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**IFPRI Discussion Paper 02340**

June 2025

## **Weather Risks and International Migration**

**Panel-Data Evidence from Tajikistan**

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## Abstract

Climate change and increased frequency of abnormal weather are becoming growing threats to people's livelihood, including in Central Asia. These threats are particularly challenging in Tajikistan, the poorest country in the Central Asia region. Despite the fact that migration is prevalent and remittances account for a significant share of GDP, evidence is scarce as to whether the decision to migrate is driven by weather shocks, whether migration is used as mitigating tool against adverse weather shocks, and how much of the loss in welfare is actually mitigated by such migration. This study aims to narrow this knowledge gap by providing evidence based on a unique panel dataset from one of the poorest and agriculturally dependent regions in Tajikistan (Khatlon province), combined with a detailed set of various climate data. In doing so, we apply a novel approach through the least absolute shrinkage and selection operator (LASSO) to identify key weather shock variables among a vast set of potential variables associated with outmigration decisions in different districts. Our results show that different types of weather shocks are associated with outmigration decisions in different districts within the province, ranging from rainfall, temperatures, drought, and windspeed in different subperiods throughout the year. Regardless, more abnormal weather is almost universally associated with more outmigration, and outmigration significantly mitigates the potentially adverse effects on household consumption and food/nutrition security in the origin households. However, more abnormal weather in the origin location is also associated with reduced remittances per month per migrant sent to the origin location. Thus, the capacity of migration to mitigate against weather shocks is still limited. Combined with migration policies that increase net earnings during migration, supplementary support to enhance climate resilience in home locations, such as climate-smart agriculture and development of the non-farm sector, remains critical.

**Keywords:** Climate change and weather shocks; LASSO; migration; panel data; Tajikistan

## **Acknowledgments**

Funding for this work was provided by the United States Agency for International Development (USAID) through the Tajikistan Evaluation and Analysis Activity, the Scaling for Impact Science Program. We are thankful to the Tajik Academy of Agricultural Sciences, and in particular academicians Nurali Asozoda, Amirshoev Fayzullo, Yatimzoda Khurshed, and Ms. Nodira Baeva for facilitating the government's support. Academician Jalil Pirizoda contributed to the survey methodology and questionnaire design. Abduaziz Kasymov, Mehrdod Yorov, and Nargis Hamidova of Zerkalo Analytics Groups made important contributions to the survey methodology and questionnaire design and organized the fieldwork in an excellent manner. We also benefited from constructive comments of the participants at the 10th Annual Life in Kyrgyzstan Conference held in Bishkek, Kyrgyzstan. The authors are responsible for all remaining errors.

## 1 Introduction

Abnormal weather has been an increasingly common phenomenon under accelerating climate change, often emerging as both relatively steady medium-term trends (such as rising temperatures over consecutive years) and more volatile short-term trends (weather shocks). These shocks have generally had adverse effects on livelihoods around the world, particularly in developing countries, through effects on agricultural productivity and food/nutrition security (e.g., Lachaud et al. 2022; Kumar & Khanna 2023; Guo et al. 2023; Gansonré 2024), general labor productivity and health (e.g., Ebenstein et al. 2023; Wang et al. 2023), and the local economy (e.g., Somanathan et al. 2021; Kiley 2024), among others.

Migration has often been considered a mitigating measure against climate risks adopted by people in low-income households (e.g., Mukherjee & Fransen, 2024). Yet overall evidence, where available, remains ambiguous about how migration decisions respond to weather shocks. In some cases, adverse weather shocks and declining climate conditions have been found to induce outmigration (e.g., Munshi 2003; Grace et al. 2018; Jessoe et al. 2018; Hauer et al. 2024).<sup>1</sup> In other cases, outmigration requires significant upfront investment for covering travel costs and other transaction costs (for example, learning about destination job opportunities) (IFPRI 2018; Lagakos et al. 2023), and adverse effects of weather shocks on liquidity and/or local transportation infrastructures subsequently constrain outmigration (e.g., Blondin 2020). Outmigration can also lower productivity in origin locations (e.g., Sauer et al. 2015), limiting the potential of migration to mitigate climate-induced losses significantly. Earnings during migration can also decline due to poor health (Pellet & de Talancé 2023), which could result from adverse weather shocks in origin locations prior to migration.

Critical knowledge gaps remain regarding the interlinkage between abnormal weather and migration, particularly in Central Asia which is a hotspot of human mobility and weather uncertainty (Piguet et al. 2018; Triandafyllidou 2024). This gap is especially pronounced for mountainous, landlocked low-income countries whose economies rely heavily on outmigration and remittances. The unique climate change and weather risk patterns in these areas further underscore the urgency of addressing this issue.

Tajikistan is a suitable case for examining the climate-migration nexus. As the poorest country in Central Asia, remittances from migrants have accounted for a significant share of GDP in Tajikistan in recent decades (reaching nearly 50 percent in 2022, one of the highest in the world) (World Bank 2024a). Thresholds for migration may be low in remittance-dependent societies, and adverse weather shocks may have a high migration propensity. On the other hand, migration markets may be rather saturated and may have limited scope for further expansion. Increasing geopolitical and socioeconomic volatility in Russia, the dominant migration destination for Tajikistan, also adds uncertainty about how well migration mitigates climate risks in Tajikistan.

This study aims to narrow this knowledge gap by providing scarce evidence based on a unique panel dataset from Khatlon province in Tajikistan, combined with a detailed set of various climate data. In doing so, we apply a novel approach through the least absolute shrinkage and selection operator (LASSO) to identify key weather shock parameters among a vast set of potential weather shock parameters associated with outmigration decisions in different districts. Our results show that different types of weather shocks are associated with outmigration decisions in different districts, ranging from rainfall, temperatures, drought, and windspeed in different

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<sup>1</sup>In this study, we refer to “outmigration” as the migration out of the home location, either to other districts within Tajikistan or to outside Tajikistan, for both temporary (at least 1 month) and long-term periods.

subperiods throughout the year. Regardless, more abnormal weather is generally associated with more outmigration, and outmigration significantly mitigates the adverse effects on consumption and food/nutrition security in the origin households. However, more abnormal weather in the origin location is associated with lower remittances per month per migrant sent to the origin households, and thus, the capacity of migration to mitigate against weather shocks is still somewhat limited.

This study contributes to various strands of literature. The literature on the climate-migration nexus in developing countries has been somewhat split between studies suggesting greater effects of climate risks on outmigration (Munshi 2003; Grace et al. 2018; Jessoe et al. 2018; Hauer et al. 2024; Karymshakov et al. 2024) and the effects of high thresholds for migration (Bryan et al. 2014; IFPRI 2018; Blondin 2020; Lagakos et al. 2023) which can be aggravated by climate shocks, and thus rather suppress migration. Our study expands this evidence base with a case study from Tajikistan.

Our study also contributes to the literature on how the outmigration of household members affects outcomes in the origin locations (e.g., Sauer et al. 2015), including those in Tajikistan (e.g., Azzari & Zezza 2011; Buckley & Hofmann 2012; Ghimire et al. 2023), by providing additional evidence about role of migration on climate risk mitigation in origin locations. Moreover, it also expands the evidence base on the determinants of remittances sent by migrants (broadly related to studies that look at earnings in migration destinations (e.g., Pellet & de Talancé 2023)) by assessing weather risks in origin locations as additional factors. By shedding light on the associations between weather shocks and household welfare, our study reaffirms the central roles of agriculture on socioeconomic development and resilience in Tajikistan and other Central Asian countries highlighted in previous studies (e.g., Kawabata et al. 2020; Takeshima et al. 2020a, 2022, 2024, 2025).

Lastly, methodologically, our study contributes to the growing literature on model selections (Tibshirani 1996; Ahrens et al. 2020), which is recognized as part of the machine-learning approaches (e.g., James et al. 2013), and their applications to development contexts (e.g., Dzanku et al. 2021; Knapp et al. 2021) by using the LASSO approach to identify key weather shock parameters.

The rest of the paper is structured as follows. Section 2 briefly discusses climate- and migration-related policies in Tajikistan. Section 3 discusses data and variables. Section 4 discusses empirical approaches. Section 5 describes the key migration and climate risk patterns in Khatlon province. Section 6 discusses results and policy implications. Lastly, section 7 concludes.

## **2 International migration and related policy issues for Tajikistan**

Tajikistan is a mountainous, landlocked country located in Central Asia. Although large parts of its mountainous terrain are unsuitable for agricultural production, agriculture constitutes an important sector of its economy. In 2020, primary agriculture accounted for about one-quarter of GDP and employed 61 percent of all workers in the country (Diao et al. 2023). With continuously high population growth, the country faces strong pressures on its arable land and available water resources (Saidaliyeva et al. 2024), which are also aggravated by deteriorating and outdated water infrastructure (World Bank 2024b) as well as climate volatility that affects glaciers and seasonal snowpacks which provide regional water resources (Groisman et al. 2018; Saidaliyeva et al. 2024; World Bank 2024b). These factors have kept economic prospects low and volatile for many Tajik populations for whom international migration has historically remained a critical livelihood alternative.

### *International migration patterns and economic implications on Tajik migrants*

Since gaining independence from the Soviet Union in the early 1990's, outmigration and remittance receipts have increasingly played a major role in Central Asia—especially so in Tajikistan, Kyrgyzstan, and Uzbekistan—as labor migrants from with limited opportunities to earn income in their home countries predominantly turn to Russia for work (Shimizutani & Yamada 2023; IOM 2021a). These arrangements were particularly attractive given the availability of unskilled jobs and significantly higher wages in Russia, whereas Central Asians benefited from historical ties among these countries, facilitating entry into Russia as well as ensuring familiarity with the language (Shimizutani & Yamada 2023). Over the past decades, therefore, the Central Asia-Russian Federation migration corridor has become one of the most significant labor migration corridors in the world (IOM 2021a).

Between 2015 and 2023, receipt of personal remittances make up an average of 32 percent of Tajikistan's GDP, with figures reaching 50 percent in 2022 and 38 percent in 2023 (World Bank 2024a). These figures are consistently higher for Tajikistan as compared to other Central Asian countries, with the exception of Kyrgyzstan between 2016 and 2020, and considerably higher than the typical figures seen among lower-middle-income countries (roughly 5 percent during this same period) (World Bank 2024a). The vast majority of remittances still originate from Russia—. For Tajikistan specifically, more than 90 percent of labor migrants work in Russia (Shimizutani & Yamada 2023).

This chronic reliance on remittances and the dominance of Russia as a destination for Tajik labor migrants has made Tajik households significantly more vulnerable to economic downturn or stagnation in Russia, as well as to Russian migration policies (Danzer & Dietz 2018; Gang et al. 2018; Shimizutani & Yamada 2023). After the global financial crisis in 2009, for example, migrants earned less and were more exposed to illegal work relations, harassment, and deportation by the Russian authorities (Danzer & Dietz 2018).

### *Migration-related policy trends in Tajikistan and key destination countries*

Tajikistan's policies toward governing outmigration have evolved in the years since the civil war, and the resulting economic devastation of the 1990s drove nascent outmigration growth (Kluczewska & Korneev 2022). When outmigration was still modest and when there were more significant concerns about domestic labor surplus and unemployment, policy stances in the early 2000s were mostly *laissez-faire*, as indicated in the first Labour Migration Concept, drafted by the Ministry of Labour and adopted in 2001, and facilitated by the 2002 removal of obligatory exit visas, a legacy of the Soviet times (Kluczewska & Korneev 2022). During the mid-2000s, the policies shifted to more proactive governance, including the strengthening of the Migration Services Agency within the Ministry of Labour; the adoption of the 2006 National Strategy for Development of Education in the Republic of Tajikistan; and subsequent creation of the Adult Learning Centres to expand vocational education, pre-departure orientation, skill-development, and certification to be used in labor market abroad (Kluczewska & Korneev 2022). However, the direction of strategies and policies became increasingly unclear during the late 2000s and early 2010s as the continued surge of outmigration started posing significant domestic challenges. Policies during this period were messy, characterized by constant reassignment of the Migration Services Agency across different Ministries and insufficient budget allocations to implement its National Strategy on Labour Migration 2011–2015, among other factors (Kluczewska & Korneev 2022). The stability and implementation of policies have improved

since the mid-2010s, starting as a response to the increased return of migrants from abroad due to the 2014 economic crisis in Russia. Since the mid-2010s, policies focused on encouraging stable labor outmigration; coordinating with Russian authorities, including negotiating amnesties (e.g., mitigating re-entry bans for some Tajik into Russia); and setting up of a new organized recruitment scheme (e.g., a state-led system of recruitment of low-skilled labor for construction and other industries abroad). The creation of the Agency of Employment Abroad (under the Ministry of Labour) in 2014 aimed to assist potential migrants in finding employment in big companies in Russia and Kazakhstan. After the expiration of the National Strategy on Labour Migration 2011–2015, subsequent strategies have not replaced it up until now, and as such, policies on governing outmigration remain ambiguous.

The overall trends in destination-country policies towards Tajik migrants have also remained generally ambiguous and volatile over time, particularly in Russia (Abashin 2016). Russia's migration policy has undergone a number of significant transformations since 1991, moving from a more open policy towards citizens of former Soviet States to more restrictive and complex policies. A key milestone has been the introduction of mandatory visas, work licenses, and insurance upon entry into Russia for citizens who previously were not required to do so, as well as a reentry ban of three years upon violation of these regulations (Abashin 2016; Shimizutani & Yamada 2023). Migration is a contested topic in political and public debates, and xenophobia remains a common phenomenon (Abashin 2016).

Tajikistan, similar to other Governments in Central Asia, has sought to improve the migration policies towards Tajik citizens in destination countries (including Russia) and to diversify migrant destinations by joining multi-country and bilateral migration dialogues and policy processes that promote migration partnerships, for example to the European Union, The Schengen Area, Turkey, Uzbekistan, and Kazakhstan. Tajikistan has migration-related memorandums of understanding (MoUs) with several countries, such as China and the United Arab Emirates (IOM 2021b). These processes, however, are also vulnerable to change. For example, in the aftermath of the Crocus City Hall attack in Moscow in 2024, Turkey rescinded visa-free travel for Tajik nationals (The Diplomat 2024), whereas the United Arab Emirates established more strict visa requirements for Tajik men (The Diplomat 2025).

### *Migration issues within climate change related policies in Tajikistan*

Given the lingering challenges associated with international migration, domestic support for these migrants, including addressing the adverse effects of climate change and weather shocks, remains crucial. While Tajikistan has gradually developed climate change adaptation strategies over the years, their linkages with emigration policies are not yet clearly articulated. Most climate change adaptation policies in Tajikistan are pursued under the broader climate change strategies, including the 2019 National Strategy for Adaptation to Climate Change, the 2016 National Development Strategy for the Period Up to 2030, and the 2018 National Strategy on Disaster Risk Reduction (Babu et al. 2024). These strategies are jointly implemented through collaborations across ministries and agencies, including The Committee for Environmental Protection (CEP), the Ministries of Energy and Water Resource, Transport, Agriculture, Industry and New Technologies, and the Agencies of Forestry as well as Reclamation and Irrigation (Babu et al. 2024). Meanwhile, the Ministry of Labour and other agencies overseeing the aforementioned emigration policies are not as closely involved in climate adaptation strategies. Thus, more evidence-driven efforts can be beneficial in integrating climate change-induced migration into the overall national strategies in Tajikistan.

### 3 Data and variables

This study primarily uses a household panel dataset collected in 2015 and 2023 by the IFPRI in the USAID Feed the Future (FTF) zone of influence (ZOI) in Khatlon province. In each survey round, a total of 2,000 households were interviewed from the 12 districts that constitute the FtF ZOI in Khatlon province. Approximately 1,600 households were successfully interviewed in both periods. Survey data were collected in the same season (February–March) in both 2015 and 2023 and covered information on migration activities of household members during the previous 12 months (March 2014–February 2015 and March 2022–February 2023), along with other information on livelihoods, consumption, and food security. After dropping observations with missing data, our analyses use panel data from 1,588 households as our primary samples.

To check for robustness, as described in the next section, we also supplement the aforementioned 2015/2023 panel data with the 2012 FEEDBACK PBS survey (Feed the Future FEEDBACK 2014). The 2012 FEEDBACK PBS survey was collected for different objectives than the 2015/2023 surveys, but it partly served as the pool of respondent households which were re-interviewed in 2015 survey. The 2012 FEEDBACK PBS survey contains information about the number of household members working abroad at the time of survey (which can be used as a crude proxy for migration activities in 2012) for approximately 1,000 households that are also interviewed in 2015/2023 panel data. We use the 2012 FEEDBACK PBS survey data only in the robustness check, due to its limited scope beyond migration information.

The sample for the 2015/2023 survey therefore consists of households initially interviewed in 2012 and is supplemented by new households interviewed in 2015. The 2012 FEEDBACK PBS survey originally followed a two-stage sampling design (Feed the Future FEEDBACK 2014). First it selected 100 clusters of households within the FTF ZOI through probability proportional to size (PPS) sampling, using the list of standard enumeration areas (SEAs) based on the Tajikistan Census of 2010. Second, 20 households were randomly selected from each of 100 clusters, constituting a total of 2,000 households. In 2015, more than half of these 2,000 households from 2012 were re-interviewed, and new households were additionally sampled through the same two-stage sampling. Thus, the total sample size reached 2,000 households. The 2023 data collection team sought to interview households previously interviewed in 2015. Households from the 2015 sample that could not be interviewed in 2023 were replaced by the nearest neighbors.

#### *Weather data*

In addition to the primary datasets mentioned above, our study relies on multiple spatial data sources to construct detailed spatiotemporal weather shock variables. Historical monthly rainfall data are from CHIRPS, which provides data at approximately 5km×5km resolutions (Funk et al. 2015). Historical drought data based on the Standardized Precipitation Evapotranspiration Index (SPEI) at 5km×5km resolutions are from Gebrechorkos et al. (2023). Historical daily temperature and wind speed data are taken from the AgERA5 dataset, which provides data at 6.0 arcminutes, about 9km at the typical latitude in the Khatlon region (Boogaard et al. 2020). Temperature data are further adjusted into higher resolutions (1km×1km) by adjusting daily data from AgERA5 with higher-resolution monthly data from WorldClim data (Fick & Hijman 2017).<sup>2</sup>

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<sup>2</sup>Similar approaches to interpolate daily temperature data at higher resolution have been used in past studies (e.g., Li 2023). Typical areas of districts in Khatlon province are in the order of 1,000 km<sup>2</sup>; therefore, grid resolutions of

## 4 Empirical analyses

Our empirical analyses focus on identifying (i) the associations between weather shocks in the origin location and outmigration decisions by household members, (ii) the effects of migration in mitigating potential adverse effects of weather shocks, and (iii) the associations of origin location weather shocks and remittances sent back to origin locations.

### 4.1 Associations between weather shocks and outmigration

Associations between weather shocks in origin locations and outmigration decisions are estimated through the standard linear panel fixed-effects model. Specifically, we estimate,

$$M_{it} = \beta + \beta_S S_{it} + \beta_X X_{it} + \beta_Z Z_{it} + c_i^M + \varepsilon_{it}^M \quad (1)$$

in which  $M_{it}$  measures indicators of outmigration decision by household  $i$  during period  $t$  (April 2014–March 2015, April 2022–March 2023 for survey years 2015 and 2023, respectively). We use three proxies for  $M_{it}$ : (1a) whether at least 1 member migrated for 1 month or more, (1b) whether at least 1 member migrated for 6 months or more; and (1c) number of household members who migrated for 1 month or more.  $S_{it}$  is a vector of variables measuring weather shocks experienced by  $i$  during suitable reference periods for  $t$  (defined in subsequent sections),  $X_{it}$  is a vector of other time-variant exogenous variables, and  $c_i^M$  is the time-invariant household fixed-effects.  $\beta$  represent estimated parameters, and  $\varepsilon_{it}^M$  represents an idiosyncratic error term.

We estimate (1) separately for samples in each district (except for N. Husrav district which is combined with nearby Shahritus district due to small sample size of the former). Doing so allows key types of weather shocks to differ across districts, which is reasonable given the potentially diverse agroclimatic conditions across districts.

#### 4.1.1 Weather shock variables

In our analyses, we first consider broad dimensions of weather shock measurements and apply the least absolute shrinkage and selection operator (LASSO) estimator (described in the later section) to identify the most influential ones for samples in different districts.

Specifically, these dimensions include (a) weather parameters such as temperatures (daily maximum, average, daily minimum, heat wave, warm nights, as well as agronomically relevant measures like growing degree days, harmful degree days, freezing days), rainfall, wind speed, and drought; (b) reference periods including summer (April–September), winter (October–March), early and late summer (April–June, July–September), early and late winter (October–December, January–March), as well as 12-month periods (April–March, October–September); (c) current year vs. one year lag; (d) 1-year shock vs. 5-year average; and (e) deviations measures such as percentiles (deviations from historical 50th percentile), z-scores, and absolute deviations from historical averages. Table 1 summarizes all dimensions of weather shocks considered in our analyses.

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1km×1km, 5km×5km and 9km×9km each corresponds to about 1,000, 40, and 12 grids per district (albeit with variations).

**Table 1. Weather shock parameters (full set initially included in the LASSO model)**

Weather parameters	Reference periods	Current vs. lag	Short-term vs. medium-term	Shock measures
<ul style="list-style-type: none"> <li>• Rainfall (total)</li> <li>• Drought (average SPEI)<sup>a</sup></li> <li>• Wind (average)</li> <li>• Temperature <ul style="list-style-type: none"> <li>• Growing degree days (potato, wheat, tomato/others)</li> <li>• Harmful degree days (potato, wheat, tomato/others)</li> <li>• Heat wave</li> <li>• Warm nights</li> <li>• Freezing days</li> </ul> </li> </ul>	<ul style="list-style-type: none"> <li>• Summer (Apr–Sept) <ul style="list-style-type: none"> <li>• Early summer (Apr–Jun)</li> <li>• Late summer (Jul–Sep)</li> </ul> </li> <li>• Winter (Oct–Mar) <ul style="list-style-type: none"> <li>• Early winter (Oct–Dec)</li> <li>• Late winter (Jan–Mar)</li> </ul> </li> </ul>	<ul style="list-style-type: none"> <li>• Current year</li> <li>• One year prior</li> </ul>	<ul style="list-style-type: none"> <li>• 1-year shock</li> <li>• 5-years average</li> </ul>	<ul style="list-style-type: none"> <li>• Percentile (deviations from 50<sup>th</sup> percentile)</li> <li>• Z-score</li> <li>• Absolute deviations</li> </ul>

Source: Authors.

<sup>a</sup>SPEI = Standardized Precipitation Evapotranspiration Index.

All weather parameters (a) have been considered potentially influential for the well-being of households in low-income countries, including wind speed, which has been less studied relative to other parameters but has been relatively more important in the hilly/mountainous regions of Central Asia, like Tajikistan.<sup>3</sup> Appendix A provides additional descriptions of how each of the temperature-based measures is computed.

The reference periods are selected to reflect the typical crop calendars for major crops in Tajikistan (e.g., Takeshima et al. 2024), in which the peak planting season seems to occur in March/April and October, with sub-peaks for early-maturing crops in June/July and December/January.

The choices (c) between weather shocks in the current year (April 2014–March 2015, April 2022–March 2023) and one year prior (April 2013–March 2014, April 2021–March 2022) reflect whether the weather shocks in the same year or the prior year are more likely to be associated with the outmigration decisions. We include both current year shock and previous year shock because past studies have been ambiguous, with some studies using past weather shock (e.g., Munshi 2003; Grace et al. 2018) and others using current year weather shock (e.g., Jessoe et al. 2018).

The choices (d) between weather shocks in a single year or over the past 5 years reflect the possibility that outmigration decisions may be more associated with a shorter-term shock or by a more medium-term shock.<sup>4</sup>

The dimensions (e) consider the various possible ways that households perceive the levels of deviations from historical norms. Each of the measures has been used in the recent literature (e.g., Takeshima et al. 2020b; Amare & Balana 2023).

#### 4.1.2 Least Absolute Shrinkage and Selection Operator (LASSO)

Identifying key weather shock parameters  $S_{it}$  in (1) among broad dimensions of potential weather shock variables described in 4.1.1 can be challenging. Specifically, including all weather-shock variables constructed from Table 1 in  $S_{it}$  would result in severe multicollinearity

<sup>3</sup>For example, in Central Asia, strong wind during summer is associated with significant dust storms (Li et al. 2019).

<sup>4</sup>Some studies also point out that the “climate change” is often observed over the longer-term, rather than single-year shocks (e.g., Stocker et al. 2013).

problems.<sup>5</sup> LASSO approaches are particularly effective in selecting the most influential variables  $S_{it}$  among many highly-collinear variables.

LASSO approaches, initially developed by Tibshirani (1996), essentially penalize the number of explanatory variables over the overall fit of the model and identify parsimonious model specifications by dropping many variables that are deemed only marginally influential or not influential at all (either unconditionally, or conditionally in the presence of other highly collinear variables). Among various LASSO estimators, we primarily apply theory-driven (“rigorous”) penalization approaches (RLASSO hereafter). The RLASSO has been found generally reliable among different classes of LASSO estimators, particularly in facilitating causal inferences in the presence of many control variables and avoiding false positives, that is falsely identifying variables as influential when in truth they are not (e.g., Ahrens et al. 2020) (Appendix B provides more details of the concepts underlying the overall LASSO approaches, as well as the RLASSO approach).

#### 4.1.3 Set of control variables $X_{it}$

The set of time-variant exogenous variables  $X_{it}$  include household demographics, exogenous wealth, access to institutions, as well as relative deprivation measures. Household demographics in  $X_{it}$  include age and gender<sup>6</sup> of household head, and household size by gender and age groups (0–15, 16–60, and 61 or above years old), and average years of formal education completed among working-age household members aged 15–60 years.

Wealth variables in  $X_{it}$  include durable assets owned and agricultural equipment, both measured in per capita value, livestock owned measured in livestock units (LU) (using conversion rates for “Transition Markets” countries defined in FAO (2011)), as well as first principal components of various indicators that characterize housing conditions and sanitary/hygienic conditions.<sup>7</sup>  $X_{it}$  also includes the size of farm areas that the household has use rights on, and whether the household has use rights to Dehkan farms<sup>8</sup> or not.

Access to institutions in  $X_{it}$  is the distance to key institutions that affect households’ welfare, specifically, nearest market and nearest bank.

Variable  $X_{it}$  also includes Relative Deprivation (RD) within the villages of the respondent household, which has been suggested as one of the key determinants of migration decisions (e.g., Kafle et al. 2020) (Appendix C describes our RD measure in more detail).

We also include  $Z_{it}$ , which is the village-level average of migration costs per distance to destination locations, among all households with migrants in the village.

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<sup>5</sup>Such high collinearity often arises because each weather parameter, such as temperature, rainfall, wind, and drought conditions, is frequently affected by each other, and each weather condition can also be serially correlated across different intra-annual subperiods or consecutive years (e.g., Grover & Sharma 2024; Singh et al. 2024).

<sup>6</sup>The 2015 round did not identify the household head but identified whether the household had any male adults or only female adults. We therefore assigned the gender of the household head as female only for those female-adults-only households. Similar to the 2015 round, we use the age of the most senior person as the age of the household head.

<sup>7</sup>Indicators associated with housing conditions include whether improved materials are used for flooring and exterior walls, whether the household owns the house, and the number of rooms. Sanitary/hygienic conditions include whether the household has access to improved source of drinking water and an improved toilet, as well as whether the community has centralized garbage collection and disposal systems, as well as a centralized sewage system.

<sup>8</sup>Dehkan farms refer to private farms formed in the late 1990s through de-collectivizing state farms operated under the former Soviet regime (Lerman & Sedik 2018). Dehkan farms are generally larger than other types of private farms, such as presidential plots and kitchen gardens which are more commonly cultivated by smallholder farmers.

## 4.2 Robustness checks for the main model (1)

We estimate additional models to check the robustness of our main model (1).

### 4.2.1 Robustness across household types

Our primary analyses for (1) focus on the entire population that includes not only agricultural households but also non-agricultural households. We first check whether the results for (1) hold if we focus only on agricultural households that own any farms. In doing so, we also check if results are robust with and without including Dehkan farms. Excluding Dehkan farms in addition to non-agricultural households would limit our samples to smallholder agricultural households only. We conduct robustness checks by excluding Dehkan farms instead of estimating separate regression exclusively for Dehkan farms because the sample size of Dehkan farms in our data is too small to derive reliable results.

### 4.2.2 Robustness controlling for the potential dynamics in outmigration decisions

Migration decisions can also be affected by more medium-to-longer-term factors. For example, if migration processes involve significant transactions costs, some of which may be fixed and incurred early on (e.g., payment for passport and other legal documents, or building network with employers in destination locations), decisions may be more persistent. If prior migration decisions are somehow correlated with current weather risks (even after controlling for household fixed-effects  $c_i^M$ ), estimates from (1) can be biased. For example, suppose a household  $i$  had someone outmigrating in previous years, which raises the likelihood of outmigration in the current year (due to positive dynamics), and happens to experience more adverse weather shocks in the current year (thus there is spurious positive correlation between the previous outmigration and the current year's weather shocks). Ignoring these dynamics can lead us to erroneously conclude that the current year's outmigration decision is due to adverse weather shocks, even though, in reality, the decision is simply due to the previous outmigration decision. In such case, the estimated associations between weather shocks and outmigration decision are biased upward. Importantly, the direction of bias can be downward if, for example, the aforementioned spurious correlation is negative instead of positive.

While our data lack a sufficient number of survey waves to formally address this issue, partial evidence of robustness can be obtained under certain assumptions. We provide such partial evidence through the application of Wooldridge's (2005) methodologies and exploit the fact that we also have information about migration behaviors from the 2012 round for about half of the panel households (as described in data section). Specifically, we estimate a dynamic panel random-effects Probit model

$$\begin{aligned} \text{Probability}(M_{it} = 1) & \\ &= \Phi(\beta + \beta_S S_{it} + \beta_M M_{i,t-1} + \beta_0 M_{i0} + \beta_X X_{it} + \beta_Z Z_{it} + \beta_{\bar{X}} \bar{X}_i + \beta_{\bar{Z}} \bar{Z}_i + r_i^M + \varepsilon_{it}^M) \end{aligned} \quad (2)$$

and a dynamic panel random-effects Poisson model

$$E(M_{it}^*) = \exp(\beta + \beta_S S_{it} + \beta_M M_{i,t-1}^* + \beta_0 M_{i0}^* + \beta_X X_{it} + \beta_Z Z_{it} + \beta_{\bar{X}} \bar{X}_i + \beta_{\bar{Z}} \bar{Z}_i) \cdot r_i^M \quad (3)$$

in which  $M_{it}^*$  is the count variable of the number of household members who outmigrated for at least 1 month. Following Wooldridge (2005) and recent studies (e.g., Gebru et al. 2019),  $M_{i0}$  and

$M_{i0}^*$  are initial levels of  $M_{it}$  and  $M_{it}^*$  (i.e.,  $M_{i,2012}$  and  $M_{i,2012}^*$ ). Notations  $\bar{X}_i$  and  $\bar{Z}_i$  are averages of  $X_{it}$  and  $Z_{it}$  at the household level across all survey rounds, inserted to control for correlated random-effects (Mundlak 1978; Chamberlain 1984).  $r_i^M$  is a household-level time-invariant random-effects corresponding to each regression (different from fixed-effects  $c_i^M$  in (1), which cannot be directly estimable in Probit or Poisson models).  $\Phi$  is cumulative standard normal distribution function. Notation  $E(M_{it}^*)$  signifies that  $M_{it}^*$  follows Poisson distribution with mean  $E(M_{it}^*)$  estimated as (3).

As in Wooldridge (2005), under a reasonable assumption that including initial levels of dependent variables ( $M_{i0}$  and  $M_{i0}^*$ ) addresses the “initial-condition problem” in a dynamic panel regression, equations (2) and (3) consistently estimate the association between weather shocks and migration decisions ( $\beta_S$ ) when the migration decision can also be significantly affected by previous migration decisions.

Importantly, unlike regression (1), regressions (2) and (3) are more reliable with a larger sample size and can be highly imprecise if (2) and (3) are estimated separately for each district as in (1), especially given that sample sizes are particularly small for certain districts. Therefore, we estimate (2) and (3) by pooling all samples across districts. While doing so restricts the associations with weather shocks (given the type of major weather shocks identified by the LASSO method) as common across all districts, it allows us to obtain estimates with more statistical power.

### 4.3 Associations between migration and weather shock damage

We then conduct supplementary analyses to assess the potential drivers of outmigration in the face of adverse weather shocks. Specifically, we assess how outmigration is associated with the impact of weather shocks on various household welfare indicators. We estimate,

$$Y_{it} = \gamma + \gamma_M M_{it} + \gamma_S S_{it} + \gamma_{MS} M_{it} S_{it} + \gamma_X X_{it} + c_i^Y + \varepsilon_{it}^Y \quad (4)$$

in which  $Y_{it}$  is a set of key welfare outcomes (described below). Notations  $\gamma$ 's represent estimated parameters,  $c_i^Y$  represents time-invariant unobserved household fixed effects, and  $\varepsilon_{it}^Y$  represents idiosyncratic errors.

Welfare outcomes  $Y_{it}$  include total household consumption per capita, indicators of household food security (whether the household experienced any type of hunger within the last 30 days), nutrition security (household dietary diversity during the last 7 days), and total agricultural production value.

In equation (4), migration variable  $M_{it}$  is endogenous because it is affected by  $S_{it}$ . We therefore estimate (4) through panel fixed-effects instrumental variable (IV) method (Baltagi 2013). As an excluded IV, we use the village-level average of migration costs per distance to destination locations ( $Z_{it}$ ).<sup>9</sup> Choosing this IV is motivated by the fact that international migration is often facilitated by the local migration network (e.g., Azzarri & Zezza 2011; Murakami et al. 2021). A statistically significant positive coefficient  $\gamma_{MS}$  would imply that migration partly mitigates damages from weather shocks. Furthermore, we apply Lewbel's (2012) IV methods, which extends the set of IVs exploiting the heteroskedastic relations between IV and endogenous variables, to improve the identification power of the IVs (a similar approach has been used on studies

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<sup>9</sup>Destination locations are mostly cities in Russia. We thus used simple straight-line (Euclidean) distances using the geocoordinates of respondents and geocoordinates of the city centers of destination cities.

in Central Asia including Karymshakov et al. (2023) as well as under different but related contexts in other developing countries (e.g., Takeshima et al. 2025b)).

Unlike (1), we estimate (4) by pooling all samples across districts by adding year×district dummy interaction terms, so that more efficient estimates can be obtained. Variable  $S_{it}$  in (4) is a single variable that consists of each weather shock variable identified in Table 5 entered for corresponding district sample.

#### 4.4 Associations between weather shocks at origin locations and remittances sent to origin locations

To provide supplementary insights on how adverse weather shocks may still hurt households despite mitigating roles of outmigration of the household members, we also estimate how remittances sent by migrants to origin households are negatively associated with weather shocks in origin locations. Specifically, we estimate,

$$\pi_{it} = \delta + \delta_S S_{it} + \delta_X X_{it} + \delta_Z Z_{it} + c_i^\pi + \varepsilon_{it}^\pi \quad (5)$$

(only for households with outmigrating members)

in which  $\pi_{it}$  is the average remittances sent back to the origin household per month per migrants in household  $i$  in year  $t$ , and  $Z_{it}$  is the key destination characteristics (nighttime light in destination cities in 2014 and 2022, respectively).

#### *Inverse probability weighting method to address potential sample-selection problems*

Since the remittance  $\pi_{it}$  is only observed for households with outmigrating members, equation (5) can be biased due to sample-selection problems. We therefore also estimate (5) using an inverse probability weight regression adjustment (IPWRA) method. Specifically, we first estimate the probability ( $\hat{p}_i$ ) that  $\pi_{it}$  is observed for household  $i$  in both the 2015 and 2023 rounds through a probit regression using base-year values of  $X_{it}$  and  $Z_{it}$ . We then compute the inverse of that probability ( $1/\hat{p}_i$ ) and re-estimate (5) applying  $1/\hat{p}_i$  as the sample weight. As is shown in the result section, results for (5) are generally similar between models with and without the adjustment for sample selection bias.

## 5 Descriptive statistics<sup>10</sup>

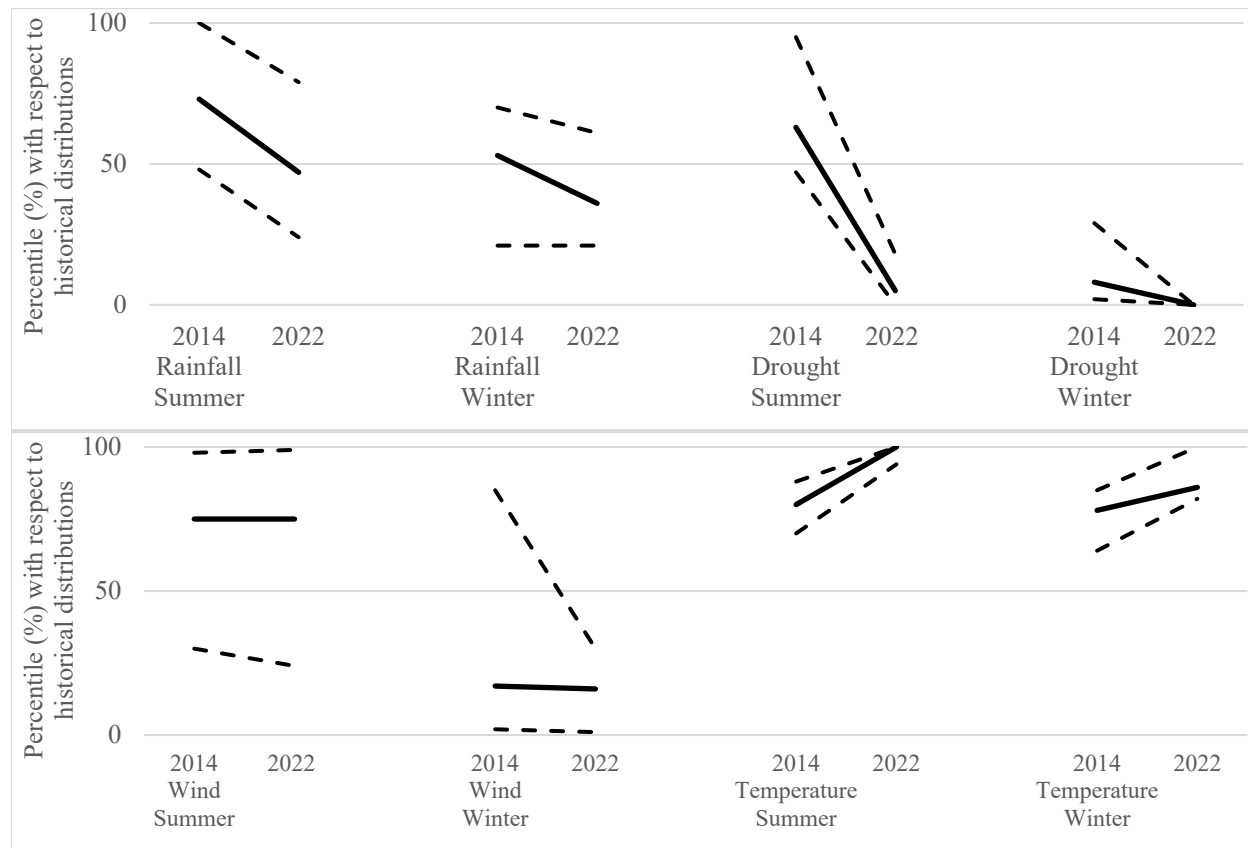
### 5.1 Weather shocks patterns

Figure 1 summarizes weather patterns in each survey round in areas where our sample households are located. Dark bold lines represent the overall sample average, while dotted lines represent the sample maximum and minimum in each year. Generally, the sample households experienced declining rainfall in both summer and winter between the 2014 and 2022 rounds. These changes are a result of above-average rainfall in summer 2014 to more normal rainfall in summer 2022 and of normal rainfall in winter 2014 to below-average rainfall in winter 2022. Drought levels changed from more or less normal in the summer of 2014 to abnormally severe in the summer of 2022, while drought in winter was already abnormally severe in 2014 and became more extreme in 2022. Windspeeds were above average in summer and below average in winter in both years, but with considerable variations across districts. In 2014, average temperatures

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<sup>10</sup>Descriptive statistics presented in this section are simple raw statistics and are not adjusted for sample weights, as the purpose here is to simply illustrate the samples on which our analyses are based.

were already above historical averages and increased further still in 2022 for both summer and winter. Importantly, however, there are still significant variations among samples, as indicated by the dotted lines of the sample maximum and minimum, which we exploit in identifying the associations between weather shocks and outmigration decisions.



**Figure 1. Overall weather patterns in 2014 and 2022 shown as percentiles with respect to historical distribution<sup>a</sup>**

Source: Authors.

Note: <sup>a</sup>Dark bold line represents overall sample average; dotted lines represent sample maximum and minimum in each year.

## 5.2 Outmigration patterns

Table 2 summarizes the patterns of migration among all sample households, as well as in each Jamoat (district), in 2014 and 2022. Figure 2 further provides visual illustrations. While these figures are not representative at the district levels they offer insights into some inter-district variations that motivate our analyses.

Overall, the share of households with at least one outmigrant (migrating for at least 1 month) has increased significantly between the 2014 and 2022 rounds, from 41 percent to 56 percent—from 39 percent to 52 percent and from 32 percent to 44 percent for those migrating for at least 3 months and 6 months, respectively. During the mid-2010s, labor migration to Russia and remittances sent back home from Russia faced significant declines due to Russia’s economic recession and a series of other adverse events (Shimizutani & Yamada 2023). The increases have

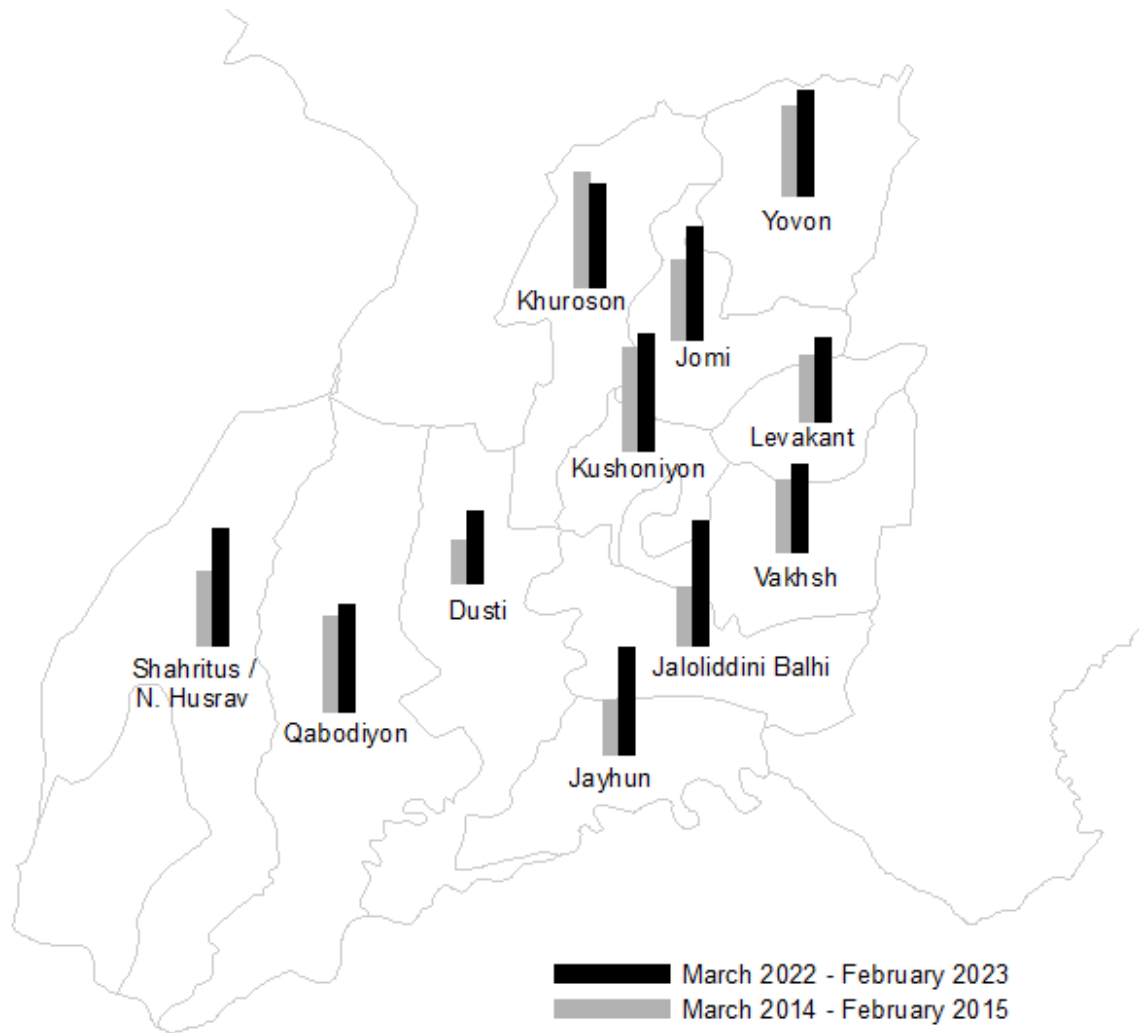
been particularly pronounced in southern districts like Jaloliddini Balhi, Jayhun, and Shahritus/N. Husrav, while relatively more modest in northern districts like Khuroson.

**Table 2. Share (%) of sample households with at least one migrant, migrating at least 1 month, 3 months or 6 months**

District	Sample size of panel households (per round)	Maximum migration duration of any migrating household members					
		at least 1 month		at least 3 months		at least 6 months	
		2014	2022	2014	2022	2014	2022
Kushoniyon	252	53	61	51	57	46	48
Vakhsh	186	37	46	34	42	28	34
Khuroson	99	60	54	57	53	48	48
Dusti	95	22	38	21	35	16	27
Qabodiyon	109	50	56	45	54	40	48
Jaloliddini Balhi	163	31	65	28	62	20	56
Jayhun	142	28	56	25	51	22	46
Levakant	48	35	44	33	42	23	33
Jomi	175	42	59	39	57	33	46
Shahritus/N. Husrav <sup>a</sup>	116	39	61	35	55	28	46
Yovon	213	47	55	43	51	36	38
<b>All samples</b>	<b>1598</b>	<b>41</b>	<b>56</b>	<b>39</b>	<b>52</b>	<b>32</b>	<b>44</b>

Source: Authors.

Note: <sup>a</sup>N. Husrav district is combined with Shahritus district figures, due to the small sample size of the former (sample size = 23).



**Figure 2. Sample shares of households with at least one migrant (migrating at least 1 month) by districts<sup>a</sup>**

Source. Authors.

Note: <sup>a</sup>Samples in N. Husrav district are combined with those with Shahritus district, due to small sample size.

Table 3 summarizes the remittances sent back to origin households by migrants, costs of migration, and destinations. A migrant typically sends about US\$50~75 per month of remittances back to origin households (sample median, in constant 2022 US\$), with somewhat higher amounts in 2022 compared to 2014 (based on exchange rates shown in Table 3 footnote). Typically, a migrant incurred \$218 and \$324 (in constant 2022 US\$) for one-way migration costs to destinations, which were usually located 3,000 km away from Dushanbe in a straight-line distance. Most destinations have been in Russia, while a small fraction migrated to Kazakhstan and other neighboring countries. In Russia, while a majority migrated to Moscow Oblast, others migrated to various parts of Russia, including Saint Petersburg/Leningrad Oblast, Yekaterinburg/Sverdlovsk Oblast, Novosibirsk Oblast, Samara Oblast, and others. The economic development levels of destination locations have remained relatively similar between 2014 and 2022, partly due to slow economic growth in Russia during this period.

**Table 3. Other migration-related variables**

Variables	2014	2022
	Median (std.dev)	Median (std.dev)
Remittance sent by outmigrant to origin location (per month per migrant, 2022 US\$)	44 (99)	74 (189)
One-way migration costs (per migrant, 2022 US\$)	218 (199)	324 (167)
One-way migration costs (per household, 2022 US\$)	264 (320)	509 (433)
Distance to migration destinations (straight line, km)	2995 (547)	2995 (606)
Migration destination country (share (%) among migrants)	Russia – 98 Kazakhstan – 1 Others – 1	Russia – 97 Kazakhstan – 2 Uzbekistan / Turkey – 1 Others – 0.5
Migration destinations (share (%) among migrants) inside Russia	Moscow Oblast – 54 Saint Petersburg/Leningrad Oblast – 19 Yekaterinburg/Sverdlovsk Oblast – 5 Novosibirsk Oblast – 2 Others - 20	Moscow Oblast – 60 Saint Petersburg – 15 Yekaterinburg/Sverdlovsk Oblast – 4 Novosibirsk Oblast – 4 Samara Oblast – 2 Others – 15
Nighttime light index in destinations (nanoWatt per cm <sup>2</sup> per square radian)	422 (188)	379 (212)
Number of obs. (among panel household samples with at least one out-migrant)	663	887

Source: Authors.

Exchange rate in 2022: US\$1 =11.0 Somoni; US\$1 =68.5 Russian Rubles (World Bank 2024a); US\$1 in 2014=\$1.25 in 2022 (US Bureau of Labor Statistics 2024).

### 5.3 Descriptive statistics of other control variables

Table 4 summarizes the descriptive statistics of other control variables. Most households are headed by male household members. Most households have use rights to about 0.3 to 0.4 hectares of farmland and modest agricultural capital. Ownership of agricultural capital increased between 2015 and 2023, indicating some asset accumulation taking place in these households. The housing conditions, sanitation infrastructure, garbage collection services, and sewage systems also improved between 2015 and 2023. The relative deprivation index declined slightly between 2015 and 2023 on average, suggesting reduced inequality within villages. Household welfare outcomes generally improved between these periods in terms of consumption, household dietary diversity score, and hunger. Nonetheless, in 2023 close to 30 percent of households still experienced hunger during the past 30 days.

**Table 4. Descriptive statistics—panel sample of households**

Variable	2015	2023	All
	mean	mean	mean
Household head age (year)	45.9	57.2	51.6
Female household head (yes = 1)	0.066 <sup>a</sup>	0.300	0.183
Male household members (number)			
0–14 years old	1.631	1.444	1.538
15–60 years old	2.298	1.546	1.922
61 and above years old	0.204	0.286	0.245
Female household members (number)			
0–14 years old	1.582	1.360	1.471
15–60 years old	2.417	2.046	2.232
61 and above years old	0.195	0.333	0.264
Average years of formal education of working-age members (years)	10.0	11.3	10.7
Durable assets per capita (2015 somoni)	13,315.6	8,872.4	10,098.8
Livestock asset (Livestock Units)	1.15	1.18	1.16
Improved sanitation (yes = 1)	0.028	0.464	0.246
Finished floor (yes = 1)	0.497	0.828	0.663
Finished wall (yes = 1)	0.133	0.091	0.111
Improved water source (yes = 1)	0.563	0.571	0.567
In community with centralized garbage collection (yes = 1)	0.065	0.107	0.086
In community with centralized sewage system (yes = 1)	0.039	0.064	0.052
Relative deprivation index	0.166	0.149	0.158
Distance to nearest food market—average of all types of markets (minutes)	30.7	24.7	26.3
Distance to nearest medical facilities—average of all types of facilities (minutes)	19.8	18.5	18.9
Distance to nearest education facilities—average of all types of facilities (minutes)	33.6	31.3	31.9
Farm area with use rights (hectares)	0.434	0.303	0.368
Has use rights to Dehkan farm (yes = 1)	0.119	0.116	0.117
Agricultural capital (2015 somoni)	49.4	233.8	183.0
<i>Welfare outcomes</i>			
Consumption (2015 somoni, per capita per day)	13.027	18.869	15.948
Household dietary diversity score	8.289	9.125	8.707
No hunger (yes = 1 if hunger score = 0)	0.608	0.722	0.665
<b>Sample size</b>	<b>1,598</b>	<b>1,598</b>	<b>3,196</b>

Source: Authors.

Note: <sup>a</sup>Figure for 2015 round refers to the proportion of households in which adult household members are women only, without male adult members.

## 6 Results

### 6.1 Associations between key weather shock parameters and outmigration

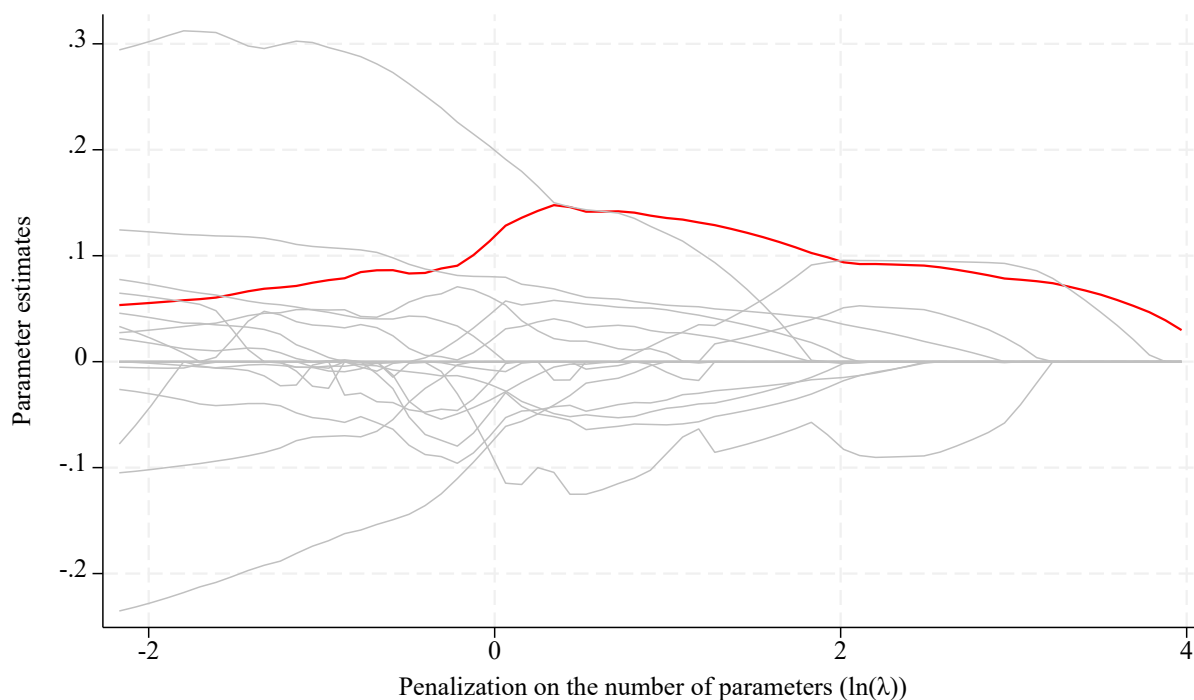
Table 5 summarizes the key weather shock parameters identified through RLASSO approaches described in the methodology section. The weather shock parameters identified vary considerably across districts, suggesting the suitability of our methodologies in accommodating such heterogeneity. For example, for samples in the Kushoniyon district, whether the household had at least one member who migrated for at least 1 month is most significantly associated with shocks in the early winter rainfall (deviations from the 50th percentile in the historical distribution of early winter rainfall). Figure 3 illustrates how this variable remains significant as the models become more parsimonious through RLASSO methods while less significant weather shock variables are eliminated. Similarly, outmigration is found to be associated most clearly with wind speed through summer over the past 5 years (Vakhsh) or early winter (Dusti), high

nighttime temperature in summer (Khuroson) and Jayhun cold days (Qabodiyon), drought in early winter (Jaloliddini Balhi) or early summer (Shahritus/N. Husrav), growing degree days (Levakant), and rainfall in winter (Jomi) or early summer (Yovon). Importantly, results in Table 5 do not mean other weather shock parameters are irrelevant. Instead, Table 5 shows that failure to consider these particular weather shock parameters may underestimate the potential significance of weather shocks on migration decisions.

**Table 5. Key weather shock parameters associated with migration decisions (by districts) identified through LASSO-selection approach**

Districts	Weather parameters	Seasons	Reference periods	Statistics (percentile, z-score, absolute deviation)
Kushoniyon	Rainfall	Early Winter (Oct–Dec)	Current year	Percentile
Vakhsh	Wind speed	Summer	Past 5 years	Percentile
Khuroson	High nighttime temperature	Summer	Past year	Percentile
Dusti	Wind speed	Early winter (Oct–Dec)	Current year	Percentile
Qabodiyon	Cold days (10°C)	Winter	Previous year	Percentile
Jaloliddini Balhi	Drought	Early winter (Oct–Dec)	Past 5 years	Absolute deviation
Jayhun	High nighttime temperature	Summer	Current year	Percentile
Levakant	Growing Degree Days	12 months (April–March)	Past year	Percentile
Jomi	Rainfall	Winter	Past 5 years	Percentile
Shahritus/NH. Husrav	Drought	Early summer (Apr–June)	Previous year	Percentile
Yovon	Rainfall	Early summer (Apr–June)	Previous year	Z-value

Source: Authors' estimations.



**Figure 3. Evolution of coefficient estimates in LASSO model selection process (example of Kushoniyon district sample)<sup>a</sup>**

Source: Authors.

Note: <sup>a</sup>Red line indicates the coefficient estimates for the early-winter rainfall shocks (absolute deviations from historical 50<sup>th</sup> percentile), the key weather shock variable selected for Kushoniyon district as in Table 5.

Table 6 summarizes the associations<sup>11</sup> of identified weather shock variables on outmigration, expressed as the association between a one-standard deviation increase in the respective weather anomaly index based on Table 5 and the likelihood that a household has at least one member who outmigrated for at least 1 month.

Results in the top panel indicate that, across all districts, more abnormal weather is statistically significantly associated with a higher likelihood of outmigration. Similarly, the middle panel of Table 6 further shows that the identified set of weather shock variables is significantly and positively associated with the likelihood of longer-term migration (6 months or more), as well as total person-months of migration. Lastly, the bottom panel indicates that results are again generally similar when the dependent variable is the “count” of household members who outmigrated for 1 month or longer. Overall, these results generally suggest that more abnormal weather the higher the number of household members who migrate, and possibly for longer lengths of time. However, the type of weather parameters that influence migration vary considerably across districts.

<sup>11</sup>We prefer the term “association” since our analyses do not consider the impact pathways and thus are not strictly causal.

**Table 6. Predictive power of the LASSO-selected adverse weather shock variables on migration decisions, by different district samples**

Variables	Districts										
	Kushoniyon	Vakhsh	Khuroson	Dusti	Qabodiyon	Jaloliddini Balhi	Jayhun	Levakant	Jomi	Shahritys/N. Husrav	Yovon
	Coef (std.err)	Coef (std.err)	Coef (std.err)	Coef (std.err)	Coef (std.err)	Coef (std.err)	Coef (std.err)	Coef (std.err)	Coef (std.err)	Coef (std.err)	Coef (std.err)
<i>Dependent variable = at least 1 member outmigrated for 1 month or more</i>											
Weather shock measures <sup>a</sup>	0.134** (0.038)	0.464*** (0.142)	0.179* (0.103)	0.374** (0.147)	0.121* (0.064)	0.297** (0.135)	0.742* (0.398)	0.167** (0.079)	0.140*** (0.041)	0.767** (0.399)	0.080** (0.035)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-square	.048	.056	.040	.089	.052	.099	.034	.171	.067	.054	.017
<i>Dependent variable = at least 1 member outmigrated for 6 months or more</i>											
Weather shock measures <sup>b</sup>	0.124*** (0.038)	0.385*** (0.126)	0.198* (0.114)	0.724*** (0.155)	0.425*** (0.155)	-0.295** (0.121)	0.577** (0.268)	0.388* (0.224)	0.123*** (0.046)	0.537 (0.392)	0.047 (0.033)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-square	.061	.038	.040	.076	.061	.115	.015	.014	.060	.065	.027
<i>Dependent variable = count of household members outmigrated for 1 month or more</i>											
Weather shock measures <sup>b</sup>	0.390*** (0.110)	0.149*** (0.048)	0.254** (0.120)	0.228** (0.090)	1.329*** (0.504)	0.974** (0.465)	1.072*** (0.327)	0.635*** (0.216)	0.347*** (0.119)	0.339 (0.242)	0.224* (0.117)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-square	.151	.071	.060	.011	.190	.170	.071	.059	.066	.017	.123
No. obs.	504	372	198	190	218	326	284	96	350	232	426

Source: Authors.

Note: <sup>a</sup>Weather shock parameters are as defined in Table 5 for respective district sample. <sup>b</sup>Weather shock parameters for these results slightly differ from those in Table 5 because dependent variables differ from the top panel, but they are still selected from LASSO methods in the same ways. Appendix Table D2 summarizes corresponding weather shock parameters for each case. FE = fixed-effects.

## 6.1.1 Robustness checks

### 6.1.1.1 *Weather shocks and migration decisions among agricultural households*

Table D1 in Appendix D summarizes the robustness of the main results Table 6 (the associations between weather shocks and outmigration), exclusively for the sample of agricultural households (top panel), as well as smallholder agricultural households that further exclude Dehkan farms (bottom panel). The results in both panels are broadly consistent with those in Table 6, that is, key types of weather shocks (selected by similar LASSO methods as in Table 6 but using only agricultural households in the sample)<sup>12</sup> raise the likelihood of outmigration, and these results hold for most districts (except Shahritus and N. Husrav districts for which associations are statistically insignificant).

### 6.1.1.2 *Results accounting for dynamic persistence in migration decisions*

Table 7 summarizes the key results of dynamic panel random-effects Probit and Poisson models (2) and (3), with the particular focus on the associations between weather shocks and outmigration decision ( $\beta_S$ ) as well as persistence of migration decisions ( $\beta_M$ ). As was described in subsection 4.2.2, the model is estimated by pooling samples from all districts. Again, results in Table 7 show that our main results in Table 6 are robust. In both models, while migration decisions are partly driven by persistence—whether and how many household members decide to outmigrate in 2023 are statistically significantly positively affected by these decisions in 2015, as indicated by coefficients for lagged dependent variables—weather shocks in 2023 still serve as additional drivers of outmigration even after controlling for such persistence effects. These results serve as a form of falsification test. Our main findings in Table 6 are more likely to correctly capture the associations with weather shocks in 2023, rather than erroneously capturing the effects of other factors (such as persistence effects) that may be coincidentally correlated with weather shocks in 2023.

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<sup>12</sup>In other words, LASSO-selected weather shock variables that correspond to the sample of agricultural households in Table 11 differ slightly from weather shock variables shown in Table 5 (which correspond to the results in Table 6).

**Table 7. Associations between weather shocks and migration decisions considering potential migration dynamics**

Variables	Wooldridge (2005) dynamic panel random effects Probit	Wooldridge (2005) dynamic panel random effects Poisson
Dependent variables	At least 1 member out-migrated for 1 month or more (yes = 1)	Count of household members outmigrating at least 1 month or more (count)
	Coef. (Std.err)	Coef. (Std.err)
Weather anomalies in origin locations (one standard deviation change)	0.131*** (0.048)	0.106** (0.043)
Lagged dependent variable	0.310** (0.157)	0.121*** (0.037)
Initial period dependent variable	Yes	Yes
Other controls	Yes	Yes
Other controls (Correlated Random Effects)	Yes	Yes
Number of observations	2082	2082
p-value (H <sub>0</sub> : variables jointly insignificant)	.000	.000
Log-likelihood	-1229.284	-2001.249

Source: Authors.

Note: \*\*\* 1% \*\* 5% \* 10%. <sup>a</sup>Number of observations only include 1041 panel samples who also provided migration information in 2012 round.

## 6.2 Associations between outmigration and possible mitigation of weather-shock damages

Table 8 summarizes supplementary results on the associations between outmigration, weather shocks on consumption and food/nutrition security outcomes estimated through equations (4). Each variable is demeaned so that coefficients on non-interacted variables represent average associations.

Outmigration on its own generally has insignificant associations with household outcomes, except positive associations with household food security (1st row). At the same time, abnormal weather conditions are generally adversely associated with these outcomes, particularly with household consumption, household food security, and agricultural production (2nd row). Notably, the coefficients for the interaction between weather shocks and migration (3rd row) are statistically significantly positive for consumption, nutrition, and food security. In other words, outmigration may be mitigating the potentially adverse effects of abnormal weather on these outcomes. Importantly, the coefficient on agricultural production value is statistically significantly negative, suggesting that such mitigating effects on consumption and nutrition/food security arise through reduced engagement in agriculture and increased engagements in other activities and reliance on different resources, including the use of remittances from outmigrants for these outcomes. Furthermore, the aforementioned mitigation effects against adverse weather shocks may be the driving force of outmigration, given the generally weak average effects when weather shocks are not factored in (1st row).

**Table 8. Effects of migration in mitigating damages from weather shocks (instrumental variable panel-fixed effects model)**

Variables	Dependent variables			
	ln (Consumption per capita)	Nutrition security (Household diversity score)	Food security (No hunger)	Value of agricultural production (1sd change)
	Coef. (Std.err)	Coef. (Std.err)	Coef. (Std.err)	Coef. (Std.err)
Migration (yes = 1)	-0.005 (0.027)	0.009 (0.028)	0.031*** (0.010)	-0.012 (0.008)
Weather shocks (one standard deviation) <sup>a</sup>	-0.030** (0.012)	-0.024 (0.028)	-0.020** (0.010)	-0.020** (0.010)
Weather shocks * Migration	0.053*** (0.013)	0.038** (0.019)	0.034*** (0.012)	-0.014*** (0.004)
Other controls	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes
No.obs	3196	3196	3196	3196
p-value (H <sub>0</sub> : variables jointly insignificant)	.000	.000	.000	.000
p-value (H <sub>0</sub> : underidentified)	.017	.017	.017	.017
p-value (H <sub>0</sub> : not overidentified)	.573	.181	.511	.325

Source: Authors. \*\*\* 1% \*\* 5% \* 10%.

Note: \*\*\* 1% \*\* 5% \* 10%. 1sd = one standard deviation

### 6.3 Associations between origin-location weather shocks and remittances sent to origin-households

Table 9 summarizes the results of equation (5), that is, the relations between the weather shocks in the origin location in Khatlon province and monthly remittances sent to the origin location per month per migrating household members. Table 9 suggests that more abnormal weather in the origin location is negatively associated with per capita monthly remittances sent by the outmigrant, conditional on having at least one outmigrant. A one-standard deviation increase in weather anomaly may be associated with as much as a 0.1 standard deviation decrease in remittances sent per migrant per month. While the impact pathway is unclear, the results are consistent with the hypothesis that weather shocks in the origin location lower the reservation wages and force migrants to accept lower income earning opportunities at the migration destination out of desperation. These findings are also consistent with Table 8, showing that abnormal weather is significantly negatively associated with household consumption and food/nutrition security, even though migration can partly mitigate these damages.

**Table 9. Standardized effects of weather shocks in home locations on remittances sent by migrants**

Variables	Original model	Inverse Probability Weight Regression Adjustment to account for sample selection <sup>a</sup>
	Remittances sent per month per migrant (standardized value)	Remittances sent per month per migrant (standardized value)
Dependent variables	Coef. (Std.err)	Coef. (Std.err)
Weather abnormality in origin locations (one standard deviation change)	-0.095** (0.038)	-0.104*** (0.037)
Other controls	Yes	Yes
Household fixed effects	Yes	Yes
Intercept	Yes	Yes
Number of observations <sup>b</sup>	1402	1402
R-square	.054	.081

Source: Authors. \*\*\* 1% \*\* 5% \* 10%.

Note: \*\*\* 1% \*\* 5% \* 10%. <sup>a</sup>The model accounts for potential sample-selection bias, due to the fact that remittances are observed only for households whose member outmigrated. <sup>b</sup>Samples only include households with at least one migrant. Samples further exclude about 10% of households whose members' migration destinations are unknown and the value of economic condition in destination locations (nighttime light) cannot be computed.

## 7 Policy implications

Our results have various implications on policies, many of which have been promoted for other countries (e.g., Bryan et al. 2014; IFPRI 2018; Lagakos et al. 2023) and which may also be applicable to Tajikistan. While the migration rate is already relatively high in Tajikistan, policies that further lower migration costs can help migrants earn increased overall incomes. These may include investing in better domestic transport infrastructure to reduce migration costs from rural to urban areas and major cities from which migrants depart to other countries, reducing bureaucratic obstacles such as high passport costs, supporting the participation of members of poor communities in legal migrant work programs, and subsidizing migration when appropriate. As in other countries like the Philippines (Beam et al. 2016), strengthening and facilitating legal contract-work programs with countries with labor shortages (Russia and other destination countries) through bilateral collaborations can also be effective in reducing transaction costs and increasing net incomes for migrant.

Similarly, policies that support reducing transactions costs of remittance transfers can further help migrants and origin households. The average cost of remitting from Russia have remained volatile in recent years partly due to financial sanctions imposed on Russian Federation since 2022, while the remittance costs from other major destinations like Turkey or other Central Asia/Eastern European countries have remained high (more than 5 percent of the remittance amount) (Prokhorova 2025; UNESCAP 2025). Continuous efforts to raise financial literacy of migrants (e.g., Gibson et al. 2014), minimizing barriers to access banking services and broader regulation of remittance service providers (e.g., Beck & Martínez Pería 2011), and investing in infrastructures for modern financial technologies (e.g., Taghizadeh-Hesary et al. 2021) are likely to remain critical in keeping remittance costs at low and stable levels for Tajik migrants. Transparency should also be enhanced through the provision of accessible information on remittance transfer costs by money transfer operators and other remittance service providers (Ahmed 2020; Prokhorova 2025). At the same time, strengthening international money transfer services through more traditional institutions like post offices also remains important. Even as late as 2019, Tajikistan had not provided international money transfer services, unlike most other countries in

Central Asia and Eastern Europe (Ilinitchi 2019), despite the fact that post offices often remain convenient remittance channels for migrants and household members with low digital literacy or with limited access to internets. Given the generally hilly/mountainous terrain, agricultural sector development in Tajikistan can also benefit from experiences in regions with similar characteristics elsewhere, including growth potentials of the livestock sector and crop-livestock integration (e.g., in the Himalayas (Brown & Waldron 2013)) as well as agroforestry (e.g., in the Andes (Rodríguez et al. 2023)), combined with measures like the promotion of biodiversity preservation (e.g., in Vietnam (Lampach et al. 2021)) and slope conversion (e.g., in China (Liao & Zhang 2008)).

These migration policies should also be supplemented by rural development policies that support the origin locations to develop climate-smart agriculture that enhances climate resilience, such as through investments in agricultural infrastructure like canals/greenhouses and addressing labor shortages resulting from migration (Ghimire et al. 2023). The promotion of water efficient technologies like drip irrigation or sprinkler irrigation can also make agriculture more resilient against growing water scarcity. Similar rural development policies can be designed to develop the nonfarm sector that may be less vulnerable to climate risks (Mukherjee & Fransen 2024), such as improving financial inclusion and access to rural banks, among others, to address liquidity constraints which are often aggravated by adverse weather, and supporting job creations through, for example, cash-for-work programs and other social protection programs (Castells-Quintana et al. 2018). As is highlighted in Mukherjee & Fransen (2024), India's Mahatma Gandhi National Rural Employment Guarantee program and Brazil's Bolsa Familia, among others, may offer useful blueprints for similar programs to be implemented in Tajikistan's rural development policies to address climate risks. Other support that can potentially lead to the growth of small and medium enterprises should also be explored, including the development of innovation systems and technological capabilities (Abrori & Natsuda 2024), business literacy training, industrial clusters, and enabling environments that avoid excessive regulation (Kluczewska 2021).

Investments in rural infrastructures like feeder roads, bridges, river embankments remain critical for countries like Tajikistan which scores low on the World Bank's Logistics Performance Index, to reduce material costs and improve access to local and regional markets, while also enhancing resilience in these infrastructures against damages from climate risks like flooding (World Bank 2024b).

## **8 Conclusions**

Climate change and increased frequency of abnormal weather are becoming growing threats to people's livelihood in developing countries, including Tajikistan. In Tajikistan, despite the fact that migration is prevalent and remittances account for a significant share of GDP, evidence is scarce as to whether migration is used to mitigate detrimental effects of adverse weather shocks and how much of the loss in welfare is actually mitigated by such migration. We narrowed this knowledge gap through a unique georeferenced panel dataset from Khatlon province in Tajikistan and detailed climate data. We applied LASSO approaches to identify the weather parameters that are most clearly associated with migration decisions in each district in the sample.

Our results suggest that the share of households with migrants generally increased between 2014 and 2022, especially in southern districts like Jayhun, Jaloliddini Balhi, and Shahritus, but also broadly among most districts. The LASSO approaches reveal that different types of weather shocks are associated with outmigration decisions in different districts, ranging from

rainfall, temperatures, drought, and windspeed in different subperiods within each year or more medium-term trends over a 5-year span. Nonetheless, regardless of such variations in the key types of weather across districts, we find that more abnormal weather induces more outmigration in most districts, and this applies consistently even when we focus on longer-duration migration. Outmigration significantly mitigates the potentially adverse effects of consumption and food/nutrition security in the households of the origin. Nonetheless, more abnormal weather in the origin location is associated with lower remittances per migrant per month sent back to origin households, and thus, migration's mitigating roles against weather shocks are still somewhat limited. While the mechanisms are less clear, findings are consistent with the hypotheses that abnormal weather in origin locations (and reduced livelihood opportunities) may force migrants to take up distress work in destination locations.

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## Appendix A: Temperature related measures

### (a1) Growing Degree Days

For growing degree days (GDDs), we consider 3 different combinations of ceiling and base temperatures, which apply to major crops grown among our sample households: potato, wheat, and tomato. Specifically, these temperature thresholds are the following: threshold 1 (minimum daily temperature =  $-4^{\circ}\text{C}$ , maximum daily temperature =  $27^{\circ}\text{C}$ , applicable to potato), threshold 2 (minimum daily temperature =  $6^{\circ}\text{C}$ , maximum daily temperature =  $29^{\circ}\text{C}$ , applicable to wheat), and threshold 3 (base = average daily temperature of  $10^{\circ}\text{C}$ , ceiling =  $30^{\circ}\text{C}$ , applicable to tomato and most other major crops like corn). These threshold figures are taken from Jackson et al. (2021) for potatoes and wheat and McDonald & Warland (2020) for tomatoes.

Using these thresholds, GDDs are calculated as

$$GDD = \sum_d^D \{ \min[\max(T_{mean,d}, T_{base}), T_{ceiling}] - T_{base} \}$$

where  $T_{mean,d}$  is the average temperature of the day  $d$  in respective production season,  $T_{base}$  and  $T_{ceiling}$  are the minimum and maximum temperatures for each crop defined above, and  $D$  is the number of days within the particular production season.

### (a2) Harmful Degree Days

Harmful degree days (HDDs) measures the extent to which temperatures cumulatively exceed the maximum temperatures suitable for each crop during the production season. Similar to GDD, HDD is computed for 3 different combinations for potato, wheat, and other crops, including tomato. Specifically, HDDs are calculated as

$$HDD = \sum_d^D \{ \max(T_{mean,d}, T_{ceiling}) - T_{ceiling} \}$$

where same notations as GDD are used.

### (a3) Heat Wave

Heat waves (HW) generally refer to consecutive days of extremely high temperatures, which may not always be captured by average temperatures during the season alone. Following Miller et al. (2021) and Jarrett & Tackie (2024), we define HW if the daily maximum temperatures exceeded 1.5 times the standard deviations above historical averages consecutively for more than 3, 4, 5, ..., 10 days, respectively, and computed the total days that meet these criteria within the hottest 3 months (June–August).

### (a4) High Nighttime Temperatures

Rising nighttime temperatures have been increasingly affecting agricultural production in distinctively different ways than average daily temperatures do, including pest activities (e.g., Takeshima et al. 2023). We define high nighttime temperatures (HNT) as the total number of days in which nighttime minimum temperatures exceeded 20, 21, 22, 23, 24, and 25  $^{\circ}\text{C}$ , respectively, during each reference period.

### (a5) Cold days and freezing days

Changes in the number of cold days or freezing days can have effects on certain winter crops. Cold days with average temperatures below 10°C could affect the production of major crops like tomatoes and maize. We therefore constructed the number of days with average temperatures dropping below 10°C during the reference period (cold days). Further, following Da et al. (2024), we also construct the number of days with minimum temperatures dropping below 0°C during the reference period (freezing days).

## Appendix B: Least Absolute Shrinkage and Selection Operator (LASSO)

The basic set-up of Least Absolute Shrinkage and Selection Operator (LASSO) applied to equation (1) is,

$$\widehat{\beta}_S(\lambda) = \underset{\beta, \beta_S, \beta_X, c_i^M}{\operatorname{argmin}} \frac{1}{n} \sum_{i=1}^n (M_{it} - \beta - \beta_S S_{it} - \beta_X X_{it} - c_i^M)^2 + \frac{\lambda}{n} \sum_S \psi_S |\beta_S|$$

$$\psi_S = \sqrt{\frac{1}{n} \sum_i S_{it}^2}$$
(6)

in which  $\lambda$  is a penalization (also called “turning”) parameter that determines how much the number of estimated parameters is penalized in selecting the model. A larger (smaller) value for  $\lambda$  implies more (less) penalization of the number of parameters, and therefore leads to selecting fewer (more) parameters in the model. Notation  $p$  is the number of parameters selected. Notation  $n$  represents the number of observations. Notation  $\psi_S$  is called a “loading” parameter, which is set specific to each variable  $S_{it}$  so that parameters  $\beta_S$  are independent of the unit of each  $S_{it}$ . Note, in our model,  $\beta_X X_{it}$ , intercept and household fixed effects (meaning  $\beta_X$  for all  $X_{it}$ , as well as intercept  $\beta$ ,  $c_i^M$ ) are always kept in the regression, and our LASSO approach focuses exclusively on identifying additional key weather shock parameters.

The literature has discussed at least three approaches for selecting the penalization parameter  $\lambda$  (Ahrens et al. 2020). These include (a) information criteria (Zou et al., 2007; Zhang et al., 2010), (b) K-fold cross-validation and h-step-ahead rolling cross-validation approach (Geisser 1975; Arlot & Celisse 2010), and (c) theory-driven (“rigorous”) LASSO (RLASSO) approach (Belloni et al. 2012, 2014, 2016).

While different approaches suit different circumstances and objectives, we use the RLASSO approach, which is considered generally more suitable for causal inference rather than forecasting and is shown to perform relatively better than other methods in terms of type-I errors (mistakenly identifying parameters to be non-zero when they are actually zero (“false positive”)) (Ahrens et al., 2020). Unlike other approaches, RLASSO selects a penalization parameter  $\lambda$  which, based on theoretical grounding, guarantees that optimal rates of convergence for parameter estimation are achieved, resulting in the size of the models having the same order as the true model, and selected parameters are consistently estimated (Ahrens et al. 2020). Specifically, according to Jing et al. (2003) and Belloni et al. (2012),  $\lambda$  in RLASSO is selected as

$$\lambda = 2c\sigma\sqrt{n}\Phi^{-1}\{1 - \gamma/(2p)\}$$
(7)

in which  $\gamma$  is the probability that a “false positive” does not occur,  $c(> 1)$  is a constant slack parameter which is set at slightly greater than 1 (often 1.1 as in Ahrens (2020)),  $\sigma$  is the standard errors of residual  $\varepsilon_{it}^M$ . The loading parameter  $\psi_S$ , as shown above, has the effect of standardizing all variables  $S_{it}$ .

### References for Appendix

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### Appendix C: Relative Deprivation measure

Following Kafle et al. (2020), we construct the relative deprivation (RD) measure as

$$RD_{itr}(w) = \int_{w_{tr}^i}^{w_{tr}^h} [1 - F(x)]dx \quad (8)$$

where  $RD_{itr}(w)$  is the measure of  $RD$  for household  $i$  in reference group  $r$  (in our case, villages) in year  $t$ ,  $w_{tr}^i$  is the wealth indicator which consists of the first principal component of five wealth related variables, namely, durable assets owned, livestock owned measured in livestock units (LU), size of farm areas that the household has use rights on, first principal components of housing conditions, and sanitary/hygienic conditions. The notation  $w_{tr}^h$  is the highest value of the wealth indicator in the reference group  $r$ , and  $F(x)$  is the cumulative distribution of  $w_{tr}^i$  in the reference group.

## Appendix D: Additional results

**Table D1. Same results as Table 6 but including only agricultural households in the sample**

Variables	Districts										
	Kushoni- yon	Vakhsh	Khuroson	Dusti	Qabodiyon	Jaloliddini Balhi	Jayhun	Levakant	Jomi	Shahritus / N. Husrav	Yovon
	Coef (std.err)	Coef (std.err)	Coef (std.err)	Coef (std.err)	Coef (std.err)	Coef (std.err)	Coef (std.err)	Coef (std.err)	Coef (std.err)	Coef (std.err)	Coef (std.err)
<i>Dependent variable = at least 1 member outmigrated for 1 month or more (agricultural households only)</i>											
Weather shock measures <sup>a</sup>	0.143** (0.037)	0.412*** (0.135)	0.194* (0.109)	0.509** (0.213)	0.123* (0.065)	0.294** (0.139)	1.085*** (0.278)	0.227** (0.058)	0.191*** (0.057)	0.564 (0.418)	0.089** (0.037)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-square	.040	.026	.040	.052	.052	.099	.031	.168	.061	.103	.020
No. obs.	500	324	182	170	206	324	268	88	334	212	358
<i>Dependent variable = at least 1 member outmigrated for 1 month or more (agricultural households only, excluding Dehkan farm)</i>											
Weather shock measures <sup>a</sup>	0.143** (0.040)	0.492** (0.190)	0.429*** (0.155)	1.279*** (0.471)	0.086* (0.048)	0.221** (0.111)	1.587*** (0.396)	0.247** (0.069)	0.161*** (0.045)	1.345 (0.899)	0.072** (0.035)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-square	.028	.044	.014	.023	.076	.061	.037	.033	.057	.143	.045
No. obs.	438	172	140	150	178	234	214	76	308	160	324

Source: Authors.

Note: <sup>a</sup>Weather shock parameters are as defined in Table 5 for respective district sample. FE = fixed-effects.

**Table D2. Same sets of results as Table 5 but for alternative migration variables used as dependent variables as in Table 6**

Districts	Weather parameters	Seasons	Reference periods	Statistics (percentile, z-score, absolute deviation)
<i>Dependent variable = at least 1 member outmigrated for 6 months or more</i>				
Kushoniyon	Rainfall	Early Winter (Oct–Dec)	Current year	Percentile
Vakhsh	Wind speed	Summer	Past 5 years	Percentile
Khuroson	High nighttime temperature	Summer	Past year	Percentile
Dusti	High nighttime temperature	Summer	Past 5 years	Percentile
Qabodiyon	Rainfall	Summer	Past 5 years	Z-score
Jaloliddini Balhi	Drought	Early winter (Oct–Dec)	Past 5 years	Absolute deviation
Jayhun	Rainfall	Late winter	Past year	Z-score
Levakant	Drought	Late winter (Jan–Mar)	Past year	Percentile
Jomi	Rainfall	Later winter (Jan–Mar)	Past year	Percentile
Shahritus/N. Husrav	Drought	Early summer (Apr–Jun)	Past year	Percentile
Yovon	Rainfall	Winter	Past year	Z-score
<i>Dependent variable = count of household members outmigrated for 1 month or more</i>				
Bokhtar (Kushoniyon)	Heat wave	Summer	Past 5 years	Z-score
Vakhsh	Wind speed	Early Summer (Apr–June)	Past 5 years	Percentile
Gozimalik (Khuroson)	Rainfall	Summer	Past 5 years	Z-score
Jilikul	High maximum temperature	Winter	Past year	Absolute deviation
Kabodiyon (Qabodiyon)	Drought	Whole year	Past year	Percentile
Kolkhozobod	Rainfall	Late winter (Jan–Mar)	Past year	Z-score
Kumsangir (Qumsangir)	Drought	Late summer (Jul–Sep)	Past 5 years	Percentile
Sarband	Rainfall	Early winter (Oct–Dec)	Past 5 years	Percentile
Khojamaston (Jomi)	Rainfall	Winter	Past 5 years	Percentile
Shahrtuz	High nighttime temperature	Summer	Past year	Percentile
Yovon	Rainfall	Early Summer (Apr–June)	Past year	Z-score

Source: Authors' estimations.

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