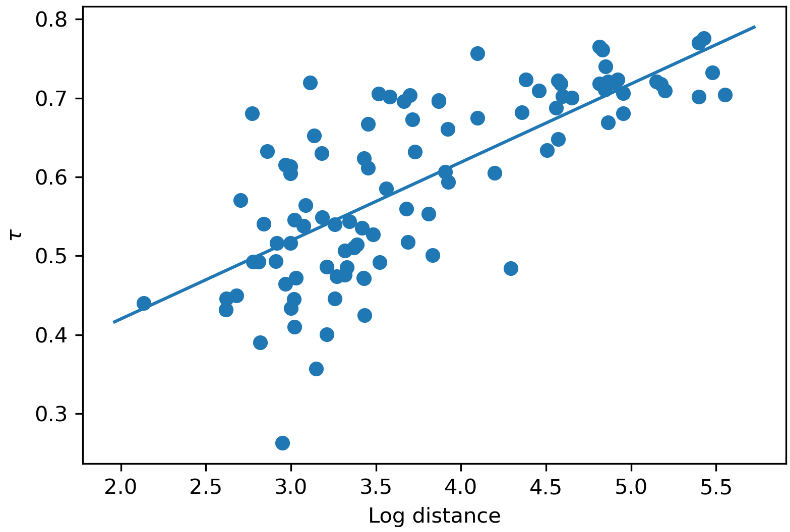
Note – Normalizations: $A^N_{Freetown} = a_{Freetown} = \exp(\phi^N)\overline{q_{1,Freetown}} = 1$. Parameters $\theta, \phi^N - \phi^A$ and σ are defined at the country level. For all other parameters, the mean at the country level is reported.

The returns to education estimates show a great differential by sector. This estimate stems from regression equation 22 with log wage as an outcome variable and can therefore be interpreted as a relative return. Returns to primary school education in non-agriculture exceed returns to education in agriculture by 25 percentage points.

Considering migration cost by sector and education level, there is a significant difference by sector. It turns out to be much more costly for people to enter the non-agricultural sector and move somewhere than the agricultural sector. Relative to Bryan & Morten (2019) who find 39% migration cost in Indonesia, I find generally higher migration cost in Sierra Leone. The average across both education levels and sectors is 56%. Like in their case, I find a strong positive correlation between my estimate of τ and log distance between two places. Figure 4 displays the strong positive relationship with distance which suggests that the estimated parameters capture something real about the cost of moving.

Another interesting fact about estimated moving cost is that there is a clear differential by education level in the agricultural sector. Uneducated people have to forego 8.4 percentage points more of their income when leaving one's origin than educated people in that sector. There is no (strong) differential by education level in non-agriculture. This could reflect a dissimilarity in crops across space whereby educated farmers are better able to adapt to different crops. Alternatively, this may also be due to an information barrier

Figure 4: Migration Cost and Distance



Note – Binscatter of the relationship between migration cost and log distance between locations. The line is the OLS line of best fit.

or the degree of connections to other chiefdoms. Educated farmers may be better informed about crops or opportunities for agricultural work elsewhere or better connected to farmers away from home. Since integration into a new chiefdom in Sierra Leone is important in order to work there, this could be a key driver of the education differential.

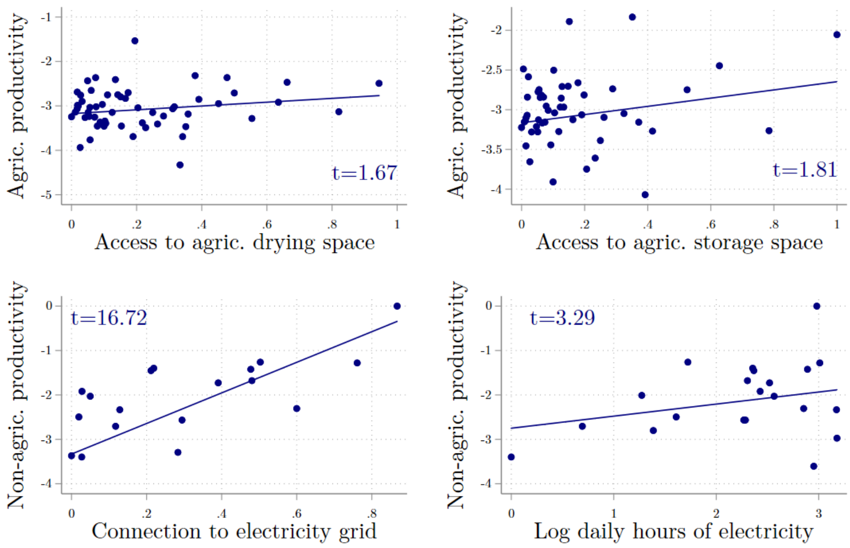
The estimates of labor unit wage rates by sector are shown in Figure B5 relative to the distribution of observed income. In line with the income distribution, labor unit wage rates in non-agriculture are higher than in agriculture. Interestingly, their variation is also greater. Generally, there is substantial variation in wage rates. The highest wage rates differ from the lowest wage rates by a factor of more than ten.

Firm-level productivities vary similarly substantially.[48] Average agricultural firm productivity is 5% of the non-agricultural firm productivity in the capital and average non-agricultural firm productivity is 11% of non-agricultural firm productivity in the capital. To assess whether these estimates are capturing something real about firm productivities in Sierra Leone, I correlate them with observed variables in the data that could plausibly be related to firm productivities: Access to agricultural drying and storage space, connectivity to the electricity grid and the number of hours electricity is available in a chiefdom. Importantly, these are variables that are *not* used anywhere in the estimation strategy. Figure 5 demonstrates the result. Agricultural productivity estimates are strongly positively correlated with access to agricultural drying or storage space. Similarly, non-agricultural productivity estimates are highly positively correlated with measures of the existence and extent of electricity connection.

In a similar exercise, I consider the estimates of average individual productivities[49] and

[48]Their distribution by sector is shown in Figure B6.
[49]Their distribution by education level is shown in Figure B7.

Figure 5: Correlates with Firm-level Productivities



Note – Binscatter plots with line of best fit of the relationship between log (non-)agricultural firm-level productivity $\ln A_d^A$ ($\ln A_d^N$) and various outcomes on the x-axis.

their relationship with information in the data that could plausibly capture them but is not used anywhere in the estimation strategy itself. These parameters are estimated off origin-education fixed effects and essentially capture the average productivity that people from a certain origin and education level possess irrespective of which destination they end up living and working in. Education and the health environment at a young age are arguably important drivers of such origin productivities. There is indeed a growing literature that suggests that the state of healthcare at a very young age (in utero or as an infant) can play a very important role for life outcomes.[50] Education is explicitly controlled for, albeit in quite a coarse way, when average individual productivities are estimated. Therefore, I consider four variables that capture the state of healthcare at birth in a chiefdom and correlate these with the estimated average individual productivities as a plausibility check: (i) the probability that a health professional is present at birth, (ii) how many times antenatal care pregnant women receive on average, (iii) the average height of infants, and (iv) the average height-for-age z score. The results are shown in Figure 6. The estimated average individual productivities are clearly positively correlated with all the four outcomes and significant at conventional levels in most cases.[51]

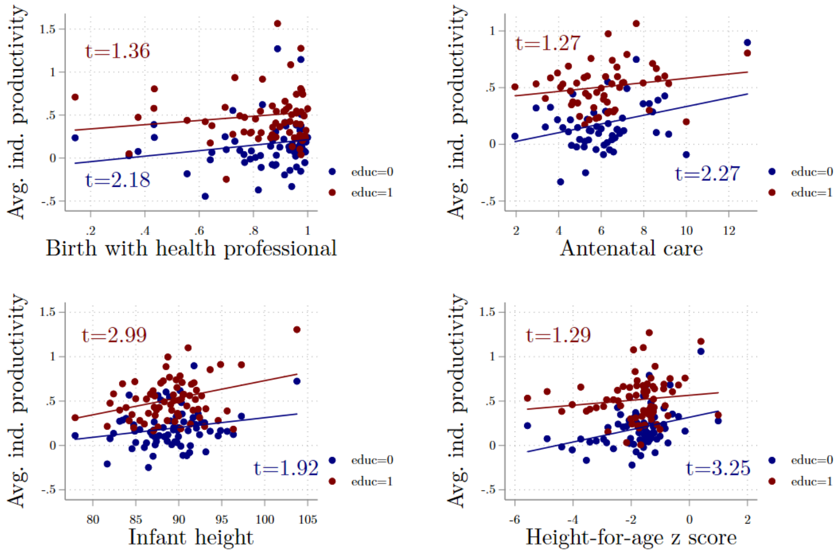
Finally, consider the estimates of amenities.[52] In a similar exercise as before, I also

[50] See for example Almond (2006); Almond & Currie (2011a,b); Maccini & Yang (2009). Since early-life health shocks can have important long-run implications, the literature analyzing the effect of conflict on health outcomes typically focuses on health at a very young age as well (e.g. Akbulut-Yuksel, 2014; Akresh et al., 2012a,b; Bundervoet et al., 2009; Galdo, 2013; Islam et al., 2016; Kesternich et al., 2014; Saing & Kazianga, 2020). To the extent that the average individual productivities $\overline{q_{ec}}$ capture the state of health at birth, the estimates of how conflict affects $\overline{q_{ec}}$ relate to this literature.

[51] When considering workers today, the relevant education and health environment that may be a key element of $\overline{q_{ec}}$ is the environment when they were young. Due to lack of accurate earlier data, however, I still consider the state of healthcare in 2018. For this sense check to work, the implicit assumption is that there is some stationarity in the state of healthcare within chiefdoms over time.

[52] Figure B8 displays the distribution of amenities across space. Compared to wage rates, firm-level

Figure 6: Correlates with Average Individual Productivities



Note – Binscatter plots with line of best fit of the relationship between log average individual productivity among the uneducated (educated) $\ln \overline{q_{0c}}$ ($\ln \overline{q_{1c}}$) and various outcomes on the x-axis.

test the plausibility of these estimates by correlating them with observed variables in the data that plausibly reflect amenities. From information on access to eight public goods and services, I construct two public good indices. In particular, the public goods indices measure whether the following public goods and services are within 30 or 60 minute reach: (i) supply of drinking water, (ii) a food market, (iii) public transportation, (iv) a primary school, (v) a secondary school, (vi) a health clinic, (vii) a hospital, and (viii) an all year motorable road. I also consider phone coverage and recharge possibilities within chiefdoms. With all these measures, amenities are strongly positively correlated as Figure 7 shows.

7.2. Conflict Effect on Parameters

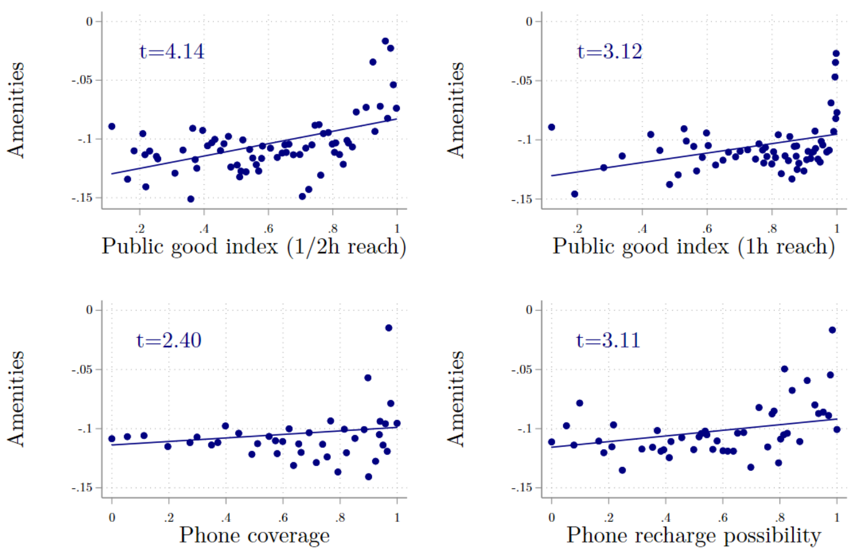
With these parameter estimates in hand, we can proceed to estimate the impact of conflict on firm productivities, location amenities and average individual productivities directly. For this exercise, I need to take a stance on the specific relationship between conflict and the parameters of the model. For all relevant continuous parameters of the model $par_c \in \{A_c^A, A_c^N, a_c, \overline{q_{0c}}, \overline{q_{1c}}\}$, I assume a log-linear relationship between the current parameter value and conflict:

$$\ln par_c = \ln \underline{par_c} + \eta \; conflict_c \tag{28}$$

where $\underline{par_c}$ is today's counterfactual value of the parameter in the absence of conflict and c is a chiefdom index. In this relationship, η captures the long-run (semi-)elasticity of

productivities and average individual productivities, amenities vary considerably less across space. Relative to the capital Freetown, average amenities are 13% smaller.

Figure 7: Correlates with Amenities



Note – Binscatter plots with line of best fit of the relationship between log amenities $\ln a_d$ and various outcomes on the x-axis. The public good index is the average of eight binary variables indicating whether the following public goods/services are within 30 (60) minutes reach: (i) supply of drinking water, (ii) food market, (iii) public transportation, (iv) primary school, (v) secondary school, (vi) health clinic, (vii) hospital, (viii) all year motorable road

the key parameters of the economy with respect to conflict and subsequently determines to what extent conflict persistently affects the economy as discussed in section 5.2. For the primary education outcome e, I assume that the probability to be educated is linearly affected by conflict. At the chiefdom level, denoting the share of primary educated individuals by e_c, the above relationship holds in levels, that is, the outcome is e_c and the counterfactual value $\underline{e_c}$.

In order to simulate what the economy would look like today, we are interested in finding the counterfactual firm productivities, amenities and average individual productivities. If the elasticities η can be estimated, an estimate of the counterfactual values would simply be given by their current value minus the estimated effect of conflict:

$$\ln \widehat{\underline{par_c}} = \ln par_c - \hat{\eta}\ conflict_c \tag{29}$$

Essentially, we would reverse the effect of conflict on the parameters. For this calculation, we need to estimate η. Returning to equation 28, let us assume that the counterfactual parameter values $\ln \underline{par_c}$ are made up of some observable and unobservable characteristics of chiefdoms. Using the same observable characteristics as in the reduced-form estimation in section 3.2, equation 28 can be rewritten as a regression equation:

$$\ln par_c = \alpha_{district} + \mathbf{X_c}'\mu + \eta\ conflict_c + u_c \tag{30}$$

This equation can be estimated for all parameters of interest $A_c^A, A_c^N, a_c, \overline{q_{0c}}, \overline{q_{1c}}$ (and the equivalent level version for e_c). However, since conflict variation is not exogenous, a simple OLS regression would yield inconsistent results. In particular, the reduced-form results from section 4 suggest that conflict intensity is higher in places that have higher income to begin with since the OLS results are considerably weaker than the IV results. In the context of the model, higher initial income in locations that experience conflict is plausibly related to better parameter values, e.g. larger productivity of firms, in such places before the war. Therefore, when investigating the effect of conflict on firm productivities, a simple OLS estimate would suffer from selection bias.

However, I can employ the same IV identification strategy as in the reduced-form analysis. Using distance to the Liberian border as an instrument for conflict intensity, I can identify the elasticity of firm productivities, amenities and average individual productivities with respect to conflict. Table 9 shows the results at the chiefdom level.[53]

Table 9: Effect of Conflict on Model Parameters

	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln A_c^A$	$\ln A_c^N$	$\ln a_c$	e_c	$\ln \overline{q_{0c}}$	$\ln \overline{q_{1c}}$
Conflict	-0.0290	-0.284	0.00470	-0.0690**	-0.122*	-0.0314
	(0.143)	(0.260)	(0.00596)	(0.0316)	(0.0734)	(0.0811)
N	150	138	151	151	151	151
R^2	0.526	0.745	0.824	0.803	0.465	0.432
Estimation Method	IV	IV	IV	IV	IV	IV
First Stage F (KP)	18.71	22.52	18.91	17.23	17.23	17.23
AR p-value	0.929	0.367	0.149	0.032	0.088	0.576
Socio-econ. Controls	✓	✓	✓	✓	✓	✓
District FE	✓	✓	✓	✓	✓	✓

Note – Outcome variables at the chiefdom level: Log firm-level productivity in agriculture and non-agriculture, log amenities, share of primary school educated people and log average individual productivity for uneducated and educated. Conflict standardized and instrumented with distance to border. Heteroskedasticity-robust standard errors at the chiefdom level in parentheses. Kleibergen-Paap robust F statistic and p-value for weak instrument robust Anderson-Rubin test of $H_0 : \beta = 0$ reported. Stars refer to standard t-tests. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The effect of conflict on agricultural firm productivity (column 1), amenities (column 3) and average individual productivity among the educated (column 6) is small and insignificant.[54] By contrast, there is a clear and strong negative impact on average individual productivity for the uneducated $\overline{q_{0c}}$. The estimate suggests that a one standard deviation increase in conflict intensity leads to a reduction in average individual productivity draws of uneducated people born in the affected location by 12.2%. The fact that the uneducated seem to be affected while the educated are not may reflect that educated workers are better able to deal with the conflict shock in terms of their individual productivity.

[53]Some firm productivities cannot be estimated since no one actually works in that sector and destination. Hence, we do not have any income information for those sector-destinations. This applies to one location in agriculture and 13 locations in non-agriculture. These chiefdoms are excluded from the analysis of firm productivities here. In the simulations, the firm productivity for those sector-destinations is set equal to zero to rationalize no worker choosing them.

[54]While $\overline{q_{1c}}$ for the educated cannot be identified separately from the human capital term $\exp(\phi^S)$ this does not matter in the log-level relationship between parameters and conflict. The human capital term is constant at the country level and enters additively in the logarithmic expression. Thus, it shows up in the constant term and does not change the slope coefficient of interest reported here.

They may have had access to better opportunities for recovery and (re)training after the war than the uneducated.

The estimate on average education at the chiefdom level also suggests a strong effect. Across all people born in a particular chiefdom, the share of people obtaining primary school education goes down by 6.9 percentage points as the chiefdom experiences one more standard deviation of conflict.[55] The results further suggest that there is a very large effect on non-agricultural firm productivity (column 2). Firm productivities in that sector decrease by 28.4% as locations experience an increase in conflict intensity by one standard deviation. While the latter estimate is not significant at any conventional level, given its non-trivial size and a potentially imprecise IV estimation on the limited sample of 138 chiefdoms, I am cautious not to simply dismiss this result as a zero effect. In the following section, I provide counterfactual simulations both with and without considering effects on non-agricultural firm productivity. On the basis of some results arising in these different scenarios, I will discuss why I consider a real effect of conflict on non-agricultural firm productivity indeed plausible.

8. Counterfactual Simulations

Drawing on the estimated model parameters and their elasticity with conflict, I can perform counterfactual simulations.[56] These simulations serve two purposes. First, by simulating away the conflict in the whole economy, I can generate a true counterfactual of what the entire Sierra Leonean economy would look like today in the absence of civil war. This allows for the estimation of *aggregate* effects. Second, by considering the effects that conflict has on the different parameters of the model separately, simulations allow me to make an assessment of the quantitative importance of different *mechanisms*.

In order to generate a no-war counterfactual of the Sierra Leonean economy, the first simulation reverts all effects that the war has on model parameters. I identify three such effects: first, a reduction in education, second, a decrease in firm productivity in the non-agricultural sector, and third, a reduction in average individual productivity among the uneducated. The IV estimates inform the size of the conflict effect.[57] By reverting the effect of the war, chiefdoms that experienced conflict have a larger educated population,

[55] Note that this estimate differs from the estimate presented in the reduced-form analysis. The reason is twofold. First, this analysis is carried out at the chiefdom level whereby chiefdom averages of control variables that vary across individuals are used. This implies that individual and chiefdom-level regressions do *not* mechanically generate the same result. Second, and more importantly, the result presented here considers the share of primary educated people in *origin* chiefdoms. The implicit timing assumption of the model is that people obtain education before moving (see section 5.2). To assess the effect of conflict on education before sector and destination choices are made therefore requires considering origin chiefdoms. By contrast, the reduced-form analysis compares education outcomes of workers across destinations. The fact that education differences across destinations with differing conflict intensity is greater than differences across origin chiefdoms speaks in favor of the kind of selective migration discussed in further detail in section 8.2: Educated people are leaving conflict locations at a higher rate than the uneducated.

[56] On a technical level, the model is solved numerically using the iterative procedure described in Appendix E.

[57] Figure B9 displays how this scenario changes the underlying distribution of educated origin populations, non-agricultural firm productivity and average individual productivity among the uneducated.

greater non-agricultural firm productivity and higher average individual productivity for uneducated people born in that chiefdom in the simulated peace counterfactual.

Unlike a partial equilibrium exercise in which everything else is kept constant, the simulation generates a new counterfactual in general equilibrium. The model traces through both the direct implications of these parameter changes for aggregate income as well as the indirect implications by changing the allocation of labor across sectors and space. In theory, changes in non-agricultural firm productivities, education and average individual productivities among the uneducated have different implications for the sectoral and spatial distribution of labor that I consider in turn. First, through their strong direct relationship with non-agricultural wages, lower non-agricultural firm productivities in affected chiefdoms lead to an outflow of non-agricultural workers into the agricultural sector and other chiefdoms.

Second, with higher returns to education in sector N than A, a less educated workforce is a greater harm to the non-agricultural sector. This implies that education losses also translate into a shift into agriculture. A counterforce to this effect is a general equilibrium effect through prices. Since human capital is harmed more in the non-agricultural sector as a result of education losses, the workforce in that sector becomes relatively less productive. In general equilibrium, a less productive workforce in a sector implies higher prices and wages. This is essentially a demand channel. Since people demand all local goods produced in the whole economy, a workforce productivity shock implies that more workers are needed to produce the same amount of the good. This results in an increase in wages and prices and subsequently an inflow of workers into the sector. Empirically, the former direct effect dominates the general equilibrium channel such that affected chiefdoms experience a growth in the agricultural labor force.[58]

In terms of migration, the same general equilibrium effect as discussed above would encourage workers in locations that experience education losses to stay and migrants to flow in with higher wages. Similarly, larger moving cost for uneducated workers in agriculture leads to more stayers in such chiefdoms.

Third, a reduction in average individual productivities among the uneducated only has a general equilibrium effect through prices and wages. Conceptually, the effect is the same as the general equilibrium effect of human capital changes described above. As the workforce is less productive in a particular sector and location, wage rates increase which leads to an inflow of workers into that sector and location. Since uneducated workers tend to work in the agricultural sector, the agricultural sector is affected by a drop in average individual productivity among the uneducated to a larger extent than the non-

[58] Note that this human capital effect at the individual level is conceptually distinct from the *firm* productivity effect. Formally, the difference can be seen in equation 18 that characterizes the equilibrium of the economy. Through perfect competition which governs that prices equal marginal cost, a firm productivity decrease in sector N (A_d^N going down) leads to a strong direct effect on wage rates since firm productivity reductions increase marginal cost. The human capital effect is a change in labor supply L_d^N. The negative relationship between wage rates w_d^N and labor supply in the same sector and location L_d^N shown in the equation reflects the general equilibrium effect described.

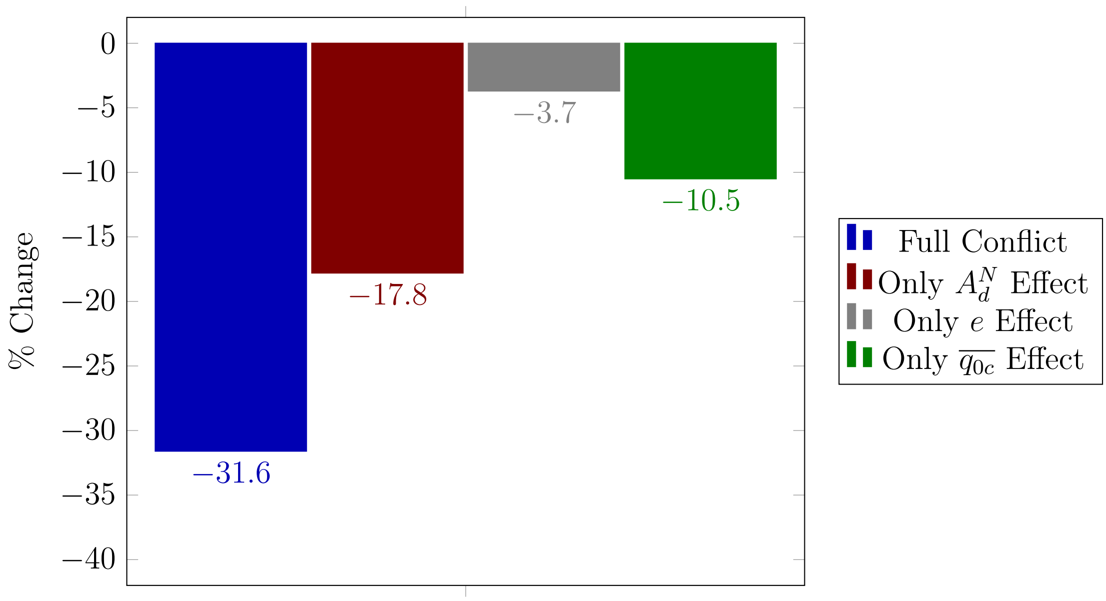
agricultural sector. Therefore, such a reduction in individual productivity leads to more agricultural workers staying and more in-migration into affected locations, in particular in agriculture.

Having simulated a peace economy by reverting the effect of conflict on all affected parameters, a second set of simulations serves the purpose of assessing different mechanisms. To this end, relative to the peace economy, I simulate three different partial war scenarios. First, I simulate an effect on non-agricultural firm productivity only. Second, I simulate an effect on education only. Third, I simulate an effect on average individual productivity among the uneducated only.

8.1. Main Results

The results for the first simulation are generated by comparing the (baseline calibrated) war economy to the (simulated) peace economy. The results on separate mechanisms are generated by comparing the (simulated) peace economy to (simulated) partial war scenarios. Figures 8 and 9 display the results for aggregate income and the aggregate employment share in agriculture.

Figure 8: Aggregate Income Effect

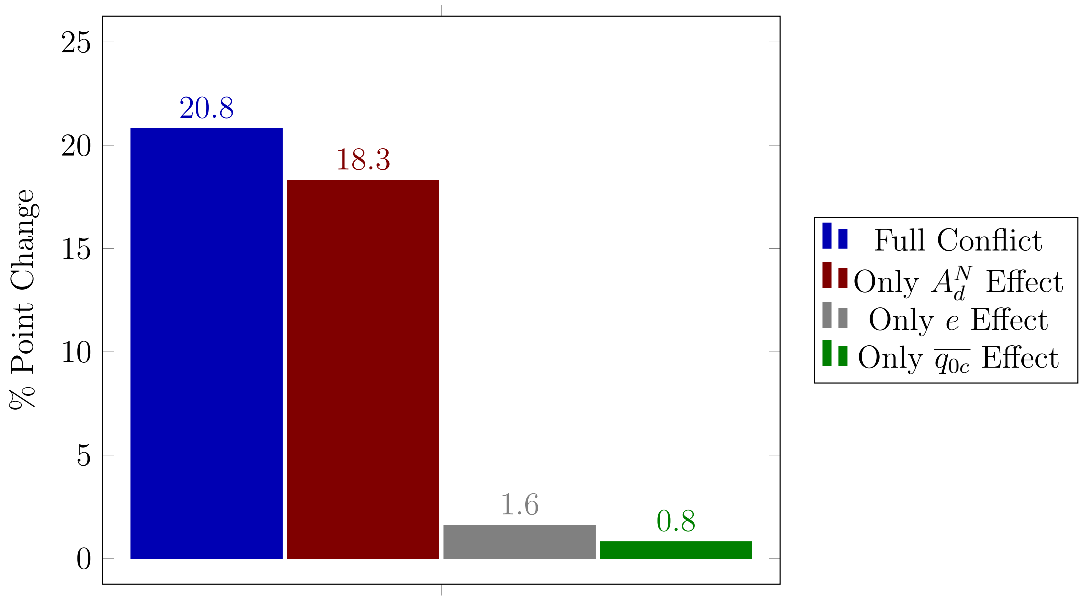


Note – Changes in aggregate income in four simulations relative to the peace economy: Full conflict effect on education, firm productivities and average individual productivities (blue), only an effect of conflict on firm productivities (red), only an effect of conflict on education (grey), only an effect of conflict on average individual productivities (green)

The first result to note is that the aggregate income effect of conflict is substantial. Income today is almost 32% lower today than it would be in the absence of the war. With lower pay in agriculture, an aggregate sector shift seems to be an important driver of this result. The economy-wide share of people in agriculture is almost 21 percentage points higher.[59]

[59]These results mask substantial heterogeneity. Considering the full reversal of the war, Figure B10

Figure 9: Aggregate Agricultural Employment Effect



Note – Changes in aggregate employment share in agriculture in four simulations relative to the peace economy: Full conflict effect on education, firm productivities and average individual productivities (blue), only an effect of conflict on firm productivities (red), only an effect of conflict on education (grey), only an effect of conflict on average individual productivities (green)

Beyond the total effect, the next three simulation results highlight the relative importance of different mechanisms. If conflict only affected non-agricultural firm productivities but left education and average individual productivities unchanged, the income loss would be almost 18%. Similarly, if it only affected education or average individual productivities, the income losses would be 3.7% or 10.5%, respectively. This highlights that a drop in non-agricultural firm productivity is the most important driver of a long-run impact of civil war on the Sierra Leonean economy.

The results are in sharp contrast to the attention firms and business activity receive in the analysis of consequences of conflict in the literature, in particular relative to the amount of analyses considering education as a mechanism. Yet, in the case of Sierra Leone, the education effect of conflict alone can only account for a small part of the full conflict effect. Even along with other individual productivity losses such as health that would be captured in the parameter estimate $\overline{q_{0c}}$, firm productivity losses remain the most important pathway of the conflict impact on the economy.

It is noteworthy that there do not seem to be important complementarities between the three mechanisms. The income effects from the three separate simulations by mechanism almost perfectly add up to the simulation which considers all of them jointly.

Interpreted more broadly, the difference between the effect driven by firm and average individual productivities including human capital capture essentially the difference between destination and origin productivities. In the data, the parameters A_d^S and $\overline{q_{ec}}\exp(\phi^S e)$ are estimated off destination(-sector) and origin(-education) fixed effects of

displays the aggregate income changes in each chiefdom with the largest losers experiencing a 64% reductions in income.

income, after controlling for selection.[60] Following this interpretation, the results imply the following. As a result of civil war, affected locations in Sierra Leone suffer from a location-level productivity decrease. Everyone who chooses to live in these locations (destinations) experiences this productivity reduction, regardless of where they are from. At the same time, individuals who are *from* locations where war took place suffer in their individual productivity by virtue of being born or growing up in conflict affected (origin) locations. No matter where they move, they carry this productivity loss with them. Both types of productivity effects have sizeable consequences for aggregate productivity. In relation to each other, the destination productivity effect is somewhat more important.

The results on the aggregate agricultural employment share for the three simulations by mechanism differ drastically. A sector shift seems to be almost entirely driven by reductions in non-agricultural firm productivity. Relative to that, education losses or average individual productivity decreases play a negligible role for the sector shift.

Given the large size of the sector shift in the reduced form, these results strongly suggest that the effect of conflict on non-agricultural firm productivity is real. In the absence of it, a sector shift in the aggregate can basically not be generated by the model. As discussed previously, the reduced-form results only identify a spatial difference and may partially capture spatial divergence between more and less affected chiefdoms by conflict. However, for the reduced-form results and the (aggregate) simulation results to be consistent in the absence of an effect of conflict on A_d^N, it would need to be true that there is an extreme degree of sector sorting across space in response to conflict without a meaningful *aggregate* change in the (total) number of agricultural workers. The reduced-form estimate suggests that a chiefdom experiencing high conflict (at the 75$^{\text{th}}$ percentile of the conflict intensity distribution) has 23 percentage point more agricultural workers than a chiefdom experiencing low conflict (at the 25$^{\text{th}}$ percentile). Therefore, this spatial difference would have to be almost entirely driven by agricultural workers sorting into high conflict locations and non-agricultural workers sorting into low conflict locations with only a slight change in the total share of agricultural workers. Even with large migration flows, this seems implausible. It is much more plausible that the total number of agricultural workers increases as a result of civil war and this contributes to a spatial difference in agricultural workers between high and low conflict chiefdoms. This is the case in the first simulation that takes into account an effect of conflict on non-agricultural firm productivity which gives rise to a strong increase in the aggregate share of agricultural workers by 18.3 percentage points.

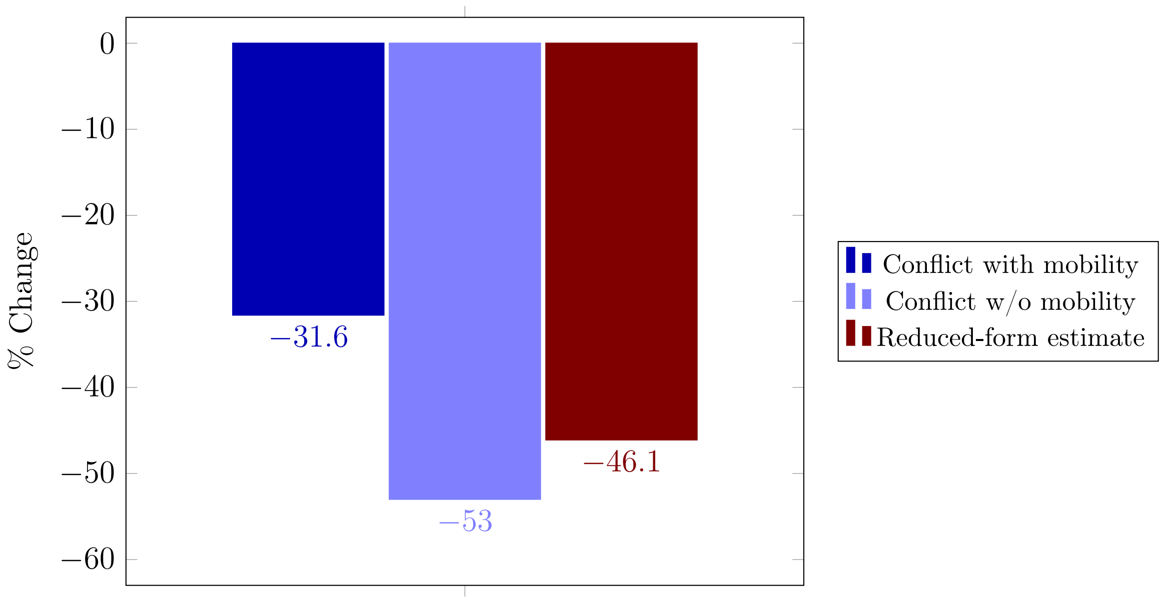
[60]This is a slightly simplified characterization of how firm productivities A_d^S are estimated. As section 6.3 explains in detail, the destination-sector fixed effects actually only identify wage rates w_d^S and the estimation of A_d^S makes use of these wage rate estimates along with the general equilibrium conditions of the model. However, since there is a strong direct relationship between wage rates w_d^S and firm productivities A_d^S in general equilibrium, it turns out that the estimates of the latter do not drastically differ from the former. To fix ideas, it is therefore a fair approximation to think of A_d^S estimates as destination-sector fixed effects.

8.2. Selective Migration

While the aggregate income effect of civil war is sizeable, it is substantially smaller than what the reduced-form estimates would suggest. If we were to take the reduced-form estimate and calculate a country-wide weighted average by conflict intensity and chiefdom population we would arrive at a 46% aggregate income loss. The fact that spatial income differences markedly exceed the aggregate income difference suggests that selective migration in response to conflict matters a great deal.

In order to get a sense of the potential importance of migration, I simulate an economy without labor mobility. In particular, relative to the peace economy, the full conflict scenario can be simulated without allowing labor movement.[61] The results of this simulation are shown in Figure 10. The aggregate income effect in this simulation is a 53% reduction which is dramatically different from the 32% reduction in the economy with labor mobility. This suggests that migration plays a large role for the aggregate effect of the war and cannot be ignored when analyzing the consequences of conflict. In particular, it is plausible that a migration response to the civil war in Sierra Leone implies that the spatial income difference between more and less affected chiefdoms is large relative to the aggregate income effect of the war. Positive selection out of conflict zones would generate such a result.

Figure 10: Aggregate Income Effect in Simulations and Reduced Form



Note – Changes in aggregate income in two simulations and in the reduced form. The first simulation corresponds to the original full conflict scenario above. The second simulation implements a full conflict scenario *without* labor mobility.

It is therefore worth considering the nature of this migration response. The full conflict scenario actually fails to generate a correlation between conflict intensity and population

[61]On a technical level, this is implemented by setting the cost of migration equal to 1, that is, a mover would keep 0% of their income. In equilibrium, no one moves.

change in a chiefdom.[62] Table 10 shows the result in column (2). The coefficient is very close to zero and insignificant. Interestingly, this slope coefficient is extremely similar to the relationship that can actually be observed in the data. Column (1) shows the result of a regression of conflict changes between 1985 before the war and 2015 after the war on conflict.

By contrast, a conflict simulation that does not account for an effect on non-agricultural firm productivity generates a markedly different result. Albeit marginally insignificant ($p = 0.128$), the coefficient for the same relationship between population change and conflict intensity in that scenario is strongly positive (column 3).[63] The fact that the relationship between population change and conflict intensity in the data is much better matched in the full conflict scenario is another piece of support for taking the effect of conflict on non-agricultural firm productivity seriously.

While the first simulation including a non-agricultural firm productivity effect suggests that the migration flows are unaffected by the war, it does not speak to the *composition* of movers that may change as a result of the war. Three facts that come from the parameter estimates would indeed indicate that the selection of migrants out of conflict zones changes with conflict in a way that out-migrants are more positively selected on productivity grounds. First, the strong reduction in non-agricultural firm productivity leads non-agricultural workers who are typically more productive and educated than agricultural workers to leave.

Second, more affected chiefdoms by conflict have a larger uneducated workforce. Uneducated workers tend to work in agriculture and migration cost is larger for uneducated agricultural workers. This implies that there are more uneducated agricultural workers who tend to be less productive among the stayers. These two effects can be interpreted as conflict opening up a local poverty trap. It leads to lower education and pushes more people into agriculture while it is relatively harder for those people to leave.

Third, the general equilibrium implication of lower average individual productivity among the uneducated implies higher wages, in particular in the agricultural sector that employs more uneducated workers. This is another selection mechanism that leads to more uneducated workers among the stayers in high conflict chiefdoms.

8.3. Limitations

There are four limitations to this analysis that qualify the results. First, the identification of aggregate effects implicitly assumes that some chiefdoms are not at all affected by the war. The identification of how conflict affects key parameters of the model rests on

[62]This result is in line with Davis & Weinstein (2002) who find that population densities of Japanese cities are unaffected by bombing in the long run.

[63]Note that this coefficient is an economically meaningful effect. It means that a one standard deviation increase in conflict implies population growth by almost 1%. The sign of the relationship is perfectly in line with the labor movement response to education and average individual productivity changes discussed above. Larger movement cost for the uneducated in agriculture and a general equilibrium effect through prices and wages gives rise to population growth in chiefdoms that are more heavily affected by conflict.

Table 10: Population Change and Conflict

	Population Change		
	(1)	(2)	(3)
Conflict	-0.0349	-0.030	0.855
	(0.0439)	(0.730)	(0.558)
Constant	0.681***	0.310	0.375
	(0.0436)	(0.713)	(0.545)
Source	Data	Full Conflict Simulation	Simulation w/o A_d^N Effect
N	151	151	151
R^2	0.00423	0.000	0.015

Note – Outcome variable: Population change in %. Conflict measure standardized. First column: Relationship in the data. Population change is measured between 2015 and 1985. Second column: Relationship from simulated data. Population change is the relative difference between the simulated peace economy and baseline calibrated war economy. Third column: Relationship from simulated data. Population change is the relative difference between the simulated peace economy and a simulated war economy whereby the simulation only takes into account the effect of conflict on education and average individual productivity among the uneducated. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

within-country comparisons of chiefdoms that are closer to or farther from the Liberian border and therefore experience conflict to varying degrees. In the counterfactual analysis, chiefdoms that are very far from the border with a zero realization on the conflict measure are assumed not to experience any effect of civil war. If those chiefdoms also suffer in some way from the war, my estimates would be an underestimate of the true aggregate effect.

Second, the estimate captures the net effect of civil war in the long run after post-conflict interventions between the end of the war and 2018. Since the international community was engaged in reconstruction work after the war, the aggregate effects I present are not the pure effect of civil war but rather how the economy still suffers after taking into account reconstruction efforts. The pure effect of the war would therefore be weakly greater than my estimate.[64]

Third, if one were to relax the assumption of costlessly tradable goods across space, the actual effect of conflict on firm productivities may be smaller and my aggregate income

[64] Another potential concern surrounding reconstruction is spatially asymmetric reconstruction that favors certain areas over others depending on their ties to the post-war government. If the extent to which chiefdoms potentially get favorable treatment is systematically related to distance to the Liberian border, this could lead to bias in the estimates of the conflict effect on parameters such as firm productivities which feed into the simulation results. The estimates would capture the effect of the war and the extent of patronage towards certain areas. While it is hard to find evidence on how and where reconstruction took place, existing writings and critiques of post-war reconstruction efforts do not seem to comment on any patronage with implications for the spatial distribution of reconstruction activities. Two important post-war policies and institutional changes were the Disarmament, Demobilization and Reintegration (DDR) program and the decentralization process that involved the reinstatement of local councils at the district level. Both were rolled out in and inherently affected the whole country. While being criticized on a number of grounds such as failing to achieve reintegration of fighters or limited progress in establishing good governance at the local level, there is typically no mention of geographic favoritism in the implementation of these programs (e.g. Sesay & Suma, 2009; Solomon & Ginifer, 2008; Zhou, 2009).

effect thus overestimated. With trade cost, my estimates of firm productivities would capture a combination of these productivities and market access of a location. Market access is the weighted sum of all other locations' real GDP where the weights are inverse trade cost (cf. equation D1 in Appendix D.1). Part of the conflict effect on firm productivities that I estimate could stem from a reduction in market access. If market access is lower because trade cost increased as a result of the war, my estimate of the aggregate income effect is not necessarily different but the mechanisms driving this result are – part of the effect would be due to increased trade cost rather than reduced firm productivity. However, if market access is lower because economic performance in close chiefdoms with low trade cost contracted, this contraction should not be loaded on a reduction in the firm productivity parameter. As a result, the actual effect on firm productivities would be less pronounced and the aggregate income effect would be smaller. However, the market access term would contaminate the firm productivity estimates for both agriculture and non-agriculture. Since I do not find any effect of conflict on agricultural firm productivity it is unlikely that the latter channel plays a major role. Therefore, any potential upward bias from assuming free trade across chiefdoms is likely to be small.

Fourth, the simulation results depend on the size of the elasticity of substitution σ. However, both the aggregate income and aggregate sector results are reasonably robust to different values of σ. Figures B11 and B12 show the aggregate income and sector shift changes for alternative σ values of 6 and 8. These alternative values reflect that the relevant literature uses values between 4 and 8.[65] Both the sector shift and aggregate income effect are stronger for higher values of σ. This is intuitive since the elasticity of substitution governs the trade-off between two competing effects of productivity changes on the sector allocation. As productivity in sector N decreases relative to sector A, the non-agricultural good gets more expensive which leads to lower demand. Hence, production in that sector goes down. At the same time, lower productivity implies that the labor input needed to produce a given amount is larger. The elasticity of substitution determines the strength of the first effect. The larger the elasticity, the stronger the substitution effect and the more people shift sector to accommodate changing demand.[66]

9. Conclusion

This paper investigates the general equilibrium impact of civil war in Sierra Leone. To this end, I first establish that conflict leads to large spatial differences in income between areas that were more and less affected. These seem to be driven by a sector shift. People are more likely to work in agriculture as a result of the war. While I can identify spatial

[65] See a brief discussion in section 6.3.

[66] As long as the $\sigma > 1$, the first effect always dominates the second effect and the precise value of σ just determines the extent to which it does. Hence, the result on the sector shift only change quantitatively. If $\sigma < 1$, the first effect is weaker than the second effect and a productivity decrease in sector N implies more people working in that sector. This is indeed Baumol's cost disease argument and shown formally in Ngai & Pissarides (2007). However, empirically, the relevant literature for the elasticity of substitution used in my context suggests values that are considerably larger than 1.

differences with an identification strategy that deals with the non-random placement of conflict, they still capture both the direct effect of conflict as well as general equilibrium forces. Thus, spatial differences are not reflective of changes in *aggregate* income or sector composition.

In order to make progress on estimating aggregate effects, this paper develops an economic geography model. To keep track of population movement and its general equilibrium implications in response to the war, labor mobility under migration cost is a key feature of the model. Besides their destination, individuals choose their sector of work subject to an individual productivity draw and firm productivities for each sector and destination. Since returns to education are sector-specific, their education realization also shapes this decision. Conflict can change education, firm productivities, average individual productivities and amenities. This affects aggregate income both directly and indirectly by changing the sector composition and spatial allocation of labor.

The key parameters of the model can be estimated in a simple recursive procedure. In particular, observed income and migration flows identify firm productivities, average individual productivities as well as location amenities. Education outcomes are directly observed in the data. Having estimated all parameters, I can assess the effect of conflict on education, firm productivities, average individual productivities and amenities. I find that education, average individual productivity among the uneducated and firm productivity in the non-agricultural sector are persistently and strongly affected by the war while amenities, agricultural firm productivity and average individual productivity among the educated are not.

Finally, these results can be taken forward for counterfactual simulations of the Sierra Leonean economy in the absence of the war. A full reversal of the war scenario involves reverting the human capital loss, non-agricultural firm productivity drop and reductions in average individual productivity among the uneducated. Comparing this simulation to the observed economy that experienced civil war, I find that Sierra Leonean aggregate income is 31.6% lower today and the economy-wide share of workers in agriculture 20.8 percentage points higher as a result of the war. Running conflict simulations in which I consider the effect on education, firm productivities and average individual productivities separately allows me to assess the quantitative importance of these different mechanisms. Firm productivity losses can account for the largest part of aggregate income reductions with income decreasing by 17.8% due to this mechanism alone. By contrast, while having received much more attention as a mechanism, the impact of conflict on education alone would only lead to a 3.7% reduction in aggregate income. Identifying exactly the relevant elements for firm productivity that are potential drivers behind this and using a similar model structure to learn about the aggregate effect and mechanisms of conflict impact in other settings are left as promising avenues for future research.

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Appendix

A. Tables

Table A2: Further Results: Education

	Years of Schooling		Primary Education	
	(1)	(2)	(3)	(4)
Conflict	-1.083*	-0.149	-0.113**	-0.0235
	(0.572)	(0.407)	(0.0501)	(0.0333)
N	18690	2656	18691	2656
R^2	0.321	0.299	0.295	0.293
Estimation Method	IV	IV	IV	IV
First Stage F (KP)	24.31	14.16	24.31	14.16
AR p-value	0.058	0.710	0.026	0.466
Sample	Young	Old	Young	Old
Socio-econ. Controls	✓	✓	✓	✓
District FE	✓	✓	✓	✓

Note – Outcome variables: Years of schooling (columns 1 and 2) and indicator for having finished primary school (columns 3 and 4). Samples: 'Old' are all individuals born before 1961, 'Young' are all individuals born after 1961. Conflict standardized and instrumented with distance to border. For the old sample, conflict is measured in birth chiefdom; for the young sample, it is measured in chiefdom of residence in 2018. Clustered standard errors at the chiefdom level in parentheses. Kleibergen-Paap cluster-robust F statistic and p-value for weak instrument robust Anderson-Rubin test of $H_0 : \beta = 0$ reported. Stars refer to standard t-tests. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
[Back to main]

Table A3: Robustness: Exclusion of Chiefdoms with Direct Border

	Log household expenditures per worker			
	(1)	(2)	(3)	(4)
Conflict	-0.0840**	-0.0979***	-0.338**	-0.514***
	(0.0348)	(0.0361)	(0.132)	(0.189)
N	13586	13586	13586	13586
R^2	0.358	0.369	0.321	0.280
Estimation Method	OLS	OLS	IV	IV
First Stage F (KP)			20.80	14.03
AR p-value			0.008	0.001
Socio-econ. Controls	✓	✓	✓	✓
Land Controls		✓		✓
District FE	✓	✓	✓	✓

Note – The sample is restricted to chiefdoms that do not have a direct border with Liberia. This excludes 10 chiefdoms from the analysis. Outcome variables: Log total expenditures per worker. Conflict standardized and instrumented with distance to border. Clustered standard errors at the chiefdom level in parentheses. Kleibergen-Paap cluster-robust F statistic and p-value for weak instrument robust Anderson-Rubin test of $H_0 : \beta = 0$ reported. Stars refer to standard t-tests. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ [Back to main]

Table A1: Sector Allocation including Unemployed Individuals

	Work in Agriculture				Work in Non-agriculture			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Conflict	0.0555***	0.0653***	0.167**	0.267***	-0.0401***	-0.0473***	-0.109**	-0.191***
	(0.0205)	(0.0210)	(0.0721)	(0.0916)	(0.0147)	(0.0134)	(0.0460)	(0.0631)
N	21407	21407	21407	21407	21407	21407	21407	21407
R^2	0.315	0.329	0.297	0.275	0.171	0.179	0.163	0.149
Estimation Method	OLS	OLS	IV	IV	OLS	OLS	IV	IV
First Stage F (KP)			23.59	15.34			23.59	15.34
AR p-value			0.028	0.001			0.025	0.001
Socio-econ. Controls	✓	✓	✓	✓	✓	✓	✓	✓
Land Controls		✓		✓		✓		✓
District FE	✓	✓	✓	✓	✓	✓	✓	✓
	Work in Manufacturing				**Work in Services**			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Conflict	-0.0104*	-0.00995*	-0.0458***	-0.0614***	-0.0296**	-0.0373***	-0.0632*	-0.130***
	(0.00588)	(0.00542)	(0.0146)	(0.0217)	(0.0140)	(0.0122)	(0.0369)	(0.0478)
N	21407	21407	21407	21407	21407	21407	21407	21407
R^2	0.0503	0.0527	0.0429	0.0385	0.143	0.152	0.141	0.138
Estimation Method	OLS	OLS	IV	IV	OLS	OLS	IV	IV
First Stage F (KP)			23.59	15.34			23.59	15.34
AR p-value			0.002	0.001			0.102	0.003
Socio-econ. Controls	✓	✓	✓	✓	✓	✓	✓	✓
Land Controls		✓		✓		✓		✓
District FE	✓	✓	✓	✓	✓	✓	✓	✓

Note – Sample includes unemployed individuals. Outcome variables: Indicator variables for sector of work. Conflict standardized and instrumented with distance to border. Clustered standard errors at the chiefdom level in parentheses. Kleibergen-Paap cluster-robust F statistic and p-value for weak instrument robust Anderson-Rubin test of $H_0 : \beta = 0$ reported. Stars refer to standard t-tests. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ [Back to main]

Table A4: Robustness: Household Expenditures

	Log household expenditures			
	(1)	(2)	(3)	(4)
Conflict	-0.0573**	-0.0670**	-0.168**	-0.286**
	(0.0259)	(0.0278)	(0.0810)	(0.113)
N	21158	21158	21158	21158
R^2	0.450	0.459	0.440	0.421
Estimation Method	OLS	OLS	IV	IV
First Stage F (KP)			23.40	15.28
AR p-value			0.039	0.002
Socio-econ. Controls	✓	✓	✓	✓
Land Controls		✓		✓
District FE	✓	✓	✓	✓

Note – Outcome variable: Log total household expenditures. Conflict standardized and instrumented with distance to border. Clustered standard errors at the chiefdom level in parentheses. Kleibergen-Paap cluster-robust F statistic and p-value for weak instrument robust Anderson-Rubin test of $H_0 : \beta = 0$ reported. Stars refer to standard t-tests. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ [Back to main]

Table A5: Robustness: Expenditures per Adult Equivalent

	Log expenditures per adult equivalent			
	(1)	(2)	(3)	(4)
Conflict	-0.0597**	-0.0688**	-0.175**	-0.286**
	(0.0258)	(0.0279)	(0.0819)	(0.112)
N	21158	21158	21158	21158
R^2	0.415	0.424	0.402	0.384
Estimation Method	OLS	OLS	IV	IV
First Stage F (KP)			23.40	15.28
AR p-value			0.035	0.002
Socio-econ. Controls	✓	✓	✓	✓
Land Controls		✓		✓
District FE	✓	✓	✓	✓

Note – Outcome variable: Log total expenditures per adult equivalent. Conflict standardized and instrumented with distance to border. Clustered standard errors at the chiefdom level in parentheses. Kleibergen-Paap cluster-robust F statistic and p-value for weak instrument robust Anderson-Rubin test of $H_0 : \beta = 0$ reported. Stars refer to standard t-tests. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ [Back to main]

Table A6: Robustness: Exclusion of Freetown

	Log household expenditures per worker				Work in Agriculture			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Conflict	-0.0877**	-0.107***	-0.306**	-0.543***	0.0668**	0.0882***	0.183**	0.344***
	(0.0369)	(0.0380)	(0.129)	(0.206)	(0.0261)	(0.0268)	(0.0796)	(0.119)
N	12194	12194	12194	12194	12263	12263	12263	12263
R^2	0.181	0.214	0.144	0.0901	0.207	0.242	0.184	0.152
Estimation Method	OLS	OLS	IV	IV	OLS	OLS	IV	IV
First Stage F (KP)			19.35	12.53			19.49	12.54
AR p-value			0.012	0.000			0.028	0.000
Socio-econ. Controls	✓	✓	✓	✓	✓	✓	✓	✓
Land Controls		✓		✓		✓		✓
District FE	✓	✓	✓	✓	✓	✓	✓	✓
	Years of schooling				Primary Education			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Conflict	-0.291*	-0.429**	-0.970*	-2.070***	-0.0305**	-0.0413**	-0.0988**	-0.187***
	(0.175)	(0.203)	(0.530)	(0.723)	(0.0154)	(0.0181)	(0.0454)	(0.0630)
N	16944	16944	16944	16944	16945	16945	16945	16945
R^2	0.306	0.320	0.299	0.289	0.293	0.303	0.285	0.276
Estimation Method	OLS	OLS	IV	IV	OLS	OLS	IV	IV
First Stage F (KP)			23.46	14.93			23.46	14.93
AR p-value			0.067	0.001			0.032	0.001
Socio-econ. Controls	✓	✓	✓	✓	✓	✓	✓	✓
Land Controls		✓		✓		✓		✓
District FE	✓	✓	✓	✓	✓	✓	✓	✓

Note – The capital Freetown is excluded from the analysis. Outcome variables: Log total expenditures per worker; indicator variable for work in agriculture; years of schooling; indicator variable for having primary education. Conflict standardized and instrumented with distance to border. Clustered standard errors at the chiefdom level in parentheses. Kleibergen-Paap cluster-robust F statistic and p-value for weak instrument robust Anderson-Rubin test of $H_0: \beta = 0$ reported. Stars refer to standard t-tests. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ [Back to main]

B. Figures

Figure B1: Map of Sierra Leone in West Africa

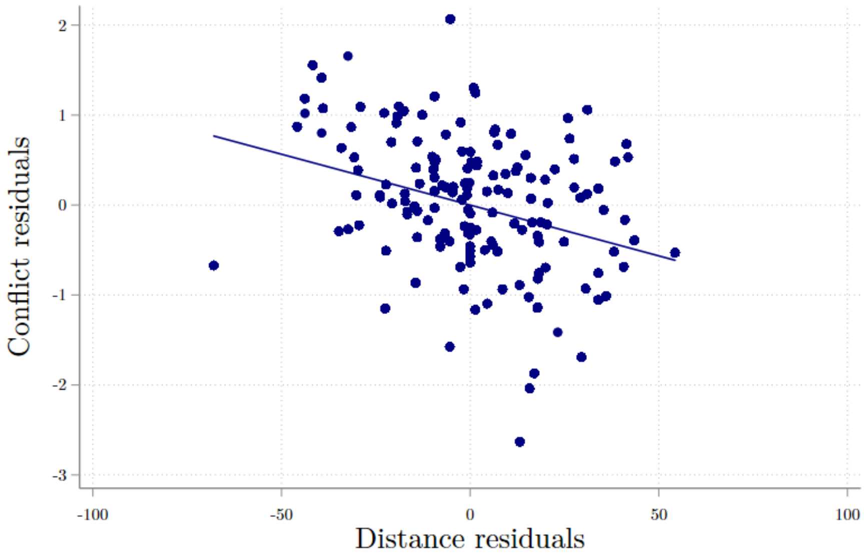
Note – Freetown is the capital of Sierra Leone. Source: Open Street Map. [Back to main]

Figure B2: ISIC Sector Classification

Section	Divisions	Description	
A	01–03	Agriculture, forestry and fishing	Agriculture
B	05–09	Mining and quarrying	Manufacturing
C	10–33	Manufacturing	
D	35	Electricity, gas, steam and air conditioning supply	
E	36–39	Water supply; sewerage, waste management and remediation activities	
F	41–43	Construction	
G	45–47	Wholesale and retail trade; repair of motor vehicles and motorcycles	Services
H	49–53	Transportation and storage	
I	55–56	Accommodation and food service activities	
J	58–63	Information and communication	
K	64–66	Financial and insurance activities	
L	68	Real estate activities	
M	69–75	Professional, scientific and technical activities	
N	77–82	Administrative and support service activities	
O	84	Public administration and defence; compulsory social security	
P	85	Education	
Q	86–88	Human health and social work activities	
R	90–93	Arts, entertainment and recreation	
S	94–96	Other service activities	
T	97–98	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	
U	99	Activities of extraterritorial organizations and bodies	

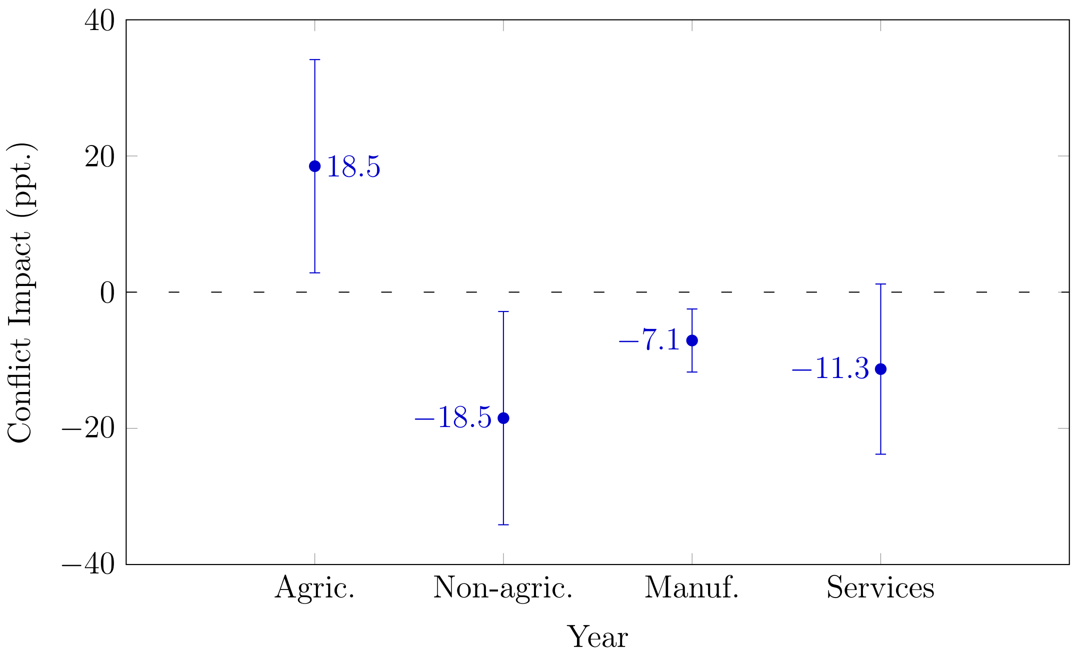
Note – From information on the ISIC section of their main professional activity, workers are classified to work in one of the three sectors according to the above figure. [Back to main]

Figure B3: First Stage Within Districts



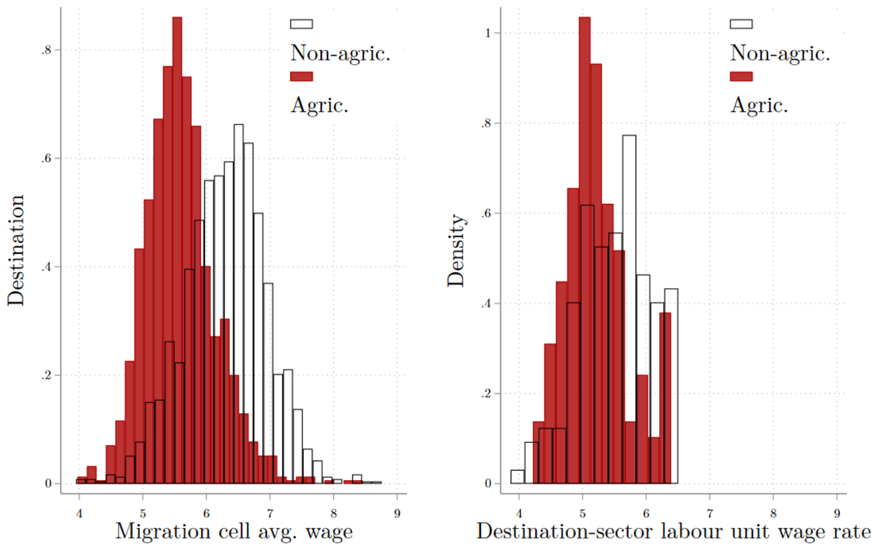
Note – The conflict measure is standardized and distance is measured in km. The straight line presents an OLS line of best fit. [Back to main]

Figure B4: Sector Shift



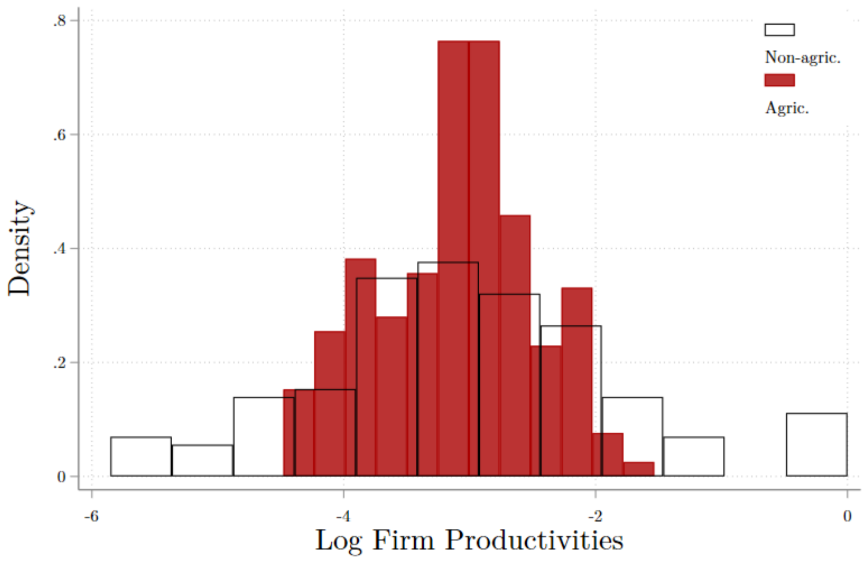
Note – IV coefficients depicted for specification with socio-economic controls, district fixed effects and minimum distance to large cities controlled for. 95% confidence intervals based on clustered standard errors at the chiefdom level. [Back to main]

Figure B5: Distribution of Labor Unit Wage Rates



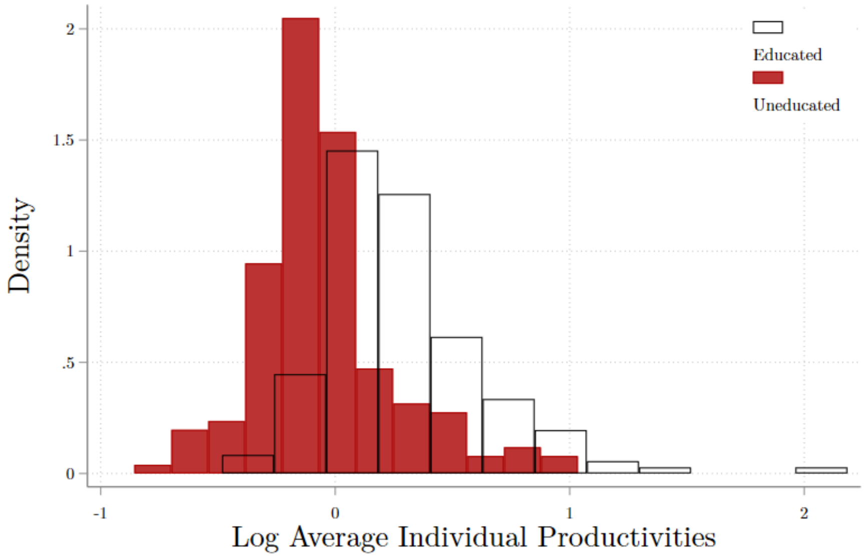
Note – Histograms of observed log income in the data $\ln \overline{m^S_{ecd}}$ and estimated log labor unit wage rates $\ln w^S_d$ by sector. [Back to main]

Figure B6: Distribution of Firm-level Productivities



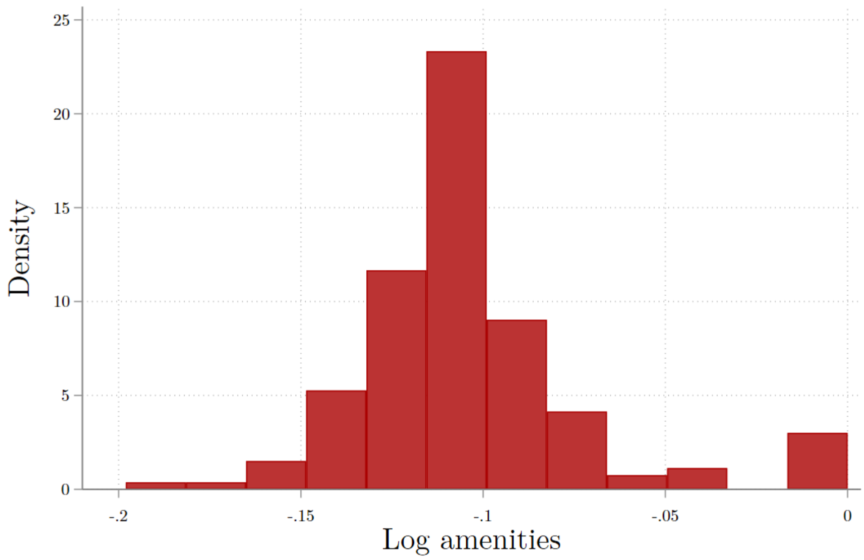
Note – Histograms of log firm-level productivities by sector. [Back to main]

Figure B7: Distribution of Average Individual Productivities



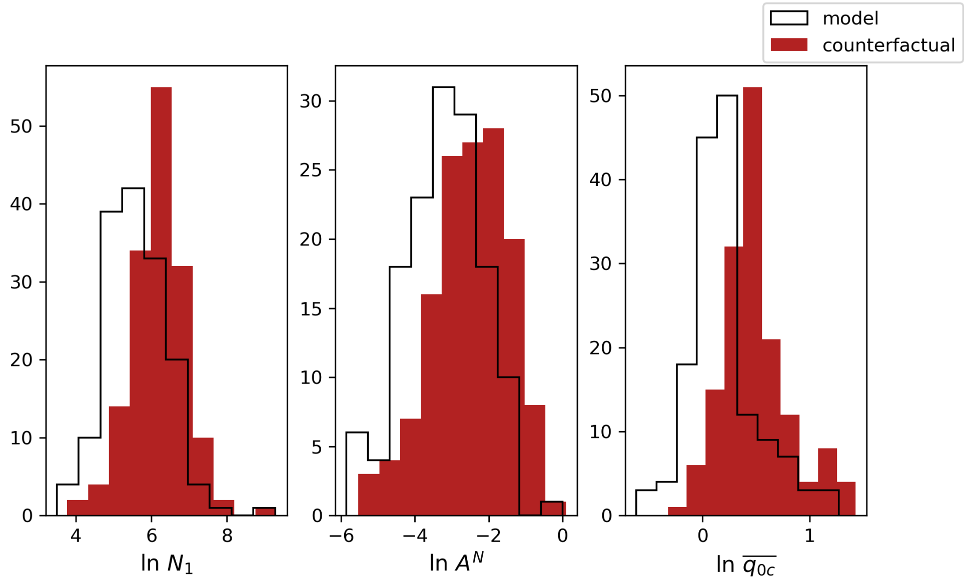
Note – Histograms of log average individual productivities by education level. [Back to main]

Figure B8: Distribution of Amenities



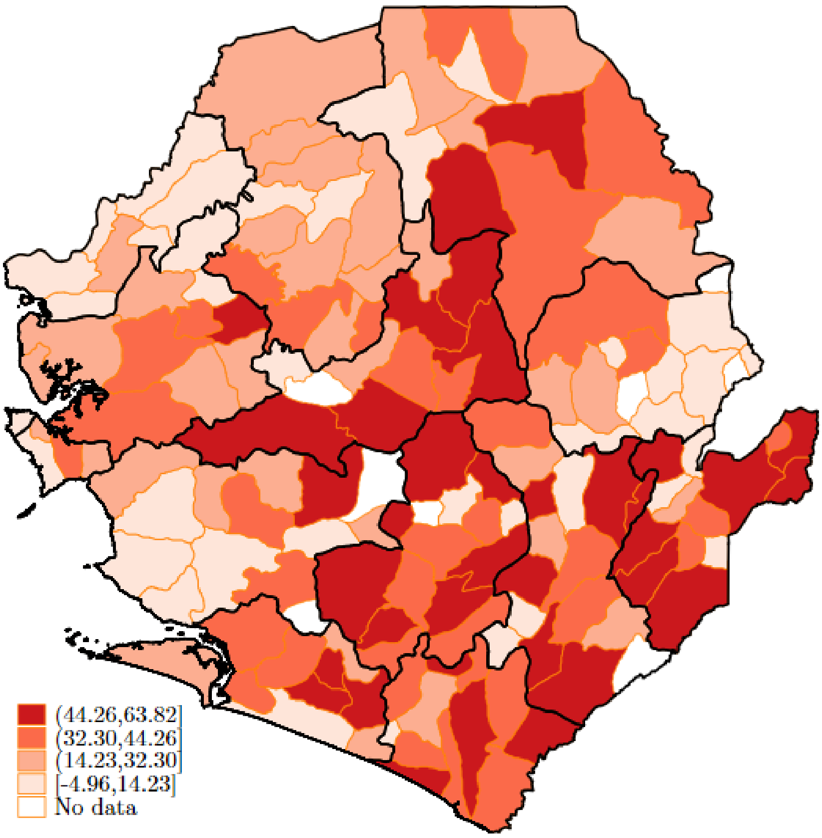
Note – Histograms of log amenities. [Back to main]

Figure B9: Parameter Changes



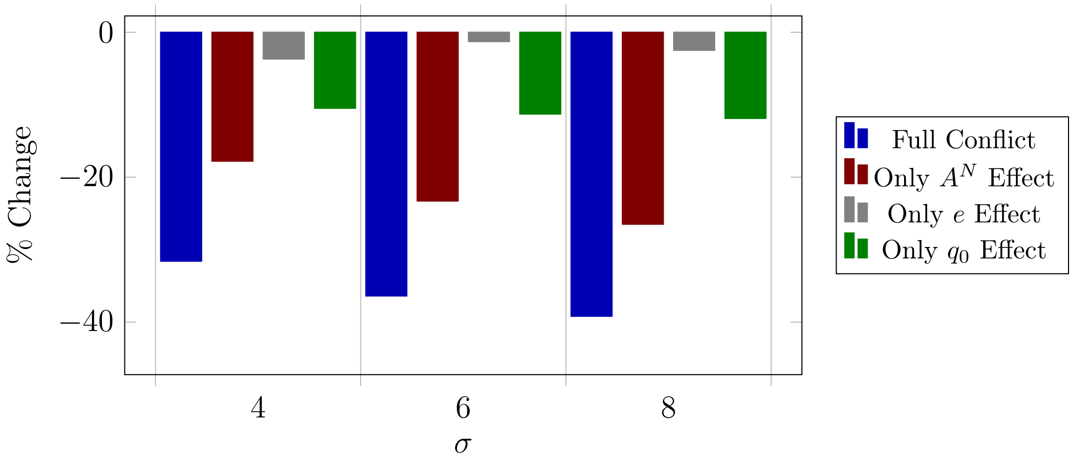
Note – Distributions of log origin populations of individuals with primary school education $\ln N_1$, log non-agricultural firm productivities $\ln A_d^S$ and log average individual productivities among the uneducated $\ln \overline{q_{0c}}$. The black histogram displays the original distributions and the red histogram displays the counterfactual distributions. [Back to main]

Figure B10: Aggregate Income Changes by Chiefdom



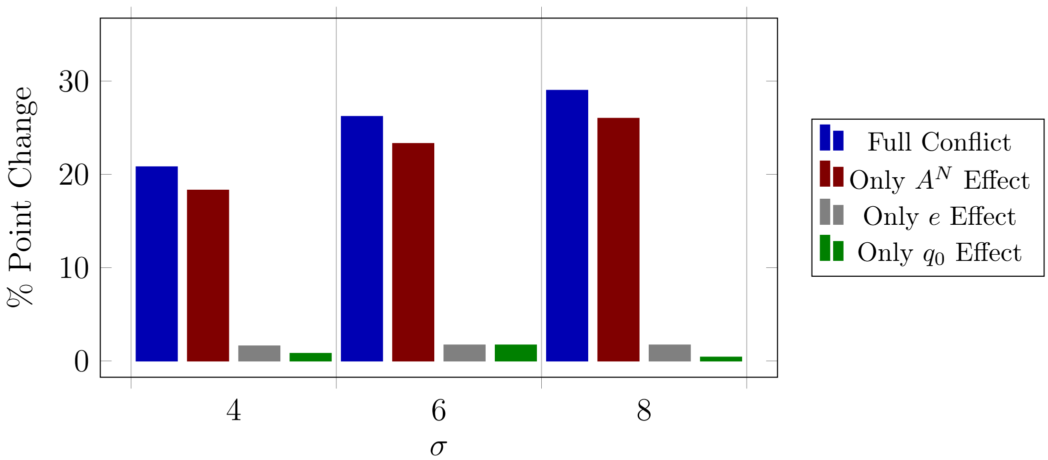
Note – Absolute value of aggregate income reductions (in %) in each chiefdom as a result of the civil war relative to a no-war scenario. Full conflict simulation considered. Estimates stem from model simulation. Missing data: 5 chiefdoms unobserved in households survey 2018; 3 chiefdoms without conflict information. [Back to main]

Figure B11: Robustness to Different σ Values: Aggregate Income



Note – Aggregate income changes for different values of the elasticity of substitution σ. [Back to main]

Figure B12: Robustness to Different σ Values: Employment in Agriculture



Note – Changes in the economy-wide size of the agricultural sector for different values of the elasticity of substitution σ. [Back to main]

C. Proofs

Proof of equation 10. Recall that individual productivity draws z_{id}^S for destination d and sector S are independently Fréchet distributed:

$$F_{ec}(z_{id}^S) = \exp\left(-\left(\frac{z_{id}^S}{q_{ecd}^S}\right)^{-\theta}\right) \tag{C1}$$

Consider the indirect utility distribution of workers *choosing* destination d and sector S, that is, the distribution of $\overline{V}_{id}^S := V_{id}^S | i \in M_{ecd}^S = \max_{d',S'}\{V_{id'}^{S'}\}$. Using the fact that $V_{id}^S = \frac{v_{ecd}^S z_{id}^S}{P}$, we have

$$\begin{aligned}
F_{\overline{V}_{id}^S}(u) &= Pr\left[V_{id'}^{S'} < u \ \forall d', S'\right] \\
&= \exp\left(-\sum_{d'}\sum_{S'}\left(\frac{uP}{v_{ecd'}^{S'} q_{ecd'}^{S'}}\right)^{-\theta}\right) \\
&= \exp\left(-u^{-\theta}\sum_{d'}\sum_{S'}\left(\frac{v_{ecd'}^{S'} q_{ecd'}^{S'}}{P}\right)^{\theta}\right) \\
&= \exp\left(-\left(\frac{u}{\left(\sum_{d'}\sum_{S'}\left(\frac{v_{ecd'}^{S'} q_{ecd'}^{S'}}{P}\right)^{\theta}\right)^{\frac{1}{\theta}}}\right)^{-\theta}\right)
\end{aligned} \tag{C2}$$

Therefore, the distribution of $\overline{V}_{id}^S$ is Fréchet itself with scale parameter

$$t_{ec} := \left(\sum_{d'}\sum_{S'}\left(\frac{v_{ecd'}^{S'} q_{ecd'}^{S'}}{P}\right)^{\theta}\right)^{\frac{1}{\theta}} \tag{C3}$$

The probability that someone chooses d and sector S is

$$\begin{aligned}
\pi_{ecd}^S &= Pr\left[V_{id}^S > V_{id'}^{S'} \ \forall d', S' \neq d, S\right] \\
&= \int_0^\infty Pr\left[V_{id'}^{S'} < u \ \forall d', S' \neq d, S\right] dF_{V_{id}^S}(u) \\
&= \int_0^\infty \frac{F_{\overline{V}_{id}^S}(u)}{F_{V_{id}^S}(u)} \theta u^{-1-\theta} \left(\frac{v_{ecd}^S q_{ecd}^S}{P}\right)^{\theta} F_{V_{id}^S}(u) du \\
&= \left(\frac{v_{ecd}^S q_{ecd}^S}{P}\right)^{\theta} t_{ec}^{-\theta} \int_0^\infty \underbrace{\theta u^{-1-\theta} t_{ec}^{\theta} F_{\overline{V}_{id}^S}(u) du}_{f_{\overline{V}_{id}^S}(u)} \\
&= \frac{(v_{ecd}^S \epsilon_{ecd}^S)^\theta}{\sum_{d'}\sum_{S'}(v_{ecd'}^{S'}\epsilon_{ecd'}^{S'})^\theta}
\end{aligned} \tag{C4}$$

where the last step makes use of the decomposition of $q_{ecd}^S = \overline{q_{ec}} \epsilon_{ecd}^S$ into an origin-education average and remaining variation.

Proof of equation 11. Using the distribution of $\overline{V}_{id}^S$, we have that $z_i | i \in M_{ecd}^S = \frac{\overline{V}_{id}^S P}{v_{ecd}^S}$ also follows a Fréchet distribution with scale parameter

$$\frac{t_{ec}P}{v_{ecd}^S} = \left(\frac{\sum_{d'} \sum_{S'} \left(v_{ecd'}^{S'} q_{ecd'}^{S'} \right)^{\theta}}{\left(v_{ecd}^S \right)^{\theta}} \right)^{\frac{1}{\theta}} \tag{C5}$$

It follows that

$$\begin{aligned} E\left[z_i | i \in M_{ecd}^S \right] &= \frac{t_{ec}P}{v_{ecd}^S} \Gamma\left(\frac{\theta - 1}{\theta} \right) \\ &= \left(\frac{\sum_{d'} \sum_{S'} (v_{ecd'}^{S'} q_{ecd'}^{S'})^{\theta}}{\left(v_{ecd}^S \right)^{\theta}} \right)^{\frac{1}{\theta}} \Gamma\left(\frac{\theta - 1}{\theta} \right) \\ &= (\pi_{ecd}^S)^{-1/\theta} q_{ecd}^S \Gamma\left(\frac{\theta - 1}{\theta} \right) \end{aligned} \tag{C6}$$

D. Extensions

D.1. Trade Cost

An introduction of trade cost in the classic iceberg format would have an implication for the estimation of A_d^S in step 3 of the estimation (section 6.3). Denote the iceberg trade cost by $\eta_{dg}^S \geq 1$ as the amount of good produced in d that would need to be bought in any other location g to consume one unit of that good in g. The market clearing conditions would contain a market access term:

$$\left(\frac{w_d^S}{w_f^T}\right)^{\sigma} = \left(\frac{A_d^S}{A_f^T}\right)^{\sigma-1} \frac{\sum_g (\eta_{dg}^S)^{-\sigma} GDP_g / P_g^{1-\sigma}}{\sum_g (\eta_{fg}^S)^{-\sigma} GDP_g / P_g^{1-\sigma}} \frac{L_f^T}{L_d^S} \tag{D1}$$

Market access is the weighted sum of real GDP in all buying locations of a good that is produced in d or f where the weights are the inverse trade cost. With trade cost, therefore, my estimates of firm productivities A_d^S are in fact a composite of firm productivities and market access. Section 8.3 discusses the implications for the results in counterfactual simulations and the estimation of the aggregate effects of civil war.

D.2. Endogenous Education

As a simple extension of the model with endogenous education choice, consider the individual productivity shock that workers draw to be sector-, destination-, *and education*-specific. Workers draw the shock z_{ied}^S for each sector S, destination d, and education level e from independent Fréchet distributions with scale parameter q_{ecd}^S. Denote the origin-specific cost of getting education level e by k_{ec} satisfying $k_{0c} = 1$ and $k_{1c} > 1$. It is assumed to enter as a denominator in your income. Therefore, workers who choose education e, sector S and destination d have indirect utility

$$\hat{V}_{ied}^S = \frac{v_{ecd}^S z_{ied}^S}{k_{ec} P} \tag{D2}$$

Workers maximise utility to choose their education level, sector and destination. Similar considerations as before give that the probability of choosing education level e, destination d and sector S is

$$\hat{\pi}_{ecd}^S := Pr\left[V_{ied}^S > V_{ie'd'}^{S'} \; \forall e', d', S'\right] = \frac{(v_{ecd}^S q_{ecd}^S / k_{ec})^{\theta}}{\sum_{e'} \sum_{d'} \sum_{S'} (v_{e'cd'}^{S'} q_{e'cd'}^{S'} / k_{e'c})^{\theta}} \tag{D3}$$

As a result, education choice can be described by the ratio of the probability to become educated and the probability to stay uneducated within a sector-destination:

$$\frac{\hat{\pi}_{1cd}^S}{\hat{\pi}_{0cd}^S} = \left(\frac{\exp(\phi^S)(1-\tau_{1cd}^S) q_{1cd}^S}{k_{1c}(1-\tau_{0cd}^S) q_{0cd}^S}\right)^{\theta} \tag{D4}$$

In this setting, the effect of conflict on education operates through an effect on the cost of education. The destruction of schools and killings of teachers in origin c make it more costly for individuals born there to get educated, that is, k_{1c} increases. Clearly, fewer people will get educated as a result. The implications of this and conflict effects on firm productivities and location amenities for sector and destination choice are the same as in the original model.

E. Numerical Solution Algorithm

All simulations described in section 8 require model solutions. Given parameter values $\{\theta, \phi^N - \phi^A, A_d^A, A_d^N, a_d, \overline{q_{0c}}, \exp(\phi^N)\overline{q_{1c}}, \tau_{0cd}^A, \tau_{0cd}^N, \tau_{1cd}^A, \tau_{1cd}^N, N_{0c}, N_{1c}\}$, the model solution is numerically found using the following recursive procedure.

Step 1. For the initial iteration $i = 0$, guess initial movement matrices $\left[\pi_{ecd}^S\right]_{i=0}$.

Step 2. In iteration i, given origin populations $\overline{N_{ec}}$ and the movement matrices, the workforce in each sector and destination can be computed.

Step 3. Given the workforce in each sector and destination, labor supply is determined according to equation 17 as:

$$L_d^S = \sum_c \sum_e \overline{N_{ec}} (\pi_{ecd}^S)^{1-\frac{1}{\theta}} h_e^S q_{ecd}^S \Gamma \left(\frac{\theta - 1}{\theta}\right) \tag{E1}$$

Note that this object can be identified even without separate identification of ϕ^S and $\overline{q_{ec}}$ since the two only enter multiplicatively. For the uneducated, $\overline{q_{0c}}$ is known. For the educated in non-agriculture, $\exp(\phi^N)\overline{q_{1c}}$ is known. For the educated in agriculture, $\exp(\phi^A)\overline{q_{1c}} = \exp(\phi^N)\overline{q_{1c}} \times \exp(\phi^A - \phi^N)$ can be computed using the known parameter values above.

Step 4. Given labor supply L_S^d and firm productivities A_d^S in each sector and destination, wage rates can be determined up to scale. Using the estimated non-agricultural wage rate in Freetown $w_{Freetown}^N$ as a normalization, all other wage rates are determined one by one using the equilibrium condition 23:

$$\left(\frac{w_d^S}{w_{Freetown}^N}\right)^{\sigma} = \left(\frac{A_d^S}{A_{Freetown}^N}\right)^{\sigma-1} \frac{L_{Freetown}^N}{L_d^S} \quad \forall S \in \{A, N\} \; \forall d \in \mathcal{K} \tag{E2}$$

Step 5. Given wage rates w_d^S, compute v_{ecd}^S and find the optimal sector and destination choice of workers according to equation 10:

$$\left[\pi_{ecd}^S\right]_n = \frac{(v_{ecd}^S \epsilon_{ecd}^S)^\theta}{\sum_{d'} \sum_{S'} (v_{ecd'}^{S'} \epsilon_{ecd'}^{S'})^\theta} \tag{E3}$$

Step 6. Update your guess of movement matrices as a convex combination (with weight $\delta = 0.9$) of the guess from the previous iteration and the computed movement matrices:

$$\left[\pi_{ecd}^S\right]_{i+1} = \delta \left[\pi_{ecd}^S\right]_i + (1 - \delta) \left[\pi_{ecd}^S\right]_n \tag{E4}$$

Step 7. Iterate from step 2 until the distance between $\left[\pi_{ecd}^S\right]_i$ and $\left[\pi_{ecd}^S\right]_{i+1}$ is sufficiently small for all movement matrices.