# HARVESTING HUNGER: OPIUM BAN AND FOOD SECURITY

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ABSTRACT. When imposing outright restrictions to eliminate substance use and production, policymakers face unintended consequences, raising questions about who bears the distributional effects and how they cope with them. In April 2022, the Taliban imposed a ban on opium cultivation in Afghanistan, the main cash crop in the country. Leveraging spatial variation in satellite-derived opium cultivation measures along with novel household survey data, we study the impact of the ban on livelihoods in the affected areas. Findings from a Difference-in-Differences framework show a substantial increase in the extreme level of food insecurity in the immediate aftermath of the ban, gradually diminishing over time. The impact depends on households' ability to reallocate production from opium, which is determined by their asset endowments or the land composition. The effect is pronounced only for households residing on non-arable soils. To cope with extreme food insecurity, they limit food consumption in the short run, deplete livestock and shift production to grains on arable soils in the medium run, and migrate as a last-resort option. These findings serve as evidence that pre-emptive provision of viable economic alternatives is imperative to avoid welfare losses when designing restrictive policies, especially when the restrictions are applied to the agricultural sector and developing states, risking deepening poverty traps.

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# 1. Introduction

Substance use is a leading cause of preventable death, and both demand and supply-side factors initiate the "deaths of despair."[1] From the consumer's perspective, the theory of rational addiction (Becker and Murphy, 1988) dictates that strong addictions can be overcome only with an abrupt cessation of consumption. Then, through the lens of Say's Law (Say, 1836), "supply creates its own demand," such cessation can be achieved only by eliminating the source – the outright destruction of the production of illicit crops.[2] This dual role compels policymakers to design interventions targeting both sides with restrictions.

However, existing research has not reached a consensus regarding the success of drug prohibition. Skeptics of restrictive policies question the extent to which prohibitions themselves are responsible for significant social costs, which might even exceed total benefits (Miron, 2004). As these policies fuel enforcement-related violence (Lindo and Padilla-Romo, 2018; Dell, 2015; Angrist and Kugler, 2008) and generate substantial spillovers across markets (Battiston et al., 2024; Castillo et al., 2020), they also often have profound unintended consequences. The debate centers on whether these prohibitions are effective at all (Mejía et al., 2015; Ibanez and Carlsson, 2010; Moreno-Sanchez et al., 2003), as they do not eliminate the market, but rather drive it underground (Miron and Zwiebel, 1995). To our knowledge, the only case that stands in stark contrast to this pattern is the opium ban in Afghanistan in 2022, which eliminated the cultivation of illicit crops almost entirely.[3] Despite remarkable effectiveness in enforcement, understanding its ramifications and distributional aspects is crucial for informing the future design of restrictive policies. We discuss the details about drug control policies, Afghanistan, and the opium ban in Section 2.

In this paper, we provide the first quasi-experimental evidence on the consequences of an effective drug prohibition in eradicating illicit production. We study the impact of the opium cultivation ban in Afghanistan on the household livelihoods, particularly their food security. For households in regions where opium constitutes the primary income-generating source, the policy's enforcement represents an initial adverse income

[1] Summarizing the existing literature on the initial causes of the opioid crisis, Alpert et al. (2021) underline worsening cultural and economic conditions as demand, and changes in treatment guidelines as supply side factors.

[2] Ruhm (2019) also shows that rising access to opioids has been a key driver of increasing overdose rates in the United States.

[3] In April 2022, the Taliban imposed a nationwide ban on opium poppy cultivation, use, and sale. At the time, Afghanistan was the world's largest opium supplier, with poppy production representing the largest share of agricultural output and the primary income source for millions of households. Satellite imageries show that after a year of the ban announcement, the opium cultivation fell by nearly 95% (Mansfield, 2023a; UNODC, 2023a).

shock, but its magnitude and ultimate effect are far from clear. Given the ongoing humanitarian crisis in the country, the extent of the ban's impact on the survival levels of food security, its net societal costs, distributional consequences, and overall efficiency remain critical empirical questions. This article addresses this gap by examining three interrelated dimensions of the ban's impact.

First, this paper analyzes the dynamics of the impact on food security to determine whether the initial adverse effects attenuate as households adapt or persist and exacerbate, potentially creating poverty traps. Second, it identifies the primary causal mechanisms, empirically disentangling the role of direct income loss from indirect price spillovers. Finally, it documents the portfolio of behavioral responses and coping strategies, including consumption smoothing, asset depletion, agricultural reallocation, and migration, that vulnerable households employ to mitigate the ban's consequences.

To answer the research questions, we construct a novel dataset combining several sources. Our primary household-level data are drawn from the Data in Emergencies Monitoring (DIEM) surveys for Afghanistan (FAO, 2025), which provide multiple rounds of data spanning the pre- and post-ban periods. From these surveys, we construct our outcome variables. The main outcome is extreme food insecurity, which represents the survival level of food security defined by Barrett (2002). Extreme food insecurity is a binary indicator derived from the eight-question food security panel, taking a value of one if a household provides affirmative responses to more than half of the questions. This baseline measure is supplemented with alternative validated and consistent metrics for robustness, including the Household Hunger Scale and the raw food insecurity score, to ensure our findings are not dependent on a single specification.

The treatment variable is constructed using high-resolution district-level satellite data on opium cultivation from the United Nations Office on Drugs and Crime (UNODC, 2023b). We define a district as treated if there is any reported opium cultivation in the pre-ban period, with non-cultivating districts serving as the control group. This design provides a strong counterfactual, as the national ban represents a direct economic shock that is binding only for households in opium-growing districts, while being effectively non-binding for those in control districts whose primary livelihoods were not directly constrained.

The empirical approach relies on an extension of the canonical Difference-in-Differences framework to estimate the causal impact of a supply-side restriction. Our specification includes district and survey-month fixed effects, along with province-specific linear time trends, to account for level differences in food insecurity measures while allowing for secular shocks and differential provincial trends over the sample period. The validity of this strategy hinges on the parallel trends assumption, which we test and confirm using an event-study design that reveals no significant pre-treatment differences in food security trajectories between the treated and control groups.

Findings show a substantial and statistically significant deterioration in household welfare following the ban. We find that the likelihood of a household experiencing an extreme level of food insecurity increased by an average of 17.3 percentage points in opium-cultivating districts relative to non-cultivating districts in the post-ban period. This represents a sharp increase, equivalent to a nearly 25% rise over the pre-ban mean for the treated group. The impact is consistent across alternative measures of food hardship, underscoring the severity of the negative shock to livelihoods.

The event-study estimates further illuminate the dynamic nature of this impact. Observations illustrate no pre-existing differential trends between treated and control districts, validating our parallel trends assumption. The adverse effect on food security is immediately apparent, with a sharp spike in extreme food insecurity following the ban's implementation. However, this effect attenuates in subsequent rounds, suggesting that households gradually adapt and deploy coping strategies to mitigate the economic shock. This dynamic pattern, characterized by a severe impact followed by partial recovery, is a key finding that highlights both the vulnerability and resilience of the affected population.

We subject our main findings to a comprehensive set of robustness checks to ensure their validity and reliability. The results are insensitive to alternative specifications, including the exclusion of survey weights, the inclusion of household-level demographic controls, and controls for time-varying weather conditions such as temperature and precipitation. Our conclusions hold when we employ alternative definitions for the treatment variable, varying the base years and thresholds for what constitutes an opium-cultivating district. Furthermore, the findings are robust to permutation tests and excluding potentially confounding geographies, such as the province of Badakhshan (known for its unique harvesting cycle) and Herat (which experienced major earthquakes), as well as districts bordering neighboring countries or adjacent control districts. We confirm that our estimates are consistent and not driven by localized shocks or spillover effects.

To disentangle the causal pathways driving the increase in food insecurity, we investigate two primary channels: a direct income shock and an indirect price effect. Our analysis provides strong evidence that the ban's impact operates exclusively through a negative income shock. When stratifying the sample, we find that the baseline effect is concentrated entirely among households that faced an economic shock. In contrast, we find no evidence of a price-level mechanism. The ban did not induce a statistically significant differential change in either food or non-food price indices in treated districts relative to controls. This rules out inflationary spillovers as a driver of our results and solidifies the conclusion that the direct loss of opium-related income is the primary channel through which the ban impacts extreme food insecurity.

Heterogeneity analysis reveals that a household's capacity to withstand the shock is fundamentally determined by its asset endowments, specifically the composition of its land. Findings show that the adverse impact of the ban is persistent and concentrated entirely among households residing in districts with lands unsuitable for grain cultivation, the next best alternative for production transition. For this group, the likelihood of experiencing extreme food insecurity increases significantly and remains elevated over time. Conversely, for households on land suitable for wheat, we observe no such impact. This sharp divergence underscores that land suitability is the key determinant of a household's ability to reallocate production and mitigate the income shock. The impact is otherwise pervasive across various demographic subgroups, but the crucial mitigating factor remains access to arable land.

In the short term, households in treated districts immediately resorted to consumption-smoothing strategies to cope with the income loss. We find a significant increase in the likelihood of households reducing the number of daily meals, limiting portion sizes, and restricting adult food consumption to ensure children are fed. These behaviors, captured in the seven-day recall data, became more prevalent immediately after the ban, reflecting an adaptation to the new reality of high food scarcity and partially explaining the eventual attenuation of the effect on extreme food insecurity.

Over the medium term, households were forced to deplete productive assets. We find a significant decrease in the number of livestock among exposed households, particularly those on non-arable land. This depletion of productive capital represents a more severe coping mechanism that, while providing immediate relief, may risk long-term food security and human capital formation. We find no significant changes in other medium-term strategies like drawing down savings or formal borrowing, reflecting the pre-existing scarcity of such resources in this crisis context.

We also examine households' migration and production reallocation patterns with respect to the opium cultivation ban. Findings indicate that households on non-arable land, who could not switch to alternative crops, were significantly more likely to engage in internal migration, indicating that relocation is a last-resort strategy when on-farm adaptation is impractical. In contrast, for households on suitable land, we observe reallocation patterns from the "other crops" to grains. This transition to wheat cultivation, where feasible, served as the primary adaptive strategy, allowing the households to avoid the severe consequences of the ban.

This study contributes to several strands of the literature. First, it advances research on substance and illicit crop production. Existing studies in this area generally conclude that sweeping regulations have been ineffective in meeting their objectives (Mejía et al., 2015; Ibanez and Carlsson, 2010; Moreno-Sanchez et al., 2003). Our study presents a counterexample when a restrictive policy proved remarkably effective in eradicating illicit crops. Prior work also emphasizes that prohibitions often increase violence (Castillo et al., 2020; Dell, 2015; Angrist and Kugler, 2008; Miron and Zwiebel, 1995) and generate spillovers (Battiston et al., 2024; Rozo, 2014), rendering them inefficient and inequitable. While we do not observe a rise in violence instances, our results are consistent with this literature in showing that, even when a ban is effective, it carries severe consequences that fall disproportionately on the asset-poor. These consequences are particularly concerning in developing countries, where they risk deepening existing poverty traps (Barrett et al., 2017). Our findings, therefore, underscore the importance of designing pre-emptive policies to facilitate transitions before restrictions are imposed. The sharp decline in illicit crops in Afghanistan without a corresponding reduction in global substance use also implies the "balloon effect," international displacement of production patterns (Windle and Farrell, 2012).

Second, our paper is related to the literature on the determinants and measurement of food security and agricultural policies. Whereas existing studies measure food security in contexts with relatively low shares of severely food-insecure households (Aranda and Ribar, 2023), we develop an empirical measure that captures changes at the survival margin of food security (Barrett, 2010) in humanitarian crises, where nearly all households face some degree of food insecurity. Our findings show that agricultural policies can generate adverse spillovers by worsening the food security of poor households (Aggarwal et al., 2024; Beegle et al., 2017). We also advance understanding of coping strategies and production transition patterns among impoverished households in developing countries, as their behavioral responses are critical for the design of equitable regulations (Barrett, 2002).

Third, we supplement the literature on household finances (Gomes et al., 2021) by documenting how financial structures operate within highly vulnerable populations in developing states. We illustrate household behavior under livelihood uncertainty, their asset allocation, consumption choices, economic mobility, and resilience to shocks.

Fourth, we add to the series of studies on the natural resource curse (Frankel, 2010). Prior works emphasize that resource wealth can be both a blessing and a curse (Hodler, 2006), raising questions about optimal ways to harness it for economic growth and to diversify economies to reduce dependence (Matsen and Torvik, 2005). We provide a unique perspective by documenting the severe consequences that arise when a developing state abruptly eliminates the market on which its economy depends.

Lastly, we contribute to the literature on Afghanistan (Blumenstock et al., 2024; Najam, 2024; Gehring et al., 2023; Lind et al., 2014) by illustrating the country's socioeconomic environment, ongoing crises, levels of food insecurity, patterns of land use, and the vulnerability and resilience of farmers. To the best of our knowledge, this is the first study to assess the consequences of the 2022 opium cultivation ban[4] and to explore the dynamics of how households adapt to the resulting increase in food hardship.

The rest of the paper is organized as follows. Section 2 reviews the literature on sweeping regulations, explains the socioeconomic environment in Afghanistan, and provides the background of the opium ban. Section 3 develops the theoretical framework guiding empirical estimations. In Sections 4 and 5, we summarize the employed data and illustrate the empirical strategy, respectively. Section 6 presents results. We discuss the policy implications in Section 7 and conclude in Section 8.

## 2. Background

This section begins with an extensive overview of the literature on restrictive policies, with a focus on substance use and eradication of illicit crops. Second, it outlines the historical structure of Afghanistan's economy, the ongoing humanitarian crisis, and the role of opium in Afghans' lives. Third, we explain what the opium poppy is, its production process, and derivatives. Finally, we provide the background of the opium ban, including its timeline and enforcement, discussing its effectiveness and potential consequences.

### 2.1. The Economics of Bans

One of the foundational challenges in public policy design is correcting for negative externalities associated with the production or consumption of certain goods. While Pigouvian taxes represent a canonical market-based solution, governments often employ strict restrictions, such as outright prohibitions. These sweeping policies are typically reserved for goods with extreme social costs that are difficult to monetize, such as illicit narcotics.

[4] In their discussion on how effective different policies are at reducing opium production in Afghanistan, Clemens (2008) notes that source-country policies in the early 2000s were largely ineffective and suggests that strict enforcement would have little, if any, impact on cultivation so long as global demand remained high. More recent informal literature (Mansfield, 2023a), however, indicates that the 2022 opium ban was effective in eliminating cultivation.

Policies designed to combat the illicit drug trade fall into two categories: demand- and supply-side interventions. Demand-side interventions often aim to reduce consumption through prevention and treatment.[5] The central debate surrounding this category of policies concerns the merits of decriminalizing substance use. The literature presents mixed evidence, dependent on market context. Some studies find decriminalization to be effective, showing no adverse impact on substance use (MacCoun and Reuter, 1997) or opioid mortality rates (Félix et al., 2017), while reducing enforcement-related violence, costs, and deaths. Others associate it with increased substance use (Williams and Bretteville-Jensen, 2014) and higher rates of overdose mortality (Spencer, 2023).

Conversely, supply-side policies seek to disrupt production and trafficking networks. These interventions commonly take the form of crop eradication, interdiction of drug shipments, and prescription reformulations. The primary challenge, however, is that such policies rarely eliminate the market. Instead, they drive it underground,[6] creating a new set of unintended consequences.[7] Not only does the existing literature show that supply-side restrictions are often ineffective,[8] but they also increase producer risks, raising prices and incentivizing the development of more potent and easily concealable products, which may have a catastrophic influence on public health.[9] The profound

[5] While well-intentioned, they may also lead to an unintended increase in overdose deaths (Packham, 2022) and opioid-related emergency visits (Doleac and Mukherjee, 2022).

[6] In their assessment of the alcohol prohibition in the US, Miron and Zwiebel (1991) find that although the alcohol consumption had initially declined, it rebounded to near pre-prohibition levels within a few years. This rebound suggests a shift to underground production. While this shift reduced the quality of the product, imposing heightened risks to health, it also led to a rise in criminal activity and violence.

[7] Alpert et al. (2018) show that supply-side interventions limiting access to opioids, such as the introduction of an abuse-deterrent version of OxyContin, lead to a substantial increase in heroin use. They underline the OxyContin reformulation as the main cause of the recent heroin epidemic in the US.

[8] The existing literature on supply-side anti-drug policies, such as coca eradication programs in Colombia and the war on drugs in Mexico, shows that these interventions have been largely ineffective. Ibanez and Carlsson (2010) find that coca cultivation is inelastic to changes in relative profit, hence investing in eradication programs might be inefficient and exert only a limited influence on cultivation. Mejía et al. (2015) and Moreno-Sanchez et al. (2003) similarly question the cost-effectiveness of aerial spraying programs. Ladino et al. (2021) and Reyes (2014) are also skeptical about the effectiveness of other crop eradiation policies. Battiston et al. (2024) indicate that the war on cartels in Mexico led to significant spillovers in other markets, pushing criminals into large-scale oil theft. Dell (2015) show that the efforts to combat trafficking in Mexico increased the drug-related violence. Castillo et al. (2020) further provide evidence that drug seizures in Colombia had international spillovers in violence. For more details on the consequences of the restrictive policies, see Battiston et al. (2024), Moreno-Sanchez et al. (2003), and papers cited therein.

[9] For example, the US and Colombia treaties on narcotics traffickers in the late 1990s and heightened security measures in the US in the early 2000s increased the smuggling risks, which ultimately led to shifting trafficking routes from Colombia to the US–Mexico borders. This shift increased the costs for

consequences of drug control policies also stem from the creation of violence (Castillo et al., 2020; Lindo and Padilla-Romo, 2018; Kulick et al., 2016; Dell, 2015; Angrist and Kugler, 2008) and corruption (UNODC, 2009; Miron and Zwiebel, 1995). Suppliers in an illegal market, who compete for market control, systematically resort to violence in the absence of legal dispute resolution mechanisms (Miron, 2004). Moreover, even limited success in achieving the objectives of sweeping policies, if any, often comes at the cost of substantial negative spillovers to other sectors (Battiston et al., 2024).

One reason making assessing the net welfare effects of restrictive policies a formidable empirical challenge is the difficulty of quantifying these spillovers. Another reason is that the social costs of these spillovers are borne disproportionately by vulnerable populations in developing countries.[10] In these states, bans can exacerbate existing inequalities by directly degrading human capital and deepening poverty traps for rural households with no alternative sources of income. Afghanistan, a country facing a humanitarian crisis where the scale of dependence on a single illicit crop is unprecedented, is a unique case for examining the consequences of a state-enforced elimination of the primary livelihood for millions of households.

### 2.2. Afghanistan: Economy, Crisis, and Food Security

Afghanistan's contemporary socioeconomic landscape is the product of decades of conflict and violence.[11] They have systematically undermined the development of robust institutions and the formal economy, leaving a legacy of widespread poverty and vulnerability (Whitlock, 2021). The withdrawal of U.S. and NATO forces from Afghanistan in August 2021 and the subsequent collapse of the Islamic Republic led to the Taliban's return to power. This transition was accompanied by a severe economic crisis, as the country was cut off from the international payment systems and development aid (World Bank, 2025; Aman, 2024). The Taliban's governance, defined by a series of decrees that severely restrict the rights and economic participation of women (Curry et al., 2023), has further eroded the country's human capital base and crippled prospects for recovery (CRS, 2024; Amnesty International, 2024). The economic collapse also worsened the humanitarian crisis. By 2023, more than 29

smugglers. Donahoe and Soliman (2025) provide the causal evidence that the supply-side adulteration of heroin to reduce these costs played the main role in the transition of the leading cause of overdose deaths from prescription opioids to heroin.

[10] A study of Colombia's anti-drug eradication program (Rozo, 2014), for example, found that a modest increase in the share of a municipality's area sprayed with herbicides substantially increased the poverty rate, infant mortality, and homicide rates.

[11] See Blumenstock et al. (2024), Najam (2024), and Blumenstock et al. (2018) for the review of violence and financial development in Afghanistan.

million Afghans required humanitarian assistance to survive (UNODC, 2023a). Food insecurity has become a pervasive feature of Afghan life.[12]

Food security, a critical measure of well-being (Aranda and Ribar, 2023), extends beyond mere food availability.[13] It encompasses the secure access to sufficient and nutritious food at all times (Barrett, 2010), and is determined by the set of consumption bundles households command through production, trade, or transfers, and their capacity to cope with shocks (Barrett, 2002). In the Afghan context, this capacity to cope with shocks is exceptionally weak (D'Souza and Jolliffe, 2016, 2014, 2013), leading to *chronic food insecurity*, or not having access to sufficient food for prolonged periods. Both excessive external risks, armed conflicts (Gehring et al., 2023; Lind et al., 2014) and climate shocks (Ahmadzai and Morrissey, 2025; Gbadegesin et al., 2024), and internal risks, defenselessness to cope, make Afghans one of the most vulnerable[14] and food insecure (D'Souza and Jolliffe, 2012). Given that achieving food security is Afghans' primary goal, it serves as an ideal measurement of the livelihoods in this context.

Helping farmers to survive in this food-insecure environment, the opium poppy cultivation has been the mainstay of the rural economy and its most valuable export (Pain, 2024). In 2022, on the eve of the ban, the farm-gate value of the opium harvest was estimated at $1.4 billion, a 29% of the agricultural sector's value added (UNODC, 2022). The economic importance of opium also extends to the household level, where it has served as a generational livelihood strategy.[15] The preference for opium over licit crops like wheat is also founded on a set of clear economic and agronomic advantages. Opium is drought-tolerant and generates higher returns per unit of land and water, a crucial trait in Afghanistan's arid climate (UNODC, 2023a). The crop is well-suited to the country's topography, and its cultivation and harvest are exceptionally labor-intensive, creating hundreds of thousands of jobs for the farmers (Pain, 2024). The processed gum is non-perishable and has a high value-to-weight ratio, making it an ideal cash crop and medium of exchange in a context where formal financial institutions

[12] The World Food Programme reported in 2025 that more than 9 million people are severely food insecure, with millions on the brink of famine (WFP, 2025).

[13] Barrett (2002) provides the extensive review of the concepts, importance, measurement, and determinants of food security. Botha et al. (2024) further underline its importance, showing that food insecurity usually co-occurs with multiple other hardships.

[14] See Chambers (1989) and Watts and Bohle (1993) for the definition of vulnerability in the face of food insecurity.

[15] Gehring et al. (2023) show that participation in opium cultivation was associated with higher household consumption expenditure, including on food, and greater asset accumulation. Wigton-Jones (2021) also explains that the reason behind farmers' preference for illicit agriculture production in Afghanistan is that poor infrastructure and little financial support hamper the livelihoods of legal production.

are largely absent.

### 2.3. Opium Poppy

The opium poppy, *Papaver somniferum*, is an annual plant cultivated for its seed pods (DEA, 1992). When these pods are incised before reaching full maturity, they exude a milky latex resin which, upon drying, becomes raw opium. The typical planting cycle in Afghanistan takes place in October and November, while the harvesting cycle is in April and May (UNODC, 2023a). The harvest itself is a delicate and highly labor-intensive process, requiring skilled workers to score each pod by hand multiple times to collect the resin. This process makes opium production a significant source of rural employment.

Raw opium is a versatile input for both illicit narcotics and licit pharmaceuticals. In the illicit supply chain, opium gum is refined into morphine base and subsequently acetylated to produce heroin (DEA, 1992). This has been the primary end-use for Afghan opium, which has long dominated the global heroin market valued in the tens of billions of dollars, where farmers receive a minuscule fraction of the final street price (Miron, 2004). In the legal pharmaceutical industry, opium is the source material for a wide range of essential medicines, including analgesics like morphine and codeine, and other alkaloids such as thebaine, a precursor for oxycodone (Deiana et al., 2023). The legal pharmaceutical market, on the other hand, is a highly regulated industry, with production restricted under stringent international controls.

### 2.4. The 2022 Opium Ban

Historically, the Taliban taxed the opium trade as a primary source of financing their insurgency (Shah and Mashal, 2016; Peters, 2009). During their first year in power, opium cultivation in the country increased by 32% (UNODC, 2022), which brought criticism to the Taliban despite the crop being planted a year ago. A year after regaining power, in April 2022, citing religious beliefs, the Taliban issued a comprehensive ban on the cultivation, use, and trade of opium poppy and all other narcotics across Afghanistan.

This announcement coincided with the 2022 poppy harvest season (Limaye, 2023; Padshah and Gibbons-Neff, 2022), which farmers were permitted to collect. Authorities did not start eradicating the standing crops right after the ban, which could have been met with resistance from the farmers.[16] However, no exemptions were granted for

[16] Resource-related income shocks are a well-documented catalyst for insurgency (Berman and Couttenier, 2015; Morelli and Rohner, 2015; Berman et al., 2011).

the upcoming planting season, and harvested produce could only be sold for a short duration following the decree.

To ensure compliance and curb potential skepticism about the enforcement, in October 2023, the ban was strengthened by a formal penal code with severe punishments (Supreme Court, 2023). This code results in imprisonment of up to one year if there is more than half an acre of opium cultivation with at least six months imprisonment for any cultivation. To further instill fear in the farmers, the Taliban has destroyed all of the discovered crops in the Fall 2022 planting season (Sabawoon and Bjelica, 2024), publishing the videos nationally.

This staged approach to policy implementation has been remarkably effective. High-resolution satellite imageries provide evidence for a 95% nationwide reduction in opium cultivation, both in the area under cultivation and tons of production (Mansfield, 2023a). In Helmand province, the traditional heartland of production, cultivation was virtually eliminated, falling by over 99% (UNODC, 2023a). In Figure 2, the spatial distribution of cultivation across years, we also show a sharp decline in the likelihood of district reporting any poppy cultivation immediately after the imposition of the ban.

Although farmers could expect the ban, they had no options for storing their harvest. With limited avenues for production reallocation, a heavy financial reliance on the most recent harvest, and Taliban's decrees, they could not afford to hold their product in hopes of a price hike, as opium functioned as a vital cash crop. Hence, given the established empirical link between opium income and household welfare in Afghanistan (Gehring et al., 2023), the immediate economic consequence was a shock of historic proportions. Aggregate farmer income from opium plummeted by over 90%, from an estimated $1.36 billion in 2022 to just $110 million in 2023 (UNODC, 2023a). This erasure of the primary source of cash income for millions of households posed a direct threat to their food security. The downstream effects of this shock are also likely to be complex, including spillovers, major disruptions to rural labor markets (Madhok et al., 2025), forced changes in coping strategies, or displacement (Pain, 2024).

Moreover, households' ability to cope and transition from illicit to licit production, if any, is not uniform across the country due to differences in land ownership, soil suitability, and occupational structures (Mansfield, 2023a). For example, wealthier landowners with larger plots would switch to grain cultivation relatively easily, while smallholder farmers and sharecroppers would face more significant challenges, leading to varying degrees of impact from the ban. Despite these differences, the widespread food hardship in the country might imply that the ban's effects reverberate across the entire population, making the extent of this impact on various subpopulations an empirical question.

While the effectiveness of this supply-side restriction is historically unique and unambiguous, this success raises urgent questions about its societal costs and efficiency. The central concern is the policy's impact on household food security. The initial shock is likely adverse, but its ultimate effect is far from clear. Do these consequences attenuate over time as markets adapt, or do they worsen, creating persistent poverty traps? By what mechanisms do these impacts propagate through the economy, and what behavioral responses are available to vulnerable families to mitigate the harm? To assess the ban's net effects and trace these dynamic causal pathways, a formal economic model is required. The next section develops such a theoretical framework guiding our empirical investigation.

## 3. Theoretical Framework

To analyze the consequences of the opium ban in Afghanistan, we adapt a stochastic dynamic optimization model of household behavior, extending the microeconomic model in producing physical well-being by Barrett (2002). This model captures the intertemporal trade-offs households with different endowments face under uncertainty, linking consumption, health, production, and asset accumulation. It provides a formal structure on how an exogenous production shock propagates through the household's finances, ultimately affecting its food security.

### 3.1. The Model Setup

A representative agent, or household, seeks to maximize its lifetime well-being, a function of both material consumption and physical health. The household's objective is to maximize the discounted stream of expected utility by choosing consumption quantities ($x$), savings ($s$), and labor allocation ($l$) in each period $t$. These choices, as well as stochastic shocks or exogenous variables ($z$), then affect the household's physical well-being ($w$) and asset stocks ($a$).

Consumption quantities represent all consumption goods and include food ($x^f$) and non-food consumption ($x^{nf}$). Assets and savings are vectors composed of three types of assets: arable land ($a^{arable}$), non-arable land ($a^{non-arable}$), and other assets ($a^{other}$). The important difference about the land types is that the multiple agricultural outputs can be produced on arable lands, however non-arable lands are not suitable for production of any other agricultural outputs than opium poppies. Labor allocation represents all productive activities and is composed of labor allocated to opium ($l^{opium}$) and other production ($l^{other}$). Vector $q$ represents produced outputs and consist of opium ($q^{opium}$)

and the output of other goods ($q^{other}$), and $k$ is the physical quantity of in-kind transfers received, such as food aid.

Household's objective function is:

$$\max_{x_t,s_t,l_t} E_o \sum_{t=0}^{\infty} \beta^t U(w_t, x_t) \ , \tag{1}$$

where $E_o$ is the expectation operator, reflecting uncertainty about the future, $\beta \in [0,1]$ is the time discount factor to capture household's intertemporal preferences, and utility $U(\cdot)$ is strictly increasing in both physical health ($w$) and consumption ($x$). Utility and health are both nonnegative, with $U(x, w|_{w=0}) = 0$, i.e., minimal health yields minimal utility independent from the level of consumption quantities.

Household's maximization problem is subject to several constraints:

$$w_{t+1} = \Theta(w_t, x_t, l_t, z_t, \phi_t^h) \ , \tag{2}$$

$$a_{t+1} = \delta a_t + s_t \ , \tag{3}$$

$$p_t^{x'} x_t + p_t^{s'} s_t = p_t^{q'} q_t + p_t^{x'} k_t \ , \tag{4}$$

$$\Lambda(q_t, l_t, a_t, w_t|\phi_t^q) = 0 \ , \tag{5}$$

$$e' l_t \leq l_0 \ , \tag{6}$$

$$a_t, l_t, x_t \geq 0 \ . \tag{7}$$

Equation (2) is the law of motion for physical well-being ($w_t$), a form of human capital evolving over time. It shows that future health depends on preexisting health conditions ($w_t$); current consumption ($x_t$); current labor activities ($l_t$); other exogenous variables like sanitation or infrastructure ($z_t$); and stochastic shocks to health ($\phi_t^h$). Food consumption enters into the utility function directly through ($x_t$) as it is composed of food and non-food consumption.

Equation (3) represents the law of motion for asset stocks ($a_t$), adjusting the current stocks for depreciation ($\delta \in [0,1]$) and net investment or stockbuilding ($s_t$). Assets are crucial as they can be liquidated as a coping strategy during adverse shocks.

Equation (4) is the intertemporal budget constraint: the monetary value of current consumption ($p_t^{x'} x_t$) and new asset acquisition ($p_t^{s'} s_t$) cannot exceed the sum of the value of output ($p_t^{q'} q_t$) and any in-kind transfers received ($p_t^{x'} k_t$).

The stochastic production technology $\Lambda(\cdot) = 0$, depicted in Equation (5) , maps inputs into a feasible set of outputs. The inputs include labor activity, the stock of assets, and physical well-being. The inclusion of well-being as an input captures the critical link between health and labor productivity. The function is also conditional on random production shocks ($\phi_t^q$), such as weather events or unemployment risk.

Relations (6) reflects the time constraint on activity patterns, where $e$ is a vector of ones. Relation (7) is the non-negativity constraint for physical quantities of assets, labor, and consumption.

The household's maximization problem is solved in Appendix A.1.

### 3.2. Comparative Statics

The opium ban is an exogeneous shock to the opium production. Announced at time $t$ and effective from period $t+1$ onwards, it causes a permanent change in the stochastic production technology, $\Lambda(\cdot)$. This production shock forces $l_{t+1}^{\text{opium}} = 0$ and consequently, $q_{t+1}^{\text{opium}} = 0$. Households, upon learning this new information at time $t$, must re-optimize their consumption, savings, and labor allocation plans for all future periods. We perform a comparative static analysis by comparing the agent's planned choices and state variables for period $t+1$ under the new regime with those of period $t$, and provide the discussion below. See Appendix A.2 for more details.

The impact of this shock is heterogeneous and depends on the agent's ability to substitute into other productive activities. This ability is determined by household's initial asset endowment, specifically its composition of land. We analyze two distinct cases: households with and without the ownership of arable lands.

Following the ban, the households endowed with land suitable for cultivating alternative crops ($a_t^{\text{arable}} > 0$) can reallocate labor from opium to other production (i.e., $l_{t+1}^{\text{other}} > l_t^{\text{other}}$). The effect of this reallocation on total utility depends on the prices of the outputs, reallocation costs, and labor productivity, and is thus indeterminate. However, assuming opium is a high-value cash crop, all else constant, the reallocation would likely result in a negative income shock ($\Delta Y^P \leq 0$). A lower expected income path increases the marginal utility of income, which raises the marginal cost of both consumption and savings. To restore optimality, the household must reduce its planned consumption ($\Delta x \leq 0$) and savings ($\Delta s \leq 0$). This reduction in consumption, particularly food, directly lowers current utility and can negatively impact future health ($w_{t+2}$), potentially leading to a decline in overall lifetime utility ($\Delta U \leq 0$).

For the households, who cultivate land suitable primarily for opium poppies and cannot substitute into other agricultural production ($a_t^{\text{arable}} = 0$), the ban triggers a catastrophic income collapse ($\Delta Y^P \ll 0$). Their ability to finance consumption is restricted to selling off existing assets (dissaving, $s_{t+1} < 0$) and relying on transfers ($k_{t+1}$). The marginal utility of income increases dramatically, forcing a drastic reduction in planned consumption ($x_{t+1} \ll x_t$).

This sharp fall in consumption for households with non-arable lands directly reduces utility and severely impairs the future evolution of physical well-being, as they are forced to skip meals. This dynamic can initiate a poverty trap, where the initial shock diminishes health, which in turn lowers future productivity and locks the household into a state of persistent food insecurity. The model thus predicts that the opium ban will have a more severe and immediate impact on the food security of households lacking the productive assets (arable land) needed to transition to alternative livelihoods.

### 3.3. Coping Strategies

How would the agent respond to the opium production shock? An income reduction (depending on the land type agent holds) for period $t+1$ and beyond tightens the future budget constraint, leading to a higher marginal utility of income. This increase is the primary channel through which coping strategies are deployed.

There are three primary scenarios for how a household might react to preserve its food security: an immediate reduction in food consumption, the dissaving of productive assets, and, in extreme cases, relocation. We discuss these potential scenarios below. See Appendix A.3 for more details.

First, an immediate response to the income shortfall is to reduce current expenditures, as the increase in the marginal utility of income raises the opportunity cost of consumption. Hence, households must adjust their planned consumption path downward. This leads to a reduction in food consumption ($\Delta x^f < 0$), which manifests as reducing the number of meals or limiting portion sizes. While this coping strategy helps manage the immediate budget shortfall in the short run, it directly lowers utility.

The second strategy is to draw down wealth to buffer consumption against the income shock. The higher marginal utility of income raises the opportunity cost of holding savings, incentivizing a reduction in planned savings. For a sufficiently large shock, planned savings for the next period may become negative, representing a net sale of productive assets like livestock. The law of motion for assets shows that when $s_{t+1} < 0$, the household is liquidating its capital stock to survive the shock's aftermath.

Finally, when productive assets are depleted and consumption cannot be reduced further, households may be forced to migrate. This occurs when the value of staying in the current location falls below the reservation utility offered by relocation. This threshold is typically crossed when repeated dissaving leads to the exhaustion of all assets ($a_{t+T} \to 0$ for some $T > 0$). At this point, the household's budget constraint collapses, consumption and health plummet, and migration becomes the optimal, last-resort choice for survival.

### 3.4. Measuring Food Insecurity: An Empirical Approach

From the theoretical framework, an agent's food security is intrinsically linked to their overall well-being or utility. The objective function is strictly increasing in physical well-being and consumption. Since consumption includes food ($x_t^f$) and well-being is itself a function of food consumption and health, the utility function serves as the definitive theoretical measure of an agent's food security status. A higher utility implies a greater degree of food security.

Consequently, the extent of *food insecurity* can be defined as the disutility, or the shortfall of realized utility relative to a benchmark level. Formally, we define a critical "reservation utility," $\bar{U}$, which represents a minimum threshold for a dignified existence. An agent is defined as experiencing *extreme food insecurity* when their realized utility falls below this threshold:

$$U(w_t, x_t) < \bar{U}$$

While the specific value of $\bar{U}$ is determined arbitrarily, it provides a clear criterion for classifying severe deprivation based on the agent's welfare.

To apply this concept empirically, we bridge the unobservable utility level, $U_t$, with observable data from surveys, described in the next section. We conceptualize household's continuous level of $\textit{Food Insecurity}_i$ as their utility shortfall:

$$\textit{Food Insecurity}_i = \bar{U} - U_i(w_t, x_t)$$

The theoretical condition for extreme food insecurity, $U_i < \bar{U}$, is thus equivalent to $\textit{Food Insecurity}_i > 0$.

In practice, surveys measure food insecurity through a series of $N$ discrete, binary questions. Let $m_{in} \in \{0, 1\}$ be the binary response of an agent $i$ to question $n$. An aggregate score, or raw food insecurity score, $M_i = \sum_{n=1}^{N} m_{in}$, is constructed by summing the affirmative (yes=1) responses. Following an existing practice (Barrett, 2002), an individual is classified as "extremely food insecure" (survival level of food security) if this score exceeds a certain fraction of the total number of questions. Let this indicator be $y_i$. For a threshold of more than 50%, the functional form is:

$$y_i = \begin{cases} 1\,, & \text{if } \frac{M_i}{N} > 0.5 \\ 0\,, & \text{otherwise} \end{cases} \tag{8}$$

This observable indicator, $y_i = 1$, serves as the empirical proxy for the theoretical state of extreme food insecurity. The likelihood of an individual being in this state can be estimated with a Linear Probability Model with the outcome variable, $y_i$.

## 4. Data

We construct a novel dataset by assembling the most complete sources to examine the impact of the opium cultivation ban on food security – Data in Emergencies Monitoring (DIEM) surveys for Afghanistan, the United Nations Office on Drugs and Crime (UNODC) data on opium cultivation, and others. Detailed descriptions of each data source are provided below.

### 4.1. Food Security Data

Data in Emergencies Monitoring (DIEM) survey, conducted by the Food and Agriculture Organization of the United Nations (FAO, 2025), collects data to assess the impact of shocks in contexts of food crisis. There are a total of ten rounds of the DIEM survey in Afghanistan, spanning from October 2020 to February 2025. The timeline of the survey rounds is depicted in Figure 1. These waves provide information before, during, and after the imposition of the opium cultivation ban, aiding our empirical strategy. For our analysis, we utilize eight rounds of these data as we exclude the first two rounds from the baseline estimates due to their pre-Taliban period and data limitations.[17]

The survey data are collected using a two-step cluster sampling method and are weighted by demographic characteristics. In the initial step, approximately 25 clusters are selected from each province in each survey round. Surveys are representative at the province level. In the second step, around eight households were randomly selected from each cluster for face-to-face interviews. A substantial portion of the surveyed households in each round are involved in the agricultural sector. We use the district of residence for the surveyed household to merge DIEM with other data sources.

We employ DIEM data for our outcome variables and to control for potential confounders in the empirical specifications. Given the main interest in identifying the causal effect of the opium ban on food insecurity of the exposed households, we use questions related to food security indicators. These questions provide household-level information on food security over the last month, and food consumption and dietary

[17] The survey round 5 (August 2022) is the first post-ban wave. Both the round 1 (October 2020) and round 2 (February 2021) correspond to the pre-Taliban period. Round 1 incorporates questions on food security that are different from standard DIEM questionnaire and is unavailable for the majority of provinces. Round 2 lacks information for some districts and comprises four questions on food insecurity (instead of standard eight). The results remain robust when incorporating data from the second round with restricted samples (Figure C8).

diversity over the last month, week, and 24 hours from the interview date. We also use DIEM surveys to examine the coping strategies of households lacking access to enough food for the household members and demographic information to control for household characteristics that might be correlated both with exposure to the opium cultivation ban and food security. This pre-determined demographic information is used to study if the estimated effects differ across various subpopulations, who may be differentially exposed to the ban.

There are a total of eight questions on food insecurity estimates (FIES) in the DIEM data. The food security panel of DIEM survey is provided in Appendix B.1. Each of those eight questions ($N = 8$ in Equation (8)) require a binary response. The affirmative responses take value one, and zero otherwise. Based on these eight questions, we construct outcomes of interest reflecting the level of food insecurity.

*Extreme (or High) FIES* is our primary outcome variable ($y_i$ in Equation (8)), representing the survival level of food security according to Barrett (2002). This is a binary variable that takes value one if the household responded affirmatively to at least five out of eight FIES questions (in accordance with the threshold of more than 50% in Equation (8)), and zero otherwise.[18] In the context of Afghanistan's severe humanitarian crisis, this survival-level specification of food security is particularly well-suited to capture the acute shocks to household livelihoods.

To ensure our findings are not contingent on a particular specification, we assess their robustness using alternative standard measurements of food insecurity. One of these measurements is the *Household Hunger Scale (HHS)*, a standard scale of food insecurity ranging from zero to six. It is constructed using the respondents' intensity of having no food to eat, sleeping hungry, and having nothing to eat during an entire day. Another alternative measurement is the *Raw FIES Score*, the sum of respondents' affirmative responses to each of the eight questions ($M_i$ in Equation (8)).[19]

Table 1 provides the summary statistics. Underscoring the severity of the humanitarian crisis, our data reveal that over three-quarters of households experienced an economic shock. Panel B of Table 1 shows that the sample is evenly balanced between households residing in opium-cultivating and non-cultivating districts. The

[18] We validate the robustness of the outcome specification using alternate extreme FIES thresholds (Figure C12).

[19] We also construct the measurements of *Average Z-Score* and *Anderson (2008) Z-score* for additional robustness tests. Average Z-Score is the arithmetic mean of the Z-score for each of the eight questions. Anderson (2008) Z-score is the Z-score constructed using the generalized least-squares (GLS) weighting procedure, which sidesteps inference problems arising due to multiple hypotheses testing. Lastly, to assess the share of households that face food insecurity at least to some extent, we construct the measurement of *Any FIES*. This is a binary variable if the respondent reports affirmatively to any of the eight questions.

assignment of the districts into the treated (opium) and control (non-opium) groups is detailed in Section 4.2.

Panel C of Table 1 reports statistics for eight questions on food security and outcome variables. 95% of the respondents are worried about not having enough food. 91% and 92% report an inability to eat healthily and having only limited food in the last month, respectively. Almost a quarter of households go without eating for the entire day and night. Panel D shows that the average raw food insecurity score for the country is 5.3 out of eight, 97% of all the households experience some food hardship, and 68% report facing extreme food insecurity.

### 4.2. Opium Cultivation Data

We employ multiple data sources to construct our treatment variables, primarily utilizing district-level estimates of opium cultivation in Afghanistan provided by the United Nations Office on Drugs and Crime (UNODC, 2023b), which are generated from satellite imagery. We also triangulate UNODC data with the data from Mansfield (2023b).

We classify households in the districts that report any opium poppy cultivation (if the area under opium cultivation is 10,000 hectares and more) in either 2020 or 2021 to be in the treatment group. We also develop alternative measurements for the treatment assignment, adjusting the base years and thresholds for the area under opium production. Results remain robust across these alternate measures, as shown in Figure C11.

Figure 2 illustrates the spatial distribution of districts with opium cultivation across the years. The decline in opium cultivation from 2021 to 2022 is striking, with only a few districts continuing to cultivate opium on more than 10,000 hectares in 2022,[20] highlighting the so-called success of the ban. In Figure C1, we also show a sharp decline in the likelihood of district reporting any opium poppy cultivation immediately after the imposition of the ban.

Panel A of Figure 2 thus indicates the spatial distribution of treated and control districts, where the treated districts are those engaged in opium cultivation in 2021, while the control districts are not involved in cultivation. This setting of the control group provides a strong counterfactual for the treated, as the ban represents a direct shock only for households whose primary and generational source of income was opium. In other words, although the policy is national, it is binding only for opium-growing households, and effectively non-binding for the others, as it did not

[20] The persistence of opium cultivation in certain districts following the ban's enforcement is largely linked to land owned by Taliban field commanders, indicating their non-compliance (Azizi, 2024).

directly constrain their existing economic activities.[21]

In Table C1, we contrast households in control and treated districts within the DIEM dataset in the pre-treatment period, i.e., in April 2022 and earlier. The observations indicate that, on average, the statistics for both groups are nearly identical in terms of household characteristics and responses to the FIES questions and outcomes. Figure C2 shows the trends for control and treated districts for all outcome variables.

### 4.3. Other Data

To validate our findings with external sources, we utilize data from the Rapid Household Assessments (UNHCR, 2024) for the years from 2021 to 2024. The assessments employ a whole-of-community approach to assess humanitarian and protection needs among vulnerable communities across all provinces of Afghanistan. From this dataset, we extract variables pertaining to households' self-reported priority needs and the consumption-smoothing mechanisms adopted in response to food insecurity. These mechanisms include adjustments such as restricting food consumption, limiting meal portion sizes, decreasing meal frequency, and exhibiting a substitution towards less preferred inferior food. We aggregate the granular daily data to the quarterly level to mitigate the statistical noise in high-frequency observations.

Data on crop suitability is derived from Fischer et al. (2021), whereby a district is designated to be suitable for a crop if it is in the top three quartiles of the crop suitability index distribution. Figure C3 shows the spatial distribution of crop suitability index across districts.

We obtain information on weather conditions from ERA5-Land climate reanalysis data and include weather controls to gauge the potential influence of temperature, humidity, and precipitation on agricultural productivity (Hersbach et al., 2020). Data on consumer price indices are derived from the National Statistic and Information Authority of Afghanistan (NSIA, 2024). Shapefiles data are from the Afghan Geodesy and Cartography Head Office.

[21] Any potential indirect impact on controls would only operate through market spillovers over a prolonged period, which we also test in the study. Further in our analysis, we find no evidence of spillover effects, reinforcing the validity of our control group.

## 5. Empirical Strategy

To estimate the causal effect of the opium cultivation ban on food security, we estimate the following specification.

$$y_{i(d,t)} = \alpha_{i(d)} + \alpha_{i(m(t))} + \alpha_{i(p)} \times \alpha_{i(t)} + \beta D_{i(d,t)} + \epsilon_{i(d,t)} \tag{9}$$

In Equation 9, $y_{i(d,t)}$ is the outcome of interest for household $i$ residing in district $d$ and surveyed on date $t$. The main outcome of interest, $y$, is extreme level of food insecurity, unless specified otherwise. $\alpha_{i(d)}$ and $\alpha_{i(m(t))}$ are district and survey month fixed-effects, respectively. While the former accounts for time-invariant characteristics correlated with both the treatment and the outcome of interest, the latter controls for time-varying secular shocks. $\alpha_{i(p)} \times \alpha_{i(t)}$ are province linear time trends. By including province linear time trends, we allow the provinces to trend differentially over time. Thus, our empirical specification leverages within district variation in exposure to opium cultivation shock after accounting for secular shocks that are common across all households and province linear time trends to study the dynamics of food security measures. $D_{i(d,t)}$ is an indicator variable that takes a value of one for all households that are surveyed post-treatment in the treated districts. $\epsilon_{i(d,t)}$ is the idiosyncratic error term clustered at the district-level (Abadie et al., 2022).

Our parameter of interest in Equation 9 is $\beta$.[22] The estimate of this parameter is the change in the average likelihood of a household reporting extreme food insecurity from the pre- to post-treatment period in the treated districts relative to control districts. Due to the limitation to directly ascertain whether a household cultivates opium poppy, the estimates of $\beta$ reflect intention-to-treat (ITT) estimates.

For $\beta$ to be interpreted causally, our empirical model should satisfy the parallel trends assumption. This amounts to outcomes in the treated and control districts trending similarly in the absence of the treatment. To empirically test this assumption, we estimate the following event-study specification.

$$y_{i(d,t)} = \delta_{i(d)} + \delta_{i(m(t))} + \delta_{i(p)} \times \delta_{i(t)} + \sum_{j \neq 0, j=-3}^{6} \lambda_j D_{i(d,t,j)} + \epsilon_{i(d,t)} \tag{10}$$

Equation 10 is the same as Equation 9 except that the single post-treatment indicator variable, $D_{i(d,t)}$, is replaced with ten indicator variables for the time relative to treatment, $D_{i(d,t,j)}$. We omit the indicator for one period (survey round four in April

[22] We also estimate specification in Equation 9 assuming logit distribution for the dependent variable. The average marginal effect estimate from this specification is very close to our baseline estimates.

2022, which coincides with the announcement of the opium ban) before treatment as the reference group, i.e., $j = 0$ in Equation 10.

Since our treatment turns on for all the treated units at the same time, we can abstract away from potential negative weighting issues highlighted by the recent literature (de Chaisemartin and D'Haultfœuille, 2022; Roth et al., 2023). We do not report estimates from TWFE estimation with a continuous measure of district-level opium cultivation as more interesting causal parameters relying on comparisons across different treatment doses estimated through TWFE include a selection bias with *apriori* ambiguous sign (Callaway et al., 2024). The sign of this selection bias term hinges on the distribution of treatment doses among the treated units, which is not equivalent to TWFE weights. Nonetheless, we establish the robustness of our main estimates to account for dynamic heterogeneous treatment effects with multiple periods (Sun and Abraham, 2021) in Figure C13.

We establish the validity of our research design through multiple empirical checks. Our estimates support the stable unit treatment value assumption (SUTVA) as Table C2 confirms that there are no significant changes in the composition of treated and control groups post-treatment, both for all households and the households engaged in the agricultural sector specifically. Figure 4 further demonstrates that inflationary pressures do not confound our treatment effects (see Section 6 for more details). While acknowledging the potential for other unobserved shocks to influence our outcome variables, such as other national reforms, we contend that our identification strategy adequately addresses these concerns. Such country-level shocks are unlikely to exert differential effects across opium and non-opium districts.[23]

## 6. Results

In this section, we first discuss the main results, the effect of the 2022 opium ban on food security in Afghanistan and its dynamics. We then establish the robustness of our findings through a battery of empirical checks. Subsequently, we examine the potential mechanisms leading to the documented changes and how the effects vary across different subpopulations. We conclude this section by studying the households'

[23] The Taliban's reforms are at a national level, not region-specific. This principle of uniform application also includes the opium ban, but it is binding only in opium-cultivating districts. It is unlikely that other national reforms would generate differential effects when comparing opium versus non-opium growing districts. However, the analysis must account for potential confounding from major idiosyncratic regional shocks, such as the 2023 earthquakes in Herat province. To ensure the validity of our estimates, we perform multiple sensitivity checks by systematically excluding regions impacted by suchlike shocks. Across all alternative specifications, the findings remain robust.

economic mobility and coping strategies to alleviate food insecurity.

### 6.1. Main Results

The estimates from the specification in Equation 9 are presented in Table 2. The outcome variables in Panels A through C are Extreme Food Insecurity estimate, Household Hunger Scale, and Raw Food Insecurity Score, respectively (see Section 4.1 for details). In all panels, the explanatory variable is the interaction ($D_{i(d,t)}$ in Equation 9) of an indicator for the households' residence district cultivating opium and an indicator for the household being surveyed after the ban enforcement, the fourth survey round. The estimate on the interaction term is interpreted as the difference in the mean of the outcome variable in opium (treated) districts compared to non-opium (control) districts in the period after the ban imposition relative to the pre-ban period.

Extreme Food Insecurity estimates serve as our baseline, representing the inability to achieve a survival level of food security. Findings from column (1) of Table 2 indicate that, on average, households' likelihood of experiencing this extreme level increases by 17.3 percentage points, *ceteris paribus*. This is a significant increase, corresponding to one-quarter of the pre-ban mean for the treated group. In other words, the share of opium-cultivating households unable to obtain the minimum level required to sustain food security at all times had risen nearly 25%. Notably, given that almost the entirety of the country faces food insecurity to some extent, which is unaffected by the ban (Figure C4), our baseline measurement of extreme insecurity serves as a reliable indicator of the livelihoods of impoverished populations in crisis.

The stark increase of 30% over the pre-ban sample mean in the hunger scale (an increase of 0.5 units), which takes into account the intensity of food insecurity, and the raw food insecurity score (an increase of 0.9 units), also echoes the catastrophic level of the impact.[24]

Figure 3 presents the main estimates from the event-study specification in Equation 10, the dynamics of the impact of the opium ban on food insecurity.[25] First, the figure shows no pre-trends in any of the outcome variables, supporting the assumption of parallel trends. In Figure C8, we demonstrate that parallel trends assumption holds even when including the data from the second round with restricted samples.

Second, the findings provide evidence of a spike in outcomes in the first two rounds after the ban, followed by a fade afterwards (starting from round seven of the

[24] The average Z-score and Anderson (2008) Z-score go up by 0.3 and 0.3 units, respectively, providing further evidence that the conclusions drawn from the preceding variables are robust to the outcome construction (Figures C5 and C6).

[25] In Figure C7, we provide the event-study estimates for each of the eight questions related to food security in the DIEM survey.

DIEM data – October 2023, a year and half afther imposition of the ban).[26] These dynamics indicate that households may have coped with the extreme food hardship by reallocating their production from opium to alternative crops or adapting to the new realities of food diversity and availability. Another possibility behind the effect fading out over time would be the financial assistance households receive in the meantime. However, in Figure C9, we rule out the second option by showing that there is no effect of the opium cultivation ban on the likelihood of receiving food assistance.

In Figure C10, we present the event-study estimates for four additional variables. The food consumption score (FCS), standardized FCS, and poor FCS, which indicate the various food consumption bundles over the last seven days preceding the survey date, resonate the reported dynamics. The healthy diet measure also suggests a decline in the likelihood of following a healthy food sustenance immediately after the ban enforcement. A diet is considered healthy if the household consumes at least four of the seven food categories on all seven days preceding the survey date.

Overall, our findings illustrate an immediate deterioration in food security following the cultivation ban, an effect that attenuates over time. This conclusion is robust to various specifications of the food security measures. Findings are substantiated by further sensitivity analyses in the next subsection.

### 6.2. Robustness Checks

We now establish the robustness of our estimates via multiple sensitivity checks. The columns (2)-(4) in Table 2 illustrate that the baseline findings are robust to excluding survey weights, the inclusion of weather controls like temperature and precipitation, individual and household controls, which include the indicator variables on whether the household head is male, is married, and households has an unsafe water supply.

The findings are also insensitive to alternate treatment definitions. Figure C11 indicates that the baseline findings remain unchanged when adjusting the treatment construction in respect to various measures of opium cultivation across different years and cultivation areas. These variations include defining a district as cultivating opium based on measures from 2021, 2020 to 2021, or 2019 to 2021, based on cultivation distribution, hectares of cultivation, and derivations from Mansfield (2023a).

We also confirm that the effect on extreme food insecurity maintains its statistical significance, magnitude, and dynamics when using alternative extreme FIES thresholds (Figure C12), dropping survey weights or using Sun and Abraham (2021) estimator (Figure C13), including household, individual and weather controls, and province

[26] Event study estimates for the Average Z-score and Anderson (2008) Z-score, shown in Figures C5 and C6, also follow similar trends.

and season fixed effects (Figure C14). The robustness of the estimates to alternative threshold specifications validates the construction of our outcome variable and lends credence to the external validity of this measurement approach for assessing survival-level food security in comparable contexts with humanitarian crises.

There are certain provinces with unique characteristics that could potentially confound our estimates. One such province is Badakhshan, known for its historic resistance to the Taliban's authority, its distinct opium-harvesting seasons due to mountainous geography and colder climate, and its role as a key gateway to the global narcotics market for Afghan opium. Another example is Herat province, where two powerful earthquakes (magnitude 6.3 on the Richter scale) struck the city of Herat in October 2023, causing thousands of fatalities and injuries. WHO estimated that around 43,400 people were directly affected by the earthquakes, which could confound our estimates of food security. The inclusion of international border districts also presents challenges, as these districts have the potential to engage in smuggling opium and its derivatives across borders, thereby affecting the livelihoods of residents involved in such activities. Additionally, the livelihoods of households in control districts adjacent to treated districts may also be impacted due to potential spillover effects from neighboring treated districts where opium cultivation occurs. We test these settings in Figure C15. Sensitivity tests demonstrate that none of these concerns alter our conclusions, as the results remain robust when international border districts, control districts adjacent to treated districts, and the provinces of Badakhshan and Herat are excluded.

We also perform the permutation exercise in Figure C16 by dropping all of the provinces, each at a time. The exercise concludes that the baseline results are unaltered, as none of the provinces solely drives the baseline effects. This robustness is further solidified by aggregating the household-level data to the district level (Figure C17). The dynamics remain unchanged when we use the collapse data as the analytical sample.

We supplement our food security metrics, derived from self-reported surveys, with objective measures, the income-to-poverty ratio. We extract the reported total household income from the DIEM data, obtain the poverty threshold for 2017 from World Bank (2018), adjust it for inflation to 2022 prices, and construct a binary measure indicating whether the total household income is below the poverty line. Dynamics pictured in Figure C18 confirm our baseline findings.

The potential concerns with limited pre-treatment periods are also addressed by the inclusion of the second DIEM survey round, despite limitations in geographical and food security measures coverage. As illustrated in Figure C8, the results remain robust also with the inclusion of data from the pre-Taliban period.

### 6.3. Mechanisms

The causal effect of the opium cultivation ban on food insecurity can be transmitted through three potential channels. The first is a direct income shock, whereby the loss of earnings constrains a household's ability to finance adequate food consumption. The second is a price effect, wherein the policy induces inflationary spillovers that erode real purchasing power, making previously affordable consumption bundles unattainable. The third channel represents the combination of both. Our theoretical framework suggests that the impact on household welfare is driven by an increase in the marginal utility of income, a condition that would arise from any of these mechanisms. It is essential to disentangle these pathways to understand how the consequences of the restriction propagate to livelihoods and to design effective remedial policies.

For analytical tractability, our theoretical framework held prices constant, a harmless assumption that we empirically test in this section. To determine if price spillovers are a driving mechanism, it is essential to consider the potential impact of both food and non-food inflation.[27] A rise in food prices would directly diminish food consumption, while an increase in non-food prices would operate indirectly by reducing the household's discretionary income available for food. As illustrated in Figure 4, we find that the ban had no statistically significant differential impact on either food or non-food price indices in treated districts relative to controls. This finding rules out price spillovers as the potential mechanism driving the observed effects on food insecurity.

Conversely, in line with the theoretical model's predictions, we provide evidence supporting that income shock is the primary causal pathway behind the baseline findings. Figure 5 shows that the effect of the ban on extreme food insecurity is concentrated only in households that report facing economic shock. This effect is absent for those who did not experience an income shock. The effects for these two groups of respondents are also significantly different from each other.

### 6.4. Heterogeneity

Our model, which allows for heterogeneity in effects, suggests that the impact of the opium ban relies on households' economic mobility to substitute into other productive activities, which is determined by their asset endowments. We empirically test this assumption by analyzing the effect of the ban on various subpopulations.[28]

As the economy is agrarian in nature, we begin with land endowments, specifically

[27] The classification of food and non-food items is provided in Appendix B.2.
[28] The classification of subpopulation in the DIEM survey data is provided in Appendix B.3.

examining the composition of land on which households reside and produce. Reports show that, after the ban enforcement, Afghan farmers demonstrated a strong willingness to reallocate their production to wheat (UNODC, 2023a), the first alternative crop. However, this alternative is suboptimal, as it is less suitable in arid climates than opium poppies. Therefore, not all soils where opium used to be grown are also available for grain production. This difference establishes a clear distinction between wheat-suitable and non-suitable lands. First, we derive data on wheat suitability from Fischer et al. (2021), and define the land as grain-suitable if it is in the top three quartiles of the suitability index distribution. Then, we test if the baseline effects vary by households residing in either type of land.

The results from this analysis are depicted in Figure 6. The findings provide strong evidence that the likelihood of reporting extreme food insecurity due to the opium ban is significantly higher and statistically significant for households residing in non-arable-for-grain districts only. For this group, the effect persists immediately after the ban and remains unchanged. Conversely, not only do residents of districts with wheat-suitable lands not experience heightened incidences of extreme food insecurity, but the effect is also negative and statistically significant in the latest post-ban rounds. The difference between these two groups of households is also statistically significant.

This stark contrast highlights the crucial role of land composition in mitigating the effects of agricultural shocks. Grain, albeit suboptimal, is the next alternative to opium in agronomical terms. If the land is unsuitable for grain, then it is unlikely to be arable for other crops as well. The observed persistence of the ban's effect on extreme food insecurity in non-arable lands points to the fact that residents of these districts never have viable options for reallocating their production, which is the foremost resilient strategy to mitigate economic shocks in vulnerable populations. We further explore households' coping strategies and production transition patterns in section 6.5.

We proceed with examining other potential differential effects of the ban across various population segments. In Figure C19, we test whether the effects on food insecurity vary by the respondent's involvement in crop production. The difference between crop-producing and non-producing households is statistically insignificant, with both groups exhibiting similar dynamics as observed in the event study. However, the effect is slightly more pronounced for respondents involved in crop production.

Figure C20 illustrates that the baseline effect, albeit with a statistically insignificant difference, is pronounced among non-agricultural laborers only, with dynamics resembling the baseline event study results. This observation is not surprising, given that agricultural laborers, who are often daily wage workers or casual employees on farms, are relatively more flexible in transitioning their work to non-opium farms than those who produce the food for their own consumption (the majority of the rural households in Afghanistan).

Figure C21 also depicts that the effects for relatively poorer and richer households are not different from each other. However, we observe that poorer respondents face extreme food insecurity immediately after the ban's imposition, whereas the relatively wealthier group experiences a lagged effect. We observe no difference in the effects of the ban by the age of the respondent (Figure C22). Figure C23 highlights the observable distinctions between subpopulations across different regions. Central Afghanistan, characterized by its predominantly urban areas, including the capital Kabul, exhibits no effect in any of the post-ban survey waves. This result aligns with expectations, as opium production is predominantly a rural activity.

In Figure C24, we observe no difference between households that own productive assets, such as animals, and those that lack them. This pattern raises the question of whether households with animals might sell their livestock to cope with the economic shock immediately after the ban, eventually experiencing extreme food insecurity, and then benefit from the asset sales in the longer term. We explore this possibility further in 6.5.

Table C3 summarizes the bivariate heterogeneity analysis, reinforcing the critical distinction between households on arable versus non-arable lands. The ban's impact is pervasive across all demographic segments, underscoring the scale of the shock and that the entire country experienced its consequences to some degree. However, irrespective of the demographic group, the adverse effects are concentrated only among residents of non-arable lands. Notably, the income shock, the primary causal channel, is also observable exclusively within this group. Altogether, these findings indicate that land endowments are the key determinant of farmer resilience to agricultural shocks in Afghanistan.

### 6.5. Coping Strategies and Transitions

The observed attenuation of the ban's impact on extreme food insecurity over time exemplifies household resilience, a dynamic with significant implications for the literature on economic shocks. This resilience is a function of the coping strategies households deploy in response to hardship. In our analysis, we distinguish between short- and medium-term coping mechanisms based on the survey's recall periods. Short-run strategies are defined as immediate, weekly responses to food or financial shortfalls, captured by questions regarding household behavior over the seven days preceding the interview. In contrast, medium-run strategies encompass more substantial adjustments made over the preceding 30 days, such as the depletion of savings or the sale of productive assets.[29]

When faced with high food insecurity, it is anticipated that respondents would reduce the number of meals and/or limit portion sizes in an effort to conserve food for the following day or to ensure that other household members have enough to eat. This type of behavior is precisely what we observe. The event-study estimates on how the exposed households cope with high food insecurity in the short run are depicted in Figure 7.[30] The estimates from these event studies indicate that households reduce the frequency of food consumption, limit portion sizes during each meal, and restrict food consumption by adults to ensure children's nutrition. These consumption-smoothing strategies become a pervasive feature of household dietary patterns in Afghanistan, reflecting respondents' adaptation to critical realities and partially explaining why the effect of the ban on food insecurity is diminishing over time.

In Figure 8, we show that after the ban was imposed, respondents were compelled to sell their animals, resulting in a reduction in livestock numbers. Productive asset dissavings, such as livestock sales, may foreshadow a long-term decline in food security measures. In Figure C25, we observe a decline in food borrowing, which is likely associated with the reduction in borrowing options nationwide. Among other medium-term coping strategies, we do not observe statistically significant changes in the sale of assets, use of savings, or borrowing money due to the April 2022 ban (Figure C26). These findings are expected, given that in a setting marked by an ongoing humanitarian crisis, where 96% of all households experience some degree of food insecurity, the possession of assets, access to savings, and availability of reliable sources for borrowing are highly unlikely.

We next examine households' agricultural reallocation patterns to determine how they replaced opium production. Building on the findings from Section 6.4 that the ban's adverse impact was concentrated in districts with soils unsuitable for wheat, we test whether land suitability also governed households' adaptive capacity. The analysis in Figure 9 supports this hypothesis, revealing a notable economic adjustment. In districts with suitable land, households consistently displayed a preference for transitioning to grain production over other agricultural alternatives.[31]

[29] The classification of medium-run coping strategies in the DIEM survey data is provided in Appendix B.4.

[30] The limitation of these seven-day response questions is that the DIEM survey started including these questions from the survey round four. Thus, the information in the pre-ban waves is missing. To demonstrate that the no pre-trends hypothesis holds, we triangulate the data on coping mechanisms with similar data on short-term coping mechanisms from the Rapid Household Assessments (UNHCR, 2024).

[31] These estimates also provide evidence of widespread cultivation of opium prior to the ban, as opium falls under the "Other Crops" category in the pre-ban period. A sandy loam soil, which is optimal for

But what coping mechanisms are available to households on non-arable land who lack viable production alternatives? We address this question by analyzing migration patterns, comparing households on grain-suitable versus unsuitable land. The findings in Figure 10 provide evidence that households unable to transition their production are significantly more likely to relocate. This effect is absent for residents on arable lands, underscoring migration as a last-resort strategy driven by the lack of on-farm adaptive capacity.[32]

Although the migration is internal (within the country), the DIEM dataset does not specify whether it occurs within districts or across them. A potential cross-district migration could confound our estimates by altering the demographic composition of the control versus treated districts, potentially violating the stable unit treatment value assumption (SUTVA). Table C2 shows that the composition of districts remains unchanged for all households and for agricultural laborers in particular. This finding aligns with Tai et al. (2022), who show that most of the internal migration in Afghanistan occurs within the same district (either from rural to urban areas, or to any arable lands within the district), driven by a strong desire to remain close to home. Taken together, the results suggest that SUTVA violations are not a concern in our setting.

Lastly, in Figure C27, we examine whether the households in the districts that previously grew opium diversified their income sources. Although suggestive, the estimates in this figure indicate that households could not diversify their income sources right after the ban, whereas they relied on multiple sources after the second post-ban round. The sharp increase in the likelihood of the household having multiple income sources from the third post-ban survey round relative to the survey round immediately preceding the ban overlaps the dynamic adjustment in food insecurity measures in these phases. Thus, economic adjustment through income source diversification could be another coping strategy through which food insecurity dynamics play out.

growing opium (U.S. Department of Justice, 1992), is also suitable for wheat cultivation. Therefore, districts with this soil type offer an effective pathway for farmers who previously cultivated opium to reallocate their agricultural land towards wheat production. The absence of such a reallocation pattern across crop types in non-wheat suitable districts lends further credence to this conclusion.

[32] This finding draws a clear parallel to Madhok et al. (2025), where urban income shocks prompt a spatial reorganization of agriculture. In our setting, the opium ban serves as a comparable shock to production capacity; however, for households on non-arable land lacking the ability to reorganize cultivation, the primary adaptive strategy is not a spatial shift in production, but out-migration.

## 7. Policy Implications

The findings of this study reveal the severe welfare losses incurred by households following the Taliban's nationwide ban on opium cultivation. The substantial increase in extreme food insecurity, particularly among asset-poor households on non-arable land, demonstrates that the policy's success in reducing cultivation comes at an immense social cost. This outcome highlights a critical disconnect between policy enforcement and its distributional consequences, underscoring both inefficiency and inequity in its design. The sheer scale of the adverse effects necessitates a fundamental reevaluation of such restrictive measures, highlighting the imperative of designing and implementing aiding and preemptive policies.[33] These preparatory interventions for restrictive policies must be meticulously tailored to the country settings, accounting for the construction of household finances, their behavioral responses to economic shocks, and the mechanisms that can ease their transition toward viable alternative livelihoods.

We propose a set of policy recommendations structured in three sequential stages to address the challenges facing Afghanistan's rural population in the long term.[34] First, a foundational stage of knowledge dissemination is required, wherein farmers are trained on the agricultural yield possibilities available on their land and guided on how to re-optimize their cultivation strategies accordingly. Second, this educational component must be complemented by a transitional support stage, providing targeted financial and material assistance, such as subsidies for alternative crops. Third, for households residing on land unsuitable for any agricultural transition and facing a dearth of local employment opportunities, a differentiated strategy must be forged to create alternative economic pathways.

The initial stage of farmer training must be preceded by an analysis of crop suitability across Afghanistan's diverse agro-ecological zones, integrating domestic demand patterns, cultivation cycles, and multicropping opportunities to generate spatially optimized production models. Then, training programs can be deployed to educate farmers on specific high-value alternatives to opium, moving beyond the

[33] Empirical tests from the US, for example, point to the critical role of policies in achieving food security. These include the positive effect of subsidized lunch policy in the 20th century (Hinrichs, 2010), Supplemental Nutrition Assistance Program (SNAP) accessibility (Bartfeld and Men, 2017; Gundersen et al., 2017), the state Earned Income Tax Credit (EITC) generosity (Lenhart, 2023).

[34] In the short term, given the undernutrition of affected households, the expansion of medical services can also complement these recommendations. Moellman and Vaughn (2024) shows that having a Medicaid-eligible child significantly alleviates the food insufficiency of the households facing extreme poverty in the United States.

default of subsistence grains.[35] Such programs should provide technical knowledge on production specifics, as existing research confirms that this is a critical determinant of livelihood adaptation in Afghanistan (Wigton-Jones, 2021). Our findings also corroborate that farmers consistently self-report that information and material assistance for production reallocation are their most pressing needs.[36]

Once farmers possess the requisite knowledge of potential reallocation patterns, the transition can be facilitated through material and financial assistance. Our results indicate that access to financial resources is a crucial factor in a household's ability to cope and adapt. Table 3 indicates that the observed effect on extreme food insecurity is concentrated in households, whose primary need is cash. Conversely, this effect is absent and negative for households that primarily need seeds and irrigation assistance, respectively. Therefore, any international aid channeled to help farmers cover the upfront costs associated with new seed varieties and planting inputs might be of immense benefit. This can be achieved through targeted subsidies, spatially differentiated based on crop suitability (Table 3 also shows that the effects are pronounced only in non-arable lands). Such an approach is superior to untargeted, one-time cash transfers, as it directly fosters long-term economic resilience rather than merely addressing short-term consumption gaps.

However, it is crucial that not all land is suitable for transitioning to alternative crops. Given the arid climate, opium was often the only viable high-yield crop in Afghanistan, requiring minimal irrigation. In regions where alternative agriculture is not feasible and non-farm employment is scarce, a regulated framework for licensed opium cultivation for pharmaceutical purposes presents a potential, albeit complex, remedy. The feasibility of this path depends on several conditions. First, the Taliban leadership would need to reconsider its religious prohibition, framing production strictly for medicinal use as permissible. Second, this re-transitioning would provide a vital source of employment and income for millions of households. Third, it could satisfy significant regional demand for opium-derived analgesics. Fourth, such a system would necessitate robust monitoring and strict enforcement to prevent diversion to illicit markets. Ultimately, the success of this strategy would depend on the Taliban regime gaining the international recognition necessary to participate in global trade.

For those farmers on non-arable land who cannot be absorbed into a potential pharmaceutical opium sector or other local industries, managed relocation may be

[35] Ibanez and Martinsson (2013) show that the knowledge dissemination on agricultural yields might be an optimal anti-drug policy in developing country settings.

[36] In Table C4, we show that receiving cash assistance helps to mitigate contemporaneous food insecurity, whereas seed assistance does not. This observation highlights the importance of targeted training programs in technical agricultural knowledge for sustainable resource allocation.

the only remaining viable option. Pre-emptive policies in this domain should focus on providing comprehensive information services, detailing opportunities in other regions, including the availability of uninhabited arable land and local security conditions. Financial support to facilitate dislocation is essential to ensure that migration is a planned transition toward opportunity rather than a desperate flight from destitution.

The policy options outlined, ranging from spatially-informed agricultural training and subsidized transitional support to regulated pharmaceutical cultivation and managed relocation, offer a multi-pronged strategy to mitigate the devastating consequences of the opium ban in Afghanistan. Moreover, these recommendations underscore a universally applicable principle. The enforcement of restrictive policies, particularly in fragile and developing states, must be preceded by carefully designed, context-specific, and preemptive interventions. Failure to do so risks not only welfare losses but also deepening of poverty traps, undermining the stability and security that such policies ostensibly aim to achieve.

## 8. Conclusion

As substance use presents a formidable threat to public health, the perceived ineffectiveness of consumption-focused interventions compels policymakers to enact profound restrictions on production. Such a grave supply-side regulation is absolute extermination, a decisive, albeit potentially rash, policy response. In this paper, we show that household livelihoods substantially deteriorated in the immediate aftermath of the opium ban by the Taliban, a unique illustration when the primary income source is restricted at the national level. The adverse effects are dynamic and disproportionately borne by households on non-arable lands, who lack the asset endowments to reallocate production. As a result, they are forced to limit food consumption, deplete productive assets, and ultimately migrate.

The findings carry significant weight for the literature on sweeping policies and household welfare. First, this study provides empirical evidence on the dynamic welfare consequences of eliminating a main livelihood source for a vulnerable population. Second, we contribute to the literature in food security by constructing robust estimates of extreme food insecurity levels to measure the immediate impacts of a large-scale economic shock in a crisis setting. The findings on household resilience and coping mechanisms offer transferable insights for how other impoverished, agrarian communities respond to economic shocks. We also underline that without the provision of viable economic alternatives, restrictive regulations risk deepening poverty traps, necessitating the administration of preemptive policies to facilitate the transition for affected populations.

The research avenues regarding the aftermath of the ban are, moreover, extensive. Reducing food intake to combat hunger and eschewing necessary medications risks long-term health consequences. Households might cut educational expenses and decrease the number of dependents, potentially by marrying off daughters at very young ages, leading to an increase in premature marriages.[37] Over time, with dwindling productive avenues, all farmers may deplete their inventories and likely follow similar strategies. Worsening in local well-being may further foster political resistance, market monopolization, an increase in violent crime, and a rise in outmigration. Since Afghanistan was the biggest exporter of poppy and its byproducts, reduced opium supply will also potentially cause quality shifts in the opium market (potency and harm) on a global scale. We leave these empirical questions for future research.

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FIGURE 1. Timeline of DIEM Survey Rounds

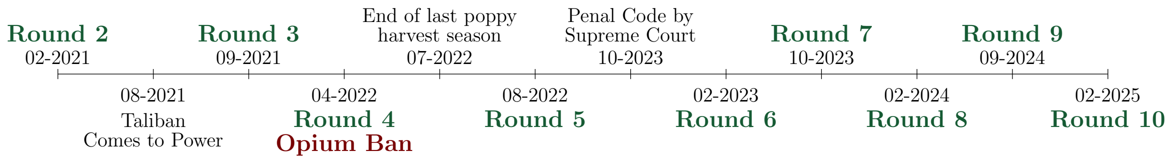
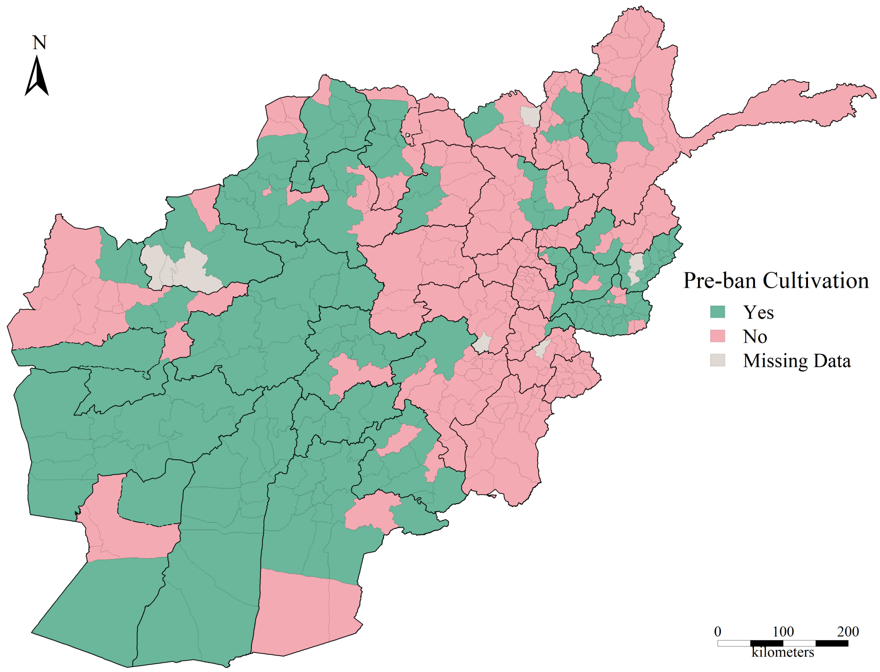
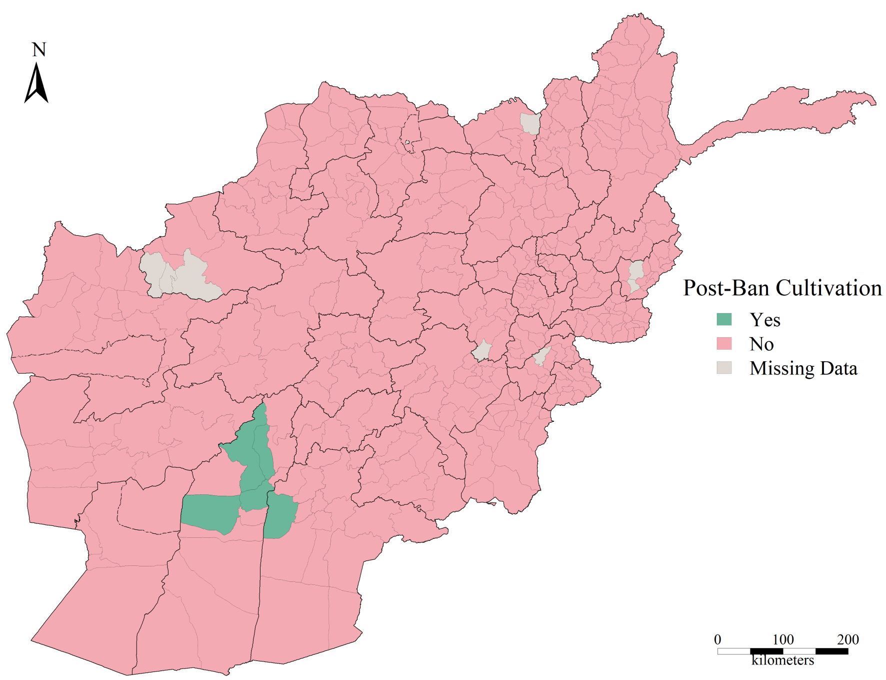


Figure 2. Spatial Distribution of Control and Treatment Districts

(a) Opium Cultivation Before the Ban



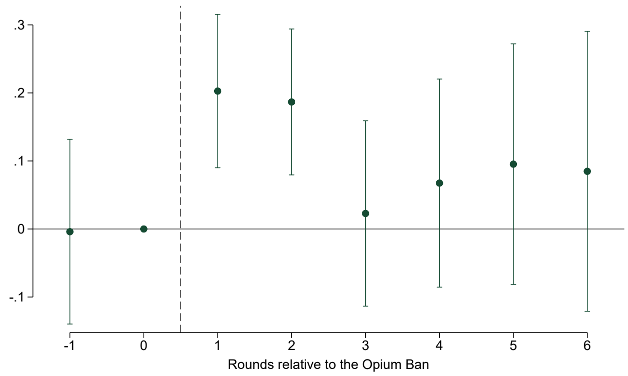

(b) Opium Cultivation After the Ban



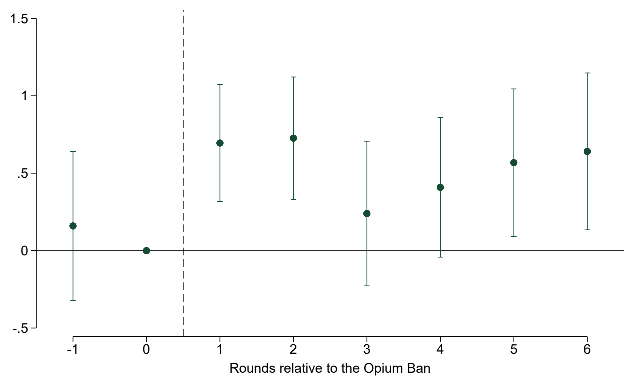

*Notes:* Shapefiles data are derived from the Afghan Geodesy and Cartography Head Office. Opium cultivation data are derived from UNODC (2023b), which provides annual information on the area under opium cultivation in hectares at the district-level. In the top panel, districts are categorized as cultivating opium if the area under opium cultivation is 10,000 hectares and more either in 2020 or in 2021. In the bottom panel, districts are categorized as cultivating opium if the area under opium cultivation is 10,000 hectares and more in 2022.

FIGURE 3. Event-study Estimates

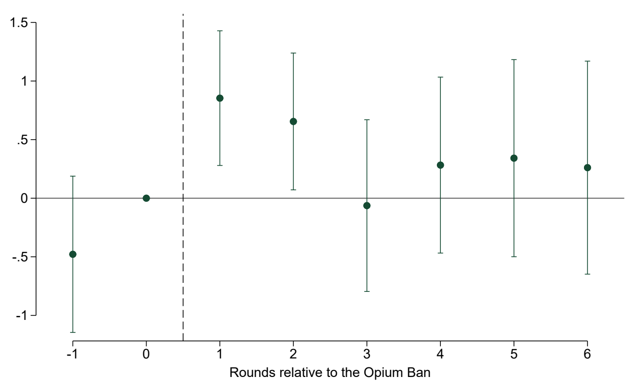
(A) Extreme Food Insecurity




(B) Household Hunger Scale

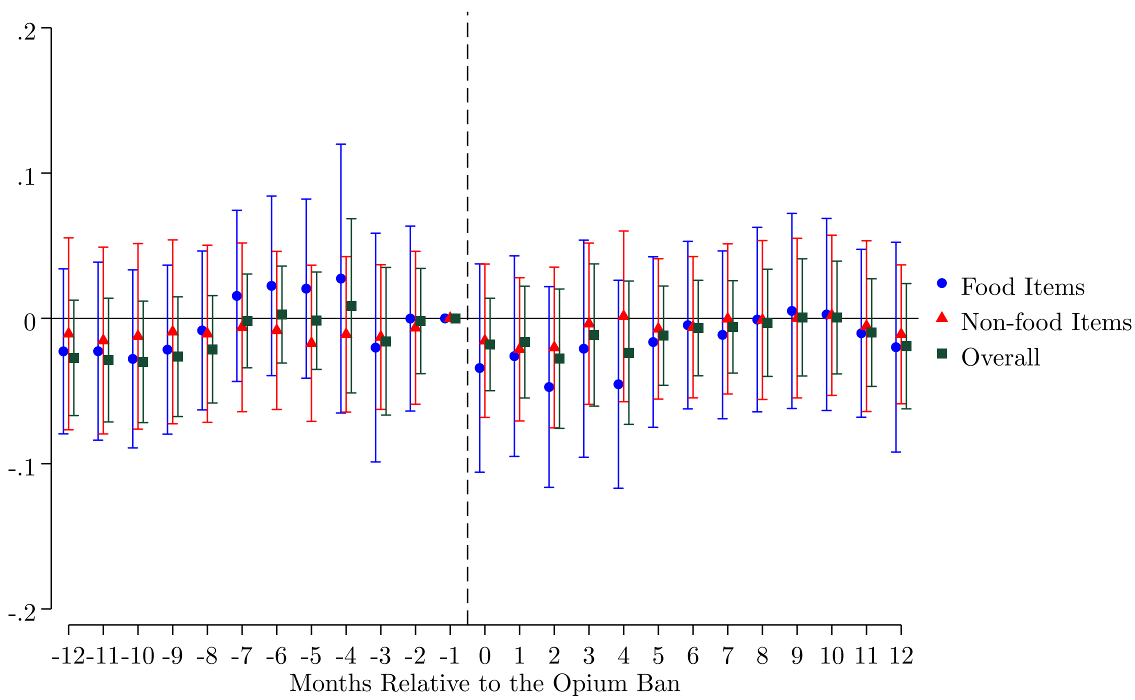



(C) Raw Food Insecurity Score



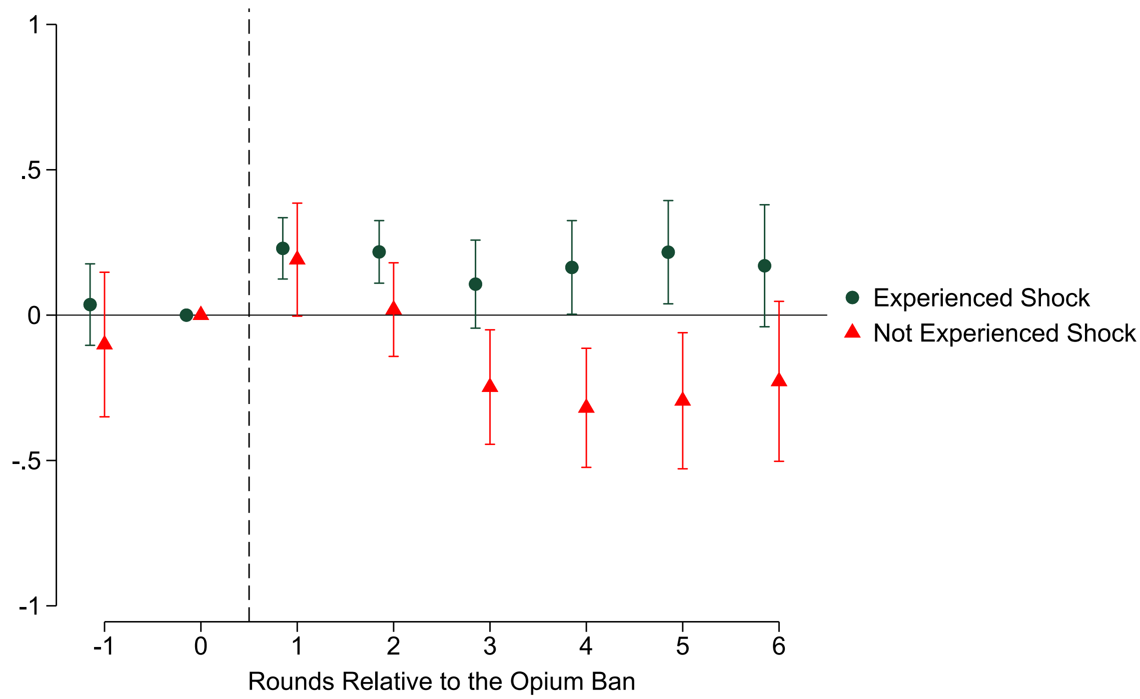

*Notes:* The dependent variable in each panel is mentioned in the panel caption. The construction of dependent variables is discussed in section 4.1. The estimates are from the specification in Equation 10. Standard errors are clustered at the district-level. 95% confidence intervals are plotted. Survey weights are used. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025.

FIGURE 4. Consumer Price Index



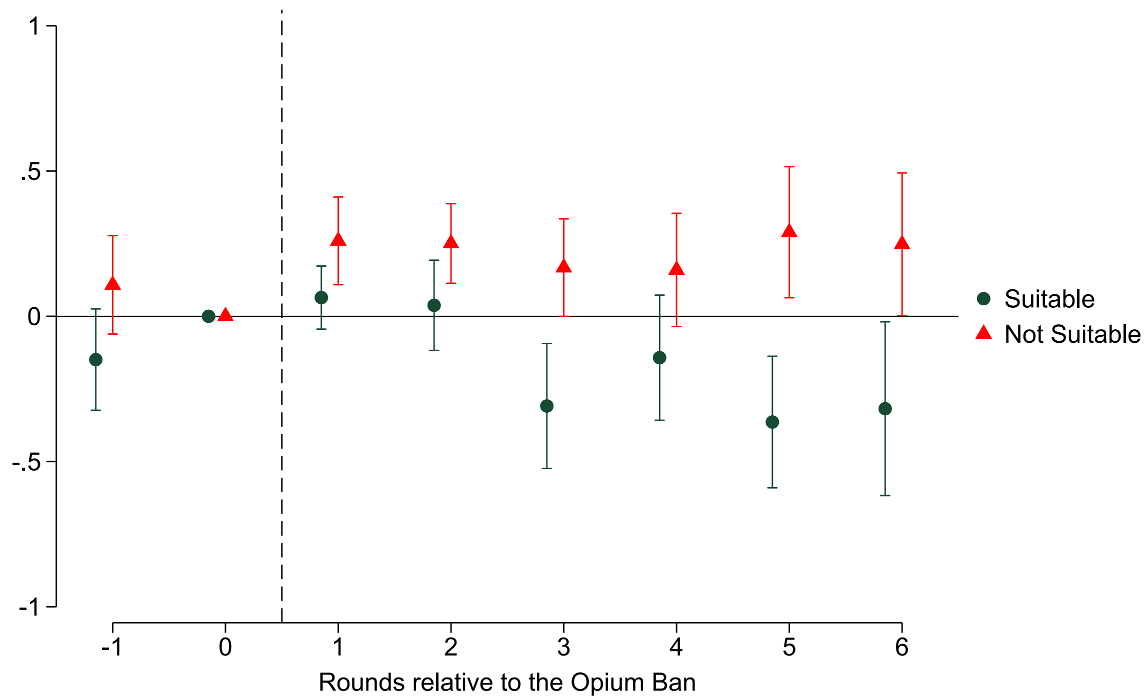

*Notes:* The dependent variable is the monthly inflation rate in percentage. The base month is April 2015. Standard errors are clustered at the district-level. 95% confidence intervals are plotted. The sample is restricted to data between April 2021 and April 2023. Overall Consumer Price Index (CPI) includes both food and non-food items. The classification of food and non-food items is discussed in Appendix B.2.

FIGURE 5. Income Shock




*Notes:* The dependent variable is Extreme Food Insecurity. The estimates are from the specification in Equation 10. Standard errors are clustered at the district-level. 95% confidence intervals are plotted. Survey weights are used. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025. For all point estimates the sample is split using an indicator variable. Indicator variable is presented in whether the household experienced an income shock.

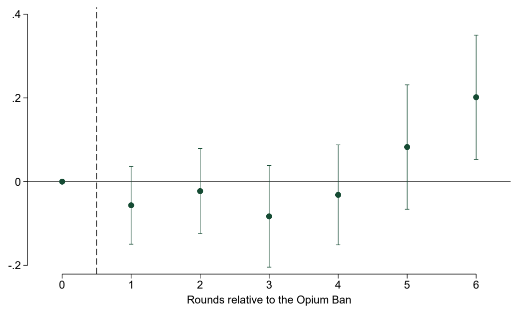
FIGURE 6. Wheat Suitability



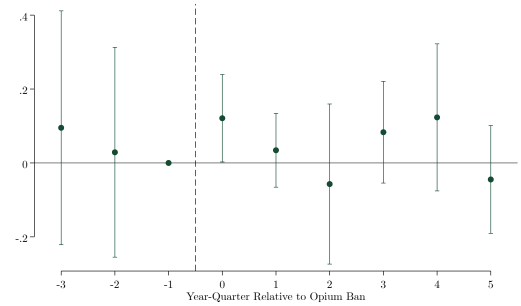

*Notes:* The dependent variable is Extreme Food Insecurity. The estimates are from the specification in Equation 10. Standard errors are clustered at the district-level. 95% confidence intervals are plotted. Survey weights are used. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025. For all point estimates the sample is split using an indicator variable. Indicator variable is presented in whether the household is residing in a wheat suitable district. The district is designated to be suitable for a crop if it is in the top three quartiles of the crop suitability index distribution.

FIGURE 7. Coping Strategies due to Lack of Food or Money to Buy Food

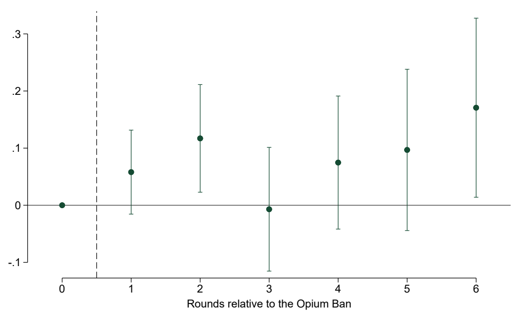
(A) Restrict Food Consumption (DIEM)



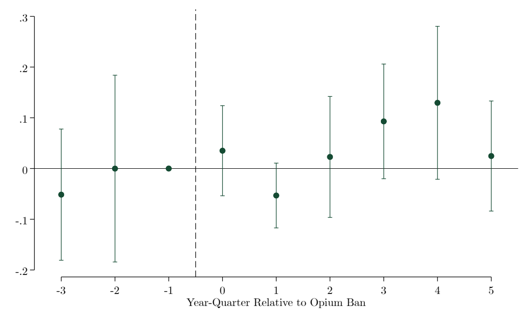

(B) Restrict Food Consumption (RHA)



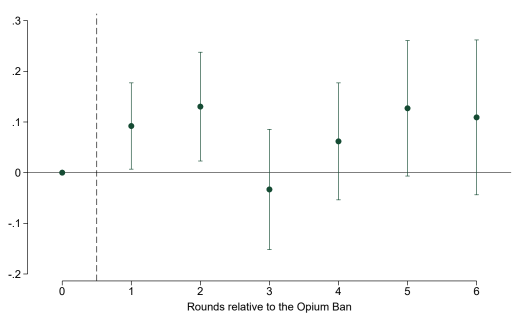

(C) Limit Portions (DIEM)



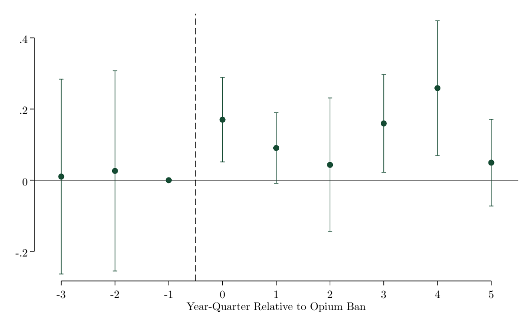

(D) Limit Portions (RHA)




(E) Reduce Number of Meals (DIEM)

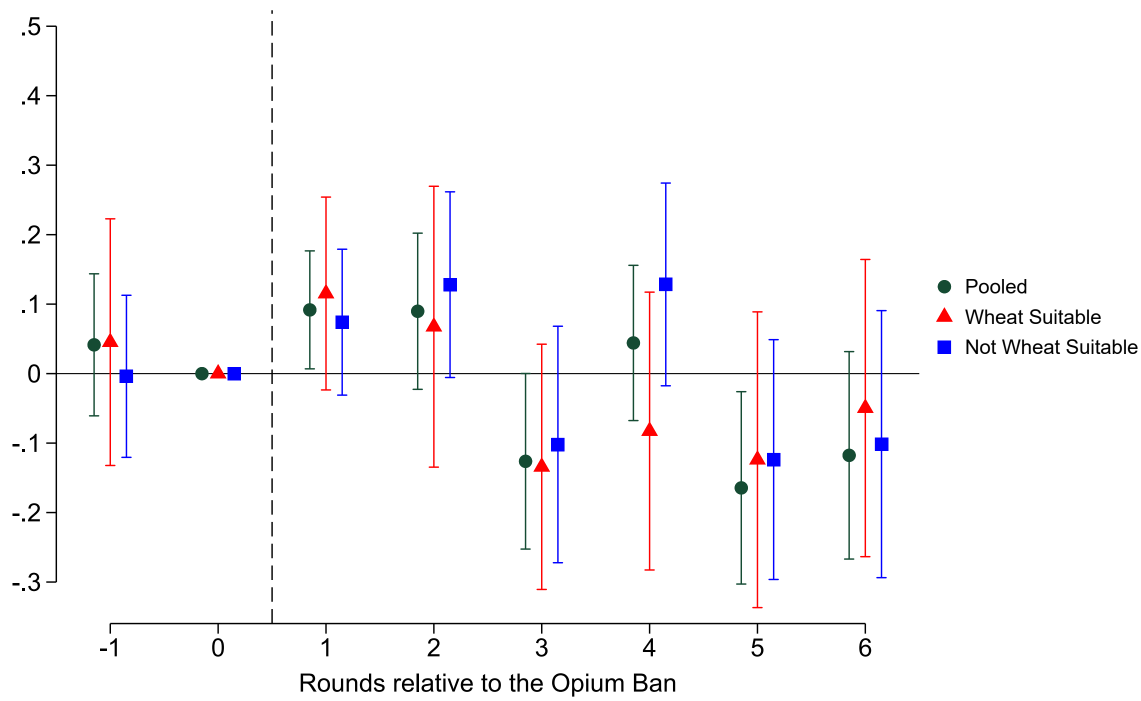



(F) Reduce Number of Meals (RHA)



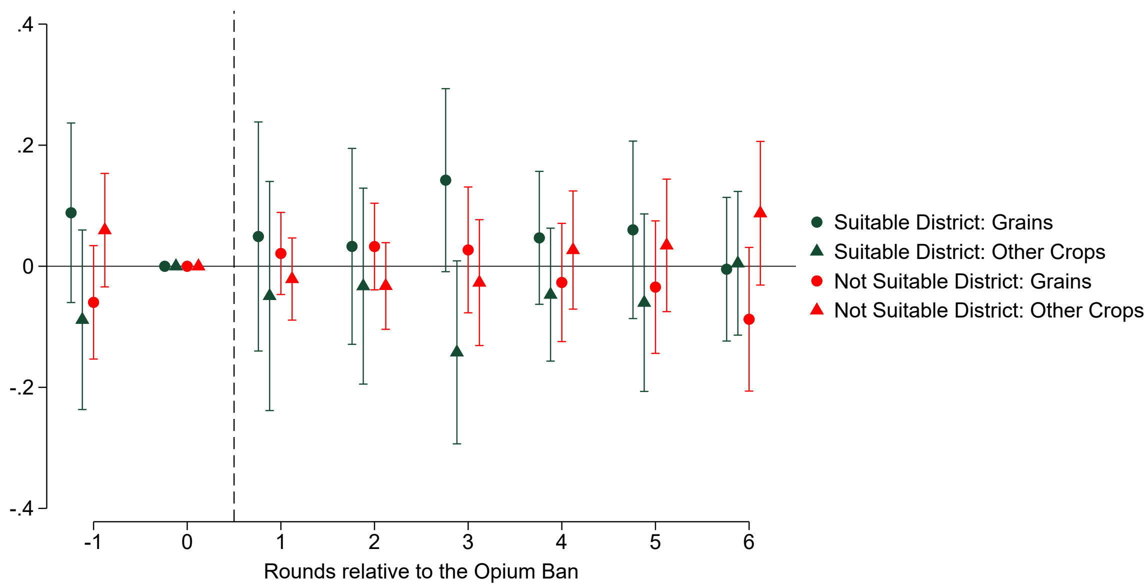

*Notes:* Data on dependent variables are derived from Food and Agriculture Organization (FAO) Data in Emergencies (DIEM) and UNHCR Rapid Household Assessments (RHA). The dependent variable and data source are mentioned in the sub-figure labels. The estimates are from the specification in Equation 10. Standard errors are clustered at the district-level. 95% confidence intervals are plotted. Survey weights are used. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025.

FIGURE 8. Decrease in Livestock



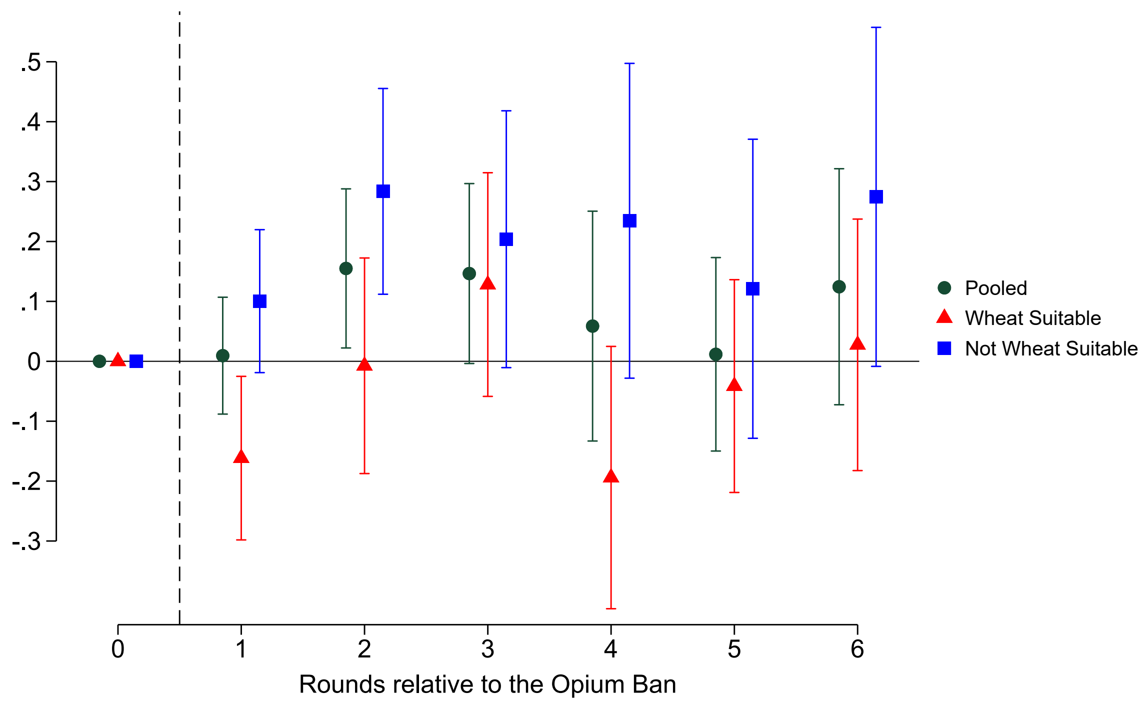

*Notes:* The dependent variable is an indicator variable for whether the household reports the decrease in the number of livestock. Households' residence district is designated to be suitable for the crop if it is in the top three quartiles of the crop suitability index. The estimates are from the specification in Equation 10. Standard errors are clustered at the district-level. 95% confidence intervals are plotted. Survey weights are used. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025.

FIGURE 9. Reallocation Patterns




*Notes:* The dependent variable is an indicator variable for whether the household reports growing the crop. "Grains" consist of all the lentils and pulses including wheat, the remaining crops are classified as "other crops." Households' residence district is designated to be suitable for the crop if it is in the top three quartiles of the crop suitability index. The estimates are from the specification in Equation 10. Standard errors are clustered at the district-level. 95% confidence intervals are plotted. Survey weights are used. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025.

FIGURE 10. Migration Patterns




*Notes:* The dependent variable is an indicator variable for whether the household reports internal migration. Households' residence district is designated to be suitable for the crop if it is in the top three quartiles of the crop suitability index. The estimates are from the specification in Equation 10. Standard errors are clustered at the district-level. 95% confidence intervals are plotted. Survey weights are used. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025.

Table 1. Summary Statistics

| | Mean | SD | Min | Max |
|---|---|---|---|---|
| *Panel A: Household Characteristics* | | | | |
| Male Headed HH | 0.989 | 0.104 | 0.00 | 1.00 |
| Total HH Income (10,000 Afghani) | 2.294 | 6.173 | 0.00 | 350.00 |
| HH Cultivate Crops | 0.728 | 0.445 | 0.00 | 1.00 |
| HH Agricultural Laborer | 0.077 | 0.267 | 0.00 | 1.00 |
| HH Income Declined in Last Three Months | 0.645 | 0.479 | 0.00 | 1.00 |
| HH Had Any Economic Shock in Last Three Months | 0.747 | 0.435 | 0.00 | 1.00 |
| *Panel B: Treatment* | | | | |
| Opium Cultivation in the District | 0.496 | 0.500 | 0.00 | 1.00 |
| *Panel C: DIEM Food Security Panel* | | | | |
| Worried about not having enough food to eat | 0.947 | 0.223 | 0.00 | 1.00 |
| Unable to eat healthy and nutritious food | 0.913 | 0.282 | 0.00 | 1.00 |
| Ate only a few kinds of foods | 0.916 | 0.277 | 0.00 | 1.00 |
| Had to skip a meal | 0.690 | 0.462 | 0.00 | 1.00 |
| Ate less than you thought you should | 0.811 | 0.392 | 0.00 | 1.00 |
| No food to eat of any kind | 0.429 | 0.495 | 0.00 | 1.00 |
| Go to sleep at night hungry | 0.339 | 0.473 | 0.00 | 1.00 |
| Go a whole day and night without eating anything at all | 0.244 | 0.429 | 0.00 | 1.00 |
| *Panel D: Food Insecurity Estimates* | | | | |
| Extreme Food Insecurity (baseline) | 0.681 | 0.466 | 0.00 | 1.00 |
| Household Hunger Scale | 1.563 | 1.415 | 0.00 | 6.00 |
| Raw Food Insecurity Score | 5.253 | 2.127 | 0.00 | 8.00 |
| Average Z-score | 0.000 | 0.638 | -4.36 | 0.76 |
| Anderson (2008) Z-score | -0.040 | 0.979 | -6.89 | 1.19 |
| Any Food Insecurity | 0.956 | 0.204 | 0.00 | 1.00 |

Notes: Data on food insecurity and household characteristics are derived from (FAO, 2025). Data on opium cultivation are derived from UNODC (2023b). Survey weights are used. The sample is restricted to data from survey round three to survey round four. These survey rounds are conducted between September 2021 and February 2022.

Table 2. Main Estimates

| | Baseline | Without Weights | Include Weather Controls | Include Individual & HH Controls | All Controls |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *Panel A: Extreme Food Insecurity* | | | | | |
| $\mathbb{1}$ (Opium District) | 0.173*** | 0.192*** | 0.149*** | 0.170*** | 0.147*** |
| $\times\mathbb{1}$ (Post) | (0.045) | (0.042) | (0.047) | (0.044) | (0.047) |
| | [24.984] | [27.710] | [21.533] | [24.433] | [21.238] |
| *Panel B: Household Hunger Scale* | | | | | |
| $\mathbb{1}$ (Opium District) | 0.515*** | 0.411*** | 0.540*** | 0.499*** | 0.534*** |
| $\times\mathbb{1}$ (Post) | (0.142) | (0.137) | (0.158) | (0.141) | (0.157) |
| | [29.871] | [23.845] | [31.363] | [28.979] | [30.978] |
| *Panel C: Raw Food Insecurity Score* | | | | | |
| $\mathbb{1}$ (Opium District) | 0.939*** | 0.915*** | 0.762*** | 0.921*** | 0.755*** |
| $\times\mathbb{1}$ (Post) | (0.213) | (0.194) | (0.240) | (0.212) | (0.238) |
| | [17.453] | [16.998] | [14.158] | [17.122] | [14.033] |
| N | 72,650 | 72,650 | 72,650 | 72,650 | 72,650 |
| Weights | Yes | No | Yes | Yes | Yes |
| Weather Controls | No | No | Yes | No | Yes |
| Household Controls | No | No | No | Yes | Yes |

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Point estimate as a fraction of the pre-treatment mean in the treatment group is in square brackets. Each observation in all columns corresponds to a unique household. The dependent variable in each panel is mentioned in the panel caption. The construction of dependent variables is discussed in section 4.1. The independent variable of interest in each column is the interaction of an indicator for the households' residence district having opium cultivation and an indicator for the household being surveyed after the opium ban in April 2022. The empirical specification differs across columns. The column header provides information on the empirical specification. In the first column, the baseline specification is estimated. In column (2), the specification excludes survey weights. Column (3) adds weather controls to the baseline specification. Weather controls are temperature and precipitation during the survey month and year. In column (4), individual and household controls are included in the baseline specification. Individual and household controls are an indicator variable for whether the household head is male, an indicator variable for whether the household head is married, and an indicator variable for the household having an unsafe water supply. Column (5) adds weather together with individual and household controls to the baseline specification. Specification in each column also includes households' residence district and month of survey fixed-effects along with linear time-trends for the households' residence province.

Table 3. Need for Assistance

| | Seeds (1) | Cash (2) | Irrigation (3) |
|---|---|---|---|
| *Panel A: Baseline* | | | |
| $\mathbb{1}$ (Opium District) | -0.029 | 0.074* | 0.136*** |
| $\times \mathbb{1}$ (Post) | (0.039) | (0.045) | (0.042) |
| N | 77,866 | 77,866 | 77,866 |
| *Panel B: Wheat Suitable Districts* | | | |
| $\mathbb{1}$ (Opium District) | 0.027 | -0.056 | 0.106 |
| $\times \mathbb{1}$ (Post) | (0.063) | (0.075) | (0.076) |
| N | 23,294 | 23,294 | 23,294 |
| *Panel C: Not Wheat Suitable Districts* | | | |
| $\mathbb{1}$ (Opium District) | -0.053 | 0.182*** | -0.042** |
| $\times \mathbb{1}$ (Post) | (0.044) | (0.053) | (0.050) |
| N | 54,572 | 54,572 | 54,572 |

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique household. The independent variable of interest in each column is the interaction of an indicator for the households' residence district having opium cultivation and an indicator for the household being surveyed after the opium ban in April 2022. The dependent variable in all the columns is extreme food insecurity. Subpopulations are denoted in the column header. $p$-value is for the test of equality of independent variable estimate across two subpopulations. Specification in each column also includes households' residence district and month of survey fixed-effects along with linear time-trends for the households' residence province. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025. Data on crop suitability is derived from Fischer et al. (2021). In "Panel B," the sample is restricted to districts suitable for wheat production. In "Panel C," the sample is restricted to districts not suitable for wheat production.

# Supplementary Appendix

## Table of Contents

# A. Theoretical Model

## A.1. Households' Optimization Problem

Household's objective function is:

$$\max_{x_t, s_t, l_t} E_o \sum_{t=0}^{\infty} \beta^t U(w_t, x_t) \quad s.t., \tag{1}$$

$$w_{t+1} = \Theta(w_t, x_t, l_t, z_t, \phi_t^h) \tag{2}$$

$$a_{t+1} = \delta a_t + s_t \tag{3}$$

$$p_t^{x'} x_t + p_t^{s'} s_t = p_t^{q'} q_t + p_t^{x'} k_t \tag{4}$$

$$\Lambda(q_t, l_t, a_t, w_t | \phi_t^q) = 0 \tag{5}$$

$$e' l_t \leq l_0 \tag{6}$$

$$a_t, l_t, x_t \geq 0 \tag{7}$$

To solve the constrained optimization problem, we form the Lagrangian ($\mathcal{L}$). This function combines the objective (utility) with all the constraints into a single equation. Each constraint is multiplied by a Lagrange multiplier ($\lambda_t$, $\mu_t$, $\psi_t$), which represents the shadow price, or marginal value, of relaxing that constraint.

$$\begin{aligned}\mathcal{L} = U(w_t, x_t) + \beta E_t[V(w_{t+1}, a_{t+1})] \\ - \lambda_t[p_t^{x'} x_t + p_t^{s'} s_t - p_t^{q'} q_t - p_t^{x'} k_t] \\ - \mu_t \Lambda(q_t, l_t, a_t, w_t | \phi_t^q) \\ - \psi_t[e' l_t - l_0]\end{aligned} \tag{8}$$

The following equations are derived by differentiating the $\mathcal{L}$ with respect to each control variable. For each *First Order Condition* (FOC), we consider the individual components of the control vectors to make the economic trade-offs explicit.

*Shorthand Notation:*

$V_w = \frac{\partial V}{\partial w_{t+1}}$: The marginal value of future health.

$V_a = \frac{\partial V}{\partial a_{t+1}}$: The marginal value of future assets.

### A.1.1. Consumption and Savings Choices

*Optimal Non-Food Consumption ($x_t^{nf}$)*:

$$\frac{\partial U}{\partial x_t^{nf}} + \beta E_t \left[ V_w \frac{\partial \Theta}{\partial x_t^{nf}} \right] = \lambda_t p_t^{x,nf} \tag{9}$$

The total marginal benefit from consuming non-food items equals its marginal cost. The benefit is composed of the immediate utility plus the expected future utility from improved health. The cost is the item's price valued at the marginal utility of income ($\lambda_t$).

*Optimal Food Consumption ($x_t^f$)*:

$$\frac{\partial U}{\partial x_t^{f}} + \beta E_t \left[ V_w \frac{\partial \Theta}{\partial x_t^{f}} \right] = \lambda_t p_t^{x,f} \tag{10}$$

The total marginal benefit from consuming food, from both immediate satisfaction and its effect on future health, equals its price valued in utility terms.

*Optimal Savings (by asset type, e.g., arable land)*:

$$\beta E_t [V_{a,arable}] = \lambda_t p_t^{arable} \tag{11}$$

This intertemporal condition equates the marginal benefit of saving (the discounted expected value of holding more of an asset in the future) to its marginal cost (the utility forgone by spending money on assets instead of consumption today).

### A.1.2. Labor and Production Choices

*Optimal Labor for Opium Production ($l_t^{opium}$)*:

$$-\mu_t \frac{\partial \Lambda}{\partial l_t^{opium}} = \psi_t - \beta E_t \left[ V_w \frac{\partial \Theta}{\partial l_t^{opium}} \right] \tag{12}$$

The marginal benefit of allocating labor to opium (its marginal productivity valued by $\mu_t$) must equal its marginal cost (the sum of the value of lost leisure time, $\psi_t$, and the expected cost to future health). A similar equation holds for other labor types.

## A.2. Comparative Statics

The 2022 opium ban is an exogeneous shock to the opium production. The ban is announced at time $t$ and becomes effective for all production activities from period $t+1$ onwards. This permanent shock is modeled as a change in the stochastic production technology, $\Lambda(\cdot)$.

$$\text{Shock effective at } t+1 : \frac{\partial \Lambda}{\partial l_{t+1}^{\text{opium}}} = 0 \quad \forall l_{t+1}^{\text{opium}} > 0$$

This shock forces $l_{t+1}^{\text{opium}} = 0$ and consequently, $q_{t+1}^{\text{opium}} = 0$. The agent, upon learning this information at time $t$, must form a new optimal plan for all subsequent periods. We perform a comparative static analysis by comparing the agent's planned choices and state variables for period $t+1$ under the new regime with those of period $t$. The impact of this shock is heterogeneous and depends on the agent's ability to substitute into other productive activities, which is determined by their asset composition, specifically the ownership of arable land ($a_t^{\text{arable}}$).

We analyze the comparative statics for two distinct types of agents.

### A.2.1. Case 1: Agent with Arable Land ($a_t^{\text{arable}} > 0$)

This agent can reallocate resources to other forms of production in period $t+1$.

*Labor Reallocation and Income Change*

The agent reallocates labor from opium to other production. We assume the labor force is constant.

$$l_{t+1}^{\text{other}} > l_t^{\text{other}}$$

The change in income from production, $\Delta Y^P$, when comparing the new plan for $t+1$ to the state at $t$, is (assuming stationary prices $p_t$ for clarity):

$$\Delta Y^P = \left( p_t^{q,\text{other}'} q_{t+1}^{\text{other}} \right) - \left( p_t^{q,\text{opium}'} q_t^{\text{opium}} + p_t^{q,\text{other}'} q_t^{\text{other}} \right)$$

While the sign of $\Delta Y^P$ is indeterminate, assuming opium as a high-value crop would mean that the income shock might be negative, $\Delta Y^P \leq 0$.

*Effect on the Marginal Utility of Income ($\lambda$)*

The effect of the ban on the Marginal Utility of Income is indeterminate. However, if the income shock is negative, it causes the shadow price of the budget constraint to rise. From the FOC for consumption (Eq. 9), a lower income path implies lower consumption, which from concavity ($\frac{\partial^2 U}{\partial x^2} < 0$) raises the marginal utility of consumption. Therefore:

$$\Delta\lambda = \lambda_{t+1} - \lambda_t \geq 0$$

*Effect on Optimal Consumption and Savings*

The change in $\lambda$, if any, alters the marginal conditions for the new optimal plan.

**Consumption ($x$):** The effect of the ban on the marginal cost (RHS) of consuming is indeterminate. However, from the FOCs for consumption (Eq. 9 and 10), if there is an increase in $\lambda$, it raises the marginal cost of consuming. To restore equilibrium, the agent's planned consumption for $t+1$ must be lower than it was at time $t$.

$$\text{If } \lambda_{t+1} \geq \lambda_t \implies \frac{\partial U}{\partial x_{t+1}} \geq \frac{\partial U}{\partial x_t} \implies \Delta x = x_{t+1} - x_t \leq 0$$

**Savings ($s$):** The intertemporal savings choice (Eq. 11) might be affected too, though the sign is indeterminate.

$$\beta E[V_a] = \lambda p^s$$

If the marginal utility of income, $\lambda_{t+1}$, is higher, it raises the opportunity cost of saving. To satisfy the Euler equation, the planned savings for period $t+1$ will be lower than savings at time $t$.

$$\text{If } \lambda_{t+1} \geq \lambda_t \implies \Delta s = s_{t+1} - s_t \leq 0$$

*Total Effect on Utility*

The agent's objective is to maximize utility, which is a strictly increasing function of consumption and well-being, $U(w, x)$. As the effect of the ban on consumption patterns is indeterminate, the overall impact on the utility is also indeterminate. But if the consumption at $t+1$ is lower than at $t$ ($\Delta x < 0$), then this directly reduces utility. This decrease in consumption can also negatively affect future health, $w_{t+2}$, via the law of motion $\Theta(\cdot)$. A decrease in the arguments of a strictly increasing utility function leads to a lower overall utility.

$$\text{If } \Delta x \leq 0 \text{ and potentially } \Delta w \leq 0 \implies \Delta U \leq 0$$

#### A.2.2. Case 2: Agent with Only Non-Arable Land ($a_t^{\textbf{arable}} = 0$)

This agent cannot substitute opium production into other agricultural production, leading to severe consequences.

*Labor Reallocation and Income Change*

This agent loses their primary source of production income from period $t+1$ onwards.

$$l_{t+1} \approx 0 \quad \Longrightarrow \quad q_{t+1} \approx 0$$

The income shock, $\Delta Y^P$, is unambiguously large and negative. The agent must finance consumption at $t+1$ from transfers ($k_{t+1}$) and dissaving ($s_{t+1} < 0$). The budget constraint at $t+1$ becomes:

$$p_{t+1}^{x'} x_{t+1} = p_{t+1}^{x'} k_{t+1} - p_{t+1}^{s'} s_{t+1}$$

*Effect on the Marginal Utility of Income ($\lambda$)*

The mechanisms are identical, but the magnitude of the shock is far greater. The catastrophic income loss leads to a dramatic increase in the marginal utility of income.

$$\lambda_{t+1} \gg \lambda_t$$

*Effect on Optimal Consumption and Savings*

**Consumption ($x$):** The sharply higher $\lambda_{t+1}$ forces a drastic reduction in consumption.

$$\Delta x = x_{t+1} - x_t \ll 0$$

**Savings ($s$):** To fund even minimal consumption, the agent is forced to dissave by liquidating assets, if present.

$$s_{t+1} < 0$$

This is a coping strategy where the non-negativity constraint on assets, $a \geq 0$ (Eq. 7), may become binding in future periods.

*Total Effect on Utility*

As established, planned consumption at $t+1$ is lower than at $t$ ($\Delta x \ll 0$), which directly reduces utility. The sharp drop in consumption, particularly food ($x_{t+1}^f$), will also negatively affect the evolution of physical well-being in the subsequent period,

$w_{t+2}$, via the law of motion for health, $\Theta(\cdot)$ (Eq. 2).

$$\text{As } \frac{\partial w_{t+2}}{\partial x^f_{t+1}} = \frac{\partial \Theta}{\partial x^f_{t+1}} > 0, \quad \text{a lower } x^f_{t+1} \implies \Delta w_{t+2} < 0$$

This creates a dynamic poverty trap, where the shock diminishes future health, lowering future productivity and utility.

## A.3. Coping Strategies

We model the agent's response to the opium production shock announced at time $t$. Based on the land endowments, the income reduction tightens the budget constraint, which leads to a higher marginal utility of income along the revised optimal path ($\lambda_{t+1} > \lambda_t$). In the light of future tighter budget constraints, there are three potential forms of coping mechanisms an agent can pursue.

### A.3.1. Reduction in Food Consumption

To cope with food insecurity, agents adjust their planned consumption path downwards. This is captured by a reduction in the optimal quantity of food consumed, $x^f$. The agent's choice of $x_t^f$ is governed by the first-order condition (Eq. 10):

$$\frac{\partial U}{\partial x_t^f} + \beta E_t[V_w \frac{\partial \Theta}{\partial x_t^f}] = \lambda_t p_t^{x,f}$$

As the news of the future income shock causes the planned marginal utility of income for the next period, $\lambda_{t+1}$, to be higher than at present, the agent adjusts their entire consumption path. To satisfy the optimality conditions across time, planned food consumption in the next period will be lower than in the current period.

$$\text{Since } \lambda_{t+1} > \lambda_t \implies \frac{\partial U}{\partial x_{t+1}^f} > \frac{\partial U}{\partial x_t^f} \implies \Delta x^f = x_{t+1}^f - x_t^f < 0$$

### A.3.2. Dissaving and Asset Sales

A second primary coping strategy is to smooth consumption by drawing down wealth. This involves adjusting the savings plan downwards. The choice to save is governed by the intertemporal condition that equates the marginal cost of saving today with the discounted expected value of holding the asset tomorrow (Eq. 11).

$$\beta E_t[V_a] = \lambda_t p_t^s$$

Upon learning of the shock at time $t$, the agent recognizes that income will be scarcer and thus more valuable in period $t+1$ (i.e., $\lambda_{t+1} > \lambda_t$). This raises the incentive to shift resources to the future. However, to smooth consumption, the agent will draw down on savings. The higher marginal utility of income raises the opportunity cost of saving, incentivizing a reduction in planned savings for all periods. For a sufficiently large shock, planned savings for the next period, $s_{t+1}$, may become negative, representing a net sale of assets. The law of motion for assets (Eq. 3) shows this explicitly:

$$a_{t+2} = \delta a_{t+1} + s_{t+1}$$

When the optimal plan involves setting $s_{t+1} < 0$, the asset stock for the period after, $a_{t+2}$, will be smaller than the depreciated stock from period $t+1$, confirming that the agent is planning to liquidate assets to survive the shock's aftermath.

### A.3.3. Migration

When assets are fully depleted and consumption cannot be reduced further, agents will be forced to the last resort, migration. We extend the model by introducing migration as a discrete choice.

Let $V_t(w_t, a_t|j = \text{home})$ be the value function for an agent at their current location, as defined by the model's objective function (Eq. 1). Let there be an option to migrate to a new location, $j'$, which offers a different stream of expected utility, $V_t(j')$. This value may be characterized by a new, stable income stream $\bar{Y}_{\text{migrate}}$, but could also involve a significant one-time utility cost of relocation, $C_m$.

$$V_t(j') = -C_m + E_t \sum_{\tau=t}^{\infty} \beta^{\tau-t} U(w'_t, x'_t)$$

The agent chooses to migrate if the value of the outside option exceeds the value of staying:

$$V_t(j') > V_t(w_t, a_t|j = \text{home})$$

This condition is triggered when the agent's state variables deteriorate to a critical level. Specifically, when repeated dissaving ($s_\tau < 0$ for $\tau \geq t$) leads to the exhaustion of all assets, the non-negativity constraint (Eq. 7) becomes binding: $a_{t+T} \to 0$ for some $T > 0$. At this point, the budget constraint collapses to consumption being funded solely by in-kind transfers, $p'x_{t+T} \leq p'k_{t+T}$. If transfers are negligible, consumption and health plummet, causing $V_t(w_t, a_t|j = \text{home})$ to fall below the reservation utility offered by migration, $V_t(j')$. Thus, migration becomes the optimal choice in this case.

# B. Classification of Variables

## B.1. Food Insecurity Questions in DIEM

Starting from round 3, the food security panel of the DIEM questionnaire (FAO, 2025) consists of eight questions, each of which takes value one if the respondent answers affirmatively and zero otherwise. These questions are as follows:

1. During the last 30 days, was there a time when you or others in your household were worried about not having enough food to eat because of lack of money or other resources?

2. During the last 30 days, was there a time when you or others in your household were unable to eat healthy and nutritious food because of lack of money or other resources?

3. During the last 30 days, was there a time when you or others in your household ate only a few kinds of foods because of lack of money or other resources?

4. During the last 30 days, was there a time when you or others in your household had to skip a meal because of lack of money or other resources to get food?

5. During the last 30 days, was there a time when you or others in your household ate less than you thought you should because of lack of money or other resources?

6. In the past 30 days, was there ever no food to eat of any kind in your house because of lack of resources to get food?

7. In the past 30 days, did you or any household member ever go to sleep at night hungry because there was not enough food?

8. In the past 30 days, did you or any household member ever go a whole day and night without eating anything at all because there was not enough food?

## B.2. Food and Non-food Items

Food items encompass bread, cereals, meat, milk, cheese, eggs, oils, fruits and vegetables, sugar and sweets, spices, and non-alcoholic beverages. Non-food items include tobacco, clothing, housing, furnishing and household goods, health, transportation, communication, information and culture, education, restaurants, hotels, and other items.

## B.3. Subpopulations

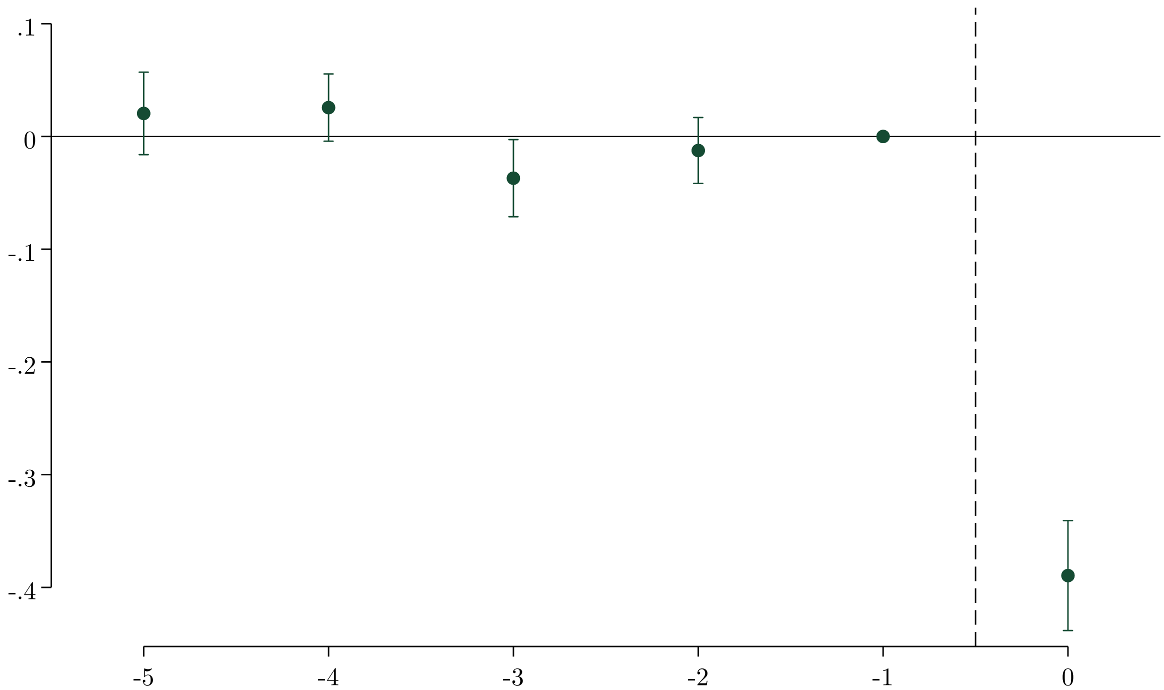
Households are classified as having experienced an economic shock if they report that during the last three months they "lost employment or working opportunities", "experienced much higher than usual food prices", "experienced much higher than usual fuel prices", "experienced external event impeding the continuation of work or business affecting all", or "experienced other economic shock". Households are classified as being involved in agricultural laborer if either of their three income sources are reported as "daily wage on farms and other casual employment in agricultural sector". Households are classified as being below median of the income distribution using the income distribution of the round in which they are surveyed.

## B.4. Coping Strategies DIEM

Estimates labeled "Sale of Assets" are from a specification where the dependent variable is an indicator variable for whether the household sold non-productive assets in the 30 days preceding the survey date because it did not have enough food or money to feed the household members. Estimates labeled "Savings Use and Debt Default" are from a specification where the dependent variable is an indicator variable for whether the household spent savings and skipped debt payments in the 30 days preceding the survey date because it did not have enough food or money to feed the household members. Estimates labeled "Sale of Animals" are from a specification where the dependent variable is an indicator variable for whether the household sold more animals than usual in the 30 days preceding the survey date because it did not have enough food or money to feed the household members. Estimates labeled "Borrowing Money" are from a specification where the dependent variable is an indicator variable for whether the household borrowed money from a formal lender or bank or non-relatives in the 30 days preceding the survey date because it did not have enough food or money to feed the household members. Estimates labeled "Household Migration" are from a specification where the dependent variable is an indicator variable for whether the household migrated in the 30 days preceding the survey date because it did not have enough food or money to feed the household members. Estimates labeled "Livestock Number Decrease" are from a specification where the dependent variable is an indicator variable for whether the household's livestock number decreased relative to last year in the 30 days preceding the survey date because it did not have enough food or money to feed the household members.

# C. Figures and Tables

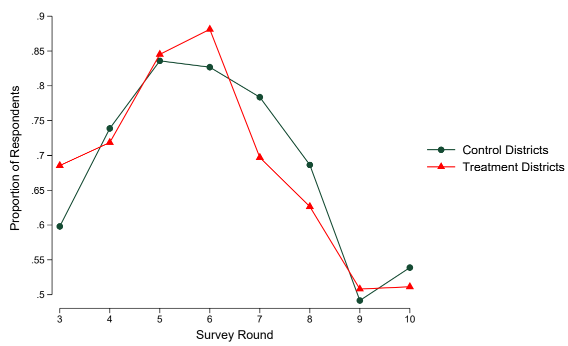
Figure C1. Any Opium Cultivation



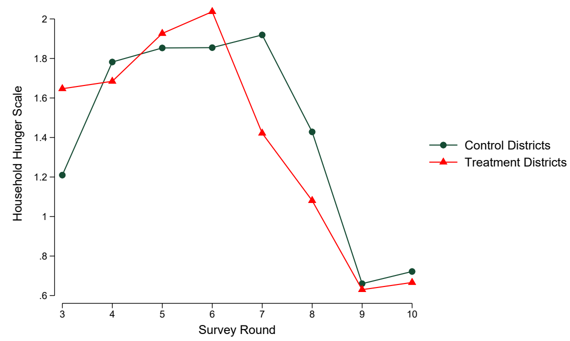

*Notes:* Districts are categorized as cultivating opium if there is any positive opium cultivation in the district. Opium cultivation data are derived from UNODC (2023b). These data provide annual information on the area under opium cultivation in hectares at the district-level. The estimates are from the specification in Equation 10. Standard errors are clustered at the district-level. 95% confidence intervals are plotted.

Figure C2. Trends in Outcome Variables

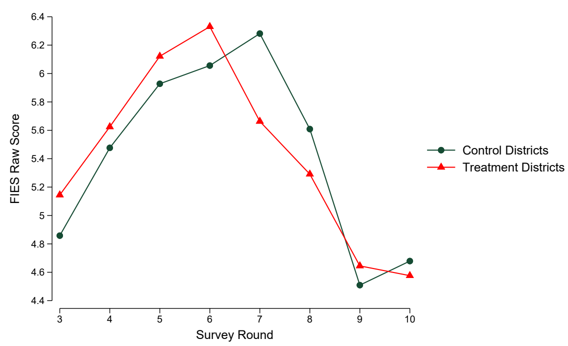
(a) High FIES



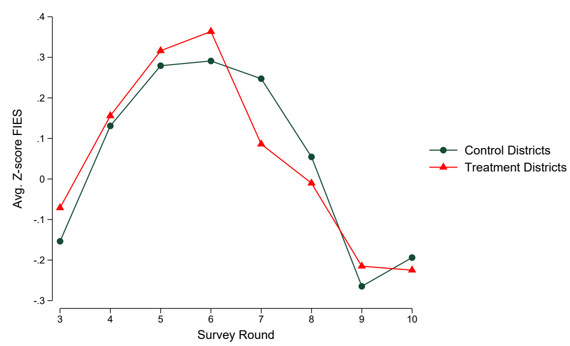

(b) HHS



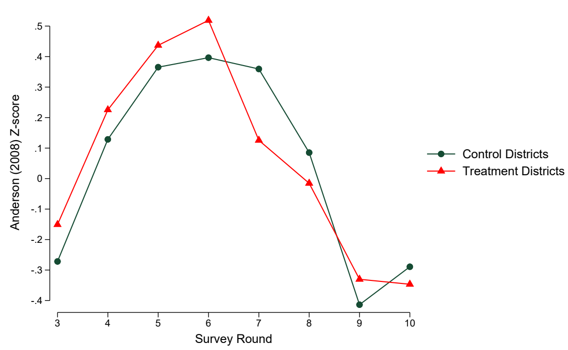

(c) Raw FIES Score



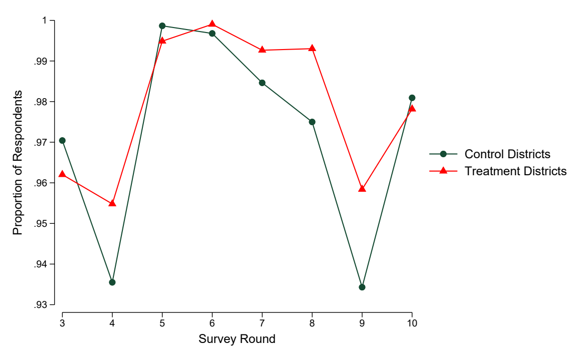

(d) Average Z-Score




(e) Anderson (2008) Z-score

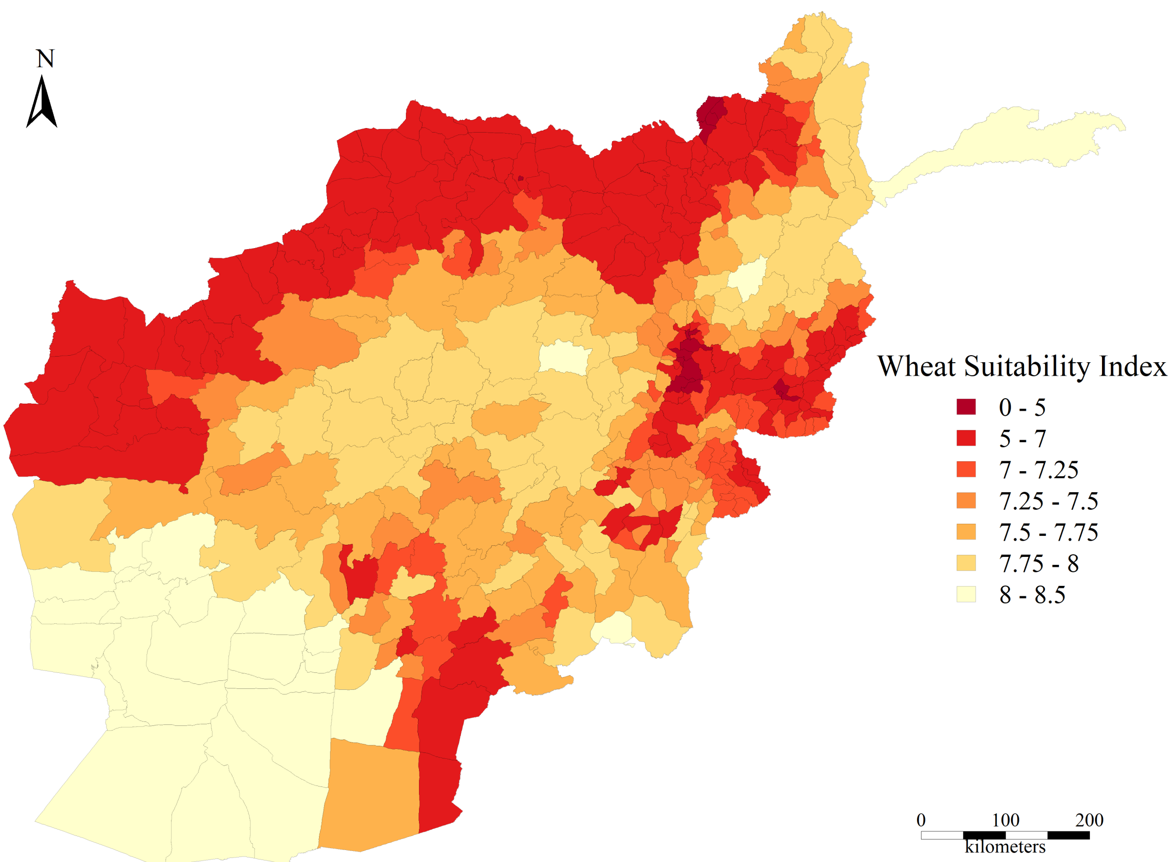



(f) Any FIES



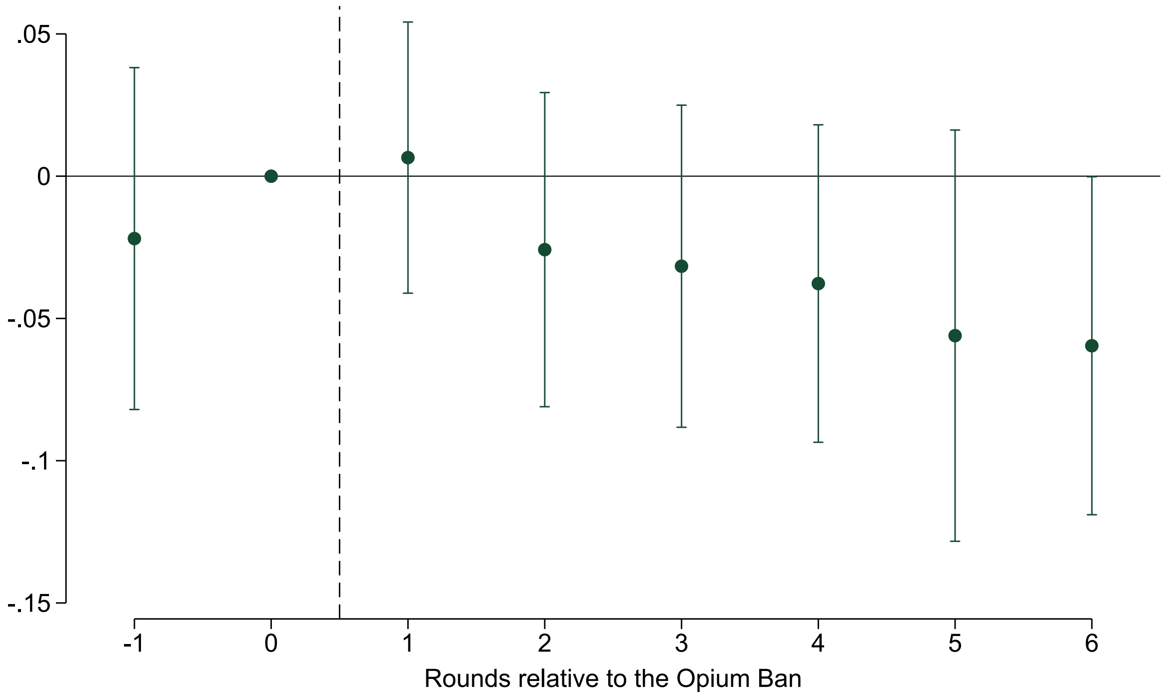

*Notes:* The dependent variable in each panel is mentioned in the panel label. The construction of dependent variables is discussed in section 4.1. The treatment definition is discussed in section 4.2. Survey weights are used. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025.

Figure C3. Soil Suitability



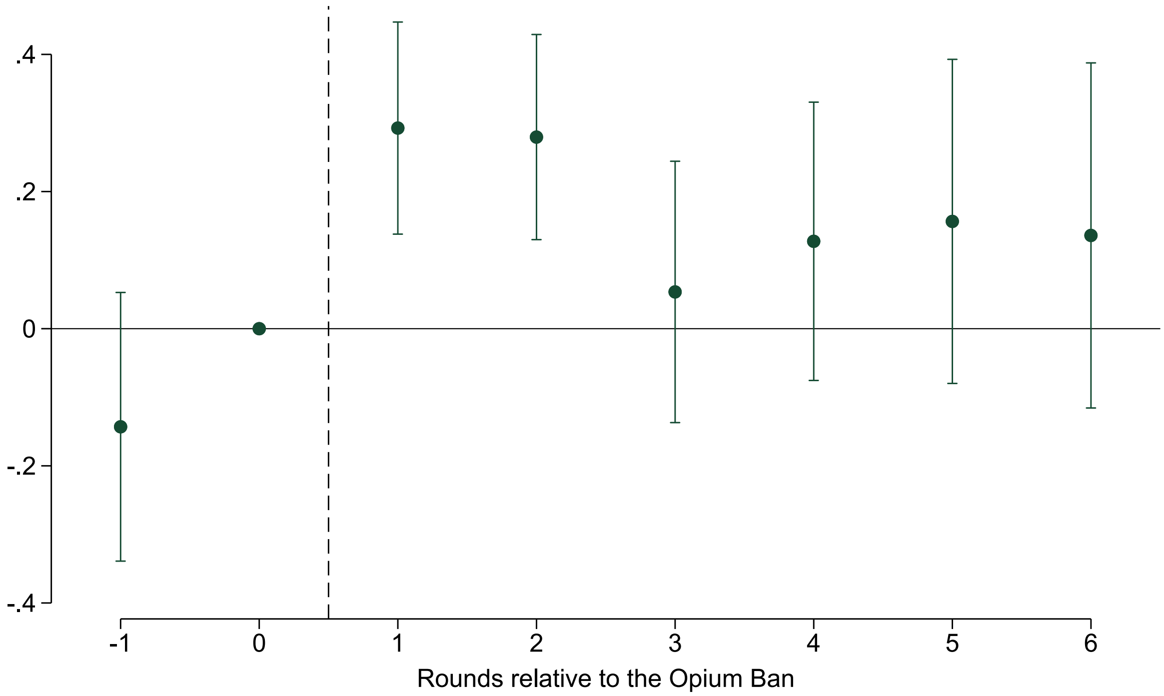

*Notes:* Shapefiles data are derived from the Afghan Geodesy and Cartography Head Office. Data on grain crop suitability index is derived from Fischer et al. (2021).

FIGURE C4. Any Food Insecurity



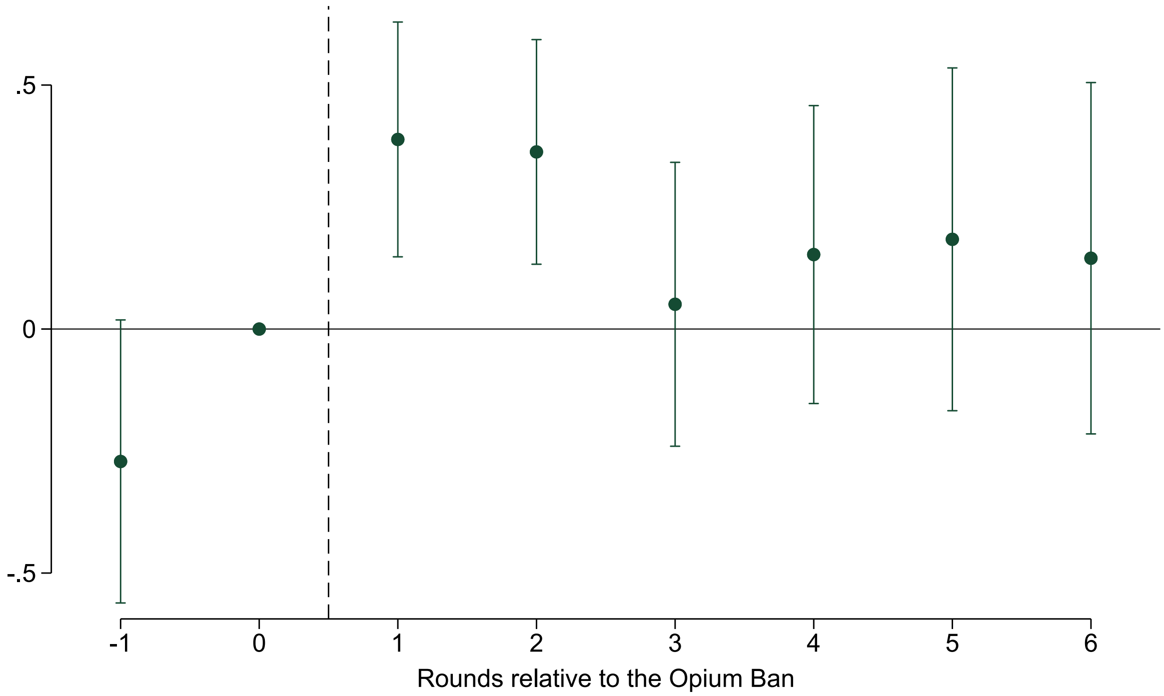

*Notes:* Data on the dependent variable are derived from (FAO, 2025). The dependent variable is a binary indicator variable for the household reporting any food insecurity. The construction of dependent variables is discussed in section 4.1. The estimates are from the specification in Equation 10. Standard errors are clustered at the district-level. 95% confidence intervals are plotted. Survey weights are used. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025.

FIGURE C5. Average Z-score




*Notes:* Data on the dependent variable are derived from (FAO, 2025). The dependent variable is Average Z-score of food insecurity. The construction of dependent variables is discussed in section 4.1. The estimates are from the specification in Equation 10. Standard errors are clustered at the district-level. 95% confidence intervals are plotted. Survey weights are used. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025.

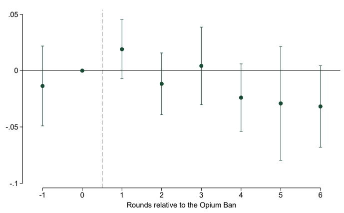
FIGURE C6. Anderson (2008) Z-score



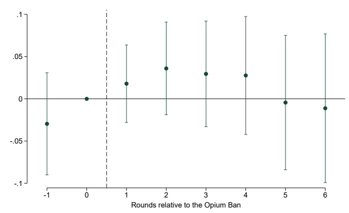

*Notes:* Data on the dependent variable are derived from (FAO, 2025). The dependent variable is Anderson (2008) Z-score of food insecurity. The construction of dependent variables is discussed in section 4.1. The estimates are from the specification in Equation 10. Standard errors are clustered at the district-level. 95% confidence intervals are plotted. Survey weights are used. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025.

FIGURE C7. Event-study Estimates for All Food Insecurity Variables

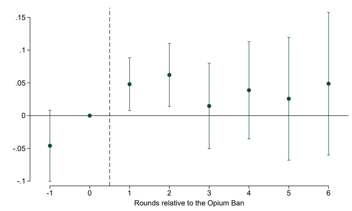
(A) Worried



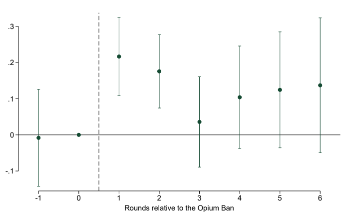

(B) Unable to Eat Healthy



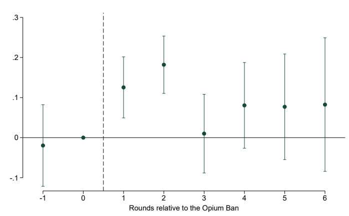

(C) Few Kinds of Foods



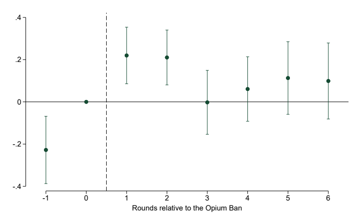

(D) Skip a Meal



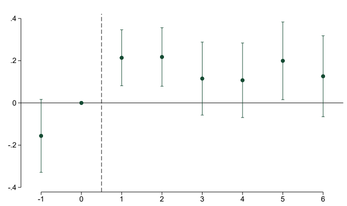

(E) Ate Less



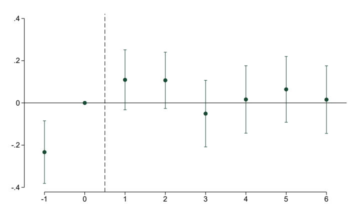

(F) No Food to Eat




(G) Sleep Hungry



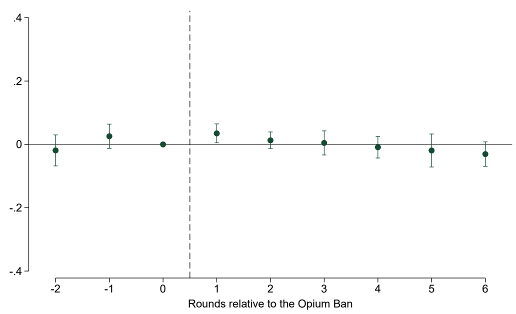

(H) Whole Day No Food



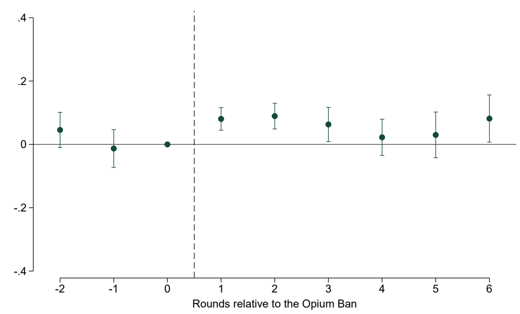

*Notes:* Data on the dependent variable are derived from (FAO, 2025). The dependent variable is an indicator variable in each sub-figure. The estimates are from the specification in Equation 10. Standard errors are clustered at the district-level. 95% confidence intervals are plotted. Survey weights are used. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025.

Figure C8. Robustness: Including Round 2

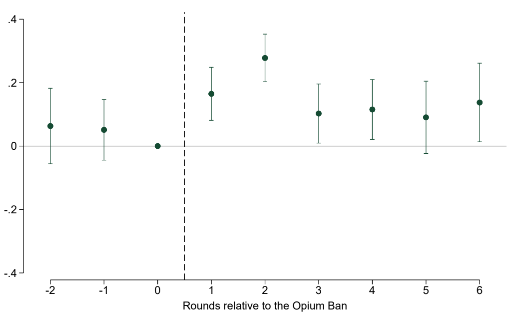
(a) Worried



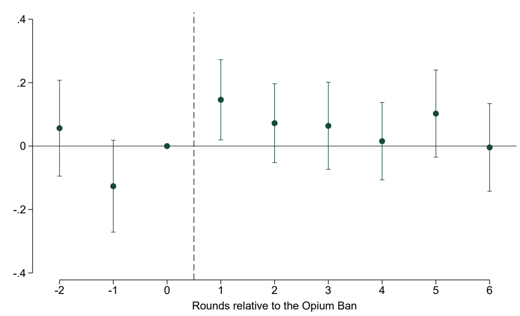

(b) Few Kinds of Foods




(c) Ate Less

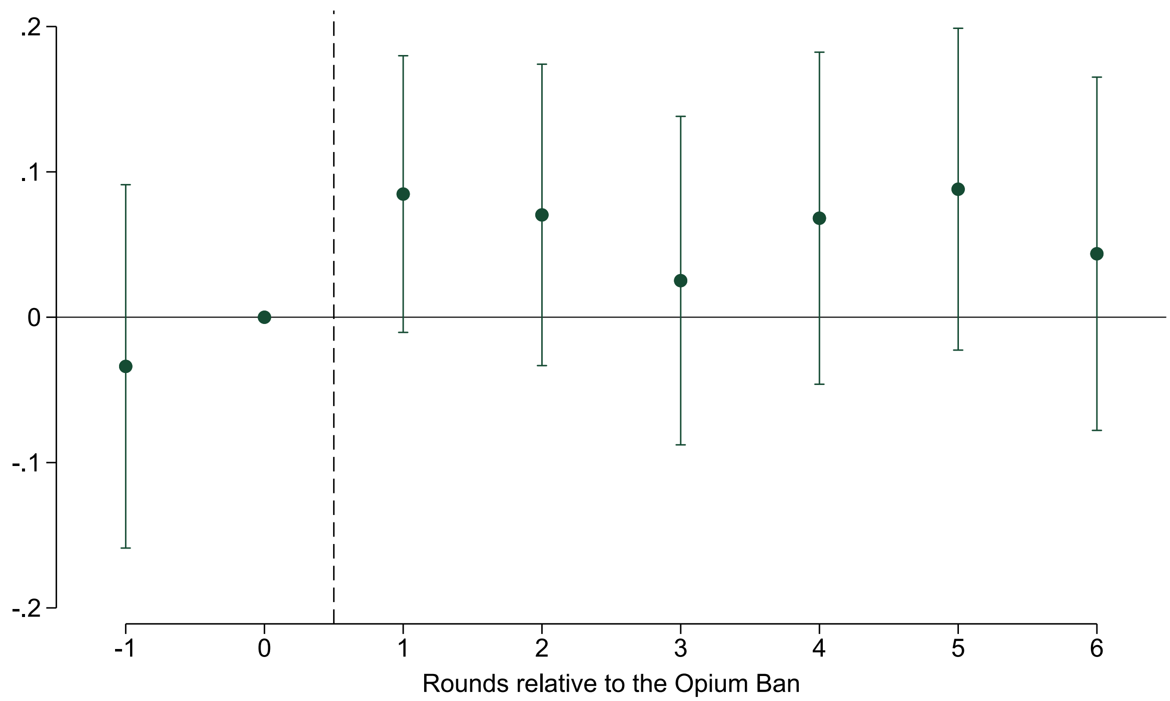



(d) No Food to Eat




*Notes:* Data on the dependent variable are derived from (FAO, 2025). The dependent variable is an indicator variable mentioned at the top of each sub-figure. The estimates are from the specification in Equation 10. Standard errors are clustered at the district-level. 95% confidence intervals are plotted. Survey weights are used. The sample is restricted to data from survey round two to survey round ten. These survey rounds are conducted between February 2021 and February 2025.

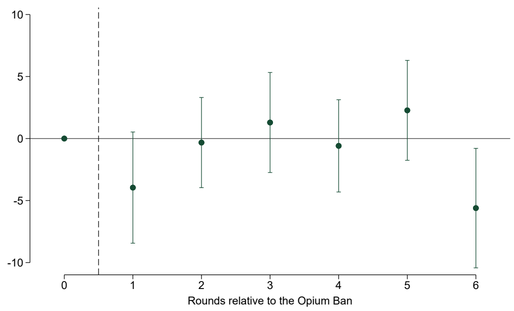
Figure C9. Receive Food Assistance



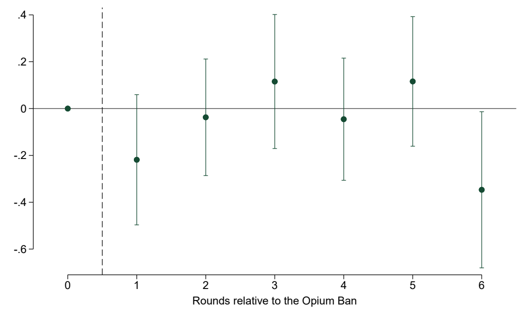

*Notes:* Data on the dependent variable are derived from (FAO, 2025). The dependent variable is an indicator variable for the household reporting receiving food assistance in the three months preceding the survey date. The estimates are from the specification in Equation 10. Standard errors are clustered at the district-level. 95% confidence intervals are plotted. Survey weights are used. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025.

Figure C10. Food Consumption Score (FCS) and Healthy Diet

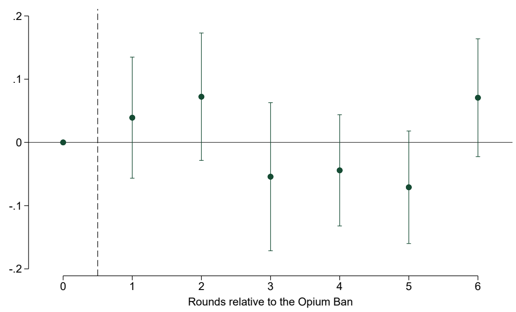
(a) Food Consumption Score (FCS)



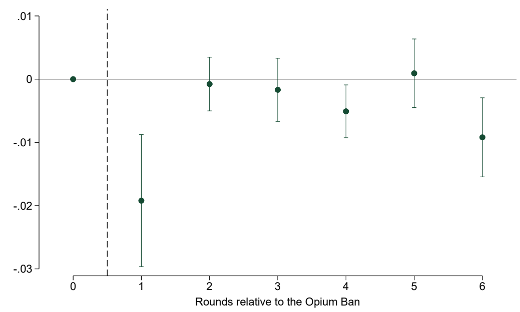

(b) Standardized Food Consumption Score (FCS)




(c) Poor Food Consumption Score (FCS)

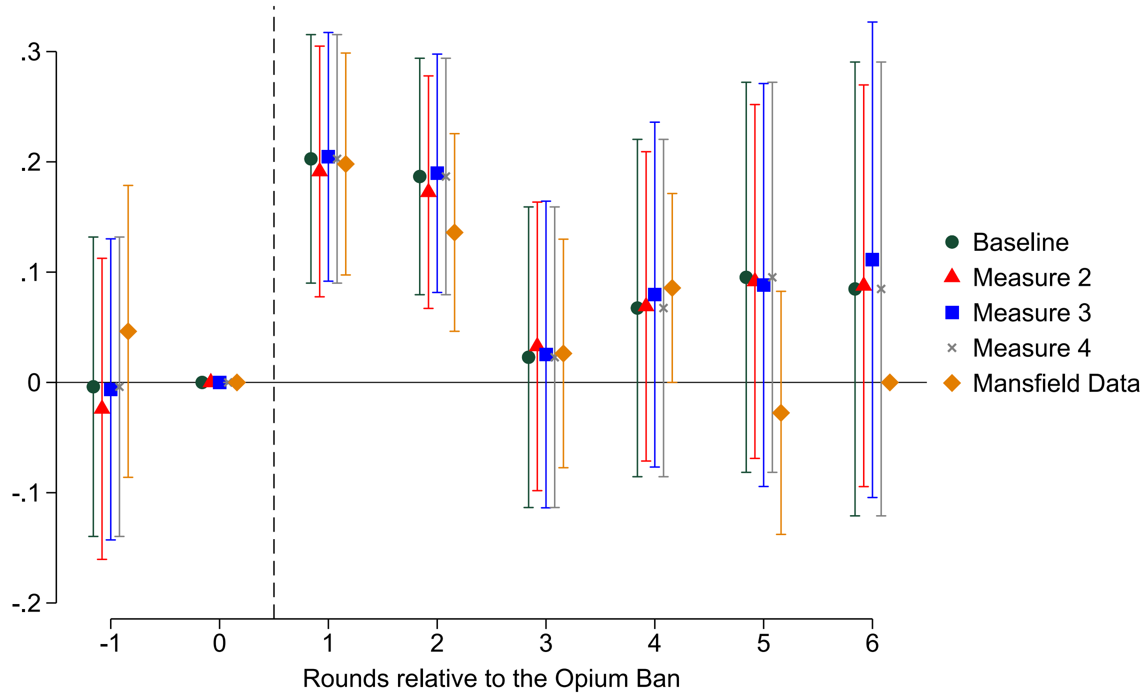



(d) Healthy Diet



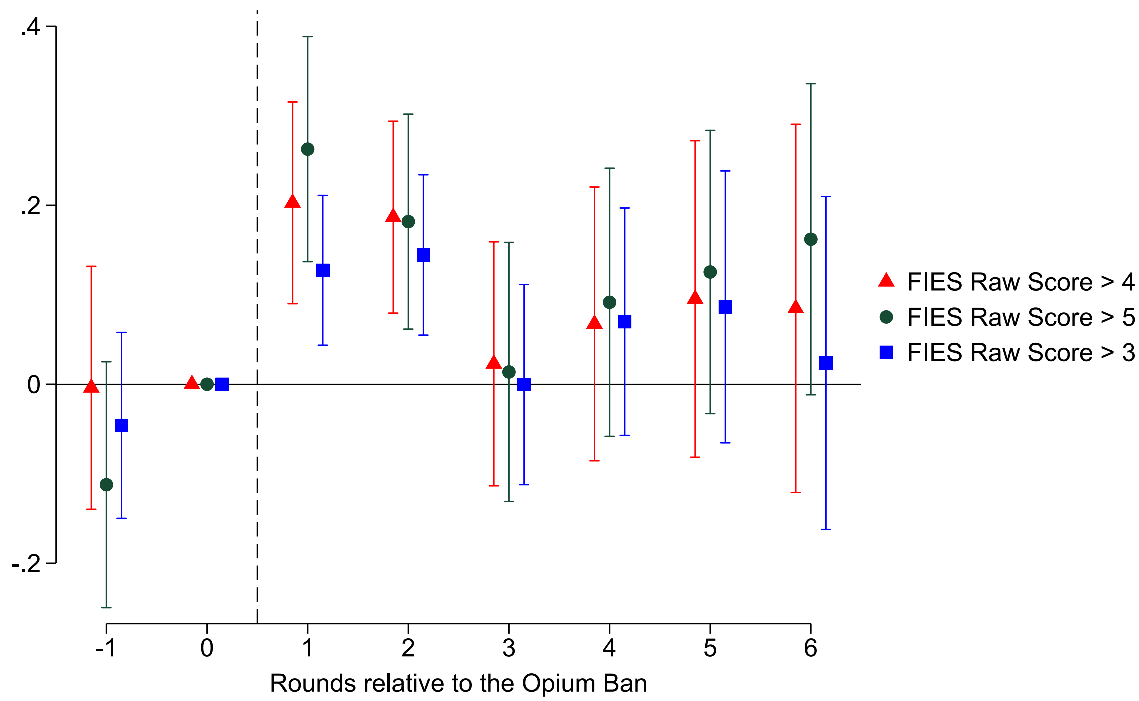

*Notes:* Data on the dependent variable are derived from (FAO, 2025). The dependent variables are the food consumption score (FCS), standardized FCS, an indicator variable for FCS to be less than 21, and an indicator for a healthy diet. FCS is a weighted measure based on the consumption of various food groups by the household over the seven days preceding the survey date. The dependent variable for the figure captioned "Healthy Diet" is an indicator variable for whether the household has a healthy diet for each of the seven days preceding the survey date. A diet is designated to be healthy if the household consumes at least four of the seven food categories. The seven food categories are starches, roots and tubers, pulses and nuts, vegetables or leaves, fruits, meat, eggs or fish, dairy products, sugar or sweet, and oil/fat/butter. The estimates are from the specification in Equation 10. Standard errors are clustered at the district-level. 95% confidence intervals are plotted. Survey weights are used. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025.

Figure C11. Robustness to Using Alternate Cultivation Measures



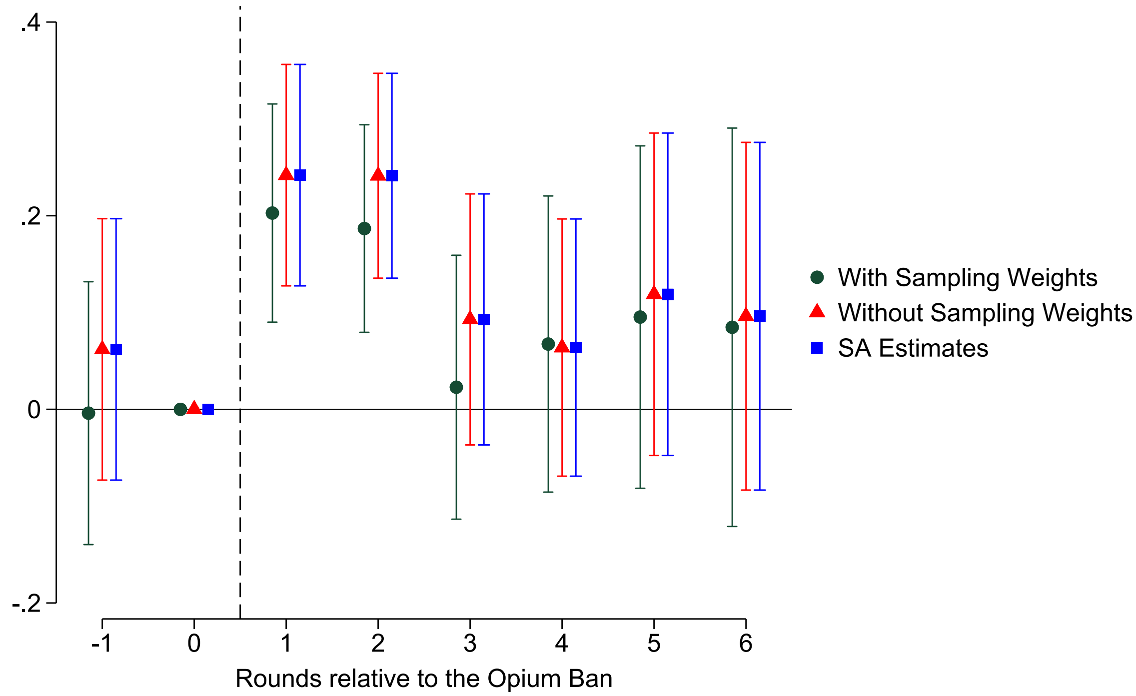

*Notes:* Data on the dependent variable are derived from (FAO, 2025). The dependent variable is whether or not the raw Food Insecurity Experience Scale (FIES) index is above four. The raw FIES index is the sum of whether the respondent reports food insecurity on each of the eight FIES questions in the survey. The estimates are from the specification in Equation 10. Standard errors are clustered at the district-level. 95% confidence intervals are plotted. Survey weights are used. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025. "Baseline" designates a district as cultivating opium if the area under opium cultivation in the district is 10,000 hectares and more either in 2020 or in 2021. "Measure 2" defines a district as cultivating opium based on 2021 opium cultivation measures only. "Measure 3" defines a district as cultivating opium based on opium cultivation measures from 2019 to 2021. "Measure 4" designates a district as cultivating opium if the area under opium cultivation in the district is above the median of the area under opium cultivation distribution. In the top panel, districts are categorized as cultivating opium if the area under opium cultivation is 10,000 hectares and more either in 2020 or in 2021. "Mansfield Data" measure is derived from Mansfield (2023a).

Figure C12. Robustness to Using Alternate High Food Insecurity Thresholds



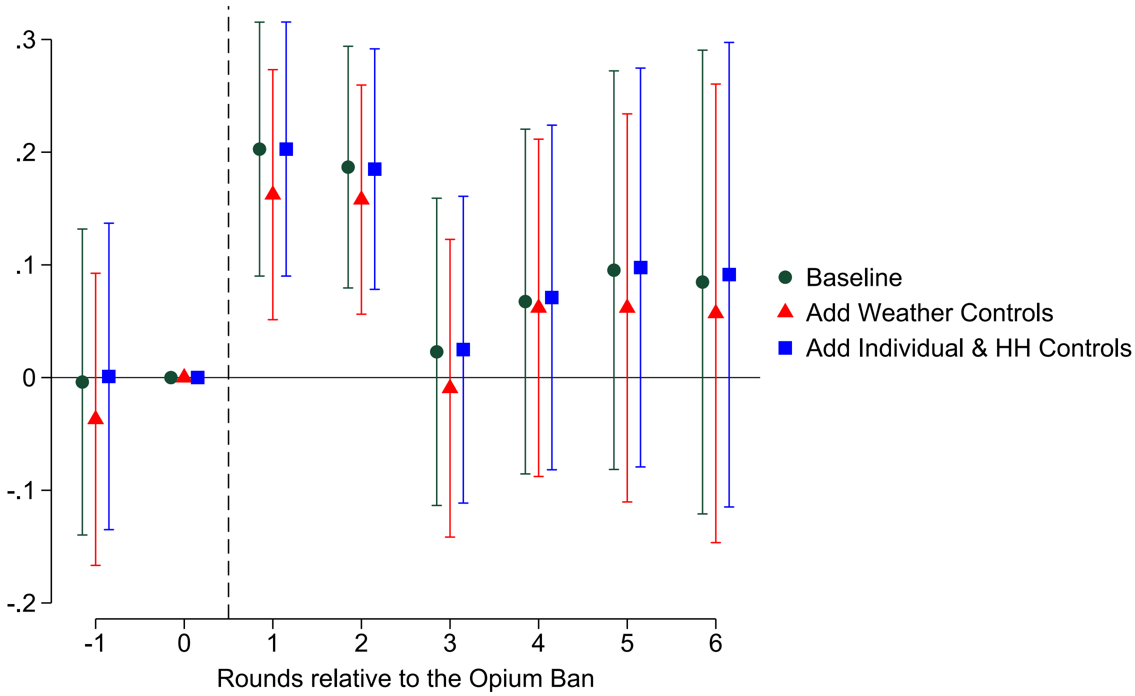

*Notes:* Data on the dependent variable are derived from (FAO, 2025). The dependent variable is whether or not the raw Food Insecurity Experience Scale (FIES) index is above three, four, or five. The raw FIES index is the sum of whether the respondent reports food insecurity on each of the eight FIES questions in the survey. The estimates are from the specification in Equation 10. Standard errors are clustered at the district-level. 95% confidence intervals are plotted. Survey weights are used. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025.

FIGURE C13. Robustness to Using Survey Weights and Sun and Abraham (2021) Estimator



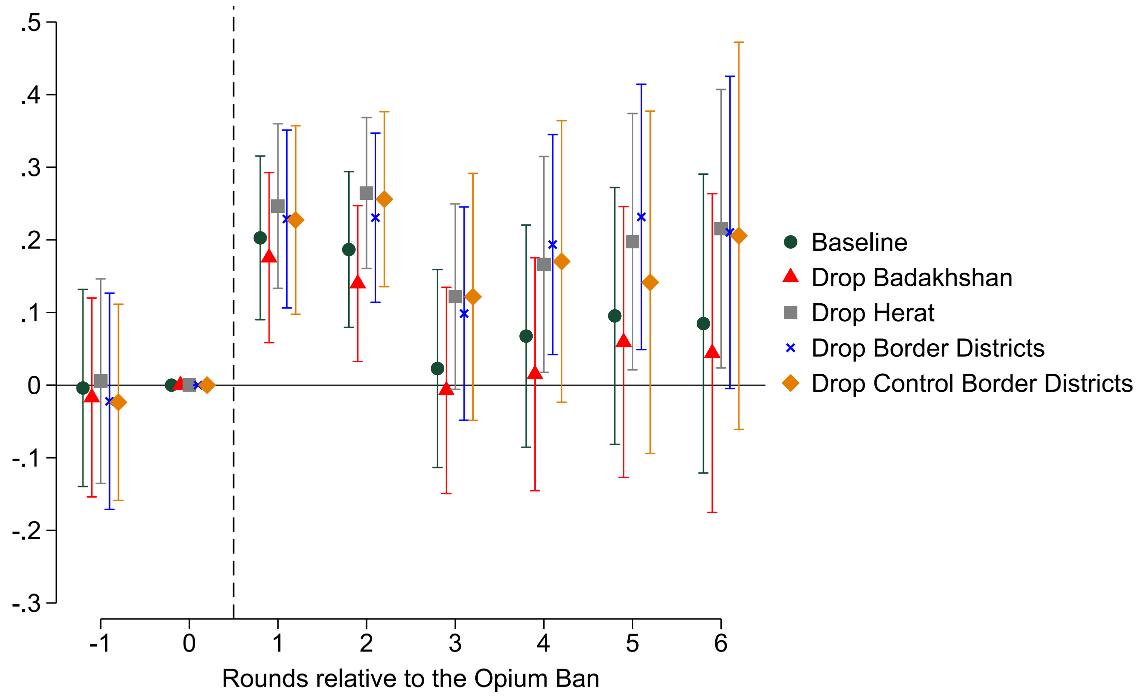

*Notes:* Data on the dependent variable are derived from (FAO, 2025). The dependent variable is whether or not the raw Food Insecurity Experience Scale (FIES) index is above four. The raw FIES index is the sum of whether the respondent reports food insecurity on each of the eight FIES questions in the survey. The estimates are from the specification in Equation 10. Standard errors are clustered at the district-level. 95% confidence intervals are plotted. Survey weights are used in the baseline estimates. Survey weights are dropped for point estimates "without sampling weights." Heterogeneous treatment effects with multiple periods from (Sun and Abraham, 2021) are reported for "SA estimates." The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025.

Figure C14. Robustness to Using Household, Individual, and Weather Controls



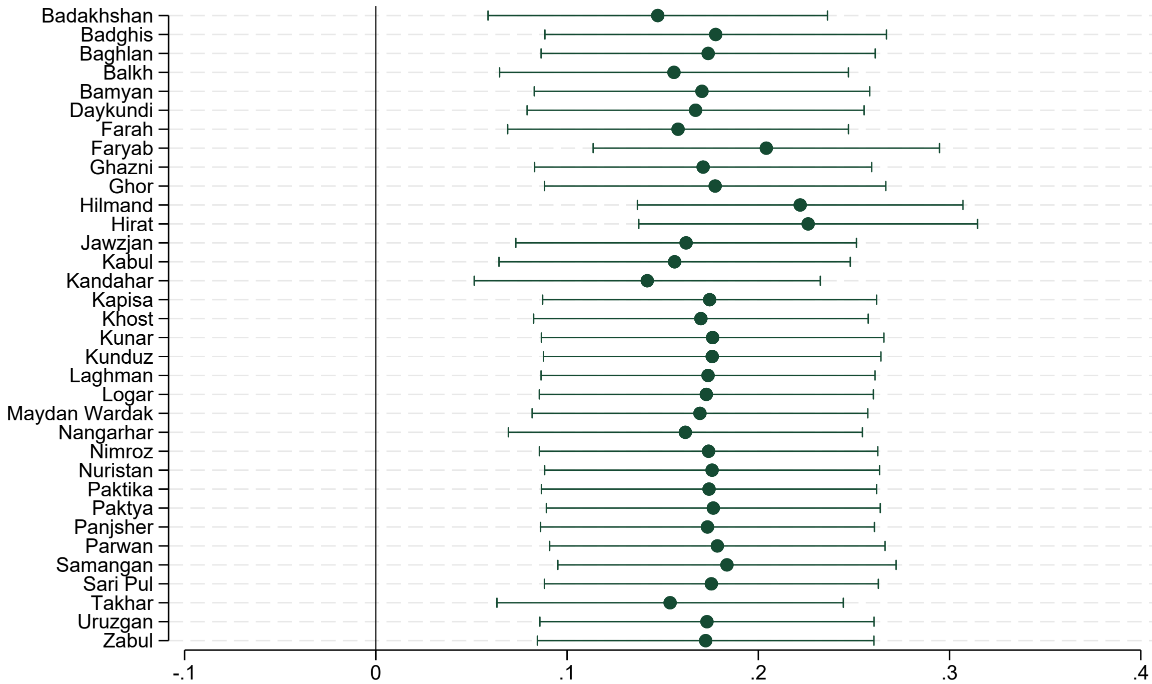

*Notes:* Data on the dependent variable are derived from (FAO, 2025). The dependent variable is whether or not the raw Food Insecurity Experience Scale (FIES) index is above four. The raw FIES index is the sum of whether the respondent reports food insecurity on each of the eight FIES questions in the survey. The estimates are from the specification in Equation 10. Standard errors are clustered at the district-level. 95% confidence intervals are plotted. Survey weights are used. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025. Weather controls are temperature and precipitation. Individual and household controls are an indicator for whether the household head is male, an indicator for whether the household head is married, and an indicator for the household having an unsafe water supply.

FIGURE C15. Robustness: Geography



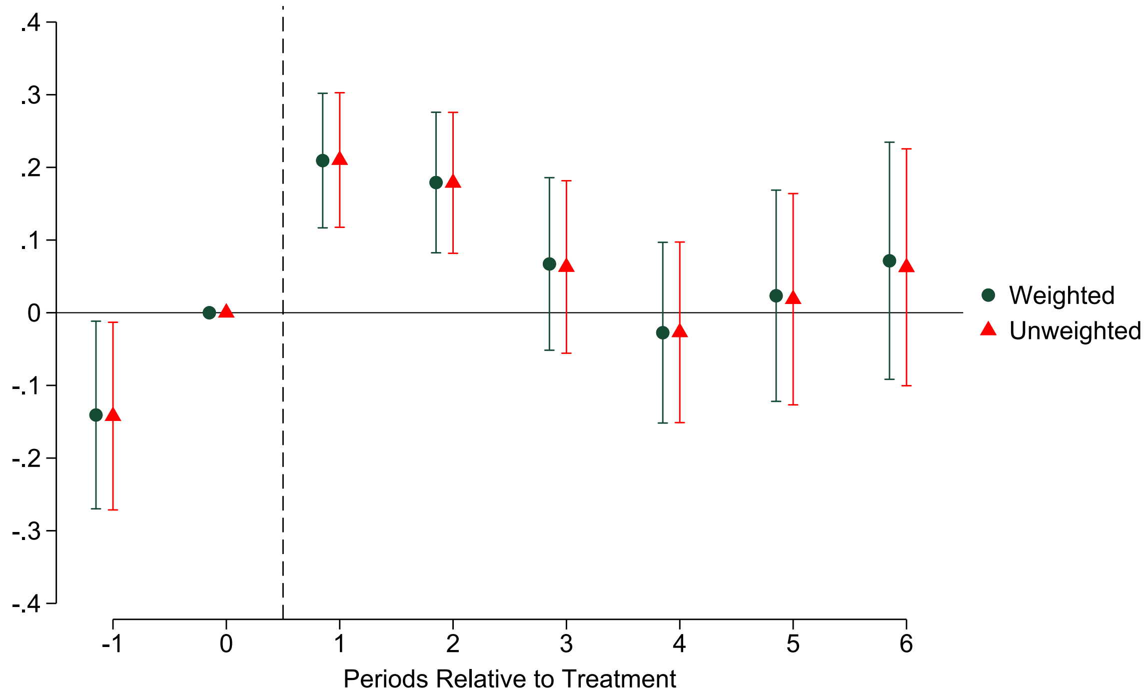

*Notes:* Data on the dependent variable are derived from (FAO, 2025). The dependent variable is whether the raw Food Insecurity Experience Scale (FIES) index is above four. The raw FIES index is the sum of whether the respondent reports food insecurity on each of the eight FIES questions in the survey. Estimates labeled "Drop Badakshan" drop Badakshan province from the estimation sample. Estimates labeled "Drop Herat" drop Herat province from the estimation sample. The estimates labeled "Drop Border Districts" drop all the districts that border neighboring countries of Afghanistan. Estimates labeled "Drop Control Border Districts" drop control group districts that border a district that is part of the treatment group. The estimates are from the specification in Equation 10. Standard errors are clustered at the district-level. 95% confidence intervals are plotted. Survey weights are used. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025.

FIGURE C16. Robustness: Dropping Provinces



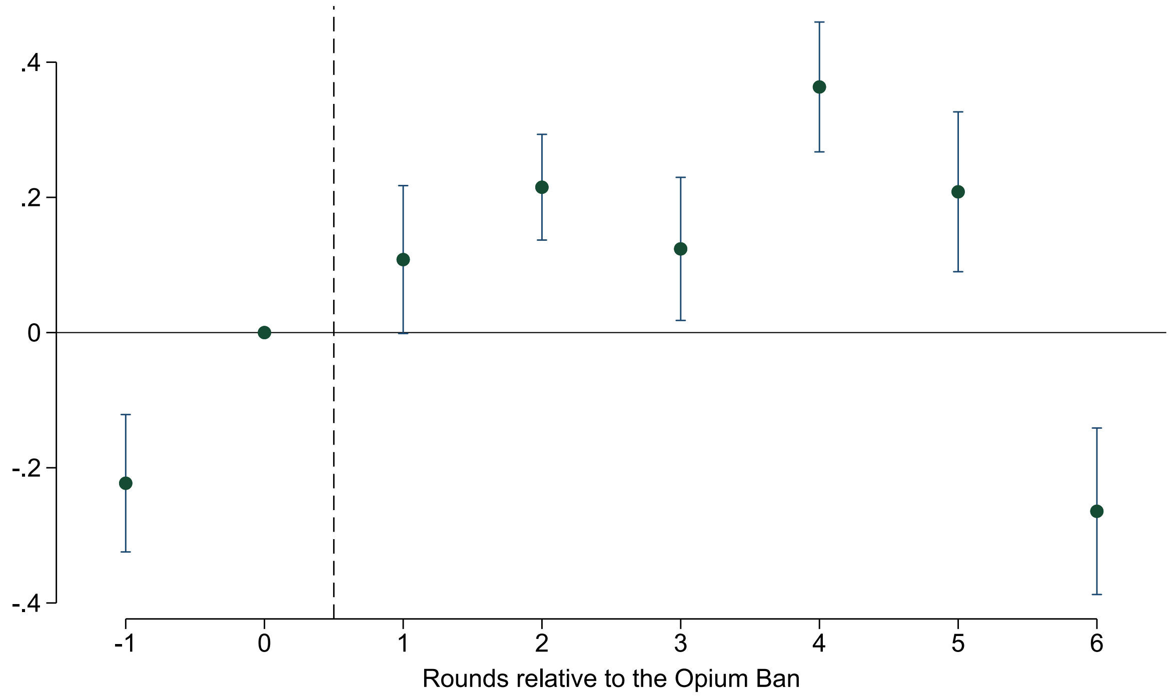

*Notes:* Data on the dependent variable are derived from (FAO, 2025). The dependent variable is whether the raw Food Insecurity Experience Scale (FIES) index is above four. The raw FIES index is the sum of whether the respondent reports food insecurity on each of the eight FIES questions in the survey. Survey weights are used. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025. Dropped provinces are mentioned on the vertical axis.

Figure C17. Robustness: District-Survey Round-Survey Month Aggregation



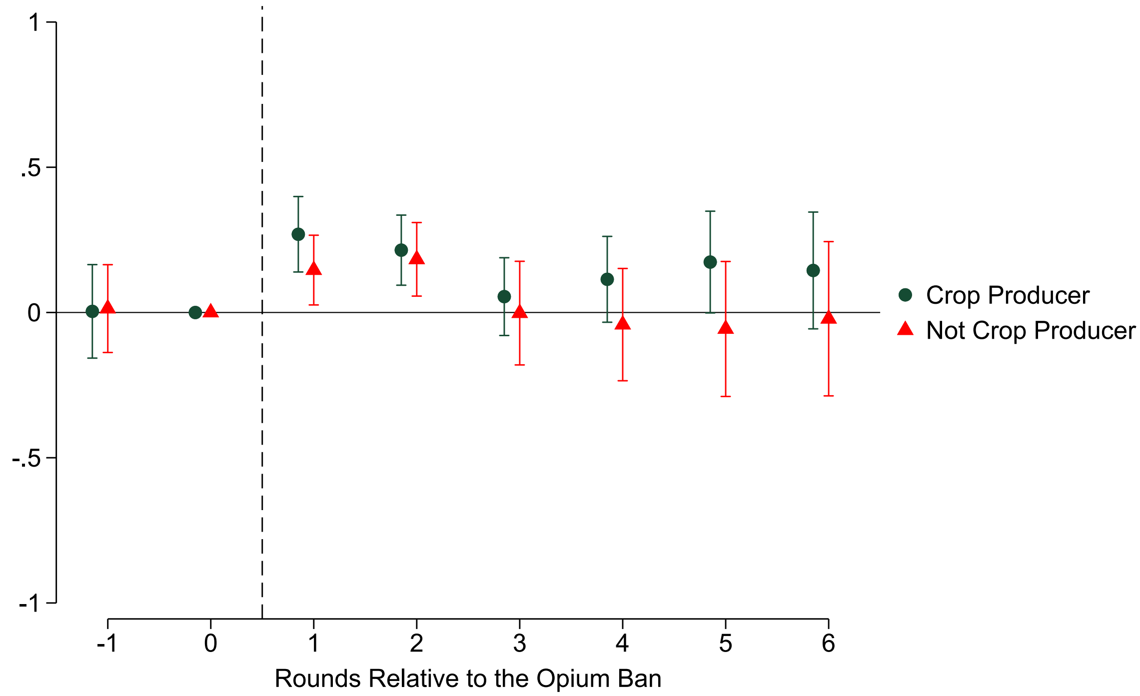

*Notes:* Data on the dependent variable are derived from (FAO, 2025). The dependent variable is whether the raw Food Insecurity Experience Scale (FIES) index is above four. The raw FIES index is the sum of whether the respondent reports food insecurity on each of the eight FIES questions in the survey. Estimates labeled "Weighted" use survey weights to aggregate outcome measures at the residence district-survey round-surevey month-level. Estimates labeled "Unweighted" do not use survey weights to aggregate outcome measures at the residence district-survey round-surevey month-level. The estimates are from the specification in Equation 10. Standard errors are clustered at the district-level. 95% confidence intervals are plotted. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025.

Figure C18. Below Poverty Line



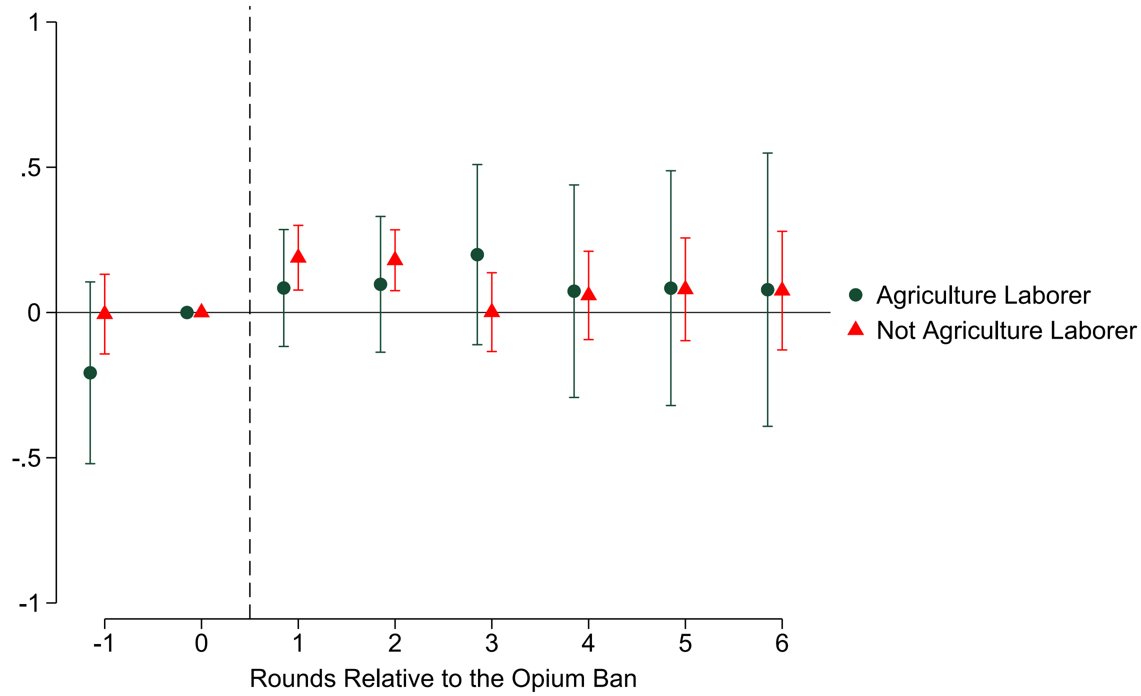

*Notes:* Data on income are derived from (FAO, 2025). Data on poverty threshold are from World Bank (2018), adjusted for 2022. The dependent variable is whether the total income of the household is below the poverty line. The estimates are from the specification in Equation 10. Standard errors are clustered at the district-level. 95% confidence intervals are plotted. Survey weights are used. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025.

FIGURE C19. Crop Production Heterogeneity



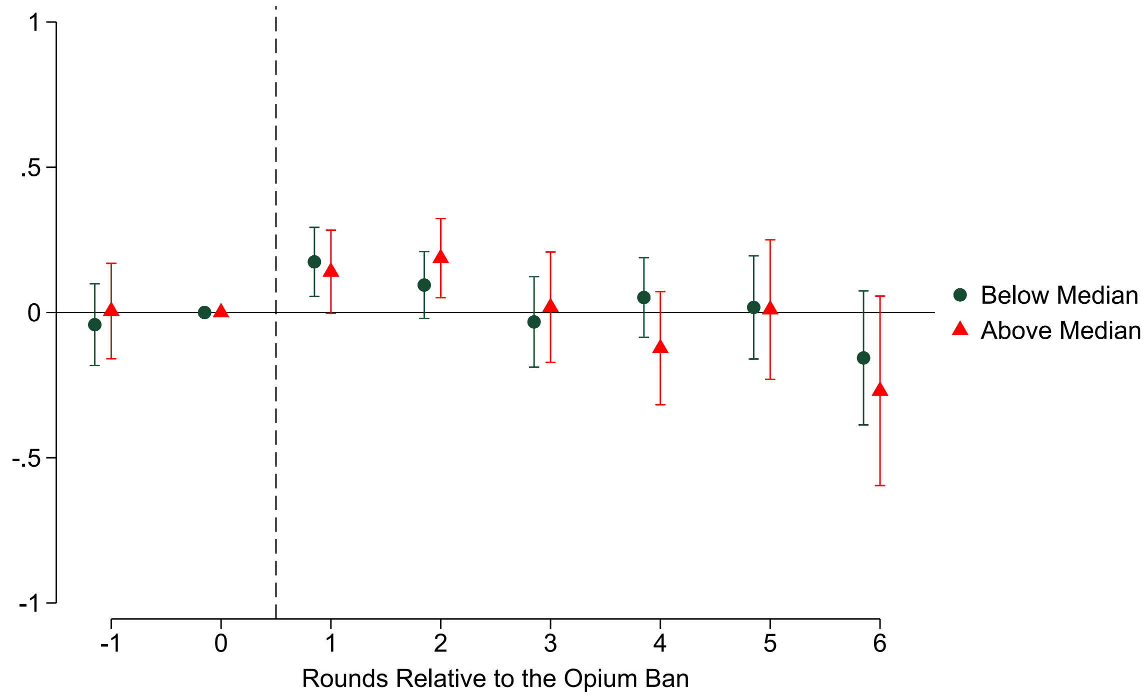

*Notes:* Data on the dependent variable are derived from (FAO, 2025). The dependent variable is whether the raw Food Insecurity Experience Scale (FIES) index is above four. The raw FIES index is the sum of whether the respondent reports food insecurity on each of the eight FIES questions in the survey. The estimates are from the specification in Equation 10. Standard errors are clustered at the district-level. 95% confidence intervals are plotted. Survey weights are used. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025. For all point estimates the sample is split using an indicator variable. Indicator variable is whether the household is involved in crop production.

Figure C20. Agricultural Labor Heterogeneity



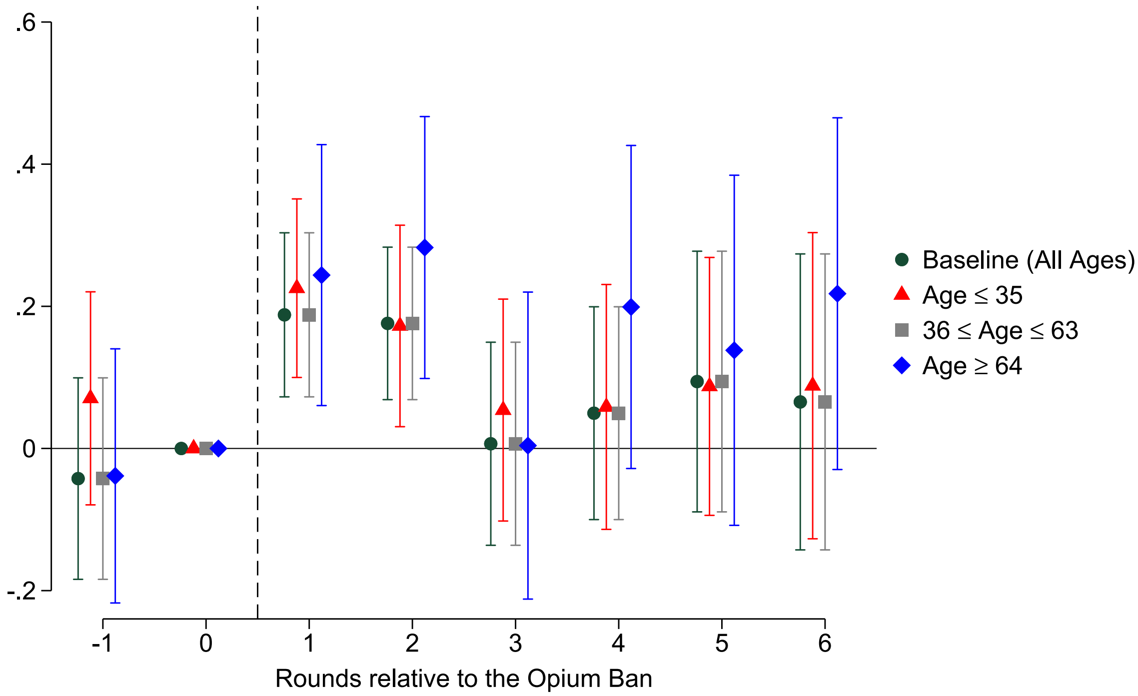

*Notes:* Data on the dependent variable are derived from (FAO, 2025). The dependent variable is whether the raw Food Insecurity Experience Scale (FIES) index is above four. The raw FIES index is the sum of whether the respondent reports food insecurity on each of the eight FIES questions in the survey. The estimates are from the specification in Equation 10. Standard errors are clustered at the district-level. 95% confidence intervals are plotted. Survey weights are used. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025. For all point estimates the sample is split using an indicator variable. Indicator variable is whether the household is agricultural laborer.

FIGURE C21. Below Median Income Heterogeneity



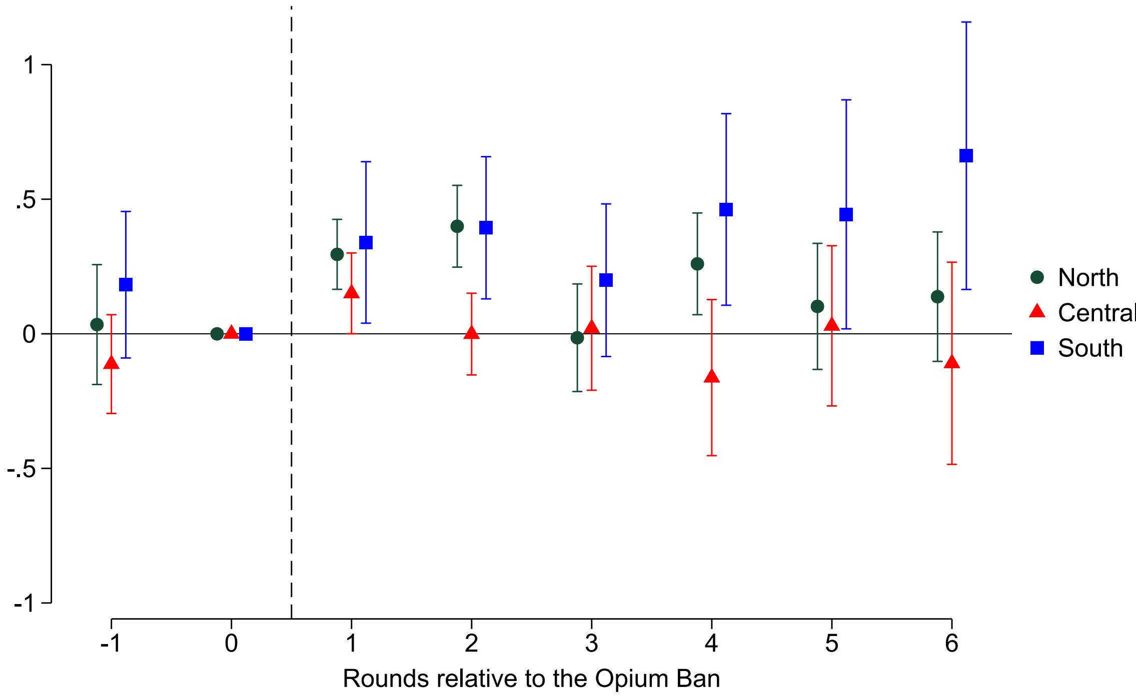

*Notes:* Data on the dependent variable are derived from (FAO, 2025). The dependent variable is whether the raw Food Insecurity Experience Scale (FIES) index is above four. The raw FIES index is the sum of whether the respondent reports food insecurity on each of the eight FIES questions in the survey. The estimates are from the specification in Equation 10. Standard errors are clustered at the district-level. 95% confidence intervals are plotted. Survey weights are used. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025. For all point estimates the sample is split using an indicator variable. Indicator variable is whether the household's income is below median income.

FIGURE C22. Age Heterogeneity



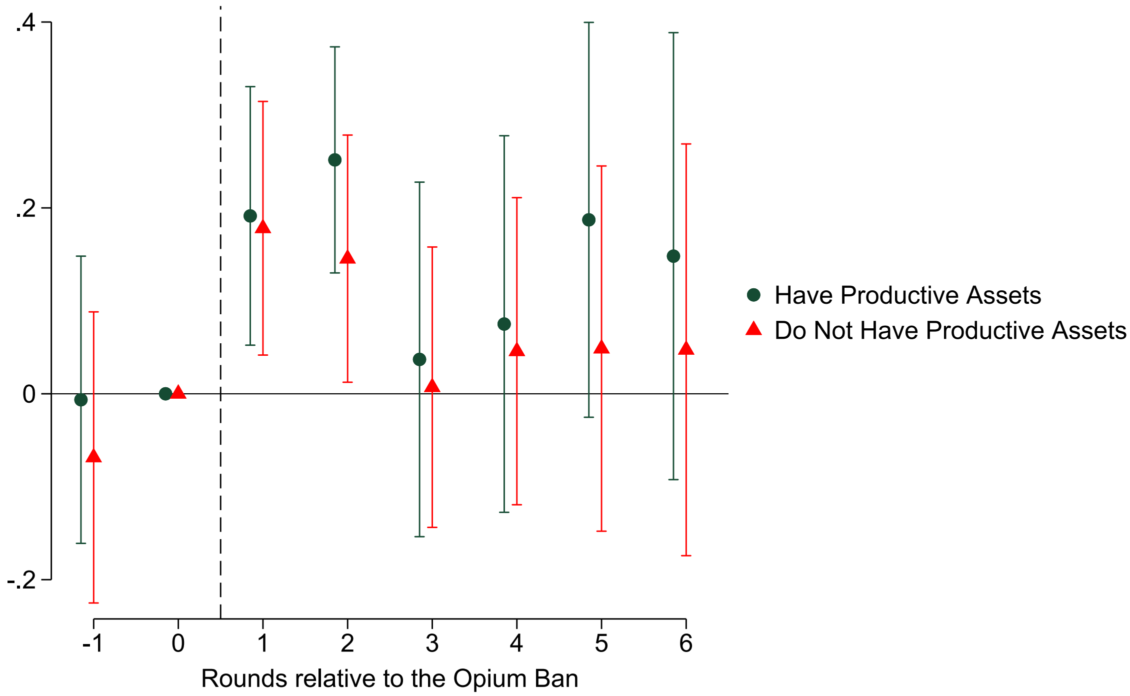

*Notes:* Data on the dependent variable are derived from (FAO, 2025). The dependent variable is whether the raw Food Insecurity Experience Scale (FIES) index is above four. The raw FIES index is the sum of whether the respondent reports food insecurity on each of the eight FIES questions in the survey. The estimates are from the specification in Equation 10. Standard errors are clustered at the district-level. 95% confidence intervals are plotted. Survey weights are used. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025. For all point estimates the sample is split using an indicator variable. Indicator variable is respondent's age group.

FIGURE C23. Residence Region Heterogeneity



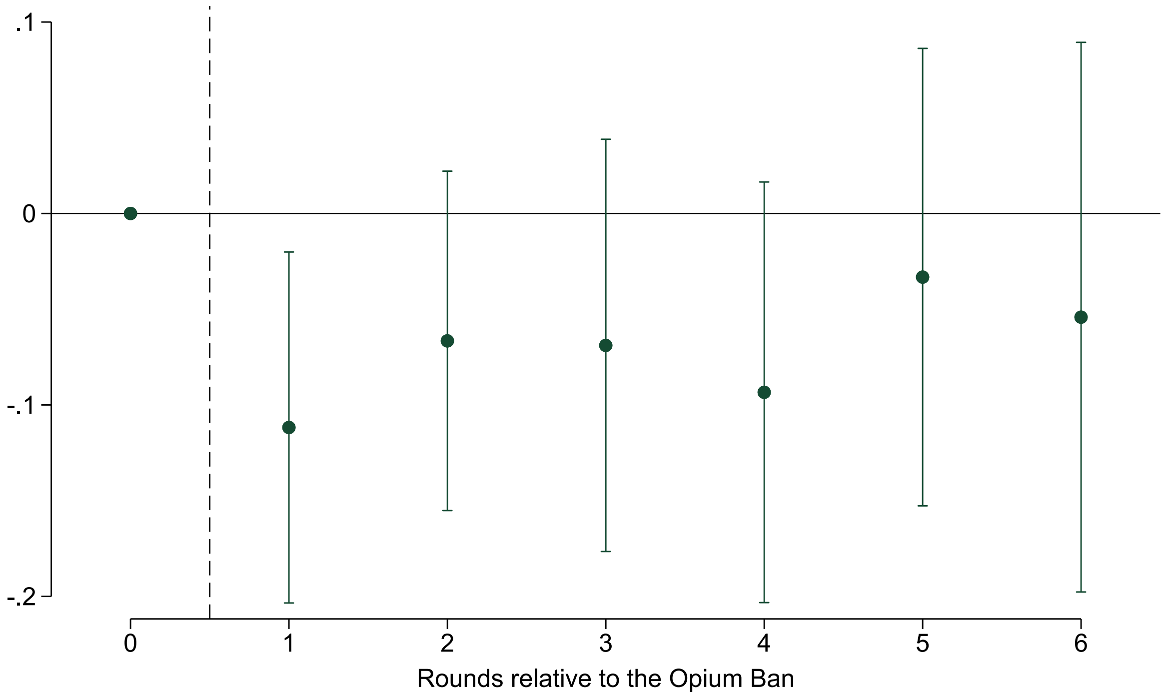

*Notes:* Data on the dependent variable are derived from (FAO, 2025). The dependent variable is whether the raw Food Insecurity Experience Scale (FIES) index is above four. The raw FIES index is the sum of whether the respondent reports food insecurity on each of the eight FIES questions in the survey. The estimates are from the specification in Equation 10. Standard errors are clustered at the district-level. 95% confidence intervals are plotted. Survey weights are used. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025. For all point estimates the sample is split using an indicator variable. Indicator variable is the household's residence region.

FIGURE C24. Productive Assets Heterogeneity




*Notes:* Data on the dependent variable are derived from (FAO, 2025). The dependent variable is whether the raw Food Insecurity Experience Scale (FIES) index is above four. The raw FIES index is the sum of whether the respondent reports food insecurity on each of the eight FIES questions in the survey. The estimates are from the specification in Equation 10. Standard errors are clustered at the district-level. 95% confidence intervals are plotted. Survey weights are used. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025. Household is designated as having productive assets if they report having raised any animal.

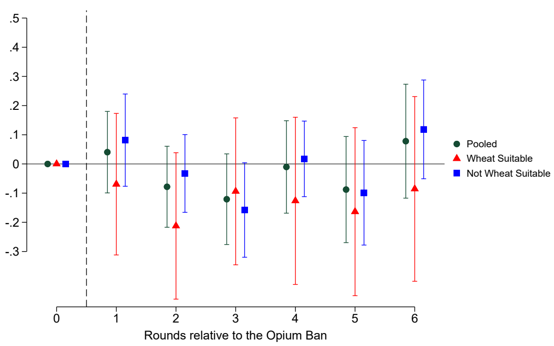
FIGURE C25. Borrow Food



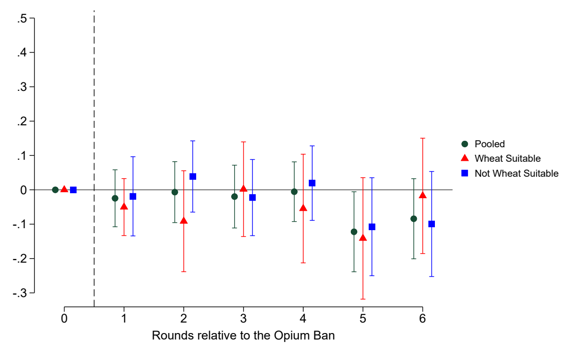

*Notes:* Data on dependent variables are derived from (FAO, 2025). The dependent variable "Borrowed Food" is an indicator variable for the household borrowing food or relying on help from a friend or relative due to lack of food or money to buy food in the seven days preceding the survey date. The estimates are from the specification in Equation 10. Standard errors are clustered at the district-level. 95% confidence intervals are plotted. Survey weights are used. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025.

Figure C26. Event-study Estimates for Medium Run Coping Strategies

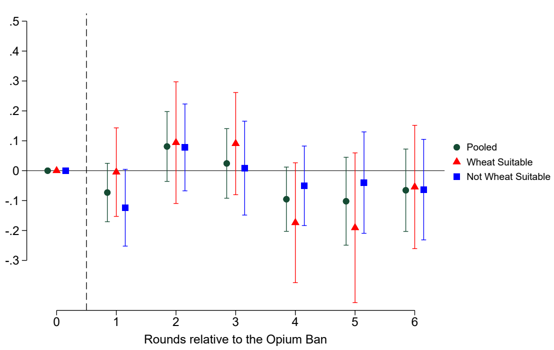
(a) Sale of Assets



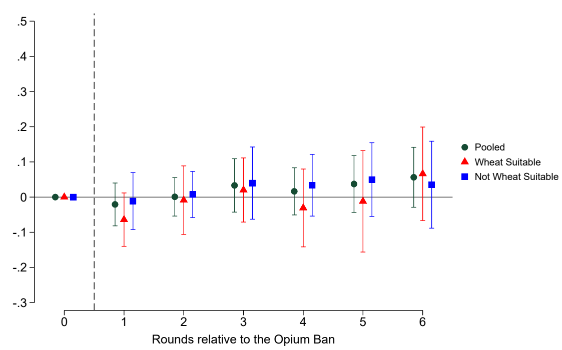

(b) Savings Use and Debt Default




(c) Sale of Animals

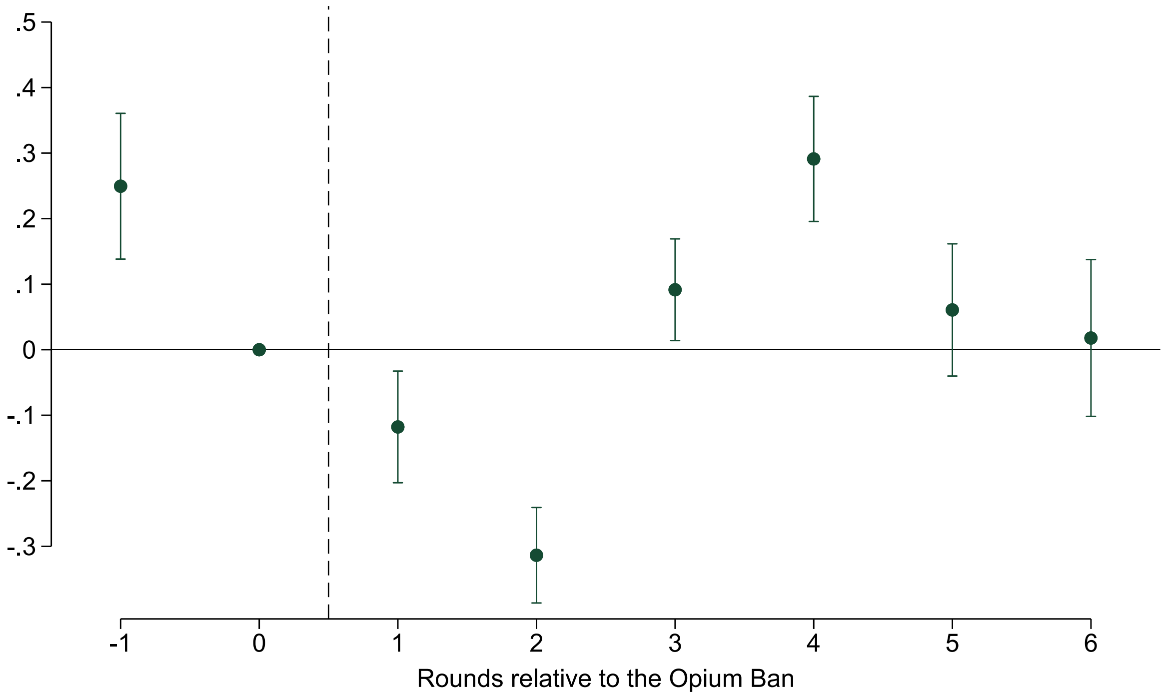



(d) Borrowing Money




*Notes:* Data on the dependent variable are derived from (FAO, 2025). The dependent variable in each panel is an indicator variable, discussed in B.4. The estimates are from the specification in Equation 10. Standard errors are clustered at the district-level. 95% confidence intervals are plotted. Survey weights are used. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025.

Figure C27. Household has Multiple Sources of Income




*Notes:* Data on the dependent variable are derived from (FAO, 2025). The dependent variable is an indicator variable for the household reporting having at least two most important sources of income. The estimates are from the specification in Equation 10. Standard errors are clustered at the district-level. 95% confidence intervals are plotted. Survey weights are used. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025.

Table C1. Summary Statistics for Pre-Treatment Period

| | Control Districts | Treated Districts |
|---|---|---|
| | (1) | (2) |
| *Panel A: Household Characteristics* | | |
| Male Headed HH | 0.988 | 0.993 |
| Total HH Income (10,000 Afghani) | 2.437 | 2.164 |
| HH Cultivate Crops | 0.742 | 0.716 |
| HH Agricultural Laborer | 0.068 | 0.087 |
| HH Income Declined in Last Three Months | 0.616 | 0.677 |
| HH Had Any Economic Shock in Last Three Months | 0.714 | 0.779 |
| *Panel B: FIES* | | |
| FIES: Worried about not having enough food to eat | 0.937 | 0.958 |
| FIES: Unable to eat healthy and nutritious food | 0.902 | 0.925 |
| FIES: Ate only a few kinds of foods | 0.924 | 0.908 |
| FIES: Had to skip a meal | 0.674 | 0.705 |
| FIES: Ate less than you thought you should | 0.815 | 0.806 |
| FIES: No food to eat of any kind | 0.425 | 0.431 |
| FIES: Go to sleep at night hungry | 0.318 | 0.357 |
| FIES: Go a whole day and night without eating anything at all | 0.212 | 0.276 |
| *Panel C: Outcomes* | | |
| HH Had High FIES | 0.660 | 0.701 |
| Household Hunger Scale (HHS) | 1.461 | 1.664 |
| FIES Raw Score | 5.129 | 5.365 |
| Average Z-score FIES | -0.033 | 0.031 |
| Anderson (2008) Z-score | -0.102 | 0.018 |
| HH Had Any FIES | 0.955 | 0.959 |
| Number of Households | 11,722 | 21,874 |

*Notes:* Data on food insecurity and household characteristics are derived from (FAO, 2025). Data on opium cultivation are derived from UNODC (2023b). Survey weights are used. The sample is restricted to data from survey round three to survey round four. These survey rounds are conducted between September 2021 and February 2022. The column header provides information on the sample. In the first column, the sample is restricted to control districts. In column (2), the sample is restricted to treated districts.

Table C2. Composition of Respondents

| | Married Household Head | Male Respondent | Below Median Income Household | Permanent Resident |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Panel A: All Household | | | | |
| $\mathbb{1}$ (Opium District) | -0.007 | -0.001 | 0.058 | 0.010 |
| $\times\mathbb{1}$ (Post) | (0.013) | (0.017) | (0.048) | (0.008) |
| N | 63,000 | 63,086 | 62,902 | 55,989 |
| Panel B: Agriculture Households | | | | |
| $\mathbb{1}$ (Opium District) | -0.000 | -0.003 | 0.074 | 0.006 |
| $\times\mathbb{1}$ (Post) | (0.011) | (0.016) | (0.052) | (0.007) |
| N | 53,827 | 53,904 | 53,723 | 47,025 |

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique household. In column (1), the dependent variable is an indicator variable for the household head to be married. In column (2), the dependent variable is an indicator variable for the respondent to be male. In column (3), the dependent variable is an indicator variable for whether the household is below the median of the income distribution. The income distribution in the survey round in which the household is interviewed is used to derive the median of the income distribution. The dependent variable in column (4) is an indicator variable for whether the household is a permanent resident. The Independent variable of interest in each column is the interaction of an indicator for the households' residence district having opium cultivation and an indicator for the household being surveyed after the the opim ban in April 2022. A district has opium cultivation if it has any opium cultivation either in 2020 or 2021. Specification in each column includes households' residence district and month of survey fixed-effects along with linear time-trends for the households' residence province. In "Panel B," all households who do not report being involved in crop cultivation are dropped from the analytical sample.

# Table C3. Heterogeneity

| | HH Produces Crop | | Agriculture Labor HH | | HH Experienced Economic Shocks | | HH Received Food Assistance | | Male Headed HH | | Head Married | | Below Median Income HH | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) |
| **Panel A: Baseline** | | | | | | | | | | | | | | |
| $\mathbb{1}$(Opium District) | 0.192*** | 0.131* | 0.221*** | 0.158*** | 0.197*** | 0.007 | 0.258*** | 0.163*** | 0.150*** | 0.274* | 0.165*** | 0.293*** | 0.155*** | 0.181*** |
| $\times\mathbb{1}$(Post) | (0.043) | (0.067) | (0.071) | (0.045) | (0.045) | (0.075) | (0.063) | (0.050) | (0.045) | (0.148) | (0.045) | (0.071) | (0.050) | (0.062) |
| | *p*-value = 0.304 | | *p*-value = 0.359 | | *p*-value = 0.583 | | *p*-value = 0.205 | | *p*-value = 0.388 | | *p*-value = 0.044 | | *p*-value = 0.685 | |
| N | 61,111 | 22,693 | 6,229 | 77,575 | 62,375 | 21,429 | 18,693 | 60,467 | 76,926 | 6,848 | 78,476 | 5,238 | 35,846 | 38,541 |
| **Panel B: Wheat Suitable Districts** | | | | | | | | | | | | | | |
| $\mathbb{1}$(Opium District) | 0.117* | -0.023 | 0.180 | 0.078 | 0.094 | -0.162 | 0.110 | 0.042 | 0.046 | 0.277 | 0.065 | 0.367*** | 0.077 | 0.036 |
| $\times\mathbb{1}$(Post) | (0.059) | (0.113) | (0.109) | (0.071) | (0.069) | (0.110) | (0.097) | (0.074) | (0.067) | (0.341) | (0.070) | (0.118) | (0.093) | (0.082) |
| | *p*-value = 0.133 | | *p*-value = 0.361 | | *p*-value = 0.301 | | *p*-value = 0.533 | | *p*-value = 0.479 | | *p*-value = 0.003 | | *p*-value = 0.648 | |
| N | 17,661 | 7,187 | 2,038 | 22,810 | 19,089 | 5,759 | 4,468 | 19,109 | 22,405 | 2,432 | 23,150 | 1,678 | 9,569 | 12,430 |
| **Panel C: Not Wheat Suitable Districts** | | | | | | | | | | | | | | |
| $\mathbb{1}$(Opium District) | 0.179*** | 0.188** | 0.258** | 0.142** | 0.214*** | 0.020 | 0.280*** | 0.178*** | 0.165*** | 0.287** | 0.170*** | 0.212** | 0.209*** | 0.223*** |
| $\times\mathbb{1}$(Post) | (0.060) | (0.078) | (0.109) | (0.057) | (0.060) | (0.079) | (0.075) | (0.065) | (0.059) | (0.117) | (0.059) | (0.091) | (0.058) | (0.083) |
| | *p*-value = 0.904 | | *p*-value = 0.235 | | *p*-value = 0.265 | | *p*-value = 0.274 | | *p*-value = 0.342 | | *p*-value = 0.603 | | *p*-value = 0.876 | |
| N | 43,450 | 15,506 | 4,191 | 54,765 | 43,286 | 15,670 | 14,225 | 41,358 | 54,521 | 4,416 | 55,326 | 3,560 | 26,277 | 26,111 |

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique household. The independent variable of interest in each column is the interaction of an indicator for the households' residence district having opium cultivation and an indicator for the household being surveyed after fourth survey round. A district has opium cultivation if it has any opium cultivation either in 2020 or 2021. The dependent variable in all the columns is whether the raw Food Insecurity Experience Scale (FIES) index is above four. The raw FIES index is the sum of whether the respondent reports food insecurity on each of the eight FIES questions in the survey. Subpopulations are denoted in the column header. *p*-value is for the test of equality of independent variable estimate across two subpopulations. Specification in each column also includes households' residence district and month of survey fixed-effects along with linear time-trends for the households' residence province. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025. Data on crop suitability is derived from Fischer et al. (2021). In "Panel B," the sample is restricted to districts suitable for wheat production. In "Panel c," the sample is restricted to districts not suitable for wheat production.

Table C4. Need for Assistance Received

| | Seeds | | Cash | |
|---|---|---|---|---|
| | Yes | No | Yes | No |
| | (1) | (2) | (3) | (4) |
| *Panel A: Baseline* | | | | |
| $\mathbb{1}$ (Opium District) | 0.138*** | 0.176*** | -0.036 | 0.179*** |
| $\times\mathbb{1}$ (Post) | (0.048) | (0.046) | (0.130) | (0.046) |
| | $p$-value = 0.401 | | $p$-value = 0.118 | |
| N | 14,927 | 64,233 | 4,273 | 74,887 |
| *Panel B: Wheat Suitable Districts* | | | | |
| $\mathbb{1}$ (Opium District) | 0.015 | 0.075 | 0.056 | 0.070 |
| $\times\mathbb{1}$ (Post) | (0.076) | (0.074) | (0.225) | (0.071) |
| | $p$-value = 0.403 | | $p$-value = 0.951 | |
| N | 4,601 | 18,976 | 1,034 | 22,543 |
| *Panel C: Not Wheat Suitable Districts* | | | | |
| $\mathbb{1}$ (Opium District) | 0.183*** | 0.181*** | -0.256* | 0.190*** |
| $\times\mathbb{1}$ (Post) | (0.063) | (0.060) | (0.138) | (0.061) |
| | $p$-value = 0.968 | | $p$-value = 0.003 | |
| N | 10,326 | 45,257 | 3,239 | 52,344 |

Notes: Heteroskedasticity robust standard errors clustered by the district are in parentheses. (* p<.10 ** p<.05 *** p<.01). Each observation in all columns corresponds to a unique household. The independent variable of interest in each column is the interaction of an indicator for the households' residence district having opium cultivation and an indicator for the household being surveyed after fourth survey round. A district has opium cultivation if it has any opium cultivation either in 2020 or 2021. The dependent variable in all the columns is whether the raw Food Insecurity Experience Scale (FIES) index is above four. The raw FIES index is the sum of whether the respondent reports food insecurity on each of the eight FIES questions in the survey. Subpopulations are denoted in the column header. $p$-value is for the test of equality of independent variable estimate across two subpopulations. Specification in each column also includes households' residence district and month of survey fixed-effects along with linear time-trends for the households' residence province. The sample is restricted to data from survey round three to survey round ten. These survey rounds are conducted between September 2021 and February 2025. Data on crop suitability is derived from Fischer et al. (2021). In "Panel B," the sample is restricted to districts suitable for wheat production. In "Panel C," the sample is restricted to districts not suitable for wheat production.