Market Integration and the Effects of Forced Displacement on Host Communities

Nicolas Polasek*

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Abstract

About half of forcibly displaced people worldwide are hosted in rural communities, where integration with external markets is often limited. This paper studies how market integration shapes host communities' responses to internal displacement in Ethiopia, where conflict displaced more than four million people between 2018 and 2022. I develop a stylized framework in which hosts produce and consume food, traded on external markets, and services that are locally supplied. Displacement expands consumer demand and low-skill labor supply, inducing hosts to enter high-skill occupations. In the framework, lower market integration limits host reallocation and causes food prices to decline. The empirical analysis instruments displacement inflows with a shift-share design that combines the origins of an area's pre-existing displaced population with subsequent conflict shocks in those origins. Displacement inflows cause a decline in low-skill wages and non-food prices. However, adjustment depends on market integration. In more integrated communities, hosts move out of agriculture and casual labor into higher-skill, non-agricultural occupations. In less integrated communities, occupational reallocation is limited. Instead, hosts hire more workers and expand agricultural production, leading food prices to decline more sharply. Host real consumption rises in both types of communities, with larger gains in less integrated areas. These findings suggest that displacement can increase host consumption through lower labor costs, with market integration shaping how communities adjust.

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*University of California, Berkeley, Department of Agricultural and Resource Economics. Email: nicolas_polasek@berkeley.edu. I am grateful to Jeremy Magruder, Marco Gonzalez-Navarro and Edward Miguel for their guidance and support throughout this project. I also benefited from comments by Francis Annan, Aprajit Mahajan, Kirill Borusyak, David Card, Supreet Kaur, Nina Buchmann, Michelle Layvant, Sheah Delaimi, Zac Pond, Ian Hardman and Javier Feinmann, as well as seminar participants at UC Berkeley and CEGA R^2. I am grateful to the IOM Ethiopia Data and Research Unit for their assistance regarding proper use of the DTM data.

1 Introduction

The number of forcibly displaced people worldwide nearly doubled over the past decade, reaching 117 million in 2025 (UNHCR, 2025). Understanding how displacement affects the communities hosting them is a key policy concern and has been studied in multiple contexts.[1] Displacement affects host economies through both consumer and labor market shocks. As consumers, displaced people increase demand for goods and services, potentially raising local prices (e.g., Alix-Garcia and Saah, 2010). As workers, they expand the local labor supply, affecting host workers' wages and employment (e.g., Foged and Peri, 2016). The effects on host communities are heterogeneous and have been shown to depend on the complementarities between displaced and host workers and the policies used for the inclusion of the displaced (Borjas and Monras, 2017; Winton, 2025). Less is known about how host communities' integration with external labor and goods markets shapes their adjustment to displacement.

This question is especially relevant in rural areas of low- and middle-income countries, which host a substantial share of displaced people (UNHCR, 2024) but often remain poorly connected to external labor and consumer goods markets (Djemaï et al., 2024). Yet, market integration profoundly defines local economies. On labor markets, higher integration through improved transportation infrastructure expands access to employment opportunities, especially outside of agriculture (Asher and Novosad, 2020; Gertler et al., 2024). Integration also connects food markets, reducing price dispersion across locations (Jones and Salazar, 2021). Market integration might interact with the effects of displacement on host communities by providing more economic opportunities to workers and limiting any price effect.

This paper studies the effects of forced displacement on labor and consumer goods markets in Ethiopia, which experienced one of the largest displacement crises ever studied with about 4.4 million people displaced in the country (IOM, 2023). I leverage nationally representative data on Ethiopian communities as well as a nearly comprehensive dataset on internally displaced people (IDPs) to assess how displacement inflows affect these communities. Guided by a stylized framework, the empirical analysis relies on a shift-share instrumental variable design based on the idea that people flee conflict and relocate where previously displaced members of their community did. This allows me to estimate causal effects of displacement on host community wages, prices, and the labor allocation of host workers. My results suggest that displacement inflows led to positive effects on host communities through decreasing prices, but that adjustment patterns varied with market integration.

In the first part of the paper, I develop a stylized, partial-equilibrium framework that captures the effects of displacement on host communities, which differ by level of market integration. The displacement shock adds low-skill workers and consumers to the communities. Consistent with the idea that integrated labor markets provide higher access to better jobs, I model market integration

[1] For a review of the effects of forced displacement on host communities, see Verme and Schuettler (2021).

on labor markets as a reduction in commuting costs for higher-skill occupations. On food markets, I define market integration as declining iceberg costs due to better transportation. The host communities produce and consume food as well as local services in the framework. Production of food uses low-skill workers and land, while services require both low and high-skill labor. With fully integrated markets, food is traded at the external price and a large share of hosts work in high-skill occupations due to the low commuting costs. In that case, the framework predicts that displacement induces a decrease in the skill premium, leading to host reallocation towards high-skill occupations, and eventually a fall in the price of local services.[2] I then allow for lower market integration, which shrinks the share of hosts in high-skill occupations due to higher commuting costs and implies with higher iceberg costs that food prices clear locally. In this case, displacement leads to a smaller reallocation of hosts towards high-skill jobs and creates downward pressures on food prices in addition to the declining service prices.

Next, I turn to the empirical analysis, which estimates the short-term effects of displacement on host communities. Displacement is defined as the net annual flow of internally displaced people (IDPs) within 25 km of the community's spatial centroid. On average, host communities experience an increase of about 2400 IDPs within that year, which accounting for the IDPs already present in the community at the beginning of the period, sums to about 6 percent of the host population by the end of that year. However, the choice of a community of destination is endogenous: IDPs probably prefer to relocate to better destinations, or to communities where they think they would have more opportunities. I rely on two facts to leverage exogenous variation in the displacement variable. First, displacement patterns in Ethiopia follow ethnic lines: members of a given ethnic group move towards destinations where their group is represented, and so previous waves of displacement would happen along these ethnic lines. Second, more than 80 percent of IDPs report that they fled their districts of origin due to conflict. I therefore build a shift-share instrument around the idea that a host community receives more IDPs when the districts of origin of its previously-displaced population experience more conflict. Specifically, the instrument interacts the existing composition of the displaced population in a host community based on their district of origin (the shares) with subsequent conflict events in these origins (the shifts). Identification requires these origin conflict shocks to affect host community outcomes such as prices, wages and sectors of employment only through displacement, conditional on community and time fixed effects. Following Borusyak et al. (2022), standard errors are clustered at the level of the origin districts.[3] An extension of this empirical strategy allows me to estimate how displacement effects vary with market integration, defined as the average proximity of each host community to market and transport infrastructure, namely asphalt roads, bus stations, and large weekly markets.

The main findings are consistent with labor-supply effects outweighing the additional consumer

[2]The price of services falls conditional on the IDP shock on the low-skill labor supply exceeding the increase in consumer demand. The reverse would make the price of local services increase.

[3]Because a single origin conflict reaches every destination hosting people from that district, regressions are estimated on a reweighted origin-level dataset, which allows standard errors to be clustered at the district of origin.

demand generated by displacement, and with the average effects being consistent with high market integration in Ethiopia. Guided by the stylized framework, which predicts a decrease in the skill premium with displacement inflows, I first estimate the effects of displacement on host communities on wages for low-skill work and high-skill labor. I find evidence supportive of a substantial increase in the skill ratio. The daily casual labor wage decreases by about 2.49 PPP dollars ($p < 0.01$) for an additional 1,000 IDPs in the host community, a 10 percent decline relative to the outcome mean. By contrast, the effect of displacement on the permanent employment daily wage is null at conventional significance levels, with a point estimate of 0.02, or a 0.6 percent increase.

Hosts reallocate labor toward high-skill activities, consistent with the framework's predicted response to a decline in the relative return to low-skill work with integrated markets. I find that hosts spend fewer hours in household agriculture and in casual labor, the low-skill occupations in empirical terms, and increase hours worked in non-agricultural self-employment and permanent wage employment, which proxy for high-skill jobs. For an increase of 1,000 IDPs in the host communities, the point estimates are equivalent to a 5 ($p < 0.01$) and 10 percent ($p < 0.05$) decrease for household agricultural work and casual labor, respectively. Hours worked increase in self-employment and permanent wage employment, both outside of agriculture, by 4 ($p < 0.05$) and 3 ($p < 0.05$) percent.

With full integration, food prices should be held fixed by trade with external markets. I directly estimate the effect of exposure to displacement on food prices and find only a modest decline. An increase in the net flow of 1,000 IDPs decreases food prices by 0.95 percent ($p < 0.10$). The framework predicts that service prices fall when the labor supply effect of displacement dominates the increase in demand. Since I do not observe service prices, I use a regional non-food CPI index as outcome variable and find a 2 percent decrease ($p < 0.01$). To examine whether tradable prices also decline, I build a price index using 9 tradable goods recorded in every market of host communities, and find a small, statistically insignificant estimate: the price decreases by 0.2 percent with 1,000 additional IDPs in host communities. Taken together, the findings indicate that displacement had little effect on the prices of tradable goods, such as food, but reduced the prices of non-tradable goods in line with the predictions of the framework with full market integration.

I then assess whether lower market integration affects these results as the framework predicts. Splitting the sample of host communities by high and low market integration, I estimate heterogeneous effects and find distinctive patterns of adjustment by host communities for the two groups.

First, hosts' reallocation in response to displacement is limited to communities with high market integration. In these communities, hosts sharply reduce their hours in household agriculture as predicted by the framework with full integration. The point estimate is -0.389 ($p < 0.01$) for an increase of 1,000 IDPs in the annual flow, a decline equivalent to 37 percent of mean hours. Hosts also spend fewer hours working in casual labor, with a -0.082 ($p < 0.05$) effect for 1,000 additional IDPs. This represents a 7 percent decrease. Hours spent in self-employment and permanent wage employment increase, by 0.153 ($p < 0.01$) and 0.231 ($p < 0.10$), respectively, representing a 3

percent increase in both categories. By contrast, sectoral reallocation is limited in areas with low market integration, consistent with the framework's prediction. I find no empirical evidence of reallocation toward nonagricultural activities in these areas. The hours worked by the hosts in household agriculture don't decline: the estimate, 0.139, is positive but statistically insignificant and very imprecise. Host workers don't increase their time spent in non-agricultural activities either. The point estimates are negative for the hours spent in self-employment (-0.042, about a 3 percent decrease) and permanent wage employment (-0.014, a 0.8 percent decrease). Both effects are statistically insignificant at conventional levels.

Second, market integration leads to different responses on consumer goods and services markets too. In the framework, food prices don't react with full market integration but fall when communities are more isolated. On the other hand, the effect of displacement on prices for local services don't vary with market integration since these markets clear locally. These predictions are verified empirically. The effect of displacement inflows on food prices is negative in communities with low integration to external markets, scaling to a 1.3 percent decline ($p < 0.01$). However, non-food prices decline by similar magnitudes in both areas: the non-food regional CPI decreases by about 2 percent ($p < 0.01$ in both cases).

The framework also predicted that agriculture expands both in terms of labor and production under low market integration. Using data on agricultural production available only for less integrated communities, I find that displacement inflows increase agricultural production by 13 percent of the mean (USD 76, $p < 0.10$), alongside rises in labor and land inputs used on household farms. Person-days of total labor increase by 19 percent with 1,000 additional IDPs (6.8 person-days, $p < 0.05$) and cultivated land areas expand by 11 percent (0.051 hectares, $p < 0.05$). The increase in farm labor includes a 30 percent increase in unpaid labor (2,2 person-days, $p < 0.05$), a category of labor for workers not compensated by wages. Previous studies documented that displaced workers often work on host land in exchange for food or access to part of the land (Whitaker, 2002; Khasalamwa-Mwandha, 2021). I therefore link the rise in unpaid labor to displaced workers since I find no effect of displacement on host-reported measures of unpaid labor. Displacement therefore leads to an expansion within agriculture in less integrated areas, suggestive of cheap access to agricultural IDP workers for local farms.

While the framework held spending for both IDPs and hosts fixed for simplicity, I assess whether host communities experienced changes in real consumption due to displacement. I find that IDP inflows led to positive effects for host communities in terms of real consumption. The gains are larger in less integrated communities, suggestive of purchasing power increasing from larger declines in tradable prices. Real total annual household consumption rises by 1.8 percent ($p < 0.01$) in communities with lower integration, against a modest rise in more integrated areas, about a 0.3 percent increase.

Taken together, these results indicate that market integration shapes how host economies react to displacement inflows. In host communities that are well integrated with external markets, the

IDP shock increases the low-skill labor supply, pushing wages for these occupations down and reallocating host workers to high-skill occupations. These findings match those from previous studies showing occupational upgrading in mostly urban settings (Foged and Peri, 2016; Winton, 2025) or sectoral reallocation away from agriculture in Sub-Saharan Africa with greater population density (Bohsali, 2025). In these communities, hosts' real consumption rises modestly. However, in host communities with lower market integration, I find no evidence of hosts reallocating away from agriculture, with evidence maybe closer to the effect of refugee camps in rural settings (e.g., Maystadt and Verwimp, 2014). With lower market integration, agricultural production expands, relying on lower labor costs. This adjustment mechanism is accompanied by larger gains in hosts' real consumption in low-integration areas.

Contributions to the literature. This study contributes first to the literature on the effects of migration and forced displacement on hosts, which started with Card (1990)'s evaluation of the effects of the Mariel Boatlift on Miami host workers. This literature blends a definition of the displaced people that is inclusive of both internally displaced people and international refugees. Though there are a few theoretical differences in their experience of displacement,[4] the literature hasn't determined systematic differences in their impacts on their places of destination (Verme and Schuettler, 2021). For both groups, average effects on labor markets are null on average, and are usually accompanied by distributional effects based on the complementarities of host workers with the displaced.[5] High-skill workers usually benefit, while low-skill workers experience longer-lasting wage declines (Alix-Garcia and Bartlett, 2015; Calderón-Mejía and Ibáñez, 2016; Ceritoglu et al., 2017; Borjas and Monras, 2017; Alix-Garcia et al., 2018; Morales, 2018; Fallah et al., 2019; Aksu et al., 2022). Where agriculture is more prevalent, winners and losers are typically defined by their role in food production: farmers hire displaced people to work on their farms and benefit from the price of their crops and livestock rising while landless laborers experience increased competition (Alix-Garcia and Saah, 2010; Maystadt and Verwimp, 2014; Alix-Garcia et al., 2018; Tsuda, 2022). A few exceptions to the complementarity narrative exist, where the displacement shock enables occupational upgrading for low-skill workers among the hosts, as with refugees in Denmark and Jordan (Foged and Peri, 2016; Winton, 2025) or sectoral reallocation for all workers present in destination communities in Uganda (Bohsali, 2025). This paper contributes to this literature by documenting that host community adjustments vary based on their integration with external markets. In particular, hosts adapt to displacement by increasing agricultural production in less integrated communities, along with real consumption gains. Though this effect has been documented in the United States and Türkiye before (Cortes, 2008; Tumen, 2016), another contribution comes from showing price decreases due to access to cheap labor from the displaced population. The fact that this effect is found in communities with limited market integration is novel and runs contrary

[4] A few distinction concern IDPs retaining the rights to work, and being under the protection of their own government, which often is involved in the conflict displacing them, instead of the international community. But lost assets, disrupted networks and psychological distress are experiences shared by both groups (Cantor and Apollo, 2020).

[5] For reviews and meta-analyses on this literature, see Becker and Ferrara (2019); Verme and Schuettler (2021); Rozo and Grossman (2025).

to worries of food shortages resulting in price spikes.

Second, this paper contributes to the literature on market integration and its link with structural transformation. Higher market integration through improvements in transportation infrastructure has been shown to increase growth, real income and economic opportunities especially out of agriculture (Dercon et al., 2009; Donaldson, 2018; Asher and Novosad, 2020; Gertler et al., 2024). Regarding agriculture, improved market access has been shown to raise productivity gains as well as land values (Donaldson and Hornbeck, 2016; Adamopoulos, 2025), and by contrast, increases in transportation costs have been shown to raise reliance on subsistence agriculture (Gollin and Rogerson, 2014). Transportation infrastructure has been shown to increase access to basic needs (Djemaï et al., 2024) and increase resilience to natural disasters (Brooks and Donovan, 2020). The link between this literature and migration has been studied before, mostly to document the barriers preventing migration to urban centers (Bryan et al., 2014; Bryan and Morten, 2019; Baseler, 2023). This study expands this literature by showing that workers exploit the expanded economic opportunities provided by market integration to adjust to shocks such as displacement inflows, by reallocating to non-agricultural sectors. Yet, another contribution is the fact that absent integrated markets, the adjustment pattern is agricultural expansion alongside real consumption improvements. Last, this paper also documents that food prices are more muted in integrated markets following displacement inflows.

Outline. The rest of this paper is structured as follows. In Section 2, I present a stylized framework to guide empirical work and highlight the channels at play with a displacement shock. Section 3 describes the study setting, Ethiopia, provides contextual information on conflict and internal displacement in the country, and introduces the datasets used in the analysis. Section 4 provides the details of its empirical strategy, including the estimating equation and the shift-share instruments. The results regarding the effects of displacement inflows on host communities are shown in Section 5. Finally, Section 6 concludes.

2 Stylized framework

This section develops a stylized framework to study displacement, defined as an increase in low-skill labor supply and expenditure demand in receiving communities, affects host occupations, local prices, and agricultural production. The first part of the framework assumes full market integration. In the second part, I allow for imperfect integration, defined as commuting costs to high-skill occupations, and as an iceberg cost on food markets. Both costs are defined by the same parameter, κ, where a higher κ means lower market integration.

In the labor market, integration determines the cost of commuting to a nearby urban center. I assume that high-skill jobs are concentrated in that center and are scarce within isolated host communities, so access to these jobs entails a commuting cost $\kappa\bar{c}$, with $\bar{c} > 0$. This mechanism is motivated by the literature on transportation infrastructure and costs, who find that rural roads and

lower transportation costs facilitate movement out of agriculture and provide suggestive evidence that workers gain access to nonfarm jobs outside their villages (Gollin and Rogerson, 2014; Asher and Novosad, 2020; Gertler et al., 2024). Treating these opportunities as high-skill work is a modeling assumption. In the food market, integration determines the cost of importing from an outside market: an iceberg cost requires shipping $1 + \kappa$ units to deliver one unit. Food prices are consequently held fixed by import parity when imports are positive, whereas sufficiently isolated markets can clear locally. The common κ links the two access frictions; $\bar{c}$ allows their monetary scales to differ.

For simplicity, I shut down feedback from changes in wages, occupational earnings, and farm income into consumption expenditure. Earnings and occupations adjust endogenously, but each host's nominal spending budget is predetermined and each displaced worker adds a fixed spending increment. This partial-equilibrium closure isolates labor-supply and expenditure-demand forces without introducing the additional income-demand feedback generated by those adjustments.

2.1 Environment and equilibrium

Workers and occupational choice. There is a unit mass of host workers and a mass D of internally displaced workers. Each supplies one unit of work time. Host i has fixed productivity $\theta_i > 0$ in high-skill work, distributed according to a continuous distribution G with density g and finite mean. A host supplies either one unit of low-skill labor or θ_i efficiency units of high-skill labor. Displaced workers supply low-skill labor. Low-skill work is available in agriculture and services at the common wage w_L; high-skill service work pays w_H per efficiency unit.

A host choosing high-skill work commutes to the urban center and earns $\theta_i w_H - \kappa\bar{c}$. The commuting cost is monetary and does not reduce productive time. The occupational cutoff and labor supplies are

$$\Theta_\kappa = \frac{w_L + \kappa\bar{c}}{w_H}, \qquad N_L = G(\Theta_\kappa), \qquad N_H = 1 - G(\Theta_\kappa), \qquad H_S = \int_{\Theta_\kappa}^{\infty} \theta \, \mathrm{d}G(\theta). \tag{1}$$

The employment measures count hosts, whereas H_S measures effective high-skill labor. The local service market comprises the host community and the urban center serving it. High-skill wages clear within this market; they are not fixed outside wages.

To translate occupations into sectors, each host has a fixed initial low-skill sector and remains in that sector when low-skill returns tie. Let $\phi \in (0, 1)$ be the agricultural share of these sector types, and assume that both types have the same skill distribution. Host agricultural and low-skill service employment are

$$L_F^H = \phi G(\Theta_\kappa), \qquad L_S^H = (1 - \phi) G(\Theta_\kappa). \tag{2}$$

Displaced workers fill residual jobs. Attention is restricted to equilibria in which these residual demands are nonnegative.

Production. Competitive farms combine fixed land $\bar{T} > 0$ with low-skill labor, while service firms combine low- and high-skill labor:

$$Y_F = A_F \bar{T}^{1-\alpha} L_F^{\alpha}, \qquad Y_S = A_S L_S^{\beta} H_S^{1-\beta}, \qquad A_F, A_S > 0, \quad 0 < \alpha, \beta < 1. \tag{3}$$

Agricultural labor includes hosts and displaced workers. Hosts own the land; its rental income does not depend on their own occupational choice. Farm labor demand and the competitive service price satisfy

$$L_F = \bar{T} \left(\frac{\alpha p_F A_F}{w_L} \right)^{1/(1-\alpha)}, \qquad p_S = \frac{1}{A_S} \left(\frac{w_L}{\beta} \right)^{\beta} \left(\frac{w_H}{1-\beta} \right)^{1-\beta}. \tag{4}$$

Agricultural expansion in this specification means greater labor use and physical output on a fixed stock of land.

Expenditure demand. Hosts and displaced workers have Cobb–Douglas preferences over food and services, with expenditure shares $\omega_F, \omega_S > 0$ and $\omega_F + \omega_S = 1$. Each host has a predetermined nominal budget $\bar{b}_H > 0$, and each displaced worker adds a predetermined budget $\bar{b}_D \geq 0$. Aggregate spending and demands are

$$B(D) = \bar{b}_H + \bar{b}_D D, \qquad q_F^d = \frac{\omega_F B(D)}{p_F}, \qquad q_S^d = \frac{\omega_S B(D)}{p_S}. \tag{5}$$

Budgets include the market value of food consumed from own production. Holding the budget parameters fixed shuts down the demand response to changes in wages, occupational choices, land income, and commuting expenses. It does not hold these income components fixed. Financing and saving adjustments are left outside the model, and occupational choices maximize earnings conditional on this simplifying spending rule.

Trade and market clearing. Services are nontraded beyond the local service market. Food can be imported at the delivered price $\bar{p}_F(\kappa) = (1+\kappa)p^*$, where $p^* > 0$ is fixed. Competitive imports satisfy

$$M \geq 0, \qquad \bar{p}_F(\kappa) - p_F \geq 0, \qquad M[\bar{p}_F(\kappa) - p_F] = 0. \tag{6}$$

Food exports and storage are excluded. Equilibrium consists of positive wages and prices and feasible allocations satisfying host choice, firm optimization, and

$$L_F + L_S = G(\Theta_\kappa) + D, \qquad w_L L_S = \beta \omega_S B(D), \tag{7}$$

$$w_H H_S = (1-\beta)\omega_S B(D), \qquad Y_F + M = \frac{\omega_F B(D)}{p_F}. \tag{8}$$

The factor-payment equations impose service-market clearing. For each low-skill sector $k \in \{F, S\}$, displaced employment is $L_k^D = L_k - L_k^H \geq 0$, with $L_F^D + L_S^D = D$.

With positive imports, $p_F = \bar{p}_F(\kappa)$ and imports absorb excess demand. With strictly unprofitable

imports, $M = 0$ and $p_F < \bar{p}_F(\kappa)$, so food clears locally. Higher iceberg costs make local clearing more likely by raising the import-price ceiling, but the regime must be checked at equilibrium. Even at $\kappa = 0$, import parity pins down the food price only when imports are positive.

2.2 Displacement under full market integration

Consider a marginal increase in D at $\kappa = 0$ with strictly positive imports. Hold technology, land, the skill distribution, budget parameters, and p^* fixed. Assume positive employment in both skill inputs, a smooth occupational margin with $g(\Theta_0) > 0$, and feasible residual employment. Write $\widehat{z} = \partial \log z / \partial D$ and define

$$\gamma = \frac{\bar{b}_D}{B(D)} \geq 0, \quad \chi = \frac{\Theta_0^2 g(\Theta_0)}{H_S}, \quad \mathcal{F} = \frac{L_F}{1-\alpha}, \quad \mathcal{C} = L_S\left(1 + \frac{\chi}{\beta}\right), \quad \Omega = \mathcal{C} + (1+\chi)\mathcal{F} > 0. \tag{9}$$

Here γ measures the spending added by a displaced worker relative to existing expenditure, and χ measures the responsiveness of effective high-skill supply to the occupational cutoff. The coefficient $\mathcal{F}$ measures agricultural labor-demand responsiveness, $\mathcal{C}$ combines service labor demand and host selection, and Ω summarizes the joint adjustment of the two labor markets. The following three propositions maintain the benchmark conditions above. Their proofs are in the appendix.

Proposition 1 (The wage ratio under full integration)**.** *For any $\gamma \geq 0$, displacement lowers the low-skill wage relative to the high-skill wage:*

$$\frac{\partial \log(w_L/w_H)}{\partial D} = -\frac{1+\gamma\mathcal{F}}{\Omega} < 0. \tag{10}$$

The result holds even when $\gamma = 0$ and requires no upper bound on the spending increment.

Each displaced worker adds low-skill labor. Relative wages adjust to absorb that labor, while additional spending also supports demand for high-skill services. The relative return therefore shifts toward high-skill work. This result concerns the wage ratio: it does not establish that the low-skill wage falls in levels or that the high-skill wage rises in levels.

Proposition 2 (Sectoral reallocation under full integration)**.** *For any $\gamma \geq 0$, the lower wage ratio reduces the occupational cutoff, $\widehat{\Theta}_0 = \partial \log(w_L/w_H)/\partial D < 0$. Host high-skill employment rises and host agricultural employment falls:*

$$\frac{\partial N_H}{\partial D} = -\Theta_0 g(\Theta_0)\widehat{\Theta}_0 > 0, \qquad \frac{\partial L_F^H}{\partial D} = \phi\Theta_0 g(\Theta_0)\widehat{\Theta}_0 < 0. \tag{11}$$

Total host nonagricultural employment, $1 - L_F^H$, rises. The share of hosts in low-skill work overall, N_L, and the share in low-skill services, L_S^H, both fall. Among hosts employed in services, the

low-skill share also falls:

$$s^H_{L|S} \equiv \frac{L^H_S}{L^H_S + N_H} = \frac{(1-\phi)G(\Theta_0)}{1-\phi G(\Theta_0)}, \qquad \frac{\partial s^H_{L|S}}{\partial D} < 0. \tag{12}$$

The wage-ratio response in Proposition 1 induces hosts near the cutoff to switch occupations. The initial-sector rule translates this switching into departures from agriculture and low-skill services. The overall low-skill share provides the most direct measure of host occupational upgrading; $s^H_{L|S}$ isolates upgrading within services. Since the host population is normalized to one, N_L and L^H_S are shares of all host workers, whereas $s^H_{L|S}$ uses only host service workers as its denominator. Shares that include displaced workers also reflect their entry into low-skill employment and need not fall. Strict host reallocation requires a positive density at the cutoff; a strictly positive spending increment is unnecessary.

Proposition 3 (Prices under full integration)**.** *Food prices remain unchanged. Service prices satisfy*

$$\widehat{p}_F = 0, \qquad \widehat{p}_S = \beta\widehat{w}_L + (1-\beta)\widehat{w}_H = \frac{\gamma[\mathcal{C} + (1-\beta)\mathcal{F}] - (\beta+\chi)}{\Omega}. \tag{13}$$

Services become cheaper if and only if

$$\gamma < \frac{\beta+\chi}{\mathcal{C} + (1-\beta)\mathcal{F}}. \tag{14}$$

Condition (14) requires the spending added by an incoming worker to be small enough relative to the production response. In equation (13), $\gamma[\mathcal{C} + (1-\beta)\mathcal{F}]$ captures upward pressure from spending, while $\beta + \chi$ captures downward pressure from additional low-skill labor and induced high-skill supply. Services become cheaper when the latter dominates. At $\gamma = 0$ their price falls; at the threshold it is unchanged; above it, it rises.

An equivalent interpretation follows from service-market clearing, $p_S Y_S = \omega_S B$:

$$\widehat{p}_S = \gamma - \widehat{Y}_S, \qquad \widehat{Y}_S = \frac{(\beta+\chi)(1+\gamma\mathcal{F})}{\Omega} > 0. \tag{15}$$

Displacement expands service output, but a price decline requires output to grow faster than nominal spending. The low-skill cost share β governs the direct contribution of cheaper low-skill labor, while χ captures effective high-skill labor supplied by switching hosts. Agriculture also absorbs incoming labor, affecting the service response. A falling wage ratio and host reallocation therefore do not alone guarantee cheaper services. Food-market imbalances instead change imports while the delivered outside price binds.

2.3 Imperfect integration in labor and food markets

The common parameter κ governs two distinct market-access mechanisms. In labor markets, the commuting charge $\kappa\bar{c}$ makes urban high-skill jobs less attractive relative to local low-skill work. In food markets, iceberg costs raise the delivered import price to $(1+\kappa)p^*$. These mechanisms affect occupational adjustment and food-price adjustment, respectively, and interact through equilibrium wages and production.

If imports remain positive, food prices equal this delivered price and imports absorb the imbalance between local supply and demand. Higher iceberg costs raise the import-price ceiling and can make importing unprofitable. Food then clears locally: a displacement-induced increase in production can reduce the food price, rather than simply reduce imports. Higher κ also changes occupations and production through commuting costs, so the trade regime must be determined jointly; positive κ alone does not imply local clearing.

The propositions below study the strict local regime, $M = 0$ and $p_F < (1+\kappa)p^*$, where food-price adjustment is possible. Vary D and κ while holding other primitives fixed and remaining within this regime. Assume g is continuously differentiable and positive near the cutoff and that employment allocations remain feasible. Within this regime, changes in iceberg costs move the import-price ceiling, while the smooth employment response to κ operates through commuting costs.

Two quantities summarize the mechanism: the total low-skill workforce $W = N_L + D$, and host reallocation per additional displaced worker, $R = \partial N_H/\partial D$. The net addition to low-skill labor is therefore $\partial W/\partial D = 1 - R$: host switching offsets incoming low-skill labor. The appendix derives these quantities.

Proposition 4 (Host reallocation with costly market access)**.** *In the strict local food regime, for any $\gamma \geq 0$,*

$$\frac{\partial N_H}{\partial D} = R > 0, \qquad \frac{\partial N_H}{\partial \kappa} < 0. \tag{16}$$

Displacement raises host high-skill employment, while greater isolation lowers its level. Suppose $g'(\Theta_\kappa) \leq 0$ and displaced workers have positive purchasing power satisfying

$$0 < \bar{b}_D \leq \frac{(w_L + \kappa\bar{c})R}{(1-\beta)\omega_S}, \qquad \textit{equivalently} \qquad 0 < \gamma \leq \frac{\Theta_\kappa R}{H_S}. \tag{17}$$

Then greater isolation weakens the reallocation response:

$$\frac{\partial^2 N_H}{\partial D\,\partial \kappa} = \frac{\partial R}{\partial \kappa} < 0. \tag{18}$$

The displacement response of total host nonagricultural employment is ϕR and has the same mixed-response sign.

Condition (17) requires the part of IDP spending paid to high-skill labor, $(1-\beta)\omega_S\bar{b}_D$, to be no

greater than the value of the additional high-skill labor supplied by switching hosts, $(w_L + \kappa\bar{c})R$. There are R switchers per incoming worker, each with productivity Θ_κ at the occupational margin, and $\Theta_\kappa w_H = w_L + \kappa\bar{c}$. Equivalently, nominal spending grows no faster than effective high-skill labor supply. The bound allows positive purchasing power and is evaluated at the equilibrium, so it can differ across locations.

Under this bound, the high-skill wage does not rise. The fixed commuting charge therefore does not become cheaper relative to high-skill earnings, and the low-skill wage falls as the net low-skill workforce expands. Higher commuting costs retain more hosts in that workforce, making an incoming worker a smaller proportional supply shock. The restriction $g'(\Theta_\kappa) \leq 0$ adds that greater isolation does not move the cutoff into a denser pool of potential switchers. Together, these forces imply weaker reallocation at higher κ.

The spending bound is sufficient, not necessary. The appendix derives a more general necessary and sufficient condition, equation (50), that can also permit rising high-skill wages. That condition accounts jointly for occupational curvature and equilibrium earnings responses and has a less direct economic interpretation; the proposition uses the sufficient bound to make the mechanism explicit.

Proposition 5 (Food prices and market integration)**.** *In the strict local food regime,*

$$\widehat{p}_F = \gamma - \alpha\frac{1-R}{W}. \tag{19}$$

Food prices fall if and only if supply growth exceeds expenditure growth:

$$\alpha\frac{1-R}{W} > \gamma. \tag{20}$$

The mixed proportional price response is

$$\frac{\partial^2 \log p_F}{\partial D\,\partial\kappa} = \underbrace{\frac{\alpha}{W}\frac{\partial R}{\partial\kappa}}_{\textit{host reallocation}} + \underbrace{\frac{\alpha(1-R)}{W}\frac{\partial \log W}{\partial\kappa}}_{\textit{initial workforce}}. \tag{21}$$

At an equilibrium with falling food prices, greater isolation makes the proportional decline larger if and only if

$$-\frac{\partial R}{\partial\kappa} > (1-R)\frac{\partial \log W}{\partial\kappa}. \tag{22}$$

Local food clearing and fixed expenditure shares make agricultural labor a fixed share of the low-skill workforce. The net addition $1-R$ raises food supply proportionally by $\alpha(1-R)/W$. As with services, food prices fall when supply grows faster than spending.

Equation (21) separates two effects of isolation. Weaker host switching leaves more incoming labor in low-skill production; the first term then reinforces the price decline. But isolation also retains more hosts in low-skill work initially, so $\partial \log W/\partial\kappa > 0$: the net labor increment is a smaller

proportional shock to a larger workforce. Falling food prices imply $1 - R > 0$, making this second term positive. A sharper decline requires stronger labor retention to outweigh this dilution effect.

Within the local regime, iceberg costs affect the import-price ceiling but do not directly enter food clearing. The smooth interaction with κ works through commuting and labor allocation. With positive imports, instead, $\widehat{p}_F = 0$ and its mixed derivative is zero: imports absorb the displacement shock. Mixed derivatives apply within a smooth regime, with one-sided responses needed at import entry or exit.

Proposition 6 (Agricultural expansion with locally clearing food markets)**.** *In the strict local food regime, total agricultural labor and physical output satisfy*

$$\widehat{L}_F = \frac{\widehat{p}_F - \widehat{w}_L}{1-\alpha} = \frac{1-R}{W}, \qquad \widehat{Y}_F = \alpha \widehat{L}_F. \tag{23}$$

Both expand if and only if the low-skill wage falls relative to the food price, equivalently $R < 1$. If food prices fall, condition (20) and $\gamma \geq 0$ imply

$$\widehat{w}_L < \widehat{p}_F < 0, \tag{24}$$

so wages fall proportionally more than food prices and agricultural labor and output necessarily expand.

This result links falling food prices to agricultural expansion within the same fixed-land model. Cheaper labor relative to output makes additional farm employment profitable despite the lower output price. It provides a framework for interpreting total farm labor and physical production; it does not predict cultivated-area changes or increases in hosts' own farm hours. Nominal production value is distinct: local clearing gives $p_F Y_F = \omega_F B$, so its proportional response is γ.

3 Setting and Data

The empirical setting of this study is Ethiopia, between 2018 and 2019. Below, I give a quick overview of the situation in the country in that period, particularly related to displacement and conflict. Then, I describe the datasets used in the analysis, define the main variables and provide summary statistics for host communities.

3.1 Ethiopia, conflict and displacement, 2018-2022

Ethiopia experienced rapid economic growth from the mid-2000s before slowing in the early 2020s. This slowdown coincides with elevated inflation, rising to 33.9 percent in 2022 (The World Bank, 2026). In terms of economic sectors, agriculture remains the principal source of employment, accounting for approximately two-thirds (67 percent) of workers despite producing roughly one-third (35 percent) of national output. The largest sector by output are services (39 percent),

followed by agriculture and manufacturing (27 percent) (ILO, 2019). Agricultural livelihoods vary substantially across the country. Smallholder farming predominates, with mixed crop and livestock production characteristic of the highlands. Farmers cultivate cereals and pulses, while livestock provide food, income, and draught power. Pastoral and agropastoral livelihoods, relying on livestock mobility to access seasonal grazing and water, are particularly important in the arid and semiarid lowlands, including Afar and Somali. Agropastoral households combining livestock rearing with crop cultivation in these areas (Jirata et al., 2016).

After two decades of relative stability, Ethiopia saw conflict escalate again from 2016 in the form of inter-ethnic violence. This escalation coincided with a period of significant political change. Abiy Ahmed became prime minister in 2018, ended the state of emergency, released political prisoners, and brokered a peace agreement with Eritrea. He was credited with curbing the use of excessive force against protesters and with opening the country to cooperation with humanitarian agencies. He also acknowledged the existence of conflict-induced internal displacement in Ethiopia, a reality the government had until then denied (IDMC, 2019). However, the crisis took a new turn in 2020 with the outbreak of war in Tigray, in the north of the country. Following tensions between Tigrayan officials and the federal government, Tigrayan troops staged a mutiny in November 2020 and took command of the regional capital, Mekelle. The federal government responded with a full offensive with paramilitary forces from the Amhara and Afar regions and with Eritrean military forces as allied. The newly established Tigray Defence Forces fought alongside the Tigray Special Forces and locally recruited militias. The war continued until a decisive federal advance forced Tigrayan forces to sue for peace in November 2022. The human toll was severe, with violations of international human rights and humanitarian law by all parties leaving tens of thousands killed and hundreds of thousands displaced (International Crisis Group, 2026).

The analysis sample in the study does not cover the Tigray region itself, but the war had consequences for conflict and displacement in the neighboring Amhara and Afar regions, which are part of the study. The variation in conflict intensity, or number of conflict events, used later in the empirical strategy can be seen from Figures 1 and 2. Conflict is prevalent in all regions of the country in both time windows of the study (explained below), but also increased over time. Most of the displacement that followed originated from conflict along the borders between the Oromia region and three of its neighbors: the Southern Nations, Nationalities and Peoples' (SNNP) region, Benishangul Gumuz, and the Somali region. Urban centers were affected as well, including Addis Ababa (dropped from the sample due to lacking coverage in one of the datasets in 2022) and Jijiga, the capital of the Somali region (the darkeest spot in Figure 1).

By 2018 the country recorded the highest number of new conflict-related internal displacements ever registered anywhere, at 2.9 million over the year, four times the figure of the year before (IDMC, 2019). But new displacements across all conflicts increasing, reaching reached more than 5 million by 2022, once again the highest figure ever recorded for a single country (IDMC, 2022). Displacement corridors are however known and pre-detrmined compared to the conflict. Most

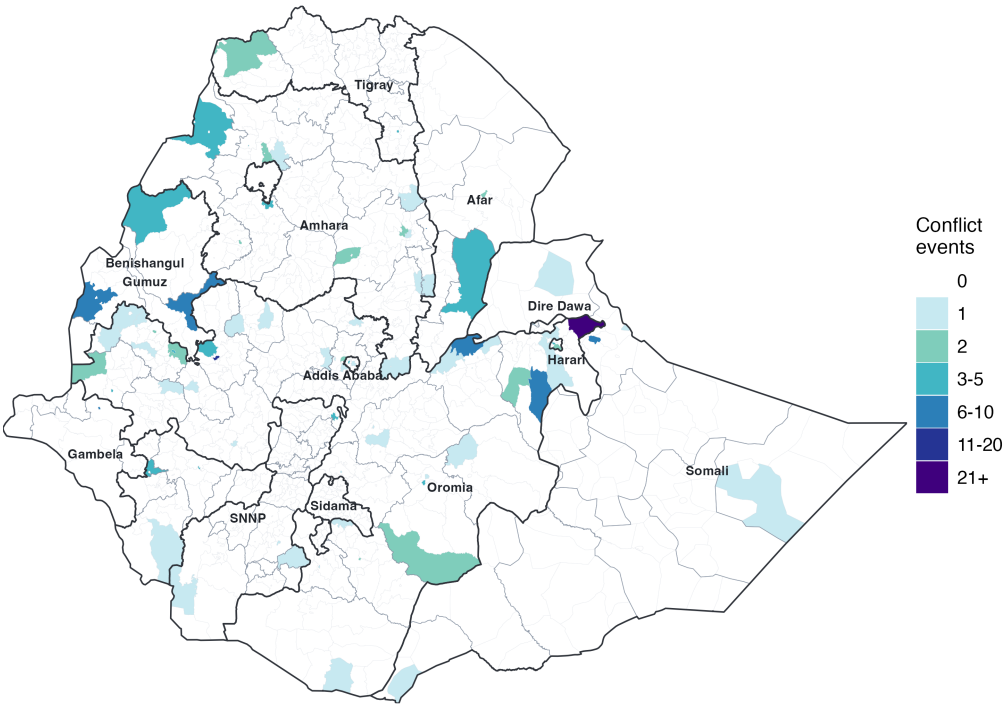


Figure 1: Conflict events, July 2018-June 2019

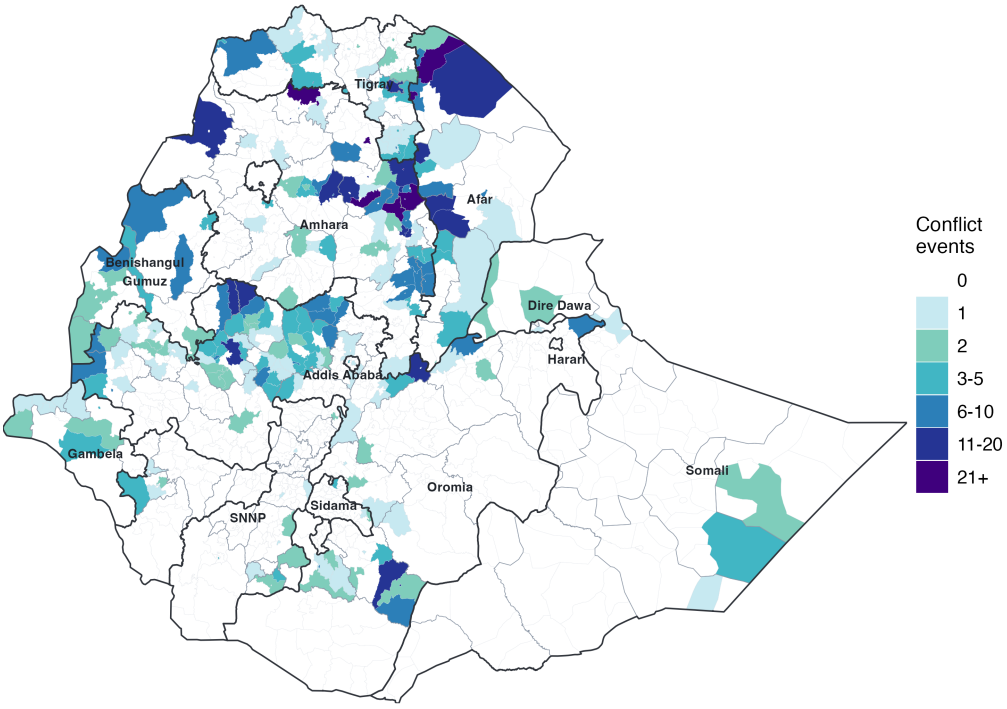


Figure 2: Conflict events, April 2021-March 2022

IDPs flee to neighboring areas where they belong ethnically or share socio-cultural ties with the resident population (REF, 2023). This persistence is what the empirical strategy exploits. If the composition of a host area's existing displaced population by area of origin reflects durable ties between the two places, then it also predicts where the next wave from those origins will settle, and the identifying variation can be built from shocks at origin rather than from conditions at destination. Section 4 develops this into the enclave instrument used throughout the analysis.

Knowing about the living conditions of the displaced is not straightforward. There is very little comprehensive information, and the data being collected is not at the individual or household level, but at the level of the group. The displacement tracking matrix (DTM) of the International Organization for Migration collects (IOM) collects nationally representative data this analysis uses. It provides information on IDPs, which I restrict to 2018 to 2022 to match the analysis, with variables being collected "for the majority of the group". Over this period, 20 percent of IDP groups record having access to income-generating activities. That does not mean that 20 percent of IDPs have access to livelihoods, but rather that in 20 percent of IDP groups, the majority of IDP do. Among the groups reporting having access, casual labor is cited as the most common occupation (45 percent), followed by agriculture (20 percent) and petty trade (6 percent). The IOM moved on to household-level surveys among IDPs in 2025, but only in a few region and select districts within the regions. The underlying data is not publicly available[6], but the reports made convey the same general idea: 43 percent of IDP households state that their main source of income comes from casual labor (IOM, 2024a,b,c).

Maybe contrary to general opinion, most IDPs are not hosted in planned camps: the DTM data indicates that only 6 percent of them are. The rest lives within host communities, either directly with the community or families (37 percent) or in spontaneous settlements (44 percent). Additional categories include collective centers (5 percent), such as schools, churches or markets being cleared to host IDPs, or dispersed settlements in rural areas (7 percent). Moreover, though disaster, such as droughts and floods also generate some forced displacement, 82 percent of Ethiopia's IDP groups report being displaced by conflict. Their most pressing needs are access to livelihoods, restoration of land and property, and an adequate standard of living: shortages of food and water produced widespread malnutrition, and low healthcare access leave many vulnerable to disease (OCHA, 2019). Two features of matters for the analysis. First, the great majority of IDPs settled among host populations rather than in planned camps, so that hosts and displaced people shared local markets for food and labor. Second, regardless of their previous occupations, IDPs work mostly in casual labor and agriculture. Therefore, I consider IDPs as additional casual and agricultural workers for host communities empirically.

[6]I am in conversations with the DTM Unit of IOM Ethiopia to access the household-level data.

3.2 Data

The empirical analysis relies three data sources: the Ethiopian Socioeconomic Panel Survey (ESS), a nationally-representative dataset built by the Ethiopian Central Statistical Agency (CSA) ; the Displacement Tracking Matrix (DTM), which contains information on groups of internally displaced people (IDPs) throughout the country; and the Armed Conflict Location and Event Data (ACLED) project, an international dataset on conflict events. They are combined into an analysis dataset at the individual level for the host community with, in addition to outcome and control variables on hosts, information on conflict in the districts of origin of the IDPs hosted in a given destination community.

ESS Data. Outcome and control variables come from waves 4 and 5 of the Ethiopian Socioeconomic Panel Survey, produced by the Ethiopian Statistical Service with technical support from the World Bank's Living Standards Measurement Study (LSMS), and used here at the individual level. Each wave bundles a household survey, a community survey, and three agricultural surveys covering the post-planting period, the post-harvest period, and livestock. These modules are fielded at different points in the agricultural calendar, with the post-planting surveys in the fall, and the household, community, and agricultural post-harvest surveys in the following spring. Wave 4 covers 2018-2019 and wave 5 2021-2022. This staggering matters for the analysis below, since outcomes drawn from different modules are observed at different dates and are therefore matched to different rounds of displacement data.

The survey is representative nationally and within each of Ethiopia's twelve regions and chartered cities with the exception of Tigray, which is excluded from wave 5 for security reasons. Addis Ababa is later dropped due to not have been covered by the DTM dataset in 2022.[7] The ESS also draws an explicit distinction between urban and rural areas, with sampling taking place differently for both types of areas, and with the agricultural surveys not being carried out in urban areas.[8] Enumeration areas (EAs) are drawn from the updated CSA 2018 pre-census cartographic database. Ten agricultural and two non-agricultural households were then randomly selected within each rural EA, against fifteen households selected without regard to economic activity within each urban EA. The household surveys also report the GPS coordinates of the centroid of each EA, though these are displaced for confidentiality: the offset ranges from 0 to 2 km in urban areas and from 0 to 5 km in rural areas, and reaches 0 to 10 km for a randomly chosen 1% of EAs, which raises locational uncertainty at the cost of little additional noise overall.

The ESS provides outcome and control variables for the analysis, as described in Section 4. Outcome

[7] Ethiopian changed its administrative boundaries several times since 2020. The definitions used in this study match the 2021 definitions, before the creation of the regions of Central and South Ethiopia. The regions are defined as Afar, Amhara, Benishangul-Gumuz, Gambela, Harari, Oromia, Sidama (created 2020), Somali, South West Ethiopia Peoples' (created 2021), Tigray, and the two chartered cities of Addis Abbaba and Dire Dawa.

[8] The CSA classifies an enumeration area (EA) as urban if it is a locality of at least 2,000 inhabitants, if it serves as an administrative capital at the regional, zonal, or woreda level, or if it is a locality of 1,000 or more inhabitants who are not primarily engaged in agriculture (OECD and PSI, 2020); all remaining localities are classified as rural.

variables from the household module include labor market outcomes for host individuals and adult-equivalent annual consumption for host households, in total, for food and for a selection of non-food items. Educational and demographic information also come from this module and is used for control variables. The community modules give information on prices in markets of the community, for food and non-food items. Lastly, the agricultural modules provide information on farm labor (family, hired and unpaid), cultivated hectares, value of land, and total production by crop.

DTM Data. Exposure to displacement is measured using Ethiopian data from the Displacement Tracking Matrix, an instrument of the United Nations' International Organization for Migration (IOM) that documents displaced populations in more than eighty countries. In Ethiopia, several site assessments per year record internal displacement figures alongside IDP needs and the services available where they have settled. Coverage is national in principle, but the areas actually assessed are determined by expected IDP caseloads; within an assessed area, every site hosting twenty or more IDPs is surveyed. Each round proceeds in three stages: key informants at the Disaster Prevention and Preparedness Office are interviewed first to establish the picture at the zone level, informants at the district level are then consulted in order to plan the assessments, and the site assessments themselves finally collect detailed information through key informant interviews.

Conversations with the Data and Research Unit at IOM Ethiopia clarified how these site assessments are conducted in practice. A typical assessment gathers seven key informants, all of them IDPs living at the site, of whom at least three are women, one is a youth, and one is an older person (with these categories permitted to overlap). Information from these interviews is then triangulated against independent sources such as shelter counts, camp registration lists, and household-level data. The first assessment dates from January 2018, after which rounds were conducted at regular intervals of roughly three to six per year through 2023, with a small number of further assessments in 2024. The unit of observation is the IDP site, and the data record its location including GPS coordinates, the number of IDPs present, the district from which the majority of the IDP in the site originate, and the humanitarian support they receive.

ACLED Data. The third source is the Armed Conflict Location and Event Data project for Ethiopia, whose staff compile a database of conflict events by reviewing journalistic and media sources, supplemented by material from the Ethiopian diaspora abroad and from official government media agencies. Each observation is a conflict event, reported with its precise location and exact type. I use information on conflicts surrounding host communities as control variables, and conflict events in the districts of origin of IDPs as part of the shift-share instrument. The type of conflict retained in these measures is shown in appendix Table 15.

Analysis dataset. The three datasets presented above are merged into an analysis datasets based on the needs of the empirical strategy, detailed in Section 4. The unit of observation is a household or an individual from the host community. I exclude potential IDP households from the

analysis dataset as follows: I use information from the ESS on self-reported exposure to conflict in the last year and find that only 19 households state that they experienced conflict. Of these households, only 3 report that household members migrated due to the shock. I consider these 3 households as potentially displaced and drop them from the analysis sample. I therefore consider EAs in the analysis sample as host communities.

Four restrictions shape the final analysis samples. The first follows from the geographic coverage of the DTM: some areas were not assessed, for reasons ranging from insecurity to low expected caseloads. The second comes from the empirical strategy set out below, which uses the shares of IDPs surrounding host households before exposure to the treatment. These shares are measured at DTM round 11, or June 2018, so that only households already exposed to IDPs within 25 km of their EA centroid can remain in the sample. The third is the requirement of a balanced panel, which permits host community fixed effects. This restricts the sample to host communities observed at both wave 4 and wave 5 in the relevant survey. The fourth simply limits the sample to individuals aged 15 or older, the population whose labor market outcomes are of interest here. Table 1 displays the effect of each restriction on sample size. Taken together, the restrictions mean the resulting sample should be read as representative of households that lived in areas assessed by the DTM, were already exposed to displacement in early to mid-2018, and were surveyed in both waves of the ESS.

Table 1: Number of unique households and individuals with restrictions applied to analysis samples

	Households	Individuals (15+)
Unrestricted data	6,880	21,513
In DTM geographic coverage	5,909	18,107
Exposed to IDPs in fixed-share baseline	3,630	11,016
EA FE regression sample	2,697	8,542

Notes: Unrestricted data includes households observed at least once. In DTM geographic coverage applies the relevant DTM region-zone coverage restriction separately to each ESS wave: Wave 4 is matched to 2019 DTM coverage and Wave 5 to 2022 DTM coverage. Exposed to IDPs further restricts to host communities with positive nearby IDP support within 25 km in the R11 (June 2018) fixed-share baseline. The final row reports the main total-consumption estimation sample with host community and year fixed effects.

3.3 Outcome variables, market integration and exposure to displacement

In this section, I present the outcome and control variables used in the estimation. Market integration, used as a measure of heterogeneity, is defined as the proximity to different market and trade infrastructure amenities. Exposure to displacement for host communities is the annual net change in the number of internally displaced people (IDPs) living near a host community.

Outcome variables. The analysis relies on outcome variables from the ESS. The labor module records both participation and intensity in the last seven days before the survey, by sector of economic activity. Each respondent is being asked if they engaged in each of these four (non-exclusive)

sectors over the seven days preceding the interview: household agricultural work, temporary wage labor (referred to as casual labor hereafter), self-employment and (permanent) wage employment. If the individual engaged in that activity, they are asked how many hours over the same period. These categories constitute the occupations used in the analysis. The ESS goes more in depth about all labor categories. In particular, wages are available for any casual work or permanent employment host workers carried out in the last year.

Table 2 displays summary statistics for the variables related to labor outcomes of the hosts. About 44 percent of them participated in any income-generating activity in the week prior to the surveys, with agriculture being the main activity by shares. However, unconditional hours of permanent wage employment are higher than hours spent in agriculture. The average daily wage in casual labor, constructed as the annual income from casual labor divided by the number of days worked, is about USD 24 in 2021 PPP. The average hourly wage in permanent employment is about USD 3 in 2021 PPP.

Table 2: Summary statistics for labor outcome variables

Outcome	N	Mean	SD	Min.	Max.
Panel A. Participation in the last 7 days (0/1)					
Any income-generating activity	11,360	0.436	0.496	0.000	1.000
Agricultural work for household	11,360	0.224	0.417	0.000	1.000
Casual labor	11,360	0.035	0.185	0.000	1.000
Self-employment	11,360	0.083	0.276	0.000	1.000
Permanent wage employment	11,360	0.123	0.329	0.000	1.000
Panel B. Hours worked in the last 7 days					
Any income-generating activity	11,360	13.410	20.898	0.000	71.000
Agricultural work for household	11,360	4.663	11.522	0.000	56.000
Casual labor	11,360	0.787	5.346	0.000	60.000
Self-employment	11,360	2.939	12.083	0.000	80.000
Permanent wage employment	11,360	5.120	15.498	0.000	84.000
Panel C. Wages (2021 PPP USD)					
Casual labor (per day)	298	23.783	37.564	0.008	129.898
Permanent wage employment (per hour)	1,304	3.063	3.359	0.026	13.705

Notes: Unweighted summary statistics for Ethiopia ESS respondents aged 15 and older in 2019 and 2022 and present in the analysis. Panel A reports employment indicators, so means are proportions. Panel B reports unconditional weekly hours, including the main specification's zero-filled missing hours; each outcome is capped at the pooled 95th percentile of positive reported hours in ESS Waves 4 and 5 before zero filling. The total-hours measure also includes unpaid apprenticeships, and is capped separately from the work-type components, so component means need not add to the total. Wages are conditional on the respective employment and valid positive wage information, converted using CPI and 2021 PPP adjustments and capped at the pooled 95th percentile among eligible workers. The casual daily wage is annual casual-work income divided by days worked in the previous 12 months. The permanent wage is measured per hour. SD denotes the sample standard deviation.

A detailed account of activities for self-employment and permanent wage employment is also provided and shown in appendix Table 16. Consistent with the framework, self-employment and wage

employment are both almost entirely non-agricultural. Local services comprise 73 percent of all wage employment activities, and 84 percent for self-employment. Considering constructions as local services (or non-tradable goods if we extend the definition), these shares raise to 84 and 86 percent, respectively. This validates the idea that the model, by splitting sectors between food production and local services, which include higher-skill, non-agricultural activities, captures the most salient features of the distribution of workers by sector.

A second set of outcome variables comes from prices. In the analysis, I use 3 main variables, whose construction is detailed in appendix Section C. The first one is a Young food price index that measures local food prices relative to national prices using fixed consumption-value weights from a previous ESS survey, wave 3 in 2015/16. It is constructed with enumeration-area-level market prices from the community module of the ESS. The index follows the Young formula, aggregating item-level local-to-national price ratios with fixed national consumption-value shares from ESS Wave 3 (2015/16). I apply these weights to prices observed in Waves 4 (2018/19) and 5 (2021/22). This index accounts for changes in prices due to displacement holding household consumption patterns fixed to a pre-shock period. This implies that any consumption adjustments to displacement from households in the sample are not captured in the index.

The second variable is a non-food regional price index. It is constructed by combining a spatial price benchmark for 2015/16 with official regional non-food consumer price indices. The spatial benchmark captures differences in non-food price levels across regions relative to the national average in 2015/16. I update this benchmark using subsequent changes in each region's non-food CPI. The resulting index incorporates both baseline geographic price differences and inflation over time, placing regional non-food prices on a common national 2015/16 reference scale. Since my measure of non-food prices cannot distinguish between prices of non-food tradable goods or local services, I construct a third variable, a Young index for tradable goods. It uses 9 goods whose prices are recorded on every market surveyed by the community module of the ESS, similar to the food prices. The basket is comprised of matches, batteries, candles, laundry soap, hand soap, charcoal, firewood, kerosene, and cigarettes.

The ESS also contains consumption modules which are aggregated to form annual measures of household consumption. Two measures of real adult-equivalent household annual consumption are retained in this analysis: total consumption and food consumption. The dataset also contains a third measure relative to non-food consumption, but the variable is not deflated due to the ESS only containing a small range of local non-food prices. I use the non-food regional CPI index to deflate it and report effects on real adult-equivalent non-food annual consumption too. The summary statistics from the price indices and consumption variables are shown in appendix Table 17.

Lastly, the ESS carried out agricultural surveys in the rural enumeration areas of its sample. This implies that agricultural variables are available for part of the analysis sample, but unfortunately, not for high-integration areas, due to the overlap between the ESS's rural EAs and the classification

as high-integration being too thin. These variables include person-days of labor on the family farm, aggregated across planting and harvest for family members, hired laborers and unpaid laborers. The unpaid category is used for labor used free of charge, exchange laborers, or labor paid by nothing in return. All categories are aggregated into total person-days of farm labor and their summary statistics are shown in Panel A of Table 3. on average, farms use 35 days of person-labor over both planting and harvest seasons, divided into 22 person-days of family labor, 6 of hired labor, and 7 of unpaid labor.

Panel B of Table 3 displays summary statistics related to host unpaid labor. These variables come from the labor module of the household survey and ask, over the previous years, whether the respondent provided any unpaid labor and how many households they provided it to. Cultivated land, in terms of hectares, and the total value of production are also recorded by the agricultural surveys of the ESS and their summary statistics are shown in Panel C and D of Table 3. The average farm has about 0.5 hectares and produces about USD 1600 worth of crops in 2021 PPP.

Table 3: Summary statistics for price indices

Outcome	N	Mean	SD	Min.	Max.
Panel A: Farm labor (person-days per household per season)					
Family labor person-days	1,231	22.049	27.546	0.000	211.175
Hired labor person-days	1,242	6.017	20.099	0.000	193.000
Unpaid labor person-days	1,242	7.245	20.969	0.000	403.000
Total labor person-days	1,231	35.322	43.113	0.000	406.500
Panel B: Host unpaid labor (per adult, past 12 months)					
Any unpaid labor (0/1)	1,826	0.154	0.361	0.000	1.000
Households worked for	1,826	0.553	1.726	0.000	20.000
Panel C: Land					
Cultivated land (hectares)	659	0.473	0.824	0.000	17.511
Panel D: Production (2021 PPP USD)					
Production value at contemporaneous prices	473	1,578.4	1,681.7	0.0	5,857.5

Notes: Unweighted summary statistics for the estimation samples. All observations are in low-market-integration areas, defined by the analysis market-distance measure strictly above 3.167 km. N counts household-year-season observations in Panel A, individual-year observations in Panel B, and household-year observations in Panels C and D. Panel A pools planting and harvest observations. Family labor sums household members' hours, including adults and children, and divides by eight to obtain person-days. Unpaid labor in Panel A is exchange or other unpaid labor used on the household's farm. Total labor sums family, hired and unpaid person-days. Panel B covers adults aged 15 or older in the union of the agricultural exchange-labor sample's planting and harvest household-years, with each adult counted once per year. Any unpaid labor indicates whether the respondent supplied unpaid or exchange labor to other households in the previous 12 months; its mean is a proportion. Households worked for counts recipient households over the same period, equals zero for explicit non-participation, and is untrimmed. These host outcomes measure labor supplied to other households, rather than person-days used on the respondent's farm. Panel C reports household cultivated area in hectares. Panel D reports household crop-production value at contemporaneous national prices in 2021 PPP USD using the harvest sample and its existing 95th-percentile winsorization.

Measures of market integration. I measure market integration using ESS-reported distances of each host community to transport infrastructure and markets. The index is the average distance in kilometers to the nearest asphalt road, bus station, and large weekly market, with lower values indicating greater integration. To preserve statistical power in the heterogeneity analysis, I divide the sample at the median, yielding two similarly sized groups. The high-integration indicator, H_c, equals one for observations at or below the median distance, while $L_c = 1 - H_c$ identifies the low-integration group.[9]

Access to transport infrastructure and markets varies widely across the sample. Table 4 reports the index and its components for the consumption estimation sample. The distance measures have long right tails: the mean distance to an asphalt road is 17.92 km, compared with a median of 1.50 km. The composite index has a mean of 10.55 km and a median of 3.00 km, which determines the cutoff between integration groups in this sample.

Table 4: Market integration index and its components

Variable	N	Mean	Median	SD	Min	Max
Nearest asphalt road (km)	4,046	17.92	1.50	41.21	0.00	397.50
Nearest bus station (km)	3,989	8.94	3.00	31.36	0.00	339.00
Nearest large weekly market (km)	4,046	5.08	0.00	11.34	0.00	92.50
Market integration index	**4,046**	**10.55**	**3.00**	**20.17**	**0.00**	**185.00**
Harris market access	3,989	159.86	59.64	170.48	8.93	1,105.49
Urban status (=1)	4,046	0.60	1.00	0.49	0.00	1.00

Notes: Unweighted summary statistics are restricted to the consumption estimation sample. The market integration index is the average distance in kilometers to the nearest asphalt road, bus station, and large weekly market; lower values indicate greater integration. High integration is defined as an index value at or below the sample median of 3 km. Harris market access (Harris, 1954) is defined as $\frac{1}{1000}\sum_{e \neq c} Pop_e / D(e,c)$. It sums destination community population divided by EA-to-EA centroid distance across all other eligible ESS enumeration areas in each survey year, excludes the origin EA, and divides the resulting sum by 1,000. Its destination universe includes eligible EAs outside the consumption estimation sample. Urban status equals one for urban and zero for rural household-years. N is the number of nonmissing household-year observations for each variable.

Survey-reported distances avoid the measurement error introduced by geographic anonymization when constructing local market-access measures. Public-use ESS coordinates are randomly displaced by up to 2 km in urban areas and small towns and up to 5 km in rural areas; an offset of up to 10 km is applied to 1 percent of enumeration areas.[10] These offsets are large relative to the median distances in the sample and can change a community's classification when access is calculated from geographic coordinates. This motivates using the survey-based index in the main specification.

The labor-market results are robust to alternative measures of market integration. The main patterns persist when each of the three index components is used separately and when integration

[9]The empirical classification uses household-year observations. For ease of exposition, the household and year subscripts are suppressed in H_c and L_c.

[10]See the confidentiality documentation for ESS Wave 4 and ESS Wave 5.

is measured using a Harris market-access index (Harris, 1954), defined as

$$MA_c = \frac{1}{1000} \sum_{e \neq c} \frac{Pop_e}{D(e,c)}, \tag{25}$$

where Pop_e is the population of destination community e and $D(e,c)$ is the distance in kilometers between the centroids of enumeration areas e and c. The index is computed separately in each survey year over all eligible ESS enumeration areas, excluding the origin community. It captures proximity to other markets, assigning greater weight to larger and closer destinations; higher values indicate greater market access. Using this measure yields similar labor-market patterns, although the estimates are less precise.

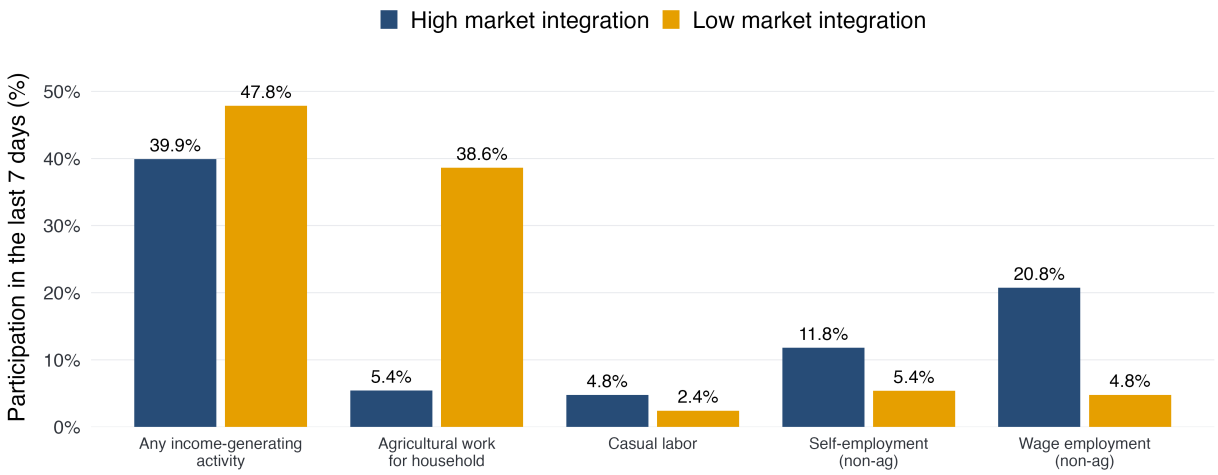
Differences in market integration across host communities imply very different economies, as show by Figure 3. In the part of the sample with higher market integration, about 40 percent of individuals aged 15 and more were engaged in any income-generating activities in the week prior to the surveys. Only about 5 percent of them were active in household agriculture. In host communities with low market integration, individuals were more active overall (about 48 percent of them reported any economic activity), but these activity were for a large majority in household agriculture: about 39 percent of individuals reported participating in those activities, which represent 81 percent of individuals recording any economic participation. Non-agricultural activities, such as non-agricultural self-employment or permanent wage employment are prevalent in high-integration areas, with about 32 percent of combined participation. However, in less integrated communities, non-agricultural participation sums to about 10 percent only. This distinction also matches Proposition 4 in the stylized framework, which shows that the share of workers in the high-skill occupations, proxied empirically by self-employment and permanent wage employment, increases with market integration. However, differences in market integration create other distinctions. For example, higher market integration comes with smaller households, higher consumption or higher educational attainment in the population of host economies. Appendix Table 18 gives a snapshot of those differences.

Treatment variable. The treatment measures the change in nearby displacement rather than the level of the displaced population. This distinction separates recent exposure from the IDP stock used to construct the instrument's baseline shares. For each IDP site, I compare the latest assessment available by the survey reference date with the latest eligible assessment conducted at least 365 days earlier. Eligible baseline assessments are restricted to round 11 or later for ESS Wave 4 and round 25 or later for Wave 5. Because DTM assessments are irregularly spaced, the interval between the two selected assessments need not be exactly one year.[11]

Exposure aggregates these site-level changes over a common geographic area around each host

[11]The annual specifications use survey reference dates of June 15, 2019, and April 15, 2022. Assessment selection is anchored to these dates, rather than to a common pair of DTM rounds.

Figure 3: Host participation in economic sectors by market integration



Notes: The figure reports participation in income-generating activities during the seven days preceding the interview, by market integration. Bars show unweighted percentages calculated among respondents with nonmissing participation information for each activity. Market integration is measured by the average distance to an asphalt road, a bus station, and a large weekly market. High market integration denotes distances at or below 3 km—the median across household-wave observations in the pooled consumption estimation samples—and low integration denotes distances above this threshold.

community. Let $\mathcal{D}_{ct}^{25}$ denote the set of IDP sites within 25 km of community c with the assessments required to construct exposure in survey year t, and let $IDP_{d,t}^{\text{current}}$ and $IDP_{d,t}^{\text{baseline}}$ denote the corresponding site populations. The treatment, measured in thousands, is

$$D_{ct} = \frac{1}{1000} \sum_{d \in \mathcal{D}_{ct}^{25}} \left(IDP_{d,t}^{\text{current}} - IDP_{d,t}^{\text{baseline}} \right), \qquad \mathcal{D}_{ct}^{25} \subseteq \{ d : \text{dist}(c,d) \leq 25 \text{ km} \}. \tag{26}$$

The measure captures net changes, including departures as well as arrivals, and can therefore be negative. Households and individuals in the same host community share the same geographic exposure. Figure 4 illustrates the construction by plotting host communities, nearby IDP sites, and the 25 km buffers.

The analysis sample contains substantial variation in exposure to displacement. Table 5 reports summary statistics for the 4,046 household-year observations used in the total-consumption specification. The mean net inflow within 25 km is approximately 2,437 IDPs, with a standard deviation of 6,170. Net changes range from a decline of 9,370 to an increase of 35,120 IDPs, capturing both departures and arrivals. On average, net inflows amount to 0.53 percent of the nearby population, while the total IDP stock amounts to 5.65 percent. The treatment thus captures changes in displacement against a larger existing displaced population.[12]

[12]Population shares are calculated for each household-year and then averaged across observations. They are not ratios of the reported sample means.

Table 5: Summary statistics for the treatment variable and the population of the host community

Variable	Observations	Mean	SD	Min	Max
IDP flow within 25 km (1,000s)	4046	2.44	6.17	-9.37	35.12
Baseline IDPs within 25 km (1,000s)	4046	10.53	10.81	0.07	103.60
Population within 25 km (1,000s)	4046	1299.23	1529.18	6.43	4447.41
IDP flow / population within 25 km (%)	4046	0.53	3.30	-13.84	38.74
Total IDPs / population within 25 km (%)	4046	5.65	10.89	0.01	81.66

Notes: Statistics use one observation per household-year from ESS waves 4 and 5 in the host-community- and year-fixed-effects total-consumption analysis sample. This descriptive table measures flows as the net change at IDP sites observed in both endpoint rounds: R11–R17 in Wave 4 and R25–R29 in Wave 5. Flows are in thousands. Baseline IDPs sum stocks at R11 in Wave 4 and R25 in Wave 5 across sites in the household-sample destination universe within 25 km of the enumeration-area centroid. Population is WorldPop population within the same radius, in thousands, using the 2017 raster for Wave 4 and the 2020 raster for Wave 5. Total IDPs sum stocks at R17 and R29, respectively, including sites without a baseline match. Percentage rows report the mean, standard deviation, minimum, and maximum of household-year ratios. The annual regression treatment instead selects assessments relative to the survey reference date, as described in the text.

4 Empirical strategy

This section presents the empirical strategy used to estimate the effects of short-term displacement on hosts' labor and consumption outcomes, both on average and by level of market integration. To address the endogeneity of displacement, I use a shift-share enclave instrument that combines the origin composition of the existing displaced population with subsequent conflict in those origins. I first present the specifications for average effects and heterogeneity by market integration, then discuss identification and first-stage evidence.

4.1 Estimating equations.

The baseline specification relates host outcomes to displacement exposure while absorbing permanent community differences and common year effects:

$$y_{ihct} = \beta D_{ct} + \mathbf{X}'_{ihct}\Pi + \lambda_c + \delta_t + \varepsilon_{ihct}. \tag{27}$$

Here, y_{ihct} is an outcome for individual i in household h and host community c in year t; the individual subscript is omitted for household outcomes. The vector $\mathbf{X}_{ihct}$ includes household size, age, gender, literacy, school attendance, and primary-school completion, measured at the relevant observation level. It also includes the numbers of local conflict events, events with fatalities, and events involving civilian targeting within 25 km. Host-community fixed effects λ_c account for time-invariant local characteristics, while year fixed effects δ_t absorb shocks common to all communities. The coefficient β measures the effect of an additional 1,000 nearby IDPs.

The interacted specification allows displacement effects to differ by market integration:

$$y_{ihct} = \beta_H(D_{ct} \times H_{ct}) + \beta_L(D_{ct} \times L_{ct}) + \mathbf{X}'_{ihct}\Gamma + \lambda_c + \delta_t + \varepsilon_{ihct}. \tag{28}$$

Interacting exposure with both indicators makes each coefficient directly interpretable as a group-specific effect. I test whether these effects differ using the null hypothesis $\beta_H = \beta_L$ and the joint covariance of the two estimates. The comparison concerns the response to displacement across integration groups, rather than the effect of changing a community's market access.

4.2 Instruments

To address the endogeneity of displacement, I use a shift-share instrument that interacts the pre-existing origin composition of the displaced population with conflict in those origin districts during the year preceding the survey. Identification relies on the exogeneity of the origin shocks, conditional on the included controls, rather than on the exogeneity of the baseline shares.

Displaced people do not settle randomly across potential destinations. Communities with improving employment opportunities or increasingly favorable policies toward IDPs may attract larger inflows while host outcomes change for reasons unrelated to displacement. Community fixed effects absorb persistent differences in destination attractiveness, but not these changes over time. Consequently, ordinary least squares need not identify the causal effect of displacement.

The instrument uses origin conflict to isolate variation in displacement generated outside the receiving community. Following the enclave logic, a conflict shock is expected to induce larger inflows into destinations where people from the affected origin have previously settled. In Ethiopia, where displaced population move along ethnic lines, this instrument is closer to using ethnic similarity or shared socio-cultural ties than migration "enclaves" as baseline shares (REF, 2023). I implement this design using the shock-based identification framework of Borusyak et al. (2022).

Baseline origin shares determine each host community's exposure to subsequent conflict shocks. Let s_{co} be the share of community c's nearby baseline IDP population originating in district, or woreda, o. I construct these shares from DTM round 11 in June 2018, using sites within 25 km, and hold them fixed across both survey waves. Let c_{ot} be the number of ACLED conflict events in origin o during the 365 days preceding the survey reference date, and let $\bar{c}_t$ be the mean across origins in the corresponding shock-assignment set. The instrument is

$$Z_{ct} = \sum_o s_{co}\widetilde{c}_{ot}, \tag{29}$$

$$\widetilde{c}_{ot} = c_{ot} - \bar{c}_t. \tag{30}$$

Recentring expresses each origin's conflict relative to its expected value under the specified reassignment of shocks (Borusyak and Hull, 2023). A community receives a larger predicted displacement shock when conflict rises more in the origins represented in its baseline IDP population.

The interacted specification uses the same origin shocks to instrument each treatment component. Specifically, the instruments for $D_{ct}H_{hct}$ and $D_{ct}L_{hct}$ are

$$Z^{H}_{hct} = H_{ct} \sum_{o} s_{co} \widetilde{c}_{ot}, \qquad Z^{L}_{hct} = L_{ct} \sum_{o} s_{co} \widetilde{c}_{ot}. \tag{31}$$

Both enter the joint estimation, which allows the effects in the two integration groups to be compared using a common set of controls and fixed effects.

The timing of the design separates the baseline settlement pattern from the subsequent displacement shocks. Figure 5 places the ESS waves alongside the DTM assessments that bracket the principal exposure periods, from 2018 to 2019 and from 2021 to 2022. The shares remain fixed at June 2018 in both periods. Annual treatment selects eligible assessments relative to the survey reference date, while origin conflict is measured over the preceding 365 days.

4.3 Identification, clustering and shift-level estimation

Identification relies on shift-level exogeneity and requires origin conflict to affect host outcomes through the displacement it induces. Time-varying links between origins and destinations could violate this restriction; I address the principal concerns through local-conflict controls and examine their implications for the results. Inference accounts for communities' exposure to common origin shocks by clustering at the origin-district level.

The identifying assumption concerns the relationship between origin conflict and unobserved changes in host outcomes. Conditional on controls and fixed effects, conflict in the origins represented in a community's baseline IDP population must be unrelated to the outcomes that community would have experienced absent the induced displacement. Community fixed effects absorb persistent origin–destination links, and year fixed effects absorb common shocks. Identification can nevertheless fail if those links transmit time-varying shocks through channels other than displacement.

Direct conflict spillovers are one potential source of such a violation. Conflict may spread from origin districts to receiving communities, affecting local employment, production, or consumption independently of IDP arrivals. I account for observed local violence through the three conflict measures within 25 km. Directly reported conflict exposure is also uncommon: only 19 households in the analysis sample report experiencing conflict during the previous year. This evidence limits the scope for direct exposure to explain the results.

Another candidate is trade disruptions. If conflict at origin disrupts the routes connecting origin districts and host communities, food prices at destination would move for reasons unrelated to the arrival of IDPs, and increasingly so as origin conflict intensifies. The sign of that movement is determined by the direction in which food travels along the disrupted route. Where origin districts supply food to a host community, disruption restricts the quantity reaching it and pushes prices there up and consumption down; where origin districts instead buy food from a host community,

disruption strands that output at home and pushes prices there down and consumption up. The fact that the analysis yields similar effects in host communities with high and low market integration, namely prices down and consumption up, limits these concerns.

Shared exposure to origin shocks also determines the appropriate level of inference. A conflict shock in one district enters the instrument of every community whose baseline IDP population includes people from that origin. Increasing the number of host households therefore does not provide an equivalent increase in independent identifying variation. Following Borusyak et al. (2022), I estimate the equivalent shock-level specification by residualizing outcomes and treatments on controls and fixed effects and aggregating at the origin level them with the baseline exposure shares. I cluster standard errors by origin district, allowing dependence across periods and, in the interacted specification, across the two integration groups. Appendix **??** details the procedure.

4.4 First stage and validation

The instruments predict an increase in displacement in host communities and are strongly relevant. Shares are slightly concentrated in a few district of origin, especially in high-integration areas, but the specification passes randomization inference test designed for shift-share instruments.

Origin conflict is positively associated with subsequent displacement in all three first stages. Table 6 reports diagnostics for total annual consumption: column 1 corresponds to the average-effects specification, and columns 2 and 3 to the high- and low-integration components of the interacted specification. The average first-stage coefficient is 0.153, corresponding to 153 additional nearby IDPs for a one-unit increase in the recentered conflict instrument. The corresponding coefficients are 0.250 and 0.255 in high- and low-integration areas. All three are significant at the 1 percent level using origin-clustered standard errors, and equality of the two subgroup coefficients is not rejected ($p = 0.928$).

The first-stage diagnostics are favorable for the two specifications. The Kleibergen–Paap statistic is 18.39 for the average-effects specification, and . With two endogenous treatment components, I also report Sanderson–Windmeijer conditional F-statistics, which assess the identifying variation for each component conditional on the other. They equal 7.26 for high-integration areas and 8.68 for low-integration areas, with p-values of 0.008 and 0.004, rejecting a lack of conditional relevance.

However, exposure weights - the shares in the instrument - are concentrated in substantially fewer shocks than the nominal origin cell counts suggest. The inverse Herfindahl index of normalized exposure weights implies effective shock counts of 6.79 in the average-effects specification, 3.08 in high-integration areas, and 24.01 in low-integration areas, compared with 176, 67, and 158 observed origin-year cells. Its interpretation is the number of equally weighted shocks that would produce the same exposure concentration as measured by the inverse Herfindhal index. For example, the average specification has approximately the same exposure concentration as seven equally weighted shocks, each accounting for about one-seventh of total exposure. As discussed in Section 3, the

DTM's recording of the majority origin at each site, instead of the origin of each IDP household, contributes to this concentration.

Randomization inference provides an additional assessment of first-stage relevance when exposure is concentrated. Following Borusyak and Hull (2023), I use 1,000 permutations of the origin shocks to construct a reference distribution for the first-stage test statistic under the null. The average-effects procedure permutes shocks within survey year; the interacted procedure applies a common permutation of pooled shock cells to both groups. The resulting p-values are 0.021 for the average effect, 0.081 for high-integration areas, and 0.010 for low-integration areas. Relevance is thus supported at the 5 percent level for the average specification, at the 10 percent level for high integration, and at approximately the 1 percent level for low integration. The interpretation of these tests rests on the specified shock-assignment process rather than on a large number of shocks. I report randomization-inference p-values alongside clustered inference in the results tables.

5 Results

In this section, I document the effects of displacement inflows on host communities, guided by the stylized framework developed in Section 2, which highlighted predictions in the case where the labor supply shock of displacement would outweigh its demand expansion on consumer markets. The effects reported below are consistent with this interpretation. Average effects are presented first, before diving into the heterogeneous effects by market integration.

5.1 Average Effects of Displacement on Host Communities

The empirical evidence related to the average effects of displacement inflows for Ethiopia is presented here. I first start by showing the effects on labor market outcomes, before turning to price effects. Overall, the evidence is consistent with displacement inflows in Ethiopia consisting in a labor-supply shock that dominated the increase in consumer demand from IDPs.

Proposition 1 of the stylized framework predicted that the wage ratio between low-skill and high-skill occupation declines with a displacement shock. I estimate the effects of 1,000 additional net displacement inflows to a host community on the permanent employment average hourly wage, a proxy for high-skill employment, and the casual labor daily wage separately. The reasons is that a wage ratio as an outcome variable would require a set of host communities where both are recorded, possibly in multiple cases, which could prove difficult with the number of respondent who reported these wages. The results are shown in Table 7 and indicate that IDP inflows did not affect the permanent employment wage but had a strong negative effect on the wage for casual labor, therefore a decline in the wage ratio. The effect is null and economically small on permanent employment wages: a 2 cent increase for a 1,000 IDP inflow shock, from an outcome mean of USD 3 per hour. This represent a 0.65 percent increase compared to the mean wage. By contrast, the daily casual labor wage decreases by USD 2.5 for the same IDP inflow, from a mean of about 24, or

Table 6: First Stage Statistics

	Average effects	**By market integration**	
Dependent variable:	IDP flow within 25 km	IDP flow × High integration	IDP flow × Low integration
Units:	Thousands	Thousands	Thousands
Recentered conflict-event shock	0.153***	0.250***	0.255***
	(0.036)	(0.075)	(0.047)
BH 2023 RI p-value	0.021	0.081	0.010
Kleibergen–Paap rk Wald F	18.39	—	—
KP rk Wald F p-value	4.30×10^{-5}	—	—
KP rk Wald F degrees of freedom	1, 96	—	—
Sanderson–Windmeijer F	—	7.26	8.68
SW F p-value	—	0.008	0.004
SW F degrees of freedom	—	1, 96	1, 96
Cluster-robust Wald test of coefficient equality			
Coefficient (High − Low)	—	-0.005	
p-value	—	0.928	
Wald test degrees of freedom	—	1, 96	
IDP flow sample mean (persons)	2,437	2,933	1,920
Household-year observations	4,046	2,063	1,983
Households (model sample)	2,697	2,697	
Origin-year cells (shifts)	176	67	158
Effective N	6.79	3.08	24.01
Origin-woreda clusters	97	38	87
Enumeration-area FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: First-stage diagnostics for total annual consumption. Column 1 is the average-effects specification; columns 2 and 3 are the high- and low-integration components of the interaction specification. All columns include host-community and year fixed effects, household demographic and education controls, and local-conflict controls within 25 km. Parentheses contain origin-woreda-clustered HC1 standard errors. Stars use clustered p-values: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Randomization-inference p-values follow Borusyak and Hull (2023) and use 1,000 permutations: within survey year in column 1 and a common permutation of pooled shock cells across groups in columns 2 and 3. Column 1 reports the Kleibergen–Paap rk Wald F statistic; columns 2 and 3 report Sanderson–Windmeijer conditional F statistics from the stacked interaction system. The equality test uses a weighted stacked first stage with group-specific intercepts and shock slopes, clustered by origin. Effective N is the inverse Herfindahl index of normalized shift-cell weights.

a 10 percent decline. The estimate is significant at the 1 percent level. When scaled by the average displacement inflow of 1400, this represent a decline of 14 percent.

Table 7: Effects of displacement inflows on wages

	Wage employment	**Casual labor**
Outcomes:	**Hourly wage**	**Daily wage**
Units:	2021 PPP USD / hour	2021 PPP USD / day
IDPs (thousands)	0.020	-2.493***
	(0.0908)	(0.6326)
	[0.849]	[0.175]
Outcome mean	3.063	23.783
Average # of IDPs (1k)	2.456	1.358
Implied effect (%)	0.65	-10.48
Observations	1,304	298
Households	829	252
Individuals	1,186	287
Shifts	101	90

Notes: Notes: Shift-share IV estimates using the 2019 and 2022 ESS. Treatment is the one-year IDP flow within 25 km, in thousands. All specifications include enumeration-area and year fixed effects and demographic, education, and local-conflict controls. Wages are conditional on employment and positive observed wages, expressed in 2021 PPP USD, and winsorized at the 95th percentile. Parentheses report BHJ (2022) standard errors clustered by origin woreda; brackets report BH (2023) randomization-inference p-values. Implied effects is the coefficient expressed as a percentage of the outcome mean. Observations are individual-years; shifts are origin-woreda conflict shocks for each survey interview window. Stars reflect BHJ p-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

In the framework, Proposition 2 shows that the decline in the wage ratio prompted a decrease in the equilibrium Roy cutoff, which made it more profitable for a number of host workers to switch from low-skill jobs to high-skill activities. If that were true empirically, we should observe a decrease in the proxy measures for low-skill occupations, hours of work in household agricultural and casual labor, and an increase in the proxies for high-skill labor, hours in non-agricultural self-employment and permanent employment. This is precisely what I find, as displayed in Table 9. Hours of labor in the last week decrease in household agricultural work by 0.224 ($p < 0.01$) and for casual labor by 0.075 ($p < 0.05$). These declines represent a 5 percent and 10 percent decrease of the outcome mean, respectively. The labor supply shock moves these workers into self-employment and permanent employment: I detect an increase in these two occupations by 0.109 ($p < 0.05$) and a 0.173 ($p < 0.05$) hours. These scale to 4 percent and 3 percent of their outcome means. Displacement inflows therefore cause the host workforce to adapt and reallocate to occupations less exposed to IDP labor.

Next, I turn to the effects of displacement inflows on the consumer goods markets of host com-

Table 8: Effects of displacement inflows on hours of work by sector

Outcomes:	**Any IGA**	**Ag work for HH**	**Casual labor**	**Self-empl.**	**Wage empl.**
Units:	Hours in the last 7 days				
IDPs (thousands)	-0.077	-0.224***	-0.075**	0.109**	0.173**
	(0.075)	(0.064)	(0.030)	(0.054)	(0.082)
	[0.667]	[0.171]	[0.030]	[0.164]	[0.091]
Outcome mean	13.410	4.663	0.787	2.939	5.120
Average # of IDPs (1k)	2.146	2.146	2.146	2.146	2.146
Implied effect (%)	-0.58	-4.80	-9.49	3.71	3.38
Observations	11,360	11,360	11,360	11,360	11,360
Households	2,696	2,696	2,696	2,696	2,696
Individuals	8,300	8,300	8,300	8,300	8,300
Shifts	180	180	180	180	180

Notes: Shift-share IV estimates for ESS respondents aged 15 and older in 2019 and 2022. Treatment is the one-year IDP flow within 25 km, in thousands. All specifications include enumeration-area and year fixed effects and demographic, education, and local-conflict controls. Outcomes are hours worked in the last seven days, including zeros for nonworkers; positive hours are winsorized at the pooled 95th percentile. IGA denotes income-generating activity; casual labor and wage employment denote temporary and permanent wage work, respectively. Parentheses report BHJ (2022) standard errors clustered by origin woreda; brackets report BH (2023) randomization-inference p-values. Implied effects is the coefficient expressed as a percentage of the outcome mean. Observations are individual-years; shifts are origin-woreda conflict shocks for each survey interview window. Stars reflect BHJ p-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

munities. Proposition 3 presented comparative statics for the prices of food and local services with respect to displacement under full market integration. The price of food is not affected by displacement with integrated markets, because it is traded at external prices. However, the price of services fell if the production response of adding displaced workers dominated the increase in spending generated by their arrival to a host community. Empirically, I show the effects of displacement inflows on a food price index, a non-food price index, and an index for non-food tradable goods. The price of food decreases modestly with a 1,000 IDP inflow, by 0.95 percentage points (equivalent here to a 0.95 percent decrease, $p < 0.10$). In comparison, the non-food price index decreases by 0.0408 units ($p < 0.01$), or a 2 percent decrease (this index is not centered at 1, so effects cannot be interpreted as percentage point effects). Since this measure does not separate the price of local services from other goods, I complement it with a price index on a basket of tradable goods found on most markets in host communities. Displacement inflows don't affect the index: I estimate a 0.06 percentage point, statistically insignificant effect, which scales to a 0.05 percent increase compared to the mean. These findings align with an interpretation according to which a displacement inflow caused the price of local services to decline, but affected the price of food and other tradable goods less. They also are consistent with the assumption in the framework that displacement led to a larger expansion of the labor supply than the consumer demand curve in this

case.

Table 9: Effects of displacement inflows on prices

	Food prices	**Non-food prices**	
Outcomes:	**Young W3 index**	**Regional index**	**Tradable goods index**
Units:	Index	Index	Index
IDPs (thousands)	-0.0095*	-0.0408***	0.0006
	(0.0048)	(0.0083)	(0.0146)
	[0.038]	[0.038]	[0.935]
Outcome mean	1.001	1.987	0.731
Average # of IDPs (1k)	2.487	2.445	2.961
Implied effect (%)	-0.95	-2.05	0.09
Observations	3,705	3,783	2,529
Households	2,549	2,612	1,373
Shifts	166	167	141

Notes: Shift-share IV estimates using the 2019 and 2022 ESS. Treatment is the IDP stock change within 25 km, in thousands (R11-R17 and R25-R29, respectively). All specifications include enumeration-area and year fixed effects and demographic, education, and local-conflict controls. The food and tradable-goods Young indices weight local/national arithmetic-mean item-price ratios within each wave using fixed Wave-3 expenditure shares, renormalized over available goods; ratios are winsorized at the 5th/95th percentiles. The regional index combines spatial price differences with regional non-food CPI. Parentheses report BHJ (2022) standard errors clustered by origin woreda; brackets report BH (2023) randomization-inference p-values. Implied effects is the coefficient expressed as a percentage of the outcome mean. Observations are household-years; shifts are origin-woreda conflict shocks for each exposure window. Stars reflect BHJ p-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5.2 Heterogeneous effects by market integration

The effects of displacement inflows by host communities with high or low market integration are presented here. In high-integration communities, displacement inflows lead to sectoral reallocation of the hosts and price declines mostly for non-tradable goods. In communities less integrated with external markets, the adjustment on labor takes place within agriculture: farms use more labor, cultivate more land, and produce more. The decline on prices extends to the price of food.

When allowing for imperfect market integration, the framework predicted that sectoral reallocation would be limited in more isolated host communities. In particular, Proposition 4 stated that under two conditions, greater isolation would weaken the sectoral reallocation response for host workers. Of these two conditions, one had an economic interpretation: the increase in IDP spending is smaller or equal to the increase in the high-skill labor supply. The other condition is purely technical.[13] We already saw with findings related to the effects of displacement inflows on prices that the economic conditions seems to hold in this context. I therefore turn to the heterogeneous effects of displacements by level of market integration on hours of labor by sector. They are presented in Table 10. The pattern of sectoral reallocation fully holds in host communities with high market

[13]The derivative of the probability distribution function of the productivity term θ is negative at the cutoff.

integration. Hours in household agricultural work fall by 0.398 ($p < 0.01$), and those in casual labor by 0.082 ($p < 0.05$). These scale to declines of 37 percent and 7 percent of the outcome means. The little agricultural work there is in high-integration areas (5 percent of workers for one hour on average per week, or 20 hours for each worker on average) is substantially replaced by IDP workers. Casual work drops importantly too, even if less dramatically. Hours of work for hosts in self-employment and permanent wage employment increase, by 0.153 ($p < 0.01$) and 0.231 ($p < 0.10$), or 3 percent of their outcome means. In total, hosts work slightly less: their total hours decrease by 0.144 ($p < 0.05$), or about 1 percent.

Reallocation is not the adjustment mechanism on labor market in host communities with lower market integration. Hosts leave casual labor, but they don't exit from agriculture or increase time spent in non-agricultural activities such as self-employment or wage employment. The effect regarding the reduction of hours in casual labor is precise (-0.053, 7 percent of the mean) and statistically significant ($p < 0.01$), but the estimate on hours of agricultural work is noisy and the estimate points to an increase (0.139, 1.7 percent of the mean) even if insignificant. The imprecision comes from the large variance of the measure, which I interpret as the fact that in remote areas, most people are involved in agricultural activities even if to some variable extent. The effects on self-employment and wage employment are also null, even though the standard errors are twice smaller than in high-integration areas. The point estimates are -0.042 and -0.014, scaling to a decline of 3 percent and 0.8 percent of the outcome means. Hosts workers simply don't seem to increase their time working in non-agricultural sectors as a response to displacement inflows.

If the adjustment on labor markets of host communities with little integration does not happen as movement away from agriculture, it probably takes place within the agricultural sector. I turn to the agricultural survey of the ESS to estimate the effect of displacement on farm labor. Prediction 6 stated that agricultural labor and total production increase if the decrease in the low-skill wage exceeds the decrease in food prices, which we know to be true in the average specification (but lack of statistical power prevents me from estimating effects of displacement on the casual labor wage in low-integration areas only, and the case of food prices for low-integration community is discussed below). The empirical effects on agricultural outcomes in those communities are presented in Table 12 and are substantial. First, we see that hosts increase their labor on their own farm during the planting and harvest seasons, by 5.7 person-days ($p < 0.01$), a 26 percent increase in the outcome mean. Second, the composition of external labor changes. Hired labor decreases by 1.2 person-days ($p < 0.01$) for a 1,000 IDP increase, but person-days of unpaid labor increases by 2.2 ($p < 0.05$). These effects represent a 20 percent decrease and a 30 percent increase of their mean, respectively. Overall, total person-days of farm labor increase by 6.8 person-days ($p < 0.01$), or 19 percent.

I interpret these effects as IDPs working on host plots in exchange of non-monetary benefits, as the literature has found. Whitaker (2002) a studies a displacement inflow in rural Tanzania and document that displaced populations often work on host land in exchange for land access or food. Moreover, Tsuda (2022) shows in the same context that hosts increase their time spent on their

Table 10: Effects of displacement inflows by market integration on hours of labor

Outcomes:	**Any IGA**	**Ag work for HH**	**Casual labor**	**Self-empl.**	**Wage empl.**
Units:	Hours in the last 7 days				
High market integration					
IDPs (thousands)	-0.144**	-0.389***	-0.082**	0.153***	0.231*
	(0.057)	(0.026)	(0.038)	(0.052)	(0.117)
	[0.018]	[0.001]	[0.083]	[0.088]	[0.146]
Outcome mean	15.170	1.060	1.214	4.507	8.677
Average # of IDPs (1k)	2.682	2.682	2.682	2.682	2.682
Implied effect (%)	-0.95	-36.70	-6.74	3.40	2.67
Low market integration					
IDPs (thousands)	-0.040	0.139	-0.053***	-0.042	-0.014
	(0.196)	(0.191)	(0.015)	(0.035)	(0.055)
	[0.697]	[0.269]	[0.011]	[0.056]	[0.639]
Outcome mean	11.711	8.074	0.379	1.441	1.738
Average # of IDPs (1k)	1.621	1.621	1.621	1.621	1.621
Implied effect (%)	-0.35	1.72	-13.99	-2.90	-0.78
Cluster robust Wald test p-value	0.606	0.003	0.446	8.59×10^{-6}	0.016
Observations	11,429	11,429	11,429	11,429	11,429
Households	2,696	2,696	2,696	2,696	2,696

Notes: Shift-share IV estimates using the 2019 and 2022 ESS. Treatment is the IDP stock change within 25 km, in thousands (R11-R17 and R25-R29, respectively). All specifications include enumeration-area and year fixed effects and demographic, education, and local-conflict controls. The food and tradable-goods Young indices weight local/national arithmetic-mean item-price ratios within each wave using fixed Wave-3 expenditure shares, renormalized over available goods; ratios are winsorized at the 5th/95th percentiles. The regional index combines spatial price differences with regional non-food CPI. Parentheses report BHJ (2022) standard errors clustered by origin woreda; brackets report BH (2023) randomization-inference p-values. Implied effects is the coefficient expressed as a percentage of the outcome mean. Observations are household-years; shifts are origin-woreda conflict shocks for each exposure window. Stars reflect BHJ p-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

farm because of reduced off-farm activities. This is consistent with IDP workers being hired for very little, or non-monetary benefits, which causes hosts to lose opportunities in casual labor or hired farm labor. In return, they use more IDP labor on their own farm. This is also consistent with the null effects of displacement on host own unpaid labor, as shown in the last column of Table 12. This variable is from the labor module and is the host own report of whether they worked as unpaid laborers for other households. This precise null effect participates in the explanation that the rise in unpaid farm laborer is not due to host labor, but IDP workers.

While farm labor increases in low-integration areas, displacement inflows also expand production. Cultivated hectares, as well as total agricultural production, increase. Table **??** shows these effects. A 1,000 additional IDPs increase cultivated areas by 0.051 hectares ($p < 0.05$), an 11 percent increase. The value of production increases by USD 76 on average ($p < 0.01$), and scales to 8 percent of the mean. These results are also consistent with the IDP labor relieving some labor

Table 11: Effects of displacement inflows on agricultural labor in low-integration communities

	Farm labor				Host unpaid labor
Outcomes:	**Family labor**	**Hired labor**	**Unpaid labor**	**Total labor**	**Any unpaid labor**
Units:	Person-days / household / season				Indicator per adult, past 12 months
IDPs (thousands)	5.706***	-1.178***	2.181**	6.813**	0.0001
	(2.0815)	(0.1755)	(0.9631)	(3.0121)	(0.0111)
	[0.043]	[0.058]	[0.062]	[0.047]	[0.984]
Outcome mean	22.049	6.017	7.245	35.322	0.154
Average # of IDPs (1k)	1.490	1.477	1.477	1.490	3.011
Implied effect (%)	25.88	-19.57	30.11	19.29	0.08
Observations	1,231	1,242	1,242	1,231	1,826
Households	374	376	376	374	376
Shifts	133	133	133	133	58

Notes: Shift-share IV estimates for low-integration areas, where average distance to an asphalt road, bus station, and large weekly market exceeds 3.167 km. Treatment is IDP exposure within 25 km, in thousands. Farm-labor models pool planting and harvest with a common treatment coefficient, seasonal exposure windows, R8 origin shares, enumeration-area-by-season and year-by-season fixed effects, and season-specific controls. The host-labor model uses annual exposure, R11 shares, and enumeration-area and year fixed effects. Farm labor is measured in household person-days per season; the host outcome indicates whether an adult performed any unpaid labor in the past 12 months. Parentheses report BHJ standard errors clustered by origin woreda; brackets report two-sided randomization-inference p-values. Implied effects is the coefficient expressed as a percentage of the outcome mean. Observations are household-year-seasons in columns 1-4 and adult-years in column 5; shifts are origin-woreda conflict shocks for each exposure window. Stars reflect BHJ p-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

constraint, which enables agricultural production overall to expand.

Next, I turn to the heterogeneous effects of displacement inflows by market integration on prices. The framework predicted in Proposition 5 that in addition to the price of local services, food prices would decline as well with lower market integration, if reallocation to high-skill occupations was limited with lower market integration. Table 13 displays the effects of displacement inflows by market integration. In the top panel relative to host communities with high market integration, I estimate similar effects as with the main specification: a null effect on food prices (equivalent to a 0.7 percent decrease compared to the mean), a decline in the non-food index (-0.0445, $p < 0.01$), that scales to 2 percent of the outcome mean, and a null effect on the tradable goods index (-1.5 percent of the outcome mean). This case is consistent with the framework in full integration. However, in the low-integration group, I find that food prices react to displacement. They decrease by 1.3 percentage points ($p < 0.01$). The empirical evidence is consistent with a decrease in the price of services in low-integration communities too: non-food prices decrease by about 1.9 percent when compared to the index mean. However, displacement leads to a rise in the price of non-food tradable goods, which provides a sanity check for the other price effects: while food and services uses local labor for production, non-food tradables do not. Therefore, a displacement shock is

Table 12: Effects of displacement inflows on agricultural labor in low-integration communities

	Land	**Production**
Outcomes:	**Cultivated area**	**Value of production at fixed Wave 3 prices**
Units:	Hectares	2021 PPP USD
IDPs (thousands)	0.051**	75.839***
	(0.0215)	(20.5257)
	[0.010]	[0.108]
Outcome mean	0.473	985.427
Average # of IDPs (1k)	0.158	1.919
Implied effect (%)	10.71	7.70
Observations	659	265
Households	373	191
Shifts	69	57

Notes: Shift-share IV estimates for low-integration areas, where average distance to an asphalt road, bus station, and large weekly market exceeds 3.167 km. Treatment is the IDP stock change within 25 km, in thousands. Cultivated area uses planting exposure; production uses harvest exposure. Both specifications use R8 origin shares, enumeration-area and year fixed effects, and demographic, education, and local-conflict controls. Cultivated area is measured in hectares. Production is valued at fixed Wave 3 (2015/16) national median farm-sales prices in 2021 PPP USD. Parentheses report BHJ standard errors clustered by origin woreda; brackets report two-sided randomization-inference p-values. Implied effects is the coefficient expressed as a percentage of the outcome mean. Observations are household-years; shifts are origin-woreda conflict shocks for each exposure window. Stars reflect BHJ p-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

uniquely composed of a demand expansion on tradable goods markets, which should increase their prices. The non-food tradable goods price index increases by about 1.7 percentage points for 1,000 additional IDPs, which scales to 2.5 percent of the mean ($p < 0.01$).

In the stylized framework, I kept feedback channels on income, through changes in wages, occupations and prices fixed. Hosts and IDPs both came into the economy with fixed spending, allocated to the two goods by the Cobb-Douglas parameters. This choice was made for simplicity. However, understanding the consumption effects of displacement enables at least a partial qualification of its impact on economic well-being of the hosts. I therefore estimate effects on three variables related to real annual consumption: total annual household consumption, household food consumption, and household non-food consumption. The first two are deflated by the ESS's own food price deflator, while I deflate non-food consumption by my regional non-food CPI index. The results are presented in Table 14. In communities with highly integrated markets, total consumption increases modestly: I detect a USD 10.6 increase, significant at the 10 percent level, and representing 0.3 percent of the outcome mean. The effects on food and non-food consumption are null, though the estimate for the former is negative and positive for the latter. The consumption effects are stronger in low-integration communities. Total annual consumption increases by USD 32.8 ($p < 0.01$) for 1,000

additional IDPs, or 1.7 percent of the outcome mean. Food and non-food consumption increase by USD 37 and USD 8.2, respectively, and are both significant at the 1 percent level. Relative to their means, they scale to 2.6 and 3.3 percent. Though it is not the case for the increase in non-food consumption, the rises in both total and food consumption are statistically different in high- and low-integration communities with the displacement shock. This brings evidence about the material well-being of hosts, as measured by real consumption, not having been negatively impacted by displacement in each type of community on average.

6 Conclusion

This paper presented the effects of one of the largest displacement shock ever studied on host communities in Ethiopia. The analysis relies on a shift-share instrumental variable strategy, guided by a stylized framework, which presented the displacement shock as composed of a labor-market supply shock, particularly in low-skill labor, and in a consumer goods demand shock due to displaced people's purchases. I show that the effects on host communities imply that the labor-supply expansion dominated the consumer product shock this context. Second, the effects of displacement on host communities differ based on how integrated these are with external markets. Host workers in high-integration communities reallocate away to IDP-exposed jobs, agricultural and casual labor, and towards, high-skill, non-agricultural occupations. They do not lose purchasing power. The opposite happens in host communities with lower integration: IDP and hosts both enter agriculture, by far the dominant sector in these settings. The findings are consistent with hosts increasing their time on their own farm and reducing hours spent in other activities, including selling agricultural labor. IDPs help hosts on their farm without being paid at the prevailing wage. These lower labor costs decrease food prices in these communities, and benefits the hosts in terms of real consumption.

These findings have a few implications for policy and development. First, in difficult times for Ethiopia, this study highlights the fact that displaced people did not hurt the communities hosting them, measured by real consumption. And many of these communities benefited on average. Of course, this is only one measure of well-being, and does not account for other political or social dimensions that were affected by the displacement inflows. There may also be distributional consequences, as shown in other contexts, depending on who owns the land and other productive assets complement to labor. Another limitation involves not having outcome data for the displaced, which limits the interpretation of these effects for hosts only.

Second, the study shows that sectoral reallocation of the hosts only takes place where markets are integrated. Otherwise, the adjustment takes place through expansion within agriculture. Sectoral reallocation being at the essence of structural transformation, this extends to a larger question regarding the inner workings of structural change. Does it only apply where markets are integrated? Recent work on road expansion in Ethiopia also points in that direction (Adamopoulos, 2025). However, the results in this study indicate that structural transformation is not the only way to increase living standards in poor, Sub-Saharan African settings. In fact, gains in living

standards can accompany agricultural expansion. Hosts benefited more from the availability of cheap agricultural labor which seem to be constrained in rural Ethiopia (Dillon et al., 2019). The increased availability of agricultural labor enabled the use of other inputs such as land and increased agricultural production overall, improving host well-being.

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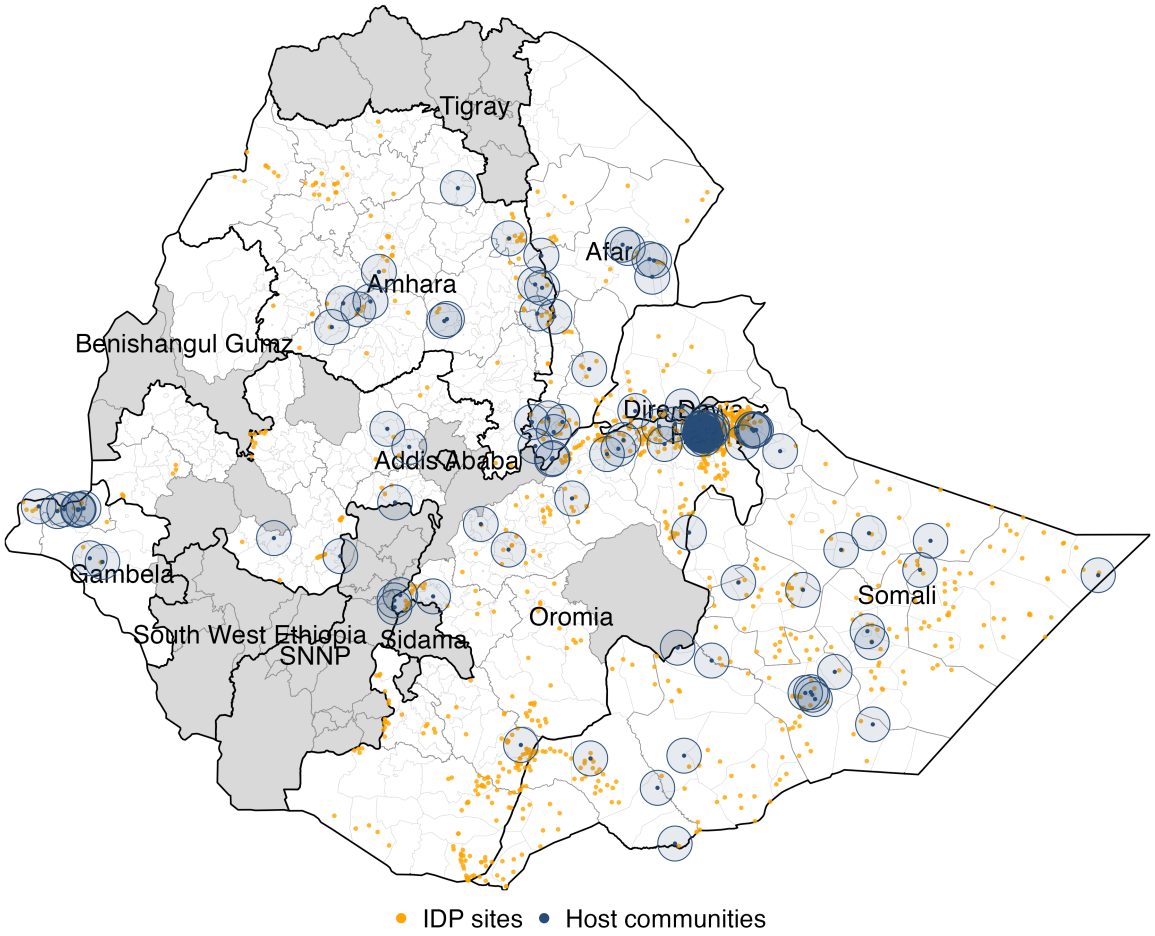
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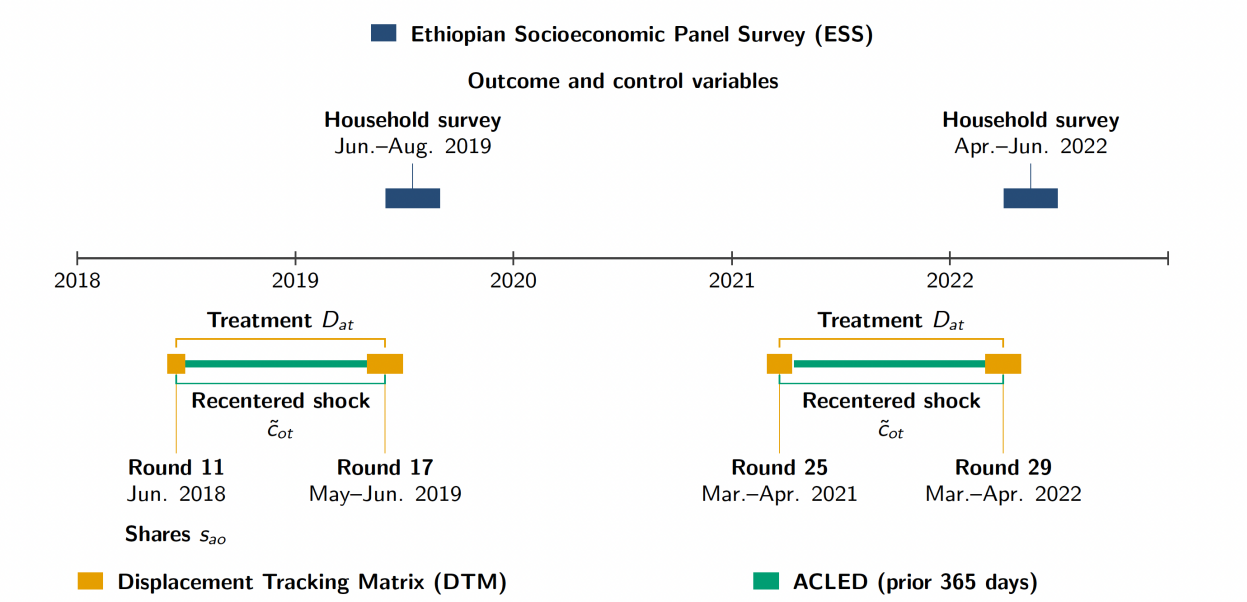
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Figure 4: Enumeration areas, IDP sites, and 25 km radius circles



Notes: Blue points mark the 127 host communities, represented by survey enumeration areas, observed in both ESS Wave 4 (2019) and Wave 5 (2022) in the estimation sample. They contain 1,586 unique households and 2,935 household-year observations; households need not be observed in both waves. Each community is plotted once at its modal public-use modified coordinate across the two waves. Blue circles show 25 km buffers. Orange points mark 968 IDP sites recorded in DTM round R17 within the common two-wave coverage area. Grey areas are zones without host-community or camp DTM coverage in at least one analysis year; white areas have coverage in both years. Woreda boundaries are light grey, zone boundaries are medium grey, and regional boundaries are black. The map restricts attention to communities observed in both waves; the summary table includes the full household-year analysis sample.

Figure 5: Data and estimation strategy timeline



Notes: The figure provides a schematic alignment of the survey waves and principal DTM rounds. Annual exposure uses the assessment-selection rule in the text; origin conflict is measured over the 365 days preceding the survey reference date. Baseline origin shares are fixed at DTM round 11.

Table 13: Effects of displacement inflows by market integration on prices

	Food prices	**Non-food prices**	
Outcomes:	**Young W3 index**	**Regional index**	**Tradable goods index**
Units:	Index	Index	Index
High market integration			
IDPs (thousands)	-0.0071	-0.0445***	-0.0116
	(0.0053)	(0.0095)	(0.0202)
	[0.035]	[0.035]	[0.240]
Outcome mean	1.000	2.073	0.773
Average # of IDPs (1k)	2.719	2.675	3.585
Implied effect (%)	-0.71	-2.14***	-1.50
Low market integration			
IDPs (thousands)	-0.0129***	-0.0357***	0.0174***
	(0.0040)	(0.0071)	(0.0053)
	[0.055]	[0.033]	[0.181]
Outcome mean	1.002	1.884	0.691
Average # of IDPs (1k)	2.212	2.170	2.372
Implied effect (%)	-1.29***	-1.89***	2.52***
High = low (p-value)	0.029	0.019	0.095
Observations	3,705	3,783	2,529
Households	2,549	2,612	1,373

Notes: Joint shift-share IV estimates for the 2019 and 2022 ESS. Treatment is the IDP stock change within 25 km, in thousands (R11-R17 and R25-R29), instrumented with fixed R11 origin shares and recentered origin-conflict shocks. All specifications include enumeration-area and year fixed effects and household and local-conflict controls. High integration denotes mean distance to an asphalt road, bus station, and large weekly market at most 3.167 km; low integration denotes greater distance. The food and tradable-goods Young indices use fixed Wave-3 expenditure weights and local/national arithmetic-mean price ratios within item/unit/wave, winsorized at the 5th/95th percentiles. Weights are renormalized over available goods; the tradable basket is fixed within each area across waves. The regional index combines 2015/16 spatial price ratios with regional non-food CPI. Implied effects is the coefficient expressed as a percentage of the outcome mean. Parentheses report BHJ (2022) standard errors clustered by origin woreda; brackets report BH (2023) randomization-inference p-values from 1,000 permutations. The equality test compares high and low coefficients in index units using their joint clustered covariance. Counts cover both groups in each outcome-specific sample; observations are household-years. Stars reflect BHJ p-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 14: Effects of displacement inflows by market integration on host consumption

Outcomes:	**Total**	**Food**	**Non-food**
	Spatially deflated	**ESS spatial**	**Reg. CPI**
Units:	2021 PPP USD per adult equivalent per year		
High market integration			
IDPs (thousands)	10.6*	-19.0	5.6
	(5.9)	(12.0)	(4.7)
	[0.029]	[0.070]	[0.107]
Outcome mean	3,278.3	1,986.5	526.7
Average # of IDPs (1k)	2.933	2.933	2.933
Implied effect (%)	0.32	-0.96	1.06
Low market integration			
IDPs (thousands)	32.8***	37.0***	8.2***
	(9.2)	(10.8)	(1.6)
	[0.003]	[0.005]	[0.004]
Outcome mean	1,853.0	1,403.9	247.0
Average # of IDPs (1k)	1.920	1.920	1.920
Implied effect (%)	1.77	2.64	3.31
Cluster robust Wald test p-value	0.011	9.54×10^{-7}	0.598
Observations	4,046	4,046	4,046
Households	2,697	2,697	2,697

Notes: Joint shift-share IV estimates for the 2019 and 2022 ESS. Treatment is the one-year change in IDPs within 25 km, in thousands. Specifications include enumeration-area and year fixed effects and household and local-conflict controls. High integration denotes mean distance to an asphalt road, bus station, and large weekly market at most 3 km (the sample median); low integration denotes greater distance. Outcomes are annual consumption in 2021 PPP USD per adult equivalent. Total consumption uses the official ESS aggregate with its food-price spatial adjustment. Food uses the ESS spatial food-price divisor; non-food uses 2015/16 regional spatial price ratios updated with regional non-food CPI. The selected-item food and non-food aggregates need not sum to the official total. Parentheses report BHJ (2022) standard errors clustered by origin woreda; brackets report two-sided randomization-inference p-values from 1,000 pooled shock permutations using studentized subgroup coefficients. Implied effects is the coefficient expressed as a percentage of the outcome mean. The Wald test compares high- and low-integration coefficients using their joint clustered covariance. Means are subgroup-specific; counts cover both groups, with observations measured in household-years. Stars reflect BHJ p-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

A Appendix

B Proofs of the comparative statics

B.1 Full market integration

Use $u = \widehat{w}_L$, $v = \widehat{w}_H$, and $t = \widehat{\Theta}_0 = u - v$. High-skill supply satisfies $\widehat{H}_S = -\chi t$. Differentiating $w_H H_S = (1-\beta)\omega_S B$ gives

$$-\chi u + (1+\chi)v = \gamma. \tag{32}$$

At $\kappa = 0$, service factor payments imply $L_S = \beta H_S/[(1-\beta)\Theta_0]$ and hence $\widehat{L}_S = -(1+\chi)t$. Host low-skill supply changes by $\Theta_0 g(\Theta_0)t$. Differentiating low-skill clearing at the fixed food price gives

$$-\mathcal{F}u - \mathcal{C}(u-v) = 1, \tag{33}$$

where $(1+\chi)L_S + \Theta_0 g(\Theta_0) = L_S(1+\chi/\beta) = \mathcal{C}$. Solving these two equations yields

$$u = \frac{\gamma\mathcal{C} - (1+\chi)}{\Omega}, \qquad v = \frac{\gamma(\mathcal{C}+\mathcal{F}) - \chi}{\Omega}. \tag{34}$$

Proof of Proposition 1. Subtracting the two wage responses gives $\partial \log(w_L/w_H)/\partial D = -(1+\gamma\mathcal{F})/\Omega < 0$, since $\gamma \geq 0$ and $\mathcal{F}, \Omega > 0$. The numerator remains positive at $\gamma = 0$, and there is no upper restriction on γ for this sign. □

Proof of Proposition 2. At $\kappa = 0$, the occupational cutoff is $\Theta_0 = w_L/w_H$. Proposition 1 therefore gives $t = \widehat{\Theta}_0 < 0$. Differentiating $N_H = 1 - G(\Theta_0)$ gives $\partial N_H/\partial D = -\Theta_0 g(\Theta_0)t > 0$. The initial-sector rule gives $\partial L_F^H/\partial D = \phi\Theta_0 g(\Theta_0)t < 0$. Total host nonagricultural employment equals $1 - L_F^H$ and therefore rises. Similarly, $\partial N_L/\partial D = \Theta_0 g(\Theta_0)t < 0$ and $\partial L_S^H/\partial D = (1-\phi)\Theta_0 g(\Theta_0)t < 0$. For the share within host service employment, differentiating $s_{L|S}^H = (1-\phi)G(\Theta_0)/[1-\phi G(\Theta_0)]$ gives

$$\frac{\partial s_{L|S}^H}{\partial D} = \frac{1-\phi}{[1-\phi G(\Theta_0)]^2}\Theta_0 g(\Theta_0)t < 0. \tag{35}$$

□

Proof of Proposition 3. Positive imports impose $p_F = p^*$, so $\widehat{p}_F = 0$. Log differentiation of service unit cost gives $\widehat{p}_S = \beta u + (1-\beta)v$. Substituting equation (34) yields equation (13). Since $\Omega > 0$, service prices fall if and only if its numerator is negative, giving condition (14). Service-market clearing gives $\widehat{Y}_S = \gamma - \widehat{p}_S = (\beta+\chi)(1+\gamma\mathcal{F})/\Omega > 0$, proving equation (15) and its equivalent supply-growth interpretation. □

B.2 Local food clearing and mixed responses

All derivatives in this subsection hold technology, the skill distribution, budget parameters, $\bar{c}$, and p^* fixed. They are taken within a neighborhood where food clears locally and the occupational margin is smooth. Thus B and γ depend on D but not on κ.

For the derivations, define $x = N_L = G(\Theta_\kappa)$, $a_L = \alpha\omega_F + \beta\omega_S$, and $a_H = (1-\beta)\omega_S$. These last two quantities are the shares of expenditure paid to low- and high-skill labor when food clears locally. Define $H(x) = \int_{G^{-1}(x)}^{\infty} \theta \, \mathrm{d}G(\theta)$, so $W = x + D$ and $H(x) = H_S$ at equilibrium.

Farm optimization and local food clearing give $w_L L_F = \alpha p_F Y_F = \alpha\omega_F B$. Adding low-skill service payments gives $w_L W = a_L B$, while high-skill payments give $w_H H(x) = a_H B$. Thus

$$w_L = \frac{a_L B}{W}, \qquad w_H = \frac{a_H B}{H(x)}, \qquad L_F = \frac{\alpha\omega_F}{a_L} W. \tag{36}$$

Let $f(x) = a_H G^{-1}(x)/H(x)$ and $s = \kappa\bar{c}/B$. The first is the marginal host's gross high-skill earnings per unit of aggregate expenditure; the second is the commuting charge normalized by that expenditure. Dividing the cutoff identity by B yields

$$f(x) - \frac{a_L}{x + D} = s, \qquad J = f'(x) + \frac{a_L}{W^2} > 0, \qquad K = \frac{a_L}{W^2} + \gamma s > 0. \tag{37}$$

Here J is the slope of the occupational equilibrium condition in x, and K measures its displacement-induced shift before occupational adjustment. These are auxiliary quantities used only in the derivation.

For clarity, write $\theta = G^{-1}(x)$, $g = g(\theta)$, and $g' = g'(\theta)$ in the following derivative expressions. Since $H'(x) = -\theta$ and $\mathrm{d}\theta/\mathrm{d}x = 1/g$,

$$f'(x) = a_H \left(\frac{1}{gH} + \frac{\theta^2}{H^2} \right) > 0, \tag{38}$$

$$f''(x) = a_H \left(-\frac{g'}{g^3 H} + \frac{3\theta}{gH^2} + \frac{2\theta^3}{H^3} \right). \tag{39}$$

Consequently, $J > 0$. In particular, $g' \leq 0$ is sufficient for $f''(x) > 0$; the model otherwise allows either curvature sign. The scalar equilibrium has at most one interior solution within the region where these conditions hold.

Proof of Proposition 4. Differentiate $f(x) - a_L/(x + D) = s$, noting that $s_D = -\gamma s$ and $s_\kappa = \bar{c}/B$. This gives

$$J x_D + \frac{a_L}{W^2} = -\gamma s, \qquad J x_\kappa = \frac{\bar{c}}{B}. \tag{40}$$

Hence $x_D = -K/J$, $R = -x_D = K/J > 0$, and $x_\kappa = \bar{c}/(BJ) > 0$. These are total equilibrium responses of x to the respective parameters, holding the other parameter fixed.

Since $N_H = 1 - x$, the commuting-cost response is $\partial N_H/\partial\kappa = -\bar{c}/(BJ) < 0$. The two first derivatives establish equation (16).

To establish equation (17), note that $H_S = H(x)$, $H'(x) = -\Theta_\kappa$, and $x_D = -R$ imply $\partial H_S/\partial D = \Theta_\kappa R$. Differentiating high-skill factor payments gives

$$\widehat{w}_H = \gamma - \frac{\Theta_\kappa R}{H_S}. \tag{41}$$

Since $w_H H_S = (1-\beta)\omega_S B$ and $\Theta_\kappa w_H = w_L + \kappa\bar{c}$, the spending bound is equivalent to $0 < \gamma \leq \Theta_\kappa R/H_S$ and therefore to a weakly nonincreasing high-skill wage with positive spending. It is compatible with strictly positive purchasing power: at a smooth zero-increment equilibrium, $\Theta_\kappa R/H_S > 0$, so sufficiently small positive increments satisfy the strict bound by continuity.

The cutoff derivative obeys

$$\frac{\partial\Theta_\kappa}{\partial D} = \frac{w_L}{w_H}\widehat{w}_L - \Theta_\kappa\widehat{w}_H = -\frac{R}{g} < 0. \tag{42}$$

Thus $\widehat{w}_H \leq 0$ implies $\widehat{w}_L < 0$. Because $w_L = a_L B/W$, it follows that $W_D = 1 - R > \gamma W > 0$. Also, $g_D = g'(\Theta_\kappa)\partial\Theta_\kappa/\partial D \geq 0$ under the density restriction.

Finally, rewrite the occupational equilibrium slope in monetary units as

$$BJ = \frac{w_H}{g} + \frac{w_H\Theta_\kappa^2}{H_S} + \frac{w_L}{W}. \tag{43}$$

Under the bound, the first term weakly falls with D, while the other two strictly fall: the cutoff falls, high-skill supply increases, the low-skill wage falls, and the low-skill workforce expands. Hence $\partial_D(BJ) < 0$. Since $\partial N_H/\partial\kappa = -\bar{c}/(BJ)$,

$$\frac{\partial^2 N_H}{\partial D\,\partial\kappa} = \frac{\bar{c}}{(BJ)^2}\frac{\partial(BJ)}{\partial D} < 0. \tag{44}$$

This establishes the attenuation result under the proposition's sufficient spending bound. Finally, host nonagricultural employment is $1 - \phi x$, whose displacement response is ϕR and whose mixed response is ϕR_κ. □

A more general condition for attenuation. The sufficient bound in Proposition 4 can be relaxed. At fixed D, the total derivatives of K and J with respect to κ are

$$K_\kappa = \gamma\frac{\bar{c}}{B} - \frac{2a_L}{W^3}x_\kappa, \qquad J_\kappa = \left(f''(x) - \frac{2a_L}{W^3}\right)x_\kappa. \tag{45}$$

Define

$$\Delta = Kf''(x) + \frac{2a_L}{W^3}\left[f'(x) - \gamma s\right] - \gamma J^2. \tag{46}$$

The quotient rule, $x_\kappa = \bar{c}/(BJ)$, and $J - K = f'(x) - \gamma s$ imply

$$\begin{aligned} R_\kappa &= \frac{K_\kappa J - K J_\kappa}{J^2} \\ &= \frac{\bar{c}}{BJ^3}\left[\gamma J^2 - K f''(x) - \frac{2a_L}{W^3}\big(f'(x) - \gamma s\big)\right] = -\frac{\bar{c}}{BJ^3}\Delta. \end{aligned} \tag{47}$$

All factors outside Δ are positive, so $R_\kappa < 0$ if and only if $\Delta > 0$. To characterize this condition with positive purchasing power, substitute $K = a_L/W^2 + \gamma s$ and collect terms in γ:

$$\Delta = \frac{a_L}{W^2}\left[f''(x) + \frac{2f'(x)}{W}\right] - \gamma\left[J^2 + s\left(\frac{2a_L}{W^3} - f''(x)\right)\right]. \tag{48}$$

Under $g'(\Theta_\kappa) \leq 0$, equation (39) implies $f''(x) > 0$, so the first term is strictly positive. Define the following threshold, using quantities evaluated at the equilibrium under consideration:

$$\bar{\gamma} \equiv \begin{cases} \dfrac{\dfrac{a_L}{W^2}\left[f''(x) + \dfrac{2f'(x)}{W}\right]}{J^2 + s\left(\dfrac{2a_L}{W^3} - f''(x)\right)}, & J^2 + s\left(\dfrac{2a_L}{W^3} - f''(x)\right) > 0, \\ +\infty, & \text{otherwise.} \end{cases} \tag{49}$$

Thus $\bar{\gamma} > 0$ and, under the maintained density restriction and positive purchasing power, $R_\kappa < 0$ if and only if

$$0 < \gamma < \bar{\gamma}. \tag{50}$$

If the denominator is positive, equality gives a zero interaction and $\gamma > \bar{\gamma}$ gives a positive interaction. If it is nonpositive, $\Delta > 0$ for every positive γ at an equilibrium satisfying the density restriction. This is a pointwise equilibrium condition: changing $\bar{b}_D$ also changes the quantities entering the threshold, which must then be reevaluated.

The first term in equation (48) captures attenuation associated with occupational curvature and the larger low-skill workforce. The second records how positive expenditure changes that balance. The term $-\gamma J^2$ in the original expression for Δ is the direct earnings-scale offset; curvature can reinforce attenuation through $\gamma s f''(x)$. This explains why the threshold can be unbounded. Neither a zero spending increment nor a separately imposed sign on a wage response is used.

Reversing the differentiation order. The maintained differentiability assumptions and $J > 0$ imply that the equilibrium allocation is twice continuously differentiable locally. Hence $\partial_D \partial_\kappa N_H = \partial_\kappa \partial_D N_H$; changing the order does not change the mixed response or remove its sign conditions. Starting instead from $\partial N_H/\partial\kappa = -\bar{c}/(BJ)$ gives

$$\frac{\partial^2 N_H}{\partial D\, \partial \kappa} = \frac{\bar{c}}{BJ}\left(\gamma + \frac{J_D}{J}\right), \qquad J_D = -R f''(x) - \frac{2a_L(1-R)}{W^3}. \tag{51}$$

Substitution reproduces $-\bar{c}\Delta/(BJ^3)$. The shorter intermediate expression still contains the equilibrium derivative J_D; treating it as fixed would omit part of the response.

Proof of Proposition 5. Since $L_F = (\alpha\omega_F/a_L)W$ and $W_D = 1 + x_D = 1 - R$, agricultural labor grows at $(1-R)/W$ and food supply grows at $\alpha(1-R)/W$. Local clearing gives $p_F Y_F = \omega_F B$, so

$$\widehat{p}_F = \gamma - \alpha\frac{1-R}{W}. \tag{52}$$

The food-price decline condition follows directly. A useful way to derive the interaction is to differentiate with respect to κ first. Since $p_F Y_F = \omega_F B$ and Y_F is proportional to W^α,

$$\frac{\partial \log p_F}{\partial \kappa} = -\alpha\frac{W_\kappa}{W}. \tag{53}$$

Now differentiate with respect to D, using $W_D = 1 - R$ and $W_{\kappa D} = -R_\kappa$. This gives the two-term expression in the main text:

$$\begin{aligned}\frac{\partial^2 \log p_F}{\partial D\,\partial \kappa} &= \alpha\left[\frac{R_\kappa}{W} + \frac{(1-R)W_\kappa}{W^2}\right] \\ &= \frac{\alpha\bar{c}}{BJW^2}\left[1 - R - \frac{W\Delta}{J^2}\right].\end{aligned} \tag{54}$$

The first line is equation (21), since $W_\kappa/W = \partial \log W/\partial\kappa$. It is negative if and only if $-R_\kappa > (1-R)W_\kappa/W$, proving condition (22). The second line is the equivalent fully evaluated expression; its sign condition is $W\Delta > J^2(1-R)$. With positive imports, $p_F = (1+\kappa)p^*$ does not depend on D, so both the displacement derivative and its derivative with respect to κ are zero as long as that regime persists. □

The proportional and level price interactions are distinct. The main text uses $\partial^2 \log p_F/(\partial\kappa\,\partial D)$, corresponding to heterogeneity in proportional price effects. Since local clearing also implies $\partial \log p_F/\partial\kappa = -\alpha\bar{c}/(BJW)$, the interaction in price levels is

$$\frac{1}{p_F}\frac{\partial^2 p_F}{\partial\kappa\,\partial D} = \frac{\partial^2 \log p_F}{\partial\kappa\,\partial D} - \widehat{p}_F\frac{\alpha\bar{c}}{BJW}. \tag{55}$$

A sign claim for one interaction therefore does not automatically apply to the other.

Proof of Proposition 6. Log differentiation of farm labor demand gives $\widehat{L}_F = (\widehat{p}_F - \widehat{w}_L)/(1-\alpha)$. Alternatively, $L_F = (\alpha\omega_F/a_L)W$ implies $\widehat{L}_F = (1-R)/W$. Fixed land gives $\widehat{Y}_F = \alpha\widehat{L}_F$. Since $0 < \alpha < 1$ and $W > 0$, both expand if and only if $\widehat{w}_L < \widehat{p}_F$, equivalently $R < 1$.

If $\widehat{p}_F < 0$, Proposition 5 implies $\alpha(1-R)/W > \gamma \geq 0$, so $(1-R)/W > 0$. In addition, $w_L = a_L B/W$

gives $\widehat{w}_L = \gamma - (1-R)/W$. Subtracting this expression from $\widehat{p}_F = \gamma - \alpha(1-R)/W$ yields

$$\widehat{p}_F - \widehat{w}_L = (1-\alpha)\frac{1-R}{W} > 0. \tag{56}$$

Hence $\widehat{w}_L < \widehat{p}_F < 0$, completing the result. □

C Data

Food prices (Young index). Formally, for enumeration area e and survey wave t, define

$$P_{et}^{Y} = \frac{\sum_{i \in A_{et}} s_{i3} \widetilde{\left(\frac{p_{iet}}{\bar{p}_{it}}\right)}}{\sum_{i \in A_{et}} s_{i3}},$$

where p_{iet} is the mean community price of item i in enumeration area e, $\bar{p}_{it}$ is its national mean community price in the same wave, and A_{et} is the set of eligible items with valid prices in that enumeration area and wave. The tilde denotes winsorization of price ratios at the item-and-wave-specific 5th and 95th percentiles. The fixed weight s_{i3} represents item i's share of the value of the national Wave-3 consumption basket.

These weights are constructed as

$$s_{i3} = \frac{\bar{p}_{i3} Q_{i3}}{\sum_{j \in B} \bar{p}_{j3} Q_{j3}}, \qquad Q_{i3} = \frac{\sum_h w_{h3} \widetilde{q}_{hi3}}{\sum_h w_{h3}},$$

where B is the matched item universe, w_{h3} is the Wave-3 household survey weight, and $\widetilde{q}_{hi3}$ is household h's weekly consumption quantity of item i, converted to kilogram equivalents and capped at the item-specific 95th percentile among positive, successfully converted household-item quantities. National quantities are valued at the corresponding Wave-3 national mean community prices and normalized to sum to one across items.

The 46 items span cereals, pulses and nuts, oilseeds, vegetables, fruit, roots and tubers, dairy products, eggs, oils, sugar, salt, and beverages. The survey's consumption basket also includes khat. The largest national weights are teff (15.54%), maize (12.92%), wheat (8.78%), and sorghum (8.23%). Before computing local and national means, I identify unit-scale miscoding and cap item prices at the pooled community-price panel's 99th percentile. The Young index construction subsequently applies the separate item-wave 5th/95th-percentile winsorization to local-to-national price ratios. The median number of priced basket items is 28 in 2018/19 and 24 in 2021/22. I imposes no additional minimum-item or minimum-weight-coverage threshold and do not require identical item availability across waves.

Non-food regional price index. For region r and survey wave t,

$$P_{rt}^{NF} = S_{r,2015/16}^{NF} \frac{\overline{CPI}_{rt}^{NF}}{\overline{CPI}_{r,2015/16}^{NF}},$$

where: - $S_{r,2015/16}^{NF}$ is the region's published non-food spatial price index relative to the national average in 2015/16. - $\overline{CPI}_{rt}^{NF}$ is the arithmetic mean of the region's monthly non-food CPI over the July–June fiscal year corresponding to survey wave t. - $\overline{CPI}_{r,2015/16}^{NF}$ is the region's baseline non-food CPI, calculated as the arithmetic mean of the four published quarterly averages for fiscal year 2015/16.

The spatial benchmarks come from Table A2 of the National Planning Commission's Ethiopia's Progress Towards Eradicating Poverty: An Interim Report on 2015/16 Poverty Analysis Study. We use the regional non-food column, which reports price ratios around one. For example, the benchmark is 0.80 for Amhara, 0.97 for Oromia, and 1.62 for Addis Ababa. These benchmarks preserve geographic differences in the initial price level. Subsequent price movements are measured using the official regional non-food CPI series published by the Central Statistical Agency. The series uses expenditure weights derived from the 2015/16 Household Income, Consumption and Expenditure Survey, adjusted to December 2016 prices. Its retail-price collection framework covers 119 selected markets in representative urban centers. I use the published regional non-food aggregate directly. Its coverage includes housing and utilities, clothing, household furnishings and equipment, health, transport, communication, recreation, education, restaurants and hotels, alcoholic beverages and tobacco, and miscellaneous goods and services. The baseline regional CPI observations are obtained from the National Bank of Ethiopia's quarterly bulletin, which reports historical values on the same December 2016 = 100 scale as the subsequent monthly series. Dividing the later CPI by its regional 2015/16 average expresses cumulative regional price growth since the benchmark period. Multiplying this growth factor by the spatial benchmark then places the index on the common national reference scale. For ESS Wave 4, I average monthly CPI observations from July 2018 through June 2019; for Wave 5, I use July 2021 through June 2022. I merge the resulting index to households by region and survey wave. All households in a given region-wave therefore receive the same price index, regardless of their enumeration area or interview month. An index value of two represents a non-food price level approximately twice the national 2015/16 benchmark. The index retains cumulative regional inflation and is not renormalized to the contemporaneous national average. Within each region, proportional changes in the constructed index exactly reproduce proportional changes in the corresponding official CPI averages.

Non-food tradable good prices (Young index). Formally, for enumeration area e and survey wave t,

$$P_{et}^{NF,ESS} = \frac{\sum_{i \in B_e} s_{i3}\, \widetilde{R}_{iet}}{\sum_{i \in B_e} s_{i3}}, \qquad R_{iet} = \frac{p_{iet}}{m_{i,u_{iet},t}},$$

where B_e is the set of eligible goods observed in both waves in enumeration area e, s_{i3} is good i's fixed national Wave-3 expenditure share, and p_{iet} is its local price per reported unit. The denominator $m_{i,u_{iet},t}$ is the national median price for the same good, reported unit, and survey wave. The tilde denotes winsorization of price ratios at the good-and-wave-specific 5th and 95th percentiles.

Specifically,

$$s_{i3} = \frac{\sum_{h} w_{h3} x_{hi3}}{\sum_{j \in B} \sum_{h} w_{h3} x_{hj3}},$$

where x_{hi3} is household h's reported monthly expenditure on good i, w_{h3} is its Wave-3 survey weight, and B contains all nine goods. These weights are calculated from 4,954 households and held fixed across the later waves. The implementation uses the reported expenditures without additional winsorization when constructing these shares.

The estimation sample contains 110 EAs. The median EA basket includes six goods, accounting for approximately 65.9% of the original national nine-good expenditure weights before renormalization. Eleven EAs have all nine goods. Units can change across waves. The paired-basket requirement applies to goods. It does not require an EA to report the same unit in both waves. Each observation is normalized by the national median for its own reported unit and wave. Scope of "tradable goods." This is the figure's grouping label. The index covers the nine listed commodities and does not classify goods using observed trade flows. For the paper, "ESS non-food goods price index" is the more precise description.

D Appendix Tables

Table 15: Caption

Included?	ACLED event type	Subtypes
Yes	Battles	Armed clash; government regains territory; non-state actor overtakes territory
Yes	Explosions / remote violence	Air/drone strike; grenade; remote explosive/landmine/IED; shelling/artillery/missile attack; suicide bomb
Yes	Violence against civilians	Attack; abduction/forced disappearance; sexual violence
Yes	Riots	Mob violence
No	Riots	Violent demonstration
No	Protests	Peaceful protest; protest with intervention; excessive force against protesters
No	Strategic developments	Agreement; arrests; change to group/activity; disrupted weapons use; headquarters or base established; looting/property destruction; non-violent transfer of territory; other

Table 16: Sector composition of wage employment and self-employment

Sector / industry	Observations	Share (%)
Panel A. Wage employment		
Agriculture and fishing	171	5.4
Mining and utilities	129	4.1
Manufacturing	204	6.4
Construction	349	11.0
Services	2,325	73.2
Public administration	378	11.9
Wholesale and retail trade	318	10.0
Education	314	9.9
Finance	222	7.0
Private household employment	213	6.7
Health and social work	203	6.4
Real estate and business services	203	6.4
Transport, storage and communications	193	6.1
Hotels and restaurants	168	5.3
Other services	113	3.6
Total	3,178	100.0
Panel B. Household nonfarm enterprises		
Agriculture, forestry and fishing	21	0.9
Mining and utilities	14	0.6
Manufacturing	275	12.3
Construction	53	2.4
Services	1,871	83.8
Wholesale and retail trade; vehicle repair	1,122	50.2
Accommodation and food services	264	11.8
Personal services and repairs	196	8.8
Transport and storage	126	5.6
Professional, financial and business services	97	4.3
Other services	34	1.5
Private household employment	32	1.4
Total	2,234	100.0

Notes: Ethiopia ESS, 2019 and 2022, pooled without survey weights. Panel A counts person-years for adults aged 15 and older reporting paid work in the previous 12 months with a valid primary wage-job industry. Panel B counts enterprise-years with a valid primary industry in the previous-12-month household enterprise module; a household may contribute multiple enterprises. Panel B is not employment-weighted. Indented rows decompose services; all shares use the full panel total. Industry categories follow each module. Other services groups residual service industries within each panel. Agriculture-coded enterprises are retained as reported. These descriptive samples are broader than the 25 km IV estimation sample. Percentages may differ from totals because of rounding.

Table 17: Summary statistics for price indices

Outcome	N	Mean	SD	Min.	Max.
Panel A: Price indices					
Food price index	3,705	1.001	0.142	0.545	1.354
Regional non-food CPI index	3,783	1.987	0.605	0.975	2.870
non-food tradable price index	2,529	0.731	0.304	0.209	1.577
Panel B: Annual adult-equivalent real household consumption					
Total consumption	4,046	2,579.8	2,086.4	68.7	15,600.3
Food consumption	4,046	1,701.0	1,435.2	0.0	18,203.2
Non-food consumption	4,046	389.6	474.0	0.0	9,973.1

Notes: Unweighted summary statistics for the estimation samples. N counts household-year observations after the original sample restrictions and fixed-effect drops. The Food price index (Young W3) uses fixed Wave-3 national expenditure shares and EA prices relative to same-wave national mean prices, with item-wave 5th/95th-percentile caps and weights renormalized over available items. The Regional non-food CPI index combines 2015/16 regional spatial price ratios with regional non-food CPI relative to its 2015/16 mean, using July 2018-June 2019 and July 2021-June 2022. The non-food tradable price index is the arithmetic ESS non-food Young index with fixed Wave-3 expenditure weights for nine goods; price relatives use same-good/unit/wave national arithmetic means and item-wave 5th/95th-percentile caps recomputed on these price relatives. Both Young indices use all valid national community quotes to calculate their same-wave reference means before estimation-sample restrictions, without survey weights. The tradable-goods index retains a common available-good basket within each EA across the two waves, with at least one paired good, renormalized weights and no imputation. Panel B reports annual real household consumption per adult equivalent in 2021 PPP USD. Total consumption is the cleaned ESS spatially deflated total-consumption measure with its existing upper-tail cap and national CPI/PPP conversion. Food consumption applies the ESS spatial food-price divisor to the food aggregate and divides by ESS adult equivalents. It does not include meals away from home. Non-food consumption uses the regional non-food CPI adjustment and divides by ESS adult equivalents. Total consumption is already per adult equivalent and is not divided again. These measures retain their distinct coverage and deflators, so food and non-food consumption need not sum to total consumption. Consumption observations with zero food or non-food spending are retained as in the original estimation samples. SD denotes the sample standard deviation.

Table 18: Summary statistics by market integration

	High market integration					Low market integration				
Variable	N	Mean	SD	Min.	Max.	N	Mean	SD	Min.	Max.
Panel A. Labor outcomes										
Participation in the last 7 days (0/1)										
Any income-generating activity	5,568	0.400	0.490	0.000	1.000	5,792	0.471	0.499	0.000	1.000
Agricultural work for household	5,568	0.062	0.241	0.000	1.000	5,792	0.380	0.486	0.000	1.000
Casual labor	5,568	0.048	0.213	0.000	1.000	5,792	0.024	0.152	0.000	1.000
Self-employment	5,568	0.118	0.322	0.000	1.000	5,792	0.050	0.219	0.000	1.000
Permanent wage employment	5,568	0.203	0.402	0.000	1.000	5,792	0.047	0.211	0.000	1.000
Hours worked in the last 7 days										
Any income-generating activity	5,568	15.155	23.179	0.000	71.000	5,792	11.731	18.286	0.000	71.000
Agricultural work for household	5,568	1.084	5.693	0.000	56.000	5,792	8.103	14.321	0.000	56.000
Casual labor	5,568	1.223	6.838	0.000	60.000	5,792	0.368	3.280	0.000	60.000
Self-employment	5,568	4.522	14.984	0.000	80.000	5,792	1.418	8.112	0.000	80.000
Permanent wage employment	5,568	8.633	19.402	0.000	84.000	5,792	1.742	9.271	0.000	84.000
Wages (2021 PPP USD)										
Casual labor (per day)	194	27.339	40.309	0.105	129.898	104	17.150	30.919	0.008	129.898
Permanent wage employment (per hour)	1,066	3.066	3.378	0.026	13.705	238	3.046	3.283	0.189	13.705
Panel B. Real consumption										
Annual 2021 PPP USD per adult equivalent										
Total consumption	2,063	3,278.3	2,324.0	68.7	15,600.3	1,983	1,853.0	1,492.9	92.8	14,393.3
Food consumption	2,063	1,986.5	1,624.4	0.0	18,203.2	1,983	1,403.9	1,133.7	0.0	11,863.7
Non-food consumption	2,063	526.7	565.8	0.0	9,973.1	1,983	247.0	292.4	0.0	4,834.2
Panel C. Demographic and education controls										
Individual-year observations, ages 15+										
Household size	5,568	5.066	2.626	1.000	18.000	5,792	6.519	2.753	1.000	15.000
Age	5,568	33.408	14.775	15.000	77.000	5,792	33.362	15.672	15.000	77.000
Male	5,568	0.453	0.498	0.000	1.000	5,792	0.489	0.500	0.000	1.000
Can read and write	5,568	0.801	0.399	0.000	1.000	5,792	0.477	0.499	0.000	1.000
Ever attended school	5,568	0.793	0.405	0.000	1.000	5,792	0.481	0.500	0.000	1.000
Completed primary school	5,568	0.576	0.494	0.000	1.000	5,792	0.190	0.392	0.000	1.000

Notes: Unweighted summary statistics for Ethiopia ESS, 2019 and 2022. High market integration denotes average amenity distance at or below 3.167 km for labor outcomes and controls, and 3 km for consumption. Low integration denotes distances above these cutoffs. N counts individual-year observations in Panels A and C and household-year observations in Panel B. SD denotes the sample standard deviation.