PATTERNS OF INTERNAL DISPLACEMENT IN AFGHANISTAN

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Content

Disclaimer

The objective of this research report is to review and assess the mobility patterns of Afghans, in the lead up to, during and after the assumption of power by the de facto authorities during the period January – December 2021. As of the date of publication, 31 December 2023, the World Bank and UNHCR, the UN Refugee Agency, acknowledge that the situation in-country has evolved considerably since 2021. The current mobility dynamics are no longer similar to those at play in 2021, as a result of various factors, including the decision of the Government of Pakistan to implement its Illegal Foreigners Repatriation Plan (IFRP) as of 1 November 2023.

As of end-2023, some 29.2 million people[1] are estimated to be in need of humanitarian assistance in Afghanistan and the country's headline inflation remains negative, indicating sustained economic weakness and depressed aggregate demand[2]. Further, the de facto authorities have introduced a series of decrees severely limiting Afghan women's and girls' access to education and work. For updated information and data on IDPs, IDP returnees and returns, including refugee returnees, kindly consult the **Afghanistan Operational Data Portal**.

1 Revised Humanitarian Response Plan, June - December 2023 https://reliefweb.int/report/afghanistan/afghanistan-revised-humanitarian-response-plan-jun-dec-2023
2 Afghanistan Economic Monitor, The World Bank , November 2023:
https://thedocs.worldbank.org/en/doc/cdfea1bf5a7804a1f570bc20b433897a-0310012023/original/Afghanistan-Economic-Monitor-November-2023.pdf

Executive Summary

Mobility data accessed by primarily tracking cellphones in Afghanistan through global positioning system (GPS) highlights a variety of findings related to mobility patterns just prior, during and after the Taliban takeover in 2021. Following 622,448 devices from January 2021 to December 2021, the analysis investigates where individuals and/or households moved in reponse to the evolution of the conflict. For each device in the dataset, the primary area of residence and subsequent movements over time were identified. Using machine learning, the research studies the factors that influenced a person's choice to move and identified the common characteristics of villages and cities where people were likely to flee to. Evident patterns related to when people chose to leave their primary areas of residence also emerged[3].

The first part of the analysis seeks to understand how individuals' mobility was affected by the Taliban takeover. It finds that in relation to the local changes in control over districts and provinces starting in April 2021, around 4% of the identified devices left their districts of habitual residence and stayed away for at least 30 days. At the provincial level, around 2% of the identified devices left their original province. These results are averages over time from an event study design and combined they suggest that most devices - approximately 95% - remained within their district of origin. Of those individuals that left their origin district, approximately half stayed with their origin province. Additional analyses suggest that the remaining individuals - those that left their origin district and province - moved closer towards Kabul.

The second part of the analysis focuses on the destinations of displaced persons following the Taliban takeover. To better understand the factors influencing the settlement patterns of displaced persons, a machine learning approach called LASSO was used to examine numerous local characteristics. Data on district-level factors such as urban classification, market availability, nighttime light output, military base locations, agricultural activity, religiosity (importance of religion to self-identity)[4], healthcare infrastructure, aid types, and geographic features were collected. The results indicate that urban areas with market access and higher economic activity attract more displaced individuals, while factors such as agricultural activity and aid, religiosity, travel time to markets, rugged terrain, and counter-narcotics efforts discourage settlement.

The third part of the analysis concludes by providing an empirical benchmark for the UNHCR 2021 Multi-Sectoral Rapid Assessments. The study links the district names and focuses on a subset of the sample that includes IDPs who have not returned to places of their habitual residence. The number of displaced devices that resettle in each district is calculated to estimate the displaced population after the 15 August 2021 transition in government. This period of study aligns with the survey period between October and December 2021. Alternative model specifications were considered and revealed that mobile device data explains a significant portion of the change in the survey-based measure of displaced households. The results indicate a strong overlap between the displaced populations identified in the UNHCR 2021 Multi-Sectoral Rapid Assessments and the mobile devices detected during the progressive Taliban takeover. Lastly, the same machine learning approach used for the mobile device data was applied to the survey data on the same determining factors and showed highly consistent results in terms of the factors and predictive directions. Although some data limitations for both the UNHCR 2021 Multi-Sectoral Rapid Assessments and mobile device data exists, they confirm the findings.

In conclusion, the analysis of device movement following the Taliban takeover in Afghanistan in 2021 demonstrates consistent and distinct movement patterns and anticipatory tendencies among the displaced. Machine learning methods identified common pull factors to high-density displacement districts, such as urban market access and economic activity. Comparisons with benchmark survey methods validated the robustness of the methodology despite some data limitations, including a drop-off in device usage following the takeover.

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3   The findings from the mobility data analysis were also compared and triangulated with the UNHCR 2021 Multi-Sectoral Rapid Assessments.
4   Religiosity is measured using survey data on the importance of religion to self-identity, compared to ethnic kinship or citizenship and nationality.

OVERVIEW

1

The humanitarian situation in Afghanistan worsened significantly in 2021. Prior to the Taliban's takeover in August, the United Nations Assistance Mission in Afghanistan reported the highest number of conflict-related casualties on record and a striking decline in the security and human rights situation in large parts of the country. After the takeover, the dramatic escalation in conflict led to even more extensive forced displacement and movement, which followed territorial shifts in the last decade. As widespread fighting intensified, many individuals and households were uprooted from their homes and forced to flee in search of safety. As of end-2022, 3.25 million people were still displaced inside the country[5]. While the exact conditions and movement patterns of those forcibly displaced are difficult to monitor since comprehensive data on their movements and experiences is scarce, this study aims to address this by using mobile device data – precisely georeferenced location information – to track the mobility of Afghan nationals from January to December 2021.

Initially, a secondary data review was conducted focusing on three core topics: displacement, destination, and return. Methodological approaches used in prior research were then discussed to highlight gaps in the factors that shape displacement dynamics. Literature on events related to departures, such as climate change, violence, and economic shocks, is also examined. Studies that use data sources such as call detail records, measures of violent events (e.g., attacks on civilians, military forces), and survey data to estimate these effects are then discussed. A review on destinations and how they are influenced by factors, such as safety, economic stability, and historical interactions between displaced populations and host communities, is also carried out. Regarding the return of IDPs and refugees globally, factors such as safety, economic viability, and housing are critical for considerations related to return decisions. Finally, in methodological approaches, the use of a benchmark event study framework is highlighted as the core model in the study. This framework allows for the heterogeneous treatment effects over time and differences in the timing of local changes in political authority.

Current practices for studying displacement in Afghanistan often employ in-person sampling methods, which are intended to identify vulnerable Afghans in need of humanitarian assistance, such as the UNHCR 2021 Multi-Sectoral Rapid Assessments. While these efforts serve as a valuable point of reference, and considering the main scope of the assessments, the methodology relies on a convenience sample, which may limit the representativeness of the findings.

Moreover, surveys based on convenience sampling are susceptible to survey-induced measurement error and often lack precision on the origins, journeys, and destinations of displaced persons. Mobile device data derived predominantly from smartphones with GPS capabilities provide a novel approach to analyzing patterns of population displacement. By tracing the movement patterns of users through GPS-enabled cell phones, spatial and temporal precision is attained while maintaining users' anonymity. Mobile device data also allows for the exploration of questions related to granular levels of population movement, including short- versus long-term relocations, as well as the duration and distance of displacement. Mobility across districts and within 2.5km by 2.5km grid cells is tracked, revealing previously undetectable microscale levels of internal displacement. The associated analysis combines multiple data sources to enhance robustness, cross-validate findings, and gain insights into movement patterns. This multi-layered approach contributes to improved assessment and tracking platforms, calibration processes, and a deeper understanding of population movements in Afghanistan.

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5 UNHCR, Asia and the Pacific Regional Trends – Forced Displacement and Stateless 2022, July 2023, https://data.unhcr.org/en/documents/details/101659

The data employed is described in detail, noting that the important descriptive patterns uncovered provide a glimpse into unfolding movement patterns, which would have otherwise been difficult to measure. While the scale of the data is large, no single data source currently available can fully capture movement dynamics. Consistency between mobile device data and the UNHCR 2021 Multi-Sectoral Rapid Assessments, however, presents reassuring evidence of the important patterns detected.

The research design has three main components. First, a database is employed, tracking the local consolidation of de facto authorities' control across the country. The expansion of district-level control was staggered in several waves, which enabled the study of local displacement patterns over time. An event study design is adopted to visualize dynamic changes in takeover-driven movement over time. The resulting findings clarify how quickly, how far, and which population hubs displaced persons relocated to. The second core research component is documenting various drivers of displacement and the destination choice. A machine learning approach, coupled with a large set of district-level measures, is used to identify the most robust factors shaping movement patterns. The final component is a benchmarking exercise, where granular mobility data is used to evaluate patterns of movement captured in the UNHCR 2021 Multi-Sectoral Rapid Assessments.

Through this methodology, new insights on mobility and mobility patterns in Afghanistan are revealed, which have the potential to improve operational responses and inform policy. By leveraging mobile device data and employing innovative methodologies and a multi-layered approach, previously undetectable variations in mobility are uncovered, thereby contributing to a deeper understanding of population movements inside Afghanistan and beyond.

An internally displaced family from Daikundi Province, she lost her husband due to cancer in 2016. She now raises her two sons while living in the outskirts of Kabul.© UNHCR/Oxygen Film Studio

CONTEXT

2

2.1 Pre-existing Population Movement Trends

This study assesses how changes in local political authority impacts population movement in Afghanistan. Earlier work by Tai et al. (2022) investigates how populations move before and after violent events and this study adds an important dimension to these findings by evaluating how territorial control impacts patterns of population movement. In the rest of this section, we describe other factors that shape population movement. Afghans have moved seasonally for work in the agricultural industry for decades and more recently in response to climate change, mainly drought. Since 2015, the inflow/outflow ratio for Afghanistan has been increasing, with net migration reaching 166,821 persons in 2020[6].

Although there are several Afghan agricultural industries that rely on or shape migration, the opium economy is particularly dependent on seasonal workers. Opium cultivation is labor intensive and many farms require additional help during the harvesting and weeding period. Evidence of this seasonal migration dates to the 1950s, which led to thousands of migrants from neighboring regions (Bradford, 2019). In Helmand – the highest opium-producing province – many seasonal workers come from Ghor, where long-existing relationships between tribes and farmers facilitate work agreements (Mansfield, 2016). There are also recruiters who can be found in cities such as Jalalabad, who work on behalf of farms and transport laborers directly to harvest locations such as Helmand. Separately, long-term migration patterns have emerged related to the search for new land for cultivation, driven by population pressures and labor agreements (Mansfield, 2016).

According to the Germanwatch Global Climate Risk Index, Afghanistan ranks as the sixth-most vulnerable country to extreme weather events (Sayed & Sadat, 2022). Increases in droughts, floods, and hot temperatures, have forced people to make permanent and temporary displacement movements. Country-wide floods and droughts in the western regions have resulted in the continued displacement of around 287,000 people in late 2019 and all regions experienced some level of sudden-onset disaster in the same year (Přívara & Přívarová, 2019). In 2021, the IDMC estimated there were over 25,000 disaster-induced IDPs in Afghanistan (Global Internal Displacement Database, n.d). This number is not an anomaly, as around 166,000 displacements occurred in the two years prior. Those displaced in the years leading up to the Taliban takeover were also likely less secure in their new locations and faced an increased risk of multiple displacements. Relevant to the following analysis, climate-induced displaced persons typically move to larger cities. Additionally, notable populations of young men have sought work for remittances in neighboring countries such as Pakistan and Iran, in addition to those who fled the country seeking international protection (Sayed & Sadat, 2022).

Although these seasonal dynamics are important features of labor migration in the Afghan context, it is unlikely that they play an outsized role in the results covered in this report. This is because the staggered transition of political control examined in this report – local changes in territorial control – did not occur simultaneously or during a related economic cycle.

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6   World Bank Indicators Data on Net Migration (year 2020).

2.2 Conflict leading up to the 2021 Takeover

Between 2009 to 2020, the Taliban expanded their control over districts across Afghanistan, increasing control from under 40 districts to more than 110. This period saw notable spikes in political violence, especially during the 2009, 2010, and 2014 elections. Violence also surged after most international forces partially withdrew from Afghanistan at the end of 2014 (Condra, Long, Shaver, and Wright 2018; Fetzer, Souza, Vande Eynde, and Wright 2021). The expansion of territorial control across parts of the periphery was preceded by significant increases in violence, as districts served as sites of contestation between military and Taliban forces. Before 2021, approximately 25% of districts that transitioned to Taliban authority reverted to government control. In 2021, less than 5% of districts experienced a reversal of Taliban control after the final withdrawal of international forces was announced (Wright 2023).

2.3 Afghanistan during the assumption of control by the de facto authorities

In 2021, UNHCR estimated up to 500,000 Afghans could potentially flee their homeland due to the Taliban takeover by the end of the year.[7] Neighboring countries were urged to keep their borders open for those seeking safety. By 15 August 2021, the Taliban controlled most of the land except for a small number of districts and cities. Soon after, UNHCR launched a Regional Refugee Preparedness and Response Plan outlining the humanitarian preparedness and priority interventions in the region in the event of outflows from Afghanistan to Iran, Pakistan, and Central Asian countries.[8] Reports received by the Afghan crisis helpline indicated executions, beatings, and media and radio station restrictions, raising concerns about safety. In particular, Afghan women expressed fear of being killed simply because of their gender.

The following research focuses on population movements triggered by the violent and humanitarian crisis resulting from the takeover. This, along with other factors, likely led to significant displacement, particularly in regions closely associated with the Ghani government and the presence of international forces. As a result, it is likely that many Afghans would have sought refuge in perceived safer areas, including neighboring countries.

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7 See UNHCR, Afghanistan Situation Regional Refugee Preparedness and Response Plan Summary & Inter-agency Funding Requirements July-December 2021, August 2021, https://data.unhcr.org/en/documents/details/88385
8 See UNHCR, Afghanistan Situation Regional Refugee Preparedness and Response Plan | July – December 2021, September 2021, https://data.unhcr.org/en/documents/details/90749

SECONDARY DATA REVIEW ON DISPLACEMENT: EXISTING EVIDENCE

3

3.1 Displacement

Estimating the causal effect of an event on individual or household departure is a crucial aspect of displacement studies. When examining such effects, it is essential to consider not only the event itself but also the potential heterogeneity that could introduce biased estimates.

Extensive literature exists on the impact of climate change, violence, and economic shocks on displacement. For example, Tai et al. (2022) investigated the effects of violence caused by the Taliban and the so-called Islamic State (ISIS) between 2013 and 2017 on displacement, utilizing Call Detail Record (CDR) data and data on violence from the Uppsala Conflict Data Program (UCDP). Meze-Hausken (2000) explored the impact of droughts in northern Ethiopia on displacement, using survey data. Henry et al. (2003) studied the effects of floods on displacement in Burkina Faso, while Ciacci et al. (2020) examined how the expansion of mobile phone networks in Myanmar influenced movements decisions. Additionally, Beine et al. (2021) investigated the economic factors driving migration in Turkey.

Potential sources of heterogeneity and the nature of the Taliban takeover, however, may introduce significant bias. As noted by Tai et al. (2022), the decision to move, within their estimation of the effect of violence on displacement, depended on whether the event involved ISIS or the Taliban. Incidents involving the Taliban increased the odds of displacement by only 1.9% the day after, compared to 12.7% when incidents involved ISIS. This suggests that regional heterogeneity in support of the Taliban might be noticeable in this project's analysis.

Moreover, the ongoing threats of natural disasters such as drought and floods in Afghanistan (United Nations, 2022) may lead to displacement independent of the Taliban takeover, as previous literature on climate-induced movement indicates (Henry et al., 2003; Ciacci et al., 2020). The effects of climate change can extend beyond these specific environmental hazards and encompass threats to livelihoods, prompting movement to regions where job opportunities and earnings are more secure (Beine et al., 2021). Therefore, economic indicators such as harvest seasons can provide insights into whether the Taliban takeover is the sole reason for individuals' decision to move. Additionally, as noted by Meze-Hausken (2000), economic variables may be influenced by factors such as family size, ethnicity, and wealth. The ratio of dependents, for instance, can contribute to movements due to food scarcity or discourage travel (Sekara et al., 2019), while wealth, in the form of the number of livestock, can also discourage mobility. To address these forms of heterogeneity, research may choose to control them using remote-sensing data on climate change and economic indicators, such as harvest timings.

To capture such displacement, mobile device data can be analyzed for any convergence of people toward a specific region that cannot be identified as a safer destination. Alternatively, if individuals from regions known to be populated by a specific ethnicity under suppression are displaced, it may imply forced movement by the regime. The most vulnerable population in this case would be the Hazaras, primarily concentrated in central Afghanistan (Mohammadi and Askary, 2021).

3.2 Destinations

Tai et al. (2022) examined how violence caused by ISIS and the Taliban between 2013 and 2017 affected the destination choices of forcibly displaced persons. The paper suggests that in the face of violence, forcibly displaced persons tend to choose larger cities or provincial capitals as their destinations. Beine et al. (2021) employ the gravity model within the Random Utility Model framework to demonstrate that the potential income or economic incentives available at the destination play a crucial role in characterizing destination demands and comparing their effects on the displaced. The direct application of such methods and results to this project's analysis could be problematic, as only movements are observable, and not individuals' intentions and reasons behind such movements. Further, patterns identified by Beine et al. (2021) may not be demonstrated by IDPs in Afghanistan.

Moreover, the pace at which an event unfolds, measured by its severity or suddenness, may relate to where IDPs choose to relocate. Research by Li et al. (2019) revealed that IDPs often display sudden and obvious movements in response to abrupt events, as evidenced in the Call Detail Records (CDR) data. To isolate these cases as IDPs, the study identified regions impacted by sudden-onset events and observed a significant drop in the number of calls immediately after the event, followed by a surge in call frequency. Most IDPs, despite considerable variation across different countries and events, tended to move just a few miles from their original location within a week of the incident. However, it is crucial to acknowledge that this study primarily offers a methodology for using CDR data to track IDP movements following sudden-onset events, predominantly natural disasters. Therefore, a direct application of these findings may not be feasible.

Pham & Luengo-Oroz (2022) note that numerous factors such as conflict, political instability, persecution, and economic or environmental conditions can influence destination choices. As such, it can be challenging to pinpoint a single cause for displacement. For instance, environmental scarcity such as drought could lead to violent conflicts over resources like water. Modeling clear distinctive destination choices between migrants and IDPs is, therefore, challenging.

Destination choices differ vastly by the reason of movement. Additionally, without access to data on the economic conditions in each region or individual-level demographic data, it becomes challenging to identify individual-level preferences or demands for specific destinations. However, as shown by Tai et al. (2022), one possible strategy is to observe converging movement patterns over time and analyze regional characteristics, such as vulnerability to climate change, historical interactions with the Taliban (e.g., with their courts), the presence of foreign aid, and economic indicators such as the harvesting period. Such a strategy may help identify regional characteristics that play essential roles in destination choices.

3.3 Return

Most literature on the return of displaced persons to their homes is focused on refugees in neighboring countries. This is likely due to the comparative ease surveyors can study these populations by using administrative refugee registers. It is far more difficult, however, to find and reliably study internal displacement. Nonetheless, there is still a fair amount of literature on internal displacement and there are some common narratives across types of displacement return outcomes that are prevalent for internal displacements. This includes findings showing that safety is a primary factor affecting return, along with access to services and status of family dwellings (Bradley, 2018).

3.4 Measurement Approaches in the Literature

Defining the scope of exploration, and internal displacement and/or outflows, is a crucial aspect of this project, requiring careful consideration. Tai et al. (2022) utilized CDR data, which does not precisely capture intra-state movement, leading to the definition of displacement as movement outside the district. This approach has limitations, as it may incorrectly identify non-displacement out-of-district movements as instances of displacement. In using mobile device data, we adopt a new measurement strategy, which has been delineated in the following sections.

It is also important to note the differences between the mobile device data utilized and CDR, which have been widely used in the relevant literature (Luca et al., 2022). According to Choi (2020), CDR data offers advantages in terms of relatively low cost and broader coverage of users, timespan, and spatial extent. It captures data points from both the devices initiating and receiving calls/texts (Tai et al., 2022). However, it may suffer from positioning errors. On the other hand, mobile device data provides high positioning accuracy and fine-grained information but comes with higher costs and greater battery usage. Furthermore, the availability of cell towers can impact the data collection process for CDR, whereas mobile device data is less dependent on it. Therefore, while mobile device data may not offer the same robustness as CDR data in analyzing social networks, which can be a significant source of heterogeneity, it provides more precise positioning data at a granular level.

Children playing in the backyard of their school in Faizabad city, Badakhshan province, Afghanistan. UNHCR supported, the installation of Refugee Housing Units to provide enough space for students to learn. ©UNHCR/Oxygen Empire Media Production

3.5 Methodological Approaches in the Literature

The two-way fixed-effect event study framework is the key model of this study. The advantage of this model is that we can allow heterogeneous treatment effects over time, as well as different timings of the treatment (Callaway and Sant'Anna, 2021). This model has also been used in multiple papers, such as Tai et al. (2022). The model is set up in the following way:

$$Y_{i,t} = \alpha_i + \alpha_t + \gamma_k^{-K} D_{i,t}^{<-K} + \sum_{k=-K}^{-2} \gamma_k^{lead} D_{i,t}^k + \sum_{k=0}^{L} \gamma_k^{lags} D_{i,t}^k + \gamma_k^{L+} D_{i,t}^{>L} + \epsilon_{i,t}$$

With the event study dummies $D_{i,t}^k = 1\{t-G_i=k\}$, an indicator for unit "i" being k periods away from initial treatment at time t, and Gt indicates for the period unit "i" is first treated. Here, the treatment in the study would be the Taliban takeover (which is not contested, as the Taliban takeover during these periods did not face any foreign opposition). The average treatment effect (for the treated) that would be estimated is (using the not yet treated group):

$$ATT(g,t) = E[Y_t - Y_{g-1}|G_g = 1] - E[Y_t - Y_{g-1}|G_g \neq 1, D_t = 0]$$

Where "G" is the group defined by the time period when a unit becomes treated, "g" is the time period when a unit becomes treated, and Yt(g) is the treated potential outcome that can vary by group and time. As this is an expansion from the Difference in Differences framework, we need a corresponding identification assumption, which is the parallel trend assumption with "clean" control groups. The "clean" control groups, according to Callaway and Sant'Anna (2021), should not be contaminated by the treatment. That is, we need a group that is never treated or not yet treated. In our study, due to the nationwide (yet, sequential) takeover of the Taliban in 2021, we have access to only the not yet treated groups. Among those, our challenge would be to identify the not yet treated group that has statistically similar characteristics to our treated groups.

To obtain more robust estimates, or in the case where the event study does not work (due to failures in identifying assumption, lack of corresponding samples, etc.), we may utilize different models. Regarding destination choices, Beine et al. (2021) and Henry et al. (2003) have extensively used random utility models. The following model is used in Beine et al. (2021). The fundamental model of indirect utility that concerns the decision to leave is:

$$U_{ii,t}^l = ln(w_{i,t}) + A_{i,t} + \epsilon_{ii,t}^l$$

Where I is the initial location of residence (for refugees, it is the first settlement, and for non-refugees, it is their residence), I is the type of individual (refugee or non-refugee), wi,t is the level of wage prevailing in location i in period t, and Ai,t captures other factors shaping the attractiveness of area i. The error term is assumed to be following type I extreme value distribution. If anyone chooses to leave, the equation becomes:

$$U_{ij,t}^l = ln(w_{j,t}) + A_{j,t} - C_{ij} + \epsilon_{ii,t}^l$$

Where j is the next location and Ci,j, is the migration cost from i to j. Now, the gravity equation is derived to be:

$$ln\left(\frac{N_{ijt}^l}{N_{iit}^l}\right) = \alpha_i^l + \alpha_j^l + \alpha_t^l + \beta_1^l ln(w_{j,t}) + \beta_2^l ln(w_{i,t}) + \beta_3^l C_{ij} + u_{ijt}^l$$

Where the left-hand side is the log of the ratio of people staying vs. leaving.

The potential application of this model in our study heavily depends on whether we can obtain data on observable characteristics of our units of interest. However, regional economic indicators, such as harvest timing (which can be a proxy for an increase in economic activity for a period like the wages of the workers for a destination candidate, and can be different by grids), can be used in the sense of "aggregate data" in the context of the model in Berry et al. (1995) to induce individual-level taste/demand from aggregate level data.

Men waiting for his turn to receive financial aid from UNHCR in Kandahar, Afghanistan. ©UNHCR/Oxygen Film Studio(Afghanistan)

DATA

4.1 Measuring Displacement

4.1.1 UNHCR 2021 Multi-Sectoral Rapid Assessments

Despite being based on convenience sampling, the UNHCR 2021 Multi-Sectoral Rapid Assessments provide a useful counterpoint to the mobile device data analysis. The following analysis is more holistic in identifying all forms of mobility, however, the displacement category found in the survey is still significant and relevant. The survey includes findings on wellbeing metrics such as assistance needs, food security and disabilities, but the analysis mostly focuses on IDP household information. The report methodology indicates that a sizable portion of the southern IDP population returned after mid-August 2021 when the assessment was taking place. A significant increase in returnees surveyed was found in the period between late August and October 2021.

This analysis will focus on the IDP sample in this survey. After assessing settlement patterns of displaced households, it was found that Kandahar was particularly saturated with observations. After filtering for IDPs, the effect is less dramatic but still existent. Figure 1 shows the top 10 districts for IDPs, where Kandahar and Kabul are particularly dominant, especially relative to the district average (red dashed line).
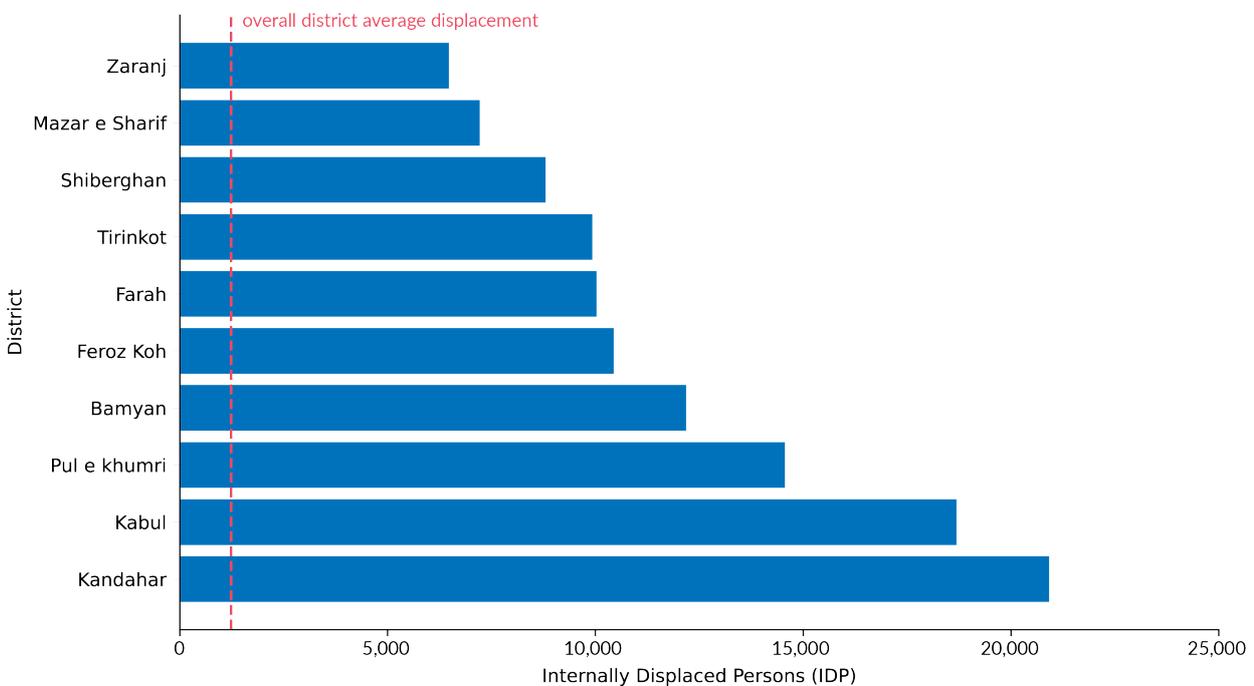

Figure 1 | **Top 10 IDP settlement locations in UNHCR 2021 Multi-Sectoral Rapid Assessments sample.**

4.1.2 Digital Traces from Mobile Devices

The project utilizes mobility data derived from the movement of devices with GPS capability to analyze population displacement and return patterns in Afghanistan[9]. Devices with GPS capabilities, such as smartphones, regularly ping satellites to determine their location. These pings are collected and stored in an anonymous database, allowing us to trace the movement patterns of users while ensuring anonymity. Because the data has been anonymized, it is not possible to identify user demographics or profiles beyond location and time of ping. This data provides spatial and temporal precision, allowing for the estimation of users' patterns of life. However, in this study it has not been possible to identify device type (i.e. cell phones versus laptops) with location capability. According to the International Telecommunication Union database, there were 57 mobile cellular subscriptions per 100 people in Afghanistan in 2021 (World Bank, n.d). While device usage is not as widespread as in other nations, device access is likely not so prohibitive as to entirely bias mobile device users from non-users. It is unclear how those who have mobile phones differ from those who do not in specific factors such as wealth and access to resources facilitating movement. There is, however, a disproportionate share of pings originating in Kabul province and in other urban areas. **The mobile device data used in this study is representative of the population that owns a mobile device in Afghanistan.**

The value of mobile device data lies in its ability to track movement across telecommunication network boundaries, including international borders. It also retains logs when cell coverage is lost, as long as the GPS remains functional. By analyzing mobile device data, normally undoable questions related to granular levels of displacement can be studied. Factors influencing intra-provincial and cross-border movements, short versus long-term relocations, and the duration and distance of displacement can be identified. The analysis will track mobility across districts but further specify within 2.5km by 2.5km grid cells. Where survey methodologies are largely limited to geographic borders, movement is tracked at finite levels at the sub-district, thereby finding previously untracked levels of mobility variation.

Mobile device data does face limitations in that there is significant variation in the number of pings per device over time. Though there are many devices that ping regularly (up to 50 times a day), a significant portion of devices ping sporadically. Particularly following 1 May 2021, many devices stop transmitting altogether or may only transmit once or twice over several months.

While survey methods like the one above can yield a useful sample, there are limitations in terms of scope and robustness. The GPS ping methodology accounts for the limitations of in-person sampling methodologies. Nonetheless, the analysis does plan to be complementary and holistic. To enhance the analysis, multiple data sources, both internal and external, are combined to cross-validate and explore dynamic patterns in mobility. The UNHCR 2021 Multi-Sectoral Rapid Assessments and a variety of administrative data provide additional information that can be linked to mobility patterns and trigger events. The insights gained from the layered approach can contribute to the improvement of assessment and tracking platforms, calibration, and a deeper understanding of population movement in Afghanistan.

The mobile device data contains over 32 million pings and 622,448 devices across Afghanistan in 2021. At various geographic levels (2.5km grid cell, district, province), primary dwell locations for each individual user are determined by finding modal pings. We use these dwell locations and continuously updated location data to measure displacement across districts and provinces, distances traveled, and settlement patterns after the events of 15 August 2021.

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9   The mobile device data contains over 32 million pings and 622,448 devices across Afghanistan in 2021 and 2022.

4.2 Assumption of control by the de facto authorities

This study used data on territorial control from the Foundation for the Defense of Democracies (FDD), which provides a near real-time mapping of shifts in political authority in 2021. The FDD project Long War Journal has released maps of control throughout the conflict, starting in 2002, and leverages a constellation of on-the-ground and secondary sources to monitor rapid changes during the 2021 period. Each update to the FDD map includes a timestamp as well as a consistent three-tier color-coded classification of each of the underlying districts (and their corresponding boundaries) in the FDD system. The three designations are: Taliban control; contested; government control. Areas controlled by either party are subject to limited violence while contested areas experienced at times significant episodes of violence. These empirical patterns have been verified using another data source, which tracks changes in political authority starting in 2009 but does not cover the 2021 transition. Some districts do not change status during this period as they were under Taliban control throughout. Parties to the conflict enjoyed freedom of movement, control of the road network, and other types of vital infrastructure. During the 2021 period, the staggered expansion of Taliban control did not include notable, sustained reversals of authority (where Taliban control switches back to government authority) as was recorded earlier in the conflict, especially during the surge in international forces between 2009 and 2011. Since underlying tabular data is unavailable, each of the map image files have been converted to a raster and the underlying average red-green-blue (RGB) values for each district have been calculated. The standardized boundary file tied to the core 398 district list is used to calculate zonal statistics[10]. The three-tier classification for each district at each map date is then reconstructed using a semi-automated clustering approach for the distribution of the RGB values (set to detect the three color-coded classifications).

A 62 year old man affected by war and conflict, the house where he was born and raised was destroyed during the conflict.
©UNHCR/Oxygen Empire Media Production

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10 This district boundary data was compiled by the Empirical Studies of Conflict Group (link here: https://shorturl.at/cflZ5), using information obtained from the Afghanistan Information Management Services. Three additional districts - from 398 to 401 - were formed in Uruzgan and Balkh. Historical data used in this study do not contain information that would facilitate an accurate within-district split to accommodate this change in boundaries.

RESULTS

5.1 Displacement during the assumption of control by the de facto authorities

A version of the event study design as described in section 4 is first implemented with a 30-day window before and after the shift in local control. This specification allows for the examination of a one-month window on either side of the date of takeover for each district. In this setting, it is important to consider that some people may be anticipating conflict and moved preventively. Individuals can reasonably be assumed to know in advance of k = 0 that with Taliban advancement, the place of their habitual residence may be affected by active conflict and had therefore begun moving in the period k < 0. The preventive movement is accommodated for by using the period k < −30 days before the district takeover as the leave-out period in the model. The estimates in this analysis capture changes in the displacement 30 days before and after the local shift in authority against this baseline period. Additionally, a lag for k = −1 and a binned lag for the window k > 30 is included in this model to reach full saturation.

To find individuals' movement using GPS data, the first step is to determine where people's habitual residences and/ or places of extended stay are. These places are referred to as dwell locations. A dwell location is the modal 2.5km × 2.5km grid cell, or the grid cell for which there are the most pings over a period. For example, if a user is in grid cell A four times in a week, grid cell B two times that week, and grid cell C once that week, then the dwell location that week is grid cell A. Being away from one's dwell location indicates movement. Throughout the analysis, unless otherwise noted, dwell locations are identified for the period before takeover. Figure 2 displays the share of devices that are outside of their modal grid cells, dwell districts, and dwell provinces over the 2021 period. At the provincial level, the percentage of devices staying in the same province remained high until the period between August and December 2021, when we see a steady increase in daily movement out of province exceeding 10% and two spikes of movement in August and September. Spikes indicate many people are moving out of their respective region on an individual day, but that a significant portion of these people return to their region within a couple of days. It may also be the case that increased device use on these key days during the Taliban takeover is picking up a large share of displaced people that are not using their devices ordinarily. The movement across districts is slightly higher compared to provinces, with more variation in daily movement in December, while the 2.5 × 2.5 km grid cells line indicates more than 60% of devices moved out of their modal cells.
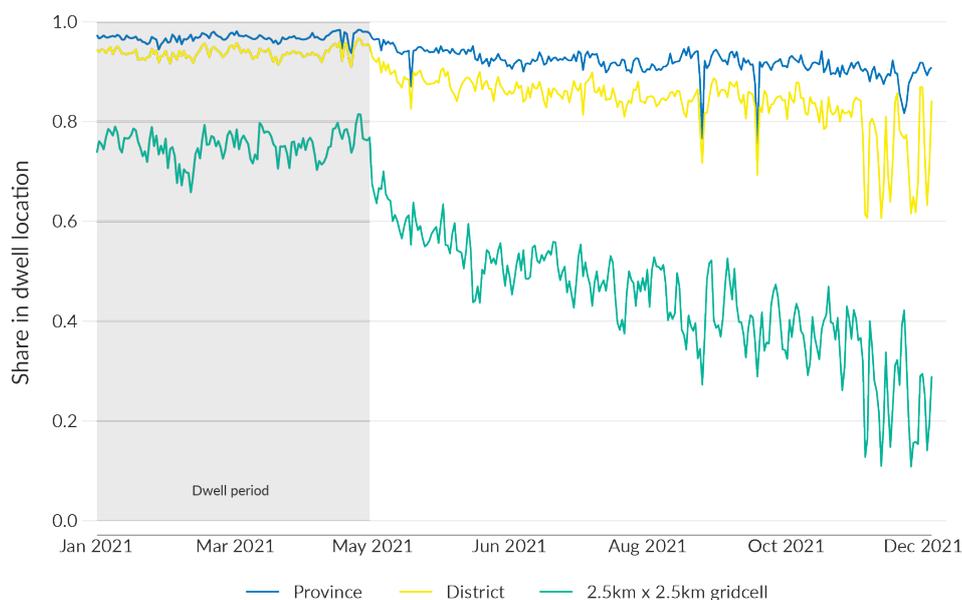

Figure 2 | **Changes in displacement patterns detected using mobile device data. The dwell period is used to identify the primary area (grid cell, district, province) of residence for each unique device. Displacement is measured using locations observed after the dwell period is complete and the device residence location is identified.**

A central question of the analysis is when and where individuals move in response to the Taliban takeover. Though there is considerable variation in active conflict, political tension, and other activities that may induce displacement throughout the country during the takeover period, the analysis can only consider the takeover as a generalized treatment because many of these variables are unobservable. The main results in Figure 3 show the estimated effects on displacement from the dwell location across district boundaries. At the district level, large displacement effects are observable; individuals are leaving their dwell districts, starting around five days before the local takeovers. This timing may reflect anticipation of takeovers or measurement errors in data on district takeover. The de facto control dates might be a few days earlier than observed. **The overall estimates suggest that around 4% of the population left their district and stayed away for at least the 30-day period measured.**
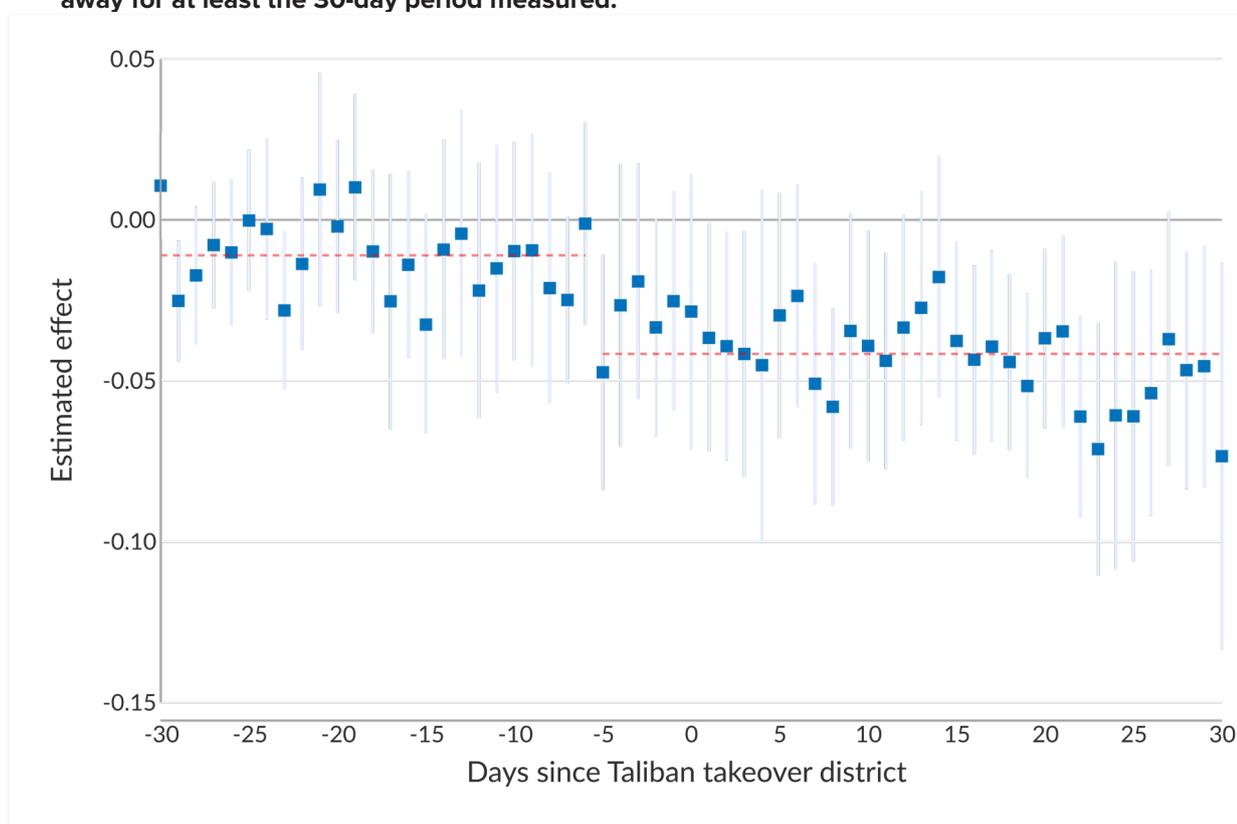

Figure 3 | **Impact of change in political authority on displacement patterns across districts. Negative effects capture population displacement and indicate a lower likelihood of devices remaining in the location of origin. The scale of effects is expressed as a probability (.05 is equivalent to a 5% shift in the likelihood of remaining at the location of origin).**

To understand where displaced persons go, a similar exercise is performed using displacement from the dwell province. These results are summarized in Figure 4. Smaller effects are seen on average – around 2% of the population leaving their original province – than at the district level. In combination, these findings suggest displaced persons are choosing, on average, to remain in their province even if they flee their district. There is, however, a sizeable group of displaced individuals who leave their province entirely, which is between 30% and 45%.
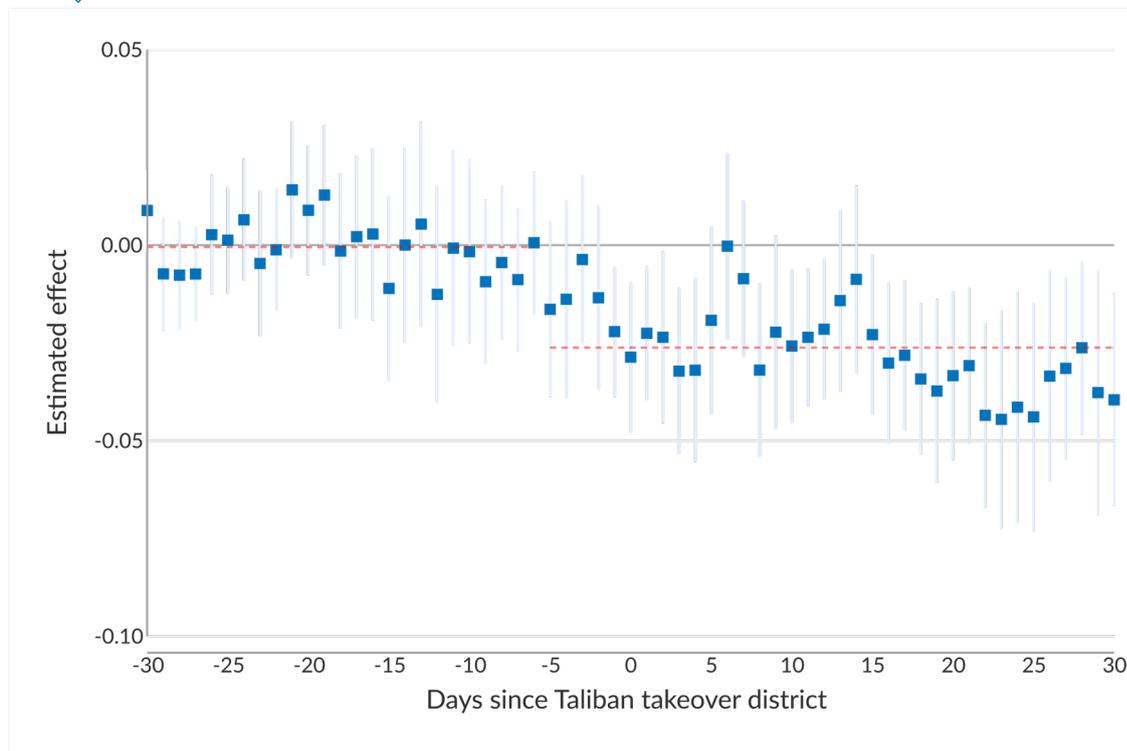
Figure 4 | **Impact of change in political authority on displacement patterns across provinces. Negative effects capture population displacement and indicate a lower likelihood of devices remaining in the location of origin. The scale of effects is expressed as a probability (.05 is equivalent to a 5% shift in the likelihood of remaining at the location of origin).**

The above results suggest significant displacement across administrative boundaries. In addition, the geographic proximity of devices to relevant reference points in response to the takeover are studied. First, Figure 5 studies the distance (in kilometers) between pings and the dwell location (measured as the modal location in the dwell period on a 2.5km × 2.5km grid). On average, displacement following takeover is in the range of 5km. This estimate is an average of movement for the entire sample, including those who remain in their dwell locations. If the sample is limited to those who have moved, the average displacement comes to more than 10km. The magnitude of this result suggests that the typical displacement is in the range of 10km – potentially crossing a district boundary but normally staying within the province. Second, the effect on the distance to both the nearest provincial capital and the national capital, Kabul, is observable. Although most devices remain within their origin province, even if they leave their origin district, it is important to study where devices travel after displacement. In Figure 6a, upon local takeover, the average movement is towards Kabul (excluding devices already dwelling in Kabul province). This change in device movement explains almost the full magnitude of total device movement. Although not all devices are going all the way to Kabul, the correlation between change in direction with Kabul's location suggests that those who are moving are more likely to be moving towards Kabul after takeover than before. Importantly, the distance traveled towards Kabul is calculated for the full sample, leading the scale of estimated effects to be closer to zero than would be true if we sampled only devices that left their origin districts. At the same time, no evidence of movement towards provincial capitals is seen – estimated effects are close to zero kilometers displaced in Figure 6b. Taken together, these results indicate that if devices leave their district of origin but remain within their origin provinces, they are unlikely to travel towards the provincial capital. If devices leave their district of origin and provinces, they are likely to travel towards Kabul instead. Given that a large share of GPS pings come from Kabul-dwelling devices, the main results might underestimate displacement effects for individuals in other provinces. To verify this, Figure 3 is reproduced using a sample that excludes devices dwelling in Kabul province. In doing this, estimated effect sizes are indeed slightly larger after dropping Kabul.
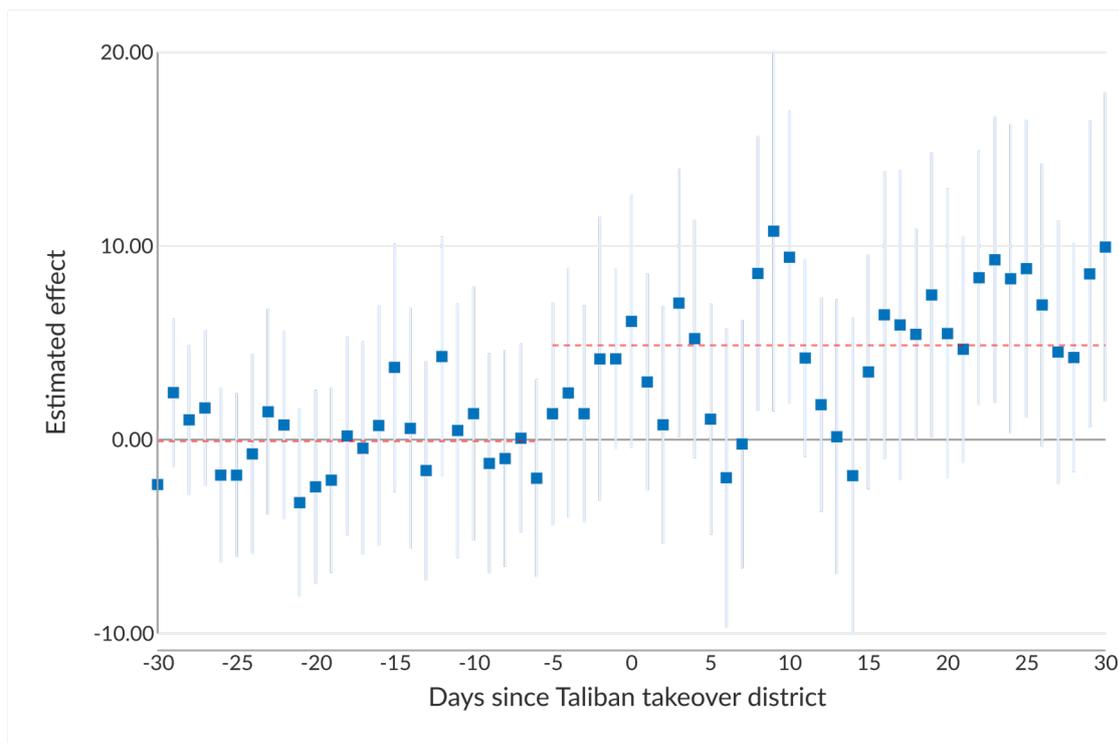
Figure 5 | **Impact of change in political authority on distance travelled in kilometers from origin. Positive values indicate devices travelling away from their primary geographic location. The scale of effects is expressed in kilometers. Regressions include all devices irrespective of whether they remain within their district of residence.**
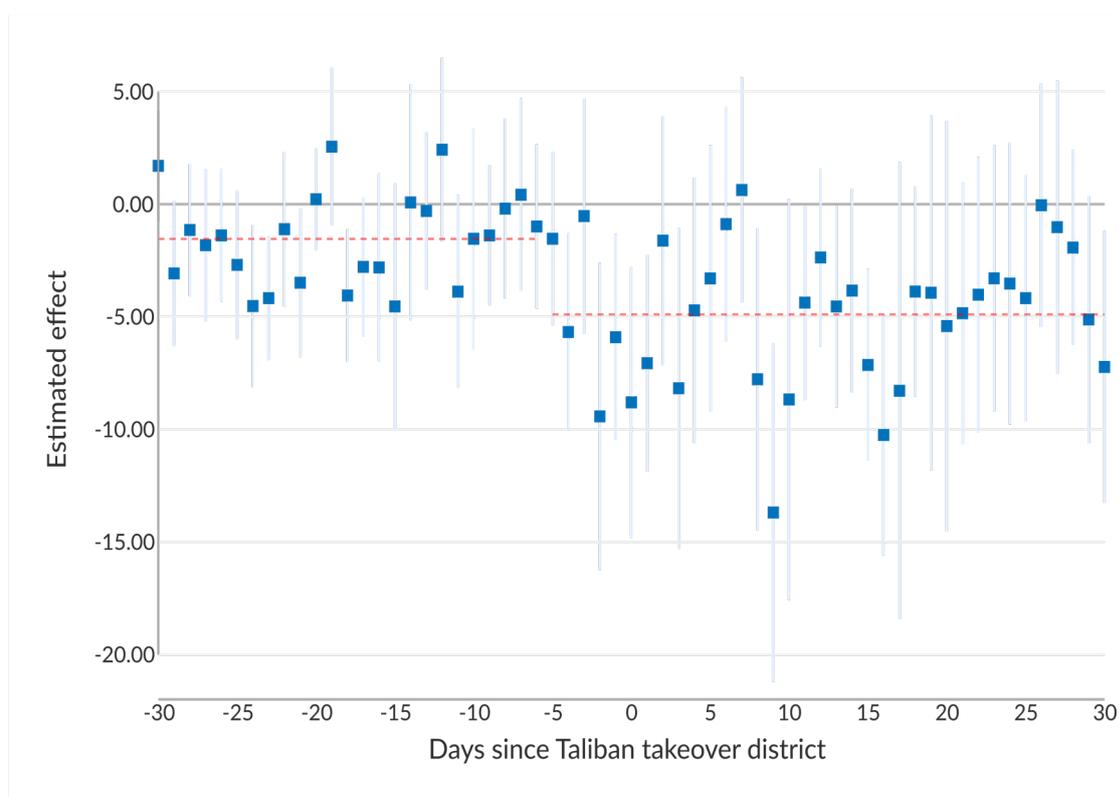

Figure 6a | **Impact of change in political authority on distance travelled to Kabul. Negative values indicate devices travelling towards Kabul from their primary geographic location. The scale of effects is expressed in kilometers. Regressions include all devices irrespective of whether they remain within their district of residence.**
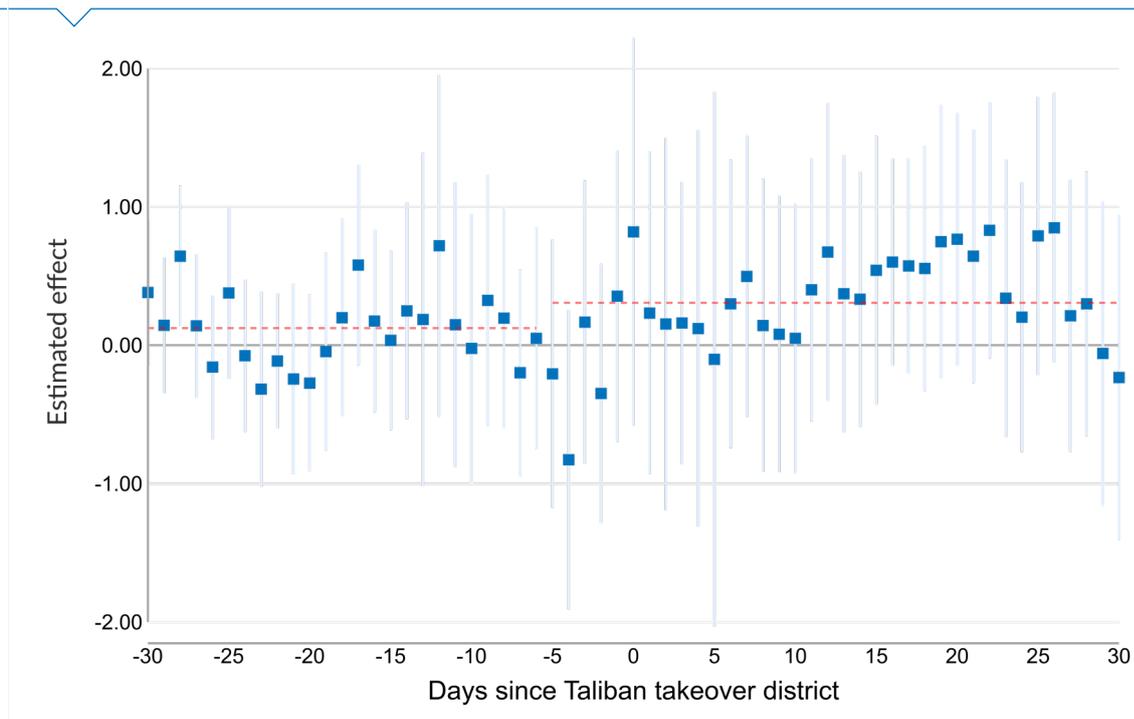
Figure 6b | **Impact of change in political authority on distance travelled to Provincial Capital. Positive values indicate devices travelling away from the provincial capital from their primary geographic location; negative values indicate devices are getting closer to the Provincial Capital. The scale of effects is expressed in kilometers. Regressions include all devices irrespective of whether they remain within their district of residence.**

It can be concluded that the events surrounding the Taliban takeover drove significant displacement. The analysis allows movement to be characterized into two archetypes. The first describes devices that are displaced within the local vicinity, potentially leaving their original district but not the province. The second describes a group who leaves their province and move towards Kabul. Extrapolating the findings within the mobile device data sample to whole Afghanistan population, it can be inferred that these groups each make up around 2% of the population.

5.2 Displacement and Destinations

The final and intermediate destinations of individuals moving internally can also be examined in greater detail utilizing mobile device data. The method used to identify the displacement location is similar to that determining dwell location from January to May 2021. 303,556 initial dwell locations can be identified for January to May 2021.

By identifying dwell locations over two-month periods following the takeover, those who have been displaced from their homes and displacement locations can be identified. Figure 7a maps pre-period device density by district. Figure 7b shows the density of displaced devices in the period after the 15 August 2021 takeover. Both map the log rather than the raw number of devices for ease of viewing. To explore these dynamics further, a LASSO approach is leveraged to study the relevance and impact of many local characteristics. In particular, the pull factors that drive the settlement patterns of displaced persons are of interest, as well as factors that block or disrupt settlement. To do this, data is gathered on a battery of district-level factors: urban classification, number of local markets, nighttime light output, military base locations, agricultural activity, religiosity (importance of religion to self-identity), district healthcare infrastructure, various types of services (electricity, microfinance, road development, water supplies etc.), as well as geographic features (e.g., ruggedness, water source access). Data on demographics and infrastructure access are drawn from the latest available National Risk and Vulnerability Assessment (NRVA) from 2016/17, as well as multi-year rounds of the Survey of the Afghan People (collected on behalf of the Asia Foundation).[11]

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[11] The 2016/7 round of data collection in line with the NRVA was renamed the Afghanistan Living Conditions Survey (ALCS). Additional details can be found here: https://shorturl.at/oKMSY. Details on the Survey of the Afghan People can be found here: https://shorturl.at/hqBX9.

Data on ruggedness, soil conditions, and military infrastructure are taken from Child, Wright, and Xiao (2023). The results of the LASSO estimation are presented in Figure 8, where the outcome of interest is mobile device activity across districts in the post-takeover period. The positive or negative direction and relative magnitude of a variable's trend line indicates the effect on the outcome of mobile device activity. **There is consistent evidence that urban areas with market access and increased economic activity see the greatest inflows.** People are less motivated to settle near areas of agricultural dependence, high local religiosity, increased agricultural aid, longer travel time to markets, greater terrain ruggedness, and heightened counternarcotics activity.
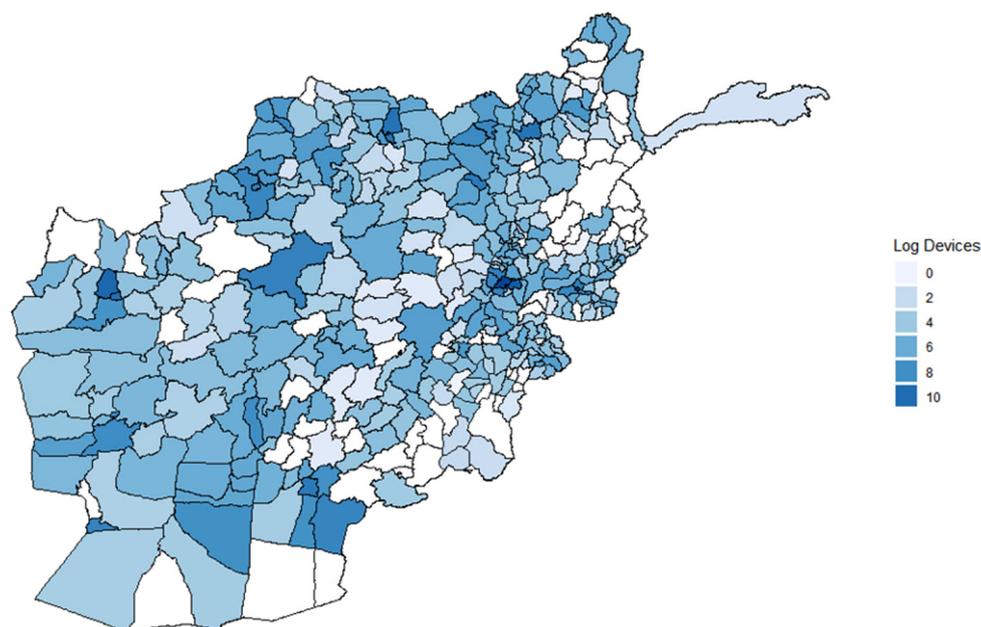

Figure 7 | **Map of displaced device activity in destination districts after 15 August 2021.**
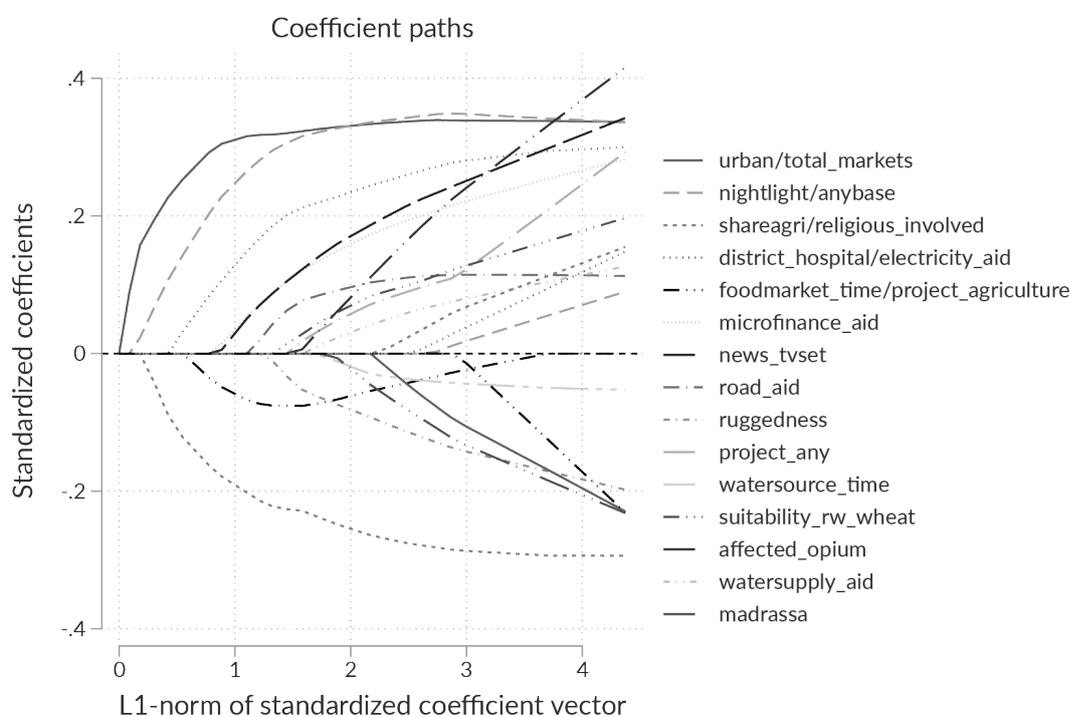

Figure 8 | **Displacement motivations. Settlement locations of displaced individuals predicted by urban infrastructure, local economic conditions using mobile device data. The trend line for each variable (or cluster of variables) indicates the direction of the estimated effect (positive or negative) on post-displacement relocation as well as the magnitude (size of the effect). The sequence of each line indicates when a given variable (or cluster of variables) is incorporated into the predictive model, indicating how relevant each component is to modeling the overall pattern of post-displacement device locations observed in the data.**

5.3. Benchmarking existing evidence

The core analysis concludes by providing an empirical benchmark and comparing information collected by UNHCR through its 2021 Multi-Sectoral Rapid Assessments. To conduct the analysis, districts have been properly matched. The primary focus is on the subset of the sample from the 2021 wave that includes IDPs that have not returned to their place of habitual residence. The household's sampling of each district is linked to the boundary file used for georeferencing the mobile device data. The volume of activity tied to devices that did not originate in a given district is then calculated after the Taliban takeover in August 2021. This aligns with the sampling period in the survey, which was primarily between October and December 2021. For ease of interpretation, a log transformation of the total number of displaced households enumerated is used in the UNHCR 2021 Multi-Sectoral Rapid Assessments and displaced device activity during the post-takeover period. A diagnostic illustration is shown in Figure 9, which illustrates a robust, approximately linear (in logs) positive correlation. The figure illustrates an elasticity of approximately .5.
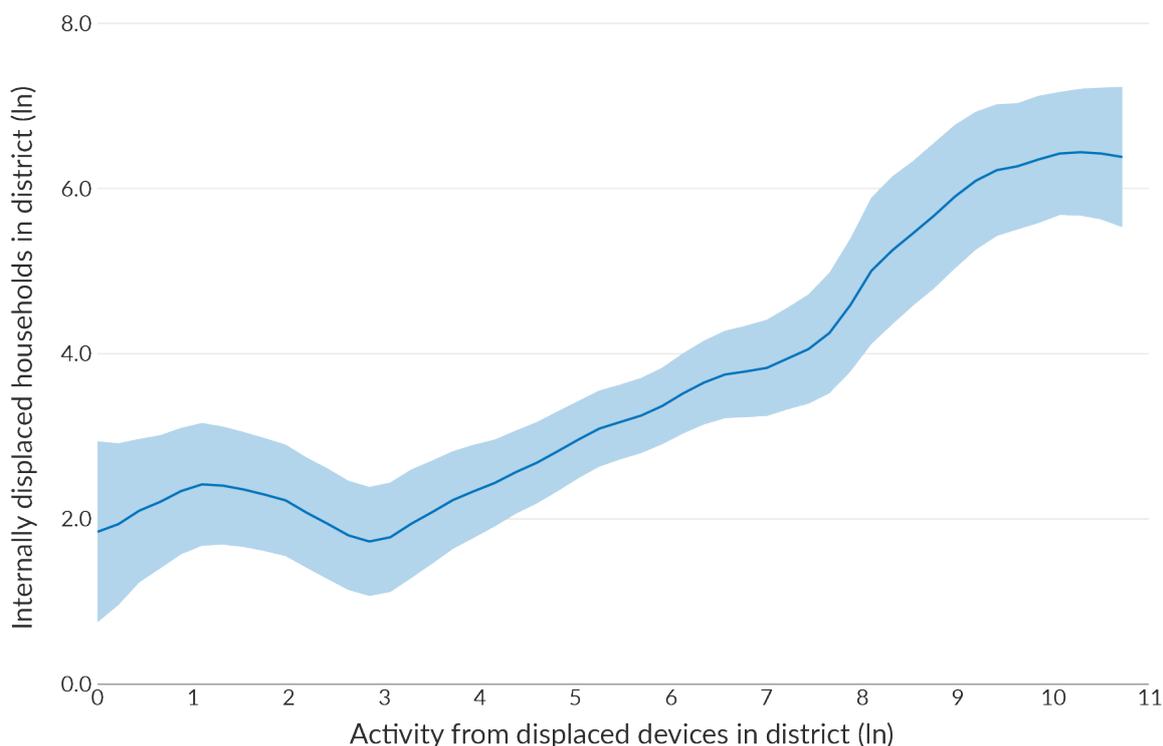

Figure 9 | **Strong correspondence resembling a positive and linear relationship between the 2021 Rapid Assessment and mobility data.**

A battery of alternative model specifications, shown in Table 1, is then considered. In column 1, the linear relationship between displaced households enumerated in the survey and displaced device activity in levels is studied. Note that device activity alone explains nearly one-third of the variation in the survey-based measure. Since device activity may be directly correlated with population levels, an official measure is included in column 2 and the model fit only changes marginally. In column 3, this specification is repeated, now incorporating province fixed effects, which account for any common shocks within provinces. The overall model fit improves significantly and the magnitude and precision of the device-based measure of displacement increases. To account for potential outliers in the underlying displacement patterns, including major urban areas like Kandahar and Kabul, a log-log specification is introduced in columns 4 through 6. Notice that the main correspondence metric (row 3 in the table) remains robust, positive, and very statistically precise. In the most conservative specification (model 6), the overall model fit improves to .54 while the magnitude of the device-based measure increases substantially. **Overall, these results suggest a strong overlap between the displaced populations captured in the UNHCR 2021 Multi-Sectoral Rapid Assessments' sampling protocol and a broader sample of mobile devices detected during the government transition.**

A final benchmark exercise compares the factors loaded in the LASSO approach for displaced mobile devices with those incorporated in an equivalent LASSO for the displaced populations surveyed in the UNHCR 2021 Multi-Sectoral Rapid Assessments. This analysis is summarized in Figure 10. While the co-efficient paths are less stable due in part to a smaller survey cross section, the factors loaded and their predictive directions are highly consistent.

Coefficient paths

Legend:
- urban/total_markets
- nightlight/anybase
- shareagri/religious_involved
- district_hospital/electricity_aid
- foodmarket_time/project_agriculture
- microfinance_aid
- news_tvset
- road_aid
- ruggedness
- project_any
- watersource_time
- suitability_rw_wheat
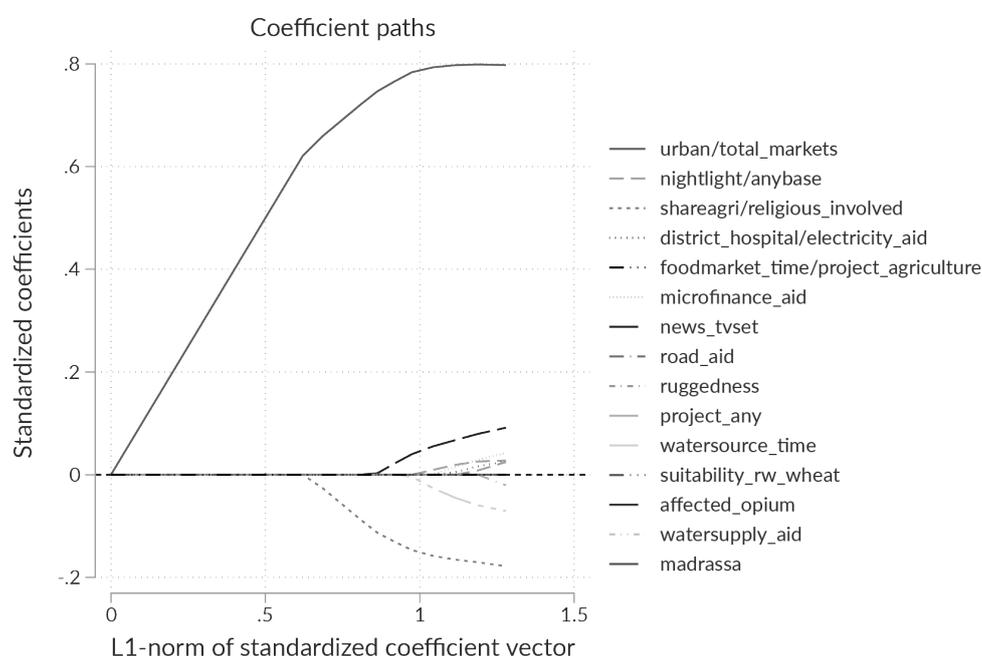- affected_opium
- watersupply_aid
- madrassa

Figure 10 | **Settlement locations of surveyed displaced households predicted by similar conditions using UNHCR 2021 Multi-Sectoral Rapid Assessments. The trend line for each variable (or cluster of variables) indicates the direction of the estimated effect (positive or negative) on household post-displacement settlement as well as the magnitude (size of the effect). The sequence of each line indicates when a given variable (or cluster of variables) is incorporated into the predictive model, indicating how relevant each component is to modeling the overall pattern of post-displacement relocation observed in the data.**

	(1)	(2)	(3)	(4)	(5)	(6)
Displaced devices, level	0.0221*** (0.00327)	0.0130* (0.00672)	0.0169** (0.00787)			
Population, level		0.438* (0.240)	0.350 (0.241)			
Displaced devices, log				0.475*** (0.0597)	0.375*** (0.0769)	0.489*** (0.0557)
Population, log					0.551** (0.235)	0.712*** (0.213)
Summary Statistics						
Outcome Mean	197.2	197.2	197.2	3.204	3.204	3.192
Outcome SD	418.2	418.2	419.4	2.363	2.363	2.364
Model Parameters						
Province Fixed Effects	No	No	Yes	No	No	Yes
Log-Log Model	No	No	No	Yes	Yes	Yes
Model Statistics						
No. of Observations	183	183	182	183	183	182
No. of Clusters	34	34	33	34	34	33
R^2	0.325	0.337	0.469	0.229	0.251	0.545

Notes: Outcome of interest is displaced households per district enumerated during the UNHCR 2021 Multi-Sectoral Rapid Assessment. Models 1-3 are level-level specifications, while models 4-6 are log-log specifications. District population is included in all models except 1 and 4 and province fixed effects are included in models 3 and 6. Standard errors clustered at the province level and are presented in parentheses, stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 1 | **Robust association between survey-based measure of population displacement and mobile device activity.**

CONCLUSION

Measuring conflict-related displacement has historically relied on survey methodologies as a primary source of data collection. These methodologies, however, may be limited in their robustness and representativeness. Through GPS location in mobile devices, precise mobility patterns of individuals were tracked over the course of the takeover. An event study, a machine learning approach, and survey benchmark method were all employed to provide a holistic and layered analysis of mobility.

The methodologies yielded consistent and significant results with applicable findings. **Individuals tend to leave their dwell locations five days before a local shift in authority, signaling anticipatory tendencies. Once people move, their displacement is patterned in a few distinct ways. People usually relocate within districts (approximately 80%), while close to 4% leave their district of origin. Of those leaving their district, approximately 40% eventually leave their province of origin (2% of the overall population).** In terms of directionality, people tend to move towards the capital city, Kabul. **Movement towards provincial capitals is not observed overall, but there are higher displacement densities in districts with major cities such as Kabul, Kandahar, Herat, and Farah.** Using machine learning methods, significant common pull factors for districts with high levels of displacement are identifiable. Districts with urban market access and increased economic activity saw the greatest inflow of individuals whereas districts with high levels of agricultural activity, local religiosity (importance of religion to self-identity), travel time to markets, terrain ruggedness, and counternarcotics activity yielded lower levels.

IDPs children in Kandahar, Afghanistan. ©UNHCR/Oxygen Film Studio (Afghanistan)

As a benchmark, the methodology and results of the UNHCR 2021 Multi-Sectoral Rapid Assessments are compared, revealing a strong correlation between displacement using the mobile device identification methodology and displacement in the survey. Across six alternative regression specifications, robust associations between UNHCR survey data and mobile device data are found and the machine learning methods employed to find pull factors in the previous analysis are recontextualized, finding consistent results in the survey analysis.

While the data shows significant improvements in precision and representativeness, there are still limitations. A drop in device usage is seen following the takeover of Kabul. The mechanism for this sample change is unclear although it could be a result of several factors, including people no longer having access to infrastructure to use their devices, a stoppage in device usage amidst the chaotic situation, or by a reduction in use of key location tracking applications from which mobile device data is collected. In some cases, device drop off may result from leaving the country. Possibly the inability to identify devices during the travel period may be a result of a deliberate decision by the user to avoid location sharing to prevent the Taliban from accessing their device locations. In addition to identifying the mechanism of device usage drop off, understanding the profiles of those who own and use devices versus those who do not would help to contextualize these findings.

The patterns observed above, especially regarding the destinations of individuals that have left their communities of habitual residence, provide actionable insights into the pull factors that influence the choice of the final destination: access to markets and water, infrastructure and medical care, and labor opportunities.

Children playing in the backyard of their school in Faizabad city, Badakhshan province, Afghanistan. UNHCR supported, the installation of Refugee Housing Units to provide enough space for students to learn. ©UNHCR/Oxygen Empire Media Production

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PATTERNS OF INTERNAL DISPLACEMENT IN AFGHANISTAN