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Market Proximity, Household Resilience, and Food Security: A Data-Driven Vulnerability Framework*

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Abstract

This study examines the impact of market proximity on household food security and resilience using data from the International Fund for Agricultural Development (2017-2018). We first amend the Vulnerability as Expected Poverty (VEP) methodology by proposing the Least Absolute Shrinkage and Selection Operator (LASSO) for variable selection and more accurately identify at-risk households. We then employ our vulnerability measure within an instrumental variable framework to explore the relationship between market access, resilience, and food security outcomes. The results indicate that closer market proximity significantly strengthens household resilience and, ultimately, reduces welfare fluctuations. These findings highlight the significance of policy interventions aimed at improving market infrastructure, enhancing resilience, and mitigating food security vulnerabilities.

Keywords: agri-food value chains, food safety, food security, vulnerability, resilience.

JEL-Codes: Q12; O12; C31, C36.

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1. Introduction

Bringing smallholder farmers into traditional market systems is often seen as a way to improve their well-being (see, *inter alia*, Montalbano et al., 2018). However, the poorest and most vulnerable groups may not benefit directly, as they often face challenges in taking advantage of market opportunities (Tuni et al., 2022; von Braun et al., 1991). The ways in which market access affects food security are complex. Rural households are exposed to price changes and have limited bargaining power (Bellemare et al., 2013). High marketing costs, unequal market power, and lack of information make it harder for prices to be passed on efficiently, which can worsen welfare (Meyer & Cramon-Taubadel, 2004). Because farmers are spread out geographically, traders can use their market power, leading to more inefficiencies (Fałkowski, 2010; Osborne, 2005). Research also shows that farmers' choices, like selling or storing grain, are often influenced by cash needs and price expectations, which can lead to less-than-ideal results (Burke et al., 2019; Stephens & Barrett, 2011). These problems are especially common in developing countries, where smallholder farmers face barriers that keep them in lower-value parts of the agri-food value chain (Gattone, 2024; African Development Bank et al., 2014). When markets are incomplete or missing, households often see food self-sufficiency as protection against market risks (de Janvry & Sadoulet, 2006; Fafchamps, 1992). While selling crops can help with food security, these benefits are often reduced by transaction costs and risk aversion (Key et al., 2000). As a result, smallholder farmers often sell most of their crops soon after harvest, which is linked to low prices and little motivation to improve quality (Purcell, 2018).

This study uses a cross-country dataset of smallholder farming households from eight countries (2017–2018), collected by IFAD, to better understand how being close to markets affects food security. We use data-driven methods like the Least Absolute Shrinkage and Selection Operator (LASSO) to improve how we measure each household's vulnerability to food insecurity. We define market proximity as the distance to the nearest urban center and use it as an instrument for a household-level measure of resilience, following recent research (e.g., Conostas, 2023; Hoddinott, 2023; Upton et al., 2023). In areas with high transaction costs, poor infrastructure, and limited mobility, market proximity is not a choice, especially for poorer households. These barriers make geographic distance to markets an outside factor, which helps address concerns about self-selection. Our analysis focuses on the stability aspect of food security, not just its level.¹ We assume our approach reveals how market proximity, resilience to shocks, and changes in food security are related, but not their absolute levels. In this context, we suggest that while long-term factors set the level of food security, short-term changes are more closely linked to a household's resilience, or its ability to handle shocks.

In particular, we find that better market access, shown by lower transaction costs, is linked to greater resilience and less food insecurity for smallholder households. Being closer to markets seems to help farmers handle shocks, likely by making it easier to sell products, stabilize prices, and find economic opportunities. Policies that lower transaction costs and improve local market connections can be especially effective if they are adapted to local needs.

The paper is structured as follows: Section 2 reviews the literature. Section 3 explains the conceptual

¹ The literature commonly conceptualizes food security as a multidimensional construct encompassing four interrelated pillars: availability, access, utilization, and stability (see Guiné et al., 2021). Availability refers to the physical presence of sufficient food through domestic production, imports, or aid; access captures households' economic and physical ability to obtain food, often shaped by income, prices, and market functioning; utilization concerns the nutritional quality of food and individuals' ability to absorb nutrients, which depends on diet composition, health, and sanitation; and stability reflects the temporal dimension of food security, emphasizing the consistency and reliability of access, availability, and utilization over time, including vulnerability to shocks, seasonality, and volatility. While many empirical studies focus on levels of food security at a given point in time, the stability dimension has gained increasing attention in analyses of climate risk, price fluctuations, and livelihood uncertainty, as it captures households' exposure to transitory disruptions rather than persistent deprivation.

framework. Section 4 covers the empirical approach and identification strategy. Section 5 presents the data and descriptive statistics. Section 6 analyzes the results. Section 7 discusses robustness checks, and Section 8 concludes with policy implications.

2. Literature Review

The literature consistently highlights that market access is, on average, associated with various positive outcomes, including increased employment, better job opportunities, access to resources, improved governance, and higher levels of food security (Minten et al., 2009). However, accessing these markets involves heterogeneous effects, depending on factors such as access costs and risk preferences of farmers (Key et al., 2000; Svensson & Yanagizawa, 2009; de Janvry & Sadoulet, 2006).

Furthermore, several empirical studies on nutrition and commercialization (Carletto et al., 2017; von Braun, 1995; DeWalt, 1993) suggest that household income growth alone may not guarantee improved food security or higher welfare levels. One reason is that cash income may not always translate into increased food intake, as households might substitute food consumption with non-food expenditures or opt for less nutritious foods (von Braun et al., 1991; Bouis & Haddad, 1990). Additionally, profits from commercialization may lead households to prioritize alternative investment opportunities, increasing the opportunity cost of current consumption and potentially driving up food costs (Popkin, 1980).

Many empirical studies, such as Barrett (2005), Osborne (2005), and Renkow et al. (2004), confirm the strong association between high transaction costs and subsistence agriculture by showing how traders foster households' predisposition towards subsistence agriculture in remote regions. In developing-country settings, smallholder farmers' engagement with markets is often shaped by high transaction costs and limited incentives to sell, which can result in a continued reliance on subsistence-oriented production strategies (Fafchamps & Hill, 2005). Still, selling one's own crop can turn in-kind income into cash income (Kennedy & von Braun, 1994), which can be potentially used to buy goods, improving, in turn, food security and welfare (Pingali, 1997; Timmer, 1997). Furthermore, Bellemare & Novak (2017) argue that farmers involved in contract farming experience a reduction in their "hungry" season.

However, the transition from subsistence to commercial farming is influenced by market accessibility and the ability to bear risk (de Janvry & Sadoulet, 2006; Fafchamps, 1992). This shift often necessitates overcoming substantial barriers, including informational asymmetries and market power imbalances that can disadvantage smallholder farmers (Key et al., 2000). Empirical evidence points to the enhancement of food security through improved market access, highlighting the importance of reducing transaction costs and mitigating risks associated with market participation (Fafchamps, 1992; Montalbano et al., 2018). This discussion also relates to the debate on contract farming as a mechanism for linking smallholder farmers to agri-food value chains, as empirical evidence shows that contractual arrangements can stabilize outcomes for participating farmers while also reshaping their exposure to market conditions and contractual obligations (Bellemare et al., 2013). The effectiveness of market access in improving food security and farmer welfare is contingent upon the terms of engagement and the broader socio-economic environment (Sexton, 2013; Fałkowski, 2010; Osborne, 2005).

The importance of information asymmetries and transaction costs in shaping market participation and outcomes is well documented in the literature, particularly with respect to price transmission, spatial isolation, and the costs faced by smallholder farmers when accessing markets (see, *inter alia*, Meyer & Cramon-Taubadel, 2004; Mulbah et al., 2021; Renkow et al., 2004). Local networks are pivotal for smallholder farmers, facilitating market information exchange and collective bargaining, thereby improving food security and welfare (Isaac et al., 2007). Their success, however, depends on the networks' structure and the social capital within communities, which can differ widely. Market access enhances farmers' access to both input and output markets, thereby potentially increasing agricultural

productivity and, by extension, food security (Montalbano et al., 2018). However, empirical findings point to substantial heterogeneity in outcomes, showing that while improved market access may be associated with better agricultural performance, the degree to which households are able to absorb or respond to shocks varies across contexts and is shaped by structural factors such as infrastructure quality and market conditions (Letta et al., 2021).

Moreover, the dynamics of food security extend beyond mere production increases. The linkage between market participation and resilience to shocks, for instance, reveals complex relationships that are mediated by dietary diversity, food preferences, and income allocation decisions within households (D'Souza & Jolliffe, 2014). The literature underscores the importance of contract schemes and standards when assessing the impact of market access on welfare (see, *inter alia*, Handschuch et al., 2013; Subervie & Vagneron, 2013; Barrett et al., 2012; Asfaw et al., 2010; Bellemare, 2010; Minten et al., 2009).

In this context, geographic proximity to markets has been shown to affect producers' integration into trading networks and price transmission processes, with evidence indicating that closer access to buyers is associated with different price dynamics, even in settings where trader margins and market power remain relevant considerations (Fafchamps & Hill, 2008; McMillan et al., 2002).

3. Market Proximity and Vulnerability to Food Security: The Conceptual Framework

The concept of food security inherently includes a dimension of risk, as the ability of households to manage adverse risks directly affects their food security status. Although this perspective has been largely overlooked, with few exceptions (e.g., Løvendal & Knowles, 2007; Haddad & Frankenberger, 2003), the importance of risk exposure in determining smallholder farmers' well-being is now clearly acknowledged in development studies, and the definition of food security itself incorporates the so-called "stability dimension". This has fostered alternative frameworks for understanding vulnerability and resilience to food security (Montalbano & Romano, 2023); yet, limited attention has been given to the connections among these concepts and commercial markets.

This study fills this gap in the literature by providing empirical evidence on the resilience-enhancing effects of market proximity in shaping farmers' vulnerability to food insecurity. It builds on Montalbano et al. (2018), which shows that different commercialization strategies influence household per-adult-equivalent total consumption, food consumption, and caloric intake, but these effects appear to occur independently of the chosen selling point. The empirical evidence in the work of Montalbano et al. (2018) focuses exclusively on maize suppliers in Uganda, thereby limiting its external validity. Nonetheless, it paved the way for further research aimed at exploring and identifying the relevance of the links among household commercialization choices, farmers' vertical integration, and food security.

Food insecurity manifests when households are unable to access sufficient, nutritious food to meet their needs for a healthy life. This state not only pertains to dietary needs and preferences but also to physical and economic access to markets. To identify the role of market proximity in determining food security, we need to control for alternative channels of influence. To this end, traditional metrics of food insecurity, such as food consumption, are not ideal, as they may be influenced not only by the usual observable and unobservable multidimensional confounders at the community and household levels, which we control for in our empirical analysis, but also by commercial markets themselves, through mechanisms other than supply, such as price heterogeneity affecting budget constraints and then demand (Ibok et al., 2019). To soften this bias in this empirical analysis, we adopted the Food Insecurity Experience Scale (FIES) developed by the Food and Agriculture Organization of the United Nations (FAO), an experiential measure based on direct household experiences, adopted by international bodies in their surveys since 2014 (Cafiero et al., 2018; Wambogo et al., 2018).

FIES's efficacy in providing an accurate reflection of food insecurity has been supported by recent

studies, highlighting its advantages over traditional objective measures (Smith et al., 2017; Coates, 2013). The FIES methodology involves respondents answering a series of eight yes/no questions, each designed to gauge a different dimension of food insecurity, ranging from anxiety about food supply to actual experiences of food deprivation. This aggregated approach yields a comprehensive raw FIES score for each household, reflecting the severity of food insecurity experienced, which does not rely on monetary metrics. This score, ranging from 0 to 8, serves as a direct indicator of a household's food security status and is not directly influenced by commercial markets, except through the household's underlying vulnerability, which also reflects constraints associated with its geographic location, hence reinforcing our exclusion restriction.

We also use total gross income as an alternative metric, providing a comparative monetary perspective on fluctuations in household welfare. Although this measure incorporates monetary dimensions, it is not directly influenced by the demand-side factors of commercial markets. Notwithstanding these virtues, we acknowledge that income volatility is not a reliable proxy for fluctuations in consumption, which is why this measure is not our preferred outcome variable to be used in our empirical analysis on vulnerability. Conversely, it supplements the subjective measure of food security with vulnerability estimates based on monetary indicators.

4. Empirical Framework

As anticipated in the introduction, by applying data-driven algorithms, we propose an improved vulnerability assessment applied in the context of food security. It builds on Chaudhuri (2003, 2001) and Günther and Harttgen (2009). The rationale for this choice is twofold: i) this framework has proven to be the most effective for handling cross-sectional data, given that the improved performance of more recent approaches relies heavily on the availability of long-term longitudinal data, which are quite uncommon in developing contexts. ii) by incorporating advanced data-driven algorithms specifically designed to handle cross-sectional data, this vulnerability framework sheds light on the critical issue of heteroscedasticity in farmers' responses. In this context, variability in residuals not only reflects the effects of idiosyncratic and covariate shocks but also considers the heterogeneous mitigating and coping strategies actually employed by households. This ensures that the remaining variability reflects the extent to which shocks determine the net welfare effects of households. Furthermore, this empirical application innovates previous studies in two ways: i) by replacing the conventional vulnerability metric of consumption with the FIES, a subjective, non-monetary indicator of food insecurity levels; and ii) by adopting a data-driven approach to filter out purely stochastic measures of volatility in food security.

As motivated above, this study implements a standardized raw FIES score as the primary outcome variable and total gross income as an alternative.

The analysis follows a three-step methodological approach:

1. *Measurement of the stochastic components of food security*: Initially, the study employs a machine learning-enhanced Feasible Generalized Least Squares (FGLS) method to filter the outcome variables and derive household-specific residuals. This step aims to isolate the stochastic components of food security, filtering out household (and community-level) observable and unobservable characteristics identified through a machine-learning algorithm. This approach acknowledges that unexplained variance in outcomes reflects the effect of both idiosyncratic and covariate shocks, net of households' risk mitigation and coping strategies.
2. *Calculation of volatility and vulnerability*: We then construct a measure of unconditional volatility of food security by classifying as "volatile" those households experiencing fluctuations above the median. Subsequently, we predict each household's ex-ante probability of food insecurity, conditional on household- and community-level observable and

unobservable confounders, using a heteroskedastic regression specification. Both variables are assumed to be proxies of the stability dimension of food security.

3. *Resilience and Market Proximity Analysis*: This final step examines how market proximity, serving as a proxy for both market access and positioning within vertical commercialization chains, shapes the relationship between resilience and vulnerability to food security. To further mitigate potential sources of endogeneity between vulnerability to food insecurity and engagement in commercial markets, although likely limited to the demand side, we employ an instrumental variable approach. Specifically, operationalizing market proximity as the distance to the nearest urban center, we use it as an instrument for a subjective, household-level measure of resilience computed by IFAD, specifically the Ability to Recover from Shocks (ATR) based on households' self-assessed ability to withstand and recover from shocks (Garbero & Letta, 2022). In line with the subjective metric used to measure food security, this subjective measure of resilience quantifies the resilience of households based on their experiences with shocks in the year preceding the survey, including events like droughts, floods, and crop diseases. The ATR index is computed as the average response across all shocks encountered by a household, as outlined in the Background paper to the IFAD9 Impact Assessment Initiative.² This instrumental variable approach allows us to empirically test the exclusion restriction that market proximity influences food security through its effect on household resilience.

More specifically, in the first step, machine learning algorithms are used to select among all possible combinations of household characteristics only the most predictive ones to obtain pure stochastic residuals, as follows:

$$y_h = \mathbf{X}_h^{(full)}\beta + e_h ; \quad [1]$$

where y_h represents the outcome variable (standardized raw FIES score or, alternatively, total gross income), \mathbf{X}_h is a bundle of observed household characteristics, β a vector of parameters, and e_h the stochastic components. The ability to filter out the pure stochastic component from the deterministic part of the target variables is key in this kind of exercise. To this end, the analysis exploits the predictive power of LASSO, a supervised machine learning routine based on regularized regression (Hastie et al., 2009). Incorporating a machine learning-enhanced Feasible Generalized Least Squares (FGLS) approach, this study integrates the LASSO technique as an integral part of the FGLS process. This methodological integration is pivotal for cleaning residuals from possible confounders, such as age, education, gender of the household head, household size, education level, land area, asset indices, and treatment status, and their multiple forms, linear, squared, and cubic (excluding dummies for inherent reasons). After selecting variables with LASSO, the analysis includes country fixed effects in the regression of standardized FIES scores. This approach accounts for unobservable country-specific differences, ensuring that the results are robust and comparable across diverse national contexts.

In the second step of the FGLS procedure, the filtered residuals from the first stage [1] are used to obtain an estimate of the variance:

$$\hat{e}_{ols,h}^2 = \mathbf{X}_h^{(lasso)}\theta + \eta_h . \quad [2]$$

It is worth noting here that X_h now includes only the combination of household characteristics not dropped by the LASSO procedure in step [1].

² Available at <https://www.ifad.org/documents/38714170/39318582/Measuring+IFAD%E2%80%99s+impact.pdf/36c251f1-854e-42de-8990-773728abe1f7?t=1540911311000>.

The predictions from [2] lead to a robust OLS estimate of the FGLS β coefficient by calculating:

$$\frac{y_h}{\hat{\sigma}_{e,h}} = \left(\frac{\mathbf{X}_h^{(lasso)}}{\hat{\sigma}_{e,h}} \right) \beta + \left(\frac{e_h}{\hat{\sigma}_{e,h}} \right); \quad [3]$$

where $\hat{\sigma}_{e,h}$, which is equal to $\sqrt{\mathbf{X}_h^{(lasso)} \hat{\theta}_{FGLS}}$, is a consistent estimate of the volatility of the household outcome variable. Using this prediction, we first construct a volatility dummy assuming as “volatile” only households lying above the median of the obtained food security distribution and then we compute a forward-looking vulnerability measure. The latter is estimated as the probability that a household h with X characteristics will be food insecure in the near future, using the predicted standardized raw FIES scores whose mean and variance are computed as follows:

$$\widehat{E}[y_h | \mathbf{X}_h^{(lasso)}] = \mathbf{X}_h^{(lasso)} \hat{\beta}_{FGLS}; \quad [4]$$

and

$$\widehat{V}[y_h | \mathbf{X}_h^{(lasso)}] = \hat{\sigma}_{e,h} = \sqrt{\mathbf{X}_h^{(lasso)} \hat{\theta}_{FGLS}}. \quad [5]$$

Hence, the final vulnerability measure will be equal to:

$$\widehat{V}_h = \Pr \left[y_h > z | \mathbf{X}_h^{(lasso)} \right] = \phi \left(\frac{\mathbf{X}_h^{(lasso)} \hat{\beta} - z}{\sqrt{\mathbf{X}_h^{(lasso)} \hat{\theta}}} \right); \quad [6]$$

where z represents the food insecurity (poverty, for income) line and $\phi(\cdot)$ the cumulative density of the standard normal. In order to test the sensitivity of these results in light of farmers’ heterogeneity (i.e., the poorer might be in a weaker position to benefit from market proximity), the FIES vulnerability measure V_h is derived considering two alternative food insecurity lines: one equal to the standardized raw FIES score median and another equal to Adjognon et al. (2021) mild food insecurity line threshold of the raw FIES score equal to 3. Note that, for the two alternative outcomes, FIES and income, the construction and interpretation of the threshold line are reversed: food-insecure households are those who move *above* the threshold in the case of FIES, whereas in the case of income households fall into deprivation if they move *below* the threshold. Reason why, the vulnerability index later introduced is constructed so that higher values always correspond to higher vulnerability.

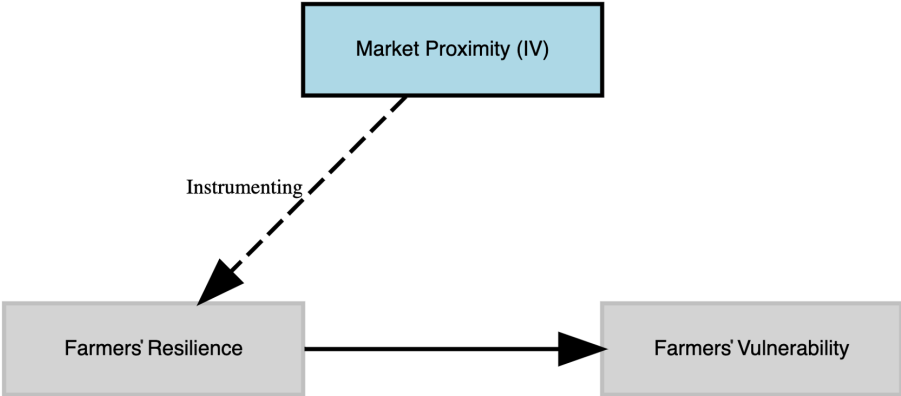
Once obtained \widehat{V}_h , i.e., an estimated measure of the probability of moving above (below) the food insecurity line in the near future, a vulnerability dummy is constructed which, in the case of food insecurity, is equal to 1 when this probability \widehat{V}_h is above 50% for the first food insecurity line and equal to 25% for the alternative line.³

After our measure of vulnerability to food insecurity is computed, we can explore how market proximity, serving as a proxy for market access and positioning, influences it by employing an instrumental variable approach. To empirically test this relationship, we examine whether proximity to markets influences short-term variations in food security primarily through its effect on household resilience. Given potential endogeneity concerns, we use market proximity as an instrument for

³ Two different thresholds are used as cutoffs for the V_h distribution, since higher levels of raw FIES score imply an increased skewness in the V_h distribution and, in turn, a lower share of vulnerable households as one moves along the distribution.

resilience, under the exclusion restriction that it affects food security fluctuations only indirectly, through its influence on resilience. This assumption is grounded in the literature on imperfect and incomplete markets (see, *inter alia*, de Janvry & Sadoulet, 2006; Key et al., 2000; Fafchamps, 1992) where rural households cannot endogenously choose their location relative to markets due to structural frictions, such as poor infrastructure, credit constraints, and limited mobility. As such, market proximity can be treated as plausibly exogenous with respect to short-term changes in food security, allowing us to identify its mediated effect through resilience. In sum, we use the variance of food security, rather than its level, under the assumption that this variance reflects resilience capacity, and that market proximity is one of its primary exogenous determinants.

Imbens (2023) elucidates the distinct roles and interpretations of IVs in establishing causal relationships. This framework underscores that an IV, when properly selected, serves to identify exogenous variations that are causally related to the outcome through the endogenous variable. Hence, following Imbens (2023), our methodology leverages the IV not merely as a tool for identification but as an integral component of the causal pathway, which is reported in Figure 1 below.



Source: Authors' elaboration.

Figure 1. The IV Conceptual Nexus.

In this segment, market proximity, depicted as the inverse of the distance to the nearest urban center, serves as an exogenous source of variation in the analysis, linking farmer resilience (the treatment variable) to farmers' volatility/vulnerability (the outcome). The premise here is that market proximity impacts volatility and vulnerability predominantly through its effect on farmers' resilience. Thus, the proximity to urban markets, used as an instrumental variable, remains exogenous concerning food security fluctuations.

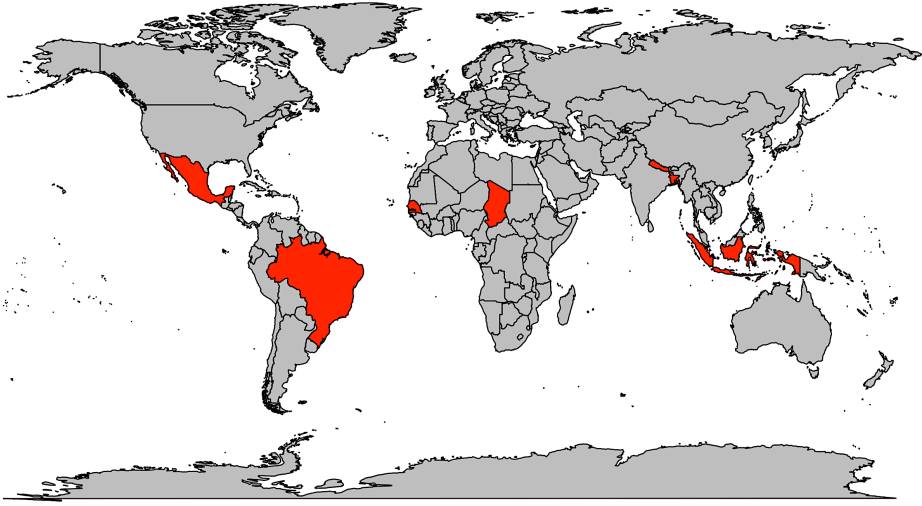
By carefully selecting market proximity as an instrumental variable and adhering to the exclusion restriction, the model effectively addresses endogeneity concerns, delivering a nuanced and accurate understanding of these dynamics, beyond what traditional IV methods offer. Additionally, LASSO was used to improve model parsimony by selecting relevant variables without compromising the robustness of the findings. While traditional methods like AIC or BIC could have been employed, LASSO's ability to handle high-dimensional data and multicollinearity ensures the stability and interpretability of the results.

Given the possibility of nonlinear relationships between market access, resilience, and food security outcomes, we further assess the robustness of our results using nonlinear probability models. Specifically, we estimate probit specifications and control-function (CF) probit models as complementary robustness checks. This choice is motivated by the discrete and bounded nature of food insecurity and vulnerability indicators, for which nonlinear binary response models are commonly employed in applied empirical work. Moreover, the CF approach provides a well-established strategy

for addressing endogeneity in nonlinear models by explicitly accounting for the correlation between endogenous regressors and unobserved determinants of the outcome, while preserving a probabilistic interpretation of estimated effects (see Blundell & Powell, 2004). The use of probit and CF probit models, therefore, allows us to verify that our results are not driven by linear functional-form assumptions and remain robust when nonlinearities and endogenous selection are explicitly taken into account.

5. Data and Descriptive Statistics

The study leverages unique cross-sectional data from farmer households across eight countries, gathered through standardized impact evaluations surveys conducted by IFAD from 2017 to 2018. This unique dataset comprises over 15,000 observations which span Bangladesh, Brazil, Chad, Indonesia, Mexico, Nepal, Sao Tomé & Príncipe, and Senegal, providing a rich basis for analyzing the relationships between market proximity, resilience, and food security volatility/vulnerability at the global level (see Figure 2 below).



Source: Authors' elaboration.

Figure 2. Country Sample.

Variable definitions are reported in Table A.1 in the Appendix, while descriptive statistics for a set of basic demographic and socio-economic characteristics of households in the sample are reported in Table A.2. Household heads in the sample are on average 48 years old, have four years of schooling, and are generally male. On average, households consist of six members, typically four adults and two children. Aside from the head, average household members have more than four years of schooling and have barely attained the first level of education. In terms of ownership, each household in the sample owns on average 5 ha of land and very few other assets (both the Asset index and the Agricultural asset index⁴ are below 15%). Households in the sample are generally poor, with a total gross income averaging below 3 thousand dollars.

To derive the distance to the nearest urban center, we integrated the Global Accessibility Map by Weiss et al. (2018) with the household-level data. The map quantifies travel time to cities in the year

⁴ Following the definition by IFAD within the Impact Assessment of the Coastal Climate Resilient Infrastructure Project (CCRIP), available at <https://www.ifad.org/en/w/publications/impact-assessment-coastal-climate-resilient-infrastructure-project-ccrip>- both indicators are composite indices constructed using Principal Component Analysis and calculated separately for household (non-productive) assets and productive (agricultural) assets.

2015 - just before the survey data were collected - at a spatial resolution of approximately one by one kilometer by integrating 10 global-scale surfaces characterizing factors affecting human movement rates and 13,840 high-density urban centers within an established geospatial-modeling framework (Weiss et al., 2018).⁵

As shown in Table 1, there is substantial heterogeneity in the distance of sampled households from primary markets. Not only does the mean distance vary considerably across country datasets, but the dispersion of observations around each country's mean is also large, particularly in the case of Chad.

Table 1. Distance from the Nearest Urban Center (km) – Descriptive Statistics.

Variable name	N. of Observations	Mean	Standard Deviation	Minimum Value	Maximum Value
Bangladesh	1,968	46.41	17.72	11.80	81.90
Brazil	1,386	63.11	17.66	3.70	106.70
Chad	1,555	57.76	44.17	4.40	181.20
Indonesia	1,553	26.96	21.24	1.00	78.70
Mexico	1,631	54.29	23.89	4.50	108.30
Nepal	2,864	44.51	22.35	1.20	84.70
Sao Tomé & Príncipe	1,153	10.12	4.72	0.40	27.50
Senegal	2,177	35.51	23.21	1.70	107.90
Average	14,287	43.08	28.05	0.40	181.20

Table 2 summarizes the statistics for the household-level raw FIES score. In this sample, the share of households that show some degree of food insecurity (i.e., households replying positively to at least one of the questions in the questionnaire) is, on average, close to 65% of the total interviewed.

Table 2. Raw FIES score – Descriptive statistics.

Variable Name	N. of Observations	Mean	Standard Deviation
Bangladesh	1,970	2.32	2.39
Brazil	1,386	2.11	2.40
Chad	2,174	3.74	3.03
Indonesia	2,028	1.50	2.15
Mexico	1,760	1.91	1.94
Nepal	2,874	1.12	1.51
Sao Tomé & Príncipe	1,269	4.17	2.71
Senegal	2,181	3.10	2.41
Average	15,642	2.39	2.52

Households with severe food insecurity levels (raw FIES score equal or above 7) make up over 10% of the total, and those with moderate food insecurity levels (raw FIES score equal or above 3) make up 41% of the total sample size. Chad is among the countries performing worst in the sample, with 493 households of the 2,174 interviewed with a raw FIES score equal to 8. Table A.3 in the Appendix

⁵ An urban center is defined by Weiss et al. (2018) as a contiguous area with 1,500 or more inhabitants per square kilometer or a majority of built-up land cover coincident with a population center of at least 50,000 inhabitants.

provides the descriptive statistics by raw FIES score.

Finally, descriptive statistics are reported for the variable capturing household resilience, the ability to recover from shocks indicator (ATR). The ATR metric is constructed based on answers to the question: “To what extent were you and your household able to recover from shock x ?”. ATR is a self-assessment from the interviewed household taking the form of an ordinal variable on a scale ranging from 1 to 5:

- a. Did not recover (=1);
- b. Recovered to some extent, but worse off than before (=2);
- c. Recovered to the same level as before (=3);
- d. Recovered, and better off than before (=4);
- e. Experienced the shock but was not significantly affected (=5)

The question is repeatedly asked for a roster of several different shocks (droughts, floods, crop diseases, etc.) potentially experienced in the years before the survey. This work follows Garbero and Letta (2022) and computes household-level ATR as an average of all the values of the various abilities to recover reported by the household for each shock of the survey module. As shown in Table 3, the investigated households tend not be resilient to shocks, as they report, on average, an inability to recover to their previous level of welfare after the occurrence of a variety of shocks and stressors.

Table 3. Ability to Recover (ATR) – Descriptive Statistics.

Variable Name	N. of Observations	Mean	Standard Deviation
Bangladesh	1,177	2.34	0.89
Brazil	1,345	2.26	1.22
Chad	1,981	1.62	0.90
Indonesia	1,104	3.69	1.02
Mexico	1,159	2.26	1.00
Nepal	1,304	2.61	1.23
Sao Tomé & Príncipe	567	2.39	1.26
Senegal	1,498	3.22	1.24
Average	10,135	2.49	1.26

Among the countries studied, only households samples from Senegal and Indonesia show an average value of resilience above the resilience threshold of 3, signaling the ability to return to the same level of welfare as before the shocks. Still, on average, households can recover from shocks only to some extent, and are worse off, in terms of welfare, compared to the pre-shock situation. The initial dataset encompasses approximately 15,600 observations. However, observations for ATR are incomplete and reduce the sample of analysis to around 10,000 units.⁶

⁶ We are aware of the fact that this may cause some selection biases in the analyzed sample; specifically, households who provided a detailed response to the ATR part of the questionnaire may differ from those that have done so. We conduct one-way ANOVA tests comparing households with and without ATRECO across the main demographic, socioeconomic, and asset-based control variables used in the empirical analysis. In particular, households with ATRECO are, on average, characterized by a slightly older household head (48.45 years versus 47.35), a marginally larger household size (5.73 members versus 5.29), and a higher incidence of female household heads (0.17 versus 0.16). Small differences are also observed in socioeconomic characteristics: households with ATRECO report fewer years of schooling of the household head (3.79 versus 4.93), a slightly lower average household education level (1.01 versus 1.05), and a larger average land endowment (5.71 hectares versus 4.88). Asset-related indicators display modest differences as well, with households providing ATR information exhibiting higher values of both the general asset index (0.15 versus 0.10) and the agricultural asset index (0.14 versus 0.13). While these

6. Main Results

This Section starts by presenting the results for the main outcome variable, i.e. FIES. The discussion of income results is reported in subsection 6.2.

6.1 Main Results on Food Insecurity

The analysis incorporates a LASSO filtering procedure (see Equation [1]), with results detailed in Table A.4 of the Appendix. This step refines the dataset by regressing estimated LASSO residuals on country dummies and household characteristics selected via LASSO, leading to filtered residuals that capture volatility related to food insecurity (Equation [2]). These residuals, as shown in Figure A.1, follow a normal distribution, validating the filtering method. The unconditional volatility dummy is constructed by identifying households above the volatility median as "volatile." The outcomes of the vulnerability estimates of food security (Equations [4] and [6]) are reported in Figure 3. This estimate quantifies the likelihood of households being above the food insecurity line. Following the existing literature, this threshold is set at the median value of the standardized raw FIES score, equal to 3. Figure 3 shows that a substantial share of sampled households (over 60%) are more likely to become food insecure than to remain food secure in the near future, corresponding to the 50% probability threshold indicated by the vertical red line, thus underscoring the critical insights yielded by this analytical approach.

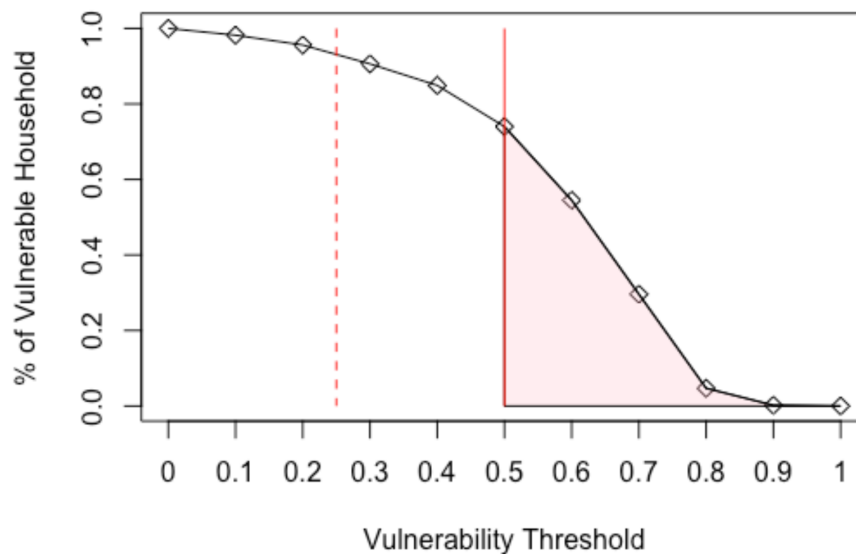


Figure 3. Percentage of households vulnerable to food insecurity across different probability thresholds (FIES outcome).

Building on this empirical evidence, we construct a vulnerability dummy by classifying as vulnerable to food insecurity all households with at least a 50% probability of becoming food insecure in the near future. For sensitivity purposes, we also test a lower probability threshold of 25%, corresponding to the dotted line in Figure 3, for broader applicability (Adjognon et al., 2021). Under

differences are statistically significant according to the ANOVA tests, their magnitude is small relative to the within-group variation of the corresponding variables. Given the large sample size, statistical significance is expected even for minor differences in means and does not necessarily imply economically meaningful imbalances between the two groups. Importantly, all variables considered in the ANOVA are explicitly included as controls in the empirical specifications, thereby mitigating concerns that sample selection related to ATRECO availability may bias the estimated relationships of interest.

this alternative threshold, more than 80% of sampled households are classified as vulnerable to food insecurity.

We finally explore the mitigating effect of resilience (proxied by ATR) on vulnerability, employing market proximity as the instrumental variable. Table 4 presents the IV model's estimated coefficients for different outcomes: the volatility dummy and vulnerability dummies based on two sets of thresholds (one for the Food Insecurity (FI) line and one for the probability of being food insecure, v_x).

Table 4. FIES IV Model.

Dependent Variable:	Food Insecurity Volatility	Food Insecurity Vulnerability (FI Line = Median, $v_x \geq 0.50$)	Food Insecurity Vulnerability (FI Line = FIES Value 3, $v_x \geq 0.25$)
ATR	-0.194*** (0.0257)	-0.157*** (0.0280)	-0.212*** (0.0289)
<i>Observations</i>	9,126	9,126	9,126
<i>First Stage F Statistic</i>	56.65	31.41	53.52
<i>Wald Chi-Squared</i>	56.66	31.42	53.53
<i>Prob>Chi-Squared</i>	0.0000	0.0000	0.0000

Notes Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The excluded instrument is the inverse of the distance from the nearest urban center. The FIES volatility dummy takes value one if FIES volatility is above the distribution's median and 0 otherwise. In the case of the food insecurity line equal to the median (FIES=2), the FIES vulnerability dummy takes value one if FIES vulnerability (v_x) is above the distribution's median and 0 otherwise. In the case of the food insecurity line equal to FIES value 3, the FIES vulnerability dummy takes value one if FIES vulnerability (v_x) is above the 25th percentile of the distribution and 0 otherwise. Robust standard errors in parentheses. Intercepts not reported.

The findings reveal a consistent negative and statistically significant relationship between resilience, instrumented through market proximity, and the stability dimension of food insecurity, proxied by unconditional volatility and estimated vulnerability of food security across different probability thresholds. The robust Wald chi-square and First Stage F statistics, both exceeding the threshold of 10, confirm the instrumental variable model's validity in addressing endogeneity, demonstrating its robustness. This confirms that the stability dimension of food security heavily depends on farmers' ability to cope with such shocks (i.e., resilience). Depending on the adopted proxies for the outcome, the reduction of the probability of being food insecure ranges between 15 and 21 percentage points (p.p.), and this capacity is significantly influenced by market proximity.

To address the concern regarding the identification strategy, Table A.5 in the Appendix reports the first-stage results of the instrumental variable model along with the Stock and Yogo F-statistic.⁷ The coefficient on inverse distance is positive and highly statistically significant, indicating that households located closer to markets are significantly more likely to report ATR.

6.2 Main Results using Income as an Alternative to FIES

Table A.6 in the Appendix shows the outcomes of the LASSO filtering methodology for income. Just as for FIES, the resulting volatility distribution using the LASSO selected variables is a good approximation of the normal distribution (see Figure A.2 in the Appendix). The analysis then reproduces

⁷ The Stock and Yogo F statistic measures the effectiveness of instruments in addressing endogeneity concerns in an IV model, and a value higher than 10 is often suggested as a guideline, although not a fixed threshold, indicating that the instruments have sufficient strength to provide reliable estimates.

the FGLS and the vulnerability procedure applied for FIES, with a poverty line threshold equal to the median value of the considered income distribution. The vulnerability estimates \widehat{V}_h for income are shown in Figure 5.

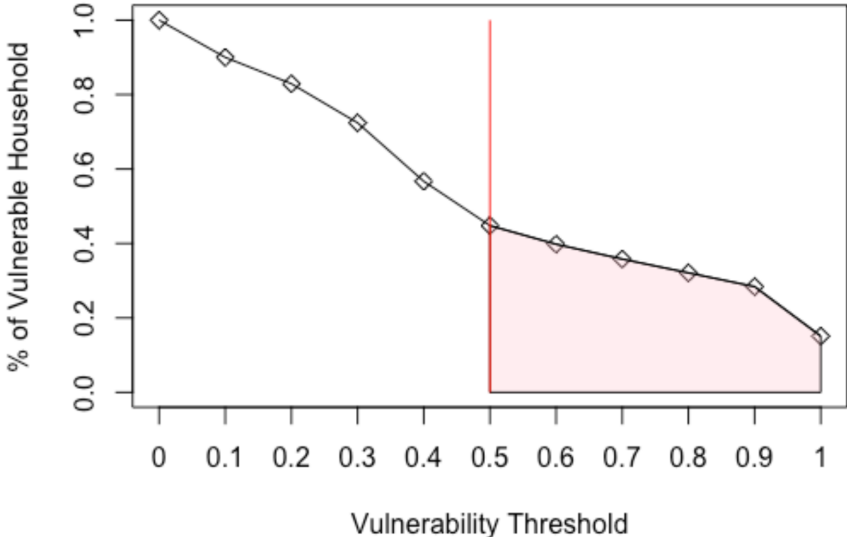


Figure 5. Percentage of households vulnerable to food insecurity across different probability thresholds (Income outcome).

In the same way as for FIES, we construct a dummy for unconditional volatility of income considering as “volatile” only those households situated above the median of the income volatility distribution and a vulnerability dummy considering as “vulnerable” only households with a probability of being vulnerable \widehat{V}_h greater than 50%.

The IV model of FIES is then replicated for income. The results are reported in Table 5 below.

Table 5. Income IV Model.

Dependent Variable:	Income Volatility	Income Vulnerability (PL Line = Median, vx >= 0.50)	Income Vulnerability (PL Line = Median, vx >= 0.25)
ATR	-0.186*** (0.0253)	-0.338*** (0.0294)	-0.0205+ (0.0126)
Observations	9,233	9,233	9,233
First Stage F Statistic	54.18	132.24	132.24
Wald Chi-Squared	56.19	132.27	132.27
Prob>Chi-Squared	0.0000	0.0000	0.0000

Notes Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The excluded instrument is the inverse of the distance from the nearest urban center. The income dummy takes value one if income volatility is above the distribution’s median and 0 otherwise. The income vulnerability dummy takes value one if income vulnerability (vx) is above the distribution’s median and 0 otherwise. Robust standard errors in parentheses. Intercepts are not reported.

Our estimates using income as outcome confirm the previous findings: resilience instrumented

through market proximity is negatively related to both income volatility and vulnerability.⁸ The first-stage estimates for the income-based specifications, reported in Table A.7 in the Appendix, confirm the strength and validity of the instrumental variable strategy. Market proximity, proxied by the inverse distance to the nearest urban center, is positively and highly significantly associated with ATR, indicating that households located closer to markets exhibit higher resilience. The magnitude of the first-stage coefficient is comparable to that obtained in the FIES-based models, ruling out concerns related to weak instruments. Overall, the results of the IV models on income align with the FIES ones, with the negative relationship between resilience and vulnerability to food security even stronger in magnitude (reaching 35 p.p. of vulnerability reduction at the median value).

The findings offer new insights into the nexus between household food security, welfare, and resilience, highlighting market proximity as a significant determinant of vulnerability. Being nearer to market hubs correlates with reduced vulnerability, aligning with prior research (Pace et al., 2022; Slimane et al., 2013). This study's estimates confirm the indirect effect of resilience via market proximity on food security and income vulnerability, reaffirming the importance of market access.

7. Robustness Checks

To address concerns regarding potential nonlinearities in the relationship between market access, resilience, and food security outcomes, and in light of the binary nature of the dependent variables, we complement the baseline linear IV estimates with nonlinear probability models, allowing the conditional probability of food insecurity to respond nonlinearly to changes in resilience while preserving a probabilistic interpretation of the outcome. Moreover, the CF probit framework provides a way to account for endogeneity in nonlinear settings by explicitly controlling for the correlation between the endogenous regressor and unobserved determinants of food insecurity.

Table 7 reports probit estimates of the relationship between household resilience, measured by ATR, and alternative/sensitivity indicators of food insecurity volatility and vulnerability.

Table 7. Probit Model Results.

Dependent Variable:	Food Insecurity Volatility	Food Insecurity Vulnerability (FI Line = Median, vx \geq 0.50)	Food Insecurity Vulnerability (FI Line = FIES Value 3, vx \geq 0.25)
ATR	-0.192*** (0.0101)	-0.123*** (0.0107)	-0.164*** (0.0102)
Constant	0.617*** (0.0281)	1.059*** (0.0309)	0.941*** (0.0294)
<i>Observations</i>	<i>10,136</i>	<i>10,136</i>	<i>10,136</i>

*Notes: Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.*

The probit estimates reported in Table 7 show a consistently negative and statistically significant association between households' ATR and all measures of food insecurity volatility and vulnerability. The estimated effects are stable across alternative food insecurity thresholds and probability cutoffs, suggesting that higher resilience is systematically associated with a lower likelihood of experiencing food insecurity and future vulnerability. These findings confirm that the baseline results are robust to nonlinear modeling of the outcome variable and are not an artifact of the linear probability specification.

⁸ As in the case of FIES, F-test statistics from the first stage strongly reject the hypothesis of a weak instrument.

Table 8 presents CF probit estimates, which extend the probit framework by explicitly accounting for potential endogeneity in household resilience.

Table 8. Control Function Probit Model Results.

Dependent Variable:	Food Insecurity Volatility	Food Insecurity Vulnerability (FI Line = Median, vx \geq 0.50)	Food Insecurity Vulnerability (FI Line = FIES Value 3, vx \geq 0.25)
ATR	-0.523*** (0.0729)	-0.458*** (0.0736)	-0.574*** (0.0734)
Control function residual	0.390*** (0.0737)	0.381*** (0.0743)	0.460*** (0.0740)
Constant	1.400*** (0.182)	1.865*** (0.184)	1.927*** (0.184)
<i>Observations</i>	<i>9,126</i>	<i>9,126</i>	<i>9,126</i>

*Notes: Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.*

The coefficient on the CF residual is positive and statistically significant across all specifications, providing evidence that unobserved factors jointly influence resilience and food insecurity outcomes. Importantly, once this source of endogeneity is accounted for, the estimated effect of ATR remains negative, statistically significant, and larger in magnitude than in the standard probit model. While differences in coefficient magnitudes relative to the linear IV estimates are expected, given the nonlinear nature of the probit model and the scale normalization inherent in binary response models; nevertheless, the direction, significance, and relative ordering of effects are fully consistent with the baseline results, reinforcing the conclusion that greater resilience reduces food insecurity volatility and vulnerability.

8. Conclusions and Policy Implications

The exploration of crop commercialization's role in economic development has a long history in the literature, starting with the foundational work by Key et al. (2000), von Braun (1995), and Fafchamps (1992). However, the relationship between market proximity, resilience, and food security vulnerability has not been comprehensively addressed. This study seeks to fill that gap by using cross-country microdata to investigate whether closer market access strengthens resilience and mitigates food insecurity. The findings reveal a positive association between market proximity and improved resilience and food security outcomes.

The study is grounded in established frameworks that emphasize geographic distance as a key determinant of market access (Xu et al., 2009; Feleke & Zegeye, 2006; Amarasinghe et al., 2005). The results are consistent with conceptual contributions that emphasize access and stability as central dimensions of food security and resilience. In particular, Constas (2023) stresses the role of physical and economic access to food within vulnerability and resilience frameworks, while Hoddinott (2023) and Upton et al. (2023) highlight the significance of local and regional food systems and markets in shaping households' capacity to withstand and respond to shocks. These insights further solidify the practical and theoretical relevance of market access in determining both resilience and food security outcomes.

Our findings point to several policy directions aimed at strengthening smallholder farmers'

resilience and reducing their vulnerability to food insecurity. First, improving market access through investments in rural infrastructure can enhance farmers' access to economic opportunities, information, and institutional support, thereby improving their capacity to manage risks. Second, encouraging income diversification beyond agriculture, including off-farm employment and small-scale agro-processing, can reduce households' exposure to market volatility and lower vulnerability to food insecurity. Third, the use of data-driven tools to predict household vulnerability based on observable characteristics offers policymakers a way to design more proactive interventions, such as early warning systems and targeted social protection, even before food insecurity emerges. In addition, policies that reduce transaction costs, improve market information, and strengthen farmer organizations can mitigate market power asymmetries and support more equitable price transmission.

These new understandings also build on the existing literature, supporting targeted agricultural policies as advocated by Garbero & Jäckering (2021), Mulbah et al. (2021), and Renkow et al. (2004). Our amendment of the classic VEP model, which applies LASSO variable selection to more accurately predict households' vulnerability to future food insecurity, is rooted in the idea that better predictive approaches are needed to allow for a more targeted policy intervention design, enabling policymakers to proactively address food insecurity and bolster resilience among smallholder farmers.

Lastly, while this study does not aim to establish definitive causal relationships, the associations it documents between market proximity, resilience, and food security merit attention. In the development economics literature, geographic distance is commonly used as an empirical proxy for market access, reflecting variation in households' physical access to markets and trading opportunities (Xu et al., 2009; Feleke & Zegeye, 2006; Amarasinghe et al., 2005). Despite acknowledging the potential for self-selection, the exogeneity of geographic distance is upheld, especially in regions where institutional barriers limit the ability of households to relocate closer to markets. In this framework, our results reinforce the notion that improving market access plays a crucial role in strengthening household resilience and reducing vulnerability to food insecurity.

To conclude, this work further clarifies the relationship between household resilience and food security by showing that market access influences food security indirectly through its impact on resilience. The IV results highlight the importance of market proximity in facilitating governance, risk management, and information exchange, key factors that help farmers manage and absorb shocks. These findings, in turn, underscore the necessity of policy interventions aimed at enhancing market access and developing infrastructure, which are critical for improving rural resilience. By offering new cross-country empirical insights, this study contributes to the ongoing discussion of market access in agricultural development and food security. Future research, especially with more granular data on market dynamics and specific shock types, should deepen the understanding of these relationships and guide more effective policy decisions.

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Appendix

Table A.1. Variable Definitions and Other Basic Information.

Variable name	Definition	Time Period	Source
Age of the Household Head	Age of the household head (<i>decimals</i>)	2017 – 2018	International Fund for Agricultural Development
Education Years of the Household Head	Years of schooling of the household head (<i>decimals</i>)	2017 – 2018	International Fund for Agricultural Development
Gender of the Household Head	Gender of the household head (<i>binary, 1=female</i>)	2017 – 2018	International Fund for Agricultural Development
Household Size	Number of people in the household (<i>decimals</i>)	2017 – 2018	International Fund for Agricultural Development
Household Average Education Level	Average education level attained by the household members (<i>values from 0 to 3</i>)	2017 – 2018	International Fund for Agricultural Development
Land Area	Area of land owned by the household (<i>ha</i>)	2017 – 2018	International Fund for Agricultural Development
Total Gross Income	Household total gross income from all sources (<i>USD</i>)	2017 – 2018	International Fund for Agricultural Development
Asset Index	Asset index based on common durable assets (<i>values from 0 to 1</i>)	2017 – 2018	International Fund for Agricultural Development
Agricultural Asset Index	Agricultural assets index based on common durable assets (<i>values from 0 to 1</i>)	2017 – 2018	International Fund for Agricultural Development

Table A.2. Summary Statistics – Whole Sample.

Variable Name	N. of Observations	Mean	Standard Deviation	Minimum Value	Maximum Value
Age of the Household Head	15642	47.71	13.80	12	110
Education Years of the Household Head	15642	4.11	4.20	0	28
Gender of the Household Head	15642	0.17	0.37	0	1
Household Size	15642	5.76	3.83	1	30
Household Average Education Level	15642	0.94	0.85	0	3
Land Area	15642	5.33	10.25	0	281
Total Gross Income	15894	2732.39	6943.331	0	97497
Asset Index	15642	0.13	0.14	0	1
Agricultural Asset Index	15642	0.14	0.18	0	1
Treated	15642	0.48	0.50	0	1

‘Gender of the household head’ is a dummy taking value 1 if the household head is female and 0 otherwise. ‘Household education level’ is a categorical variable which can take the following values: 0=no education; 1=primary education; 2=secondary education; 3=higher education. ‘Total gross income’ is calculated as the sum of total cash and in-kind wage from agricultural employment; total cash and in-kind wage from all non-agricultural employment; sales of crop and other products, together with own consumption; sales of livestock, carcasses, and other products, together with own consumption; total sales and earnings from self-employment activities; private funds (remittances, transfers from individuals) and public funds (pensions, social transfers); and other sources of income like a land rental. ‘Asset Index’ and ‘Agricultural Asset Index’ are standardized measures of assets which range from 0 to 1 and have been generated for each country sample via factor analysis, using exclusively the assets that were common across all the datasets. ‘Treated’ is a dummy taking value 1 if the household was in the treatment group and 0 otherwise.

Table A.3: The FIES Questionnaire and Raw Score Descriptive Statistics.

During the last 12 months, was there a time when a lack of money or other resources?
(Q1) You were worried you would not have enough food to eat (WORRIED)
(Q2) You were unable to eat healthy and nutritious food (HEALTHY)
(Q3) You ate only a few kinds of foods (FEW FOODS)
(Q4) You had to skip a meal (SKIPPED)
(Q5) You ate less than you thought you should (ATE LESS)
(Q6) You ran out of food (RAN OUT)
(Q7) You were hungry but did not eat (HUNGRY)
(Q8) You went without eating for a whole day (WHOLE DAY)

Number of Observations by Raw FIES Score									
	0	1	2	3	4	5	6	7	8
Bangladesh	737	157	198	358	138	110	109	108	55
Brazil	602	114	130	153	144	107	37	32	67
Chad	445	248	235	264	126	128	110	125	493
Indonesia	1,073	259	180	187	112	56	42	68	51
Mexico	541	371	302	204	126	83	76	57	0
Nepal	1,531	285	559	369	62	19	7	5	37
Sao Tomè & Principe	235	80	61	99	106	176	177	248	87
Senegal	473	165	258	433	261	174	182	108	127
Total	5,637	1,679	1,923	2,067	1,075	853	740	751	917

Table A.4. FIES LASSO Filtering Methodology.

Dependent Variable:	Standardized Raw FIES Score
Age of the Household Head	-0.00185
Education Years of the Household Head	-0.0349
Household Size	0.0152
Land Area	-0.00404
Education Years of the Household Head ²	-0.000256
Gender of the Household Head (<i>1=female</i>)*Land Area	-0.00252
Age of the Household Head*Asset index	-0.00298
Age of the Household Head*Treated	-0.0000811
Education Years of the Household Head*Treated	-0.00410
Asset Index*Agricultural Asset Index	-0.972
Asset index*Treated	0.0406
Asset Index ²	-0.427
Agricultural Asset Index ²	-0.284
Constant	0.249
<i>Observations</i>	<i>15,865</i>

Notes: The variables whose coefficients were set to zero by the LASSO model are dropped. Only retained coefficients are shown. Estimates signal correlation and not causality.

Residual Density Distribution - Standardized raw FIES Score with LASSO Controls

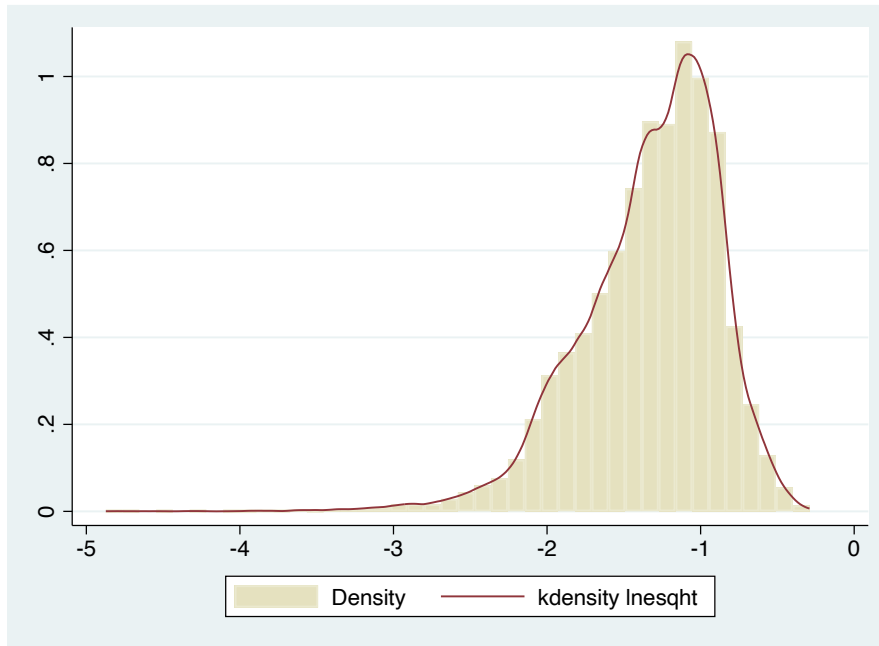


Figure A.1. FIES FGLS-Generated Variance.

Table A.5. First Stage Results Instrumental Variable Model – FIES.

Dependent Variable:	ATR
Inverse Distance	2.663*** (0.1992)
Observations	9,126
Stock and Yogo F statistic	100.839

Notes Robust standard errors in parentheses.

** $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.*

Table A.6. Income LASSO Filtering Methodology.

Dependent variable:	Total gross income
Age of the Household Head	0.0131
Education Years of the Household Head	0.133
Gender of the Household Head (<i>1=female</i>)	-0.376
Household Education Level	0.0332
Age of the Household Head*Household Size	0.000528
Age of the Household Head* Household Education Level	0.00192
Age of the Household Head*Land Area	0.000200
Household Size*Land Area	0.000197
Gender of the Household Head (<i>1=female</i>) *Land Area	0.00183
Age of the Household Head* Agricultural Asset Index	0.00200
Age of the Household Head*Treated	0.00221
Education Years of the Household Head*Treated	0.0303
Household Size*Treated	0.00652
Household Education Level*Asset Index	0.0620
Asset Index*Treated	-1.372
Asset Index ²	2.203
Agricultural Asset Index ²	3.435
Constant	4.243
<i>Observations</i>	<i>16,119</i>

Notes: The variables whose coefficients were set to zero by the LASSO model are dropped. Only retained coefficients are shown. Estimates signal correlation and not causality.

Residual Density Distribution - Natural Log Income with LASSO Controls

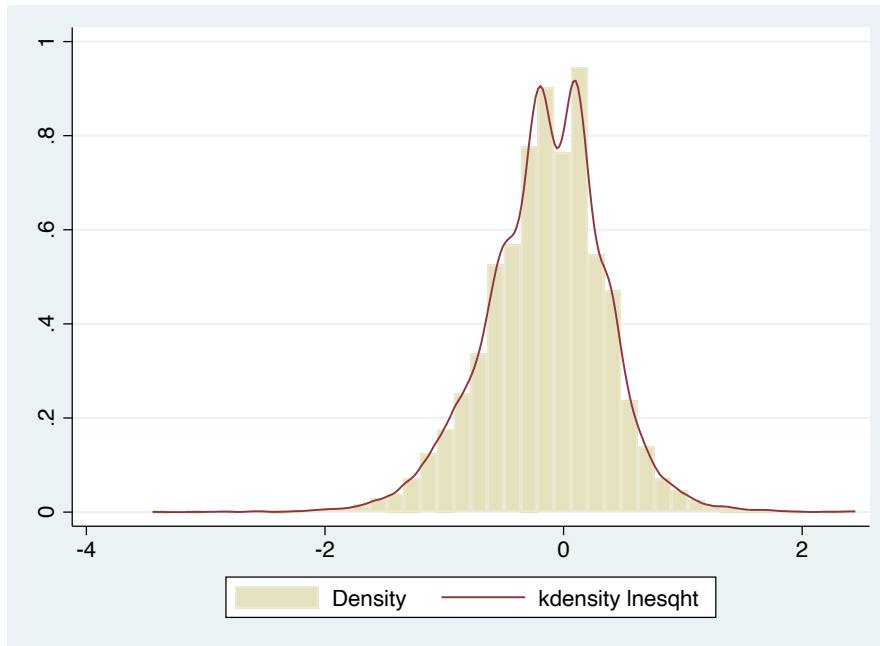


Figure A.2. Income FGLS-Generated Variance.

Table A.7. First Stage Results Instrumental Variable Model – Income.

Dependent Variable:	ATR
Inverse Distance	2.505*** (0.1922)
<i>Observations</i>	9,233
<i>Stock and Yogo F statistic</i>	101.684

Notes Robust standard errors in parentheses.

** $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.*