UN peacekeeping and households' well-being in civil wars*

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Abstract

Civil wars affect the economic conditions of households by disrupting economic transactions and harming their psychological well-being. To restore basic conditions for local economic recovery in conflict-torn regions, the international community has only a limited number of tools at its disposal. We ask whether UN peacekeeping is one instrument to mitigate the negative effect of conflict on households' economic well-being. We argue that, by reducing violence and heightening perceptions of safety, UN missions *(i)* encourage labour provision and economic exchanges, and *(ii)* instill confidence by reducing the psychological impact of daily stressors. Combining high-frequency household survey data and information on subnational deployment of UN peacekeepers in South Sudan, we show that peacekeepers military presence improves security (observed and perceived), which in turn revitalize local economies and households' subjective well-being. These improvements ultimately boost households' consumption, partially countering the negative effect of ongoing civil wars by keeping local communities' economy afloat.

Verification Materials:
The data and materials required to verify the computational reproducibility of the results, procedures and analyses in this article are available on the *American Journal of Political Science Dataverse* within the Harvard Dataverse Network, at: `https://doi.org/10.7910/DVN/KVPF3F`.

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Introduction

The link between development and security is widely acknowledged and represents a major challenge to tackle to avoid conflict relapse. To stabilize conflict zones and protect civilians, the United Nations (UN) have launched more than 70 peacekeeping missions in highly volatile areas. The vicious cycle of insecurity and underdevelopment has become a priority of contemporary peacekeeping, whose "multidimensional" mandates are not limited to containing violence, but also aim to create conditions for economic recovery. In this article we investigate whether peace missions can mitigate the negative effect of conflict on economic well-being and show that the deployment of peacekeepers can improve households' welfare.

Peace operations can address the development-security nexus when their direct contribution to security indirectly enables improvements in households' economic welfare. A wealth of studies shows that peacekeeping reduces violence in ongoing civil wars and the odds of conflict relapse (e.g., Di Salvatore and Ruggeri, 2017; Beardsley, 2011; Ruggeri, Dorussen and Gizelis, 2017; Hultman, Kathman and Shannon, 2019). We first contribute to this literature by establishing a direct link between peacekeeping and households perceived and reported security by investigating whether a mission's conflict-reducing effect also improves peace-kepts' safety. Second, we contribute to the debate on whether peacekeeping missions have any impact on economic outcomes.[1] Some studies outline a critical role for peace operations in revitalizing agricultural production (Caruso, Khadka, Petrarca and Ricciuti, 2017), while others find this contribution to be rather modest (Mvukiyehe and Samii, 2020) or short-lived (Beber, Gilligan, Guardado and Karim, 2019).[2] Collectively, empirical results are inconclusive and some focus on cases where conflict had ceased for years. Hence, we know even less about whether and how peace missions can avoid

[1] Qualitative studies have explored positive but also nefarious impact of peacekeeping economies, such as their gendered nature (Jennings, 2014) and peacekeepers' involvement in transactional sex (Beber, Gilligan, Guardado and Karim, 2017).

[2] At the macro level, Bove and Elia (2018) compare countries hosting peace operations with countries that experienced conflicts without UN intervention, and conclude that peacekeeping does not significantly affect economic development.

complete economic collapse and keep local economies afloat during civil wars. In addition, research that detects a potential economic effect of peacekeeping missions could not pin down *how* security provided by peacekeepers boosts households' well-being.

Against this background, we ask whether interventions that provide security during civil wars, i.e., UN peacekeeping, mitigate poverty-conflict. Rather than exploring how peace missions support households once peace is achieved, we are interested in how peace missions support households' welfare in the midst of violence. As a tangible measure of living conditions and economic well-being, we focus in particular on households' consumption (Beegle, De Weerdt, Friedman and Gibson, 2012; Deaton, 2019). In addition to being "conventionally viewed as the preferred welfare indicator" (World Bank, 2000, p.17), its use is well-suited for context of widespread poverty (see e.g., Meyer and Sullivan, 2003). Consumption standards are also relevant indicators for the poverty line and are used to evaluate the effectiveness of transfer programs.

This article develops a parsimonious theoretical framework to explain how peacekeepers can improve the material well-being of households in conflict. Our framework builds on existing theories to explain how improvements in security (less observed violence, higher perceived safety) can foster consumption patterns via two main channels. First, uncertain and violent environments produce costly habit changes for households, such as reduced labor supply and economic transactions that worsen their economic well-being. When security conditions improve, households are likely to return to the *economic habits* that violence alters, such as participating in the labor market (e.g. returning to work) and engaging in economic transactions (e.g. going to local markets). Thus, we expect an increase in economic exchanges and employment opportunity as labour demand grows. Second, improved security conditions can provide *psychological relief*. While long-term traumas linked to violence exposure are unlikely to be addressed by contingent reduction in violence, peace missions can attenuate daily and chronic stressors responsible for worsening households' subjective well-being. These improvements are expected to make households more optimistic and confident about the future. Put together, we expect the return to relatively ‘normal’ economic habits and reduced psychological distress to contribute to visible improvement in households material living conditions.

We investigate whether security improves households’ economic well-being in the context of the South Sudanese civil war, using the UN mission in the country (UNMISS) as a security-provision intervention. We analyse household-level data based on the four survey rounds of the World Bank South Sudan High Frequency Survey (HFS) from 2015 to 2017, and combine the survey with data on where and when UNMISS operated. UNMISS is the second largest UN peacekeeping mission and has a multidimensional mandate that includes civilians protection, creating conditions for aid delivery and preventing human rights abuses. In 2013, two years before the first round of the HFS survey, a new civil war broke out in South Sudan, leading to what is currently one of the direst humanitarian crises (UNOCHA, 2020). As such, South Sudan provides a laboratory - and a “hard case” - for understanding whether peace missions help keeping local communities’ economy afloat.

The combination of household-level data with information on peacekeepers’ local deployment allows us to explore variation in deployment and economic conditions for treated and untreated groups. At the same time, this rich dataset allows us to shed light on some of the theoretical mechanisms underlying the relation between peacekeeping and consumption using causal mediation analysis (Imai and Yamamoto, 2013; VanderWeele and Vansteelandt, 2014). In our analysis we account for the effect of peacekeeping on households’ perceptions of safety, regardless of the reported levels of violence, as households may for example feel safer in presence of UN troops even though reported violence does not decrease at all. Furthermore, we can distinguish and reasonably separate the effect of improved security on locals’ subjective well-being vis-à-vis its incidence on economic behaviors.

Our analysis provides three key findings. First, UNMISS presence produces tangible improvements in households’ economic well-being measured by consumption of food and durable goods. Second, in terms of underlying mechanisms, we show that the presence of peacekeepers revitalizes economic exchanges through more participation to the labor market and easier access to local markets. Furthermore, peacekeepers presence improves subjective well-being, specifically assessments about future living conditions and life satisfaction that are expected to stimulate consumption. By exploring these dynamics concerning households' experiences and subjective assessments, this article does not simply zoom in at the individual level but also aspires to contribute to the 'everyday turn' in peacekeeping studies (Jennings and Bøås, 2015).

Our finding are robust to a wide range of empirical specifications that deal with some of the most important threats to causal identification. In particular, we address endogeneity concerns due to selection bias in peacekeepers' deployment by showing that treated and untreated counties do not differ in terms of pre-deployment trends of violence; by demonstrating that local deployment is not driven by observed levels of violence; by controlling for pre-deployment factors associated with UN presence; and by contrasting our main findings with those from a matched sample and an instrumental variable regression. Taken together, the results suggest that the presence of peacekeepers can help to contain economic collapse during civil war by sustaining households' consumption in one of the most unstable region of the world.

Theoretical Framework

In this section, we develop a parsimonious theoretical framework to explain how local deployment of UN peacekeepers affects households' economic well-being, in particular standard indicators of consumption of food and durable goods items. We outline the process through which UN missions can contribute to households' consumption in Figure 1, which captures the main relations under scrutiny by drawing on economic development, psychology and conflict research.

We concentrate on mission's impact on the security environment (channel A). In contrast with previous studies, we distinguish the effect that UN missions have on objective security conditions, i.e. reported violence and on subjective perceptions of safety. Our theoretical framework also accounts for the direct economic effect of UN missions (channel B) - i.e. how missions' spending and need for personnel may stimulate opportunities for economic exchanges and employment as part of so-called peacekeeping economies.[3] We could expect peacekeeping to increase employment opportunities and revival of local markets because of local mission procurements, wages paid to local staff and the international mission subsistence allowance (MSA) spent on the local economy.

Notably, however, the impact of the mission's spending in our case study is limited. UNMISS is a "bunkerized" and "self-sufficient" mission, and even the limited amount of money spent by UNMISS in the country by-passes the population and the economy, as it largely involves foreign businesses (Rolandsen, 2015, 367). Furthermore, the direct channel (B) is also limited geographically (i.e. few nationals are hired and transactions occur in a limited radius where UN personnel moves, see Jennings and Bøås, 2015)[4] and temporally.[5] Jennings and Nikolić-Ristanović (2009) illustrate the "temporariness" of peacekeeping economies, whose effect lasts as long as the mission is present; among the few quantitative studies on the matter, Beber et al. (2019) also find that in Liberia, the boost in demand for low-skilled work lined to UNMIL's spending did not survive the mission withdrawal. Hence, this channel is not only less relevant to the UNMISS case, but is also unlikely to significantly affect reported economic well-being among respondents in our sample. As such, in the following section, we further elaborate on how UN peacekeeping can support improvements in material economic well-being through its effect on the security environment.

[3]Jennings and Bøås (2015, 282) define peacekeeping economies as "economic activity that either would not occur, or would occur at a much lower scale and pay-rate, without the international presence".

[4]In 2020, UNMISS hired less than 1,000 South Sudanese in a mission with more than 18,000 personnel, hence offering limited employment opportunity in a country with more than 10 million inhabitants. See https://peacekeeping.un.org/sites/default/files/unmiss_aug20.pdf

[5]Note also that, given the lack of data on how much the mission is hiring or spending locally, we are unable to empirically verify this mechanism.

Contributing to the Economy by Contributing to Security

The framework in Figure 1 consists of several elements outlining how the impact of peace operations on households' economic well-being materializes through its contribution to security (channel A). Civil wars disrupt economic activities, destroy critical infrastructures, reduce investment and worsen food insecurity, with the least-developed societies enduring the highest costs (Gates, Hegre, Nygård and Strand, 2012). The threat of violence itself may have dire economic consequences, for example by preventing farmers from planting or harvesting crops, hence causing food shortages.

The entry point of our theoretical framework is based on conflict research showing that peacekeeping missions curb violence (e.g., Hultman, Kathman and Shannon, 2019; Ruggeri, Dorussen and Gizelis, 2017; Di Salvatore and Ruggeri, 2017). If peacekeepers reduce conflict, they should also create conditions for economic recovery. To investigate whether peacekeepers curb conflict, researchers have so far relied on data on violence as reported in newspapers. Yet, media sources can severely underreport events in African countries and, more importantly, changes in reported violence levels may not reflect how households perceive their personal safety. For missions to boost economic recovery, we need to assess how their presence affect households' assessment of risk. As such, in addition to violence levels as measured by frequency of conflict events, we consider whether peacekeeping improves individuals' perceptions of safety. Peace missions may improve perceptions of safety by either reducing actual levels of violence or by signalling and deterring via highly visible activities such as community patrolling. Notably, research has shown that individuals' perceptions do not unambiguously match reported levels of crime (Velásquez, Medina, Yamada, Lavado, Nunez-del Prado, Alatrista-Salas and Morzán, 2020) or electoral fraud (Daxecker, Di Salvatore and Ruggeri, 2019), and other factors contribute to how these perceptions are formed. Similarly, perceived safety does not necessarily mirror actual violence, which suggests that households' perceptions may be decoupled from actual conflict-reducing effects of peacekeeping, especially if rising levels of non-conflict violence remains a source of insecurity (Di Salvatore, 2019). While we do not delve into how these perceptions are formed in the first place, we acknowledge that peacekeepers may neither be a sufficient nor a necessary condition for violence reduction, but their presence can still heighten perceptions of safety.

When peacekeeping improves the security environment (by reducing violence or boosting perceived safety), we should observe positive effects on households' economic behaviours (A1) and psychological well-being (A2), which in turn affect their consumption patterns. A safer environment can revitalize economic exchanges and participation in the labor market. For one, widespread violence may push individuals to change their habits in economically costly ways to reduce risks. Economic development research has identified these changes as often involving avoidance behaviors, which range from reducing time spent on the street and in public spaces to changes in working habits (DuBow, McCabe and Kaplan, 1979). Exposure to conflict can adversely affect people' willingness to participate in market activities and, more generally, engage in transactions involving trade with people they do not belong to their kinship groups (Cassar, Grosjean and Whitt, 2013). In fact, domestic trade and market activities are a key channel through which war-induced mistrust affects the economy (Rohner, Thoenig and Zilibotti, 2013; Costalli, Moretti and Pischedda, 2017). Yet, when some degree of security is restored, households may revert these behaviors.

When peacekeepers are deployed in their vicinity, households have more access to markets, as both sellers and buyers would perceive less physical and economic risks. For example, the Amiet common market in South Sudan was forced to suspend trading activities because of security incidents in the areas, and was later re-opened when peacekeepers stabilized the area. As one community chief put it, peacekeepers played "a key role in safeguarding not just the villages and the market, but also securing highways leading to Amiet".[6] Similarly, the town of Tonga in Upper Nile State became a "ghost town" when conflict re-erupted, but civilians return to the city and the local market when some level of normalcy was established [7].

[6] https://tinyurl.com/y5s2eytl
[7] https://tinyurl.com/y68a72fk

Local markets are one type of economic activity that suffers from insecurity, and their revival can itself provide more employment opportunities. This beneficial effect of security on employment is the result of both increasing demand for labor, but also decreasing risks of individuals' victimization (BenYishay and Pearlman, 2013; Hamermesh, 1999), in line with the reduction of avoidance behavior mentioned above. The establishment of secure buffer zone in Malakal had allowed South Sudanese to get back to farming; as a farmer put it "we are well protected, when we are here we are not afraid".[8] In several occasions of restored stability, the South Sudanese government has informed worried employees that they could safety return to work, and should have done so as soon as possible.[9] With market revivals and employment opportunities providing a positive income change, households are expected to respond with more consumption of necessary items (Jappelli and Pistaferri, 2010).

Whereas the psychological legacy of individuals' violence exposure is well-documented, and civil wars produce devastating consequences for individuals' mental conditions (Siva, 2010), we expect security improvements to also boost households' psychological well-being. As the Malakal farmer put it above, not being afraid contributes to a return to normalcy. Extant psychology research documents long-term mental health consequences of exposure to violence, especially among former combatants and refugee populations (Summerfield, 2000). They also explore how civilians cope in ongoing civil wars. For example, Gelkopf, Berger, Bleich and Silver (2012) show that 7 years of daily mortar attacks in the city of Sderot (Israel) act as chronic stress and worsen mental health among civilians. Overall, exposure to violence makes individuals hopeless and pessimistic about the future (Moya and Carter, 2014), while also reducing levels of happiness and life satisfaction (Welsch, 2008; Frey, Luechinger and Stutzer, 2004). Consequently, improvements in security brought about by peacekeepers should improve households' assessment of their living conditions. Importantly, recent psychological research tends to emphasize the importance of "daily stressors" rather than direct exposure to war as a fundamental source of psychological

[8] https://tinyurl.com/y677dbrt

[9] https://tinyurl.com/y2x7h3rc; https://tinyurl.com/y6kbupqe

distress (Miller and Rasmussen, 2010). This means that peace missions do not necessarily need to bring a nation-wide halt to civil war to exert a positive effect on households' subjective well-being; in fact, UN missions can exactly tackle the daily sources of chronic stress concerned with basic needs, safety and sheltering. In the protection site in Tong Ping, people were initially skeptical about UNMISS capacity to protect them against violence, but then developed a sense of trust and, to some extent, safety thanks to UNMISS active patrolling (Gorur, 2014).

[Figure 1 about here]

If peacekeeping operations can provide relief from daily, chronic stressors and foster households' psychological well-being, this should in turn encourage consumption by increasing confidence in the future. A wealth of economic studies demonstrate that feelings are central to changes in consumption patterns. Bozzoli, Brueck and Muhumuza (2011) show how conflict results in negative expectations about future economic performances; in turn, optimism or pessimism of households about future prospects crucially drive variations in consumption (Carroll, Fuhrer and Wilcox, 1994; Nowzohour and Stracca, 2020). Not only psychological distress reduces labor supply and consumption (de Quidt and Haushofer, 2017), but pessimism about future opportunities may become self-enforcing and entangles individuals in a"vicious cycle of pessimism, hopelessness, and persistent poverty" (Moya and Carter, 2014, 2). To summarize, we expect UN peace missions to improve household economic well-being, in particular consumption, by delivering a secure environment and increasing personal safety. Whereas the framework displays the main channels linking peacekeeping to economic welfare, other mechanisms could be at play. This however does not question the relevance of these channels, which we will test using mediation analysis.

Background and Case Selection

On 9th January 2005, the Government of Sudan and the Sudan People's Liberation Movement/Army (SPLM/A) signed the Comprehensive Peace Agreement (CPA) that ended the Second Sudanese War (1983-2005). From 2005 to 2011, South Sudan had a semi-autonomous status, and began independent after a referendum held in July 2011. The SPLM became the governing party. The aftermath of independence was not peaceful. When violence re-erupted in December 2013, some observers focused on ethnic divisions between the Dinka President Salva Kiir and Nuer former Vice President Riek Machar, to whom some SPLA members had defected. The fact that South Sudan was a new state led to conclude that violence was the consequence of lack of state authority. In relation to the analysis of this article, both conclusions would indicate a uniqueness of the South Sudan case, thus invalidating any claim of external validity. While there are specificities to the South Sudanese case, as there are in all single-case studies, the two concerns above do not hold up to scrutiny. In relation to the tribal nature of the conflict, increasing centralization rather than ethnicity more likely triggered the 2013 violence. The SPLM/A was so fragmented that "timing of the eruption of violence may have been unpredictable but the nature of the crisis that unfolded was eminently foreseeable" (De Waal, 2016, 4). Second, Pendle (2014, 229) points that the claim that South Sudan was "created from scratch" is not accurate; since its autonomy in 2005, South Sudan had its own judicial system, government and an elected assembly (Emmanuel, 2011).

Worsening security conditions also pushed the UN Security Council to re-orient the mandate of the UN mission in South Sudan (UNMISS), which had been authorized in the aftermath of the 2011 referendum. In December 2013, the UN Security Council authorized a rapid deployment of additional 6,000 security forces on top of the almost 9,000 originally deployed since 2011. In May 2014, the Council heavily shifted the mission's mandate from nation-building to the prioritization of civilian protection and authorization to use force. The situation in South Sudan is, however, not unique as similarly critical humanitarian needs exists in Sudan (Darfur) or DRC (UNOCHA, 2020). Furthermore, the UN response and UNMISS mandate are substantially in line with the last generation of peace missions that operate with a robust mandate, a focus on civilians' protection and peacebuilding goals. Hence, our theory is generalizable to cases where these two scope conditions (ongoing violence and sizeable military deployment) materialize, including recent and prominent missions such as MINUSCA, MINUSMA, MONUSCO, UNOCI and UNAMID.

It is important to mention that the UN had already a peacekeeping mission in Sudan before South Sudan's independence. When the CPA was signed in 2005, the UN mission to Sudan (UNMIS) was deployed to verify the implementation of the agreement. Yet, in terms of both mandate and deployment size, UNMIS and UNMISS present clear differences. Furthermore, some counties (e.g. Renk, Tambura, Pibor, and Pariang) had never hosted UN peacekeepers before UNMISS. The difference in deployment strategies between UNMIS and UNMISS are sufficient enough to allow an assessment of UNMISS' impact on the welfare of South Sudanese people. Indeed, in the Supplementary Information (SI C.5, p.13) we outline the differences between the mission in more detail.

As other single-case studies, we do not claim that the findings presented and the magnitudes of the detected effects would be the same in other contexts. When comparing the South Sudanese case with other contemporary cases and their respective UN approach, the differences would not lead us to believe the conclusions we draw are uniquely based on idiosyncrasies of the selected case. In fact, the case of South Sudan may be a hard test for our hypotheses, considering the extreme violence and humanitarian tragedy it has been facing.

Data

To investigate the local economic impact of peacekeeping during civil wars, we combine two main data sources. First, based on Hunnicutt and Nomikos (2020)'s RADPKO data, the deployment of military personnel in a given month and location is derived from UN

Secretary General reports on UNMISS and used to create a dummy variable for peacekeeping military presence between 2015 and 2017.[10] Second, we combine data on county-level deployment with the High-Frequency Survey (HFS) carried out in South Sudan by the World Bank from 2015 to 2017 (Pape, 2015, 2016*a*,*b*, 2017). The HFS is designed as a representative survey of South Sudanese population across 7 states, based on the 2008 national census. The World Bank, who carried out the survey, interviewed 22,072 respondents in wave 1 (February-September 2015), 8,207 in wave 2 (February -June 2016), 11,430 in wave 3 (September 2016-March 2017) and 4,588 in wave 4 (May-August 2017). However, not all questions were asked to all household members. For this reason, we focus on household heads as they are the main respondents in the survey. Also, the main outcome variables are at the household level, hence based on what heads report about their household. Some of the respondents were interviewed in more than one survey wave, but in most cases migration and security problems did not allow to keep the panel consistent across waves. Using each wave as a cross-section reduces concerns over attrition rates, which are paramount with panel data. Respondents were interviewed across 7 states in four waves. Wave 1 was conducted in 6 out of 10 South Sudan states,[11] and another state (Warrap) was added for wave 2, 3 and 4. The excluded states are Upper Nile, Unity and Jonglei, which were not surveyed because of unstable security conditions. Figure 2 shows the 46 counties sampled across HFS waves, that have (not) had deployment.[12]

The exclusion of some states does not imply that the surveys only includes states that were in fact at peace, which would undermine our goal to assess the economic impact of peacekeeping during civil wars. While the 2013 civil war has severely affected Upper Nile, Unity and Jonglei states, violence spread and escalated in the other states as well

[10] We check the RADPKO data against our own coding of the UN deployment maps, and the only small note to report concerns the deployment of UNMISS in the neighboring counties of Mundri and Maridi. Deployment maps indicate UN presence in Mundri, though the coordinates retrieved from Google Maps are located in Maridi when projected. Also, UNSG reports refer to the existence of a UN base in Maridi up to 2013, then in Mundri (UNSG, 2013, 2016). This discrepancy could also be due to changes in the administrative boundaries.

[11] After 2015, the number of states changed to 28 and then 32 in 2017. The survey refers to the original 2010 states.

[12] Maps are created in ArcGIS (v. 10.5.1).

(Rolandsen, Glomnes, Manoeli and Nicolaisen, 2015). More peaceful Equatoria states, once known as the bread baskets of the country, reported worrisome levels of food insecurity (WFP, 2017). Figure 3 shows the total number of deaths in each South Sudanese county since the beginning of the civil war in 2013 from the Uppsala Conflict Data Program (UCDP) (Sundberg and Melander, 2013). The level of violence is certainly very high in the north-eastern area, which includes the three above-mentioned states; but counties such as Juba, Wau and Tonj East have also been severely hit by violence. SI A (p.2) provides additional details on the survey and discusses possible data quality concerns.

[Figure 2 about here]

[Figure 3 about here]

Outcome Variables and Mediators from HFS

To capture households' living conditions, we borrow from the development economics literature and use four measures of consumption, each capturing the consumption profile and the welfare of households in different ways (see e.g., Beegle et al., 2012; Friedman, Beegle, De Weerdt and Gibson, 2016, for a discussion of how to measure household consumption through surveys). To begin with, we compute the total amount of per capita consumed food within the household. We complement it with a measure that considers not only the amount of consumed food but also households' access to it. Households are asked whether there was no food to eat in the house in the last weeks. According to the Food Agricultural Organization, food insecurity exists even when households' food consumption is met if their access to food is irregular and unreliable (FAO, 2012). We expected peacekeepers to not only foster consumption of food items but also make such consumption more regular and less uncertain by improving security conditions. We also use per capita amounts of purchased food as outcome variable to estimate whether consumption is mostly dependent on households' capacity to buy food as opposed to e.g., their capacity to restore production for subsistence (Caruso et al., 2017). Finally, we also include per capita durable goods (i.e. non-food) within the household.

We also use the HFS data to construct the potential mediators of our theoretical model. We focus respectively on the security environment (A in Figure 1), economic habits (A1) and psychological well-being (A2). We construct two measures of security. We measure perceptions of safety using a dummy variable measuring whether respondents feel safe from violence when walking in their neighborhood. We also measure observed violence reduction by using a question asking respondents whether they have seen less violence in their neighborhood in last six months. By doing so, our analysis departs from existing research examining the security effect of peace operations based on conflict data from media reporting,[13] which may not reflect households' knowledge about conflict events. Even if these data did not suffer from the reporting biases documented in the literature (Weidmann, 2016), it likely differs from local populations' awareness and feelings of safety. Interestingly, the correlation between average number of conflict events and average households' reported conflict reduction in each South Sudanese county is very weak (ρ <0.17, based on ACLED (Raleigh, Linke, Hegre and Karlsen, 2010)); the correlation is even lower when comparing the same conflict events with perceptions of safety (ρ <0.02).

To test whether peacekeeping missions can alter economic behaviors (channel A1, Figure 1) that households adopt in insecure environment (e.g. reduction in labour supply and demand, and limited economic exchanges), we measure recent employment status of household heads. We focus on this measure to capture whether the respondent has recently been paid for work. By doing this, we aim to capture potential income effects of recent employment activities. Furthermore, if security is a stimulus for local economic exchanges and, at the same time, deployment itself creates demand for goods, we expect travelling distance to local markets to be shorter for respondents nearby UN bases. Notably, revitalization of local market is itself a source of labour demand and employment opportunities. For example, violence in Akobo forced the population to flee, and destroyed the local economy; after the arrival of the UNMISS, the economy started a slow recovery and areas closer to the UN base were repopulated.[14]

[13] A notable exception is Dorussen (2015).

[14] `https://tinyurl.com/y5qejrjm`

The last set of variables we measure focuses on psychological well-being (channel A2, Figure 1), which missions are expected to boost by reducing the impact of daily stressors and uncertainty experienced by households in conflict zones. Household heads are asked to assess their future living conditions, and we use this question to create one dummy variable that equals 1 when respondents' assessment is fairly/very good. In addition, we move away from individuals' economic welfare to psychological well-being and use a question about whether household heads are satisfied with their life to measure *experienced* utility. As such, we investigate whether individuals' subjective living conditions and life satisfaction are higher where peacekeepers contribute to more secure environments, and how this improvement in turns affects households' economic welfare. We provide more information on survey design and questions wording in SI A (p.2) and show descriptive statistics for all variables described here in SI B (p.6).

Empirical Strategy

In this section we present the empirical approach taken in this article to investigate the impact of peacekeeping on households' material well-being and the possible mechanisms underlying it.

We first consider our four measures of consumption - i.e., consumed and purchased food, irregular food consumption and non-food items - and ask whether peacekeeping significantly affects them. These four outcomes of interest are measured at the household level across the four waves of the HFS. Hence our unit of analysis is the household-wave. We begin with the following baseline model specification:

$$y_{ict} = \delta pk_{ct-1} + \beta_k' x_{ict} + \alpha_k' z_{ct} + f_c + f_t + \varepsilon_{ict} \tag{1}$$

The variable of interest is pk_{ct-1}, which is a binary indicator for the lagged presence of peacekeepers. It equals 1 if UN military forces operate in a county c at time $t -$

1 (i.e. the period before each wave), and zero otherwise. Notice that since we have data on deployment before the first wave as well, using a lag of UNMISS peacekeepers presence does not result in the first wave being dropped in the analysis. The use of lagged presence is motivated by the expectation that the impact of peace missions is not immediate, especially when they shape individuals' economic habits and subjective well-being. Furthermore, some questions in the survey refer to months before the survey; hence the lag of peacekeepers' presence is key to reduce obvious concerns of reverse causality. Therefore, with δ we evaluate the effect of presence vs. absence of peacekeepers. The vector x_{ict} contains an array of household characteristics taken from the HFS such as ethnicity (dummy for Dinkas), household's size and dummies for whether respondents live in rural areas and have migrated within the same county. Since survey respondents are household heads, we also control for individual-level characteristics such as married status, gender (dummy for women), age, educational attainment and religion (dummy for Christians). To remove county-level heterogeneity that might affect simultaneously the likelihood of UNMISS deployment and the level of variables y_{ict} in a county, we add a vector z_{ct} of county-level characteristics. These characteristics are identified as important confounders based on a set of tests we carry out to mitigate concerns about selection bias in SI C (p.7). Additional unobserved county-level heterogeneity is controlled for with the inclusion of county fixed effects f_c. The vector f_t is a set of three wave dummies that capture the effect of possible macro-shocks affecting all units in a given wave. Finally, ε_{ict} is the disturbance term. We report robust standard errors clustered at the household level throughout the analysis, to control for arbitrary group-wise heteroskedasticity. We estimate all models using ordinary least squares (OLS).

To reassure that our results do not depend on selection bias we carry out the following three tests (shown in SI C, p.7). First, we test for parallel trend in violent events between exposed and unexposed counties before the mission deployment (SI C.1, p.7). We show that the two groups exhibit the same trends in violence. Second, we check whether past county-level violence is a predictor of deployment (SI C.2, p.7). We do not detect any effect of past violence on peacekeepers' deployment. Third, we examine which counties' pre-deployment characteristics are relevant determinants of the presence of peacekeepers in a county (SI C.3, p.8). We identify factors most likely to predict deployment based on the existing literature (Ruggeri, Dorussen and Gizelis, 2018; Townsen and Reeder, 2014). We find that only agricultural and pasture land, and previous presence of UNMIS between 2005-2010 are significant predictors of deployment. We add the first two factors to the model (1) and we use the UNMIS indicator to implement an instrumental variable model (SI C.5, p.13). The land-related variables are from PRIO-GRID (Tollefsen, Bahgat, Nordkvelle and Buhaug, 2016) and are measured in 2010 - one year before deployment. They are interacted with survey waves dummies to allow them to differ by wave. This allows us to further corroborate our argument, which holds even when pre-deployment factors driving selection are accounted for.

To test our argument that peacekeeping contributes to the economic well-being of households via different channels, we proceed as follow. We first estimate the effect of UNMISS on the outcomes of interest using the model in equation (1) (Table 1). Second, we explore the relevance of some of the underlying channels or mediators using mediation analysis in presence of multiple mediators (Imai and Yamamoto, 2013; VanderWeele and Vansteelandt, 2014). In particular, we assess the effect of peacekeeping on the mediators outlined in Figure 1 - i.e., violence, safety, economic transactions and psychological well-being (Table 2). Once we can conclude that peacekeeping affects both economic welfare *and* the mediating factors underlying this relationship, we then estimate the total indirect effect of peacekeeping on the outcomes of interest through all mediators considered. To do so, we follow previous studies (Preacher and Hayes, 2008; VanderWeele and Vansteelandt, 2014) and estimate a seemingly unrelated regression model that includes one regression for the outcome controlling for all mediators and separate regressions for each of the mediators.[15] Then we calculate the total indirect effect (IE) for each outcome j as the sum of the specific indirect effects, i.e.,:

[15]The approach flexibly allows for the possibility that mediators affect one another (see VanderWeele and Vansteelandt, 2014, pp.13-14).

$$IE_j = \sum_i \alpha_{pk[model_i]} \times \beta_{i[model_j]} \tag{2}$$

$$j = \{\text{consumed food, irregular consumption, purchased food, durable goods}\}$$

where α_{pk} is the coefficient of peacekeeping in the model for the mediator i (Table 2), β is the coefficient of the mediator i in the model for the outcome j (Table E.3 in SI), so that i indicates the specific mediator i.e., perceived safety, decreased violence, employment, market distance, future living conditions and life satisfaction. To check the significance of the indirect effects, we calculate standard errors via bootstrap. We also provide bias-corrected and percentile confidence intervals since they better reflect the skewness of the sampling distribution of the product of the coefficients in eq. 2 (VanderWeele and Vansteelandt, 2014).

Results

We first examine households' consumption and then move to testing our proposed causal mechanisms linking them to peacekeeping presence. The main difference across all models shown is the dependent variable. Since most outcomes are dichotomous, coefficients correspond to marginal effects on linear probabilities. The only exceptions are per capita goods (in units) and traveling time to closest market (in hours). The tables below report results for the main independent variables, but full tables are available in SI E (p.17).

In Table 1, we assess whether the presence of peacekeepers improves households' well-being by looking at food consumption, irregular consumption, food purchases and durable (non-food) goods respectively. Column (i) suggests that households report higher per capita food consumption - by about 24 units per capita - when peacekeepers operate in their county. The estimated magnitude is not only statistically significant but also economically meaningful as average food consumption is 86 units per capita. In column (ii) we estimate the probability that households could not consume food several times in the last month. Results show that peacekeepers' presence reduces the probability of a household reporting lack of food by almost 10 percentage points. Column (iii) shows that households purchase about 23 more units of food per capita in counties where peacekeepers are deployed, suggesting an improvement in households' capacity to buy food, which in turn partly explains increased consumption. Finally, in column (iv) we also detect a positive albeit modest effect of peacekeepers' presence on durable goods within the household, indicating that households do not only increase their consumption of food when peacekeepers operate in their county.

[Table 1 about here]

In Table 2, we show whether UNMISS is associated with the variables that theoretically explain its effect on households' well-being. To reiterate, these mediators proxy the channels we illustrate in Figure 1. We first focus here on the effect of peacekeeping on security, measured in terms of perceptions of safety and reported violence reduction within households' neighborhoods (columns (i) and (ii)). Households more likely report heightened perceived security within UNMISS deployment counties by approximately 12.5 percentage points. This is complemented by the result in column (ii) which supports the violence-reducing effect of peace missions. Respondents are more likely to report a decrease in violence levels in their areas and the effect is statistically significant at the conventional levels. [16]

In column (iii) and (iv) we test whether UNMISS contributed to changing economic habits and behavior and the implication this has on employment and access to local markets. First, we explore whether the household head was currently in employment when the survey was carried out to understand whether UN missions' safety-enhancing

[16] We find no statistically significant effect when we estimate the same model using the county-level violent events from ACLED.

effect may also foster labour demand and/or reduce the cost of labor supply for workers who need to move within very unsafe areas. We find confirmation that likelihood of employment for household heads is higher, namely they are 7 percentage points more likely to report they have worked for a salary or wage recently. As we argue, this should in turn bolster consumption as it increases households' capacity for consumption. Furthermore, we would expect peace operations to revitalize local markets and communities as they create conditions for the revival of economic exchanges. Consistently, our analysis finds that traveling time to local markets is shorter when households are in UNMISS counties, and the magnitude of the effect is a sizeable reduction of more than one hour. As we know from anecdotal evidence, peace missions facilitate the return of market activities by improving security conditions, thus reducing the cost of going to the market either as seller or buyer. This return to markets, we posit, enables improvements in consumption pattern as their presence allows more regular access to products.

Finally, we show that UNMISS is also linked to improvements in psychological well-being. More specifically, respondents in counties with UN troops are more likely to expect that their living conditions will improve in the future (column (v)). In particular, expectations that living conditions become at least "fairly good" is 14 percentage points higher in counties where peacekeepers are deployed. If respondents in counties with UN deployment are more optimistic about future living conditions, they should also report higher levels of life satisfaction. Our findings suggest that life satisfaction is almost 5 percentage points higher in areas where peacekeepers are deployed (column (vi)). Coupled with the finding that peacekeepers improve perceived safety and observed violence, this is an interesting insight that beliefs about future conditions are updated and tend to be more optimistic. These are renown factors explaining patterns of consumption as they tend to increase propensity to consume.

[Table 2 about here]

To summarize, Table 1 shows that UNMISS increased consumption of food and durable items for households in counties hosting peacekeepers; Table 2 provides evidence that UN-

MISS also improved the security environment, restored economic opportunities and had a positive impact on households' psychological well-being, thus indicating that these may be possible mechanisms through which the mission exerted the positive economic effect estimated in Table 1. But if this is the case, the effect of UNMISS should be mediated by these factors to different degrees, as we originally hypothesized in our theoretical framework. In Table 3 we report the indirect effects of UNMISS on households' consumption mediated by the variables in Table 2. These are calculated as shown in eq. (2). Column (i) indicates that the mediated effect of peacekeeping via violence, safety, economic opportunities and psychological well-being is about 2 units increase in household per capita food consumption. However, this effect is not statistically significant at the conventional levels. At the same time, we find a positive impact of peacekeeping when all intervening factors are included in the model in Table E.3, thus pointing out the existence of other channels that could that could affect household consumption

In column (ii) we assess the total indirect effect on the probability that household may have irregular access to food. We find that the effect of UNMISS through all mediators corresponds to about 2 percentage point decrease in the household likelihood of reporting irregular food consumption, and this is significant at conventional levels. Moreover, we also find no statistically significant effect of peacekeeping in the model controlling for all mediators, confirming that the effect is mediated and the variables - i.e. violence, safety, economic transactions and psychological well-being - fully mediate between irregular consumption and peacekeeping. Column (iii) reports the estimated mediated effect of peacekeeping on food purchases, and we again detect a positive and significant mediated effect, about 5.5 units increase in per capita food purchases for households living in areas where peacekeepers operate. As the effect of peacekeeping is insignificant when all mediators are factored in, the positive effect of peacekeeping on food purchases is fully mediated by the variables considered. Finally, in column (iv) we uncover a positive mediated effect of peacekeeping on durable goods owned. Also in this case the battery of mediators seems to fully capture the channels through which UNMISS produce its economic-enhancing effect.

[Table 3 about here]

Robustness checks

In the SI, we provide some extensions to corroborate the robustness of our main conclusions. The first set concerns endogeneity. The estimation of the models using OLS quantifies the relationship between the presence of peacekeepers and households' well-being through the parameter δ, while keeping constant all other factors. This coefficient gives a measure of conditional correlation. There could be an ex-ante positive correlation between the deployment of peacekeepers and local economic conditions because of county-specific time-varying features, which are not absorbed by the county fixed effects. If this is the case, the OLS estimates of δ is biased. The severity of the bias will depend on the extent to which these factors can be observed and thereby controlled for. In terms of direction, on the one hand, if peacekeepers are associated with the end of an otherwise short-term spell of violence, reported economic well-being could be biased toward improvement. On the other hand, if locals associate the peacekeepers to expectations of imminent or future episodes of violence, then the results would be biased against finding a positive effect of peacekeeping on economic conditions. We believe that the latter bias is more likely to be present, not the least because we focus on active civil wars where violence begets violence. Households in conflict are likely to maintain high levels of risk aversion (Jakiela and Ozier, 2019), which make them less likely to expect immediate improvements from peacekeeping. This is crucial if peacekeepers tend to deploy to locations where violence lingers rather than disappearing completely. If this is the case, our estimates are biased towards zero, which makes South Sudan an even harder case-study.

In addition to checking the presence of parallel trends (SI C.1, p.7) and including the drivers of peacekeeping deployment in the main models (C.2 and C.3, p.7-8), we further address this issue using two additional complementary strategies: a matching approach (C.4, p.10), in particular a propensity score matching and an inverse probability weighted regression adjustment (IPWRA); and an instrumental variable approach (C.5, p.13) that leverages plausibly exogenous variations in the presence of previous infrastructures built to host the previous mission in Sudan (UNMIS). We discuss the details of both strategies in the SI, including the validity of the instrument. We acknowledge that these approaches have limitations but addresses the problem of endogeneity in different ways, both confirming the plausibility of the results we presented. The only result that loses statistical significance is the positive effect of UNMISS on irregular consumption.

Finally, SI D (p.15) details other robustness checks. Because of space limitations, the tables are not reported but can be reproduced using our replication material. First, we estimate the baseline equations using logistic and poisson regression. Second, we exclude respondents in the capital Juba and exclude wave 3, which was partly carried out remotely. Third, we investigate the issue of spatial dependence and include spatial lags of the dependent variables. Fourth, we replace the dummy for UNMISS presence with the logged size of the deployment from RADPKO.[17] Finally, we also control for conflict events, which we do not do in our main models to avoid post-treatment bias, and past UNMIS presence. Overall, results are not substantively affected and models yield estimates in line with those reported in Table 1, with the possible exception of food consumption.

Conclusions

The UN has long been concerned with helping conflict-torn countries by creating the conditions for lasting peace. Many studies have shown that UN peacekeeping is effective in reducing the level of violence in ongoing conflicts but, as of yet, despite the strong link between economic recovery and conflict re-occurrence, empirical evidence on whether security interventions can mitigate the negative effect of conflict on households' living conditions has been limited. Moreover, the extent to which security-enhancing interven-

[17]Recent research suggests that also nationality heterogeneity or gender diversity affect mission effectiveness (Karim and Beardsley, 2016; Bove and Ruggeri, 2019; Bove, Ruffa and Ruggeri, 2020). As such, another important question for future research is how diverse composition is also relevant to enhance missions' capacity to sustain local economies.

tions can specifically support households' well-being is even less theoretically understood in a unified framework. These are gaps we aim to fill in this article.

Combining insights from development economics, psychology and conflict research, we argue that security improvements associated with UN missions can enable a return to normality in households' economic behaviors and reduce the psychological impact of daily traumatic stress. These changes are expected to boost consumption as households are more likely to be able and willing to consume. We provide a novel analysis of this household-level economic impact of peacekeeping using the case of UNMISS in South Sudan. We use survey and deployment data to show that households living in locations with UN military presence have improved consumption patterns in relation to food and non-food items overall. Mediation analysis indicates that these improvements are due to the indirect effect of peacekeeping, via the channels we have identified in our framework. In deployment locations, respondents report violence reduction and enhanced perceptions of safety; they are also more likely to have been employed recently and have easier access to markets. Finally, households report better subjective well-being conditions, as they are more optimistic about the future and more satisfied with their lives.

Overall, we find that UNMISS acted as an economic and capacity stimulus to boost households' consumption, and thus their general economic well-being. This holds notwithstanding the hard empirical test of the ongoing civil war in South Sudan. Our case study can yield general theoretical insights with comparative implications. A main advantage of our study is the use of high-frequency household-level data, which allows comparison of several units to mitigate the problem of unit heterogeneity, and controlling by construction for national-level variables that may confound cross-national comparative work (see Snyder, 2001; Pepinsky, 2019). Also, data are likely to be more consistently coded within one national case and this improves the measurement of key economic variables. Perhaps more important, the assumptions required for causal inference are more likely to be met using granular sub-national data. At same time, we agree with Pepinsky (2019) that whereas case-studies do not necessarily guarantee internal validity, cross-national regressions do not automatically increase external validity. The generalizability of the inferences drawn from our case study partially depends on the scope conditions and intervening factors, such as those we outlined above.

Given the trade-off between empirical accuracy and generalizability, we hope that future studies will be able to leverage comparable high-frequency household-level data across different regions and investigate the extent to which our findings apply to other peacekeeping-host countries.

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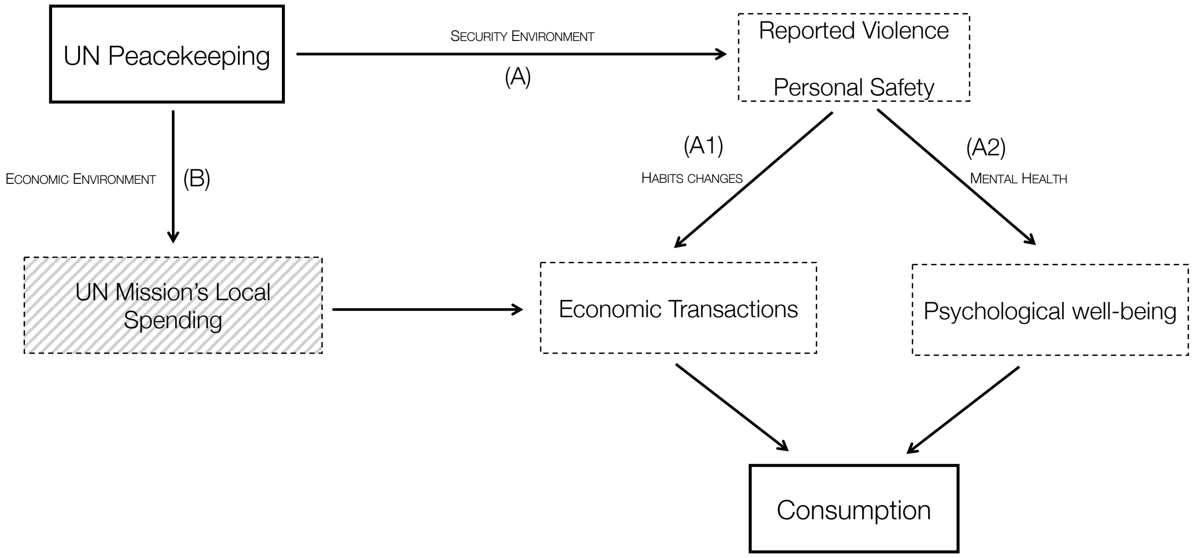

Figure 1: Theoretical Framework

A graphical representation of the theoretical framework linking peacekeeping to households' welfare.

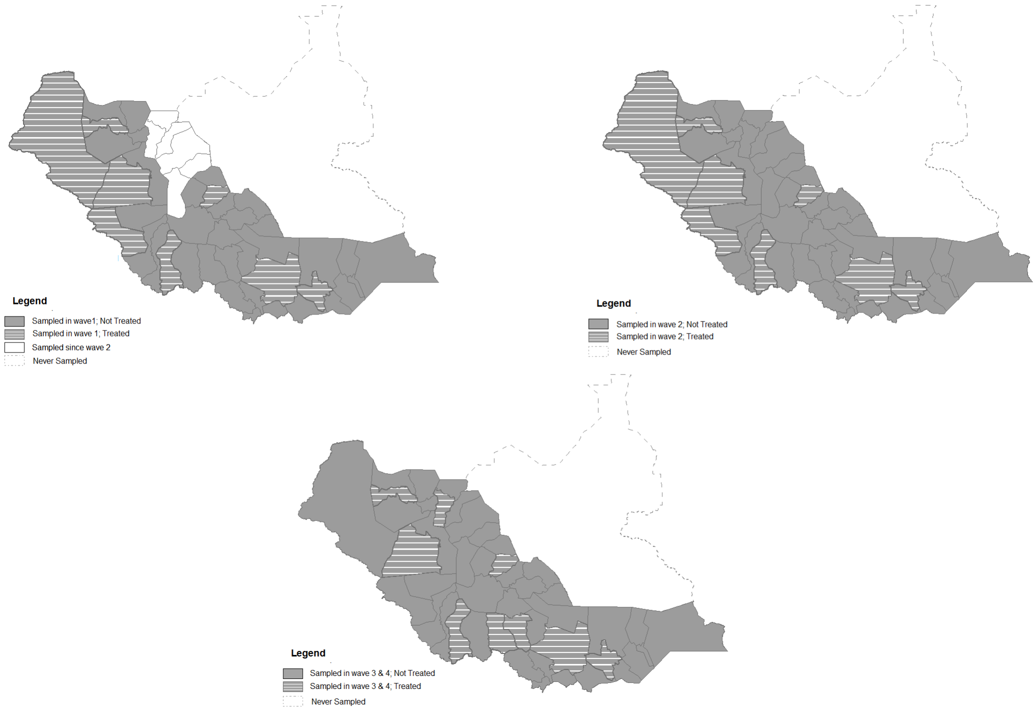

Figure 2: HFS Sampled Counties & UNMISS Deployment.

A map of counties included in the HFS sampling by wave. Stripes indicate counties that also hosted UNMISS troops (lagged at previous time period/wave).

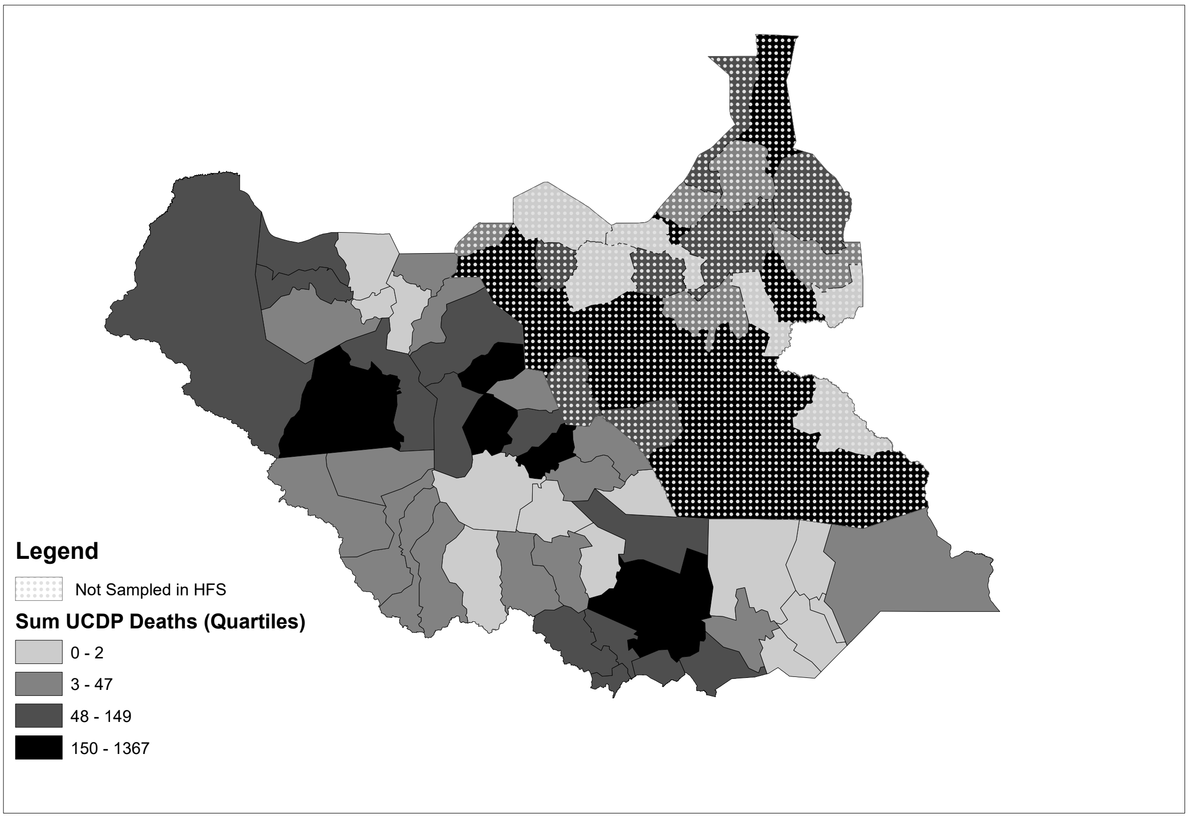

Figure 3: Number of Deaths since 2013 by county.

A map of the number of conflict-related deaths recorded in UCDP since 2013; dotted are is not included in the HFS survey.

Table 1: Peacekeeping impact on consumption

	Consumed Food	Irregular Consumption	Purchased Food	Durable Goods
PKO presence	24.284*	-0.097*	22.855†	0.304*
	(11.594)	(0.040)	(11.898)	(0.127)
Observations	6068	6068	6068	6068
Adjusted R^2	0.103	0.160	0.093	0.353

$\dagger p < 0.10, *p < 0.05, **p < 0.01$
Standard errors clustered by household (in parentheses).
Regressions include county fixed effects, wave dummies, individual- and county-level controls (see Empirical Strategy)

Table 2: Peacekeeping impact on mediators

	Security Environment		Economic Transactions		Psychological Well-Being	
	Perceived Safety	Decreased Reported Violence	Employment	Market Distance	Future Liv. Cond	Life Satisfaction
PKO presence	0.125**	0.100*	0.071*	-1.355**	0.139**	0.052**
	(0.039)	(0.047)	(0.028)	(0.432)	(0.034)	(0.015)
Observations	5936	4967	6068	5324	6065	5959
Adjusted R^2	0.100	0.189	0.248	0.124	0.048	0.135

$\dagger p < 0.10, *p < 0.05, **p < 0.01$
Standard errors clustered by household (in parentheses).
Regressions include county fixed effects, wave dummies, individual- and county-level controls (see Empirical Strategy)

Table 3: Total indirect effects of Peacekeeping on Consumption.

	Consumed Food	Irregular Consumption	Purchased Food	Durable Goods
Indirect Effect	1.760	-0.019*	5.594*	0.028†
	(3.230)	(0.007)	(2.773)	(0.015)
	[-4.651 8.139] (P)	[-0.035 -0.006] (P)	[0.515 11.547] (P)	[0.001 0.059] (P)
	[-4.767 7.717] (BC)	[-0.036 -0.006] (BC)	[0.844 12.227] (BC)	[0.001 0.061] (BC)

$\dagger p < 0.10, *p < 0.05, **p < 0.01$
The figures in the first row represent the mediated effects of UNMISS via all mediator variables, i.e. violence, safety, economic transactions and psychological well-being. Bootstrapped standard errors in parentheses (500 replications). Percentile (P) and bias-corrected (BS) confidence intervals are in brackets.

— Supplementary Information —
UN peacekeeping and households' well-being in civil wars

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A Survey design and questions

The High-Frequency Survey (HFS) is designed as a representative survey of South Sudanese population across 7 states, and builds on the 2008 national census. The World Bank, who carried out the survey, interviewed 22,072 respondents in wave 1, 8,207 in wave 2, 11,430 in wave 3 and 4,588 in wave 4. Some of the respondents were interviewed in more than one survey wave, but in most cases migration and security problems did not allow to keep the panel consistent across waves. For this reason, our analysis uses each wave as an independent cross-section.

The HFS has a stratified two-stage design. In collecting the data, the World Bank planned ahead for the risk that conflict could have disrupted the survey, making the collected data of no use for statistical analysis. As documented in their methodology (Pape, Parisotto, Phipps-Ebeler, Mueller, Ralston, Nezam and Sharma, 2018), each stratum was split into two equal-sized parts, each surveyed in a different phase. This two-phase approach safeguarded the representativeness of the data if conflict erupted in the mid of the wave. Furthermore, enumeration areas were replaced when deemed necessary. This was particularly important for wave 3, when violence re-erupted while the survey was ongoing and it had to be completed remotely (i.e. without World Bank staff in the field). The two-phase strategy and the replacement of enumeration areas is expected to mitigate concerns over representativeness of the surveyed population.

Most households and individuals never moved from the county of birth of the household head. In fact, we have identified 635 household heads and 4,267 individuals (out of 46,297) who are not located in the county where they were born. As such, the survey shows that about 10% of the surveyed population moved from the county of origin. It is interesting that the share of internally displaced people (IDPs) in South Sudan was 13% of the total population[1] based on 2018 UNHCR.[2] Considering that the survey does not cover the most unstable states that produced more than 60% of all IDPs in 2018[3], the survey shows good accuracy and representativeness. Some household heads also reported if they moved within the same county, *forcibly or not*. We include a dummy variable for within-county movements. In addition, we exclude individuals who moved across states as they cannot be geolocated. Below, we list the questions from the four waves of the High Frequency Survey that we used to create our outcome variables and the mediators, and indicate which values were used to dichotomize them when necessary.

[1] Notice these numbers only consider IDPs, thus not including refugees and asylum seekers that left the country.

[2] `https://data2.unhcr.org/en/documents/download/63786`

[3] `https://reliefweb.int/sites/reliefweb.int/files/resources/South_Sudan_2019_Humanitarian_Needs_Overview.pdf`

A.1 Economic welfare

A.1.1 Per Capita Consumed Food in Household

Food items include: bread, coffee, cooking bananas, fish, fruit, meat, milk products, mineral water, oil, sugar, tobacco, pulses, and other products (e.g. fresh vegetables, cereals).

- Wave 1, 2 & 3: What was the total quantity consumed by the household in the last days?
- Wave 4: What was the total quantity of [food item category] consumed by the household in the last 7 days?

A.1.2 Irregular Food Consumption

- Wave 1 & Wave 4: In the past 4 weeks, was there ever no food to eat of any kind in your house because of lack of resources to get food?
  - 0 = Never (1), Rarely (1-2 times) (2)
  - 1 = Sometimes (3-10 times) (3), Often (>10) (4)
  - Missing = Don't know (-98), Refused to respond (-99)
- Wave 2 & Wave 3: In the past 4 weeks, was there ever no food to eat of any kind in your house because of the lack of resources to get food?
  - 0 = No (0)
  - 1 = Yes (1)
  - Missing = Don't know (-98), Refused to respond (-99)

A.1.3 Per Capita Purchased Food in Household

- Wave 1, 2, 3 & 4: What was the total quantity purchased by the household in the last 7 days?

A.1.4 Per Capita Durable Goods in Household

Durable goods include: bicycles, cars, computers, electric ironer, fan, axes, mattresses or beds, mobile phones, motorcycles, radios, refrigerators, television, mosquito nets, DVD or CD players and ploughs.

- Wave 1, 2, 3 & 4: How many [durable good category] does your household own in total today?

A.2 Safety Perceptions

A.2.1 Perceived Safety at Daytime

- Wave 1, 2, 3 & 4: How safe do you feel when walking around during the day?
  - 0 = Very unsafe (5), unsafe (4), neutral (3)
  - 1 = Very safe (1), safe (2)
  - Missing = Don't know (.a), Refused to respond (.b)

A.2.2 Decreased Observed Violence

- Wave 1, 2 & 3: Do you agree or disagree with the following statements? - The level of violence in my neighborhood has increased in the last 6 month.
  - 0 = Strongly agree (4), agree (3)
  - 1 = Strongly disagree (1), disagree (2)
  - Missing = Don't know (.a), Refused to respond (.b)

A.3 Economic opportunities

A.3.1 Recent Employment Status

- Wave 1, 2 & 3: What was the main employment status of [household member] during their most recent (or current) employment?
  - 0 = Unpaid family worker (4), Unpaid working for others (5)
  - 1 = Paid employee (1), Employed (2), Own account worker (self-employed but without continuous employees) (3)
  - Missing = Don't know (-98), Refused to respond (-99)
- Wave 4: In the last 7 days, [household member] worked for someone else [paid work]? In the last 7 days, [household member] worked on his own business?
  - 0 = No (0)
  - 1 = Yes (1)
  - Missing = Don't know (-98), Refused to respond (-99)

A.3.2 Food Market Distance

- Wave 1, 2 & 4: How long does it usually take to walk (one way) to the closest food market from this dwelling?
  - Number of hours
- Wave 3: How long does (in minutes) does it usually take to walk (one way) to the closest food market from this dwelling?
  - Number of hours = Minutes/60

A.4 Psychological Well-Being

A.4.1 Future Living Conditions

- Wave 1, 2, 3 & 4: Personal living conditions here are your assessment of the state of your life, i.e. health or housing. Looking ahead, would you expect your own personal living conditions to be better or worse in three-month time?
  - 0 = Much worse (5), worse (4), the same (3)
  - 1 = Better (2), much better (1)
  - Missing = Don't know (-98), Refused to respond (-99)

A.4.2 Life Satisfaction

- Wave 1, 2, 3 & 4: Overall, how satisfied are you with your life these days? Please state how satisfied you feel, on a scale from 0 to 10. 0 means you feel "not at all satisfied" and 10 means you feel "completely satisfied".
  - 0 if score < 7
  - 1 if score $>= 7$
  - Missing = .

B Descriptive Statistics

Table B.1: Descriptive statistics

	Mean	Standard deviation	# Obs.
Outcome variables			
Consumed Food p.c.	86.70066	241.3045	6068
Irregular Food Cons.	.4128214	.4923818	6068
Purchased Food p.c.	79.13058	241.8438	6068
Durable Goods p.c.	1.385227	1.449416	6068
Mediators			
Perceived Safety	.7585916	.4279734	5936
Decreased Violence	.7429032	.4370772	4967
Employment	.2008899	.4006989	6068
Time to Market	1.658383	3.422356	5324
Future Living Cond.	.3034066	.4597679	5959
Life Satisfaction	.0849134	.2787758	6065
Individual-level variables			
Married	.7666447	.4230013	6068
Household Size	6.35646	3.196441	6068
Woman	.4062294	.4911688	6068
Age 15-64	.8436058	.3632586	6068
Primary Education	.4250165	.4943862	6068
Secondary Education	.3833223	.4862358	6068
Rural area	.6029993	.4893165	6068
Migrant Household	.7186882	.4496763	6068
Christian	.8744232	.3313991	6068
Dinka Tribe	.3849703	.4866284	6068
County-level variables			
% Agriculture Land	10.14711	4.387637	46
% Pasture Land	74.91727	9.274238	46
PKO presence	.336849	.4726718	46
PK-UNMIS presence	.4034278	.4906256	46

The descriptive statistics are calculated on the sample used for the estimation.
County-level variables refer to 2010.

C Selection Bias

In this section we present a number of additional results to assess the robustness of our main findings to the main threats to identification. In particular, we address selection bias arising from both observed and unobserved differences in treated and control counties. We use five complementary strategies. First, we check whether treated and untreated counties differ in terms of pre-deployment trends of violence (C.1); second, we investigate whether deployment is driven by levels of violence using leads and lags of conflict events at the county level (C.2); third, we explore whether peacekeeping deployment is driven by other county-specific characteristics to make sure they are not omitted from the main models (C.3); four, we present results from the matching models based on two different matching strategies to show results are not driven by covariates imbalance between treated and control group (C.4); and finally, we propose an instrumental variable analysis (C.5). Each of these strategies address different sources of possible endogeneity, and they report results that are overall consistent with the main models reported in the article.

C.1 Parallel Trends in Violence

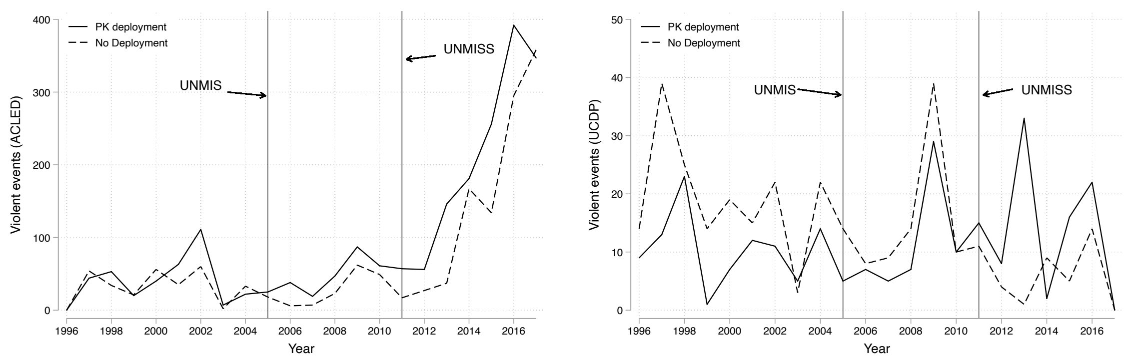
We check for the presence of parallel trends in conflict by visual inspection of the time series of violence between the group of surveyed counties where peacekeepers operate and the control group with surveyed counties without deployment. If there is constant difference between the two groups in the occurrence of violence before deployment, we can infer that decision of where to locate peacekeepers is not fully driven by violence. Figure C.1 shows the evolution of total violent events between groups of exposed and unexposed surveyed counties over the period 1996-2017. Counties are exposed if they ever receive the treatment at some point (i.e. UNMISS deployment). This time period includes years before UNMISS, when UNMIS was deployed to the area. We use conflict data from ACLED (Raleigh, Linke, Hegre and Karlsen, 2010) as well as conflict data from the UCDP (Sundberg and Melander, 2013). It is clear that the two groups exhibit the same trends in levels of violence. These findings significantly reduce worries about potential correlation between persistent trends in violence and UNMISS deployment, thus alleviating concerns of endogeneity due to omitted variable bias.

C.2 Past Violence as Determinant of Peacekeeping Deployment

To further probe that trends in violence do not predict the locality of peacekeepers as the previous section suggests, we regress the dummy for the presence of peacekeepers in county c at time t on leads and lags of total number of violent events. Our aim is to investigate whether violence occuring years before UNMISS initial deployment predicts peacekeepers presence in each county. So we use county-year as unit of analysis and include lags and leads, respectively for 5 years before and 4 years after UNMISS arrival. Statistically insignificant coefficients on the lags would mitigate concerns on potential endogeneity of pk_{ct} indicator in the estimated equation (1) in the article. The estimated parameters reveal whether past violence is correlated with the presence of peacekeepers and ascertain whether the relationship we uncover in the main analysis is consistent with a causal interpretation. As clear from results in Table C.2, we do not detect any correlation between past violence and deployment, i.e., all coefficient $\beta_{t-1,.,t-5}$ are both individually and jointly statistically insignificant at conventional levels. Results also suggest that the presence of peacekeepers may be associated with increased violence three to four years later. Overall, this reinforces the idea that the deployment of troops is not fully driven by previous levels of violence in a county.

C.3 County-level Determinants of Peacekeeping Deployment

In the previous subsections, we have shown that UNMISS is not systematically more likely to deploy to conflict-affected counties. This, however, does not exclude the possibility that deployment is driven by other county-specific features. For instance, better transportation infrastructure, more developed economic facilities as well as less harsh environmental conditions could facilitate the daily activities of UN contingents (Ruggeri, Dorussen and Gizelis, 2018; Townsen and Reeder, 2014) and increase the success of the mission, thereby being key determinants of deployment decision. If so, outcomes measured in the aftermath of deployment will incorporate the effects of these additional factors and the causal impact of UNMISS will be difficult to disentangle from such dynamics. To examine this issue, Table C.3 shows the cross-county relationship between peacekeeping



(a) ACLED (b) UCDP

Figure C.1: Violent events in counties with and without prospective UNMISS deployment, 1996-2017

Table C.2: UNMISS Deployment and Trends of Violence

	Dependent variable: UNMISS Deployment
Violent events$_{t+4}$	0.002*
	(0.001)
Violent events$_{t+3}$	0.002*
	(0.001)
Violent events$_{t+2}$	0.001
	(0.001)
Violent events$_{t+1}$	0.001
	(0.001)
Violent events$_{t}$	0.002
	(0.002)
Violent events$_{t-1}$	-0.002
	(0.001)
Violent events$_{t-2}$	0.000
	(0.002)
Violent events$_{t-3}$	0.004
	(0.003)
Violent events$_{t-4}$	0.003
	(0.002)
Violent events$_{t-5}$	0.001
	(0.002)
F-test $\beta_{t-1-t-5}$=0	0.397
Observations	948
R^2	0.177

Regressions include county dummies.
$*p < 0.05$
Robust standard errors in parentheses are clustered at the county level.

deployment and a variety of potential determinants measured in 2010. In this cross-sectional setting, peacekeeping deployment is measured as 1 if peacekeepers will ever be sent to a county. The county-specific right-hand-side variables are from Tollefsen, Bahgat, Nordkvelle and Buhaug (2016) and measure the average travel time to the closest urban centre (in minutes), the average distance (in kilometers) to the capital (Juba), the percentage of land surface devoted to agriculture and pasture, the intensity of nightlights as a proxy for socio-economic development, the share of urban land and the average annual precipitation (Henderson, Storeygard and Weil, 2012). We also control for the previous presence of UNMIS in each county. Columns (i) to (ix) in Table C.3 report bivariate correlations between each variable and deployment, and column (x) report the results of a multivariate model. Agricultural land, pasture land and UNMIS presence report a coefficient that is consistently significant at conventional levels in the multivariate model. To account for this cross-county variation in the probability of deployment, we include agricultural and pasture land in our models, as specified in the article (Section 5), because they are also likely associated with households' welfare. We do not include UNMIS presence among our controls as we propose to use it to instrument UNMISS deployment post-2013. We explain in Section C.5 below why we believe UNMIS deployment is likely to predict UNMISS deployment after 2013 and discuss possible violations of the exclusion restriction. We report, however, that the results presented in the article are robust to the inclusion of UNMIS presence as control variable (models not shown, included in the Dataverse documentation with additional analyses).

Table C.3: The determinants of peacekeepers deployment across South Sudan counties.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)
Time to urban centre (min)	0.008									0.001
	(0.038)									(0.031)
Distance to capital (km)		0.049								-0.064
		(0.042)								(0.086)
Agriculture land (%)			-2.115							5.389**
			(1.554)							(2.563)
Pasture land (%)				1.000*						1.894**
				(0.538)						(0.832)
Night lights					4.215					-4.292
					(3.119)					(3.830)
Population (000)						-0.003				-0.008
						(0.002)				(0.006)
Urban land (%)							-0.303			0.207
							(0.460)			(0.918)
Precipitations								0.040		0.079
								(0.028)		(0.048)
PK-UNMIS presence									0.717***	0.816***
									(0.138)	(0.108)
Observations	46	46	46	46	46	46	46	46	46	46
R^2	0.001	0.027	0.054	0.045	0.042	0.053	0.009	0.036	0.480	0.622

$*p < 0.10, **p < 0.05, ***p < 0.01$
Huber-White robust standard errors in parentheses.

C.4 Matching Households

A number of factors have the potential to determine local deployment of peacekeepers. If these factors also predict consumption - our main outcome of interest - it is possible that the estimated impact of peacekeepers might be biased. To reduce this possibility we re-estimate our models by matching. households This methodology assures that individuals in counties without mission deployment are comparable to individuals in counties where UN troops have been deployed so that differences in observed characteristics do not bias our estimates. Matching is implemented on the covariates included in our main model, namely: married status, gender, age, educational attainment, religion (dummy for Christians), ethnicity (dummy for Dinkas), household's size, dummies for whether respondents live in rural areas and have migrated within the same county, state of residence and survey period.[4] Since county-level factors might have an impact on consumption, we also match on two county-level characteristics, i.e. the percentage of land surface devoted to agriculture and pasture as measured in 2010. It should be noted that almost all variables (possibly with the exception of migration status) used in the matching are either

[4]We use state dummies rather than county dummies as the latter almost perfectly predict deployment of blue helmets and therefore cannot be estimated with a sufficient degree of accuracy.

pre-deployment or they measure household heads' characteristics that are unlikely to be shaped by the deployment of a mission.

We implement two different matching procedures. The first one uses propensity score matching, which estimates the impact of peacekeeping as equal to the average of the difference in consumption between treated and matched controls. The second approach is the inverse probability weighted regression adjustment (IPWRA) which, in addition to identifying appropriate comparison units, also controls for the potential impact that covariates might in turn have on consumption outcomes. The IPWRA estimate one model for the treatment and one for the outcome and is "doubly robust" in that it is able to provide correct estimates even though one of the models is misspecified (Wooldridge, 2010). Table C.4 shows that both matching approaches are able to balance covariates between treated and control groups. Indeed the variance ratio of each covariate is very close to one after matching, as we would expect in a balancing test. This is reassuring to the extent that it indicates that matching is able to reduce selection bias based on observed covariates. Results of both analyses are shown in Table C.4. We find results that are overall similar to the baseline model in the article (Table 1) and thus confirm the positive and significant effect of mission's deployment on households' consumption.

Table C.4: Covariate balance summary. Variance ratio for each covariate.

	Variance ratio		
	Raw	Matched after PSM	Matched after IPWRA
Married	1.430701	0.8987095	.9606822
Household size	1.338955	1.058863	1.113128
Woman	1.010733	0.974167	1.002588
Age between 15-64	1.071956	1.102118	1.187189
Primary education	1.004381	1.006054	0.9860713
Secondary education	0.985058	0.9605096	0.9641044
Rural area	1.137485	1.017048	0.9951463
Migrant household	1.097654	.878891	.9500672
Christian	1.037459	0.9689472	1.259253
Dinka tribe	0.9400636	0.9069925	0.9446752
Wave 1 × Agriculture Land (2010)	0.3826801	1.086238	0.9723184
Wave 2 × Agriculture Land (2010)	0.3829529	1.033016	1.021974
Wave 3 × Agriculture Land (2010)	0.7841014	1.16966	1.132294
Wave 4 × Agriculture Land (2010)	2.258013	1.015425	1.197245
Wave 1 × Pasture Land (2010)	1.064238	1.120209	1.004986
Wave 2 × Pasture Land (2010)	1.555896	1.114818	1.115608
Wave 3 × Pasture Land (2010)	0.9787861	0.8329977	0.8912042
Wave 4 × Pasture Land (2010)	2.498429	0.6500204	0.8768266
Northern Bahr el Ghazal	0.6038533	1	1.100217
Western Bahr el Ghazal	2.905531	1.472749	1.690404
Lakes	0.9230704	1.020988	0.9568189
Western Equatoria	1.583012	0.9240868	0.8186095
Central Equatoria	0.2445565	0.5463447	0.7329535
Eastern Equatoria	0.6553684	1.498457	1.180611
Wave 2	1.368759	1.142242	1.125912
Wave 3	0.8893823	0.8607408	0.9107914
Wave 4	2.25832	0.6952638	0.8912913
Treated observations		2044	
Control observations		4024	

Table C.5: PK impact on consumption. IPWRA and propensity score matching estimates.

	Consumed Food	Irregular Consumption	Purchased Food	Durable Goods
PROPENSITY SCORE MATCHING				
PKO presence	20.474*	-0.066†	14.032†	0.196†
	(9.383)	(0.036)	(8.175)	(0.107)
INVERSE PROBABILITY WEIGHTING REGRESSION ADJUSTMENT				
PKO presence	30.451**	-0.061**	24.379**	0.302**
	(8.111)	(0.019)	(6.904)	(0.055)
Treated observations		2044		
Control observations		4024		

$\dagger p < 0.10, *p < 0.05, **p < 0.01$
Robust standard errors in parentheses.

C.5 Instrumenting Peacekeeping

To address concerns on selection bias due to unobserved variables, we estimate an instrumental variables model using the location of the previous UN operation, i.e. UNMIS, as instrument for UNMISS deployment. UNMIS completed its mandate as South Sudan became an independent country on July 9, 2011 and UNMISS was established on the same day. In order for UNMIS deployment to be a valid and credible instrument for UNMISS, two conditions need to be met.

First, for the relevance of the instrument, UNMIS deployment should correlate with UNMISS deployment. It is not surprising that this condition holds considering that UNMISS took over from UNMIS and expanded its presence using UNMIS bases. At least initially, this ensured a smoother transition from UNMIS to UNMISS. Indeed, by looking at RADPKO data (Hunnicutt and Nomikos, 2020) almost half of UNMISS bases were in the same counties where UNMIS was deployed. However, the logics according to which UNMIS was deployed in relation to its mandate and in response to a specific conflict (Sudan vs South Sudan) were largely irrelevant for UNMISS. If this is the case, as we argue below, UNMIS deployment could be argued to be exogenous to households' conditions in South Sudan in 2013, and only affect them via the subsequent UNMISS deployment. This would provide support to the second condition for the validity of the instrument, namely the exclusion restriction: past UNMIS deployment does not affect current households' economic well-being except through its effect on UNMISS deployment. We further motivate this claim below.

To begin with, UNMISS had a multidimensional mandate to support state-building since its inception, while UNMIS was a traditional verification mission. Furthermore, the current size of UNMISS, indeed, is almost twice the size of UNMIS at its maximum deployment in the entire Sudanese territory. In some counties, UNMISS took advantage of existing UNMIS infrastructure that were put together temporarily in support of the referendum, and were then expanded for UNMISS goals. In a sense, this indicated that the presence of UNMISS was related to UNMIS deployment, and that the latter had little to do with the imminent challenges UNMISS had to face, including the outbreak of the new civil wars in South Sudan in 2013.

The outbreak of civil war in 2013 forced an important reconfiguration of UNMISS, making operational differences and challenges between the two missions even more remarkable. As mentioned, UNMIS main task were verifying and assisting the implementation of the 2005 peace agreement, and assisting the government in ensuring security conditions were met. UNMISS, on the other hand, heavily focused on protection of civilians as soon as the 2013 civil war erupted. This required not only a strategic re-orientation of the mission, but also a significant geographic reconfiguration (see UNSC resolution S/RES/2109, 2013).

One could also argue that, with UNMIS deployed since 2005, people in South Sudan had become familiar with peacekeepers and thus being less responsive to their presence. On the one hand, if this is the case, it adds more evidence that South Sudan and UNMISS are a hard case, and our analysis is in fact underestimating what would have happened had local populations not been previously exposed to peacekeeping. On the other hand, we have compared the locations of UNMIS and UNMISS deployment. Some counties (e.g. Renk, Tambura, Pibor, and Pariang) had never hosted UN peacekeepers before UNMISS. This is in line with the expectations that the two missions are in fact different and UNMISS was not simply the follow-up mission after UNMIS.

A final note concerns that possibility that, if our argument is correct, UNMIS had already improved economic conditions for households, suggesting that what we see in the analysis is simply the legacy of UNMIS rather than the direct effect of UNMISS. However, we argue in the article that the main channel through which peacekeepers can improve households' welfare is by improving security conditions, thus enabling changes in economic habits and psychological well-being. If security is a precondition for the economic effect of peace missions, this effect is likely to last as long as security is maintained, and it is not expected to hold long-term effects. Furthermore, UNMIS deployed in post-accord phase with a relatively light military component. As our argument focuses on civil war contexts where interventions focused on security-provision take place, our argument would not necessarily apply to UNMIS as it does to UNMISS. But even if UNMIS might have improved Sudanese households welfare, the brutal and widespread civil wars in 2013 likely obliterated that, thus reducing the impact of any UNMIS economic-enhancing legacy.

We acknowledge that we cannot directly test the exclusion restriction, and that we are proposing a first tentative subnational instrument for peacekeeping; but based on UNMISS reliance on UNMIS infrastructure and the changes in the conditions where the missions operated and their specific goals, there are reasons to consider UNMIS deployment as a valid instrument for UNIMSS deployment *after 2013*. Since the information on UNMIS deployment is time-invariant, we pool all the HFS waves and estimate a pooled two-stage least square model (2SLS). Table C.5 presents the results of this analysis. The bottom part of the table reports that conventional diagnostics instrumental variable regressions. As it is apparent, the instrument highly predicts the UNMISS deployment and the coefficient is strongly statistically significant. Moreover, the large F-statistics reassures on the relevance of the instrument used. As for the impact on consumption, we find that all indicators for household consumption are affected in the expected direction and all impacts, except for irregular food consumption, are statistically significant at the conventional levels. Finally, as is usual in 2SLS model, the magnitude of the effects is somewhat larger than OLS estimates in the main model.

Table C.6: PK impact on consumption. Two-stage least square estimates.

	Consumed Food	Irregular Consumption	Purchased Food	Durable Goods
PKO presence	55.148**	-0.006	46.954**	0.316**
	(13.948)	(0.021)	(9.918)	(0.068)
First-stage coefficient of UNMIS			0.717**	
			(0.011)	
F-test of excluded instruments			4132	
Observations	6068	6068	6068	6068
Adjusted R^2	0.037	0.126	0.047	0.256

†$p < 0.10$, $*p < 0.05$, $**p < 0.01$
Standard errors clustered by household (in parentheses).
Regressions include, wave dummies, individual- and county-level controls (see Section 5)

D Robustness Checks

In this section, we detail the additional tests we have conducted to show that the findings do not depend on specific decisions in the research design. Because of space constraints, we do not report the results in this Appendix but include all these additional analyses in the replication files on Dataverse. We re-estimate and are able to replicate our main results from Table 1 as summarized in Figure D.2:

1. Excluding respondents from the country capital Juba. We show that our results are not due to significant improvements in living conditions in the capital, which is often the focal point of missions' activities.

2. Removing households from wave 3 where, due to re-eruption of violence, interviews were taken remotely.

3. Accounting for possible spatial interdependencies. We include a spatial lag of the dependent variable based on a binary queen contiguity-based spatial matrix. Notice, though, that no spatial interdependence was detected by standard tests (Moran's I and Lagrange multiplier), hence these results should be evaluated accordingly.

4. Including ACLED conflict data as control variable.

5. Including UNMIS deployment interacted with waves as control variable.

6. Using a logistic regression and poisson regression rather than OLS.

7. Using the logged number of peacekeepers deployed in a given county from Hunnicutt and Nomikos (2020).

Figure D.2: Summary of other models (Robustness and Appendix)

E Tables with All Parameters

Table E.1: PK impact on consumption

	Consumed Food	Irregular Consumption	Purchased Food	Durable Goods
PKO presence	24.284*	-0.097*	22.855†	0.304*
	(11.594)	(0.040)	(11.898)	(0.127)
Married	-12.947	-0.017	-2.948	-0.112*
	(11.878)	(0.017)	(8.602)	(0.056)
Household size	-10.046**	-0.007**	-9.783**	-0.119**
	(1.040)	(0.002)	(0.999)	(0.007)
Woman	-9.316	0.004	-10.424†	-0.268**
	(5.944)	(0.013)	(6.035)	(0.042)
Age between 15-64	4.497	-0.021	4.207	0.064
	(7.638)	(0.017)	(6.853)	(0.050)
Primary education	-5.380	-0.017	11.426	0.122*
	(7.932)	(0.018)	(13.526)	(0.059)
Secondary education	11.503	-0.062**	8.889	0.296**
	(10.534)	(0.020)	(9.662)	(0.070)
Rural area	-21.231**	0.094**	-39.042**	-0.413**
	(7.375)	(0.015)	(8.461)	(0.039)
Migrant household	2.783	0.001	-11.254	-0.206**
	(5.741)	(0.015)	(7.433)	(0.041)
Christian	-10.172	-0.017	-3.362	0.009
	(7.639)	(0.020)	(6.919)	(0.064)
Dinka tribe	2.197	0.038	23.621**	-0.226**
	(12.964)	(0.031)	(8.359)	(0.059)
wave=1 × Agriculture Land (2010)	9.190**	-0.011*	7.017**	0.130**
	(1.747)	(0.005)	(2.432)	(0.018)
wave=2 × Agriculture Land (2010)	7.747**	0.001	6.977**	0.080**
	(2.479)	(0.005)	(2.406)	(0.017)
wave=3 × Agriculture Land (2010)	1.571	-0.004	0.753	0.103**
	(1.091)	(0.005)	(1.029)	(0.016)
wave=1 × Pasture Land (2010)	3.233**	0.007*	1.387	0.046**
	(1.168)	(0.003)	(0.964)	(0.013)
wave=2 × Pasture Land (2010)	2.006	0.009**	2.273	0.041**
	(1.479)	(0.003)	(1.405)	(0.013)
wave=3 × Pasture Land (2010)	2.849*	0.002	2.913**	0.059**
	(1.141)	(0.003)	(0.995)	(0.013)
Observations	6068	6068	6068	6068
Adjusted R^2	0.094	0.154	0.086	0.353

$\dagger p < 0.10, *p < 0.05, **p < 0.01$
Standard errors clustered by household (in parentheses).
Regressions include county fixed effects, wave dummies, individual- and county-level controls (see Section 5)

Table E.2: PK impact on mediators

	Perceived Safety	Decreased Violence	Employment	Market Distance	Life Satisfaction	Future Liv. Cond
PKO presence	0.125**	0.100*	0.071*	-1.355**	0.052**	0.139**
	(0.039)	(0.047)	(0.028)	(0.432)	(0.015)	(0.034)
Married	0.018	-0.010	0.008	0.140	0.008	-0.061**
	(0.016)	(0.018)	(0.012)	(0.137)	(0.010)	(0.016)
Household size	-0.002	-0.004*	0.001	-0.014	0.002	-0.006**
	(0.002)	(0.002)	(0.002)	(0.013)	(0.001)	(0.002)
Woman	-0.009	-0.012	-0.102**	-0.066	0.004	-0.039**
	(0.012)	(0.013)	(0.010)	(0.100)	(0.008)	(0.013)
Age between 15-64	-0.007	0.016	0.040**	0.409**	-0.009	0.014
	(0.015)	(0.016)	(0.012)	(0.110)	(0.010)	(0.016)
Primary education	-0.019	0.006	0.034*	-0.138	-0.007	-0.029†
	(0.018)	(0.020)	(0.014)	(0.105)	(0.011)	(0.017)
Secondary education	0.005	0.002	0.120**	-0.193	-0.000	-0.027
	(0.020)	(0.022)	(0.020)	(0.126)	(0.014)	(0.020)
Rural area	-0.011	0.036*	-0.090**	1.703**	-0.011	0.049**
	(0.014)	(0.015)	(0.012)	(0.110)	(0.009)	(0.014)
Migrant household	-0.013	0.046**	-0.036**	0.188†	-0.003	-0.040**
	(0.015)	(0.015)	(0.013)	(0.104)	(0.010)	(0.014)
Christian	-0.008	-0.035†	0.033*	-0.728**	-0.027†	0.010
	(0.017)	(0.018)	(0.014)	(0.179)	(0.014)	(0.019)
Dinka tribe	0.026	0.033	-0.031	0.019	0.002	-0.016
	(0.028)	(0.030)	(0.025)	(0.240)	(0.015)	(0.030)
wave=1 × Agriculture Land (2010)	-0.006	0.004	0.003	-0.075*	-0.009**	0.042**
	(0.004)	(0.003)	(0.005)	(0.036)	(0.003)	(0.005)
wave=2 × Agriculture Land (2010)	0.006	0.017**	0.008	-0.030	-0.007*	0.049**
	(0.005)	(0.005)	(0.005)	(0.022)	(0.003)	(0.005)
wave=3 × Agriculture Land (2010)	-0.017**		0.009†		-0.008**	0.045**
	(0.004)		(0.005)		(0.003)	(0.004)
wave=1 × Pasture Land (2010)	0.001	0.003*	-0.002	0.055**	-0.005**	0.022**
	(0.002)	(0.001)	(0.003)	(0.015)	(0.001)	(0.003)
wave=2 × Pasture Land (2010)	0.005	0.000	0.001	0.077**	-0.003†	0.022**
	(0.003)	(0.002)	(0.003)	(0.016)	(0.002)	(0.004)
wave=3 × Pasture Land (2010)	-0.000		-0.001		-0.004**	0.023**
	(0.002)		(0.003)		(0.001)	(0.003)
Observations	5936	4967	6068	5324	6065	5959
Adjusted R^2	0.098	0.188	0.243	0.120	0.045	0.129

†$p < 0.10$, $*p < 0.05$, $**p < 0.01$
Standard errors clustered by household (in parentheses).
Regressions include county fixed effects, wave dummies, individual- and county-level controls (see Section 5)

Table E.3: PK impact on consumption and controlling for mediators.

	Consumed Food	Irregular Consumption	Purchased Food	Durable Goods
PKO presence	28.520†	-0.048	19.139	0.117
	(14.928)	(0.045)	(15.699)	(0.138)
Perceived Safety	-27.406**	0.000	-1.440	-0.059
	(9.340)	(0.017)	(7.822)	(0.040)
Decreased Violence	18.885**	0.056**	12.505*	-0.014
	(6.569)	(0.017)	(6.376)	(0.042)
Employment	68.628**	-0.017	51.508**	0.250**
	(11.629)	(0.018)	(11.170)	(0.042)
Time to Market	-1.713**	0.015**	-1.413*	-0.022**
	(0.505)	(0.001)	(0.611)	(0.004)
Life Satisfaction	-13.850	-0.085**	31.257	0.114*
	(9.874)	(0.027)	(31.273)	(0.056)
Future Liv. Cond.	5.910	-0.002	-0.124	-0.081**
	(8.905)	(0.015)	(6.969)	(0.029)
Married	-16.152	-0.021	-4.836	-0.147*
	(15.969)	(0.020)	(11.268)	(0.063)
Household size	-10.613**	-0.006**	-10.595**	-0.107**
	(1.232)	(0.002)	(1.157)	(0.007)
Woman	-3.607	0.016	-5.978	-0.239**
	(7.212)	(0.015)	(7.547)	(0.041)
Age between 15-64	-3.007	-0.027	-2.699	0.042
	(9.601)	(0.019)	(8.646)	(0.049)
Primary education	-11.962	-0.028	11.389	0.079
	(9.801)	(0.021)	(18.729)	(0.053)
Secondary education	12.457	-0.062**	6.405	0.239**
	(13.720)	(0.023)	(12.932)	(0.064)
Rural area	-12.235	0.092**	-36.332**	-0.396**
	(9.704)	(0.017)	(11.549)	(0.038)
Migrant household	6.404	-0.021	-7.576	-0.175**
	(6.375)	(0.016)	(8.190)	(0.042)
Christian	-7.592	0.011	2.016	0.032
	(8.784)	(0.023)	(7.833)	(0.056)
Dinka tribe	6.038	0.021	31.106**	-0.178**
	(16.082)	(0.034)	(10.413)	(0.064)
wave=1 × Agriculture Land (2010)	7.627**	-0.007†	6.381*	0.012
	(1.502)	(0.004)	(3.143)	(0.009)
wave=2 × Agriculture Land (2010)	6.665*	0.009†	5.603*	-0.031*
	(2.797)	(0.005)	(2.743)	(0.012)
wave=1 × Pasture Land (2010)	0.460	0.004*	-1.476*	-0.013**
	(0.601)	(0.002)	(0.741)	(0.004)
wave=2 × Pasture Land (2010)	-1.024	0.007**	-1.181	-0.020**
	(1.286)	(0.002)	(1.242)	(0.007)
Observations	4802	4802	4802	4802
Adjusted R^2	0.107	0.188	0.088	0.337

$\dagger p < 0.10, *p < 0.05, **p < 0.01$
Standard errors clustered by household (in parentheses).
Regressions include county fixed effects, wave dummies, individual- and county-level controls (see Section 5)

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