Supplementary Materials for Dynamics of Internal Displacement and Conflict in Somalia

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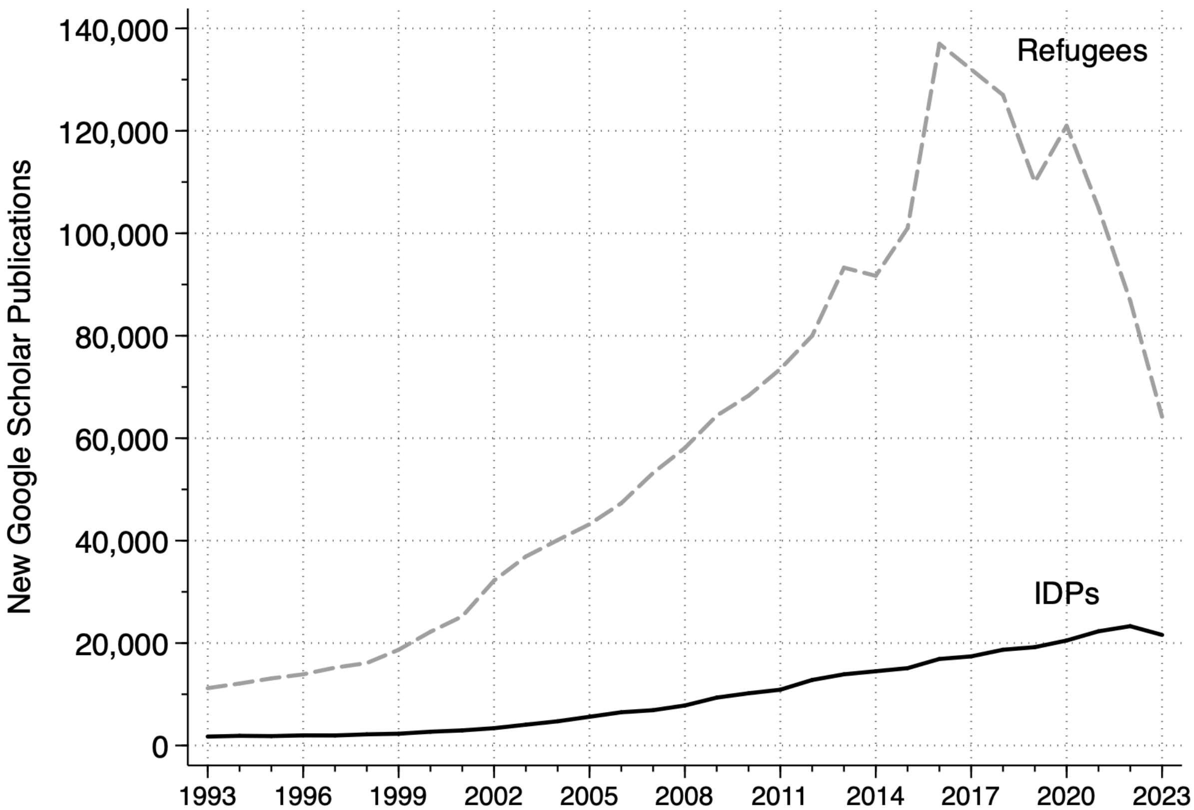
Contents

A Empirical Appendix

A.1 Prevailing Scholarly Neglect of Internal Displacement

Figure A-1: Scholarly Attention to Internal Displacement Lags Relative to Attention to Refugees



Note: The solid black line shows the number of new publications logged in Google Scholar referencing ("IDP" OR "Internal displacement" OR "IDPs" OR "internal displacement" OR "Internal Displacement") by year. The dashed grey line shows the number of new publications logged in Google Scholar referencing ("refugee" OR "Refugee" OR "Asylum" OR "asylum") by year. All data come from Google Scholar.

A.2 Literature on Migrant Decisionmaking

Scholars of migration generally analyze migrant flight patterns in terms of a choice-based, rationalist, utility-maximizing framework (Czaika, 2009; Hanson and McIntosh, 2016). In seminal models, individuals weigh the costs of leaving versus the prospective benefits of migrating to various destination countries before deciding whether, when, and where to go, subject to uncertainty and budget constraints. Factors driving individuals to leave their homes are "push" factors, while factors inducing gravitation toward certain destinations are "pull" factors.[44] While this model of migrant decisionmaking has been thoroughly tested in the context of *international* migration, little existing work systematically analyzes patterns of *internal* displacement.

Push Factors The literature on refugee and asylum-seeker decisionmaking emphasizes a limited set of push and pull factors that influence the expected costs and benefits of flight. Corresponding with the legal definition of forced migrants as individuals fleeing persecution, conflict and repression in home countries raise the costs of staying (Moore and Shellman, 2007; Giménez-Gómez, Walle and Zergawu, 2019). Apart from its immediate implications for physical integrity, moreover, violence induces out-migration by destroying economic opportunities and individual livelihoods (Adhikari, 2013), by weakening property rights (Millán-Quijano and Pulgarín, 2023), and by changing local, ethno-political power structures (Steele, 2017). Displacement thus increases with victimization and ethnopolitical discrimination. Eliminationist policies aimed at minoritization, expulsion, or eradication of specific populations are one of the foremost drivers of displacement (Mylonas, 2012; Balcells and Steele, 2016; Lichtenheld, 2020; Garrity, 2023).

Pull Factors Existing research also highlights several key pull factors. Above all, distance raises migration costs (Iqbal, 2007), so we should observe asylum-seekers and IDPs pulled in greatest numbers to neighboring areas. Similarly, migrant networks—whether based on ethnicity, kinship, or political affiliation—are a powerful draw to specific destinations (Fitzgerald, Leblang and Teets, 2014; Balcells, 2018). Before individuals migrate, kin groups can relay information about conditions in prospective destinations, as well as risks along the way (Blair, Grossman and Weinstein, 2022*b*). Within destination communities, these networks ease integration (Rüegger and Bohnet, 2018), reduce the risk of xenophobic attacks (Freibel, Gallego and Mendola, 2013), and help incoming migrants secure higher-paying jobs (Munshi, 2003) and better housing (Light, Bernard and Kim, 1999).

Political and economic conditions in prospective host communities also exert a powerful influence on migrants' decisionmaking. This is instinctive when migration is viewed, as in choice-based models, as an inter-temporal optimization problem (Czaika, 2009). Prior research identifies the important role of security and civil liberties as pull factors. Migrants

[44] Future work should consider whether other determinants of migration choice vary when the primary impetus for displacement is eliminationist or not. Choice is obviously circumscribed in cases of forced relocation.

being forcibly relocated or fleeing persecution are naturally less likely to relocate to destinations perpetrating the same abuses from which they are fleeing in the first place (Moore and Shellman, 2007; Echevarria and Gardeazabal, 2016). Instead, conflict-induced migrants often gravitate toward less violent areas around security infrastructure (Czaika and Kis-Katos, 2009). Economic conditions also matter. Even for forcibly displaced persons, whose chief motive is personal security, factors like relative differences in GDP per capita, labor supply, and prices are taken into account (Fitzgerald, Leblang and Teets, 2014; Hanson and McIntosh, 2016). These factors pull migrants toward strong, growing economies.

Finally, gravitation toward politically liberal host communities and away from restrictive ones raises the prospect that specific migration policies also shape the calculus of fleeing migrants (Czaika, 2009). Increasingly, Global North countries wield externalization policies intended to deter inflows (Norman, 2020). These policies are predicated on the notion that anti-migrant restrictions can dissuade future migrants from attempting migration journeys. The converse of this dynamic is that displaced people often gravitate toward host communities with more liberal de jure migration policies, such as laws guaranteeing work rights and integration support (Blair, Grossman and Weinstein, 2022*b*).

In the context of internal displacement, existing work finds broad support for utility-maximizing theories of migration choice. For instance, Atuesta and Paredes (2016) find that IDPs in Mexico flee violent, cartel-controlled areas and gravitate toward safer and more prosperous host communities. Similar patterns govern internal displacement in Ukraine—civilians from rural areas near the frontlines typically flee to government-controlled urban centers (Mykhnenko, Delahaye and Mehdi, 2022; Mehrab et al., 2024). In Libya, Di Maio, Sciabolazza and Molini (2023) show that IDPs flee along network paths toward areas with more co-ethnics and previous migrants, toward road-connected areas, and toward safer and more prosperous communities. Colombian IDPs also move short distances to safer areas populated by previous waves of migrants (Lozano-Gracia et al., 2010; Balcells and Steele, 2016; Saldarriaga and Hua, 2019). In Somalia, a significant portion of IDP outflows are also driven by climatic conditions, like droughts and floods (Yuen, Warsame and Checchia, 2022; Momeni et al., 2024; Oh et al., 2024). The confluence of climatic and conflict-related displacement drivers spurs internal displacement into safer and more climate-resilient localities (Thalheimer, Schwarz and Pretis, 2023).

A.3 Literature on the Consequences of Displacement

In fragile, conflict and post-conflict settings, the potential impacts of mass displacement on security are significant and diverse. Prior work has focused on two related outcomes: armed conflict and social strife. Existing scholarship offers rich but often contradicting findings on how displacement affects these outcomes, suggesting that FDP may variously exacerbate or dampen militant and communal violence. Lehmann (2020) provides an excellent overview of this literature, and theoretical perspectives on how displacement, aid, and violence intersect. I help adjudicate these perspectives in the context of Somalia.

Displacement and Militancy The effect of civil conflict in spurring large-scale forced displacement is well-known. But displacement may also serve as a cause of conflict. For one, refugee flows can spur conflict spillovers from origin countries into neighboring regions where refugees flee. Salehyan and Gleditsch (2006) show that displacement can broaden rebel networks, and contribute to the cross-border diffusion of arms, ideologies, and combatants. Refugee encampments may serve as particularly dangerous conduits for insurgent recruitment and training (Zolberg, Suhrke and Aguayo, 1989). For instance, the Afghan Taliban grew from a network of settlements and madrassas for Afghan refugees in Pakistan (Harpviken and Lischer, 2013). Militants embedded among displaced populations can also manipulate humanitarian aid (Lischer, 2006), instrumentalize ethnicity (Whitaker, 2003), and conscript vulnerable youths into rebel organizations (Haer and Hecker, 2018). Consequently, refugee flows are associated with increased terrorism (Milton, Spencer and Findley, 2013), though much of this effect is because displaced people are targets, rather than perpetrators, of violence (Onoma, 2013; Fisk, 2018).

Many of the same dynamics are magnified in the case of internal displacement. Where militants have infiltrated displaced populations, mass movement can give fighters cover to enter localities for attacks (Lischer, 2008). When refugees migrate to contested or insurgent-held communities, governments may engage in preemptive repression (Stein and Cuny, 1994), sparking further conflict and repeated flight (van Houte, 2017). Conditions in host communities can also drive returnees to support militants. Poor and low-skilled migrants are often forced into itinerant or illicit jobs (Petrin, 2002; Fransen, Ruiz and Vargas-Silva, 2017), making them ripe targets for rebel recruitment (Haer and Hecker, 2018). Price shocks resulting from mass displacement also reduce the opportunity costs of rebellion Camarena (2016*a*). Further, migration can strain fragile institutions in origin countries (Camarena, 2016*b*), increasing dissatisfaction with the state (Schultz, 2011; Lakhani and Amiri, 2020). Even where displaced people support government forces, violence may increase as insurgents launch retributive attacks to deter collaboration (Kalyvas, 2006; Steele, 2017; Balcells, 2018; Lichtenheld and Schon, 2021). Humanitarian aid to displaced people may also reduce the number of potential fighters, as Masterson and Lehmann (2020) find in Syria.

Displacement and Social Conflict In addition to militancy, displacement may affect social conflict. As Schwartz (2019, p. 110) notes, "conflict between returning and non-migrant populations after civil war is a nearly ubiquitous issue for societies recovering from such wars." Migration-induced competition over jobs (Petrin, 2002; Bhavnani and Lacina, 2015), housing (Harild, Christensen and Zetter, 2015; Perelli-Harris et al., 2024), and land (Schwartz, 2019; Osman and Abebe, 2023) may spur criminality and communal strife. In countries like Somalia, where livelihoods are tied to agriculture, property disputes are a particularly common source of grievance. In these settings, violent land clashes have erupted between returnees and host community members (Van Leeuwen and Van Der Haar, 2016; Kamminga and Zaki, 2018; Ruiz and Vargas-Silva, 2021). These clashes have significant welfare implications. Economically, they may destroy the productivity of land by increasing contamination with mines or damaging irrigation infrastructure (Seefar, 2019). Socially, land conflicts are likely to metastasize into broader tribal disputes or honor feuds, which can spur recriminatory killings (Murtazashvili, 2016). Property disputes can also exacerbate insurgent violence (Albertus, 2020), especially where migrants or hosts ally with militants to combat alleged usurpers (Lakhani and Amiri, 2020).

If local elites politicize identity (Whitaker, 2003; Balcells and Steele, 2016; Gaikwad and Nellis, 2021*a*) or make threats to dissuade demographic change (Gaikwad and Nellis, 2017) in response to returnee inflows, displacement can spur ethnic conflict (Bohnet, Cottier and Hug, 2018). Migration status may itself take on identity salience if policies attach privileges to those collective categories. For instance, when government regulations were perceived as benefiting returnees in Burundi, violent cleavages erupted between returnee and non-migrant community members (Schwartz, 2019). This dynamic is especially likely to unfold over humanitarian assistance. Marginalized hosts frequently clash with FDP who they believe hold disproportionate access to aid (Duncan, 2005; Breslawski, 2024).

Displacement and Stability A third approach emphasizes the contributions of displaced people to security and stability. Above all, this perspective views migrants as a source of human capital, and hence an engine for peacebuilding and development (Loescher, 1996). Past experiences of violence foster emotional attachments to home (Blitz, Sales and Marzano, 2005), as well as self-efficacy and expertise in risk assessment (Ghosn et al., 2021). These factors make migrants a crucial asset for post-conflict reconciliation. Displaced peoples' familiarity with hardships of war may also lead them to oppose future violence.

Developmental contributions of returnees can also foster stability. Zhou and Shaver (2021) show that large, concentrated populations of displaced people reduce local conflict by improving economic conditions. Humanitarian assistance targeting FDP may raise living standards for whole communities (Kreibaum, 2016). Aid spillovers from displaced beneficiaries to non-migrant neighbors also improve community relations, increase market exchange, and foster positive social contact (Lehmann and Masterson, 2020). In Afghanistan, some non-returnee urban poor have benefited from infrastructural investments targeting refugee repatriates (Harild, Christensen and Zetter, 2015). In east Africa, IDP flows have facilitated entrepreneurship and market exchange (Jacobs, Kubiha and Katembera, 2020; Yasukawa, 2020). Additionally, migrants may bolster production in destination communities by bringing skills acquired while displaced (Bahar et al., 2024). Under these conditions, migration can reduce conflict and bolster economic productivity.

A.4 Summary Statistics

Table A-1: Summary Statistics for Gravity Analyses

	Observations	Mean	Std. Dev.	Min	Max
Dependent Variables					
Total IDP Flow	219040	0.011	0.386	0.000	99.116
Conflict-Induced IDP Flow	219040	0.003	0.167	0.000	28.583
Climate-Induced IDP Flow	219040	0.007	0.336	0.000	99.116
Other Driver IDP Flow	219040	0.000	0.036	0.000	12.414
Covariates					
Conflict in Origin	219040	0.180	0.494	0.000	4.800
Conflict in Destination	219040	0.180	0.494	0.000	4.800
Military Base in Destination	219040	0.248	0.432	0.000	1.000
NDVI Anomaly in Origin	219040	95.752	9.068	67.017	146.702
NDVI Anomaly in Destination	219040	95.752	9.068	67.017	146.702
Growing Season in Origin	219040	0.253	0.435	0.000	1.000
Growing Season in Destination	219040	0.253	0.435	0.000	1.000
Distance	219040	-0.000	1.000	-1.721	3.363
Same District Dyad	219040	0.014	0.115	0.000	1.000
Same Region Dyad	219040	0.062	0.241	0.000	1.000
# of Clan Ties	219040	0.370	0.980	0.000	16.000
Dominant Clan Tie	219040	0.038	0.191	0.000	1.000
Population in Origin	219040	1.925	2.388	0.267	18.037
Population in Destination	219040	1.925	2.388	0.267	18.037
Road Connected Dyad	219040	0.748	0.434	0.000	1.000
Relative Road Connectivity	219040	0.354	0.478	0.000	1.000
Relative Economic Development	219040	-0.000	1.000	-1.096	3.345
Nighttime Light Ratio	219040	-0.002	1.107	-347.818	95.227

Note: Summary statistics are from the main estimation sample between January 2016 and April 2019. The sample is a perfectly balanced panel of directed, district dyad–months. Dependent variables are expressed in 1000s of IDPs flowing. Conflict covariates are expressed in 10s of attacks. Military base denotes whether a destination district hosts a Somali, AMISOM, or US base. NDVI anomaly is expressed as a percentage of the long-run historical average, so values below 100 signify drought conditions. Growing season denotes district-specific timing of biannual wet seasons. Clan ties are calculated by summing the number of clans that share a historical settlement zone between districts. Dominant clan tie denotes whether districts share the same dominant clan. Relative road connectivity is the number of primary roads in a destination district relative to an origin district. Relative economic development is a z-standardized index that takes into account relative levels of agricultural productivity, charcoal suitability, and deepwater harbor access between destination and origin districts. Nighttime light ratio is the ratio of average nighttime luminosity in a destination district compared with an origin district.

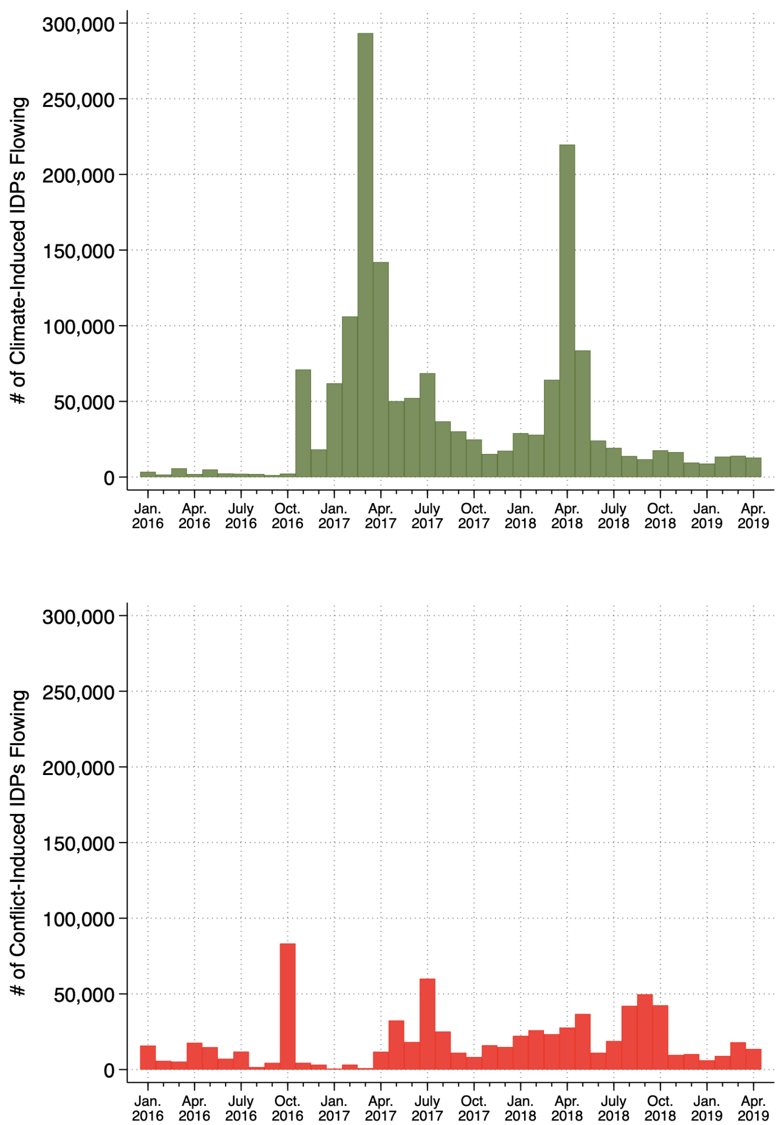
Table A-2: Summary Statistics for District Analyses

	Observations	Mean	Std. Dev.	Min	Max
Dependent Variables					
Social Unrest	2886	0.202	0.402	0.000	1.000
Communal Conflict	2886	0.212	0.409	0.000	1.000
Insurgent Spy Operations	2886	0.030	0.170	0.000	1.000
Insurgent Social Control	2886	0.124	0.330	0.000	1.000
Assassinations	2886	0.070	0.255	0.000	1.000
Insurgent Intimidation	2886	0.093	0.290	0.000	1.000
Independent Variables					
Between-District IDP Inflow	2886	1.978	6.864	0.000	72.834
Predicted Between-District IDP Inflow	1998	2.001	5.328	0.000	52.585
Within-District IDP Inflow	2886	0.703	3.853	0.000	99.116
IDP Outflow	2886	1.193	4.589	0.000	99.869
Control Variables					
Dominant Clan: Daarood	2886	0.194	0.396	0.000	1.000
Dominant Clan: Dir	2886	0.196	0.397	0.000	1.000
Dominant Clan: Hawiye	2886	0.470	0.499	0.000	1.000
Dominant Clan: Reewin	2886	0.140	0.347	0.000	1.000
Minority Clan	2886	0.552	0.497	0.000	1.000
Historical Violence	2886	10.687	14.281	0.000	63.132
Military Base	2886	0.455	0.498	0.000	1.000
Road Access	2886	0.919	0.273	0.000	1.000
Trade Routes	2886	0.902	0.297	0.000	1.000
NDVI Anomaly	2886	95.446	9.137	67.017	146.702
Growing Season	2886	0.274	0.446	0.000	1.000

Note: Summary statistics are from the main estimation sample between January 2016 and April 2019. The sample is a perfectly balanced panel of district–months. Dependent variables are expressed as the extensive margin of various conflict-related outcomes. Independent variables are expressed in 1000s of IDPs flowing. Clan covariates are indicators for historical clan settlement zones. Minority clan denotes whether a district is home to a minority clan (Hill, 2010). Historical violence is the sum of insurgent attacks in 2016. Military base denotes whether a destination district hosts a Somali, AMISOM, or US base. Road access and trade routes denote whether primary roads or livestock trade routes respectively pass through a district. NDVI anomaly is expressed as a percentage of the long-run historical average, so values below 100 signify drought conditions. Growing season denotes district-specific timing of biannual wet seasons.

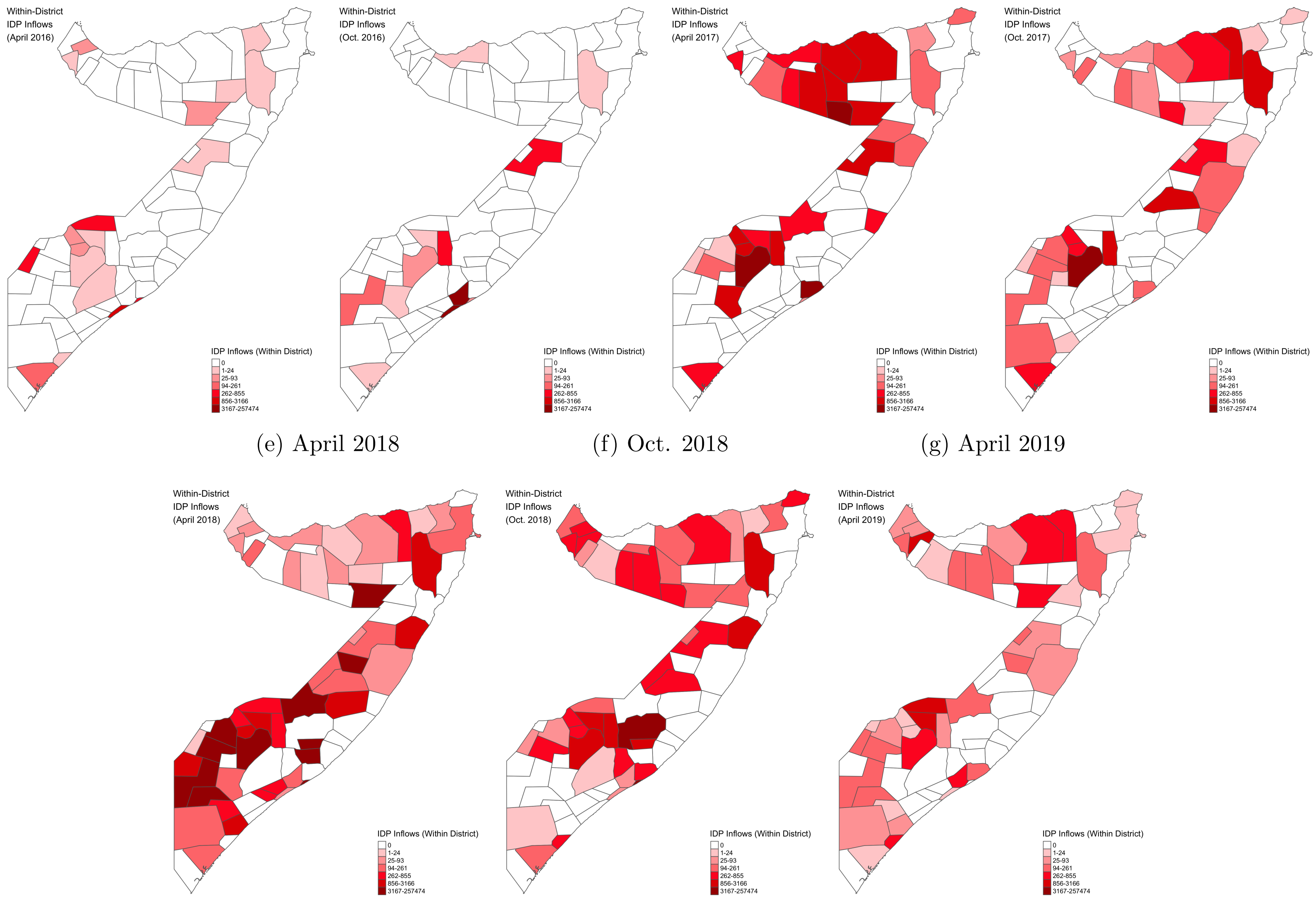
A.5 Patterns of Internal Displacement in Somalia

Figure A-2: Time-Series of IDP Flows in Somalia by Driver



Note: Bars denote the number of IDPs induced by the respective driver of flows by month.

Figure A-3: Within-District IDP Inflows

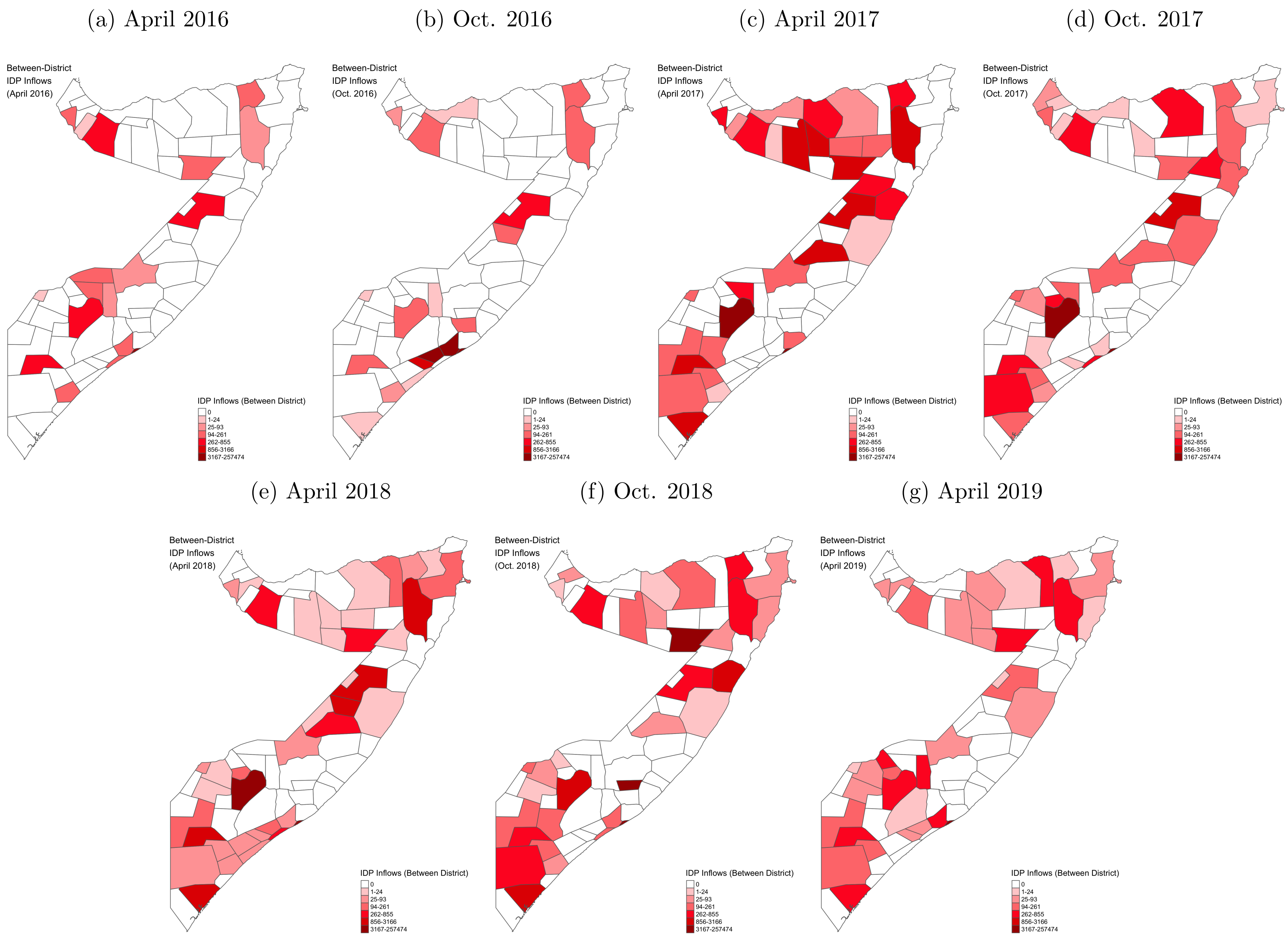


(a) April 2016 (b) Oct. 2016 (c) April 2017 (d) Oct. 2017

(e) April 2018 (f) Oct. 2018 (g) April 2019

Note: Panels shade districts by the number of IDP inflows originating from within the focal district.

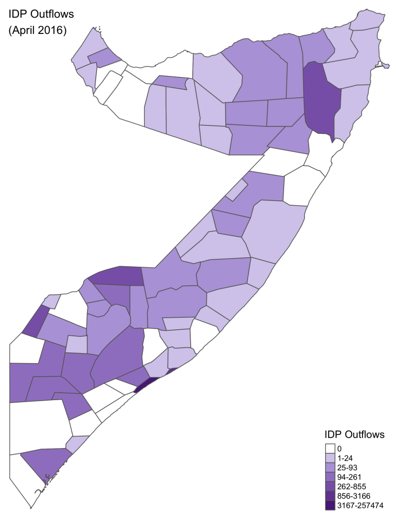
Figure A-4: Between-District IDP Inflows



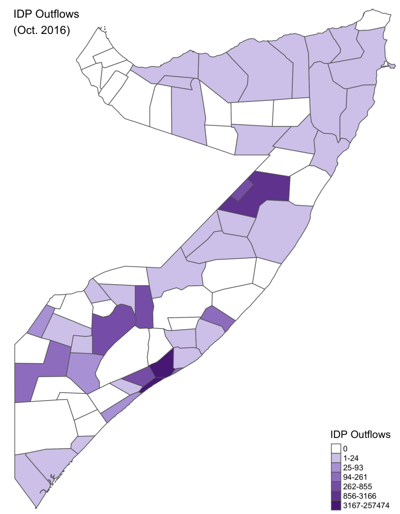
Note: Panels shade districts by the number of IDP inflows originating from outside the focal district.

Figure A-5: IDP Outflows

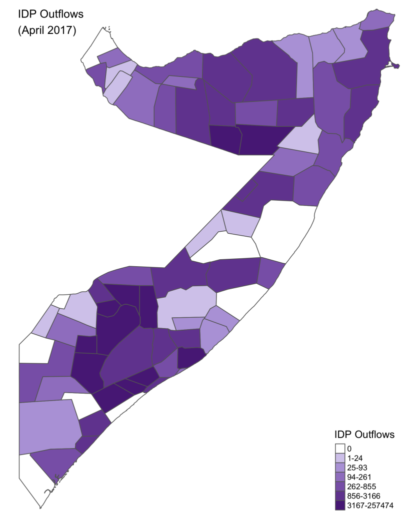
(a) April 2016



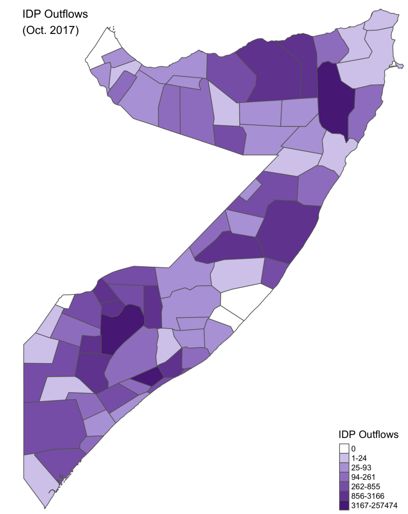
(b) Oct. 2016



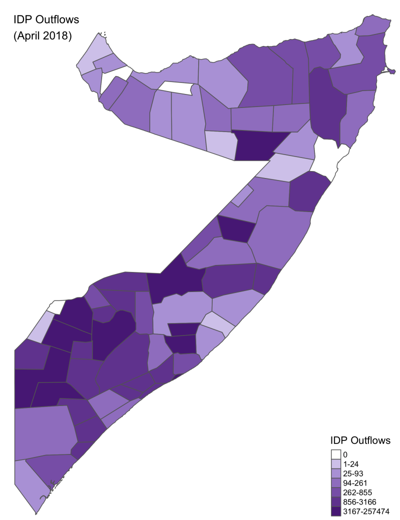
(c) April 2017



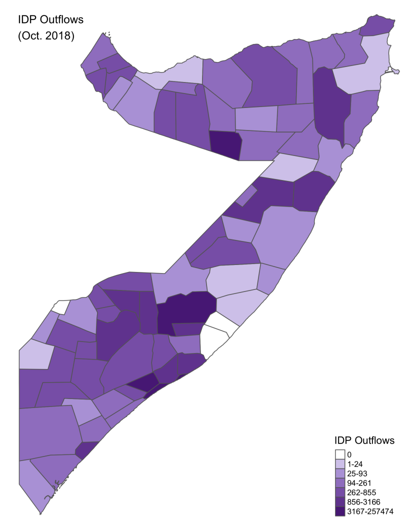
(d) Oct. 2017



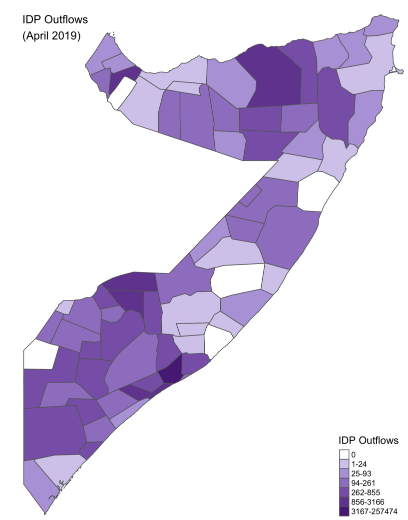
(e) April 2018



(f) Oct. 2018

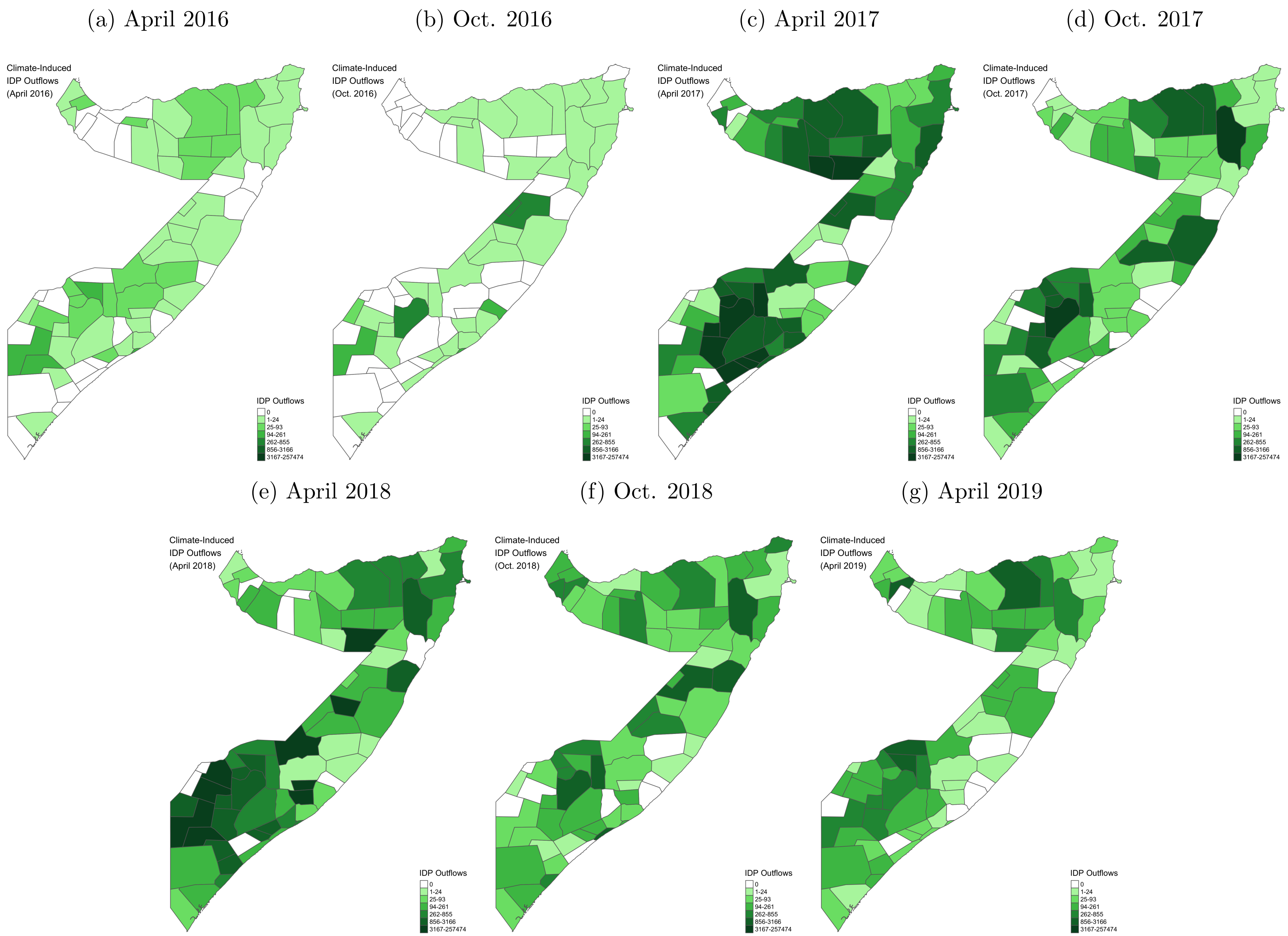


(g) April 2019



Note: Panels shade districts by the number of IDP outflows from the focal district.

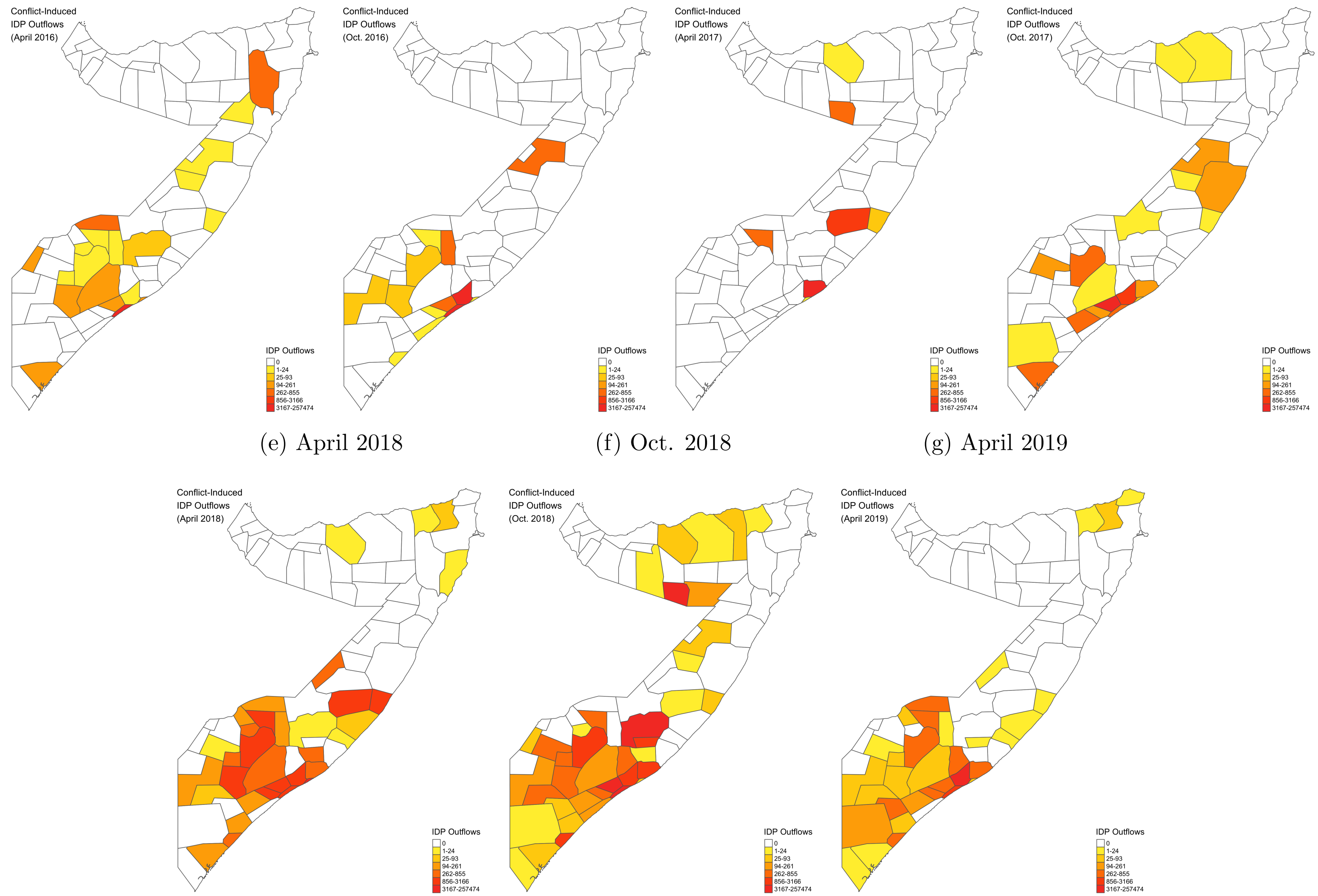
Figure A-6: Climate-Induced IDP Outflows



Note: Panels shade districts by the number of climate-induced IDP outflows from the focal district.

Figure A-7: Conflict-Induced IDP Outflows

(a) April 2016 (b) Oct. 2016 (c) April 2017 (d) Oct. 2017 (e) April 2018 (f) Oct. 2018 (g) April 2019



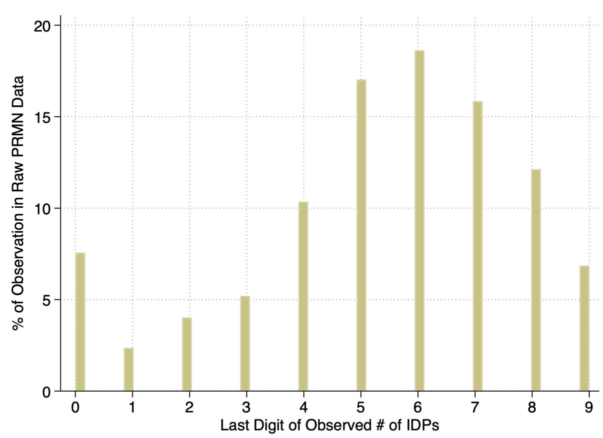
Note: Panels shade districts by the number of conflict-induced IDP outflows from the focal district.

A.6 Digit Heaping in PRMN Data

Our IDP data draw from the Protection & Return Monitoring Network (PRMN) in Somalia. The primary concern with these data is that monitors responsible for tracking and reporting IDP flows rely on field access to measure internal displacement. As UNHCR-Somalia staff note, "[t]here are periods of time where certain regions will have a reduced monitoring footprint as a result of external events, changes in field partners or other reasons" (UNHCR-Somalia, 2017). Endogeneity between field conditions and the quality of measurement would raise concerns about multiple forms of bias in the IDP flow data. For instance, if PRMN monitors can only operate in districts free from al-Shabaab influence, the data might systematically undercount flows of conflict-induced IDPs moving within insurgent-controlled regions. We might also worry that monitors have a harder time accurately measuring displacement in large urban centers, where IDPs can settle, unbeknownst to enumerators, in large, informal settlements.

To investigate and build confidence in the quality of the PRMN data, I turn to a data forensic technique. Specifically, I examine digit heaping, which occurs when the last digit of a set of numbers disproportionately ends in a particular value. Digit heaping results from terminal digit preference, a well-known human bias towards recording specific final digits when making notes or otherwise tallying numbers. Because humans often round or estimate, terminal digit preference often results in an excessive number of measurements ending in 0 or 5. Applying this insight, researchers examining state capacity and census-taking have noted that digit heaping in census age data is a sign of weak or limited on-the-ground presence by government-affiliated enumerators (Lee and Zhang, 2017; Suryanarayan and White, 2021).

Figure A-8: Distribution of Last Digits in PRMN Data



Note: Bars denote the percent of observations of IDP flows from the PRMN data that end in the respective digit denoted in the x-axis.

I examine digit heaping on 0 and 5 in the raw IDP flow data from PRMN field monitors.

If field conditions constrain monitors from accurate assessment, we should see systematic patterns of digit heaping in the raw PRMN data. In Figure A-8 I plot the last digit of every reported IDP flow from PRMN. There is no systematic evidence that values ending in 0 or 5 appear disproportionately. Combined, just 24.6% of observations end in 0 or 5. This is well-within the 10–29% range used to define zero preference in clinical trials (Thavarajah, White and Mansoor, 2003, p. 821).

To assess digit heaping more systematically I calculate the share of all observed flows that end in 0 or 5 in each district-month. If measurement accuracy is endogenous to field conditions, I would expect systematic, distinguishable correlations between digit heaping and security variables. For instance, if violence constrained the ability of PRMN monitors to access certain districts, we would expect to observe the incidence of conflict to be positively correlated with digit heaping. In Table A-3 I find no distinguishable effect of conflict or the presence of military bases on digit heaping. The negative coefficient on nighttime luminosity represents limited evidence that digit heaping is less likely in more economically developed and prosperous districts.

Table A-3: Digit Heaping in Measurement of IDP Flows

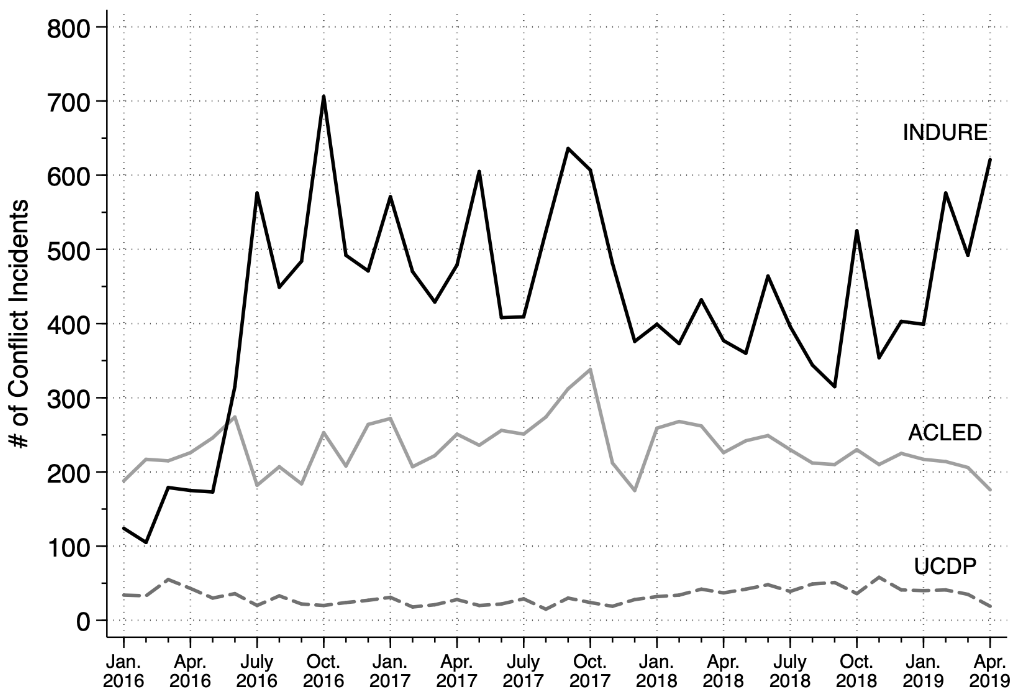
	Digit Heaping (Share of Observed IDP Flows Ending in 0 or 5)			
	Total	**Conflict-Driven**	**Climate-Driven**	**Other-Drivers**
	(1)	(2)	(3)	(4)
Conflict	-0.002	-0.000	-0.001	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)
Military Base	-0.012	0.007	-0.016	0.010
	(0.033)	(0.018)	(0.038)	(0.009)
NDVI Anomaly	-0.000	-0.001**	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.000)
Population	0.004	-0.039	0.044	0.013
	(0.070)	(0.027)	(0.058)	(0.014)
Nighttime Light	-0.012	-0.008**	-0.003	0.003*
	(0.010)	(0.004)	(0.009)	(0.002)
Observations	2960	2960	2960	2960
AIC	-1048	-3979	-1949	-8195
PARAMETERS				
District FE	Yes	Yes	Yes	Yes
Year-Specific Month FE	Yes	Yes	Yes	Yes
Any IDP Flow (=1)	Yes	Yes	Yes	Yes

Note: * p <.10, ** p <.05, *** p <.01. Robust, district-clustered standard errors are in parentheses. Any IDP flow is an indicator variable for district-months with any positive inflow of IDPs.

A.7 Comparing Violent Event Data from Somalia

Conflict records in the main analyses come from the International Distributed Unified Reporting Environment (INDURE), a restricted-access platform maintained by the US Defense Department. I also consider a number of outcomes from the Armed Conflict Location & Event Dataset (ACLED) (Raleigh, Kishi and Linke, 2023). Figure A-9 compares my INDURE data to data from the Armed Conflict Location & Event Dataset (ACLED) and the Uppsala Conflict Data Program Global Event Dataset (UCDP), the two most prominent open-source conflict trackers used in extant analyses of the war in Somalia (e.g., Maystadt and Ecker, 2014; Schon, 2016; Thalheimer, Schwarz and Pretis, 2023; Oh et al., 2024). On average over the study period I observe 194 more events per month in INDURE than ACLED and 394 more events per month in INDURE than UCDP.

Figure A-9: Comparing Coverage of Prominent Conflict Trackers

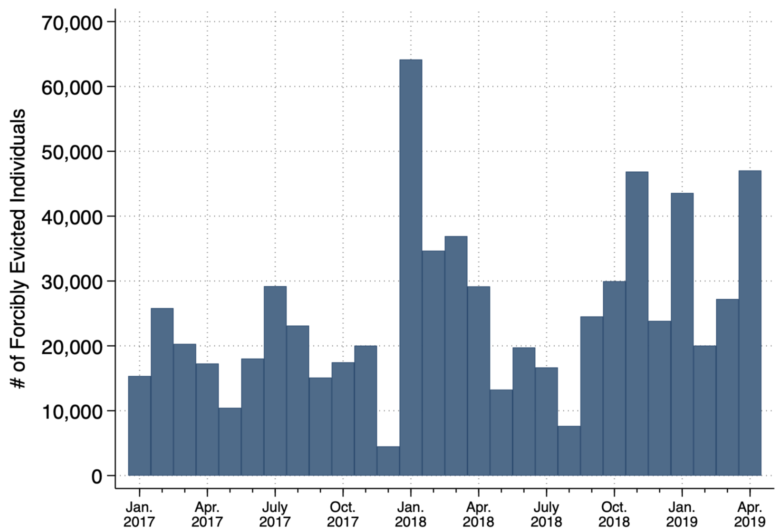


Note: Lines show the number of events per month observed in Somalia in the INDURE data (solid black line), the ACLED data (solid gray line), and the UCDP data (dashed black line).

A.8 Forced Evictions

Data on forced evictions in Somalia come from the NRC–Somalia office's Information, Counselling and Legal Assistance (ICLA) team.

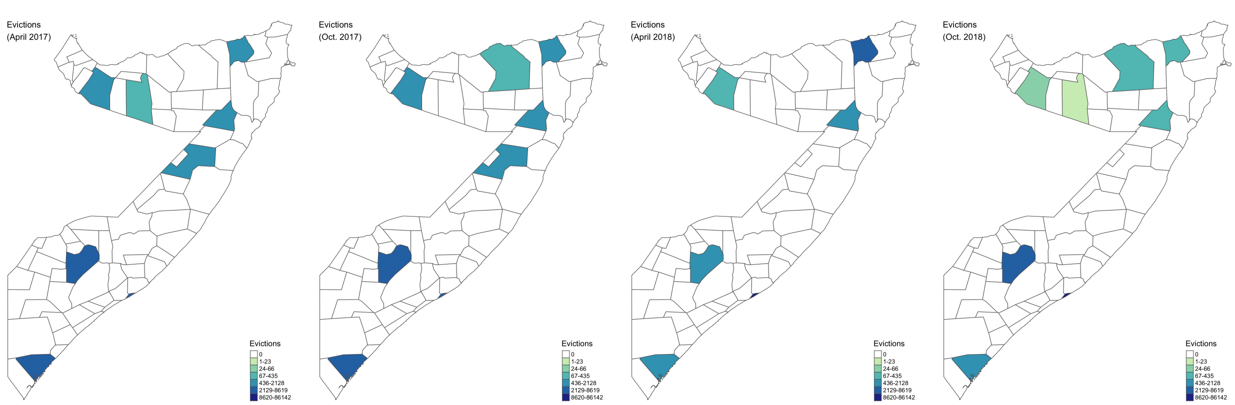
Figure A-10: Forced Evictions Over Time in Somalia



Note: Bars denote the number of individuals forcibly evicted by month.

Figure A-11: Mapping Forced Evictions in Somalia

(a) April 2017 (b) Oct. 2017 (c) April 2018 (d) Oct. 2018



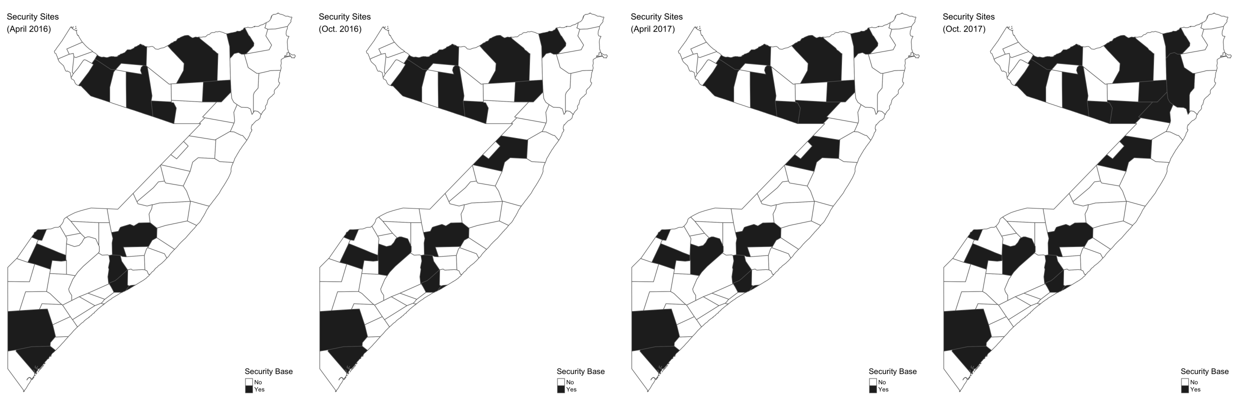
Note: Panels shade districts by the intensive margin of individuals forcibly evicted.

A.9 Security Infrastructure

Data on security infrastructure in Somalia come from the US Government's GEOnet Names Server (GNS), maintained by the US National Geospatial-Intelligence Agency and the US Board on Geographic Names.

Figure A-12: Mapping Security Infrastructure in Somalia

(a) April 2016 (b) Oct. 2016 (c) April 2017 (d) Oct. 2017



(e) April 2018 (f) Oct. 2018 (g) April 2019

Note: Panels shade districts by the extensive margin of security infrastructure.

A.10 Gravity Estimation

To understand descriptive patterns of internal displacement in Somalia, I first estimate a series of gravity models. Head and Mayer (2014) offers a comprehensive review of research on gravity estimation. Gravity models are the workhorse empirical tool for analyzing migration and trade flows (Anderson, 2011). Classical work has applied this class of models to understand dynamics of international commercial exchange (Rose, 2004), flows of refugees (Giménez-Gómez, Walle and Zergawu, 2019), and diffusion of violence (Carter and Ying, 2021). Gravity estimators model flows between an origin location and a destination location as a function of dyadic factors, like distance or shared ethnic ties between localities, as well as location-specific factors, like violence in origin communities or employment opportunities in destination communities. Applications of gravity models to understand patterns of *internal displacement* are relatively rare in extant literature, although this class of models is well-suited for applied research on IDPs (Lozano-Gracia et al., 2010; Saldarriaga and Hua, 2019). Most extant work on IDP flow uses agent-based (Pham and Luengo-Oroz, 2023; Mehrab et al., 2024) or network models (Oh et al., 2024) to study flows of IDPs.

The central debate in the gravity literature is between proponents of log-linearized versus exponential specifications. In the log-linearized transformation, the dependent variable is logged and then estimated with ordinary least squares. However, Jensen's inequality holds that $E[ln(y)] \neq ln[E(y)]$. Owing to this inequality, OLS estimates of the log-linearized transformation are inconsistent in the presence of heteroscedasticity (Santos Silva and Tenreyro, 2006). A second problem with the log-linear transformation relates to its handling of zero values. In standard migration gravity models, many zeroes are typically observed as flight is rare within some dyads. In the PRMN data, 0 IDP flow is observed in 96.7% of directed dyad-months. The log-linear transformation drops observations with zero values because $ln(0)$ is undefined. Generally, researchers have avoided this problem by adding a small positive quantity to the dependent variable prior to logging—most often $ln(\text{Dependent Variable} + 1)$. However, this procedure leads to inconsistent parameter estimates because the gravity framework requires that 1 is added to both the dependent variable and the explanatory regressors. In turn, if 1 is added to variables on both sides of the equation, the log-linear transformation is rendered infeasible (Echevarria and Gardeazabal, 2016, p. 266).

In light of these problems, some scholars advocate for zero-truncated (Rüegger and Bohnet, 2018) or zero-inflated models (Moore and Shellman, 2007). Unfortunately, neither of these approaches alleviates methodological concerns. Truncated estimators that exclude zero-valued observations suffer from significant bias (Martin and Pham, 2020). Zero-inflated models make the untenable assumption that some zero-valued observations are structural and others arise naturally from a count process (Cameron and Trivedi, 2013). In the context of internal displacement, zero-inflation is theoretically inappropriate because IDP flows are generated by a single process. There are no structural factors precluding flight within any dyad, merely factors, like distance, making it more or less probable. Secondarily, zero-inflated estimators suffer the additional drawback that they are sensitive to the scale of the dependent variable.

I estimate a Poisson pseudo-maximum likelihood (PPML) gravity estimator, which models the conditional mean of the dependent variable using an exponential function. PPML is a weighted, non-linear least squares estimator, and critically, neither requires that the data follow a Poisson distribution nor that they take strictly integer values (Santos Silva and Tenreyro, 2006, p. 645). The PPML estimator also shares the same first-order conditions as the standard Poisson maximum likelihood estimator. Alleviating concerns about the presence of many zeroes, Santos Silva and Tenreyro (2011) show that PPML is well-behaved in the presence of excess zeroes, and that the estimator makes no assumptions about dispersion. Because PPML only requires that the conditional variance is proportional to the conditional mean, not necessarily equal to it, the estimator is valid in the presence of under-, equi-, and over-dispersion. Martin and Pham (2020) conclude that PPML is the preferred gravity estimator under broad conditions. While advantages to multiplicative gravity estimation are generally recognized in the economics literature (e.g., Beine, Bertoli and Moraga, 2016), best practices have not diffused as widely to political science (but see Giménez-Gómez, Walle and Zergawu, 2019).

This gravity equation is expressed as:

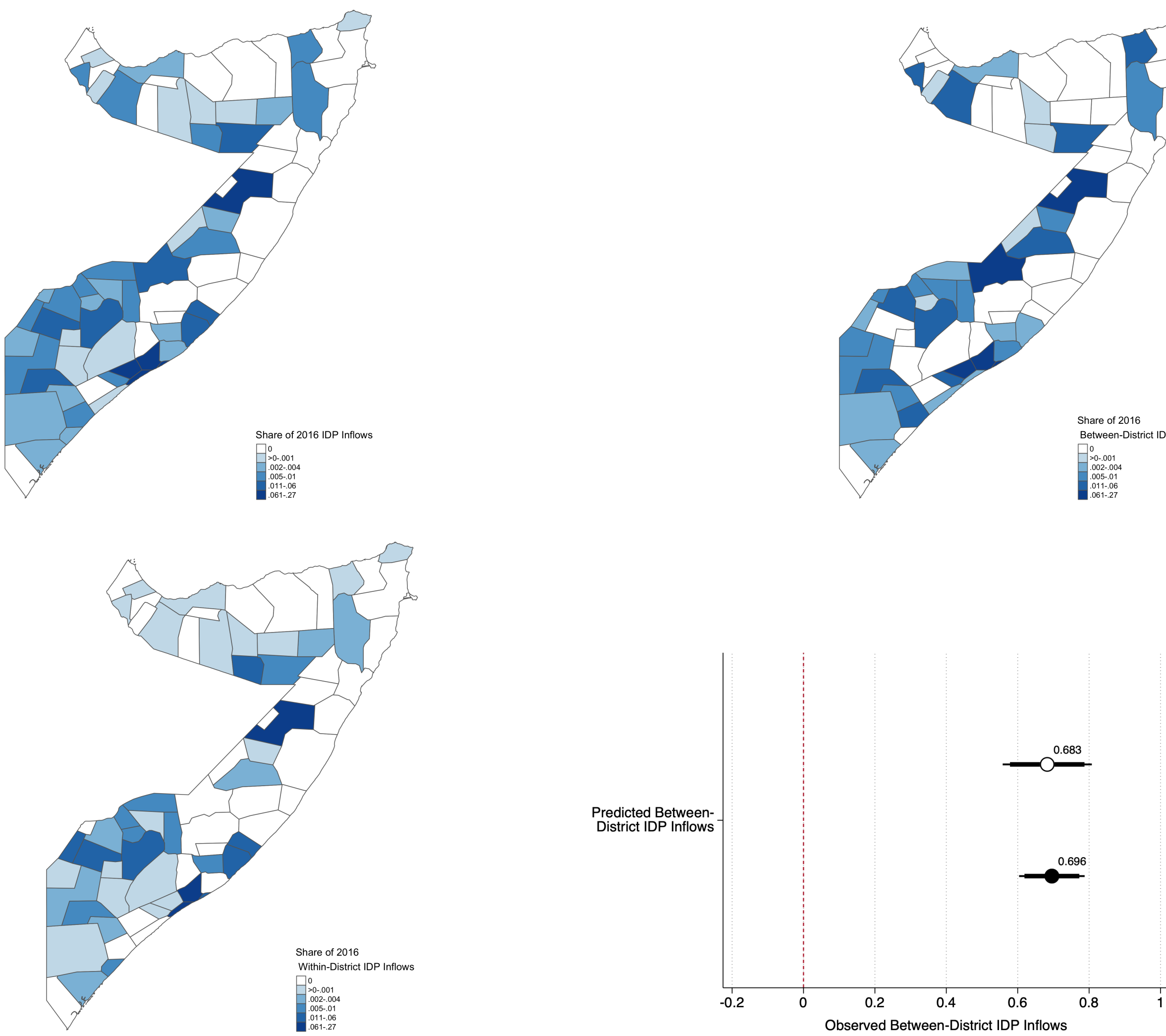
$$Y_{p,t+1} = exp(\alpha_o + \beta_d + \gamma_t + \lambda(G_{u,t}) + \phi(X_{o,t}) + \mu(Z_{d,t}) + \epsilon_{u,t}) \quad \text{(A1)}$$

where p indexes directed pairs of origin–destination district dyads, o indexes districts of origin within Somalia, d indexes destination districts within Somalia, t indexes year-specific months, and u indexes undirected pairs of origin–destination district dyads. $Y_{p,t+1}$ is the number of IDPs flowing within a directed dyad-month. $G_{u,t}$ is a vector of dyadic controls for undirected dyad u; $X_{o,t}$ is a vector of lagged covariates specific to origin o; and $Z_{d,t}$ is a vector of lagged covariates specific to destination district d. α_o are origin district fixed effects; β_d are destination fixed effects; and γ_t are year-specific month fixed effects. This fixed effects structure accounts for "multilateral resistance"—the barriers between each origin district and flows to all potential destination districts in each month (Fally, 2015). $\epsilon_{u,t}$ is the error term. Standard errors are clustered by undirected dyad to account for correlated disturbance terms within origin-destination pairs.

A.11 Predicting IDP Flows Using Historical Settlement Patterns

To construct a measure of prior IDP settlement patterns, I use data on the universe of IDP flows in 2016, the earliest available year in the PRMN matrix. I sum all nationwide IDP flows in 2016, and then calculate the share of the total, nationwide 2016 IDP flow that arrived in each district. Formally, this share is expressed as $\frac{\text{District IDP Inflows}_{2016}}{\text{Nationwide IDP Inflows}_{2016}}$. Shares of all IDP flows, between-district flows, and within-district flows are plotted below.

Figure A-13: Historical IDP Settlement Patterns



Note: Maps shade districts by the share of total, nationwide 2016 IDPs arriving. The top left panel examines overall shares, the top right panel examines shares of between-district IDPs, and the bottom left panel examines shares of within-district IDPs. The bottom right panel shows the results of a regression of observed between-district IDP inflows on predicted between-district IDP inflows.

A.12 Determinants of IDP Flows

Table A-4 reports results from the core gravity models. Columns 1-2 study all IDP flows, while columns 3-4, 5-6, and 7-8 respectively consider conflict-induced, climate-induced, and other IDP flows as identified by PRMN monitors.[45] Across specifications, I document spatiotemporal patterns of internal displacement in Somalia that generally comport with choice-based, utility-maximizing models of migrant decisionmaking. For instance, across all specifications I find a large, distinguishable negative effect of distance on IDP flows. Increasing inter-district distance by one standard deviation ($\approx$ 350 kilometers) is associated with a 3763% reduction in the expected total number of IDP flowing. Similarly, 405% more IDPs flow within the same district, and 137% more flow between districts in the same administrative region.

Apart from distance, infrastructure and economic development are also important. Functionally, most IDPs in Somalia travel along primary road networks. An additional primary road in a destination district relative to an origin district increases expected IDP inflows 85%. A one standard deviation increase in levels of relative economic development between a destination and an origin district is associated with a 33% increase in IDP flows. This finding comports with a large extant literature that finds migrants, even those making decisions under severe constraints like in emergencies or forced displacement crises, often gravitate toward more prosperous areas (Hanson and McIntosh, 2016). Turning to identity- and conflict-related factors, I find evidence that tribal and clan connections shape internal displacement. An additional clan linkage between districts increases expected IDP flows 15%. Additionally, IDPs tend to gravitate toward military infrastructure, where state authority and security provision are often strongest. Destination districts hosting military bases attract 186% more IDPs. Finally, I also find evidence that prior networks of displaced people draw IDPs toward specific destinations, confirming classical accounts (e.g., Munshi, 2003). Inflows increase 2% for every thousand IDPs that flowed within a directed dyad in the prior month.

Turning to columns 3-8, I document a number of substantively intuitive differences in displacement dynamics between flows that PRMN officials identified as having been induced by conflict, climate, or other drivers.[46] These intuitive differences raise confidence in the PRMN classification exercise. For instance, I find that the incidence of violence in origin and destination districts shaped displacement patterns of IDPs identified as conflict-driven but not climate-driven. An additional 10 attacks in an origin district increased outflows of conflict-driven IDPs 19%, while an additional 10 attacks in a destination district decreased inflows of conflict-driven IDPs 71%. This finding suggests that PRMN monitors accurately captured substantive differences in violence-induced versus disaster-induced displacement,

[45] Effect magnitudes referenced in this and the next paragraph refer to column 2 of Table A-4.

[46] IDPs displaced by other drivers were mostly individuals uprooted from urban slums by land conflicts, evictions, or economic shocks (Bryld, Kamau and Sinigallia, 2014; Sert, 2014).

Table A-4: Gravity Model of IDP Flows

	IDP Flows							
	Total		Conflict-Driven		Climate-Driven		Other Drivers	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Conflict in Origin	0.213	0.227	0.209**	0.173**	0.204	0.266	-0.339	-0.413
	(0.213)	(0.220)	(0.088)	(0.086)	(0.401)	(0.410)	(0.717)	(0.734)
Conflict in Destination	-0.169	-0.147	-0.584***	-0.538***	0.488*	0.488	-1.847*	-2.029*
	(0.197)	(0.197)	(0.179)	(0.173)	(0.280)	(0.306)	(1.036)	(1.113)
Military Base in Destination	1.081***	1.050***	1.687***	1.681***	0.253	0.242	1.830***	1.833***
	(0.333)	(0.303)	(0.438)	(0.429)	(0.379)	(0.366)	(0.600)	(0.608)
NDVI Anomaly in Origin	-0.020*	-0.018*	-0.028*	-0.026*	-0.030**	-0.028**	-0.019	-0.019
	(0.011)	(0.010)	(0.016)	(0.015)	(0.012)	(0.012)	(0.022)	(0.022)
NDVI Anomaly in Destination	0.009	0.007	-0.014	-0.010	0.055***	0.053***	-0.045**	-0.045**
	(0.016)	(0.014)	(0.019)	(0.018)	(0.014)	(0.013)	(0.020)	(0.020)
Growing Season in Origin	0.312	0.304	0.513	0.528	-0.398	-0.375	0.050	0.025
	(0.316)	(0.303)	(0.413)	(0.421)	(0.268)	(0.278)	(0.499)	(0.512)
Growing Season in Destination	-0.598*	-0.586*	-0.919**	-0.913**	-0.276	-0.282	-0.640	-0.647
	(0.325)	(0.326)	(0.435)	(0.433)	(0.350)	(0.361)	(0.510)	(0.512)
Distance	-3.676***	-3.654***	-6.858***	-6.739***	-3.217***	-3.191***	-1.393***	-1.389***
	(0.378)	(0.378)	(0.807)	(0.799)	(0.351)	(0.350)	(0.389)	(0.391)
Same District Dyad	1.632***	1.620***	2.165***	2.189***	1.393***	1.376***	1.549***	1.555***
	(0.348)	(0.346)	(0.376)	(0.379)	(0.324)	(0.321)	(0.382)	(0.382)
Same Region Dyad	0.862***	0.863***	1.232***	1.226***	0.885***	0.884***	2.115***	2.125***
	(0.223)	(0.221)	(0.378)	(0.369)	(0.191)	(0.190)	(0.551)	(0.554)
# of Clan Ties	0.151**	0.141**	-0.073	-0.068	0.182**	0.173**	-0.055	-0.058
	(0.064)	(0.065)	(0.081)	(0.080)	(0.075)	(0.076)	(0.087)	(0.087)
Dominant Clan Tie	-0.076	-0.070	-0.136	-0.202	0.137	0.148	1.107***	1.112***
	(0.279)	(0.276)	(0.251)	(0.258)	(0.241)	(0.237)	(0.345)	(0.346)
Population in Origin	-0.038	0.018	-2.679	-2.584	0.840	0.930	3.141***	3.251***
	(1.124)	(1.051)	(2.227)	(2.250)	(1.704)	(1.573)	(1.098)	(1.139)
Population in Destination	0.516	0.459	1.288**	1.193**	-0.710	-0.726	-0.914	-0.870
	(0.490)	(0.467)	(0.514)	(0.500)	(0.771)	(0.764)	(0.978)	(0.974)
Road Connected Dyad	0.478	0.474	-0.724	-0.710	1.027*	1.014*	3.896***	3.892***
	(0.680)	(0.675)	(0.711)	(0.707)	(0.571)	(0.568)	(0.824)	(0.825)
Relative Road Connectivity	0.641**	0.616**	1.119***	1.151***	0.611**	0.568*	-0.495	-0.492
	(0.280)	(0.274)	(0.383)	(0.380)	(0.299)	(0.295)	(0.593)	(0.595)
Relative Economic Development	0.286*	0.288*	0.438*	0.426*	0.328*	0.330*	0.260	0.254
	(0.152)	(0.150)	(0.239)	(0.238)	(0.176)	(0.175)	(0.194)	(0.195)
Nighttime Light Ratio	0.008	0.007	0.003	0.003	0.007	0.006	-0.002	-0.002
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.015)	(0.015)
Migrant Network		0.020***		0.037***		0.016***		-0.133
		(0.007)		(0.013)		(0.006)		(0.112)
Observations	216080	216080	193120	193120	210160	210160	164160	164160
AIC	12087	12006	3596	3584	8037	8001	593	594
Parameters								
Origin District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Specific Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: * p <.10, ** p <.05, *** p <.01. Robust, undirected dyad-clustered standard errors are in parentheses. Observations are dropped in columns 3-8 because the PPML estimator excludes panels where the dependent variable is constant, or where panels are singletons or separated by fixed effects.

and reinforces Bohnet, Cottier and Hug (2021)'s claim that flows of conflict- and climate-displaced people bear unique security implications.

Turning to climatic conditions, I find that IDPs gravitate to more climate-resilient destinations, and flee more climate change-affected, and especially drought-affected places. A one percentage point increase in vegetative greenness over the long-run historical average in a destination district—that is, an increase in vegetative health and destination climate resilience—increased inflows of climate-displaced IDPs by 5%. Conversely, a one percentage point decrease in vegetative greenness over the long-run historical average in an origin district—that is, a reduction in vegetative health and an increase in drought exposure at origin—increased outflows of climate-displaced IDPs by 3%. Consistent with research on the intersection of drought, conflict, and displacement (Ash and Obradovich, 2020; Thalheimer, Schwarz and Pretis, 2023), I also find that drought conditions at origin are associated with increasing outflows of conflict-induced IDPs. This finding reinforces scholarship on the "mixed migration" paradigm, which highlights multiple, overlapping causes of flight, including violence, disasters, and economic opportunity, in many displacement settings (Norman, 2020; Arias and Blair, 2022). This result also comports with Maystadt and Ecker (2014)'s research on how drought conditions amplify conflict in Somalia.

To ensure the robustness of these results, I conduct a number of additional tests. In Table A-5 I re-estimate the primary specifications using an alternative fixed effects structure. Table A-4 accounts for multilateral resistance with origin district, destination district, and year-specific month fixed effects; an alternative approach is to incorporate directed dyad fixed effects instead of origin and destination fixed effects. Directed dyad fixed effects absorb all time-invariant factors common to pairs of origin and destination districts, such as distance and shared clan ties. Using this approach, I find substantively similar effects of the time-varying, district-specific covariates (e.g., conflict at origin and destination), which are not absorbed by directed dyad fixed effects. Further, in Table A-6 I re-estimate the core specifications using an alternative negative binomial pseudo-maximum likelihood estimator. Results are again substantively unchanged.

Together, these gravity results offer broad support for utility-maximizing theories of migrant decisionmaking. IDPs in Somalia gravitate to nearer, more developed, safer, more climate-resilient, clan- and network-connected areas. Conflict-induced IDPs are intuitively more sensitive to conflict dynamics at origin and destination. Climate-induced IDPs are also intuitively sensitive to climatic conditions, though climate-related factors like drought intersect with militancy to exacerbate conflict-induced displacement as well.

A.13 PPML Model with Directed Dyad Fixed Effects

In Table A-4 I estimate a PPML model with origin district fixed effects, destination district fixed effects, and year-specific month fixed effects. In Table A-5 I re-estimate this model with directed dyad fixed effects but not origin and destination district fixed effects. Directed dyad fixed effects absorb dyadic variables like distance.

Table A-5: Gravity Model of IDP Flows with Directed Dyad Fixed Effects

	IDP Flows							
	Total		**Conflict-Driven**		**Climate-Driven**		**Other Drivers**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Conflict in Origin	0.229	0.246	0.257***	0.220***	0.172	0.230	-0.439	-0.515
	(0.210)	(0.207)	(0.086)	(0.085)	(0.397)	(0.403)	(0.677)	(0.705)
Conflict in Destination	-0.188	-0.178	-0.627***	-0.579***	0.499*	0.486	-1.796*	-1.990*
	(0.202)	(0.205)	(0.186)	(0.179)	(0.291)	(0.316)	(0.970)	(1.060)
Military Base in Destination	1.092***	1.081***	1.731***	1.723***	0.226	0.216	1.815***	1.819***
	(0.336)	(0.331)	(0.432)	(0.424)	(0.381)	(0.368)	(0.612)	(0.620)
NDVI Anomaly in Origin	-0.024**	-0.023**	-0.032*	-0.029*	-0.039***	-0.036***	-0.020	-0.020
	(0.012)	(0.012)	(0.017)	(0.016)	(0.014)	(0.014)	(0.025)	(0.025)
NDVI Anomaly in Destination	0.013	0.014	-0.010	-0.006	0.063***	0.060***	-0.042*	-0.041*
	(0.017)	(0.017)	(0.021)	(0.019)	(0.015)	(0.015)	(0.022)	(0.022)
Growing Season in Origin	0.523	0.536	0.661	0.677	-0.342	-0.319	0.040	0.014
	(0.340)	(0.341)	(0.465)	(0.472)	(0.249)	(0.259)	(0.493)	(0.505)
Growing Season in Destination	-0.806**	-0.790**	-1.065**	-1.061**	-0.285	-0.287	-0.644	-0.655
	(0.399)	(0.402)	(0.503)	(0.502)	(0.384)	(0.389)	(0.518)	(0.518)
Population in Origin	-0.034	-0.165	-2.493	-2.384	0.728	0.821	3.121***	3.285***
	(1.072)	(1.159)	(2.066)	(2.076)	(1.658)	(1.529)	(1.127)	(1.187)
Population in Destination	0.579	0.564	1.290***	1.183**	-0.620	-0.628	-0.891	-0.891
	(0.469)	(0.461)	(0.487)	(0.467)	(0.754)	(0.751)	(0.997)	(1.010)
Nighttime Light Ratio	0.006	0.006	0.003	0.003	0.007	0.006	-0.000	0.000
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.009)	(0.009)
Migrant Network		0.248**		0.037***		0.014**		-0.140
		(0.108)		(0.013)		(0.006)		(0.114)
Observations	37440	37440	15440	15440	33320	33320	11360	11360
AIC	10249	10219	3223	3212	6723	6698	513	514
PARAMETERS								
Directed Dyad FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Specific Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: * p <.10, ** p <.05, *** p <.01. Robust, undirected dyad-clustered standard errors are in parentheses.

A.14 NBPML Model

In Table A-4 I estimate Poisson pseudo-maximum likelihood (PPML) models. A second, related estimator, the negative binomial pseudo-maximum likelihood (NBPML) estimator, has also gained some acceptance. NBPML is a modified PPML estimator, but unlike PPML it is sensitive to the scale of the dependent variable (Santos Silva and Tenreyro, 2011). Results in Table A-6 are substantively similar using the NBPML model.

Table A-6: NBPML Gravity Model of IDP Flows

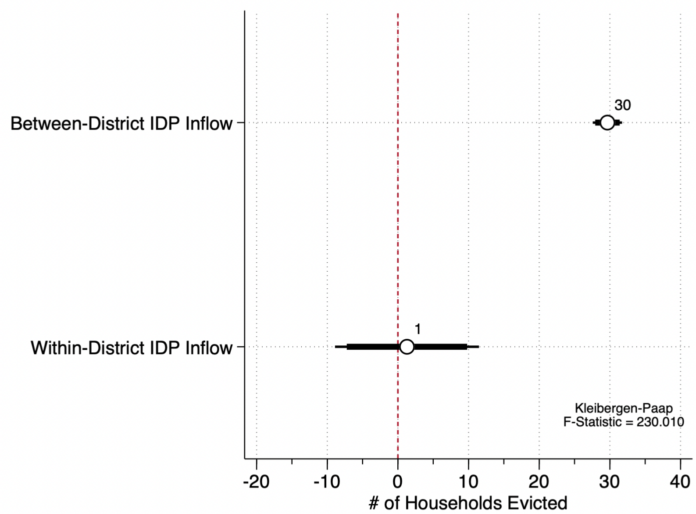
	IDP Flows						
	Total		Conflict-Driven		Climate-Driven		Other Drivers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Conflict in Origin	0.002	-0.009	0.213**	0.207**	-0.037	-0.017	-0.241
	(0.137)	(0.136)	(0.097)	(0.098)	(0.293)	(0.295)	(0.640)
Conflict in Destination	-0.042	-0.027	-0.242**	-0.224*	0.306	0.288	-1.563*
	(0.113)	(0.109)	(0.117)	(0.117)	(0.191)	(0.194)	(0.852)
Military Base in Destination	1.087***	1.020***	1.310***	1.319***	0.566*	0.521*	1.798***
	(0.223)	(0.201)	(0.413)	(0.409)	(0.291)	(0.270)	(0.531)
NDVI Anomaly in Origin	-0.017**	-0.016**	-0.018	-0.016	-0.031***	-0.031***	-0.017
	(0.008)	(0.008)	(0.013)	(0.012)	(0.010)	(0.010)	(0.020)
NDVI Anomaly in Destination	0.024**	0.025***	-0.014	-0.009	0.064***	0.061***	-0.037**
	(0.010)	(0.009)	(0.014)	(0.013)	(0.011)	(0.010)	(0.018)
Growing Season in Origin	0.009	0.065	-0.010	0.016	-0.252*	-0.188	0.007
	(0.157)	(0.165)	(0.265)	(0.282)	(0.142)	(0.142)	(0.462)
Growing Season in Destination	-0.536***	-0.522***	-0.758**	-0.825***	-0.210	-0.160	-0.620
	(0.188)	(0.187)	(0.318)	(0.315)	(0.180)	(0.180)	(0.475)
Distance	-3.508***	-3.420***	-6.323***	-6.134***	-3.011***	-2.988***	-1.403***
	(0.370)	(0.365)	(0.776)	(0.763)	(0.332)	(0.333)	(0.386)
Same District Dyad	1.322***	1.296***	1.657***	1.657***	1.292***	1.247***	1.546***
	(0.281)	(0.280)	(0.360)	(0.360)	(0.282)	(0.282)	(0.385)
Same Region Dyad	0.809***	0.804***	1.196***	1.196***	0.816***	0.807***	2.088***
	(0.190)	(0.187)	(0.356)	(0.344)	(0.176)	(0.175)	(0.544)
# of Clan Ties	0.159***	0.147**	0.021	0.026	0.186***	0.174**	-0.049
	(0.056)	(0.058)	(0.087)	(0.086)	(0.065)	(0.068)	(0.087)
Dominant Clan Tie	0.165	0.157	-0.108	-0.152	0.267	0.278	1.104***
	(0.236)	(0.234)	(0.275)	(0.279)	(0.216)	(0.213)	(0.344)
Population in Origin	-0.175	-0.183	-1.611	-1.541	1.020	1.059	2.668***
	(1.036)	(0.988)	(1.422)	(1.412)	(1.117)	(1.063)	(0.909)
Population in Destination	0.288	0.253	0.903**	0.819**	-0.254	-0.248	-1.279
	(0.311)	(0.307)	(0.415)	(0.402)	(0.450)	(0.440)	(0.891)
Road Connected Dyad	0.820	0.833	0.006	0.043	1.058**	1.048**	3.909***
	(0.584)	(0.569)	(0.713)	(0.707)	(0.531)	(0.526)	(0.824)
Relative Road Connectivity	0.383	0.355	0.906**	0.912**	0.456*	0.406	-0.503
	(0.261)	(0.256)	(0.366)	(0.359)	(0.275)	(0.273)	(0.589)
Relative Economic Development	0.318**	0.324**	0.377	0.381*	0.373**	0.370**	0.289
	(0.144)	(0.141)	(0.230)	(0.224)	(0.164)	(0.162)	(0.196)
Nighttime Light Ratio	0.014	0.014	0.008	0.008	0.007	0.007	-0.001
	(0.016)	(0.018)	(0.007)	(0.007)	(0.007)	(0.007)	(0.015)
Migrant Network		0.088***		0.087**		0.057**	
		(0.031)		(0.023)		(0.022)	
Observations	219040	219040	219040	219040	219040	219040	219040
AIC	10307	10245	3238	3207	7319	7290	955
PARAMETERS							
Origin District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Specific Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

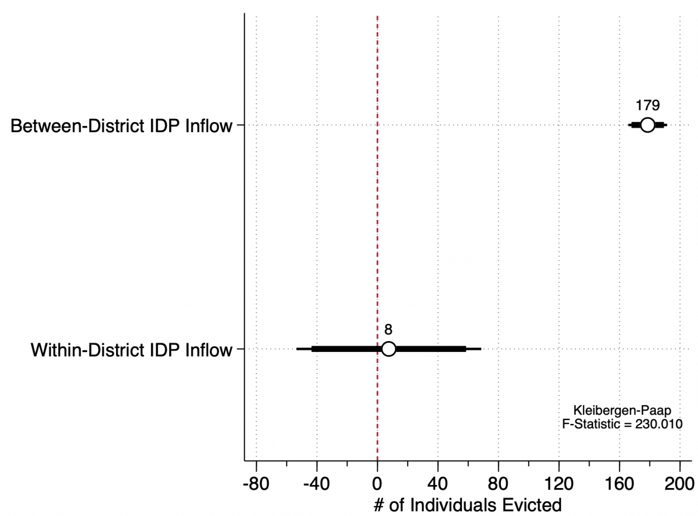
Note: * p <.10, ** p <.05, *** p <.01. Robust, undirected dyad-clustered standard errors are in parentheses.

A.15 IDP Inflows and Forced Evictions

To test whether inflows of outsider IDPs also risk exacerbating eliminationist policies, such as forced expulsions, I study data on evictions in Somalia. I estimate a regression of evictions on IDP inflows following the same core specification from Table 1. For each inflow of 1000 outsider IDPs, I find that evictions increase by 30 households or 179 people. In the average district this implies 76 households and 455 individuals evicted as a result of IDP inflows.

Figure A-14: IDP Inflows Increase Forced Evictions





Note: Estimates are coefficients from a two-stage least squares (2SLS) regression of evictions on IDP inflows. The core specifications follow Table 1. Thick and thin bars are 90 and 95% confidence intervals based on robust, district-clustered standard errors.

A.16 OLS Estimator

In Tables 1 – 3 I use a two-stage least squares (2SLS) estimator. Tables A-7 – A-9 reveal that substantively identical results are obtained using a naive OLS estimator. In Tables A-7 – A-9 I estimate effects over the full period of available data (January 2016–April 2019). The 2SLS results in the main text estimate effects over the period from January 2017–April 2019, using 2016 data to construct the instrument based on predicted IDP flows. OLS estimates available upon request are substantively unchanged in this more limited estimation sample.

Table A-7: OLS Estimator – Insurgent Surveillance

	Insurgent Spy Operations (=1)			**Insurgent Social Control (=1)**		
	(1)	(2)	(3)	(4)	(5)	(6)
Between-District IDP Inflow	0.003***	0.003***	0.003***	0.006***	0.006***	0.006***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Within-District IDP Inflow	-0.001	-0.001	-0.001	-0.006**	-0.006**	-0.001
	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)	(0.005)
IDP Outflow			0.001			-0.004
			(0.002)			(0.003)
Observations	2886	2886	2886	2886	2886	2886
AIC	-2368	-3137	-3135	1186	537	538
Parameters						
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Specific Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Clan Covariates		Yes	Yes		Yes	Yes
Historical Conflict		Yes	Yes		Yes	Yes
Military Base		Yes	Yes		Yes	Yes
Road Access		Yes	Yes		Yes	Yes
Trade Routes		Yes	Yes		Yes	Yes
NDVI Anomaly		Yes	Yes		Yes	Yes
Growing Season		Yes	Yes		Yes	Yes

Note: * p <.10, ** p <.05, *** p <.01. Robust, district-clustered standard errors are in parentheses. The estimation sample includes district-months from January 2016–April 2019. See table notes from Table 1.

Table A-8: OLS Estimator – Insurgent Intimidation

	Assassinations (=1)			**Insurgent Intimidation (=1)**		
	(1)	(2)	(3)	(4)	(5)	(6)
Between-District IDP Inflow	0.009***	0.008***	0.008***	0.003***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Within-District IDP Inflow	-0.004**	-0.003**	-0.003	-0.005***	-0.005***	-0.009**
	(0.002)	(0.001)	(0.003)	(0.001)	(0.002)	(0.003)
IDP Outflow			-0.000			0.003
			(0.002)			(0.002)
Observations	2886	2886	2886	2886	2886	2886
AIC	-366	-1000	-998	641	59	60
Parameters						
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Specific Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Clan Covariates		Yes	Yes		Yes	Yes
Historical Conflict		Yes	Yes		Yes	Yes
Military Base		Yes	Yes		Yes	Yes
Road Access		Yes	Yes		Yes	Yes
Trade Routes		Yes	Yes		Yes	Yes
NDVI Anomaly		Yes	Yes		Yes	Yes
Growing Season		Yes	Yes		Yes	Yes

Note: * p <.10, ** p <.05, *** p <.01. Robust, district-clustered standard errors are in parentheses. The estimation sample includes district-months from January 2016–April 2019. See table notes from Table 2.

Table A-9: OLS Estimator – Social Conflict

	Social Unrest (=1)			**Communal Conflict (=1)**		
	(1)	(2)	(3)	(4)	(5)	(6)
Between-District IDP Inflow	0.008***	0.007***	0.007***	0.005***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Within-District IDP Inflow	-0.001	0.001	0.001	0.002	0.001	0.003
	(0.004)	(0.004)	(0.005)	(0.002)	(0.002)	(0.003)
IDP Outflow			0.000			-0.002
			(0.003)			(0.003)
Observations	2886	2886	2886	2886	2886	2886
AIC	1984	1379	1381	1963	1375	1377
Parameters						
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Specific Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Clan Covariates		Yes	Yes		Yes	Yes
Historical Conflict		Yes	Yes		Yes	Yes
Military Base		Yes	Yes		Yes	Yes
Road Access		Yes	Yes		Yes	Yes
Trade Routes		Yes	Yes		Yes	Yes
NDVI Anomaly		Yes	Yes		Yes	Yes
Growing Season		Yes	Yes		Yes	Yes

Note: * p <.10, ** p <.05, *** p <.01. Robust, district-clustered standard errors are in parentheses. The estimation sample includes district-months from January 2016–April 2019. See table notes from Table 3.

A.17 Intensive Margin of Outcomes

In the main text I study the extensive margin of key conflict-related outcomes. This approach helps mitigate concerns about reporting biases or other systematic undercounting of events by only leveraging variation in the extensive margin. Nevertheless, there are substantive reasons to consider the intensity of violence rather than simply the incidence of violence. In Table A-10 I find similar results when considering outcomes in levels. The estimate is marginally imprecise in column 6 ($p = 0.125$).

Table A-10: IDP Inflows Increase Outcomes in Levels

	2SLS					
	Insurgent Spy Operations (#)	**Insurgent Social Control (#)**	**Assassinations (#)**	**Insurgent Intimidation (#)**	**Social Unrest (#)**	**Communal Conflict (#)**
	(1)	(2)	(3)	(4)	(5)	(6)
Between-District IDP Inflow	0.007***	0.012***	0.034***	0.005***	0.009***	0.006
	(0.001)	(0.004)	(0.002)	(0.001)	(0.001)	(0.004)
Observations	1998	1998	1998	1998	1998	1998
AIC	1162	2915	1834	990	1047	3967
Kleibergen-Paap F-Statistic	149.178	149.178	149.178	149.178	149.178	149.178
Parameters						
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Specific Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Within-District IDP Inflow	Yes	Yes	Yes	Yes	Yes	Yes
Clan Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Historical Conflict	Yes	Yes	Yes	Yes	Yes	Yes
Military Base	Yes	Yes	Yes	Yes	Yes	Yes
Road Access	Yes	Yes	Yes	Yes	Yes	Yes
Trade Routes	Yes	Yes	Yes	Yes	Yes	Yes
NDVI Anomaly	Yes	Yes	Yes	Yes	Yes	Yes
Growing Season	Yes	Yes	Yes	Yes	Yes	Yes
IDP Outflow	Yes	Yes	Yes	Yes	Yes	Yes

Note: * p <.10, ** p <.05, *** p <.01. Robust, district-clustered standard errors are in parentheses. The estimation sample includes district-months from January 2016–April 2019. See table notes from Table 1.

A.18 Additional Covariates

In the primary specifications from the main text I control for a range of covariates, including clan dynamics, historical conflict trends, the presence of military infrastructure, access to primary roads and trade routes, and climatic conditions. In Table A-11 I incorporate a range of additional covariates to address concerns about other factors correlated with the instrument (predicted IDP inflows) and with outcomes. I add a pretreatment measure of agricultural intensivity defined as the percentage of each district's landmass under crop, which I interact with year-specific months to flexibly capture agricultural productivity and land allocation. I add a lagged, time-varying measure of nighttime luminosity to capture economic production and consumption. I add a pretreatment measure of humanitarian aid projects completed between 2000–2014, which I interact with year-specific months to flexibly capture access to humanitarian assistance. Finally, to capture broad differences in conflict over time across areas of al-Shabaab control, I interact a pretreatment indicator of districts with al-Shabaab presence with year fixed effects. The core results are robust across all specifications.

Table A-11: Robustness to Controlling for Additional Covariates

	2SLS					
	Insurgent Spy Operations (=1)	**Insurgent Social Control (=1)**	**Assassinations (=1)**	**Insurgent Intimidation (=1)**	**Social Unrest (=1)**	**Communal Conflict (=1)**
	(1)	(2)	(3)	(4)	(5)	(6)
Between-District IDP Inflow	0.003***	0.008***	0.005***	0.007***	0.011***	0.005***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Observations	1998	1998	1998	1998	1998	1998
AIC	-1946	196	-954	86	791	742
Kleibergen-Paap F-Statistic	150.961	150.961	150.961	150.961	150.961	150.961
Parameters						
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Specific Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Within-District IDP Inflow	Yes	Yes	Yes	Yes	Yes	Yes
Clan Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Historical Conflict	Yes	Yes	Yes	Yes	Yes	Yes
Military Base	Yes	Yes	Yes	Yes	Yes	Yes
Road Access	Yes	Yes	Yes	Yes	Yes	Yes
Trade Routes	Yes	Yes	Yes	Yes	Yes	Yes
NDVI Anomaly	Yes	Yes	Yes	Yes	Yes	Yes
Growing Season	Yes	Yes	Yes	Yes	Yes	Yes
IDP Outflow	Yes	Yes	Yes	Yes	Yes	Yes
Agricultural Intensivity	Yes	Yes	Yes	Yes	Yes	Yes
Nighttime Light	Yes	Yes	Yes	Yes	Yes	Yes
Humanitarian Aid	Yes	Yes	Yes	Yes	Yes	Yes
al-Shabaab Control	Yes	Yes	Yes	Yes	Yes	Yes

Note: * p <.10, ** p <.05, *** p <.01. Robust, district-clustered standard errors are in parentheses. The estimation sample includes district-months from January 2017–April 2019. See table notes from Table 1.

A.19 Entropy Balancing

Districts more or less exposed to IDP inflows are likely to differ along a range of pre-treatment covariates. For instance, the gravity estimations suggest IDP-receiving communities are likely to be less violent and more economically prosperous. Hainmueller (2012) introduces an entropy balancing method to improve covariate balance between treatment and control units. Following this approach, I define a binary indicator for districts highly-exposed to inflows of between-district IDPs, which takes a value of 1 if inflows are greater than the median and 0 otherwise. Then, I balance treated and control units as defined by this treatment indicator on the following covariates: historical violence, clan dynamics, and access to primary roads and trade networks. The results in Table A-12 are generally robust to the incorporation of entropy balancing weights, though the estimated effect becomes imprecise in column 2 (p = 0.432).

Table A-12: Robustness to Entropy Weighting

	2SLS					
	Insurgent Spy Operations (=1)	**Insurgent Social Control (=1)**	**Assassinations (=1)**	**Insurgent Intimidation (=1)**	**Social Unrest (=1)**	**Communal Conflict (=1)**
	(1)	(2)	(3)	(4)	(5)	(6)
Between-District IDP Inflow	0.002**	0.005	0.005**	0.013*	0.008**	0.011***
	(0.001)	(0.007)	(0.002)	(0.007)	(0.004)	(0.004)
Observations	1998	1998	1998	1998	1998	1998
AIC	-2633	277	-1478	-502	122	505
Kleibergen-Paap F-Statistic	8.557	8.557	8.557	8.557	8.557	8.557
Parameters						
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Specific Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Within-District IDP Inflow	Yes	Yes	Yes	Yes	Yes	Yes
Clan Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Historical Conflict	Yes	Yes	Yes	Yes	Yes	Yes
Military Base	Yes	Yes	Yes	Yes	Yes	Yes
Road Access	Yes	Yes	Yes	Yes	Yes	Yes
Trade Routes	Yes	Yes	Yes	Yes	Yes	Yes
NDVI Anomaly	Yes	Yes	Yes	Yes	Yes	Yes
Growing Season	Yes	Yes	Yes	Yes	Yes	Yes
IDP Outflow	Yes	Yes	Yes	Yes	Yes	Yes

Note: * p <.10, ** p <.05, *** p <.01. Robust, district-clustered standard errors are in parentheses. The estimation sample includes district-months from January 2017–April 2019. See table notes from Table 1.

A.20 Disaggregating IDPs by Displacement Driver

In the main specifications I study total inflows of IDPs, pooling both conflict- and climate-induced migrants. The PRMN data also make it possible to identify IDP groupings by their primary driver of displacement: conflict or climate. In Table A-13 I study whether inflows of conflict-induced and climate-induced IDPs differ in their effects on conflict. I find few distinguishable differences across displacement drivers. Between-district inflows of both climate and conflict-induced IDPs are associated with distinguishable increases in insurgent spy operations, insurgent social control, assassinations, and social unrest. In contrast, increases in insurgent intimidation and communal conflict are driven mostly by climate-induced IDPs.

Table A-13: Disaggregating IDPs by Displacement Driver

	OLS					
	Insurgent Spy Operations (=1)	**Insurgent Social Control (=1)**	**Assassinations (=1)**	**Insurgent Intimidation (=1)**	**Social Unrest (=1)**	**Communal Conflict (==1)**
	(1)	(2)	(3)	(4)	(5)	(6)
Between-District, Conflict-Induced IDP Inflow	0.002**	0.008***	0.014***	-0.005***	0.009***	-0.003
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Between-District, Climate-Induced IDP Inflow	0.004***	0.006***	0.006***	0.007***	0.006***	0.005***
	(0.000)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Within-District, Conflict-Induced IDP Inflow	-0.003	-0.003	-0.018**	0.019	-0.023**	0.033*
	(0.006)	(0.012)	(0.009)	(0.016)	(0.009)	(0.018)
Within-District, Climate-Induced IDP Inflow	0.002	-0.005	-0.000	-0.011**	0.008	0.006
	(0.003)	(0.005)	(0.004)	(0.005)	(0.007)	(0.005)
Conflict-Induced IDP Outflow	0.002	-0.006	0.006*	-0.006	0.009***	-0.009
	(0.002)	(0.005)	(0.004)	(0.006)	(0.003)	(0.006)
Climate-Induced IDP Outflow	-0.003	0.001	-0.002	0.004	-0.004	-0.008
	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Observations	2886	2886	2886	2886	2886	2886
AIC	-3135	543	-1013	26	1378	1358
PARAMETERS						
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Specific Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Clan Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Historical Conflict	Yes	Yes	Yes	Yes	Yes	Yes
Military Base	Yes	Yes	Yes	Yes	Yes	Yes
Road Access	Yes	Yes	Yes	Yes	Yes	Yes
Trade Routes	Yes	Yes	Yes	Yes	Yes	Yes
NDVI Anomaly	Yes	Yes	Yes	Yes	Yes	Yes
Growing Season	Yes	Yes	Yes	Yes	Yes	Yes

Note: * p <.10, ** p <.05, *** p <.01. Robust, district-clustered standard errors are in parentheses. The estimation sample includes district-months from January 2017–April 2019. See table notes from Table 1.

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