CGPA WORKING PAPER
2025-30

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Forced migration and food crises*

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Abstract

This paper analyses the effects of food crises on forced international migration (FIM) flows using a structural gravity model, thereby testing the influence of liquidity constraints in the context of heterogeneous migration costs and economic resources of potential migrants. We construct a dataset that measures food crises' severity, intensity, and causes. Our results suggest that food crises increase forced international migration. While mild food crises skew international migrants to developed and non-neighbouring countries, more severe events divert them to closer destinations. The results indicate that food crises tighten liquidity constraints on migration, and this worsens as they intensify. Under more severe food crises, migrants may lack the necessary resources to afford the higher costs of migrating internationally, particularly to a developed nation, thus choosing a closer destination or migrating internally.

JEL classification: F22, O15, Q18

Keywords: Forced migration; Food crisis; Food insecurity; liquidity constraints; heterogeneous migrations costs; Gravity equation

*We are very grateful for the comments from Jeff Bergstrand, Yoto Yotov, Jesús Fernández-Huertas, Jesús Crespo-Cuaresma, Taryn Dinkelman and the participants of the 24th INFER Conference, the 38th meeting of the European Economic Association (EEA-ESEM 2023), the XXIV Applied Economics Meeting, the XXIII Conference on International Economics, the G4 meeting of the European Central Bank and the seminar series of Banco de España, and the Midwest International Trade Conference. This research was conducted as part of the Projects PID2021-122133NB-I00 and PID2023-148534NB-I00 financed by MCIN/ AEI / 10.13039/501100011033 / FEDER, EU. This study was also financially supported by the Research Challenges Programme of MICINN and MINECO (Spanish Government & FEDER) (RTI2018-100899-B-I00), the Generalitat Valenciana (CIAICO/2021/006), the Junta de Andalucía (SEJ 413) and the Kellogg Institute for International Studies (University of Notre Dame). The views expressed in this paper are those of the authors alone and do not necessarily reflect the views of the Banco de España or Eurosystem. Declaration of interest: none.

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1 Introduction

> "(...) I've been warning about the perfect storm brewing due to Covid, conflict, climate shocks & now, rising supply chain costs. It is here. 45M lives are at stake - and increasing daily. If you don't feed people, you feed conflict, destabilization & mass migration." David Beasley

On May 19, 2022, the cover story of The Economist (2022), "The coming food catastrophe", described a daunting scenario where the war on Ukraine hits a global food system already weakened by Covid-19, climate change, and energy shocks. That same day, the Executive Director of the UN World Food Programme, David Beasley, declared that the Ukraine conflict "will be a declaration of war on global food security", and that "it will cause famine, destabilization and mass migration in nations around the world". At the same time, the UN secretary-general warned against "the spectre of a global food shortage".

In 2022, the population that could not be sure of getting enough to eat increased to 2.4 billion people - around 30% of global population - and up to 783 million faced hunger (FAO, 2023). Indeed, since 2020, food prices have risen steeply, and over the last years the FAO food price index has reached historical record high levels. The breakdown of the Black Sea Grain Initiative, the imposition of new food-export restrictions in more than 20 countries and the persistence of severe drought and "El Niño" phenomenon further compounded the problem. [1] Accordingly, in their 2023 Global Risk Report, experts from the World Economic Forum ranked a global food supply crisis the fourth among the top risks for 2023 with the greatest potential impact on a global scale (World Economic Forum, 2023).

[1] See the International Food Policy Research Institute's (IFPRI) Covid-19 Food Trade Policy Tracker for more detailed information.

The connection between food insecurity and forced migration (FM) appears evident to policymakers (Concern Worldwide and Welthungerhilfe, 2020; FAO, 2016; FAO et al., 2018).[2] However, existing literature on FM has largely overlooked the role of food crises and security in forced international migration (FIM) flows.[3]

There is evidence that food insecurity significantly contributes to rural-urban migration and internal displacements in developing countries. Factors such as land scarcity, hunger, low crop yields, an inability to provide for families, famines, and food price volatility are driving forces behind internal migration flows (e.g., Corbett, 1988; FAO, 2016; FAO et al., 2018; O'Rourke, 1995; Regassa and Stoecker, 2012; Tegegne and Penker, 2016; van der Geest, 2011). However, most of these studies have concentrated on the micro-level links between food insecurity and internal displacements. Concerning international migration, the existing evidence on the connection with food security is limited.[4]

A coordinated international food security and migration policy agenda requires a deeper understanding of their connection. Nonetheless, there is limited knowledge regarding the impact of food crises on FIM flows, primarily due to three common challenges: theoretical foundations, data availability and empirical models. By advancing the literature in these three areas, this paper contributes in several ways.

First, by gaining a more comprehensive understanding on how various food crises affect FIM flows, this paper contributes to the literature on the role of liquidity constraints on

[2]We employ the term FM to broadly refer to forced domestic and international migration.

[3]Forced migration encompasses individuals displaced by either human-made or natural factors. Human-made displacement occurs when people flee their homes due to armed conflicts (e.g., civil wars), persecution (religious, political, or social), and development efforts (e.g., dams). Natural displacement arises from natural disasters (e.g., floods, earthquakes) or climate change (e.g., deforestation, desertification). Previous literature has widely explored both drivers of FM (e.g., Abel et al., 2019; Brottrager et al., 2023; Feng et al., 2010; Hatton, 2009; Neumayer, 2005; Schmeidl, 1997; Yang, 2008).

[4]Studies by Sadiddin et al. (2019) and Smith and Floro (2020) examined, at the micro level, the relationship between the intention and preparation to migrate and food insecurity.

migrations. Specifically, it aims at testing how heterogeneous migration costs and the economic resources of potential migrants may influence those financial constraints.

Second, we compile a novel database by processing and categorizing reports and unstructured information from FAO's Global Information and Early Warning System (GIEWS). This dataset aims to measure the occurrence, severity, intensity, and underlying causes of food crises and is accessible to researchers. Although some international organizations collect and report information on these events, data is often not readily available to researchers in a user-friendly format.[5] Indeed, Sadiddin et al. (2019) emphasize that data unavailability may be one of the factors contributing to the relatively limited research on migrations and food crises.

Thirdly, this paper employs a structural gravity model that encompasses both domestic and international flows. Estimating a gravity model to achieve unbiased results necessitates the control of the multilateral resistance terms (MRTs) and third-country effects, which, in turn, calls for the inclusion of origin-year and destination-year fixed effects (Anderson, 2011; Paniagua et al., 2021). However, due to collinearity, this inclusion makes it impractical to assess the impact of any country-specific variable that varies across origins and over time, such as our focal variable in this paper. Consequently, most previous studies employing the gravity equation to investigate FIM have typically omitted origin-year fixed effects (Hatton, 2009, 2016).[6] However, this omission comes at the cost of introducing bias into

[5]Other commonly used indicators of food insecurity, such as the Prevalence of Undernourishment (PoU), may be more readily available over extended periods. However, using PoU has been discouraged when examining the link between hunger and migration (see FAO et al. (2018)). This is because PoU is designed to reflect chronic hunger. As individuals experiencing chronic hunger often lack the necessary resources to afford migration costs, the PoU would capture instances of significant financial constraints and liquidity limitations more akin to our severe food crises indicator. Moreover, our paper does not enable us to analyse the influence of liquidity constraints on the relationship between food security and migrations, which we can capture with our food crises indicators.

[6]Except for Carril-Caccia et al. (2021), who adopt a fully specified structural gravity equation

the estimates.

Our empirical approach allows us to overcome this limitation, enabling us to obtain consistent and country-specific estimates of the impact of food crises on FIM. It also mitigates several potential biases commonly present in gravity equations, as underscored by Bergstrand et al. (2015), Beverelli et al. (2023), and Heid et al. (2021). Specifically, this empirical strategy mitigates: (1) omitted variable bias; (2) endogeneity issues between FM and food crises; and (3) variations over time in the border effect, i.e., the ratio of FIM to Internally Displaced People (IDP, i.e. domestic FM).

Finally, we introduce an alternative instrumental variable (IV) approach. This approach employs a two-step strategy in line with Eaton and Kortum (2002), Head and Mayer (2014), and Lanati et al. (2023), employing the level of US wheat stocks weighted by the probability of a country receiving food aid as the instrument (Nunn and Qian, 2014).

Our findings indicate that, on average, food crises lead to a significant 101% increase in FIM compared to IDP. Furthermore, the severity and intensity of these crises appear to be influential factors. While less severe food crises exhibit the most pronounced effects, these effects gradually diminish as the crises become more intense and severe. Specifically, mild food crises encourage more individuals to consider migration to developed and non-neighbouring countries. Conversely, more severe events tend to redirect them towards closer destinations. Additionally, our results suggest that severe food crises have a less pronounced impact on FIM in the context of liquidity constraints.

These results highlight the interplay of two opposing forces. On one hand, food crises stimulate FIM as individuals seek to enhance their food security. On the other hand, severe food crises can exacerbate liquidity constraints related to migration. In such instances, individuals may need to allocate their resources towards immediate food needs, thereby

containing MRT and internal migration flows.

limiting their capacity to migrate to other countries (Smith and Floro, 2020).

Additionally, our analysis underscores the importance of fostering multilateral cooperation on food security and migration policies. Given the ongoing Ukraine conflict, the risks derived from the fragmentation of trade and commodity markets, and the emergence of a global food crisis, our findings provide an additional argument for the need for a ”food corridor”, such as the one proposed by the IMF in their last World Economic Outlook (International Monetary Fund, 2023).

The rest of the paper is organized as follows. Section 2 presents the theoretical framework on the link between FM and food crises. Sections 3 and 4 describe the empirical methodology and data, respectively. Section 5 discusses the results, and Section 6 concludes.

2 Theoretical framework

This section outlines the theoretical framework underpinning the relationship between FM and food crises, from which we derive our empirical approach. To achieve this, we adopt the model proposed by Smith and Floro (2020), which explains migration intentions and preparation at the microeconomic level drawing on the works of Byerlee (1974), Harris and Todaro (1970), and Dustmann and Okatenko (2014). These micro-foundations are subsequently integrated into a structural gravity framework that models FM flows at the macro level, following the approach by Paniagua et al. (2021). These models are also grounded on prior research that has sought to explain bilateral migration through gravity models or has emphasized that migration decisions are rooted in individuals' pursuit of utility maximization (see, for example, Beine et al. (2011), Beine et al. (2016), or Grogger and Hanson (2011)).

Consistent with earlier literature, Smith and Floro (2020) commence with the premise that individuals will migrate abroad if they anticipate achieving a higher standard of living. The authors present the following utility function for an individual born in country i considering staying in that same country i:[7]

$$u_{ii} = \ln(f_{ii} \times x_{ii} \times \eta_{ii}), \tag{1}$$

where f_{ii} denotes individual food security status in the origin country i, x_{ii} individuals' observable characteristics related to their traits (e.g., education) but also to those of their origin country or household, which may affect their intention to migrate, and η_{ii} stand for random individual heterogeneity. Smith and Floro (2020) posit that there is an inverse relationship between the utility of staying in the country i and the level of food insecurity suffered.

The expected utility of migrating to country j is represented by:

$$E(u_{ij}) = E(\ln \varphi_{ij}/\tau_{ij}), \tag{2}$$

where τ_{ij} represents both monetary and psychological costs of migrating to the country j, and φ_{ij} bundles the rest of the parameters. Assuming that when deciding whether to migrate or not, individuals compare the utility u_{ii} of staying in their current location with that of migrating to a potential destination country, an individual will have the intention to migrate if:

$$u_{ii} < E(u_{ij}). \tag{3}$$

[7] Smith and Floro (2020) develop a model for both male and female migrants. Due to data limitations in the present study, we exclude the gender dimension. We use a multiplicative version of their model.

Smith and Floro (2020) also point to the existence of a budget constraint on migrations. That is, an individual may only have a certain amount of resources available (a_{ij}) to cover the monetary costs of migration $m(\mathit{\Gamma}_c)$, so they will only be able to migrate if:

$$a_{ij} \geq m(\Gamma c). \tag{4}$$

In this context, the authors highlight that an individual's capacity to cover the financial costs of migration may be negatively affected by their level of food insecurity. This is because individuals in such situations must allocate a larger portion of their resources to meet immediate food needs, leaving fewer resources available for migration (a_{ij}). In other words, while a food crisis might drive migration intentions by reducing the attractiveness of remaining in the home country (u_{ii}), it can also divert resources away from migration in order to satisfy basic dietary requirements. In fact, both Smith and Floro (2020) and Sadiddin et al. (2019) demonstrate that food crises increase the likelihood of migration intentions but reduce the likelihood of migration preparations (which could eventually lead to actual migration). In simpler terms, even if migration promises an improvement in utility ($u_{ii} < E(u_{ij})$), it may not materialize due to financial constraints ($a_{ij} < m(\mathit{\Gamma}_c)$).

This framework aligns with a broader body of literature on liquidity constraints in migration. Essentially, since migration incurs initial expenses, migrants require access to financial resources to fund the migration process. Financial constraints have consistently been identified as barriers to both internal (Chernina et al., 2014; Mendola, 2008) and international (Angelucci, 2015; Bazzi, 2017; Cai, 2020; Dustmann and Okatenko, 2014; Mckenzie and Rapoport, 2007) migration. The costs associated with migration are another significant factor limiting the migration decision. In the case of international migration, crossing borders incurs higher costs compared to internal displacements, which forced migrants may struggle to cover. Heterogeneity in liquidity constraints and migration costs significantly shapes migration behaviour. For instance, Mendola (2008) found that households with greater initial wealth, thus facing fewer liquidity constraints, tend to engage in higher-return international migration. Conversely, impoverished households often opt for lower-cost but also lower-return internal migration. The relaxation of liquidity constraints, achieved through measures such as guaranteed income (Angelucci, 2015), positive income shocks (Bazzi, 2017), or access to credit (Cai, 2020), has been shown to stimulate migration flows, especially among the poorest or towards destinations associated with high migration costs (Angelucci, 2015; Bazzi, 2017; Cai, 2020; McKenzie and Rapoport, 2010). Nevertheless, persistent income shocks could reduce the incentive to migrate.

The framework described above can be integrated into a structural gravity model to examine the influence of food crises on FM. In this endeavour, we drew upon the gravity model outlined by Paniagua et al. (2021), which is grounded in economic theory. We apply this gravity model to FM flows, formally introducing multilateral resistance terms (MRTs) for FIM flows, following the approach by Anderson and Van Wincoop (2003) in trade and Bertoli and Fernández-Huertas Moraga (2013) in migration.

This model starts from the assumption that the aggregate FM from i to j is determined by:

$$FM_{ij} = G(u_{ij})N_i, \tag{5}$$

where $G(E(u_{ij})) = \frac{e^{u_{ij}}}{\sum_k e^{u_{ik}}}$, all potential destinations being k, and N_i is country i population. In this way, $G(E(u_{ij}()))$ stands for the proportion of individuals that seek to migrate to j from country i, and the probability of a random FM selecting a particular destination is given by a multinomial logit form. Now, making use of Equation (2), which decomposes the expected utility into its two components, we can show that:[8]

$$FM_{ij} = \frac{FM_j N_i}{FM} \times \frac{\varphi_{ij}/\tau_{ij}}{\Omega_j L_i}, \qquad (6)$$

where FM_{ij} is the predicted aggregate flow of FMs from country i to country j. In the first term of the equation, FM_j is the number of FM to country j, N_i is the origin country i population, and FM stands for the world's total FMs. In a frictionless world, FM_{ij} would be equal to the first term of the equation. That is to say, the share of FMs into j would be proportional to the country's i population.

The second term stands for the factors that foster or limit FM. φ_{ij} represents the potential benefits associated with migrating internationally. These benefits partly depend on an individual's food security (Equations 1 and 2). As in Smith and Floro (2020), we assume that the utility gain from migrating internationally (u_{ij}) is positively related to the degree of food insecurity that the individual suffers in the origin country (f_{ii}). Thus, in order for international migration to take place, it should improve an individual's food security status ($f_{ij} > f_{ii}$, $\varphi_{ij} > 0$).

The potential utility gain is also conditioned by the general cost of moving to country j, τ_{ij} ($\tau_{ij} > 1$), from Equation (2), and the individual idiosyncratic cost of moving abroad ϵ_{ij} ($\epsilon_{ij} > 1$, which is linked to η_{ij} from Equation (2)). Migration will take place if $\varphi_{ij} > \epsilon_{ij}\tau_{ij}$. Thus, from Equation (6) it can be inferred that migration from country i to j will be negatively affected by bilateral costs τ_{ij}. The more distant the country j, the more resources the migrant will need to invest.

Moreover, FM is influenced by the multilateral resistance, signifying the relative appeal of country j and the relative feasibility of migration from country i (Anderson and

[8] See Paniagua et al. (2021) for an in-depth description of the steps from equation (5) to (6).

Van Wincoop, 2003; Head and Mayer, 2014). FM is discouraged (or encouraged) by the relative expense of migrating to country j (or the relative attractiveness of country j), represented by Ω_j. Likewise, outward FM from country i is negatively (or positively) influenced by the relative discouragement (or pull) factors of leaving country i, denoted as L_i.

Consistent with the ambiguous impact of food crises on individuals' migration decisions, food crises manifest in L_i in two ways. Firstly, as migrants seek to move abroad to enhance their food security, food crises act as a push factor for FIM. Secondly, the intensity and severity of food crises can hinder migration. This implies that potential migrants must allocate more resources to meet their dietary needs rather than cover the costs associated with migration. It also suggests that migration to countries with higher initial expenses will become less prevalent as food crises intensify.

Since travel costs are not directly observable, after adding a time dimension (t) we represent them with:

$$ln\tau_{ij} = \lambda_{ij} + \varepsilon_{ijt} \tag{7}$$

where λ_{ij} captures time invariant drivers of bilateral migration such as distance, common language, or religious affinity, and ε_{ijt} is an unobserved i.i.d. friction. By substituting Equation (7) in Equation (6) we obtain a tractable empirical structural gravity equation:

$$lnFM_{ijt} = ln\varphi_{ij} + \lambda_{ij} + \Omega_{jt} + L_{it} + \varepsilon_{ijt} \tag{8}$$

Therefore, FM from country i to country j is influenced by: (1) the potential utility gain, which is inversely associated with the level of food security in the country of origin; (2) bilateral migration costs, which are directly tied to the distance between the countries; and (3) the MRTs Ω_{jt} and L_{it}. Importantly, L_{it} integrates the impact of a food crisis through the two channels elucidated earlier.

3 Empirical strategy

The gravity model presented in the preceding section is log-linear (as in Equation 8) and is commonly employed in empirical studies on FM. For estimation, we adopt the non-linear equation proposed by Santos-Silva and Tenreyro (2006). They demonstrate that employing ordinary least squares can introduce heteroscedasticity bias and yield unreliable estimates. Moreover, taking the logarithm FM_{ijt} typically excludes zeros from bilateral variables in the analysis. To address these two limitations, we follow the approach by Santos-Silva and Tenreyro (2006) and employ a Poisson-Pseudo Maximum Likelihood (PPML) estimator to estimate the following structural gravity model:[9]

$$FM_{ijt} = \exp\left(\alpha FOOD_{it-1} \times INT_{ij} + \mu X_{it-1} \times INT_{ij} + \gamma RTA_{ijt-1} + \gamma Migration_{ijt-5} + \beta INT_{ij} \times Year + \lambda_{ij} + \lambda_{it} + \lambda_{jt}\right) \times \varepsilon_{ijt} \tag{9}$$

where FM_{ijt} is the number of forced migrants. When $i = j$, FM_{ijt} takes the value of IDP and $i \neq j$ refers to the number of FIMs. Estimating a gravity model with unbiased results necessarily implies the inclusion of origin-year and host-year fixed effects (respectively λ_{it} and λ_{jt}). This set of fixed effects controls for the MRT and third-country effects (Anderson and Van Wincoop, 2003; Head and Mayer, 2014). As described in Section 2, these vectors (L_{it} and Ω_{jt} in Equation 6) represent the relative capacity (or attractiveness) of migration

[9] Given the inclusion of a substantial number of fixed effects, we utilize the high-dimensional fixed effects PPML estimator provided by Correia et al. (2019).

from country i (or migrating to country j) and control for all country-specific push and pull factors of migration (e.g. violence, total remittance inflows, natural disasters or job opportunities).

Additionally, the model incorporates directional country-pair fixed effects (λ_{ij}), which account for time-invariant bilateral factors influencing FMs, such as geographical distance or the presence of a shared language. Including these fixed effects is crucial as they do not assume that the negative effect of factors like geographical distance on migration between two countries is uniform. For instance, the impact of distance on migration from Venezuela to Argentina might differ from the effect in the reverse direction, from Argentina to Venezuela. Similar to international trade (Agnosteva et al., 2019; Egger and Nigai, 2015), not adequately addressing bilateral migration costs can introduce bias into estimates of country-specific variables. Furthermore, this set of fixed effects helps to mitigate potential endogeneity issues between FM and bilateral trade agreements (Figueiredo et al., 2016).

Our primary variable of interest is $FOOD_{it-1}$, which is an indicator variable representing the occurrence of food crises. It aims to serve as a proxy for individuals' food insecurity, which may drive them to engage in international migration to enhance their personal well-being. One significant challenge in the context of structural gravity models is the inclusion of origin-year fixed effects, as it makes it impractical, due to collinearity, to measure the effect of any variable that varies both over time and across origins, such as our focal variable (food crises). To address this limitation, we adopt the approach taken by Heid et al. (2021) and Beverelli et al. (2023). We incorporate domestic and international flows into our estimations, and interact our variable of interest $FOOD_{it-1}$ with an indicator variable that takes the value one when the flow is international (INT_{ij}). This interaction serves three key purposes.

First, as demonstrated by Heid et al. (2021), the interaction of $FOOD_{it-1}$ with INT_{ij} enables us to determine the extent to which food crises drive individuals toward international migration while accounting for origin-year fixed effects (λ_{it}). Without including IDP in the dependent variable and the interaction of $FOOD_{it-1}$ with INT_{ij}, it would be challenging to fully control for MRTs and simultaneously estimate the impact of food crises on migration. Properly controlling for MRT is crucial because not doing so could lead to biased results, particularly regarding the effect of country-specific variables like food crises (Head and Mayer, 2014).

Second, the associated coefficient (α) quantifies the impact of food crises on the number of FIMs relative to the number of IDP. In terms of the theoretical model presented in Section 2, if α is positive and statistically significant, it indicates that $\varphi_{ij} > \epsilon_{ij}\tau_{ij}$ and that food crises stimulate FIM to a greater extent than forced domestic migration. This also implies that, overall, individuals have sufficient resources to migrate abroad ($a_{ij} \geq m(\mathit{\Gamma}_c)$).

Third, the interaction mitigates potential endogeneity issues that may arise between FIMs and food crises. We leverage domestic data to create an exogenous international border dummy, which we then interact with the potentially endogenous variable. As demonstrated by Nizalova and Murtazashvili (2016), the interaction of a potentially endogenous variable (food crisis) and an exogenous variable renders it exogenous as long as the variable used for interaction is uncorrelated with both the factor of interest and the omitted variables.

As explained by Beverelli et al. (2023) the international dummy takes a value of one for all international flows, so it is independent of any specific country choice and does not systematically vary with food crises. The reason is that INT_{ij} varies at the country-pair level (for all countries) and does not vary systematically with the $FOOD_{it}$ variable, which is country-specific (and only for certain countries) and varies for both IDP and FIM.

Therefore, the interacted coefficient measures the impact of food crises on FIM relative to IDP, effectively capturing the difference-in-differences between domestic and international migration. Therefore, the identification requirements are fulfilled as long as INT_{ij} is not correlated with omitted variables. Since we include origin-year, destination-year, and country-pair fixed effects, the likelihood of omitted variable bias is reduced to covariates at the country-pair-time dimension. Furthermore, with the PPML estimator, these fixed effects map into the multilateral resistance terms of the theoretical model (Fally, 2015). Reverse causality is also ruled out in our setting since we intentionally exclude from the estimations those food crises that coincide with identified migration flows (see Appendix A.2). In any case, in Section 5, we test the robustness of our results by employing an alternative instrumental variable (IV) approach, which departs slightly from canonical gravity, but aids in the identification of the effect if some spurious correlation with some time-varying country-pair omitted variable is still present.[10]

It is important to emphasize that the aforementioned fixed effects do not account for factors that affect FIM differently compared to IDP. This omission allows us to isolate the effect of food crises on FIM relative to IDP. Thus, in addition to food crises, the model incorporates X_{it-1}, which is a vector of control variables interacted with the international border dummy (INT_{ij}) related to country-origin variables that may influence FIM relative to IDP ($X_{it-1} \times INT_{ij}$). This vector includes a binary indicator, which take the value one when a country experiences a financial crisis, an index measuring government voice and accountability, GDP per capita growth, and the number of violent deaths due to organized violence per 1,000 population.

The interpretation of the associated coefficient μ is analogous to α mentioned earlier. For example, the estimated coefficient for the voice and accountability index indicates

[10] The IV strategy yields very similar estimates to the baseline results.

the impact of a change in voice and accountability on FIM relative to the number of IDP. Consequently, these variables aim to control for other factors (specifically, economic conditions, violence, and institutional quality) that may differently affect international and domestic FM.[11]

RTA_{ijt-1} represents a dummy variable that takes the value of one when a pair of countries sign a regional trade agreement. The signing of a trade agreement is expected to promote migration between countries by increasing awareness of new partner countries, strengthening economic ties, and enhancing diplomatic relations between signatory nations. Moreover, trade agreements can have a positive impact on international migration, particularly when they include provisions related to visas, asylum, and labour market access (Figueiredo et al., 2016; Orefice, 2015). $Migration_{ijt-5}$ denotes the population from country i who resided in country j five or more years prior to time t. This variable is included to account for the network effect, which may facilitate FIM from country i to j. Past migrants can assist future migrants by providing support and reducing transaction costs (Beine et al., 2011; Hatton, 2016; Mckenzie and Rapoport, 2007). RTA and migrants' networks are expected to reduce the bilateral migration costs outlined in the theoretical model (τ_{ij} in Equation 6). A similar argument is presented for the context of the trade-migration and the FDI-migration links (e.g. Giovannetti et al., 2024; Peri and Requena-Silvente, 2010).

However, it is important to note that our empirical approach does not consider other time-varying bilateral factors that could also influence FIM. For example, we do not account for policies such as border externalization efforts by the European Union, United States, or Australia, changes in migration routes chosen by forced migrants due to policy alterations or

[11] Please note that λ_{it} and λ_{jt} already account for the origin and destination drivers of FM. Thus, the potential for omitted variable bias is limited. Excluding X_{it-1} from the analysis leads to similar results.

events, or the potential influence of migrant diasporas in transit countries on the likelihood of reaching their final destination (Bertoli et al., 2020; Frelick et al., 2016; Moreno-Lax and Lemberg-Pedersen, 2019; Thielemann, 2004; Wissink et al., 2020).

All time-varying variables are set at time $t-1$ because asylum applications, our proxy for FIM, typically occur in a later period after the events that prompt individuals to leave their home country. This period extends to the point they arrive in the country where they seek asylum. Forced displaced migrants frequently traverse arduous and protracted routes or wait in refugee camps in various transit countries (Hatton, 2017, 2020). Additionally, asylum seekers are not always required to file their applications immediately upon arrival; for instance, in the USA, they have up to one year to do so, and in Spain, they have one month. Furthermore, the literature on food security and migration has suggested that food crises initially trigger internal migrations, with migrants opting for international migration only if the situation persists (FAO et al., 2018). Therefore, including food crises at time $t-1$ enables us to determine whether a food crisis ultimately fosters FIM to a greater extent than domestic migration.

INT_{ij} is an indicator variable that equals 1 when $i \neq j$, indicating international migration between two distinct countries. Similar to the trade literature (McCallum, 1995) and research on foreign direct investment (FDI) (Mayer et al., 2010), this variable reflects people's inclination or ability to migrate internationally rather than domestically within their country. It is important to note that this indicator variable is correlated with country-pair fixed effects (λ_{ij}). To address changes in the border effect over time, we include the international dummy interacted with the year variable ($INT_{ij} \times Year$), effectively controlling for temporal variations in the border effect. Lastly, ε_{ijt} represents the error term. In all our estimates, we compute standard errors clustered at the origin-destination level.

The model specification described in this section minimizes several, well established by the previous gravity literature, sources of bias that may affect our approximation of the effect of food crises on FIM. In Appendix A.3, we show that deviating from our preferred empirical strategy has relevant implications not only for the effect of of food crisis on FIM, but also in other policy-relevant variables, such as violence or RTA. In a nutshell, alternative model specifications can be subject of bias as a result from omitted variable, endogeneity or not properly accounting for the bilateral travel costs.

4 Data

Data on forced migration

The analysis in this study examines the impact of food crises from 2009 to 2017 on FM during the period of 2010 to 2018. Our sample consists of 114 developing countries as origins and 139 countries as destinations, of which 101 are also developing countries (For a detailed list of countries included in the sample, please refer to Table A.1 in the appendix).[12] Throughout our analysis period, 40 countries experienced a food crisis. Descriptive statistics for all variables can be found in Table A.2 in the appendix.

We collected bilateral data on FIM, which is represented by the number of asylum seekers, from the United Nations Refugees Agency. As shown in Figure 1, the number of new asylum applications grew significantly during the refugee crisis in 2014-2016 and has

[12]We classify countries based on the United Nations Conference on Development and Trade's categorization to identify developed and developing nations. The sample of developing countries is not fully balanced. Some appear only as origin and others only as destination. This is due to data limitations, which exclude certain country-years, and cases where countries lack asylum application data by country of origin. For instance, Vietnam reports statistics on refugees and not on asylum applications, thus it is not available as a destination country. Additionally, some countries appear only as origin, and not as destination, because they were recipient of asylum seekers from few countries. These cases are fully accounted for by the model's fixed effects. For example, Grenada received asylum applications only from Iran in 2010. This observation is not present in the analysis as it is perfectly explained by the country-pair fixed effects (and thus dropped).

remained relatively high since them.

The migrants originate from all five continents, with predominant asylum seeker flows stemming from Asia and Africa, although in some years the flows from Europe and South America are also significant. Figure 2 systematically presents the countries that have submitted the highest volume of new asylum applications within the analysed period, ranging between 200,000 and 1.5 million applications. Notably, this encompasses nations such as Syria, Zimbabwe, Ukraine, and Venezuela, alongside Serbia and Kosovo, Iran, Ethiopia, or Albania. To provide a more comprehensive overview, Figure A.1, included in Appendix A.2, further extends the previous figure to include countries with new asylum applications ranging between 100,000 and 200,000.

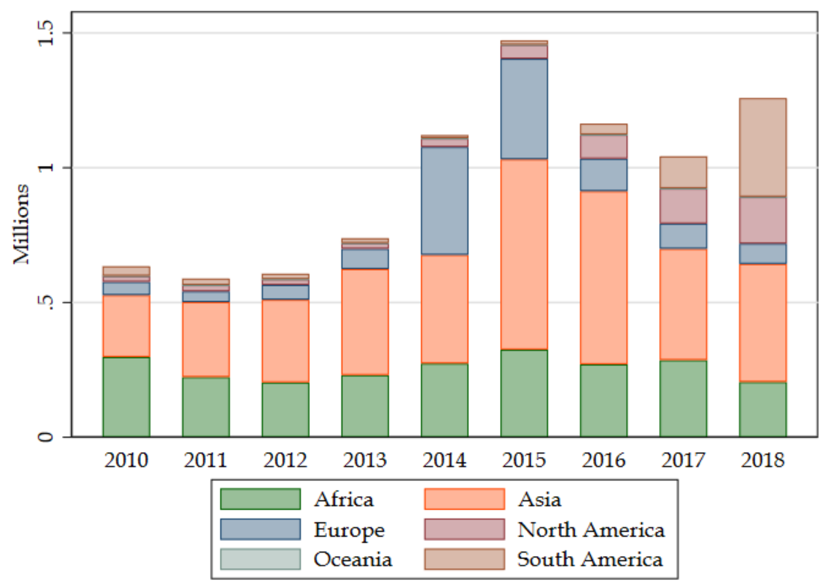

Figure 1: Regional evolution of the number of asylum applications (2010-2018)

It is worth noting that not all asylum seekers meet the criteria defined by the Geneva Convention for refugees, but seeking asylum through an application is one strategy that

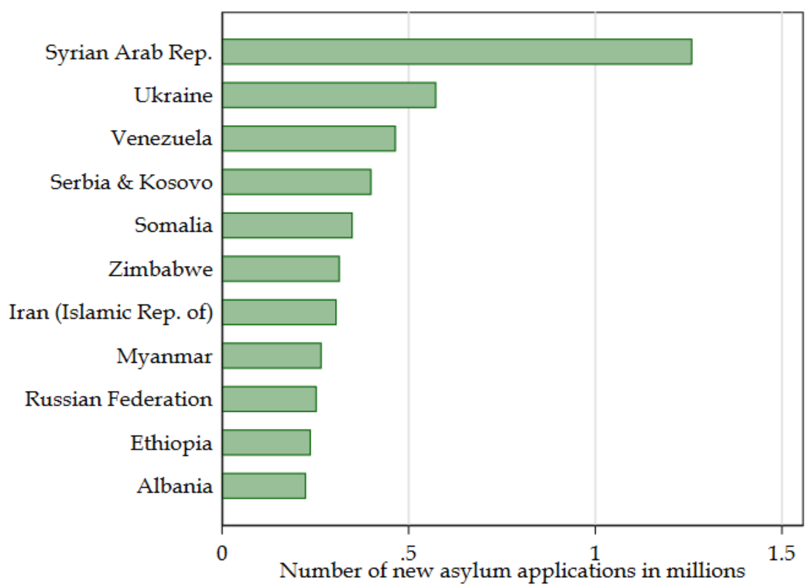

Figure 2: Countries with the highest number of new asylum applications during the period 2010-2018

Authors' own elaboration based on United Nations Refugees Agency asylum application statistics.

FIMs may use to remain in the host country. Over the period of 2010 to 2018, advanced nations recognized between 30% and 50% of asylum seekers as refugees (Hatton, 2020).[13] Rejections do not necessarily imply that applicants did not meet the criteria to be considered refugees, but some rejections may result from applications by FIMs facing hardships not explicitly outlined in the Geneva Convention.

Moreover, the processing of asylum applications takes time, during which potential refugees and other types of FIMs may reside in the host country with specific legal rights that prevent their deportation. For instance, the average asylum application processing time in Italy is eighteen months, and in Spain it ranges from one to two years (AIDA, 2016). Consequently, applying for asylum is a common strategy for foreign individuals who arrive in a country without proper documentation, potentially enabling them to remain in the country in the long term. It is one of several strategies used, even if the rejection of the application is the expected outcome, after which migrants may need to live as undocumented residents and participate in the informal economy (Bloch et al., 2011). People displaced due to food crises would flee and seek asylum to overcome their nourishment necessities, regardless if they meet the refugee legal standard since the time to process petitions is generally longer than the average food crises. In contrast, using recognized refugees would only account for one type of FIM and probably exclude the potential ones due to food crises, while total migrant flows would include international migration not exclusively driven by extreme circumstances. Therefore, we consider the number of asylum applications a more suitable proxy for FIM flows than bilateral migration flows or flows of recognized refugees. Additionally, asylum application data allows us to account for migrant flows between developing countries, unlike other reliable bilateral migration flow

[13] These statistics represent the acceptance rate for processed asylum applications, not the total number of applications made during the period.

data, which is mainly available for flows from developing to OECD countries.

We obtained data on internally displaced people (IDP) from the Global Internal Displacement Database. As illustrated in Figure 3, the size of domestic and international forced migration is not negligible, globally each year, on average, there are nearly 29 millions new forced migrants. Figure 3 also shows that the share of forced international migrants has grown significantly during the period 2010-2018.

The positive trend illustrated in Figure 3 needs to be taken with caution. Although it coincides with a period in which asylum applications have grown significantly, this positive trend could be partially driven by measurement errors from the underlying data. FIM and IDP data are obtained from two different data sources which follow different data collection strategies with potentially different measurement errors. Related to this point, it is also important to note that, as described in the previous section, the dependent variable incorporates FIM and IDP. This implies that a source of bias in our empirical strategy could stem from differences in measurement errors. Nevertheless, the empirical approach that we follow limits this source of bias in two ways. First, the difference in differences strategy serves for suppressing any systematic difference between the way in which FIM and IDP data is collected. Second, the inclusion of a rich set of fixed effects (origin-year, destination-year, and country pair) serve for eliminating the differences between alternative methods for measuring IDP (Campos et al., 2021).[14] Related to this, the destination-year fixed effects account for destination countries characteristics that vary over time. In this way, countries' changes in collection data from FIM and IDP should also be partially be controlled by this set of fixed effects. Furthermore, in the sensitivity analysis with Instrumental Variables we only employ data on FIM and the conclusions from the baseline

[14]This is demonstrated for the case of international and domestic trade by Campos et al. (2021). Unfortunately, we are not aware of an alternative IDP data source that covers our sample of analysis that would allow us to test the sensitivity of our results in the way in which IDP is measured.

analysis remain unchanged.

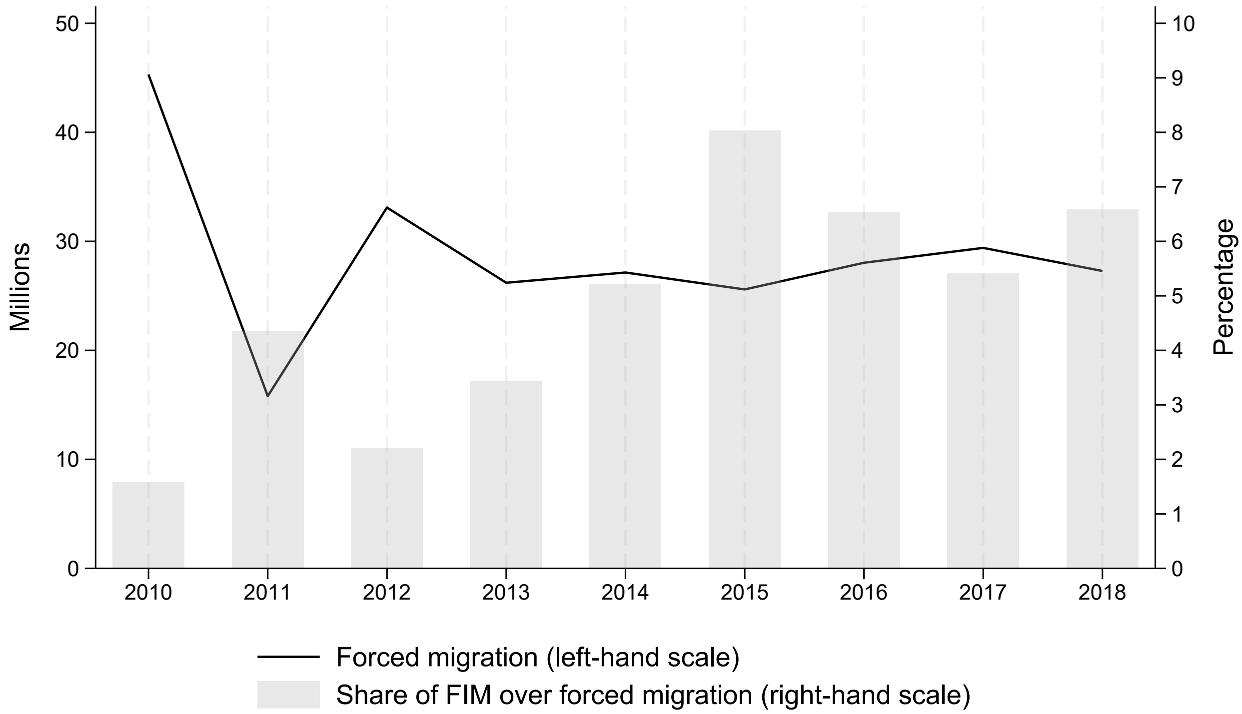

Figure 3: Forced migration flows

Authors' own elaboration based on United Nations Refugees Agency and the Global Displacement Database. Total forced migration is the sum of the number of internally displaced persons and asylum seekers. FIM refers to forced international migrants.

Data on food crises

To analyse the impact of food crises on forced international migration (FIM), we compiled a database that quantifies the occurrence, intensity, and causes of food crises consistently across countries. We sourced this data from the United Nations Food and Agricultural Organization's (FAO) GIEWS (Global Information and Early Warning System) and structured it into a dataset suitable for our analysis.

Working with the FAO data presented challenges due to its unstructured nature, necessitating further processing and organization. We initially scraped the information available on the GIEWS website and transformed it into a database suitable for our research. Since 2009, the GIEWS has been releasing quarterly reports that identify countries experiencing food crises and require external food assistance, amounting to around 1425 records that represent the occurrence of food crises. Our goal was to consolidate this information into a concise set of valuable variables.

The quarterly reports were first condensed into our primary variable of interest "Food Crisis", which is a binary variable that takes the value of 1 for the years when a country is listed in the GIEWS reports. Figures A.4 and A.5, available in the appendix, provides a thorough description of the countries experiencing food crises and the evolution of such crises over time. Two maps showing the geographic distribution of food crises in 2009 and 2019 are also incorporated into the appendix. To additionally test how the duration of a crisis may affect migration flows, we employ an ordinal variable that counts the number of quarterly reports ("No. Q. Food Crisis") that a given country experiences a food crisis for a given year. This variables takes values that range from 0 to 4, 0 representing the no occurrence of a food crisis, and 4 indicating that the country was affected by a food crisis during the whole year. During 2009-2019, 67.7% of the recorded food crises affected the whole year, while 7% only one quarter, 13.6% two quarters and 11.7% three quarters.[15]

Additionally, within each quarterly report, countries are categorized into three levels of food crisis: i) exceptional shortfall in aggregate food production/supplies (Level 1), ii) severe localized food insecurity (Level 2), and iii) widespread lack of access (Level 3). On this regard, it is important to note that during a year a country may have different levels

[15]It is important to note that for the year 2009 only 3 reports are available in the GEIWS database. In the present work we assume that the food crises that occurred during this year did not affect the whole year. However, estimates are robust to assuming that countries with 3 reports are affected by a food crisis during the whole year. To conserve space, these estimates are available under request.

of food crisis. Employing this information, we created a set of indicator variables ("Food Insecurity, lv. 1, 2, and 3") that indicate the types of crises prevailing in each country during the year. Figure 4 provides an overview of the number of food crises classified by the level of food insecurity and their evolution over time, with Level 2 crises being the most frequent type experienced by countries.

We also exploited the number of quarterly reports in order to account for the intensity and duration of food crises. Based on the number of quarterly reports, we created a set of variables that reflect the number of occurrences of each type of food crisis for a given year and country. These variables are named "Intensity Food Insecurity, lv. 1, 2, and 3", and take values ranging from 0 to 4, 0 indicating that a given level of food insecurity has not occurred, and 4 that a given level of food insecurity has occurred during the whole year.

In addition, the GIEWS reports include descriptive paragraphs explaining the origins and causes of each food crisis. We have utilized this information to categorize the crises based on their underlying causes. However, since the primary focus of our analysis does not revolve around the origin and causes of these crises, we have placed a detailed description of this feature of the database in the appendix.[16]

[16]It is worth noting that food crises caused by migration are excluded from the present analysis.

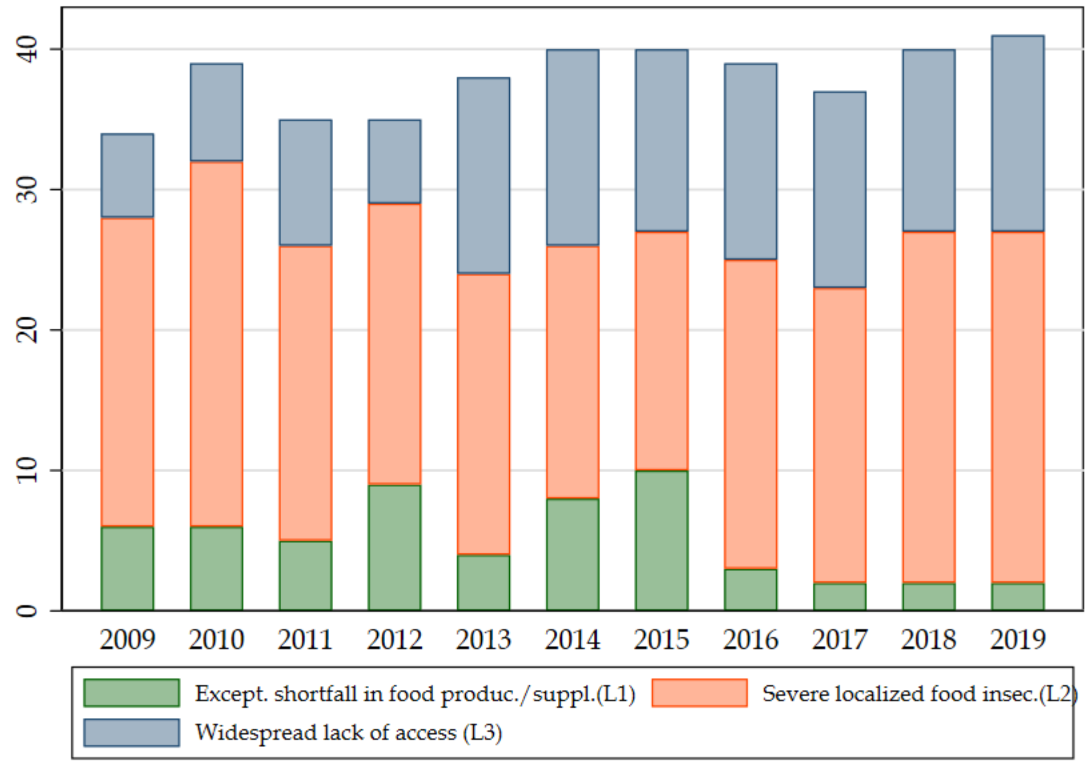

Figure 4: Food crises by year and level

Authors' own elaboration based on GEIWS database.

Other data sources

Data on regional trade agreements are from Mario Larch's Regional Trade Agreements Database (Egger and Larch, 2008). We collected data on the bilateral stock of migrants for the years 2005 and 2010 from the United Nations Population Division. To approximate domestic population figures, we subtracted the stock of inward migrants from each country's total population.

Information on countries that experienced a financial crisis comes from Laeven and

Valencia (2020). Data on countries' GDP per capita growth and population from the World Bank's World Development Indicators. The voice and accountability index is from the Worldwide Governance Indicators (Kaufmann et al., 2011). Finally, from UCDP we obtained data on the number of deaths due to organized violence (Davies et al., 2024; Sundberg and Melander, 2013).

5 Results

The impact of food crises on FIMs

Column (4) in Table 1 displays the estimation of Equation (9), which represents our preferred specification. In column (1) we estimate Equation (9) only with our variable of interest, food crisis, and the fixed effects. From columns (2) to (4) we progressively incorporate the remaining independent variables. As it can be gathered, the inclusion of additional co-variates in the empirical model does not have significant implications on the size and significance of food crisis.[17]

[17] The results reported on Table 1 are robust to the inclusion of additional independent variables related to the origin country: an indicator variable that equals one in the presence of natural disasters, the unemployment rate, and the political stability and absence of violence index from Kaufmann et al. (2011). These variables are excluded from the analysis due to their lack of significance and high correlation with the already included independent variables. To conserve space, these results are available on Table A.5 from the Appendix A.4.

	(1)	(2)	(3)	(4)
Food crisis	0.689**	0.690**	0.661**	0.699**
	(0.299)	(0.300)	(0.299)	(0.304)
Financial crisis			0.717***	0.760***
			(0.216)	(0.215)
GDP pc growth			0.008	0.037
			(0.033)	(0.034)
Voice and accountability				-3.249***
				(0.958)
Violent Deaths per 1,000 Population				2.905***
				(0.742)
Regional Trade Agreement		0.307*	0.318*	0.361**
		(0.164)	(0.164)	(0.161)
Migration stock		-0.039	-0.043	-0.042
		(0.070)	(0.070)	(0.070)
Observations	32074	32074	32074	32074
Country pair FE	X	X	X	X
Origin-year FE	X	X	X	X
Destination-year FE	X	X	X	X
$INT_{ij} \times Year$ FE	X	X	X	X
IDP	Yes	Yes	Yes	Yes
$FOOD_{it-1} \times INT_{ij}$	Yes	Yes	Yes	Yes
$X_{it-1} \times INT_{ij}$	Yes	Yes	Yes	Yes

Note: This table reports our main estimates of the effect of food crises on FIM relative to IDP using the PPML estimator (Specification (9)). The dependent variable is the number FIM and IDP between the origin (i) and destination country (j). Our main variable of interest is an indicator variable that takes the value 1 when the origin country suffers from a food crisis. All country level variables and Regional Trade Agreement are included in $t-1$, while migration stock in $t-5$. All country level variables are interacted with the INT_{ij} dummy and take the values for the origin country (i).
Significance levels are designated as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered by country pair.

Table 1: The effect of food crises on FIMs

In Column (4), we observe that a food crisis has a statistically significant positive impact on the number of FIMs relative to the number of IDP. This finding implies that a food crisis in year $t-1$ leads to a larger increase in the number of FIMs in year t than in the number of IDP. Specifically, our estimate suggests that the occurrence of a food crisis results in a 101% growth in FIM relative to IDP ($(e(0.699) - 1) \times 100$). It is important to note that this estimate does not imply that the volume of FIM is greater than that of IDP. Specification (9), which includes origin-destination fixed effects, already accounts for the existing difference in size between domestic and international FM. Furthermore, the inclusion of international-year fixed effects helps control for the changes over time in the propensity of forced migrants to migrate internationally relative to domestically

(Bergstrand et al., 2015; McCallum, 1995).

As a sensitivity analysis we replaced the food crisis indicator variable by a ordinal variable that counts the number of quarterly food crisis reports by country and year. Estimates confirm the positive effect of food crises on FIM relative to IDP, as it suggests that an additional quarter in which the country suffers from food crises is associated to an increase in FIM relative to IDP, indicating that the duration of the crisis matter (See Table A.6 in the Appendix A.4.).

In order to illustrate our results more effectively, Figure 5 shows the evolution of the international-year fixed effects for countries that do not suffer ($INT_{ij} \times Year$) and do suffer from a food crisis ($FOOD_{it-1} \times INT_{ij} \times Year$).[18]

The interaction between the border variable and time is commonly interpreted as a common effect due to globalization. In trade, the magnitude of the border effect has reduced over time (Bergstrand et al., 2015). In forced migration, however, we do not observe this trend. For countries that have no food crisis, estimates show the change on the propensity to migrate internationally between 2011-2018 relative to the base year 2010. For countries that suffer from a food crisis, estimates show the extent to which this affects the propensity to migrate internationally relative to the countries that do not suffer from a food crisis. As can be gathered, for each year the international dummy is usually larger for the countries that suffer from a food crisis, suggesting that these countries have had a larger reduction of the border effect than those that did not suffer from a food crisis. In other words, the propensity for migrating internationally relative to domestically has increased more in countries that suffered from a food crisis.

Estimates reveal that financial crises also increase FIM relative to IDP, while GDP per

[18]To obtain these estimates, specification (9) is modified by replacing the $FOOD_{it-1} \times INT_{ij}$ by $FOOD_{it-1} \times INT_{ij} \times Year$. This allows us to obtain yearly estimates on the effect of food crisis on FIM relative to IDP.

capita growth do not have a significant effect. The deterioration in government voice and accountability fosters FIM relative to IDP as well as an increase in the number of violent deaths per 1000 population. The signing of a Regional Trade Agreement increases the amount of FIM by 43% ($(e(0.361) - 1) \times 100$). Migration stock is insignificant, suggesting that the population of migrants does not significantly reduce transaction costs for today's FMs. The fact that the coefficient is not significant might also hide several opposite forces. For example, having a strong community in the potential destination might help perspective migrants to move before they are forced to and to reach the destination regularly.

For some internationally forced migrants the process of migration takes longer than a year (International Organization for Migration, 2024). Unfortunately, to the best of our knowledge, there are not systematic statistics that approximate the average length of the journey that a forced migrant has from the country of origin until the destination, in which the asylum application is filed, is reached. Furthermore, this is likely to significantly differ between origin-destination countries, routes, and the specific circumstances that forced individuals out of their country of origin.

Acknowledging this limitation of our empirical analysis, as a sensitivity analysis we lagged all country specific variables and RTA in two periods ($t - 2$).[19] Estimates confirm the positive effect of food crises on FIM relative to IDP. Alternatively, financial crisis and violence become non-significant, which suggests that in $t - 2$ the included independent variables in the empirical model have a lower capacity of explaining FIM relative to IDP (See Table A.7 in the Appendix A.4).

[19]With the exception of migration stock which is specified in $t - 5$.

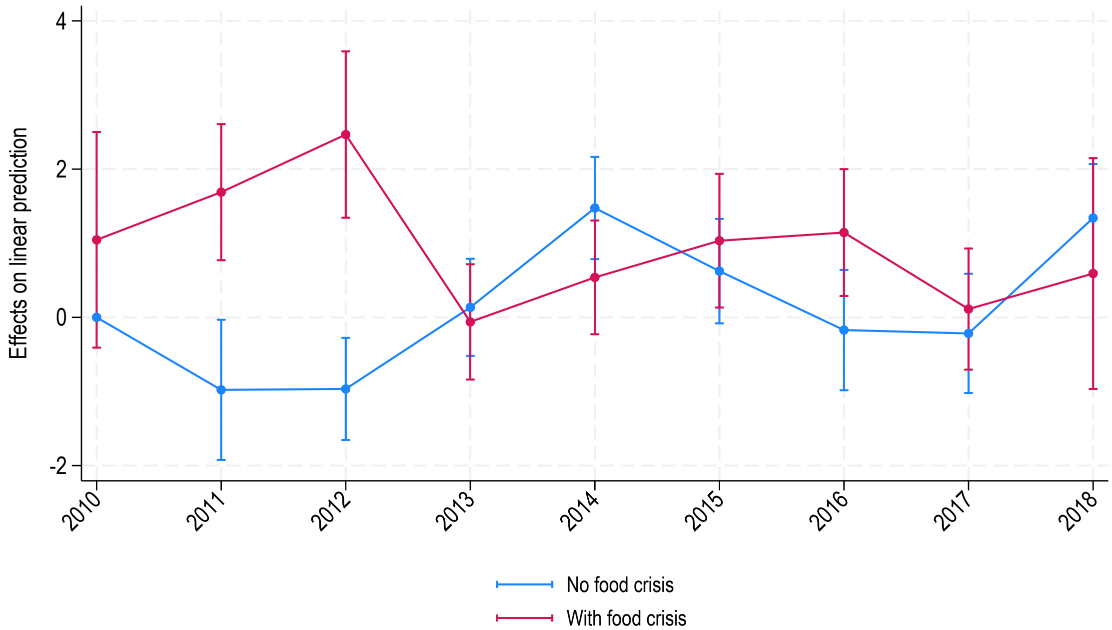

Figure 5: Estimates on the evolution of the border effect ($INT_{ij} \times Year$)

Authors' own elaboration. To obtain these estimates, specification (9) is modified by replacing the $FOOD_{it-1} \times INT_{ij}$ by $FOOD_{it-1} \times INT_{ij} \times Year$. This allows us to obtain yearly estimates on the effect of food crises on FIM relative to IDP.

Liquidity constraints: The impact according to the level of food insecurity

Previous research has provided mixed insights into the impact of negative shocks in origin countries on FIMs. On one hand, such shocks may drive FIM due to deteriorating living conditions and security in the home country. On the other hand, worsening liquidity constraints could limit migrants' ability to move abroad (Angelucci, 2015; Bazzi, 2017; Cai, 2020; Mayda, 2010; Missirian and Schlenker, 2017; Neumayer, 2005). The findings presented in Table 1 reveal that food crises lead to a larger increase in the number of FIMs compared to IDP. This aligns with the hypothesis that negative shocks stimulate FIMs. In this section, we investigate whether this relationship depends on the level of severity of the food crisis.

Table 2 examines the effect of food crises based on their level of insecurity (Column (1)) and the intensity of that insecurity (Column (2)). Figure 6 illustrates the overall impact of food crises on FIM relative to IDP, and the effect by different levels of food insecurity. Food crises with the most pronounced positive effect on FIMs are those classified as Level 1 (mildest crises), while Level 2 still exerts a positive and significant effect but to a lesser degree. These crises increase FIM more than IDP by 643% and 91%, respectively (calculations based on estimates from Column (1)). In contrast, food crises classified as Level 3 in terms of food insecurity do not significantly affect FIM differently from IDP.

	(1) Level of food insecurity	(2) Intensity of food insecurity
Food insecurity, lv. 1	2.006***	
	(0.616)	
Food insecurity, lv. 2	0.646**	
	(0.305)	
Food insecurity, lv. 3	-0.515	
	(0.795)	
Intensity Food insecurity, lv. 1		0.635**
		(0.299)
Intensity Food insecurity, lv. 2		0.411***
		(0.094)
Intensity Food insecurity, lv. 3		-0.107
		(0.361)
Financial crisis	0.735***	0.744***
	(0.207)	(0.210)
GDP pc growth	0.027	0.026
	(0.034)	(0.034)
Voice and accountability	-3.362***	-3.452***
	(0.953)	(0.954)
Violent Deaths per 1,000 Population	2.770***	2.721***
	(0.728)	(0.709)
Regional Trade Agreement	0.367**	0.368**
	(0.161)	(0.161)
Migration stock	-0.045	-0.043
	(0.070)	(0.070)
Observations	32074	32074
Country pair FE	X	X
Origin-year FE	X	X
Destination-year FE	X	X
$INT_{ij} \times Year$ FE	X	X
IDP	Yes	Yes
$FOOD_{it-1} \times INT_{ij}$	Yes	Yes
$X_{it-1} \times INT_{ij}$	Yes	Yes

Note: This table reports the estimates of the effect of food crises by level of insecurity and degree of intensity on FIM relative to IDP using the PPML estimator. The dependent variable is the number FIM and IDP between the origin (i) and destination country (j). In column (1), our main variables of interest are a set of indicator variables that takes the value 1 when the origin country suffers from a food crisis of level 1, level 2 or level 3. In column (2), our main variables of interest are a set of variables measure the occurrence and intensity of the different levels of food crisis. These variables take values between 0 and 4, representing 0 the no occurrence of a food crisis of a given level, and 4 the highest degree of intensity (see Section 4 for a more in detail description). All country level variables and Regional Trade Agreement are included in $t-1$, while migration stock in $t-5$. All country level variables are interacted with the INT_{ij} dummy and take the values for the origin country (i).
Significance levels are designated as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered by country pair.

Table 2: The effect of food crises on FIMs by level of food insecurity and intensity

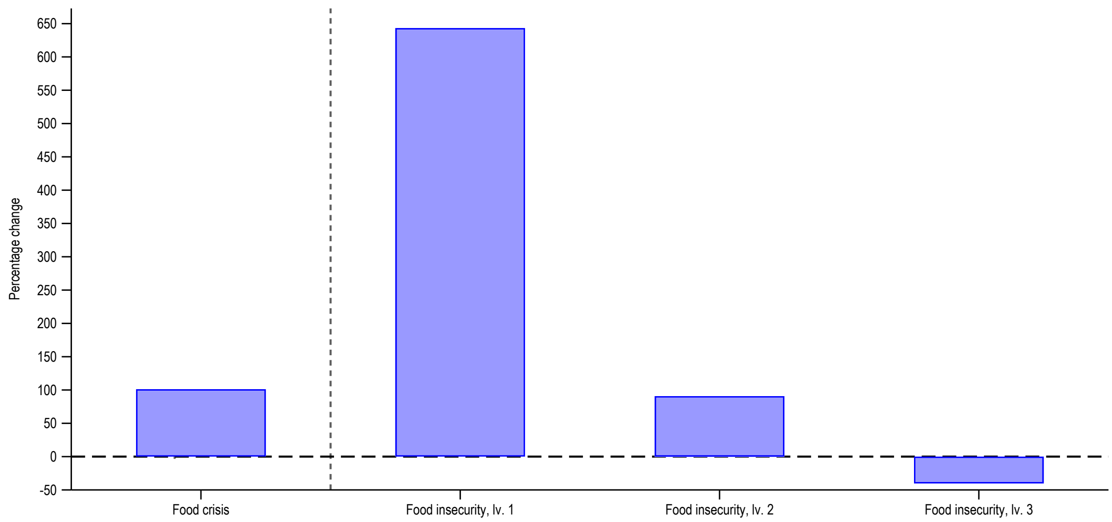

Figure 6: Impact of food crises on FIM relative to IDP (%)

Authors' own elaboration. The overall effect of a food crisis is obtained from column (1) in Table 1. The overall effect for each level of food insecurity is calculated based on estimates from column (1) in Table 2 for the respective indicator variable associated to each level of food insecurity (e.g. food insecurity lv.1 (exp(2.006)-1)×100).

Estimates of intensity (Column (2)) align with the overall findings for each level of food insecurity. An increase in the intensity of food crises with food insecurity Level 1 has a more substantial impact on FIM relative to IDP than an increase in the intensity of food crises with food insecurity Level 2. Furthermore, changes in the intensity of food crises classified as Level 3 do not appear to significantly affect FIM relative to IDP. From these estimates, it can also be inferred that each additional quarter in which a country experiences Level 1 and Level 2 food crises leads to an increase in migration flows. This suggests that the duration of a food crisis is a significant factor in explaining migration patterns.[20]

The results concerning the level of food insecurity and intensity provide some evidence

[20] As described in Section 4, the intensity of food insecurity is constructed with the yearly count of quarterly reports.

that, as the severity and intensity of food crises increase, the positive effect of these crises on FIMs relative to IDP diminishes. These findings align with the work of Smith and Floro (2020) and Sadiddin et al. (2019), who demonstrate that severe food crises can increase an individual's intention to migrate while decreasing preparations for migration. This pattern also resonates with the literature on the impact of financial constraints on migration decisions.

As outlined in our theoretical framework, during food crises, potential migrants may need to allocate their resources to address urgent food needs, reducing the availability of resources (a_{ij}). This, in turn, tightens financial and liquidity constraints, limiting their ability to undertake migration. Consequently, our results suggest that when food crises are less severe, implying fewer financial constraints, migrants may still manage the higher costs associated with international migration. However, as food crises intensify and liquidity constraints become more significant, individuals' ability to engage in international migration may be restricted. While the studies by Smith and Floro (2020) and Sadiddin et al. (2019) focus on individual migration intentions and preparations at the micro level, our analysis demonstrates that the intensity of food crises can negatively impact actual FIM at the macro level, corroborating our proposed theoretical framework.

Testing the mechanisms of liquidity constraints: heterogeneous costs and resource availability

In this section, we conduct several additional tests to ascertain whether financial constraints indeed drive the reduced impact of more intense food crises on FIM relative to IDP. We expect that changes in either migrants' resource availability (a_{ij}) or migration costs ($m(\mathit{\Gamma}_c)$) would influence the positive effect of food crises on FIM. To explore this, we perform three different tests.

The first two tests relate to the costs associated with migrating abroad. We differentiate between migration to developed countries, which tend to have higher costs due to factors such as bureaucratic requirements and travel expenses, and migration to neighbouring countries, which typically have lower costs. We hypothesize that as the intensity of food crises increases, there will be a reduced propensity to migrate to developed countries and an increased propensity to migrate to neighbouring countries.

The third test focuses on broader macroeconomic factors that may affect potential migrants' resource availability (a_{ij}). Specifically, we examine whether the impact of more intense food crises on FIM relative to IDP is lessened when potential migrants' income decreases.

To conduct these tests, we estimate nine separate regression models, interacting the different food crisis variables with indicator variables that account for destination country characteristics (developed, neighbouring) or source country characteristics (negative GDP per capita growth). The main results are summarized in Table 3, while full estimates are available in the Appendix A.4.

		Developed	Neighbour	GDP pc negative growth
		Test 1	Test 2	Test 3
Estimate 1	Food crisis	0.752**	0.553*	0.717**
		(0.310)	(0.305)	(0.305)
	x Interaction	-0.142	0.611	-0.308
		(0.162)	(0.487)	(0.666)
Estimate 2	Food insecurity, lv. 1	1.729***	2.170***	1.994***
		(0.651)	(0.509)	(0.630)
	x Interaction	0.313	-1.281	3.786***
		(0.280)	(0.829)	(0.868)
	Food insecurity, lv. 2	0.755**	0.504*	0.749**
		(0.312)	(0.295)	(0.299)
	x Interaction	-0.298*	0.951**	-0.746*
		(0.169)	(0.397)	(0.392)
	Food insecurity, lv. 3	-0.370	-0.597	-0.206
		(0.798)	(0.805)	(0.788)
	x Interaction	-0.554**	0.854	-1.923**
		(0.249)	(0.564)	(0.860)
Estimate 3	Intensity Food insecurity, lv. 1	0.408	0.741***	0.646**
		(0.310)	(0.247)	(0.304)
	x Interaction	0.311***	-0.582***	0.949***
		(0.096)	(0.156)	(0.190)
	Intensity Food insecurity, lv. 2	0.455***	0.380***	0.463***
		(0.100)	(0.096)	(0.097)
	x Interaction	-0.098*	0.201	-0.252***
		(0.053)	(0.126)	(0.083)
	Intensity Food insecurity, lv. 3	-0.051	-0.127	0.110
		(0.366)	(0.351)	(0.330)
	x Interaction	-0.161*	0.177	-0.549
		(0.083)	(0.174)	(0.387)

Note: This table reports the mechanisms of the effect of food crises on FIM relative to IDP using the PPML estimator (Specification (9)). The dependent variable is the number FIM and IDP between the origin (i) and destination country (j). In estimate 1 our main variable of interest is an indicator variable that takes the value 1 when the origin country suffers from a food crisis. In estimate (2) our main variables of interest are a set of indicator variables that takes the value 1 when the origin country suffers from a food crisis of level 1, level 2 or level 3. In estimate 3, our main variables of interest are a set of variables measure the occurrence and intensity of the different levels of food crisis. These variables take values between 0 and 4, representing 0 the no occurrence of a food crisis of a given level, and 4 the highest degree of intensity (see Section 4 for a more in detail description). Food crisis variables are interacted by an indicator variable that takes the value 1 when the destination country is a developed one (Test 1), an indicator variable that takes the value 1 when the destination country is a neighbour one (Test 2), and an indicator variable that takes the value 1 when the country of origin has a negative GDP per capita growth (Test 3). Full estimates are available in the Appendix A.4. Tables A.8, A.9 and A.10 respectively refer to Test 1, 2 and 3.
Significance levels are designated as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered by country pair.
All time-varying variables are included in $t-1$. Estimates include as control variables financial crises, voice and accountability, GDP per capita growth, and a proxy for conflicts (the number of violent deaths due to organized violence) interacted with the INT dummy, and Regional Trade Agreements and past migration. Standard errors clustered at origin$\times$destination level are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: The effect of food crises on migration: Migration costs and income availability

Column (1) in Table 3 investigates whether the impact of food crises on FIM differs depending on whether the destination country is developed. Overall, food crises appear to affect FIM to developed and developing countries similarly. However, when considering the level of food insecurity, a different pattern emerges. Under milder food crises (Level 1), food crises also affect FIM to developed and developing countries similarly. However, as crises become more severe (Levels 2 and 3), the interaction terms become negative and statistically significant indicating that the propensity to migrate to developed countries diminishes. Similar findings are observed when examining the level and intensity of food insecurity. In this case, food crisis with level 1 of food of insecurity have a statistically higher effect on FIM to developed countries.

Column (2) explores whether food crises have a differential impact on FIM in neighbouring and non-neighbouring countries. Overall, food crises appear to propel FIM to both types of destinations. However, when accounting for the level and intensity of food insecurity, estimates to certain extent support the financial constraints hypothesis. Level 2 food crises have a larger impact on FIM to neighbouring countries, while for Level 3 the estimated coefficient of the interaction is positive and close the the standard levels of significance. When the intensity of each level of food insecurity is accounted for, estimates show that Level 1 food crises have a significantly lower effect on FIM to neighbour countries. That is, migrants show lower propensity to migrate to neighbouring countries (as opposed to non-neighbouring ones). However, the lower propensity dissapears when crises of Level 2 and 3 are considered. These results suggests that as the level of food insecurity decreases (and its duration), FIM show a higher propensity to migrate to less costly neighbouring destinations.

Column (3) assesses whether food crises have a different effect on FIM when the source country experiences negative GDP per capita growth, representing a negative income shock that may reduce the availability of resources. While food crises do not appear to have a significant overall effect on FIM concerning the source country's GDP per capita growth, considering the level of food insecurity yields more nuanced results. Specifically, a negative GDP per capita growth seems to increase FIM relative to IDP when the food crisis is at Level 1. In contrast, when the food crisis reaches Levels 2 or 3, a negative GDP per capita growth leads to a statistically lower number of FIM relative to IDP. These findings align with the hypothesis that FIM is constrained by the economic-resource availability of potential migrants.

In summary, our results support the predictions outlined in the theoretical framework. Migration to developed countries typically entails higher upfront costs (parameters τ_{ij} and C_{ij} in the theoretical framework), whereas migration to neighbouring countries is expected to involve lower costs. Additionally, severe food crises may divert more resources towards covering immediate food needs, thereby reducing migrants' ability to finance the higher migration costs associated with moving to developed countries (by diminishing available resources a_{ij}) and increasing their propensity to select a closer destination. Similar conclusions can be drawn from the perspective of income or financial constraints. As shown in Table 3, in the context of intense food crises and negative GDP per capita growth, FIM becomes less likely. These findings are consistent with the existing literature on liquidity constraints and migration costs, which suggests that shocks to liquidity constraints negatively impact migration flows, particularly in cases involving the poorest regions or high migration costs (Angelucci, 2015; Bazzi, 2017; Cai, 2020; Mayda, 2010; McKenzie and Rapoport, 2010).

Instrumental variable (IV) approach

In this section we assess the robustness of our results by employing an instrumental variable (IV) approach. To do so, we begin with the two-step empirical strategy inspired by previous research such as Eaton and Kortum (2002), Head and Mayer (2014), and Lanati et al. (2023). This approach allows us to address the limitations of dyadic gravity models and use an instrument that varies over time and across countries.[21]

Our first step was to estimate a gravity model that incorporates the full set of fixed effects, including origin-year, destination-year, and country-pair fixed effects, as well as baseline bilateral time-varying control variables. To extract the origin-year fixed effects for all countries and years, we estimate the model without a constant term and focus solely on FIM flows.

$$FIM_{ijt} = \exp(\gamma RTA_{ijt-1} + \gamma Migration_{ijt-5} + \lambda_{ij} + \lambda_{it} + \lambda_{jt}) \times \varepsilon_{ijt} \tag{10}$$

The estimated origin-year fixed effects, retrieved from previous estimations, are then regressed on our variable of interest (food crisis), denoted as $FOOD_{it-1}$, as well as on time and origin-country fixed effects:

$$\hat{\lambda_{it}} = \gamma FOOD_{it-1} + \lambda_i + \lambda_t + \omega_{it} \tag{11}$$

where λ_i and λ_t are, respectively, origin and time fixed effects, and ω_{it} is the error term.

With no bilateral data and country-year fixed effects in this second step, we can use our proposed instrumental variable, which relies on variability over country and time.

[21] As previously discussed, our empirical approach, which includes domestic flows and the interaction of food crises with the international border dummy, is designed to mitigate issues related to endogeneity (for a more detailed discussion, see Heid et al. (2021) and Section 3).

Instrument choice and validity

Regarding the instrument for food crises, following Nunn and Qian (2014) we aim to exploit exogenous variation in US wheat stocks. According to Nunn and Qian (2014), in years of favourable weather and high levels of wheat production, the US government tends to accumulate excess stock, which often finds its way in the form of food aid shipments to developing countries in the following year. As shown in Figure 7, this relation holds for the period 2010-2018 covered in our sample: the level of food aid sent by the US is positively correlated to the level of US wheat stock in the previous year.

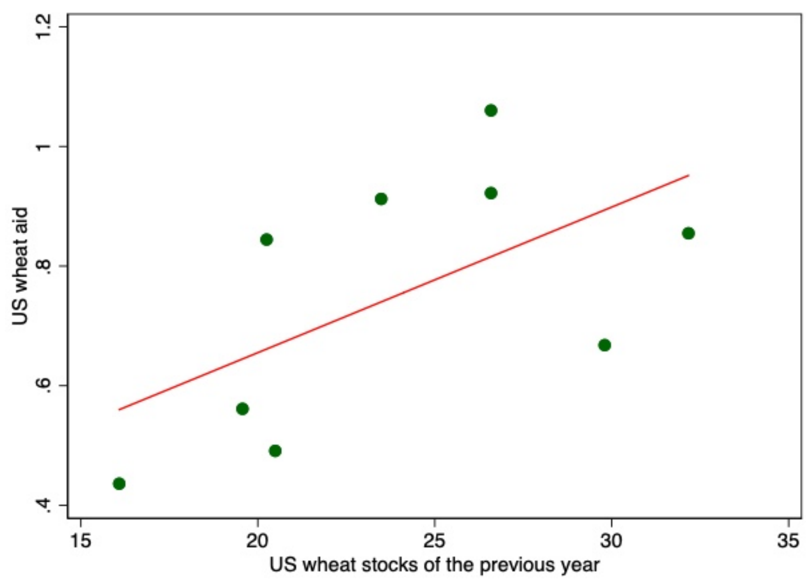

Figure 7: US wheat stock and aid

Authors' own elaboration based on the United States Agency for International Development (USAID) and the United States Department of Agriculture

The United States consistently maintains a prominent role as the primary contributor to global food assistance, accounting for an average of approximately 60-70% of the total

(a) US food aid (% of total OECD) (b) Share of wheat (as % of total US food aid)

Figure 8: Descriptive statistics of US food aid

Source: Authors' own elaboration based on OECD Data and yearly U.S. International Food Assistance Reports from the United States Agency for International Development (USAID)

OECD food aid during the period 2010-2018, as depicted in Figure 8 (a). Furthermore, it is worth noting that a substantial portion of this food aid typically comprises wheat, as illustrated in Figure 8 (b).[22]

Through its effects on subsequent food aid shipments, US wheat stocks of the previous year are therefore expected to be negatively correlated to food crises in countries that are recipients of food aid, while being exogenous to any other domestic condition that could explain migration flows. Additionally, it helps us to isolate the supply-side determinants of food aid, which is an improvement over using food aid itself as an instrument. In essence, when countries experience food crises, they are more likely to request additional food assistance. Consequently, the correlation between the amount of food aid received and the

[22]Data regarding US wheat stocks and US food aid, categorized by the destination country, has been sourced from the United States Department of Agriculture (USDA) and the United States Agency for International Development (USAID), respectively. The information pertaining to the proportion of food aid in the form of wheat was manually extracted from the annual U.S. International Food Assistance Report, jointly published by these organizations. OECD data was obtained from the OECD Database.

occurrence of food crises can be influenced by the interplay of supply and demand factors, making the net direction and magnitude less clear. Nevertheless, all else being equal, a decrease in US wheat stocks should lead to a reduction in received food aid, regardless of the level of hardship in the recipient country.

To ensure that the instrument primarily affects countries that are recipients of food aid, we follow the approach outlined by Nunn and Qian (2014). We weigh US wheat stocks by the probability of a country receiving food aid, which is measured by the proportion of years in which a particular country has received such aid. Let p_{it} be a binary indicator reflecting whether a given country has received any food aid in year t. Then, $\bar{p}_i = \frac{1}{T}\sum_{t=1}^{T} p_{it}$ represents the fraction of years that each origin country has received food aid over the period covered in our study. Our instrument is computed as follows:

$$Instrument\, US\, wheat\, stock_{it-1} = US\, wheat\, stock_{it-1} * \bar{p}_i \tag{12}$$

Having constructed this instrumental variable, we can use it to instrument the term $FOOD_{it-1}$ by applying two-stage least squares (2SLS) to Equation (11).

Table 4 presents the results of the 2SLS estimates. Regarding first stage statistics, as anticipated, the level of US wheat stock in the previous year is significantly and negatively correlated with food crises in a first-stage IV regression (Column 2). This finding suggests that an accumulation of US wheat stock in a given year, through its effect on subsequent food aid shipments, can ultimately lead to a decreased likelihood of food crises in the following year. The instrument's relevance is additionally confirmed by the rejection of the Kleibergen-Paap LM rk test for underidentification at the significance level of 5%. Reduced form estimates in column 1 also align with expectations: an increase in the level of US wheat stock in the previous year is significantly and negatively correlated with migration outflows (Column 1).

	(1) Reduced form	(2) 1st stage IV	(3) 2nd stage IV	(4) 2nd stage no IV	(5) 2nd st. IV + contr.	(6) 2nd st. no IV + contr.
US wheat stock$_{instrument}$	-0.294***	-0.332**				
	(0.076)	(0.142)				
Food crisis			0.887*	0.008	0.886**	0.001
			(0.453)	(0.013)	(0.447)	(0.012)
Financial crisis					0.020	-0.000
					(0.051)	(0.034)
Voice and accountability					-0.013	-0.001
					(0.057)	(0.022)
No. violent deaths (% pop)					-0.175	0.059**
					(0.126)	(0.024)
GDP pc growth					0.002	0.002**
					(0.002)	(0.001)
Observations	919		919	919	919	919
Country FEs	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X
Dependent variable	$\hat{\lambda}_{it}$	$FOOD_{it-1}$	$\hat{\lambda}_{it}$	$\hat{\lambda}_{it}$	$\hat{\lambda}_{it}$	$\hat{\lambda}_{it}$
Kleibergen-Paap test		6.206			6.351	
p-value		0.013			0.012	

Note:Estimates from column (1) are the result of regressing estimated origin country fixed effects from the first stage of the 2-step approach on the level of US wheat stock in the previous year. Column (2) shows the results of the 1st stage IV in which the indicator variable of food crises is regressed on US wheat stocks and the full set of country and year fixed effects. Estimates in columns (3) and (5) are obtained from estimating specification (11) with 2SLS, and the estimates in columns (4) and (6) are obtained with OLS. Standard errors are clustered by origin country.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Robustness to IV approach

While the validity of the instrument cannot be directly tested as the model is just identified, the argument supporting its validity has been explained above.

Reassuringly, the magnitude of our 2SLS estimate of Equation 11 (Column 3) closely aligns with that obtained using our baseline empirical strategy (see Table 1, Column 4). This supports the effectiveness of our strategy in addressing endogeneity within a gravity model context and underscores the robustness of our results when employing alternative methods to tackle endogeneity [23]. Furthermore, these results remain robust even when

[23] Unfortunately, we are only able to test the results pertaining the effects of food crises without distinguising by the level of the crisis, as making that distinction would imply relying on (at least)

additional control variables related to the prevalence of financial crises, voice and accountability, the number of death due to violence, and GDP per capita growth are included (Column 5). Columns 4 and 6 present the same estimations when Equation 11 is estimated through ordinary least squares (OLS), highlighting that neglecting endogeneity can spuriously lead to non-significant results. It is worth highlighting that the lack of significance resemble the estimates from Columns (5) and (8) presented in Table A.6 in the Appendix.

6 Conclusions

The paper investigates the relationship between food crises and FM and makes two key contributions to the literature. Firstly, it quantifies their impact, shedding light on the mechanisms through which food crises influence FM flows. Secondly, it presents a comprehensive database that documents the occurrence, severity, intensity, and causes of food crises, potentially stimulating further research in this policy-relevant field.

Our findings indicate that, on average, food crises lead to an increase in the number of potential FIMs in both developed and developing countries (by 101% relative to internally displaced people or IDP). However, this effect varies depending on the severity and intensity of the food crises. Milder food crises have the most significant impact on FIM, increasing it by up to 643% compared to IDP. In contrast, as the severity and intensity of the food crises escalate, the positive effect on FIM relative to IDP diminishes or even disappears.

Furthermore, the intensity of food crises has different effects on the amount of FIM, de-

three different instruments, which is extremely difficult in this context. Nevertheless, this exercise is only a attempt to show that our baseline results -which is indeed our preferred specification and the one favored by the literate to deal with endogeneity, as discussed in previous sections- are robust to the use of alternative possible ways to deal with possible sources of endogeneity, at least to the extent we are able to test it.

pending on heterogeneous migration costs related to distance and the level of development of the destination country. Less severe crises tend to promote FIM to both developed and non-neighbouring countries, while more severe food crises tend to divert migrants towards closer destinations. Our results also suggest that the impact of more intense food crises on FIM is reduced when potential migrants have fewer economic resources available. These findings align with the notion that food crises can act as both a push factor and a constraint on migration due to worsening liquidity, with the constraint becoming more pronounced as food crises intensify. This constraint limits individuals' capacity to migrate in general, particularly to countries with higher migration costs, such as developed or non-neighbouring countries.

These results hold significant implications for public policy, as gaining a deeper understanding of food crises and their impact on migration will become crucial in shaping the agendas of international organizations in the coming years. Our results highlight that even after accounting for other determinants, food crises directly influence FIM flows.

Additionally, our analysis underscores the importance of fostering multilateral cooperation on food security and migration policies. Given the ongoing Ukraine conflict, the risks derived from the fragmentation of trade and commodity markets, and the emergence of a global food crisis, our findings provide an additional argument for the need for a "food corridor", such as the one proposed by the IMF in their last World Economic Outlook (International Monetary Fund, 2023).

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A Appendix

A.1 Sample and descriptive statistics

Only origin	Only destination	Origin and destination		Developed countries
Bhutan	Central African Rep.	Afghanistan	Kenya	Australia
Cabo Verde	Chad	Albania	Kuwait	Austria
Comoros	Dem. Rep. Congo	Algeria	Kyrgyz Rep.	Belgium
Dominica	Nauru	Angola	Lebanon	Bulgaria
Equatorial Guinea	Niger	Argentina	Lesotho	Canada
Grenada	Yemen	Azerbaijan	Liberia	Croatia
Kiribati	Zambia	Bahrain	Madagascar	Cyprus
Lao People's Dem. Rep.		Bangladesh	Malawi	Czech Republic
Maldives		Belarus	Malaysia	Denmark
Myanmar		Belize	Mali	Estonia
Rwanda		Benin	Mauritania	Finland
Samoa		Bolivia	Mexico	France
Sao Tome and Principe		Bosnia & Herzegovina	Mongolia	Germany
Seychelles		Botswana	Morocco	Greece
Sierra Leone		Brazil	Mozambique	Hungary
Solomon Islands		Burkina Faso	Namibia	Iceland
Uzbekistan		Burundi	Nepal	Ireland
Vietnam		Cambodia	Nicaragua	Israel
Vincent & the Grenadines		Cameroon	Nigeria	Italy
		Chile	Oman	Japan
		China	Pakistan	Latvia
		Colombia	Panama	Lithuania
		Costa Rica	Papua New Guinea	Luxembourg
		Cote d'Ivoire	Paraguay	Malta
		Cuba	Peru	Netherlands
		Dominican Rep.	Philippines	New Zealand
		Ecuador	Qatar	Norway
		Egypt	Russian Federation	Poland
		El Salvador	Saudi Arabia	Portugal
		Ethiopia	Senegal	Rep. of Korea
		Fiji	Somalia	Romania
		Gabon	South Africa	Slovak Republic
		Gambia	Sri Lanka	Slovenia
		Georgia	Sudan	Spain
		Ghana	Syrian Arab Rep.	Sweden
		Guatemala	Tajikistan	Switzerland
		Guinea	Tanzania	United Kingdom
		Guinea-Bissau	Thailand	United States
		Haiti	Togo	
		Honduras	Trinidad & Tobago	
		Hong Kong	Tunisia	
		India	Turkey	
		Indonesia	Uganda	
		Iran	Ukraine	
		Iraq	Uruguay	
		Jordan	Venezuela	
		Kazakhstan	Zimbabwe	

Table A.1: Sample

Food crisis variables				
	Mean	**Std. Dev.**	**Min**	**Max**
Food crisis	0.25	0.43	0	1
Food insecurity, Lv. 1	0.05	0.22	0	1
Food insecurity, Lv. 2	0.15	0.36	0	1
Food insecurity, Lv. 3	0.04	0.19	0	1
Intensity Food insecurity, Lv. 1	0.18	0.77	0	4
Intensity Food insecurity, Lv. 2	0.52	1.25	0	4
Intensity Food insecurity, Lv. 3	0.14	0.68	0	4
Dependent & other control variables				
	Mean	**Std. Dev.**	**Min**	**Max**
Forced migrants	4111.08	113000	0	9610000
Financial crisis	0.06	0.23	0	1
GDP pc growth	2.33	4.31	-22.50	19.94
Voice and accountability	-0.66	0.72	-2.17	1.17
Violent Deaths per 1,000 Population	0.06	0.44	0.00	4.21
Regional Trade Agreement	0.32	0.47	0	1
Migration stock	5.56	4.04	0	20.93

Authors' own elaboration. All variables have 32074 observations. The descriptive statistics of the food crisis variables, and the the remaining country specific variables (financial crisis, GDP pc growth, voice and accountability, and Violent Deaths per 1,000 Population) are interacted with the INT dummy.

Table A.2: Descriptive statistics

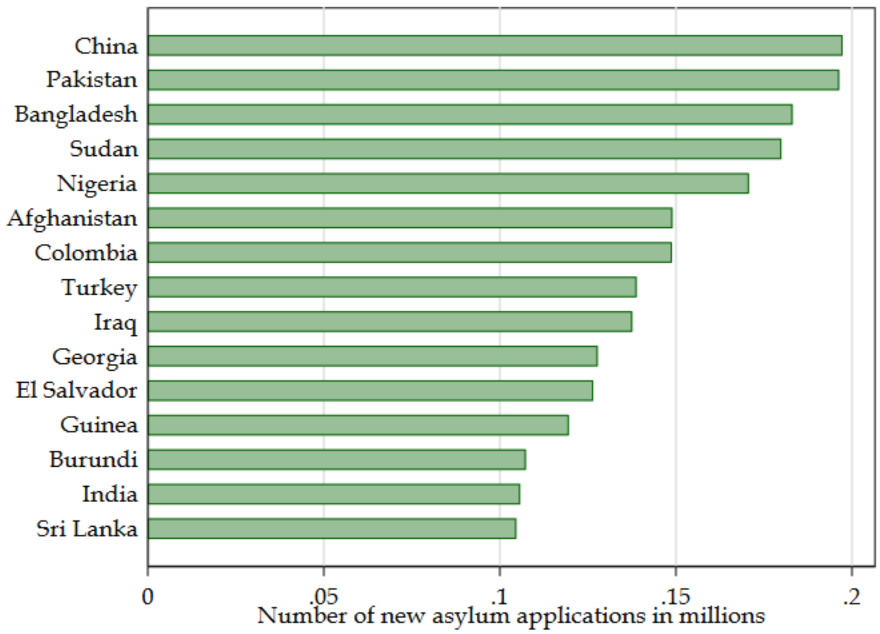

Figure A.1: Countries between 100,000 and 200,000 asylum applications

Authors' own elaboration based on United Nations Refugees Agency.

A.2 Food crises database

Figures A.2 and A.3 present the geographical distribution of all food crises present in the database in the years 2009 and 2019, respectively. As can be seen, between both years the number of affected countries changed, and in 2019 the severity of food crises was higher than in 2009. We can also observe that sub-Saharan countries are the most affected by food crises. Likewise, Figures A.4 y A.5 a more thorough description of the countries experiencing food crises and the evolution of such crises over time.

As mentioned in Section 4, the newly constructed food crisis database provides insight into their causes. We also scraped this information from GIEWS reports. We employed a taxonomy of keywords that led to the inclusion of each crisis among each of the types (see the list of keywords and causes/origins of food security crises in Table A.3[24]). Overall, we detect four leading causes: 1) Economic, 2) Political instability & violence, 3) Weather & diseases, and 4) Migration. For the present study, we exclude those country-years affected

[24]The choice of the terms to be included in the taxonomy was made after a careful and iterative inspection of the dataset. The authors reviewed all the crises to make sure they were classifying them properly, and included new terms in the taxonomy if this was not the case.

by a food crisis caused by migration pressures since most of these pressures result from large movements of IDP, thus generating an issue with our dependent variable when $i = j$.

As is to be expected, a food crisis does not always only have one cause. Figure A.6 illustrates this phenomenon. The most frequent cause of a food crisis is a combination of economic and weather (or disease) factors, followed by food crises caused by economic and political instability factors, and economic and migration factors.

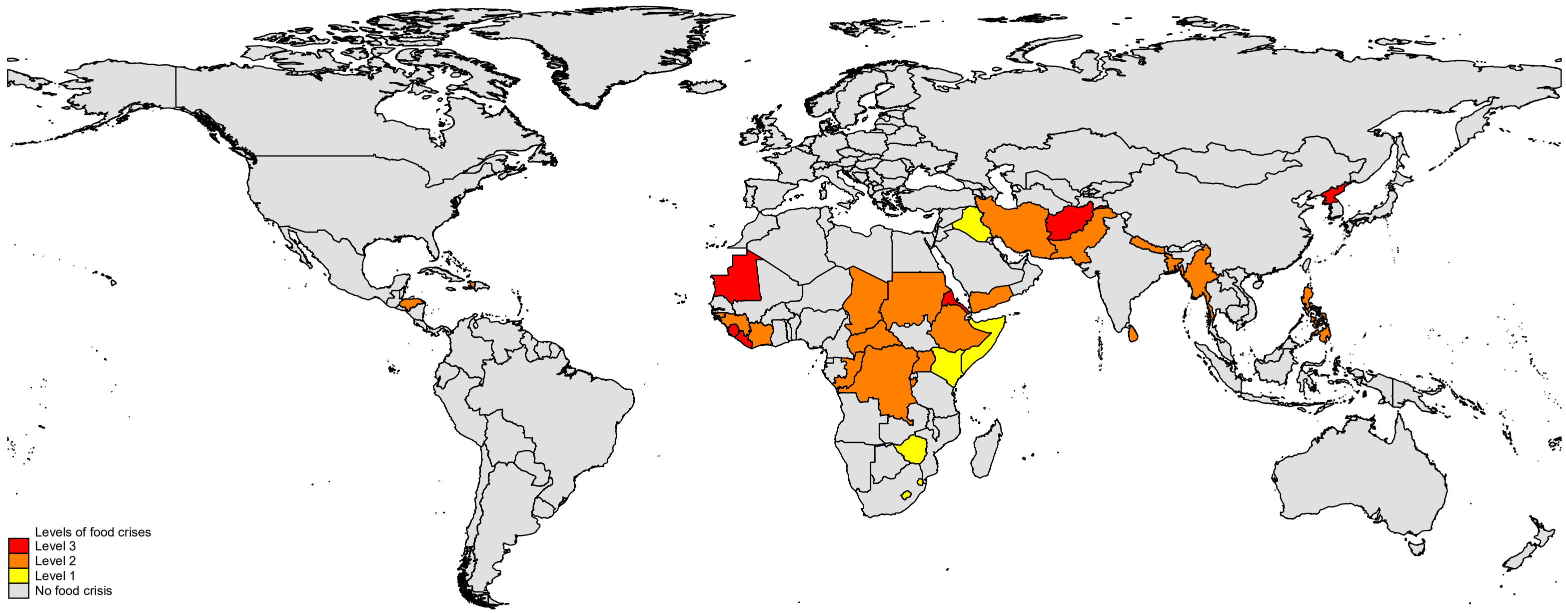

Figure A.2: Food crises in 2009

Authors' own elaboration based on the GEIWS database.

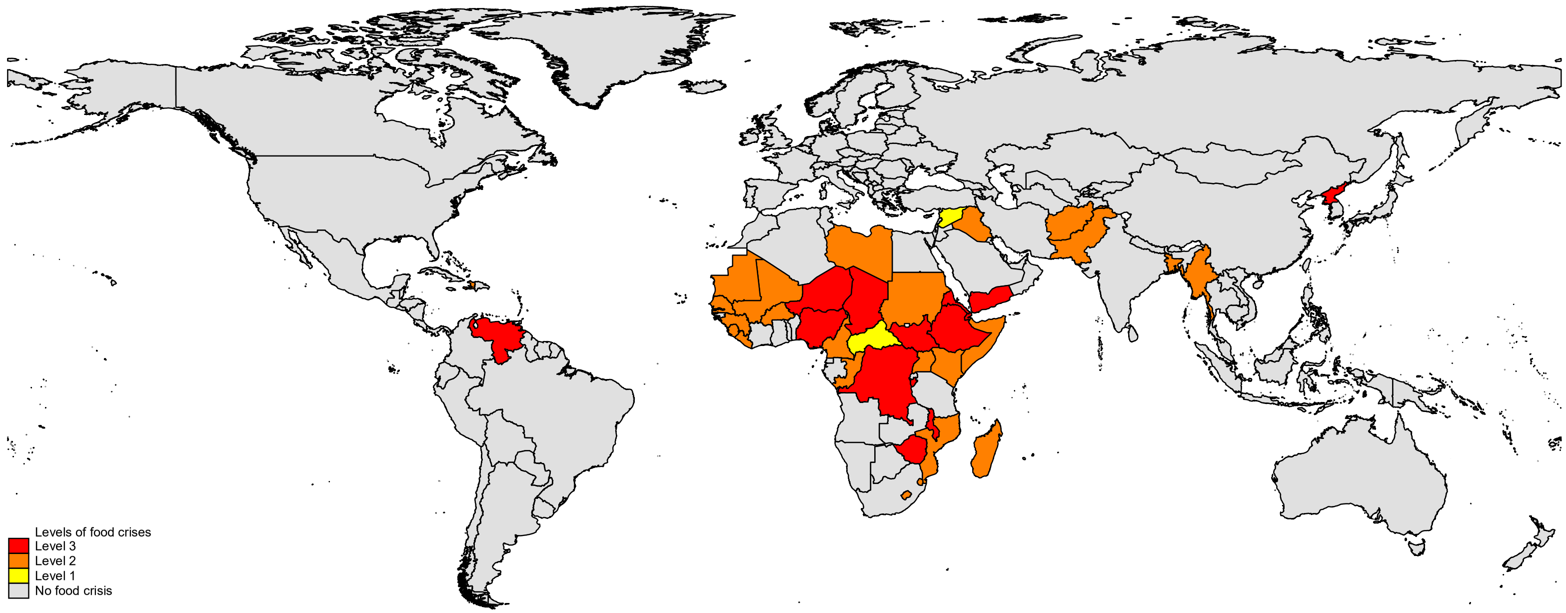

Figure A.3: Food crises in 2019

Authors' own elaboration based on the GEIWS database.

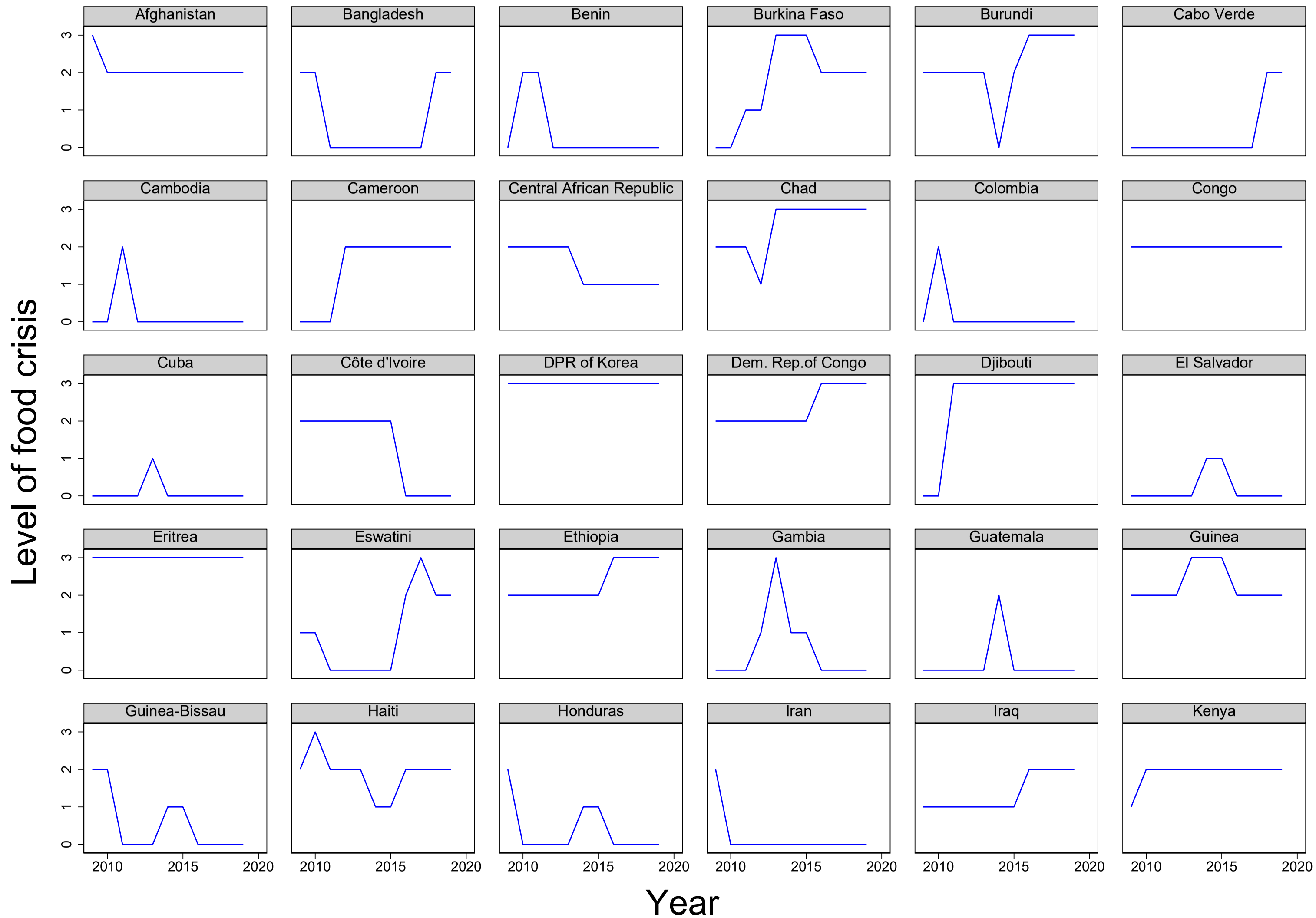

Figure A.4: Food crises by country and evolution over time (I).

Authors' own elaboration based on GEIWS database.

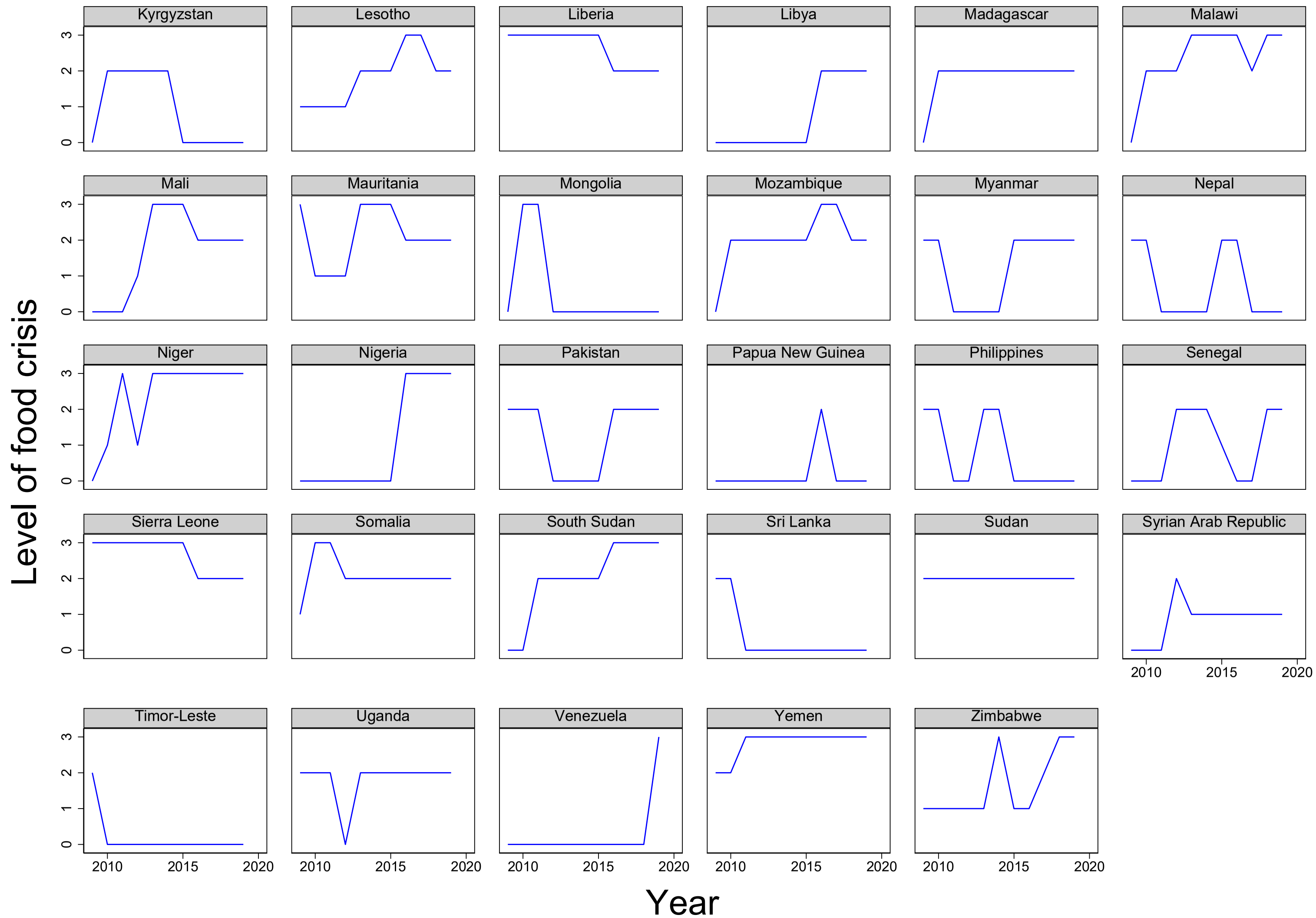

Figure A.5: Food crises by country and evolution over time (II).

Authors' own elaboration based on GEIWS database.

Cause	Keywords
Economic	Economic crisis; economic constraints; Poor market access; Low productivity; Economic downturn; Currency depreciation; Loss of Remittances; Reduced employment opportunities; Production shortfalls; Compromising the final output; Poor pastoral conditions; Cereals harvest; Crop production and livestock; High Food prices; High inflation; Price spikes; Declining purchasing power; Fuel prices; Dependant on the import; poverty; low incomes; Depletion of household assets; Falling income; Damage to housing; Pests; Localized crop failure; Transportation difficulties; Disrupt distribution systems; Restricted access.
Political instability & violence	Socio-political tensions; Social unrest; Ethnic conflicts; Conflict; Insecurity; Civil strife; War.
Weather & diseases	Drought; Insufficient rainfall; Floods; cyclone; Hurricane; Dry spells; Adverse weather; Earthquake; belg and “subgum” meher; Ebola; Cholera.
Migration	Internally displaced persons; Returnees; Refugees; Population displacement.

Authors’ own elaboration. This table presents the used keywords to classify the food crises into four main categories.

Table A.3: Causes of food crises & keywords

graph_causes-eps-converted-to.pdf

Figure A.6: Causes of food crisis, 2009-2019

Authors’ own elaboration based on the GEIWS database. Pol.Instab refers to political instability and violence.

A.3 Model specification

In Section 3, we presented the baseline specification: a gravity model with a rich set of fixed effects and IDP. In order to show the extent to which the model specification derived from the theoretical model matters to gauge the effect of food crises on FIM, we estimate variations of specification (9).

These new estimates are presented in Table A.4. For ease of comparison, estimates presented in column (1) are the baseline estimates previously presented in column (4) from Table 1. From column (2) to column (8) we progressively reduce the fixed effects included in the specification, and exclude IDP from the dependent variable. Thus, these estimates are subject to larger biases due to omitted variable bias and endogeneity, and as a result this have relevant implications for the different estimated coefficients in general.

First, in column (2), we exclude $INT_{ij} \times Year$. This has implications on the size of some of the estimated coefficients. This is to be expected, not controlling for the evolution of the border effect (i.e. the growth in the proportion of FIM relative to IDP) is likely to bias the estimate of those variables which had a positive (or negative) evolution in parallel with globalization as their estimates may capture some of the common globalization effects (Bergstrand et al., 2015). However, as the period of analysis is relatively short (2010-2018), thus excluding $INT_{ij} \times Year$ has not relevant implications on the size of the estimated coefficients.

In column (3) we replace λ_{ij} with a matrix of bilateral time-invariant determinants of migration or asylum seekers (e.g. Figueiredo et al., 2016; Neumayer, 2005; Wesselbaum and Aburn, 2019). This matrix includes the logarithm of geographic distance, a series of dummy variables that equal 1 when a pair of countries shares a border, language, legal origins, and colonial ties.[25] Omitting origin-destination fixed effects have relevant implications on the estimated coefficients. In the case of food crises, the associated coefficient turns negative, while financial crises looses significance, GDP per capita growth becomes significant and negative, and the number of violent deaths per 1,000 population turns negative. In addition, the size of the estimated coefficient for RTA almost triples, and migration stock becomes positive and significant.

There are two factors that drive these substantial changes in the estimated coefficients. First, it highlights the importance of accounting for the bilateral costs of FM. Just as in international trade (Egger and Nigai, 2015), using traditional gravity variables like geographical distance may not correctly approximate bilateral travel costs, significantly biasing estimates. This is likely to be particular relevant in the context of FM as travel costs between country pairs are not only subject to the distance between country pairs, but are also conditioned by the availability and degree of difficulty associated to migration routes. As pointed in the theoretical model, food crises will not propel FIM if potential migrants do not have enough resources to cover the costs associated to migration, thus it is expected that how bilateral travel costs are accounted for will have implications on the size, sign, and significance of the countries' characteristics that determine FIM relative to IDP. Second, excluding directional country pair fixed effects also introduces a source of bias due to the potential endogeneity between FIM and the included bilateral time-varying variables (RTA and migration stock).

Although subject to the biases mentioned above, the specification employed in Column (3) allow us to approximate the border effect on FM. In order to be able to compare its estimate with the previous trade and FDI literature, in Column (4) we estimate this

[25]Information on geographical distance, border sharing, common language, and colonial ties is sourced from CEPII (Conte et al., 2021).

specification without the country specific variables interacted by INT_{ij}. The coefficient associated with the international dummy is negative and significant, indicating that IDP outnumber FIMs by sixty-six times ($1/e(-4.190)$). This border effect's magnitude is substantially larger than those previously calculated for international trade and FDI. For instance, Bailey et al. (2021) find that trade within a country is five to nine times larger than observed international flows. In the case of FDI, Carril-Caccia et al. (2022) demonstrate that cross-border Mergers & Acquisitions (M&As) are five times less frequent than domestic ones. This substantially larger border effect for FIM in comparison with the ones reached by the previous trade and FDI literature is to be expected as the degree of internationalization of FM is much more lower than the one reached by trade and M&As. Indeed, according to UNCTAD's statistics, in 2018 international trade represented 56.2% of the global GDP, and according to Carril-Caccia et al. (2022) during the period 1995-2015 cross-border M&As represented 22.8% of global M&As. As reported in Figure 3, the relevance of FIM over total FM is much more limited, during our period of analysis it ranges from 1.6% to 8%.

In column (5) and when IDP are excluded from the analysis (Columns (6) to (8)), estimates do not incorporate the origin-year and destination-year fixed effects. In these case, the food crises variable becomes non-significant. In addition to not fully controlling for the MRT, since the food crisis variable is not interacted with the international dummy (INT_{ij}), the food crisis estimates are also prone to being biased as a result of endogeneity. On this regard, is important to highlight that in our sensitivity analysis employing an instrumental variable, we also find that not instrumenting food crisis results in a non-significant effect on FIM.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Food crisis	0.699**	0.745***	-2.483***		-0.256	-0.010	-0.048	-0.035
	(0.304)	(0.255)	(0.619)		(0.182)	(0.074)	(0.085)	(0.086)
Financial crisis	0.760***	0.352*	-0.326		0.392**	-0.116	-0.192	-0.167
	(0.215)	(0.213)	(0.464)		(0.182)	(0.076)	(0.194)	(0.173)
GDP pc growth	0.037	0.011	-0.106***		0.011	0.017***	0.020	0.024*
	(0.034)	(0.033)	(0.036)		(0.036)	(0.006)	(0.014)	(0.013)
Voice and accountability	-3.249***	-3.904***	-2.291***		0.676	-0.530***	-1.029***	-1.229***
	(0.958)	(0.775)	(0.339)		(0.675)	(0.169)	(0.321)	(0.364)
V. Deaths per 1,000 Pop.	2.905***	3.514***	-0.850***		-0.011	0.505***	0.719***	0.719***
	(0.742)	(1.218)	(0.289)		(0.399)	(0.119)	(0.127)	(0.126)
Log(GDPpc origin)					-1.079**	-0.418***	0.045	-0.093
					(0.461)	(0.157)	(0.289)	(0.293)
Log(GDPpc Dest.)					1.285**		1.771**	1.905**
					(0.626)		(0.689)	(0.800)
Log(Pop. Origin)					5.032	2.829***	1.649	1.605
					(3.210)	(0.821)	(1.289)	(1.448)
Log(Pop. Dest.)					-6.011**		-8.974***	-10.387***
					(2.629)		(1.857)	(2.031)
RTA	0.361**	0.366**	0.971***	0.910***	0.873***	0.116	0.362*	1.096***
	(0.161)	(0.160)	(0.185)	(0.186)	(0.215)	(0.129)	(0.201)	(0.183)
Migration stock	-0.042	-0.061	0.264***	0.288***	0.314***	-0.055	-0.716	0.271***
	(0.070)	(0.070)	(0.032)	(0.036)	(0.041)	(0.093)	(0.548)	(0.033)
International			-4.697***	-4.190***	-3.569***			
			(0.476)	(0.503)	(0.623)			
log(Distance)			-1.017***	-1.035***	-1.018***			-0.857***
			(0.113)	(0.114)	(0.143)			(0.120)
Contiguity			0.353	0.375	0.145			0.493**
			(0.252)	(0.275)	(0.322)			(0.248)
Common language			0.182	0.095	-0.070			0.180
			(0.168)	(0.179)	(0.221)			(0.177)
Colonial ties			0.073	0.143	0.490			-0.252
			(0.281)	(0.310)	(0.399)			(0.306)
Observations	32074	32074	32074	32074	32074	31555	31789	31789
Origin FE					X			X
Destination FE					X			X
Country pair FE	X	X				X	X	
Year FE					X		X	X
Origin-year FE	X	X	X	X				
Destination-year FE	X	X	X	X		X		
Border-year FE	X							
IDP	Yes	Yes	Yes	Yes	Yes	No	No	No
foodt-1 ties INT	Yes	Yes	Yes	No	No	No	No	No
xit-1 times int	Yes	Yes	Yes	No	No	No	No	No

Note: This table reports our main estimates of the effect of food crises on FIM relative to IDP using the PPML estimator (Specification (9)). The dependent variable is the number FIM and IDP between the origin (i) and destination country (j). Our main variable of interest is an indicator variable that takes the value 1 when the origin country suffers from a food crisis. All country level variables and Regional Trade Agreement are included in $t-1$, while migration stock in $t-5$. All country level variables are interacted with the INT_{ij} dummy and take the values for the origin country (i).
Significance levels are designated as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered by country pair.

Table A.4: The effect of food crises on FIMs with alternative gravity model specification

A.4 Sensitivity analyses and full tables

	(1)
Food crisis	0.776**
	(0.331)
Financial crisis	0.797***
	(0.232)
GDP pc growth	0.034
	(0.041)
Voice and accountability	-4.019***
	(0.925)
Violent Deaths per 1,000 Population	3.007***
	(0.837)
Disaster	-0.288
	(0.293)
Political stability	0.758
	(0.474)
Unemployment	0.083
	(0.129)
Regional Trade Agreement	0.378**
	(0.162)
Migration stock	-0.046
	(0.070)
Observations	31936
Country pair FE	X
Origin-year FE	X
Destination-year FE	X
$INT_{ij} \times Year$ FE	X
IDP	Yes
$FOOD_{it-1} \times INT_{ij}$	Yes
$X_{it-1} \times INT_{ij}$	Yes

Note: This table reports our main estimates of the effect of food crises on FIM relative to IDP using the PPML estimator (Specification (9)). Our main variable of interest is an indicator variable that takes the value 1 when the origin country suffers from a food crisis. All country level variables and Regional Trade Agreement are included in $t-1$, while migration stock in $t-5$. All country level variables are interacted with the INT_{ij} dummy and take the values for the origin country (i).
Significance levels are designated as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered by country pair.

Table A.5: The effect of food crises on FIMs (Sensitivity analysis)

	(1)	(2)	(3)	(4)
No. Q. Food Crisis	0.374***	0.374***	0.378***	0.402***
	(0.103)	(0.102)	(0.104)	(0.116)
Financial crisis			0.725***	0.767***
			(0.219)	(0.218)
GDP pc growth			0.007	0.035
			(0.033)	(0.034)
Voice and accountability				-3.323***
				(0.967)
Violent Deaths per 1,000 Population				2.833***
				(0.729)
Regional Trade Agreement		0.308*	0.319*	0.362**
		(0.164)	(0.164)	(0.161)
Migration stock		-0.037	-0.042	-0.040
		(0.070)	(0.071)	(0.069)
Observations	32074	32074	32074	32074
Country pair FE	X	X	X	X
Origin-year FE	X	X	X	X
Destination-year FE	X	X	X	X
$INT_{ij} \times Year$ FE	X	X	X	X
IDP	Yes	Yes	Yes	Yes
$FOOD_{it-1} \times INT_{ij}$	Yes	Yes	Yes	Yes
$X_{it-1} \times INT_{ij}$	Yes	Yes	Yes	Yes

Note: This table reports our main estimates of the effect of food crises on FIM relative to IDP using the PPML estimator (Specification (9)). The dependent variable is the number FIM and IDP between the origin (i) and destination country (j). Our main variable of interest is No. Q. Food Crisis. It is an ordinal variable that ranges from 0 to 4. It takes the value 0 when there is no occurrence of a food crisis and 4 when the food crisis takes place during the whole year. All country level variables and Regional Trade Agreement are included in $t-1$, while migration stock in $t-5$. All country level variables are interacted with the INT_{ij} dummy and take the values for the origin country (i). Significance levels are designated as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered by country pair.

Table A.6: The effect of food crises on FIMs (Sensitivity analysis)

	(1)	(2)	(3)	(4)
Food crisis	0.798*	0.840**	0.707*	0.795*
	(0.432)	(0.409)	(0.417)	(0.438)
Financial crisis			-0.033	-0.181
			(0.454)	(0.457)
GDP pc growth			0.054	0.034
			(0.041)	(0.040)
Voice and accountability				-3.150***
				(1.024)
Violent Deaths per 1,000 Population				16.284
				(10.989)
Regional Trade Agreement		0.373*	0.371*	0.405**
		(0.206)	(0.205)	(0.202)
Migration stock		-0.054	-0.052	-0.049
		(0.078)	(0.077)	(0.075)
Observations	26955	27040	26955	26955
Country pair FE	X	X	X	X
Origin-year FE	X	X	X	X
Destination-year FE	X	X	X	X
$INT_{ij} \times Year$ FE	X	X	X	X
IDP	Yes	Yes	Yes	Yes
$FOOD_{it-2} \times INT_{ij}$	Yes	Yes	Yes	Yes
$X_{it-2} \times INT_{ij}$	Yes	Yes	Yes	Yes

Note: This table reports our main estimates of the effect of food crises on FIM relative to IDP using the PPML estimator (Specification (9)). The dependent variable is the number FIM and IDP between the origin (i) and destination country (j). Our main variable of interest is an indicator variable that takes the value 1 when the origin country suffers from a food crisis. All country level variables and Regional Trade Agreement are included in $t-2$, while migration stock in $t-5$. All country level variables are interacted with the INT_{ij} dummy and take the values for the origin country (i).
Significance levels are designated as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered by country pair.

Table A.7: The effect of food crises on FIMs (Sensitivity analysis in $t-2$)

	(1) Estimate 1	(2) Estimate 2	(3) Estimate 3
Food crisis	0.752**		
	(0.310)		
x Developed	-0.142		
	(0.162)		
Food insecurity, lv. 1		1.729***	
		(0.651)	
x Developed		0.313	
		(0.280)	
Food insecurity, lv. 2		0.755**	
		(0.312)	
x Developed		-0.298*	
		(0.169)	
Food insecurity, lv. 3		-0.370	
		(0.798)	
x Developed		-0.554**	
		(0.249)	
Intensity Food insecurity, lv. 1			0.408
			(0.310)
x Developed			0.311***
			(0.096)
Intensity Food insecurity, lv. 2			0.455***
			(0.100)
x Developed			-0.098*
			(0.053)
Intensity Food insecurity, lv. 3			-0.051
			(0.366)
x Developed			-0.161*
			(0.083)
Financial crisis	0.760***	0.708***	0.713***
	(0.215)	(0.208)	(0.212)
GDP pc growth	0.036	0.026	0.026
	(0.034)	(0.034)	(0.033)
Voice and accountability	-3.214***	-3.440***	-3.540***
	(0.956)	(0.955)	(0.942)
Violent Deaths per 1,000 Population	2.921***	2.694***	2.636***
	(0.738)	(0.706)	(0.682)
Regional Trade Agreement	0.352**	0.376**	0.381**
	(0.162)	(0.161)	(0.160)
Migration stock	-0.044	-0.053	-0.043
	(0.070)	(0.067)	(0.066)
Observations	32036	32074	32074
Country pair FE	X	X	X
Origin-year FE	X	X	X
Destination-year FE	X	X	X
$INT_{ij} \times Year$ FE	X	X	X
IDP	Yes	Yes	Yes
$FOOD_{it-1} \times INT_{ij}$	Yes	Yes	Yes
$X_{it-1} \times INT_{ij}$	Yes	Yes	Yes

Note: This table reports thee effect of food crises on FIM relative to IDP on developed and non-developed countries using the PPML estimator. The dependent variable is the number FIM and IDP between the origin (i) and destination country (j). The estimates of this table are employed in test 1 from Table 3. In estimate 1 our main variable of interest is an indicator variable that takes the value 1 when the origin country suffers from a food crisis. In estimate (2) our main variables of interest are a set of indicator variables that takes the value 1 when the origin country suffers from a food crisis of level 1, level 2 or level 3. In estimate 3, our main variables of interest are a set of variables measure the occurrence and intensity of the different levels of food crisis. These variables take values between 0 and 4, representing 0 the no occurrence of a food crisis of a given level, and 4 the highest degree of intensity (see Section 4 for a more in detail description). Food crisis variables are interacted by an indicator variable that takes the value 1 when the destination country is a developed one. All country level variables and Regional Trade Agreement are included in $t-1$, while migration stock in $t-5$. All country level variables are interacted with the INT_{ij} dummy and take the values for the origin country (i).
Significance levels are designated as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered by country pair.

Table A.8: The effect of food crises on migration: Developed countries

	(1) Estimate 1	(2) Estimate 2	(3) Estimate 3
Food crisis	0.553^{*}		
	(0.305)		
x Contiguity	0.611		
	(0.487)		
Food insecurity, lv. 1		2.170^{***}	
		(0.509)	
x Contiguity		-1.281	
		(0.829)	
Food insecurity, lv. 2		0.504^{*}	
		(0.295)	
x Contiguity		0.951^{**}	
		(0.397)	
Food insecurity, lv. 3		-0.597	
		(0.805)	
x Contiguity		0.854	
		(0.564)	
Intensity Food insecurity, lv. 1			0.741^{***}
			(0.247)
x Contiguity			-0.582^{***}
			(0.156)
Intensity Food insecurity, lv. 2			0.380^{***}
			(0.096)
x Contiguity			0.201
			(0.126)
Intensity Food insecurity, lv. 3			-0.127
			(0.351)
x Contiguity			0.177
			(0.174)
Financial crisis	0.739^{***}	0.710^{***}	0.736^{***}
	(0.215)	(0.204)	(0.212)
GDP pc growth	0.035	0.022	0.025
	(0.033)	(0.033)	(0.033)
Voice and accountability	-3.263^{***}	-3.327^{***}	-3.559^{***}
	(0.926)	(0.923)	(0.916)
Violent Deaths per 1,000 Population	2.876^{***}	2.731^{***}	2.748^{***}
	(0.727)	(0.703)	(0.708)
Regional Trade Agreement	0.342^{**}	0.365^{**}	0.369^{**}
	(0.162)	(0.164)	(0.162)
Migration stock	-0.044	-0.044	-0.034
	(0.069)	(0.069)	(0.069)
Observations	32074	32074	32074
Country pair FE	X	X	X
Origin-year FE	X	X	X
Destination-year FE	X	X	X
$INT_{ij} \times Year$ FE	X	X	X
IDP	Yes	Yes	Yes
$FOOD_{it-1} \times INT_{ij}$	Yes	Yes	Yes
$X_{it-1} \times INT_{ij}$	Yes	Yes	Yes

Note: This table reports thee effect of food crises on FIM relative to IDP on developed and non-developed countries using the PPML estimator. The dependent variable is the number FIM and IDP between the origin (i) and destination country (j). The estimates of this table are employed in test 2 from Table 3. In estimate 1 our main variable of interest is an indicator variable that takes the value 1 when the origin country suffers from a food crisis. In estimate (2) our main variables of interest are a set of indicator variables that takes the value 1 when the origin country suffers from a food crisis of level 1, level 2 or level 3. In estimate 3, our main variables of interest are a set of variables measure the occurrence and intensity of the different levels of food crisis. These variables take values between 0 and 4, representing 0 the no occurrence of a food crisis of a given level, and 4 the highest degree of intensity (see Section 4 for a more in detail description). Food crisis variables are interacted by an indicator variable that takes the value 1 when the destination country is a neighbor one. All country level variables and Regional Trade Agreement are included in $t-1$, while migration stock in $t-5$. All country level variables are interacted with the INT_{ij} dummy and take the values for the origin country (i).
Significance levels are designated as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered by country pair.

Table A.9: The effect of food crises on migration: Neighbour countries

	(1) Estimate 1	(2) Estimate 2	(3) Estimate 3
Food crisis	0.717**		
	(0.305)		
x Negative growth	-0.308		
	(0.666)		
Food insecurity, lv. 1		1.994***	
		(0.630)	
x Negative growth		3.786***	
		(0.868)	
Food insecurity, lv. 2		0.749**	
		(0.299)	
x Negative growth		-0.746*	
		(0.392)	
Food insecurity, lv. 3		-0.206	
		(0.788)	
x Negative growth		-1.923**	
		(0.860)	
Intensity Food insecurity, lv. 1			0.646**
			(0.304)
x Negative growth			0.949***
			(0.190)
Intensity Food insecurity, lv. 2			0.463***
			(0.097)
x Negative growth			-0.252***
			(0.083)
Intensity Food insecurity, lv. 3			0.110
			(0.330)
x Negative growth			-0.549
			(0.387)
Financial crisis	0.765***	0.787***	0.816***
	(0.217)	(0.208)	(0.213)
GDP pc growth	0.034	0.035	0.031
	(0.034)	(0.034)	(0.034)
Voice and accountability	-3.270***	-3.816***	-3.855***
	(0.968)	(0.975)	(0.960)
Violent Deaths per 1,000 Population	2.858***	2.895***	2.763***
	(0.734)	(0.750)	(0.725)
Regional Trade Agreement	0.361**	0.370**	0.370**
	(0.161)	(0.161)	(0.161)
Migration stock	-0.042	-0.044	-0.042
	(0.070)	(0.070)	(0.069)
Observations	32074	32074	32074
Country pair FE	X	X	X
Origin-year FE	X	X	X
Destination-year FE	X	X	X
$INT_{ij} \times Year$ FE	X	X	X
IDP	Yes	Yes	Yes
$FOOD_{it-1} \times INT_{ij}$	Yes	Yes	Yes
$X_{it-1} \times INT_{ij}$	Yes	Yes	Yes

Note: This table reports thee effect of food crises on FIM relative to IDP on developed and non-developed countries using the PPML estimator. The dependent variable is the number FIM and IDP between the origin (i) and destination country (j). The estimates of this table are employed in test 3 from Table 3. In estimate 1 our main variable of interest is an indicator variable that takes the value 1 when the origin country suffers from a food crisis. In estimate (2) our main variables of interest are a set of indicator variables that takes the value 1 when the origin country suffers from a food crisis of level 1, level 2 or level 3. In estimate 3, our main variables of interest are a set of variables measure the occurrence and intensity of the different levels of food crisis. These variables take values between 0 and 4, representing 0 the no occurrence of a food crisis of a given level, and 4 the highest degree of intensity (see Section 4 for a more in detail description). Food crisis variables are interacted by an indicator variable that takes the value 1 when the country of origin has a negative GDP per capita growth. All country level variables and Regional Trade Agreement are included in $t-1$, while migration stock in $t-5$. All country level variables are interacted with the INT_{ij} dummy and take the values for the origin country (i). Significance levels are designated as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered by country pair.

Table A.10: The effect of food crises on migration: Negative GDP pc growth