# Food Security in Developing Countries: Gender and Spatial Interactions

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## Abstract

Food security in developing countries is determined by a variety of economic constraints. Smallholder farmers living near one another face similar socioeconomic conditions but may have different levels of food security. Neighbors can potentially ease economic constraints and promote food security by acting as channels of resources and information. These spatial effects are likely mediated by gender roles and norms. We estimate gendered spatial effects using a sample of households located across seven countries in Africa and Asia. We find that for every 100 additional calories that neighbors consume, own food security increases by 17 calories, i.e. a 17% increase. This effect is larger for female-headed households (49%) than for male-headed households (15%). We examine homophily and find that that female-headed households benefit more from their female-headed neighbors (68%) than male-headed households benefit from their male-headed neighbors (16%). These results show that gender and space interact in promoting food security.

*Keywords:* food security, gender, spatial effects, homophily, West Africa, East Africa, South Asia.

# 1. Introduction

In 2021, the number of food-insecure people was estimated to be 768 million, or 9.8% of the global population, with the overwhelming majority of cases in developing countries. The prospects for the near future are worrying, with preliminary assessments suggesting that the COVID-19 pandemic and the war in Ukraine pose serious challenges for achieving the global food security target of ending hunger and malnutrition by 2030 (FAO et al. 2022).

Understanding mechanisms underlying food security is crucial for helping to align government policies with local situations faced by smallholder farmers. Accordingly, a large number of studies investigate factors affecting food security. Within this literature, two key areas are gender and spatial relationships. Gender studies identify numerous types of constraints faced by females that may hinder the production of food (Agarwal 2018). Spatial studies investigate whether locations of households, e.g. relative to one another, influence their food security (Krishnan and Patnam 2014).

While the literature finds that both gender roles and spatial patterns are important determinants of food security, most papers examine these effects in isolation. Little is known about how gender and space interact to shape food security of smallholder farmers (Dzanku 2019). This absence is important because spatial relationships, often measured by proximity to neighbors, can improve food security via learning and technology transfers (Lim, Wichmann, and Luckert 2021). However, previous research has shown that spatial patterns and the connectivity among neighbors display high levels of gender segregation (Marsden 1987; D'Exelle and Holvoet 2011). To understand the nuances of these interactions, gender and space should be jointly examined.

Our objective is to contribute to the literature by developing and estimating empirical models to study interactions between gender and spatial patterns in influencing food security in developing countries. We employ a rich dataset collected by the Climate Change, Agriculture, and Food Security (CCAFS) research program in early 2010 through late 2012. The data contain geocoded information from 1496 households located across seven different countries in West Africa, East Africa, and South Asia. These data allow us to estimate the impacts that spatial relationships among households have on food security, and test new hypotheses regarding how differing gendered structures, represented by female- and male-headed households, mediate such spatial impacts.

Our approach is based on a variety of spatial autoregressive models to capture the influence of neighbor's food security on own food security. The spatial models are developed to unpack gender mechanisms through which male- and female-headed households spatially affect one another in terms of food security. Specifically, we are interested in answering the following research questions:

- What is the overall impact of neighbor's food security on own food security?
- What is the impact of neighbor's food security on…
    - the food security of female-headed households?
    - the food security of male-headed households?
- What is the impact of the food security of…
    - female neighbors on the food security of female-headed households?
    - male neighbors on the food security of male-headed households?

In pursuit of our objective and research questions, we develop three types of models. First, we construct a spatial autoregressive model (SAR model) to estimate the effect of neighbors' food security on own food security. We use the standard approach in the spatial econometrics literature of weighting the strength of the spatial relationship between two neighbors inversely proportional to the distances between the two farms (Anselin 1988; 2001). We employ an instrumental variable (IV) strategy that allows us to control for the endogeneity of neighbor's food security that could arise because of reverse causality – a household's food security may be influenced by, and influences, neighbors' food security. Our identification strategy follows Kelejian and Prucha who show that first and second order spatial lags of control variables can be used as instruments for the endogenous food security of neighbors (Kelejian and Prucha 1998).

Second, we build ego-gender spatial models to estimate the influence of neighbors' food security on the food security of female- and male-headed households.[1] We approach this objective by estimating split-sample variants of the SAR model (one for each gender). The approach allows us to use information on all households to construct the spatial peer group, but the influence of spatial patterns on each gender is examined separately by predicting the food security of female- and male-headed households in separate models.

Finally, we estimate another variation of the SAR model to explore gender homophily, i.e. the tendency for individuals of the same gender to have stronger influences on one another (Zeltzer 2020).[2] This model explores how food security of female-headed households is affected by their female-headed neighbors. Similarly, the male-homophily model estimates spatial effects of male-headed neighbors on the food security of male-headed households.

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[1] The "ego" terminology is typically used in the fields of spatial analysis and social networks to refer to a specific node (in a network) or position (in a neighborhood). Hence, the "ego" household is the household of reference, which is influenced by its neighbors.

[2] Homophily can operate at the extensive and intensive margins (Girard, Hett, and Schunk 2015). For example, at the extensive margin, homophily predicts that individuals with similar characteristics (e.g. gender) are more likely to be socially connected. At the intensive margin, connections between individuals with similar characteristics might be more meaningful.

The main parameter of interest is the spatial effect parameter, which describes how the food security of neighbors affects own food security. We compare estimates of the spatial parameter from ego-gender models (female interactions with all neighbors *vs* male interactions with all neighbors) and gender homophily models (female interactions with female neighbors *vs* male interactions with male neighbors) to explore how gender and neighborhood effects interact in generating food security spatial spillovers. That is, we develop an ego-gender decomposition by comparing spatial effects estimates from the ego-gender models with that from the SAR model. This approach allows us to learn how all neighbors affect own food security differently according to the gender of the household head. The spatial effect can be further decomposed to examine gender homophily. We compare spatial effects estimates of homophily models against those from ego-gender models. This decomposition allows us to learn how households from each gender are spatially influenced differently by all neighbors vs same gender neighbors.

The remainder of this paper is organized as follows. Section 2 contains a literature review of factors influencing food security, with a focus on gender and spatial interactions. Our data and methods are presented in Section 3. Results and robustness checks are reported in Section 4. In Section 5 we draw conclusions.

## 2. Food Security and Gendered Spatial Interactions

Food insecurity has been identified as being caused by a host of factors, including lack of access to international markets, weak agricultural policies, climate change, poverty, and gender inequality (Godfray et al. 2010; Lim et al. 2020; Mallick and Rafi 2010; Tibesigwa and Visser 2016; Wheeler and von Braun 2013). Gender can play important roles in understanding food security (Ibnouf 2011; Kassie, Ndiritu, and Stage 2014; Modirwa and Oladele 2012). Women often supply labour, and may be responsible for growing, selecting, and preparing food for household members, especially children (USAID 2011; World Bank, IFAD, and FAO 2008). These roles in smallholder food systems make women instrumental in improving livelihoods (Godfray et al. 2010). But women tend to be disadvantaged in producing food, as is evidenced by female-headed households that may be more vulnerable and less food secure than male-headed households (Broussard 2019; Kassie, Ndiritu, and Stage 2014). Energy stress from seasonally high workload in agriculture can have negative impacts on women's nutritional outcomes (Rao and Raju 2019). Women also face numerous constraints that negatively affect available resources which influence production levels, thereby affecting the availability of food for household consumption and potential income. Gender constraints that influence food security may include restrictions on: access to land ownership and assets, information, and credit (C. Doss, Summerfield, and Tsikata 2014; Kassie et al. 2015; Kennedy and Peters 1992), access to shares of household income (Meinzen-Dick, Raney, and Croppenstedt 2014), women's migration (Pickbourn 2022), educational opportunities (Duflo 2012; Rammohan and Vu 2018; Kassie, Ndiritu, and Stage 2014), labor force participation (Mallick and Rafi 2010), and access to human capital (C. R. Doss 2001; Oseni et al. 2015; Scholz and Abdulai 2022).

Spatial relationships between households, which operate within more complex relationships of social networks, can also influence food security. Social networks occur within geographical spaces, with interactions more likely amongst spatially closer households or neighbors (Nolin 2010). For instance, farmers learn and acquire information from the experiences of their neighbors, where the flow of information relies on the structure of these interactions (Foster and Rosenzweig 1995; Krishnan and Patnam 2014). Also, having neighbors with significant endowments of social capital improves the likelihood of acquiring social capital. Moreover, these interactions may produce spillover effects (or spatial multipliers) where information and other externalities are transferred to others (Johny, Wichmann, and Swallow 2017).

Individuals can be affected by their neighbor's behavior in many spheres (i.e., agricultural, financial, health, social). These interactions may impact, for example: the adoption of microfinance loans (Banerjee et al. 2013); the influence of adopting contraceptives (Behrman, Kohler, and Watkins 2002); the facilitation of better employment outcomes (Munshi 2003); agricultural adaptation strategies (Lim, Wichmann, and Luckert 2021; Di Falco, Doku, and Mahajan 2020; Krishnan and Patnam 2014); and food security through food sharing among households as a coping strategy (Ambikapathi et al. 2018). All of these may generate spatial effects.

The literature has identified a variety of mechanisms through which interactions with neighbors may generate spatial spillovers and benefit smallholder farmers. These mechanisms include social learning (Foster and Rosenzweig 1995), diffusion of innovation (Conley and Udry 2010), risk-sharing (Attanasio, Barr, and Cardenas 2012), imitation, sometimes among like individuals (Mcpherson, Smith-lovin, and Cook 2001), and social capital (Katungi, Edmeades, and Smale 2008).

All these factors tend to be influenced by gender. For example, women are more likely to accumulate social capital than men (Kairiza et al. 2023). Women may join groups that are not able to mobilize as many resources as groups made up of men (Maluccio, Haddad, and May 2003). Similarly, gendered differences in resources endowments may impact the formation of social capital and the exchange of information (Katungi, Edmeades, and Smale 2008). Social capital can influence women's relationships in numerous ways. For example, women's relationships may be characterized by people who know each other well (i.e., kinship, neighbors), while men's interactions may be comprised of people who are not well connected (Hanson and Blake 2009). Moreover, women may have a higher opportunity cost of time than men (e.g. from a high domestic workload), which reduces their participation in organizations or other social interactions (Meinzen-Dick and Zwarteveen 1998). This constraint may motivate women to engage in relationships that are spatially closer, and perhaps develop fewer but more meaningful relationships. Conversely, men's interactions may be more geographically dispersed, with more connections regarding civic affairs (Maluccio, Haddad, and May 2003).

The potential for gender to interact with neighborhood effects is further increased by homophily – the preference of individuals to interact with like peers (Stehlé et al. 2013). Gender homophily can be especially important in the context of food security in developing countries. For instance, role models may be gender specific. Women may imitate labor market practices of other women, and men may imitate men. This imitation can result in gender-segregated economic opportunities (Gittinger 1990). In this sense, homophily can perpetuate existing social norms and therefore act as a barrier to reducing gender gaps in food security (Cleaver 2005). Gendered norms may constrain neighborhood effects as geographic distance can limit women's interactions with like neighbors (D'Exelle and Holvoet 2011).

In summary, though the potential importance of gender and spatial interactions is widely recognized, there is little empirical evidence about how such interactions influence food security. In the approach that follows, we develop methods to directly examine gender-space interactions and their impacts on food security in a multi-country application that allows us to identify central tendencies in some of the most food insecure regions of the world. We hypothesize that closer spatial relationships between households positively influence food security, but that these relationships differ depending on whether households are female- or male-headed.

# 3. Methods

## 3.1 Data

The paper uses a rich geocoded dataset from the Integrated Modelling Platform for Mixed Animal Crop systems (IMPACT) Lite collected from 2010 to 2012 by Climate Change, Agriculture, and Food Security (CCAFS)[3]. The information collected includes household characteristics and assets, food consumption, livelihood strategies, and production technology (see Table 1). The data is from twelve districts in seven countries in three world regions: East Africa (Kenya and Tanzania), West Africa (Ghana and Senegal), and South Asia (India, Nepal, and Bangladesh). Figure 1 shows the location of the study sites. These regions represent areas with high levels of vulnerability and poverty, different institutional and social contexts, and weather-related challenges, all of which contribute to significant levels of food insecurity (Förch et al. 2011).[4] Online Appendix A (supplemental materials) discusses the study sites and sampling procedures.

Empirical methods must consider the significant heterogeneity present in a multi-country sample. This heterogeneity must be considered when developing an empirical approach to measure food security such that local/seasonal changes are accounted for. It also makes it challenging to specify food security models controlling for all relevant factors with observable information. In other words, it is possible for unobservable site-specific effects to be correlated with drivers of food security (e.g., neighbors' food security), which would introduce confounding bias in our estimates. Below we discuss how our measurement of food security and the use of site fixed effects

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[3] The IMPACT Lite data is available online at https://data.ilri.org/portal/. Global Positioning System (GPS) coordinates of individual households are not publicly available and were obtained through a data agreement with CCAFS to maintain information security and privacy.

[4] As we discuss below, 80% of households in our sample are classified as food insecure.

allow us to control for the challenges of our multi-country sample. Despite identification challenges, our study benefits from having observations from various developing countries which enhances external validity of our findings.

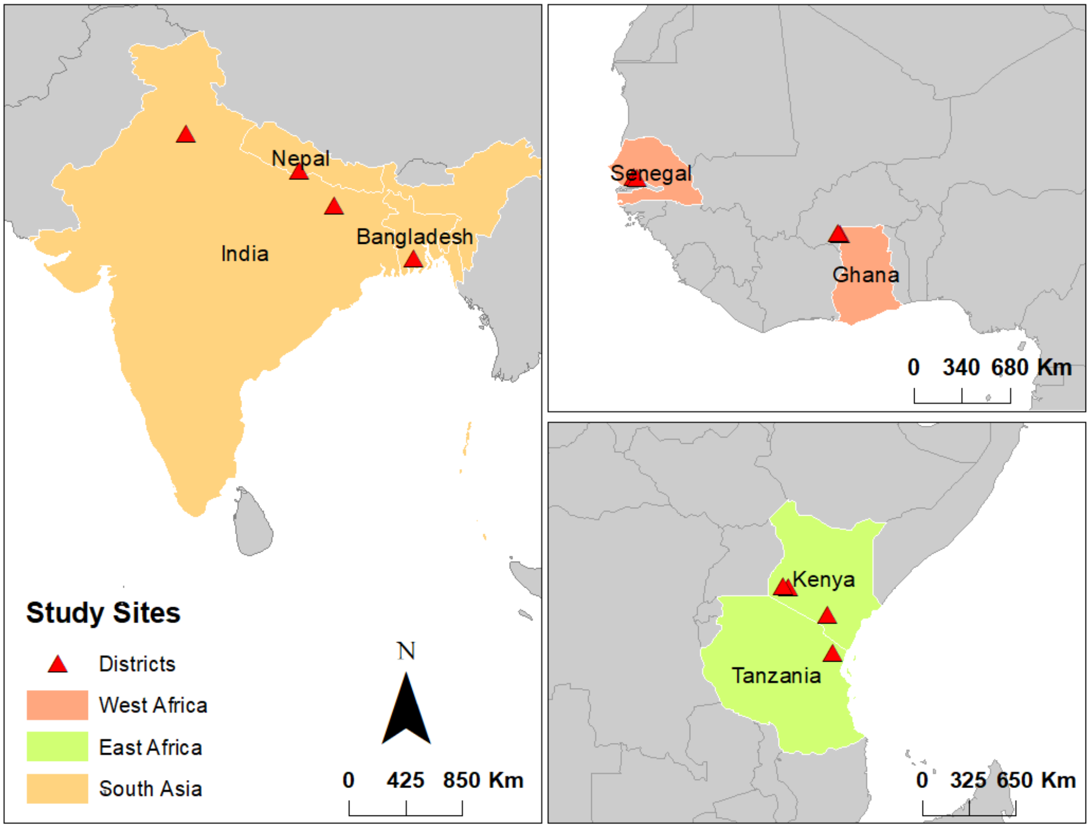

Figure 1: Location of Study Sites

## 3.2 Spatial Autoregressive Model

The goal of our baseline model is to test for food security neighborhood effects. We test this hypothesis by estimating a spatial autoregressive (SAR) model. In SAR models, observations are characterized by their location, often measured using Global Positioning System (GPS) coordinates. Our model is based on the work, discussed above, that shows that many mechanisms can be at play to generate spatial spillovers. We conceptualize a spatial system where food security at one specific location depends on the food security of neighbors (Anselin 1988).

Considering a set of $n$ cross-sectional units, the SAR model, in matrix notation, is:

$$Y = \rho WY + Z\gamma + \varepsilon \tag{1}$$

where $Y$ is an $n \times 1$ vector of observations on the dependent variable, i.e. *food security*, $\rho$ is the spatial autoregression parameter, $W$ is a spatial weight matrix, i.e., an $n \times n$ neighborhood matrix that accounts for the spatial interactions (dependencies) among the spatial data, $Z$ is an $n \times k$ matrix of observations on $k$ explanatory variables, e.g., *age of the head*, *assets*, $\gamma$ is a $k \times 1$ vector of regression coefficients, and $\varepsilon$ is an $n \times 1$ vector of unobservable errors.

We use a truncated distance matrix to calculate spatial weights. Specifically, $w_{ij} = 0$ if households at locations $i$ and $j$ are further than 20 kilometers apart.[5] For households under the 20km threshold, spatial weights are determined by the row-normalization of their inverse distance matrix (LeSage and Pace 2009; Bramoullé, Djebbari, and Fortin 2009). Refer to Online Appendix D for a formal presentation.

In the SAR model, the main term of interest is $WY$, the left multiplication of the food security column vector $Y$ by the matrix of spatial weights $W$. The term $WY$ is a weighted average of neighbors' food security, where weights increase with spatial proximity. This term is also known as the spatial lag of $Y$.[6] Therefore, the spatial autoregressive parameter $\rho$, often referred to as the

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[5] Online Appendix B summarizes the spatial distribution of households by showing average and standard deviation of the distance between pairs of households for every district in our sample. We choose 20 km truncation for being a distance just below the sample mean of 25 km; i.e., a distance that defines neighbors that are more likely to influence food security. As a robustness check, we perform sensitivity analyses on this truncation assumption in presenting our results. Online Appendix C shows the distribution of neighbors within 20 km, also referred to as the degree distribution in the social network literature (Jackson 2010), by district. On average, households in our sample have 104.4 neighbors, with standard deviation of 54.6.

[6] Using scalar notation, the food security of $i$'s neighbors is $\sum_j w_{ij} y_j$, where $j$ indexes neighbors of $i$. Note that own food security is not part of the neighbor's outcome because $w_{ii} = 0$.

spatial effect, captures the marginal effect of neighbors' food security on own food security. For example, when $\rho > 0$, an increase in neighbors' food security of *x* calories leads to an increase in own food security of $\rho x$ calories.

The SAR model captures spatial multipliers. As $W$ is row-normalized, the spatial multiplier can be approximated by $\frac{1}{1-\rho}$ (Anselin 2003; Lim, Wichmann, and Luckert 2021). Therefore, the spatial spillover depends on $\rho$, with larger spatial effects generating larger spillovers. A formal presentation of the spatial multiplier and a discussion about its interpretation are provided in Online Appendix E (also see Wichmann 2015).

In scalar notation, our baseline SAR model is:[7]

$$Y_{id} = \rho \sum_{j} w_{ij} Y_{jd} + X'_{id}\beta + C'_{c}\theta + D'_{d}\delta + T'_{t}\alpha + \varepsilon_{id} \tag{2}$$

where $Y_{id}$ is a measure of food security of household $i$ located in district $d$ and $\sum_j w_{ij} Y_{jd}$ is the spatially weighted food security of $i$'s neighbors (indexed by *j*). We expand our notation of the control variables ($Z$ in model 1) to include not only typical control variables but also a series of fixed effects. $X'_{id}$ contains socioeconomic characteristics of household $i$ that have been shown in the literature to influence food security; $C'_c$ represents crop fixed effects; $D'_d$ represents district fixed effects; $T'_t$ represents technological fixed effects; $\beta, \theta, \delta$ and $\alpha$ are parameter vectors; $\rho$ is the spatial effect parameter; and $\varepsilon$ is an error term that captures unobserved determinants of food security.[8]

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[7] Note that equation (2) is the scalar notation equivalent of equation (1), where $Z = [X, C, D, T]$

[8] Specific measures used for each of the variables are discussed in section 3.4.

## 3.3 Gender-Specific Spatial Models

To examine multiple pathways through which gender may interact with neighborhood effects, we construct two variants of our baseline spatial model: the Ego-Gender model and Gender-Homophily model. The first gendered model considers impacts of both male- and female-headed neighbors on the ego household, while the second model considers impacts of like-gendered households. We assume that each ego household can be either female- or male-headed. All households located within 20km from the ego are defined as comprising the ego's neighborhood. Note that a female-headed ego can have both male- and female-headed neighbors. Conversely, a male ego may have neighbors of both type of gendered households.

### 3.3.1 *Ego-Gender Models*

Using an ego-centric perspective, where a household $i$ of gender $g \in \{M, F\}$ is influenced by $i$'s neighborhood, the ego-gender spatial mode in scalar notation is:

$$Y_{id}^{g} = \rho^{g}\tilde{Y}_{id}^{g} + X_{id}^{g\prime}\beta^{g} + C_{c}^{g\prime}\theta^{g} + D_{d}^{g\prime}\delta^{g} + T_{t}^{g\prime}\alpha^{g} + \varepsilon_{id}^{g} \qquad (3)$$

where the superscript $g$ indicates that only observations of ego-centric gender $g$ are included in the regression. The variable $\tilde{Y}_{id}^{g}$ represents the weighted average of the food security of the neighborhood of ego $i$ of gender $g$, or simply $\tilde{Y}_{id}^{g} = \sum_{j} w_{ij} Y_{jd}$ for ego-centric household $i$ of gender $g$. Note that while all neighbors of $i$ are considered, observation $\tilde{Y}_{id}^{g}$ is calculated only for households of gender $g$. In other words, model (3) collects the rows of model (1) with gender $g$.

In contrast with the traditional SAR model, where all households in a village may have some (direct or indirect) influence on one another, the ego-gender models focus on ego neighborhoods; i.e., gender-based immediate (first degree) neighbors, as opposed to the entire village (which also includes the neighbors of opposite gender). In other words, while the SAR model imposes no restrictions on the second- and higher-order spatial effects, the ego-gender models only consider second- and higher-order effects amongst the set of immediate neighbors of the ego household $i$ of gender $g$.

The ego-gender models allow us to estimate gender-specific spatial effects based on gender-specific direct neighborhoods. As such, the ego-gender models capture different types of spatial effects. To see why, consider the following example. In the standard SAR model, a spatial multiplier for a female (ego) household captures the effects of all her neighbors (males and females) on her food security. Therefore, the standard SAR effect allows the female ego household to benefit (or be influenced) directly by her neighbors, and also indirectly by the food security of neighbors of her male and female neighbors (second-degree neighbors), and by neighbors of neighbors of neighbors (third-degree neighbors), and so on. By splitting the sample, our ego-gender model imposes constraints on these indirect channels from opposite gender ego-networks. Estimates of spatial effects in the female ego-gender model do not allow women-headed households to benefit from men-headed neighbors. Conversely, the male model does not allow for men-headed households to benefit from women-headed neighbors. Instead, the ego-gender model offers an assessment of the spatial effects for a specific region of the village characterized by the ego-centered neighbors and their multipliers.

We estimate a regression model for each type of gendered household. The parameter $\rho^M$ is estimated when model (3) has gender $g = M$ and therefore uses 1298 male-headed ego-centric observations, while $\rho^F$ uses 198 female-headed ego-centric observations.[9] A comparison of $\rho$

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[9] Note that while 1298 (198) observations are used to estimate the parameters of male (female) model, all 1496 observations are used in computing the variable $\tilde{Y}_{id}^{g} = \sum_j w_{ij} Y_{jd}$. A discussion of the estimation strategy is provided below.

from equation (2) and $\rho^g$ from equation (3) reveals how the spatial effect differs by gender. As $\rho$ can be viewed as an average spatial effect in the entire sample, we expect $\rho$ to be a weighted average of female ($\rho^F$) and male ($\rho^M$) marginal effects. This approach can be thought of as a decomposition of the overall spatial effect by gender headship of the households.

### *3.3.2 Gender Homophily Models*

In homophily models, we are interested in estimating the effect of the food security of neighbors of gender $g$ on the ego household of same gender $g$. Therefore, not all neighbors are considered when calculating the weighted average of neighbors' food security. Instead, we define the set of ego-households with gender $g$ as $G$.[10] We construct the spatial lag measure $\bar{\bar{Y}}_{id}^{g} = \sum_j w_{\{i,j\}\in G} Y_{jd}$, which captures food security as being influenced by spatial interactions, for an ego of gender $g$.

Note that this equation does not correspond to a row of system (1), as the weights are recalculated (via row normalization) for the case of same gender neighborhood $G$. To calculate the weights $w_{\{i,j\}\in G}$ we construct a new spatial matrix $W^G$ that collects the influences of column individuals on a row (ego) individual, where all individuals have the same gender $g$. Therefore, in the female homophily model, this matrix is a $198 \times 198$ square matrix, and a $1298 \times 1298$ matrix in the male homophily model. As in the baseline model, the matrix is truncated at 20km, row-normalized, with weights inversely proportional to the distance between $\{i,j\} \in G$.[11] Note

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[10] Recall that $G$ has 198 households in the female-headed set, and 1298 households in the male-headed set.

[11] Formally,

$$\begin{cases} w_{\{i,j\}\in G} = \dfrac{\left({}^{1}\!/_{d_{ij}}\right)}{\left[\sum_j \left({}^{1}\!/_{d_{ij}}\right)\right]} & \text{if} \quad i \neq j \text{ and } d_{ij} \leq 20, \forall \{i,j\} \in G \\ w_{\{i,j\}\in G} = 0 & \text{if} \quad i = j \text{ or } d_{ij} > 20, \forall \{i,j\} \in G \end{cases}$$

Refer to Online Appendix D for additional details.

that elements $w_{\{i,j\}\in G}$ of $W^G$ are different from elements $w$ of the baseline matrix $W$ in model (1) because the matrix $W^G$ considers a subset of households. Therefore, the number of elements in the normalizing sum $\sum_j \left({}^{1}/_{d_{ij}}\right)$, $\forall\{i,j\} \in G$ is different from the number of elements in the baseline normalizing sum $\sum_j \left({}^{1}/_{d_{ij}}\right)$, $\forall\{i,j\}$ in the sample. As the number of households change, thereby changing the normalizing factor, the distribution of spatial weights in a row of $W^G$ also changes and is different from the distribution of weights in the corresponding row of $W$.

The construction of $W^G$ is based on the concept of homophily. In this model, the spatial matrix considers weights of neighbor $j$ on ego $i$ when $j$ and $i$ have the same gender (weight 0 otherwise). This is a homophily construction as weights reflect influences of households headed by of same gender. Note that without row normalization, the homophily model would be influenced by the number of neighbors that each household has, rather than considering the shape of the distribution of weights within the homophily neighborhood. Estimates from such a model would bias results toward egos with more neighbors. By row normalizing $W^G$, we focus on the homophily distribution of weights, which allows for a comparison of coefficients across other models (above and in the literature) that are also row-normalized.

The discussion above leads to the following model of gender homophily, shown here in scalar notation $\forall\{i,j\} \in G$:

$$Y_{id}^{g} = \rho_H^g \sum_j w_{\{i,j\}\in G} Y_{jd}^{g} + X_{id}^{g\prime}\beta_H^g + C_c^{g\prime}\theta_H^g + D_d^{g\prime}\delta_H^g + T_t^{g\prime}\alpha_H^g + \varepsilon_{id}^{g} \qquad (4)$$

A comparison between $\rho_H^g$ (model 4) and $\rho^g$ (model 3) reveals, for egos of gender $g$, how marginal spatial effects depend on all neighbors, as opposed to how much spatial effects depend on gender-homophily (same gender) spatial interactions.

## 3.4 Variables

### *3.4.1 Measuring food security*

Estimation of our model requires empirical measurement of the food security of households in our sample (vector $Y$ in model 1). Numerous measures have been developed in order to address the multi-faceted concept of food security (Jones et al. 2013). The approach used in this study leverages the correlation between the complex concept of food security with supply-side indicators that are often measured in daily calories consumed per person. Accordingly, this study uses a calorie gap measure of food security (Ncube et al. 2016).

The IMPACT Lite survey contains detailed dietary information collected through recall of household-level consumption over a week for different seasons of the year. This is important because food supply can vary significantly within the year, depending on the growing season. We note that the growing season varies between districts due to many factors, including local weather and crop mix. The site-specific survey instrument considers the timing and site-specific seasonal characteristics to determine relevant seasons[12].

The calorie gap metric is defined as the difference between the actual daily calorie intake and a recommended daily calorie intake. For each household in our sample, we use the Food and Agriculture Organization and the World Health Organization (FAO/WHO 2008) recommended household-level caloric intake delineated by gender and age information (see Ncube et al. 2016). A positive calorie gap implies the household is food or calorie-rich (actual caloric intake is greater than recommended intake); conversely, a negative gap indicates that a household is food or calorie-

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[12] As we discuss below, we also use fixed effects to capture the impacts of local unobserved variation to improve the identification of gender and neighborhood effects.

poor (actual caloric intake is smaller than recommended intake). Details are available in Online Appendix F.

### 3.4.2 *Determinants of food security*

Following the model specifications above, in this section, we describe the main determinants of food security (matrix $X$ in model 2). Based on a number of studies, e.g., Millimet, McDonough, and Fomby (2018), Yen et al. (2008), Kassie, Ndiritu, and Stage (2014), we consider determinants of food security in three categories: household characteristics, assets, and livelihood strategies. Our choice of variables within each category is largely dictated by data availability. The variables we employ are listed in Table 1.

Our key household characteristic of interest is *Female-headed Household.* We also consider two characteristics of households that are thought to influence agricultural production; *age of household head* (Fekadu and Muche Mequanent 2010; Bussolo et al. 2015), and *household size* (Garrett and Ruel 1999). To control for household assets, we consider *domestic* (Bryan et al. 2009)*, transport* (Kassie, Ndiritu, and Stage 2014) and *productive assets* (Gittinger 1990). We construct indices for each of these categories using procedures adapted from Njuki et al. (Njuki et al. 2011) (see Online Appendix G). *Off-farm income*, can serve as a diversification strategy (Fekadu and Muche Mequanent 2010). We use a dummy variable to indicate whether the household earns cash from activities outside the farm, including remittances. In promoting food security, authors have also identified the potential importance of livestock (FAO 2018; Little et al. 2006), crops (Grootaert and Narayan 2004; Fekadu and Muche Mequanent 2010) and combinations of livestock and crops (Frelat et al. 2016). Following these authors, one can think of livestock and agricultural land as various combinations of inputs that provide various levels of food security; much like production decisions represented by isoquants of food security output levels. As is typically the case with isoquants, these authors show a convex relationship between inputs (i.e., livestock and agricultural land) that provides alternative levels of food security. Because of the non-linear relationships between livestock and agricultural land, we specify a variable that is the ratio of livestock and land size in a polynomial specification. The specification includes the number of *ruminants per acre* and the number of *ruminants per acre squared.*

## 3.5 Identification

One important concern with multi-country studies is the influence of unobserved site-specific determinants of food security. These can include, for example, institutional settings and weather-related phenomena. Unobserved country- (or site-) specific factors may interact with socioeconomic determinants of food security ($X$ in model 2) and, if left unchecked, these influences could bias estimates through their correlations with $X$.

We employ a variety of fixed effects to attenuate potential omitted variable bias. For instance, cash transfers have been commonly used as a social protection scheme to alleviate malnutrition in Africa (Burchi, Scarlato, and d'Agostino 2018). But these transfers not only improve food security but also a variety of other household outcomes (Premand and Barry 2022). As a result, cash transfers may drive the availability of household assets. Failing to control for these district-level programs would then lead to confounding effects and bias our model estimates.[13] Clearly, there are many other district-level drivers of food security that are often unobserved by researchers (especially in a multi-continent study such as ours). Examples include local weather, soil quality, and social norms (Schlenker and Roberts 2006; D'Exelle and Holvoet 2011). We control for these unobserved district-level confounding factors by augmenting our model with district fixed effects ($D$ in model 2).

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[13] As we discuss below, the exogeneity of observables is also important in implementing our instrumental variable strategy for addressing the endogeneity of neighbors' food security.

The production of different types of crops may also result in different levels of food security. For example, smallholder farmers switch land use practices in reaction to changes in pricing dynamics (Dislich et al. 2018; Ncube et al. 2016). Crop-specific productivity can lead to variation in nutritional quality of the household's diet (Immink and Alarcon 1991), and may also represent diversification strategies, which have implications for agricultural intensification (Chen et al. 2018). Our spatial models are augmented with crop controls by including 14 crop dummy variables that represent the main crops of households in our sample ($C$ in model 2). Each of these crops are cultivated by at least 2% of the households.

Moreover, the adoption of agricultural technologies is typically correlated with unobservable farmers' characteristics such as risk and uncertainty preferences (Crost et al. 2007). Therefore, controlling for technology and agricultural practices ameliorates model specification reducing the potential for omitted variable bias. To capture technology effects, we include indicators for intercropping and land fragmentation ($T$ in model 2). Intercropping indicates whether a household implements cultivation of two or more crops simultaneously on the same field. Fragmentation is measured using a Herfindahl index.[14] Households with a normalized index value that is less than the mean are designated with a dummy variable as having high land fragmentation. Descriptive statistics for the fixed effect variables are available in Table 1.

The endogeneity of the spatial lag is another important threat to identification. Equation (1) shows that the spatial lag term of the SAR model is correlated with the error term (i.e., the outcome $Y$ is on both sides of the equation). Even when controls, $Z$, are exogenous, for $\rho \neq 0$, the

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[14] $HI_i = \sum_{n=1}^{N} ({}^{p}/_{t})^2$, where $p$ is the area of the plot of household $i$, $N$ is the number of $i$'s plots, and $t$ is the total area of all $i$'s plots. The index is normalized, so that it ranges from 0 to 1: $NH_i = \frac{(HI_i - {}^{1}/_{N})}{1 - {}^{1}/_{N}}$.

food security of neighbors affect egos' food security, and vice-verse, which leads to reverse causality. In this situation, ordinary least squares estimation of the SAR model delivers biased and inconsistent estimates (Anselin 1988).

There are several approaches available for consistent estimation of SAR models, e.g. Maximum likelihood and Bayesian Markov Chain Monte Carlo, with some approaches being more computationally intensive than others (LeSage and Pace 2009). A simple and increasingly popular spatial effect estimation approach is to use instrumental variables. We address the endogeneity of the spatial lag by implementing a Generalized Methods of Moments Instrumental Variable (GMM/IV) strategy, which was first proposed by Kelejian & Prucha (Kelejian and Prucha 1999; 1998) and is currently well-established in the literature (Arraiz et al. 2010; Bramoullé, Djebbari, and Fortin 2009). The approach relies on instruments that are constructed as spatial transformations of the variables in the SAR model. This approach delivers a powerful identification method under the assumption of exogeneity of $Z$. The approach can be easily computed, and, as we will discuss below, it can be adapted to the estimation of gender-specific spatial effects and gender homophily spatial effects.

Specifically, Kelejian & Prucha propose an IV approach implemented via an over-identified GMM. They show that first and second order spatial lags of control variables, namely $WZ$ and $W^2Z$, respectively, can be used as instruments for the spatial lag of the outcome $WY$ in SAR models. Similar to the Neumann series discussion above, these instruments have interesting economic interpretations. The first-order spatial lags $WZ$ are the weighted averages of the determinants of food security of ego's neighbors (first-order neighbors), and $W^2Z$ are the weighted averages of the determinants of food security of the ego's neighbors' neighbors, or second-order neighbors (LeSage and Pace 2009).

This literature shows that identification of the parameters of model (2) can be accomplished using a GMM approach with the moment conditions $E[Z'\varepsilon] = 0$, $E[WZ'\varepsilon] = 0$, and $E[W^2 Z'\epsilon] = 0$, where $Z = [X, C, D, T]$ is a matrix that captures, respectively, determinants of food security, crop effects, district effects, and technology effects. The approach can be easily adapted to reflect moment conditions of our two variations of the SAR model. Using the same principle, identification of model (3) can be accomplished using the subsets of constant-gender of the above moment conditions; the rows with the same ego-gender of the conditions $E[Z'\varepsilon] = 0$, $E[WZ'\varepsilon] = 0$, and $E[W^2 Z'\epsilon] = 0$. Similarly, the estimation of homophily models (equation 4) relies on the restrictions $[Z'\varepsilon] = 0$, $E[W^G Z'\varepsilon] = 0$, and $E[{W^G}^2 Z'\epsilon] = 0$.

# 4 Results

## 4.1 Descriptive Statistics

Table 1 shows descriptive statistics, by region (Africa and Asia). A vast majority of the households in our sample have a caloric deficit and are therefore considered food-insecure households (82% in Africa and 79% in Asia). The prevalence of calorie deficits indicated by these results are consistent with United Nations food security estimates which indicate that since 2005 Africa and Asia are the continents that remain with the highest prevalence of undernourishment (FAO et al. 2022).

## Table 1: Descriptive Statistics

| Category / Variable | Definition | **Africa** (n=928) | | **Asia** (n=568) | |
|---|---|---|---|---|---|
| | | **mean** | **st. dev.** | **mean** | **st. dev.** |
| **Dependent Variable**[a] | | | | | |
| *Calorie Gap* | Household caloric intake minus WHO recommended caloric intake (per day) | -8,352.5 | 10,629.7 | -4,842.9 | 7,053.4 |
| **Household Characteristics** | | | | | |
| *Female-headed Household* | Dummy: 1 if the woman is the household head | 0.17 | 0.37 | 0.08 | 0.27 |
| *Age of Household Head* | Household head's age in years | 50.98 | 15.01 | 48.35 | 13.98 |
| *Household Size* | Number of people living in a household | 6.95 | 3.72 | 5.52 | 2.65 |
| **Household Assets**[b] | | | | | |
| *Domestic Assets* | Index of domestic assets | 9.96 | 7.44 | 9.50 | 6.89 |
| *Transport Assets* | Index of transport assets | 9.34 | 17.32 | 12.73 | 20.72 |
| *Productive Assets* | Index of productive assets | 5.14 | 3.47 | 3.67 | 3.85 |
| **Household Livelihood strategies** | | | | | |
| *Off-farm Income* | Dummy: 1 if the household earns off-farm income | 0.82 | 0.38 | 0.89 | 0.31 |
| *Ruminants per Unit of Land* | Number of ruminants (cattle, buffaloes, goats, sheep) per acre | 1.82 | 4.25 | 3.11 | 7.56 |
| **District Fixed Effects** | | | | | |
| *Birkelane (Senegal)* | | 0.09 | 0.29 | | |
| *Kaffrine (Senegal)* | | 0.12 | 0.32 | | |
| *Jirapa (Ghana)* | | 0.07 | 0.26 | | |
| *Lawra (Ghana)* | | 0.12 | 0.32 | | |
| *Makueni (Kenya)* | | 0.20 | 0.40 | | |
| *Nyakach (Kenya)* | | 0.08 | 0.27 | | |
| *Kericho (Kenya)* | | 0.12 | 0.32 | | |
| *Lushoto (Tanzania)* | | 0.20 | 0.40 | | |
| *Bagerhat (Bangladesh)* | | | | 0.30 | 0.46 |
| *Karnal (India)* | | | | 0.15 | 0.36 |
| *Vaishali (India)* | | | | 0.25 | 0.44 |
| *Rupandehi (Nepal)* | | | | 0.30 | 0.46 |
| **Crop Fixed Effects** | | | | | |
| *Aquaculture fish* | | | | 0.18 | 0.38 |
| *Beans* | | 0.03 | 0.18 | | |
| *Groundnuts* | | 0.20 | 0.40 | | |
| *Lentils* | | | | 0.11 | 0.31 |
| *Maize* | | 0.37 | 0.48 | 0.09 | 0.29 |
| *Mangoes* | | 0.05 | 0.22 | 0.01 | 0.12 |
| *Millets* | | 0.12 | 0.32 | | |
| *Mustard Seed* | | | | 0.26 | 0.44 |
| *Rice Paddy* | | | | 0.85 | 0.36 |
| *Potato* | | 0.02 | 0.14 | 0.14 | 0.35 |
| *Sorghum* | | 0.04 | 0.20 | 0.00 | 0.04 |
| *Sugarcane* | | 0.03 | 0.17 | 0.00 | 0.06 |
| *Vegetables* | | | | 0.09 | 0.29 |
| *Wheat* | | | | 0.64 | 0.48 |
| **Technological Fixed Effects** | | | | | |
| *Intercropping* | | 0.82 | 0.39 | 0.23 | 0.42 |
| *Fragmentation* | | 0.35 | 0.48 | 0.04 | 0.20 |

[a] See Online Appendix F for details. [b] See Online Appendix G for details.

Female-headed households are more common in Africa (17%) than in Asia (8%). On average, the age of the household head is 51 years old in Africa, and 48 years old in Asia. African households have, on average, 7 people while Asian households have 5.5. Households in Africa and Asia have similar levels of domestic assets, but Asian households have higher levels of transportation assets while African households have higher levels of production assets. A vast majority of the households earns off-farm income (82% in Africa and 89% in Asia). On average an African household owns 1.8 ruminants per acre and Asian households have a higher density at 3.1 ruminants per acre. The most common crop in Africa is Maize (grown by 37% of households) followed by groundnuts (20%). In Asia, the most common crop is rice (85%) followed by wheat (64%). Most African households implement intercropping (82%) while this proportion is far less in Asia (23%). Finally, 35% of African households are considered to have high land fragmentation, while this proportion is only 4% in Asia. Online Appendix H shows descriptive statistics by gender.

## 4.2 Spatial Effects Estimates

Table 2 shows the IV estimates of our models. While the IV approach is theoretically justified in the spatial autoregressive models, Table 2 also reports the first stage F statistic. For the models with the entire sample (column 1) or male-headed household (columns 3 and 5), the F statistic is above or very close to the rule of thumb level of 10. For the female-headed models, where the number of observations is small, the first stage F statistic hovers around 8.5. The table also shows that the fits of the models are better in the full sample or male-headed models (columns 1, 3, and 5 with r-squared of approximately 0.72), compared to the female-headed models (columns 2 and 4 with r-squared of approximately 0.48). Nevertheless, as we discuss below, the estimates of the spatial effects are significant in all models.

**Table 2: Regression Results**

| Dependent Variable: Calorie Gap Measure$^+$ | SAR Model | Ego-Gender Models | | Gender Homophily Models | |
|---|---|---|---|---|---|
| Model | (1) | (2) | (3) | (4) | (5) |
| Description 1 – Gender of Ego | All | Females | Males | Females | Males |
| Description 2 – Gender of Neighbors | All | All | All | Females | Males |
| *Food Security of Neighbors (ρ)* | 0.166*** | 0.491*** | 0.146*** | 0.684** | 0.163*** |
| | (0.044) | (0.124) | (0.041) | (0.291) | (0.038) |
| Household Characteristics | | | | | |
| *Female-Headed Household* | -988.492** | | | | |
| | (496.816) | | | | |
| *Age of Household Head* | -42.269*** | -1.697 | -47.583*** | 4.531 | -47.679*** |
| | (9.642) | (24.143) | (10.782) | (24.973) | (10.682) |
| *Household Size* | -1558.375*** | -1431.371*** | -1566.164*** | -1534.631*** | -1566.449*** |
| | (125.271) | (248.710) | (134.133) | (222.328) | (133.669) |
| Household Assets | | | | | |
| *Domestic Assets* | -22.309 | -50.761 | -27.729 | -56.711 | -26.935 |
| | (29.807) | (74.737) | (31.742) | (85.778) | (31.540) |
| *Transport Assets* | 5.062 | 104.795*** | 0.977 | 108.344*** | 0.892 |
| | (9.584) | (23.339) | (9.301) | (25.310) | (9.309) |
| *Productive Assets* | -12.213 | 28.233 | -24.35 | 79.706 | -24.495 |
| | (32.475) | (114.573) | (34.955) | (116.251) | (35.391) |
| Household Livelihood Strategies | | | | | |
| *Off-farm Income* | 601.02 | 1783.541** | 466.019 | 2255.870** | 464.166 |
| | (560.737) | (722.775) | (492.517) | (877.453) | (492.212) |
| *Ruminants per Unit of Land* | 152.080** | 160.107 | 153.826** | 156.637 | 153.748** |
| | (60.475) | (154.744) | (62.445) | (164.779) | (61.709) |
| *Ruminants per Unit of Land Squared* | -2.478*** | -5.964 | -2.361*** | -5.818 | -2.367*** |
| | (0.821) | (6.426) | (0.869) | (7.284) | (0.860) |
| N | 1496 | 198 | 1298 | 198 | 1298 |
| R-squared | 0.710 | 0.473 | 0.723 | 0.484 | 0.723 |
| First Stage F statistic | 9.985 | 8.268 | 24.832 | 8.551 | 10.593 |

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level. Standard errors are clustered at the site level. All regressions include crop, district, and technology fixed effects. First stage F statistic is based on Kleibergen-Paap cluster-robust statistic (Kleibergen and Paap 2006). $^+$ The Calorie Gap Measure is the difference between the actual daily calorie intake of a household and the calorie intake recommended by the WHO.

We start by discussing the estimate of the spatial effect (i.e., *Food Security of Neighbors*) from the *SAR Model* (full sample model, Table 2, column 1). We estimate a spatial effect parameter $\rho = 0.166$ ($p<0.01$).[15] This result suggests that the food security of neighbors has a positive influence on own food security. Specifically, a household's food security increases by approximately 17 calories in response to an increase of 100 calories in neighbors' food security.

The results of the *Ego-Gender* models are shown in columns (2) and (3) of Table 2. Specifically, we estimate spatial parameters equal to $\rho = 0.491$ ($p<0.01$) and $\rho = 0.146$ ($p<0.01$) for female- and male-headed households, respectively. These estimates show that the ego-gender spatial effect for male-headed households is similar to that of the *SAR model*. Interestingly, female-headed households benefit more from their neighbors than their male-headed counterparts. For female-headed households, food security increases by 49 calories when neighbors' food security increases by 100 calories.

The results of the *Gender Homophily* models are shown in columns (4) and (5). We estimate the spatial effects parameters $\rho = 0.684$ ($p<0.01$) and $\rho = 0.163$ ($p<0.01$) for female- and male-headed households, respectively. The gender homophily spatial effect for male-headed households, i.e., male ego influenced by other male-headed households, is similar to that of the male *Ego-Gender* and *SAR* models. In contrast, women-headed households benefit much more from their women-headed neighbors. Results from the *Gender Homophily* model in column (4) show that female-headed household's food security increases by 68 calories in response to an

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[15] Recall that these models are estimated by examining households that live within 20 kilometers of one another. We also perform a sensitivity analysis by estimating the SAR model with distances of 15 and 25 kilometers. Online Appendix I reports the estimates of the SAR model with these assumptions. The spatial coefficients do not substantially change in comparison with the estimates reported in Table 2.

increase of 100 calories in female-headed neighbors' caloric intake. These results support the idea that spatial homophily enhances smallholder farmer food security, but only for women.

Collectively, the spatial effects estimates reported in Table 2 can be used to decompose gender mechanisms that interact with space to generate spillovers. This decomposition interpretation is based on fact that the ego and homophily models impose increasing gender-based restrictions on the spatial relationships captured by the *SAR* model. That is, the *Ego-Gender* models exploit spatial effects by the gender of the ego household to answer: how do spatial relationships with all neighbors affect the food security of gender-specific ego households? Imposing further restrictions, the *Gender Homophily* model exploits same gender spatial relationships: how do same-gender neighbors affect the food security of gender-specific ego households?

To examine how gender shapes spatial effects for women and men, let $\rho^{(i)}$ denote the spatial coefficient in column $i$ of Table 2. One way to interpret our results is to define $\Delta_i^{EG} = \rho^{(i)} - \rho^{(1)}$, for $i = 2{,}3$ as an ego-gender decomposition of the general spatial effect $\rho^{(1)}$. Similarly, $\Delta_i^{GH} = \rho^{(i)} - \rho^{(i-2)}$ , for $i = 4{,}5$ can be thought of as an additional decomposition, this time capturing homophily effects.

An important result from the results in Table 2 is that for male-headed households $\Delta^{EG} \approx \Delta^{GH} \approx 0$. Food security gains in male-headed households from spatial interactions are invariant to the explored gender-based mechanisms of interaction. That is, average food security spatial effects in the districts are similar to food security spatial effects for male-headed households, which in turn is similar to male-headed spatial benefits from male-headed neighbors. On the other hand, for women-headed households we find that $\Delta^{GH} > \Delta^{EG} > 0$. Food security gains in female-headed households from spatial interactions with neighbors are stronger than average spatial benefits in for the entire district ($\Delta^{EG} > 0$). Moreover, the results point to the important role of women-headed households in generating spatial food security benefits for other female-headed households ($\Delta^{GH} > \Delta^{EG}$).

In summary, our results show that women-headed households significantly benefit from their spatial and homophilic interactions, while the spatial gains for male-headed households are not driven by gender or homophily effects. This finding is consistent with findings from the literature. Spatially correlated social capital can be an important determinant of food security. Having neighbors with significant endowments of social capital improves the likelihood of acquiring social capital. And social capital also has a gender dimension. Female-headed households are more likely to have bonding social capital than male-headed households (Kairiza et al. 2023). Kairiza et al. also find that women are more successful than men in leveraging social capital to produce food security.

Estimating spatial effects using data from multiple countries in Africa and Asia is both an advantage and a disadvantage for the study. An important advantage is that multiple sites provide greater variation and enhances the external validity of our findings. A disadvantage, however, is that our empirical strategy models expected food security of multiple regions of the world. In other words, the model adopts a homogeneity assumption to estimate an average spatial effect; i.e. one spatial coefficient for all households, regardless of their world region. To explore heterogeneity in the spatial relationships between gender and food security in different settings, we estimate a model where we interact the spatial lag of the dependent variable, i.e. food security of neighbors, with a dummy for observations in Asia (Africa is the baseline).[16] Results are reported in Online

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[16] Formally, the baseline model with regional interaction can be written as $Y_{id} = \rho_1 \sum_j w_{ij} Y_{jd} + \rho_2 A_{id} \sum_j w_{ij} Y_{jd} + X'_{id}\beta + C'_c\theta + D'_d\delta + T'_t\alpha + \varepsilon_{id}$, where $A_{id} = 1$ if household $i$ in district $d$ is in Asia, 0 otherwise. The parameter $\rho_1$ represents the spatial effect in Africa, while $\rho_1 + \rho_2$ represents the spatial effect in Asia. Estimation is based on instruments $WZ$, $W^2Z$, $AWZ$, and $AW^2Z$.

Appendix J. We find only weak evidence that spatial effects are differentiated by world region. The spatial coefficient for African households (first line of coefficients in Online Appendix J) are statistically significant and slightly higher than those of the main specification (reported in Table 2). The spatial coefficient of the interaction term captures the differential spatial effect for Asian households (with African households as the benchmark). This coefficient, in all five models, is negative (which suggests weaker spatial effects in Asia), albeit statistically insignificant.

Finally, for comparison purpose, we also report estimates from the OLS estimator that is typically inconsistent in the presence of spatial effects. These results are reported in Online Appendix K. We find that OLS standard errors are larger than the errors obtained from the IV strategy. This is in line with a tendency toward larger standard errors when the estimation does not account for the spatial effects (Muto, Sugasawa, and Suzuki 2023). For the full sample and male-headed households, the OLS estimates of the spatial effects are slightly smaller than the IV estimates. However, for the female-headed households, OLS estimates of the spatial effect coefficients are significantly smaller in magnitude and statistically insignificant.

## 4.3 Traditional Determinants of Food Security

Our estimates in Table 2 show that most of the determinants of food security are significant and their signs are in line with the empirical evidence presented above. Comparing results of the *SAR Model* in column (1) with models (2) and (3), provides insights into how non-spatial determinants vary by gender of the ego household.[17] Below we discuss our results, breaking them down by three categories: household characteristics, assets, and livelihood strategies.

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[17] Comparing coefficients across *Ego-Gender* and *Gender-Homophily* models is problematic because homophily models restrict samples in both ego and neighborhood dimensions. Hence, in the following discussion, we restrict

### *4.3.1 Household characteristics*

The *SAR Model* in column (1) allows us to estimate, using the full sample, the average difference between food security of a female and male-headed household, controlling for many other factors (e.g., demographics, assets, livestock), including spatial effects. The coefficient on *Female-Headed Household* indicates that the food security of these households is 990 calories lower than their male-headed counterparts. This negative impact of *Female-Headed Household* on food security is in line with other studies in the literature (Broussard 2019; Kassie, Ndiritu, and Stage 2014; Mallick and Rafi 2010). These results are also consistent with the wide range of constraints, regarding access to land, credit, information, labor, and socio-cultural norms, that contribute to negative consequences for the food security of female-headed households, as discussed above.

We also find that *Age of Household Head* is a significant predictor of food security.[18] The coefficient in model (1) indicates that an additional year of age decreases food security by 42 calories *($p<0.01$)*. Our results are in line with the findings of Bussolo et al., who note that older farmers cannot work as hard as younger farmers, thereby reducing food security, and with Modirwa and Oladele, who reason that older farmers may be less inclined to adopt modern technologies, and are less adaptive and willing to try new methods than younger people (Bussolo et al. 2015; Modirwa and Oladele 2012). But our results run contrary to the idea that older farmers have more experience and knowledge that could increase food security (Fekadu and Muche Mequanent 2010).

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ourselves to coefficients of models (1)-(3) (i.e. the *SAR* and *Ego-Gender* models). Nevertheless, it is reassuring that the covariates in models (4) and (5) are similar to their ego-gender counterparts, i.e. models (2) and (3), respectively.

[18] We have estimated models with a quadratic specification of age and obtain similar results.

To gain gender insights into impacts of *Age of Household Head* we compare the age coefficient of the full sample model in column (1) with the *Ego-Gender* results from columns (2) and (3). This comparison indicates that higher ages reduce food security for male-headed households, but not for female-headed households. The finding that age is a food security constraint for males but not females has been previously reported in the literature (Lutomia et al. 2019). Gender roles in smallholder farming households may help us understand this result. Typically, women are focused on household tasks and agricultural labour (Duflo 2012), while men are focused on market work and "heavy-lifting" in agricultural activities (Meinzen-dick, Raney, and Croppenstedt 2014). Therefore, the negative effect of age for men's food security might arise, for example, as a reflection Duflo's findings, where older males are less able to do the "heavy lifting" and may have less access to market income as they age. But we are unable to identify the underlying mechanisms that may be causing these results, as well as the small and insignificant effect of age on the food security of female-headed households reported here and elsewhere. Focusing on these mechanisms could be the object of future research.

With respect to *Household Size*, model (1) results show that an additional individual in the same household decreases food security by 1558 calories *($p<0.01$)*. This finding is supported by a number of empirical studies that underline the impacts of household size on household's food security (Feleke, Kilmer, and Gladwin 2005; Fekadu and Muche Mequanent 2010; Frelat et al. 2016; Garrett and Ruel 1999). Food requirements increase with the number of people in a household thus potentially compromising food security.[19] However, our results contradict other

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[19] We also estimate models where household composition is controlled for by considering age and sex of household members, i.e. number of male adults, number of male children, number of female adults, and number of female children. Overall, the models' results are similar to those reported in Table 2. Estimates of the parameters of the

studies that indicate the importance that additional members may have on improving food security, because additional family members add additional labor that can improve production (Duflo and Udry 2004; Mallick and Rafi 2010; Modirwa and Oladele 2012). For instance, Ncube and co-authors suggest that children are important in collecting foods or providing labour for agricultural activities (Ncube et al. 2016). But none of these studies investigate results across female- and male-headed households. Comparing *Household Size* coefficients across models, we find that impacts are similar across gendered households. The coefficient in column (1) is very similar to the coefficients of columns (2) and (3), all of which are significant. This comparison indicates that additional family members in the household reduce food security for both female- and male-headed households.

### *4.3.2 Household Assets*

The full sample model in column (1) does not indicate that food security is influenced by any type of asset, (i.e., *domestic*, *transport*, or *productive*). In the literature, there is mixed evidence regarding the role of assets in influencing food security. Assets may have a positive impact on food security because they improve the household wellbeing allowing the exchange of information, access to markets, and enhancing the production (Gittinger 1990; Kassie, Ndiritu, and Stage 2014). In contrast, Silvestri et al. fail to find significant evidence of an influence of assets on food security (Silvestri et al. 2015). However, when comparing the full sample estimates of model (1) with those from models (2) and (3), we find that the effect of assets may depend on the gender of the head of the household. While the food security of male-headed households does not seem to benefit from any type of asset, model (2) indicates that *transport assets* are a statistically

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household composition variables are statistically significant and have intuitive magnitudes, with males demanding more calories than females, and adults demanding more calories than children.

significant predictor of food security for female-headed households. Results indicate that for every additional weight and age adjusted *transport asset* (i.e., motorcycle, bicycle, car) owned by a female-headed household, their food security increases by 105 calories. This is in line with the findings that transportation increases women's access to markets, promote access to information and social capital (Kassie, Ndiritu, and Stage 2014), bargaining power (Rubin and Manfre 2014), and safety in travelling (Meinzen-dick, Raney, and Croppenstedt 2014).

### *4.3.3 Household Livelihood Strategies*

*Off-farm Income* is another component that is not statistically significant for model (1) but has differential gendered effects, as is evident from results in models (2) and (3). Though *Off-farm Income* is not significant for model (3) the *Ego-Gender* male model, it is a significant predictor of female's food security in model (2). We find that female households that earn off-farm income gain an additional 1783 calories of food security. Our results are supported by empirical studies that have documented the positive effect of *Off-farm Income* on women's food security (Tsiboe, Zereyesus, and Osei 2016; Dzanku 2019). Tsiboe, Zereyesus, and Osei find that female-headed households that participate in non-farm work significantly enhance household nutrient availability when compared to males (Tsiboe, Zereyesus, and Osei 2016). These effects might be related to the fact that women tend to have the primary responsibility to plan and prepare household meals (Tsiboe, Zereyesus, and Osei 2016), and because households tend to benefit more from women's greater control over resources, than when such resources are controlled by men (Dzanku 2019).

In considering livestock vs. farming livelihood strategies, results from model (1) show that average food security increases (reflected in the positive sign of *Ruminants per Unit of Land*), but at a decreasing rate (reflected in the negative sign of *Ruminants per Unit of Land Squared*). For the average household, every additional *Ruminant per Unit of Land* owned by the household, increases food security by of 39 calories.[20] The relationships between livestock and cropland suggest diminishing returns to scale; that is, an increase in both inputs (livestock and cropland) leads to a less than proportional increase in food security. Our results highlight the role of substitutions between livestock and land size in promoting food security in developing countries (Maxwell and Wiebe 1998; FAO 2018).

Interestingly, *Ruminants per Unit of Land* influence the food security of male-headed, but not female-headed households. For female-headed households, model (2) shows that neither of the coefficients on *Ruminants per Unit of Land* are statistically significant. This finding is supported by empirical studies that underline the importance of male's abilities on income generating from livestock and cropland. Males are in control of buying and selling livestock while women are generally responsible for caring for them (Ibnouf 2011). Likewise, grazing land is considered key to livestock production in many areas that are generally controlled by men, thereby encouraging men's ability to increase production and make long term investments in livestock (FAO 2018). These gendered roles could cause *Ruminants per Unit of Land* to positively influence the food security of men, but not of women.

# 5 Conclusions

## 5.1 Summary and Discussion

Empirical papers have examined a number of determinants of food security, including the role of gender. However, empirical evidence regarding the potential importance of spatial effects on food

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[20] The marginal effect is calculated as $39 = 152.08 - 2 * 2.47 * 38.5$, where $152.08$ and $2.47$ are the coefficients on ruminants per acre and ruminants per acre squared, and $38.5$ is the average ruminant per acre for the sample.

security, and the interactions of these effects with gender, have not been explored. In this paper, we address this gap in the literature by exploring how gender and homophily (i.e., people with similar characteristics influencing one another) interact with spatial multipliers to influence food security. We design empirical models to make four main contributions to the literature.

The first contribution is to include spatial effects as a determinant of food security to estimate a multi-region *SAR Model.* We employ a rich geocoded data set from the CCAFS IMPACT Lite survey collected in three developing regions (East Africa, West Africa, and South Asia). Along with traditional determinants of food security, we find a positive and significant spatial effect on the food security of households. Specifically, for every 100 additional calories that neighbors consume, own food security increases by 17 calories. This result implies that spatial effects of neighbors generate a positive spillover effect as they improve others' food security. The relevance and magnitude of spatial effects in influencing food security suggest that spatial interactions are fundamental aspects of food security. As such, measurements of spillover effects can help in the design of policy interventions.

The second contribution is to specify gendered spatial interactions as a determinant of food security. Our *Ego-Gender* approach demonstrates that female-headed households benefit more from their neighbors than male-headed households. Notably, the food security of female-headed households increases by 49 calories when neighbors' food security increases by 100 calories, while male-headed households increase far less at 15% (a result similar to the non-gendered SAR model). Insights into these differing results may be gleaned from literature on gendered social capital that suggests women's relationships are characterized by people who know each other well, and relationships among men are comprised of people who are not well connected (Hanson and Blake 2009). This difference suggests that spatial interactions are more important for women. This result also suggests that policy interventions that are directed to areas with more female-headed households could have larger effects on food security, no matter whether the intervention is directed to male or female-headed households.

The third contribution is to specify homophily spatial effects as a determinant of food security. Our *Gender Homophily* model suggests that female-headed households benefit more from female-headed neighbors than from male-headed neighbors. Specifically, the food security of female-headed households increases by 68 calories in response to an increase of 100 calories in female-headed neighbors' food security. For men, the homophily effect is again similar to other spatial effects. Male-headed household calories increase by 16% from the presence of male-headed neighbors, which is a result consistent with the non-gendered SAR model. A policy implication of these results is that food security development projects could consider investing in social protection transfers, behavioral change and capacity-building that magnifies the positive aspects of networking and promotes spillovers that overcome weaker spatial interactions between male-headed households.

The fourth contribution arises from comparing determinants of food security across gendered and non-gendered models. The impacts of socioeconomic drivers of food security may be markedly different between the aggregated model and the disaggregated gendered models. In the aggregate model, the age of the head of the household decreases food security; a result that is also reflected in the male models. But this determinant has no affect in the female models. Similarly, though none of the types of household assets affect food security in the aggregate model, transport assets significantly help food security in the two female models. In summary, comparisons across models indicate that determinants of food security differ between male- and female-headed households, even after controlling for differences in gendered heads.

Our findings largely corroborate results from the women empowerment literature that emphasizes the importance of women in development (Annan et al. 2021; Quisumbing, Meinzen-Dick, and Malapit 2021; Sraboni et al. 2014; Duflo 2012). The importance of spatial spillovers is magnified when considering that women are crucial for development. Duflo highlights two rationales regarding why it is important to support active policies that promote women (Duflo 2012). First, women tend to be worse-off than men, and this inequality between genders is unethical. Second, it is necessary to reduce the gender gap, not only in food security, but also in education and employment opportunities, because such changes will have beneficial consequences on many other development outcomes.

Our paper contributes to a growing literature that shows that women experience greater food insecurity than men, and this food security gap continues to increase (CARE 2022). While women play a crucial role in food production, persistent gender inequalities continue to underline many of the agriculture and food system inequalities. A report from Care International offers a recent review of global policies and find that only a small share (4%) of policies conceptualizes women as leaders who are instrumental in developing and supporting food security.[21] Our results show that improving food security has spatial multipliers that help all households, but that these spatial multipliers help female-headed households more; especially if the spillover is between two female-headed households (i.e., homophily). This result corroborates policy recommendations of gender-targeted interventions from the women empowerment literature (Quisumbing, Meinzen-Dick, and Malapit 2021). The finding that spillover effects are larger for women than men means that a policy

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[21] Source: Care Evaluations. Don’t Leave Them Behind: Global Food Policies Continue to Fail Women (December 2021). Available online at https://www.careevaluations.org/evaluation/dont-leave-them-behind-global-food-policies-continue-to-fail-women-december-2021/

that exogenously increases food security will be subject to gender-differentiated effects, even if the direct policy effect is identical for men and women, due to the larger spillover between female neighbors. These results are encouraging news for development and the reduction of the food security gap, because policies that aim to target aid can have the largest positive spillover effects where they are needed most.

## 5.2 Limitations and Future Research

Limitations of this study suggest directions for future research. Though our dataset includes traditional determinants of food security and different types of fixed effect controls (i.e., districts, crops, and agriculture technology) that account for relevant (observable and unobservable) determinants of food security, omitted variable bias is frequently a concern in models with observational (i.e., non-experimental) data. Our IV estimates of spatial effects are consistent under the assumption of exogeneity of control variables. To the extent that unobservable factors within districts, crops, and agricultural technology are confounded with traditional determinants of food security, the interpretation of our estimates move away from causal effects to correlations. For example, if unobserved factors that drive (or are correlated with) female headship are also determinants of food security, then our results represent correlations rather than causation. This identification challenge suggests that a valuable extension to our work could be to implement randomized control trials (RCTs) designed to further examine how the interactions between gender and space impact food security. Nonetheless, our results are comparable with those from the food security literature where most papers rely on cross-sectional data and are also vulnerable to biases from unobserved household-level heterogeneities and confounding factors (Kassie, Ndiritu, and Stage 2014; Kassie et al. 2015; Lim et al. 2020). Moreover, our results reflect an expansive dataset representing multiple countries, a scale that would be costly to replicate within a RCT framework.

Though our dataset allows us to explore a large and far-ranging sample, it was limited in that some countries, (i.e., Uganda, Ethiopia, Burkina Faso) from the IMPACT Lite survey were missing reliable GPS coordinates. The paper is also limited in that only 198 of the sampled households are female-headed. Though our main results are strongly statistically significant, and robust to various model specifications, the small sample of female-headed households, and their resulting spatial connections, prevents us from developing a more detailed examination of spatial heterogeneity. For instance, our sample does not allow for estimation of spatial effects by subsamples, e.g. country-level analysis. Future research could address this limitation by implementing stratified sampling to increase the sample of female-headed households.

Another limitation is that our analysis considers only one definition of food security: food availability. We do not interrogate other dimensions of food security, including access and utilization, necessary to ensure universal access to sufficient, safe, and nutritious food (Barrett 2010). Future work could investigate how gender and neighborhood effects interact to shape other facets of food security, such as food risks and dietary quality (e.g., micronutrient gaps).

While our study offers policy relevant and generalizable results about gendered spatial effects and food security, our results also point to other areas of future research. Fundamentally, the positive implication of spatial effects on food security suggests that such considerations are important in the future specification of models. Moreover, gendered dimensions of these spatial effects matter. It could, therefore, be useful to provide more resolution in understanding gendered household structures and their environments; for example, moving beyond the consideration of gendered household heads, to investigating other gendered aspects of households, such as the number of present adult males and females (Dassanayake et al. 2018).

The results of this study also suggest more nuanced investigations into neighbors' interactions could be fruitful. For example, learning about homophily interactions is essential to a better understanding of food security as it captures a reduced-form arrangement of how social ties grow into complex structures to generate opportunities for sharing and distributing food resources at the community level (Mertens et al. 2015). The different types of interactions individuals carry with one another may act as elements that could be leveraged to ease the barriers and constraints to food security. While our paper focuses on gender, homophily can operate through a variety of channels, like religion, race, professional trade, and age. Future work could further explore the role of homophily in promoting food security. Understanding neighbor influences beyond spatial relationships could also be valuable (Johny, Wichmann, and Swallow 2017).

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