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Food security lags economic development, raising questions about whether food insecure households can leverage local economic development and livelihood diversification opportunities as effectively as their food secure counterparts. In a dynamic model incorporating production and utility risk, household consumption and livelihood portfolios depend on vulnerability, described by proximity to their stochastic minimum consumption threshold. Using granular data on smallholder farmers' livelihood choices, the threshold effect is significant, with approximately 25% of household wealth allocated to satisfying the consumption threshold. Costly income smoothing strategies are most prevalent among the vulnerable and food insecure. However, results show that popular programs targeting livelihood diversification benefit primarily food secure households. In contrast, food safety net programs that directly reduce vulnerability carry the largest livelihood diversification benefits for food insecure households. These findings highlight the importance of reducing vulnerability to food insecurity, as it hinders smallholder farmers from accessing high-value market opportunities.

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JEL Classification: O13, G11, Q12, D81, Q18

Anke D. Leroux: Department of Economics, Monash University, Caulfield East, Victoria 3145, Australia. (email: anke.leroux@monash.edu); Vance L. Martin : Department of Economics, The University of Melbourne, Parkville, Victoria 3010, Australia (retired). (email: vancemartin2020@gmail.com).

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Life at the brink: Livelihood portfolios of the food insecure

Anke D. Leroux [*1] and Vance L. Martin [†2]

[1]Department of Economics, Monash University, Caulfield East, Victoria 3145, Australia.

[2]Department of Economics, The University of Melbourne, Parkville, Victoria 3010, Australia (retired).

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[†] Email: vancemartin2020@gmail.com

Abstract

Food security lags economic development, raising questions about whether food insecure households can leverage local economic development and livelihood diversification opportunities as effectively as their food secure counterparts. In a dynamic model incorporating production and utility risk, household consumption and livelihood portfolios depend on vulnerability, described by proximity to their stochastic minimum consumption threshold. Using granular data on smallholder farmers' livelihood choices, the threshold effect is significant, with approximately 25% of household wealth allocated to satisfying the consumption threshold. Costly income smoothing strategies are most prevalent among the vulnerable and food insecure. However, results show that popular programs targeting livelihood diversification benefit primarily food secure households. In contrast, food safety net programs that directly reduce vulnerability carry the largest livelihood diversification benefits for food insecure households. These findings highlight the importance of reducing vulnerability to food insecurity, as it hinders smallholder farmers from accessing high-value market opportunities.

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1 Introduction

Over the past decade, food insecurity has been rising.[1] Today, one in three people is food insecure, with almost 12% classified as severely food insecure, compared to 20% and 8%, respectively, in 2014. The rise in severe food insecurity affects every region of the world, with lower-middle- and low-income countries being the hardest hit. Almost one in five children living in poor rural households is stunted and 5% suffer from wasting (FAO 2022).

Eradicating food insecurity and malnutrition have been of critical importance to policymakers and are primary indicators of progress toward the second sustainable development goal (UN 2015). Over the past 10 years around 10% of official development assistance has been allocated to food and agriculture (OECD 2024). A key strategic focus are market-based producer-focused policies aimed at increasing food access by facilitating participation in high value markets and income generation by the most vulnerable, namely rural smallholder households with a high dependency on subsistence farming (World Bank Group 2015, USAID 2023). For example, community based livelihood diversification programs provide inputs, subsidies, training, and support to smallholder farmers to grow, market, and negotiate the sale of high value crops (IFAD 2015). The expectation is that by growing high value crops, food insecure subsistence farmers can use the income generated from these activities to purchase additional and more nutritious food to supplement their staple diet. With mixed empirical evidence regarding the relationship between diversifying into cash crops and food security (see, for example, Hashmiu et al. (2020), Rhubara et al. (2020), and Thanichanon et al. (2018)) and the growing realization that time is running out to meet the SDG food security targets, the policy discourse is starting to shift from being predominantly producer-focused toward tackling food insecurity directly at the consumer level (FAO 2022).[2]

Using highly granular data to estimate optimal livelihood portfolios of smallholder farmers in Lao People's Democratic Republic (PDR), we provide theoretical and causal empirical evidence that food insecure households are less able than their food secure counterparts to leverage the benefits of market-based, producer-focused policies.[3] In line with earlier literature on income smoothing, our research shows that *ceteris paribus* food insecurity causes households to invest a greater share of their wealth in the production of subsistence crops and allocate significantly less wealth to higher return cash crops.

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[1] As per the United Nations Food and Agriculture Organization's (FAO) definition, a person is food insecure when they lack regular access to enough safe and nutritious food for normal growth and development to achieve an active and healthy life.

[2] In its State of Food Security and Nutrition report, the United Nations' Food and Agriculture Organization advocates for re-purposing fiscal subsidies for producers as food subsidies and nutrient sensitive social protection programs for the benefit of food insecure consumers (FAO 2022).

[3] A household's livelihood portfolio is defined as the mix of income and non-income generating activities a household engages in to ensure its survival and maximize its welfare (see, for example, Ellis (2000)).

We estimate that, on average, 25% of household wealth is allocated to satisfying the threshold and show systematic differences in the portfolio composition of households, with food insecure households allocating approximately 24% less of their land to cash crops compared with their food secure counterparts.

Food insecurity is shown to be an important barrier to the success of livelihood diversification programs, aimed at encouraging the uptake of higher return crops, in effect by increasing their expected net returns and decreasing their riskiness. We show that efforts to encourage food insecure households to adopt cash crops are less successful than for the average, food secure smallholder household. A 1% increase in the expected return of the cash crop results on average in increases in land allocation to cash crops of 0.5% and 3% for severely and moderately food insecure households respectively, compared to average food secure smallholder households of 18%. Qualitatively similar results are obtained for the reduction in cash crop risk. These findings also help to explain why the evidence base of these programs' effectiveness for food security remains weak despite the growing number of program designs and implementations (see Ton et al. (2015), Moore et al. (2021), and van Vugt et al. (2023) for systematic reviews of the related impact evaluation literature).

The marginal effects on cash crop adoption from livelihood diversification programs are contrasted with alternative programs that focus on the provision of food safety nets, all year round road access or insurance. These alternative programs are shown to be more successful in encouraging food insecure farmers to diversify into cash crops. Our theoretical and empirical findings reveal new insights into how food insecurity acts as a major barrier, hindering smallholder farmers from diversifying their livelihoods and accessing high-value market opportunities. We thus contribute to the growing body of evidence that documents why the world has gone backward in food security despite total, worldwide support for food and agriculture, accounting for nearly USD 630bn per year (FAO 2022). Given that nearly 70% of these resources have targeted agricultural production, our findings support recent expert calls to redirect some of this funding toward addressing food insecurity directly at the consumer level (Gadenne et al. 2021, FAO 2022).

The theoretical framework is a continuous, dynamic stochastic model that characterizes optimal livelihood portfolio choices across key productive activities that are subject to risk. In this framework, households consider an endogenous minimum consumption threshold and jointly optimize consumption and the livelihood portfolio, subject to two types of risk.[4] The first is standard and involves return risk, whereby the returns from productive activities are subject to yield, price, and other market shocks. The second is utility risk which arises from shocks to the household's minimum consumption threshold.

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[4] The concept of a threshold is to be distinguished from the use of the term recently adopted by Balboni et al. (2022) to model poverty traps based on a nonlinear difference equation of income that yields multiple equilibria.

It is this channel that provides a fundamental role in establishing the linkage between livelihood portfolio composition and food security. We derive closed-form solutions of the model and show that the optimal portfolio of livelihood activities depends, among others, on household vulnerability, described by household's proximity to the minimum consumption threshold. The model's solutions are shown to be a nonlinear function of the unknown parameters which are estimated by generalized method of moments.

Our investigation into the livelihood portfolios of smallholder farmers contributes to the extensive literature that seeks to lift this population group out of poverty and food insecurity by understanding the determinants of livelihood choices and facilitating their market participation and transition toward higher return activities (Key et al. 2000, Ellis 2000, Allen and Atkin 2022). Typically, smallholder farmers are exposed to significant market and production risks, are risk averse, and have limited access to formal credit and insurance products (Binswanger 1980, Morduch 1995, Yesuf and Bluffstone 2009). They differ in their capacity to smooth consumption ex-post, for example, by relying on informal insurance, leveraging household labor supply, or selling assets (Rosenzweig and Wolpin 1993, Townsend 1994, Kochar 1995). As a result, many households resort to managing these risks ex-ante using costly income smoothing strategies, which include choosing livelihoods and making production decisions that are lower risk but also yield lower expected returns (Binswanger 1980, Morduch 1995, Rosenzweig and Binswanger 1993).

Other studies investigate production and consumption decisions jointly within a theoretical framework (Fafchamps 1992). Kurosaki and Fafchamps (2002) provide empirical evidence of greater self-sufficiency resulting from utility risk among smallholder farmers in Pakistan. The dynamic theoretical framework proposed here has a similar flavor but explicitly models and estimates utility risk in the form of shocks to the consumption threshold. We find that for food insecure households, this effect is quantitatively more important than being isolated from markets for part of the year and that consumption and income smoothing strategies are complements.

This paper also contributes to the extensive literature that empirically tests the theoretical foundations of dynamic portfolio models. Linking survey-based measures of beliefs and preferences to investors' financial portfolios reveals, in line with theoretical predictions, that the likelihood of investors holding stocks increases with the stocks' expected returns (Dominitz and Manski 2007, Hurd et al. 2011) and investor risk tolerance (Barsky et al. 1997, Dohmen et al. 2011, Guiso et al. 2018). These results also hold at the intensive margin, where the share of wealth held in stocks is found to be sensitive to investor beliefs (Giglio et al. 2021) and risk preferences (Kimball et al. 2008, Ameriks et al. 2020). However, this sensitivity is often significantly weaker than predicted by theory. Giglio et al. (2021) and Ameriks et al. (2020) point to investor-specific characteristics and behaviours as factors that would explain the sensitivity gap.

Building on previous literature by Constantinides (1990), Campbell and Cochrane (1999) and van Bilsen (2020), an important feature of our model is the inclusion of a stochastic endogenous consumption threshold, which is conditional on past consumption and subject to utility risk. Allowing for household vulnerability and utility risk to impact optimal portfolio shares moderates the effects of returns, riskiness, and risk attitudes on portfolio composition. That the empirical setting in this study differs dramatically from that of well-to-do financial investors residing in high-income countries is further evidence of the general applicability of dynamic portfolio models to household allocation decisions.

The remainder of the paper proceeds as follows. A theoretical model of portfolio choice subject to an endogenous minimum consumption threshold is developed in Section 2. Section 3 describes the data collection and provides a high-level characterization of our sample households. The empirical model is described and tested in Section 4, with extensions allowing for a deeper understanding of household vulnerability and its relationship with food insecurity presented in Section 5. Section 6 analyses the effects of food insecurity on livelihood portfolios. Section 7 provides a discussion of the results and Section 8 concludes. Appendices A to C contain key model derivations and survey instructions.

2 A stochastic dynamic livelihood portfolio model

We describe a theoretical framework capable of replicating the key features of the recurring livelihood decisions faced by smallholder farmers with varying levels of food security. Firstly, determining the mix of livelihood activities and their intensity that maximizes the householder's utility through time requires a dynamic portfolio model. Secondly, given the interaction between the livelihood portfolio and the level of food security, the framework incorporates a minimum consumption threshold in the utility function.

The model involves constructing an optimal livelihood portfolio for a risk averse, smallholder household that recognizes the existence of an endogenous, stochastic minimum consumption threshold. The optimal portfolio allocates scarce, productive household wealth to livelihood activities to maximize household utility from current and future consumption by explicitly taking into account the relative returns and risks of each activity and the effect of livelihood choices on future household wealth. We introduce the three key components of the model, the utility function, the dynamic wealth constraint and the dynamic minimum consumption threshold one-by-one before presenting the closed-from solution to the maximization problem and discussing model interpretations and special cases.

2.1 Utility function

The instantaneous utility function of the household is given by

$$u = \frac{(c-y)^b}{b}, \tag{1}$$

where c is consumption relative to the minimum consumption threshold, y. The householder's risk attitude is given by the parameter b with risk aversion, $b < 1$, ensuring concavity of the utility function. The form of the utility function (1) represents a general and flexible framework in which to model the livelihood portfolio behaviour of households as it allows for heterogeneous risk behaviour across households through the risk parameter b, and the stochastic threshold, y. An important special case of (1) is the power utility function given by setting $y = 0$, which is widely adopted in the finance literature to construct and understanding models of portfolio choice and risk management in general (see for example, Cochrane (2009)). A further special case of power utility is logarithmic utility by imposing the joint restrictions $y = 0$ and $b = 0$.

An important property of the model is that by allowing for the existence of y implies for the Arrow-Pratt measure of relative risk aversion (RRA) that the household's risk attitude is non-constant according to variations in consumption, c, relative to the minimum consumption threshold, y (Campbell and Cochrane 1999). For $b < 1$, the RRA increases as c approaches y from above. For the special case of power utility, setting $y = 0$ yields a constant relative risk aversion parameter as in Merton (1969, 1971).

Consumption threshold levels have entered portfolio models in different ways in the literature. Seeking to understand the effect of a binding and fixed consumption threshold on optimal portfolio composition, Ameriks et al. (2020) and Rosenzweig and Wolpin (1993) use a similar formulation to equation (1), whereby consumption above the reference point is maximized. Within the class of deterministic threshold models, Constantinides (1990) and Campbell and Cochrane (1999) amongst others, allow for endogeneous thresholds by specifying y as a function of a set of past characteristic variables.[5] The utility function (1) extends previous models by allowing for utility risk through the specification of a stochastic threshold where y is subject to shocks as in Nakagawa (2012) and Leroux et al. (2018). Under certain parameterizations, the model nests the deterministic class of threshold models by testing for the presence of utility risk.

Further flexibility of the stochastic threshold utility function in (1) is achieved by allowing for heterogeneous risk aversion via the parameter b that varies across households. In the empirical case study of farmers in Lao PDR, risk aversion data are collected using the approach of Eckel and Grossman (2008). Not only does this data provide additional

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[5] This literature describes risk averse preferences being maximized above the threshold. Another strand of the literature is based on prospect theory where utility is maximized above as well as below the threshold (Curatola 2017, Hlouskova et al. 2019, van Bilsen et al. 2020).

information for improving inferences, but it enables the identification of parameters that would not otherwise be feasible if risk aversion also needed to be parameterized.

2.2 Wealth equation

A household, endowed with initial wealth $W(0) = W_0$, generates returns by allocating household wealth to productive activities. In the context of a smallholder farming household, wealth is the scarce factor of production, for example, land or labor, while livelihood activities can include different types of crops, raising livestock, commercial activities, or employment outside of the farm. The dynamic wealth constraint captures changes in household wealth, dW, which is a function of the return and riskiness of its livelihood portfolio and household consumption decisions, c. In the empirical application, the focus is on $n = 3$ livelihood activities consisting of a subsistence crop (activity 1), a cash crop (activity 2), and a risk free activity (activity 3).[6] In a smallholder setting, growing subsistence crops is typically viewed as a lower-risk and lower-return activity as compared with growing cash crops, as the latter requires market transactions before output can be converted into consumption.

Let μ_1 represent the expected return on the subsistence crop, μ_2 the expected return on the cash crop, and μ_3 the return on a risk free activity. Shocks to the returns on the risky activity $j = 1, 2$ over the time interval dt are given by $dz_j \sim N(0, dt)$, with investment risk σ_j, and covariance σ_{12}. By definition $\sigma_3 = 0$ for the risk free activity. Wealth formation is assumed to evolve continuously over time according to

$$dW \quad = \quad ((\mu_1 - \mu_3)w_1 W + (\mu_2 - \mu_3)w_2 W - c)\, dt + \sigma_1 w_1 W dz_1 + \sigma_2 w_2 W dz_2, \qquad (2)$$

where w_j, $j = 1, 2, 3$ is the share of land allocated to activity j, with the shares satisfying the summation property $\sum_{j=1}^{n} w_j\,(t) \equiv 1$. This is the standard Merton wealth equation (Merton 1969, 1971) and derived from first principles in Appendix A.1. The first term is the expected change in wealth, which is determined by the difference in the livelihood portfolio investment allocations of land, $(\mu_1 - \mu_3)w_1 W + (\mu_2 - \mu_1)w_2 W$, and consumption, c. The next terms, $\sigma_1 w_1 W dz_1 + \sigma_2 w_2 W dz_2$, capture movements in wealth from shocks to the two risky crops, with the size of the movements determined by the portfolio share allocations to these activities. Equation (2) excludes the possibility of borrowing or lending, thereby inherently assuming that households either lack access to or face the absence of functioning credit and insurance markets.[7]

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[6] In the current context, fallowing could be considered the risk free activity.

[7] The current framework can be used to derive a risk premium m as the fraction of the expected livelihood portfolio return rate $E(r)$ that the households are willing to forego to mitigate risk. Following footnote 2 in Morduch (1995), the risk premium is given by $m/E(r) = \gamma cv^2/2$, where γ is the relative risk aversion evaluated at r and $cv = (w_1^2\sigma_1^2 + w_2^2\sigma_2^2 + 2w_1w_2\sigma_{12}^2 + \beta^2 + w_1\beta)/E(r)$, is the coefficient of variation.

2.3 Stochastic consumption threshold

The United Nation's Food and Agricultural Organization does not define food security in relation to a fixed and exogenously determined subsistence level, such as a minimum caloric intake (see footnote 1). Instead, it emphasizes the notion of food being consumed in ways that support normal growth and development to achieve an active and healthy life. From a household's perspective, this concept is inherently endogenous, as it depends on what is perceived to be an active and healthy life and what is the minimum consumption level required to achieve it. It follows that such perceptions are partially informed by one's past consumption experience, as well as being subject to adjustments in response to shocks outside the household's control.

We model the dynamic process determining the consumption threshold, y, as given in equation (1), according to

$$dy = (ec - fy)\,dt + \beta y dz_1, \tag{3}$$

where e, f, and β are constants. Equation (3) consists of two parts. The first term allows for y to vary deterministically over time. In particular past consumption affects the household's perceptions of y via the parameter e, while higher values of f accelerate the adjustment of the minimum threshold in response to a shock. In equilibrium, the expected (long-run) threshold-to-consumption ratio is a constant $\tau = y/c = e/f$, which requires the condition that $e \leq f$ for the ratio to be less than unity. A value of $\tau = 1$ implies that the household is consuming at its perceived minimum level in the long run, whereas at the other extreme $\tau = 0$ implies $y = 0$. This formulation of an endogenously determined reference level is consistent with, for example, Constantinides (1990), Campbell and Cochrane (1999), and van Bilsen et al. (2020).

For the second part, variations in y are driven by stochastic shocks, thereby exposing the household to utility risk, as measured by the parameter $\beta \geq 0$. Unanticipated movements in y in (3) are assumed to be driven by dz_1 and correspond to shocks to the subsistence activity, that is the production of the staple food (see also Nakagawa (2012) and Leroux et al. (2018) for a similar approach). Positive shocks raise household expectations of y, both for minimum everyday consumption and potentially by triggering life events such as births or marriages. We expect negative shocks to staple food production to result in households adjusting their expectations of the minimum required consumption threshold downward, thereby lowering y. The special case of no utility risk, $\beta = 0$, results in time variations in y being deterministic.

2.4 Portfolio optimization

The household maximizes intertemporal utility by jointly choosing its consumption, c, relative to the minimum threshold, y, and the livelihood portfolio shares, w_1 and w_2.

Formally, the dynamic maximization problem is given by the value function

$$V = \max_{c, w_1, w_2} E \int_0^\infty e^{-rt} \frac{(c-y)^b}{b} dt, \tag{4}$$

subject to the constraints (2) and (3) and the initial conditions $W(0) = W_0$ and $y(0) = y_0$, where r is the discount rate.[8]

The closed-form solution to the dynamic problem is given by the generic solution to the value function

$$V = A(W + By)^b. \tag{5}$$

This function includes wealth, W, the consumption threshold y, the relative risk aversion parameter b and the constants A and B, which are functions of the parameters of the model. The optimal solutions for the land shares allocated to the subsistence and cash crops are respectively

$$\begin{aligned} w_1 &= \frac{\sigma_2^2(\mu_1 - \mu_3) - \sigma_{12}(\mu_2 - \mu_3)}{\sigma_1^2 \sigma_2^2 - \sigma_{12}^2} \frac{1}{1-b}\left(1 + B\frac{y}{W}\right) - \frac{\beta}{\sigma_1} B \frac{y}{W} & (6) \\ w_2 &= \frac{\sigma_1^2(\mu_2 - \mu_3) - \sigma_{12}(\mu_1 - \mu_3)}{\sigma_1^2 \sigma_2^2 - \sigma_{12}^2} \frac{1}{1-b}\left(1 + B\frac{y}{W}\right), & (7) \end{aligned}$$

where $B < 0$ is given by

$$B^{-1} = -\mu_3 + e - f - \frac{(\mu_1 - \mu_3)}{\sigma_1}\beta, \tag{8}$$

as $\beta \geq 0$ and $e \leq f$, and assuming positive excess returns. The optimal shares w_1 and w_2 are the key equations in the model to be empirically estimated and tested in Section 4.2. All mathematical derivations are contained in Appendices A.2 and A.3, including expressions for the optimal consumption, c, and the constant A in (5).

A distinguishing feature of the share equations in (6) and (7) is the role of the minimum consumption threshold-to-wealth ratio, y/W, which varies randomly as a result of (2) and (3). This term represents a household's level of vulnerability, as the higher the ratio, the greater the risk that a household cannot meet the minimum consumption threshold. Inspection of the share equation w_2, reveals that an increase in y/W results in a reduction in the share of land allocated to the cash crop as $B < 0$.

From (6) the relationship between y/W and the share allocated to the subsistence crop w_1, depends on the relative magnitudes of $\sigma_2^2(\mu_1 - \mu_3) - \sigma_{12}(\mu_2 - \mu_3)/(\sigma_1^2\sigma_2^2 - \sigma_{12}^2)(1-b)$ and β/σ_1. The first term represents the optimal share solely based on the net returns, return risk and risk preference. The second term, β/σ_1 represents the utility risk premium

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[8] A variation of the objective function in (4) is to replace the infinite time horizon with a finite time horizon to match the duration of agricultural cycles. This enables stochastic optimal control techniques to accommodate discrete intervals within a continuous-time framework, which, in turn, can be used to update optimal consumption and portfolio decisions by re-optimizing the value function V.

and describes the effect of being exposed to utility risk on the optimal share w_1. As $B < 0$, the relationship between w_1 and y/W is positive when the second term dominates the first term. In this scenario, more vulnerable households simultaneously increase the allocation of household wealth to the production to the subsistence crop, w_1, and decreases the share of wealth allocated to the cash crop, w_2. Alternatively, if the first term dominates the second term, more vulnerable households allocate less land to both crops. In this scenario more land is allocated to the risk free activity.

Many market-based supply-side programs to combat food insecurity aim at increasing the participation of smallholder farmers in higher-return livelihood activities, including cash crops. Within the context of the theoretical framework, this objective translates to raising the share of wealth that is allocated to the cash crop w_2, effectively by raising the net return on cash crop investment, μ_2, and by reducing its riskiness, σ_2^2. At the margin, the effects of such programs on household wealth allocation to the cash crop are given by

$$\begin{aligned} \frac{dw_2}{d\mu_2} &= \frac{\sigma_1^2}{\sigma_1^2\sigma_2^2 - \sigma_{12}^2} \frac{1}{1-b} \left(1 + B\frac{y}{W}\right) & (9) \\ \frac{dw_2}{d\sigma_2^2} &= -\frac{\sigma_1^2\left(\mu_2 - \mu_3\right) - \sigma_{12}\left(\mu_1 - \mu_3\right)}{\left(\sigma_1^2\sigma_2^2 - \sigma_{12}^2\right)^2} \frac{\sigma_1^2}{1-b} \left(1 + B\frac{y}{W}\right). & (10) \end{aligned}$$

Raising μ_2 or lowering σ_2^2 increases the share of household wealth allocated to the production of the cash crop. However, these effects are dampened by $By/W < 0$. The more vulnerable a household, the fewer additional resources it invests in the risky livelihood activity for a given improvement in its net returns or riskiness.

In the case of subsistence crop shares, w_1, there are three channels linking the shares with the expected returns on the subsistence crop. The first is a linear and positive relationship via $\sigma_2^2\left(\mu_1 - \mu_3\right)$. The second and third channels are nonlinear as a result of equation (6) being a function of B. The first of these is the term $(1 + By/W)$, which generates a positive relationship between w_1 and the expected return on the subsistence crop. The relationship given by the last term, $\beta By/\sigma_1 W$, is negative. In contrast, the relationship between μ_1 and cash crop shares, w_2 is also nonlinear, but unambiguously negative.

2.5 Special cases

The model contains two important special cases. The first is where the consumption threshold movements, y, is deterministic by setting $\beta = 0$ in equation (3). The share equations in (6) and (7) become respectively

$$w_1 = \frac{\sigma_2^2\left(\mu_1 - \mu_3\right) - \sigma_{12}\left(\mu_2 - \mu_3\right)}{\sigma_1^2\sigma_2^2 - \sigma_{12}^2} \frac{1}{1-b} \left(1 + B\frac{y}{W}\right) \tag{11}$$

and

$$w_2 = \frac{\sigma_1^2\left(\mu_2-\mu_3\right)-\sigma_{12}\left(\mu_1-\mu_3\right)}{\sigma_1^2\sigma_2^2-\sigma_{12}^2}\frac{1}{1-b}\left(1+B\frac{y}{W}\right), \tag{12}$$

where B is now redefined as $B = 1/(-\mu_3 + e - f)$. While both shares are still a function of household vulnerability, $\frac{y}{W}$, now the relationship between w_1 and μ_1 is unambiguously positive.

A further special case is where households do not take the consumption threshold into account. Setting $y = 0$ in equations (6) and (7) yields

$$\begin{aligned} w_1 &= \frac{\sigma_2^2\left(\mu_1-\mu_3\right)-\sigma_{12}\left(\mu_2-\mu_3\right)}{\sigma_1^2\sigma_2^2-\sigma_{12}^2}\frac{1}{1-b} \\ w_2 &= \frac{\sigma_1^2\left(\mu_2-\mu_3\right)-\sigma_{12}\left(\mu_1-\mu_3\right)}{\sigma_1^2\sigma_2^2-\sigma_{12}^2}\frac{1}{1-b}. \end{aligned}$$

These solutions correspond to the standard Merton model. In contrast to the optimal solutions in equations (6) and (7), the shares are now constant, no longer being a function of household vulnerability.

3 Case study

The theoretical model of livelihood choices is applied to a case study of smallholder farmers in Lao PDR, from whom we collected detailed information about their livelihoods, agricultural production, and food security, as well as eliciting their attitudes to risk.

Agriculture plays an important role in Lao PDR's economy, contributing around 20% to national GDP and employing about 70% of its workforce, predominantly in rice cultivation (FAO 2020). Food insecurity in Lao PDR is amongst the highest in Southeast Asia and exemplifies the patterns observed in many lower middle-income countries. Decades of strong economic growth and prioritizing food security have resulted in countries' hunger levels being downgraded from alarming to serious (Global Hunger Index 2019, World Bank 2020). Yet, with 17% of the population undernourished, one in three children under five years stunted and one in ten suffering from wasting, the country remains at the top quartile of countries worst affected by hunger and undernutrition, placing Lao PDR on par with Bangladesh and Kenya, according to the Global Hunger Index (2019).

Policies and interventions by government and non-government organizations have targeted all aspects of food security, ranging from efforts to improve the availability, access, and utilization of food to reducing the vulnerability of Laotian households. The majority of programs, however, have sought to diversify livelihoods to increase agricultural income, enabled via expanded markets and value chains (Leroux et al. 2015). While these efforts have had some success, notably in reducing undernourishment of the population as a whole, food insecurity has proven to be particularly persistent in the North of the country, where seven of the nine worst-affected provinces are situated (World Food Program 2007, FAO 2020). A recent country assessment confirms the strong link between food security and household rice production (FAO 2020). Most food insecurity is intermittent and a common coping strategy for households is to source rice from one's own production. The study also finds systematic differences in livelihood portfolios, whereby households with lower food consumption scores primarily engage in upland rice cultivation. Higher food consumption scores are typically associated with households that hold more diversified portfolios, including cash crops and, or livestock production.

3.1 Survey

Our efforts in understanding the link between food security and livelihood portfolio choice focus on areas in Lao PDR that remain food insecure despite significant investments in enabling the livelihood diversification of smallholder farmers. As is customary in Lao PDR, recruitment to participate in surveys involves the local and provincial governments. After receiving permission to conduct this research, our local partner, the National University of Laos, collaborated with provincial and local governments to compile a comprehensive list of villages in the Northern Uplands with and without year-round road access. Villages and households within villages were randomly selected for interviews.

During November and December 2016 data were collected from 269 households from 15 villages in the Pak Xeng and Viengkham districts in Louang Prabang and 15 villages from the Phoukout and Kham districts in Xieng Khouang. The survey teams spent two days in each village, separately interviewing the male and female heads of approximately ten households and the village chief. The male survey comprised mainly of questions about agricultural production as well as a risk elicitation task. The female survey focused on household composition, other household assets, including livestock, its portfolio of livelihood activities, and food security. Questions to the village chief related to village-specific characteristics such as road access, whether or not the village has a rice bank[9], and the distance to the nearest market. This information was later complemented with elevation and soil data from the 2011 Lao PDR Agricultural Census.

The enumerators were local students at the National University of Laos who had prior experience in conducting field surveys. The enumerators received specific training on this survey instrument and used ipads for the data collection. After introducing themselves and the survey, the enumerators asked the household head and spouse if they were willing to participate in the survey. They also made clear that any participation on their part was voluntary and that their answers were entirely private and anonymous.

The agricultural production part of the survey includes questions on the number of plots owned, their size, and land value. Focusing on the main subsistence (rice) and cash

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[9] A village rice bank typically involves participating households making regular rice contributions to the bank that can be withdrawn when needed, for example, in the case of crop failure or illness.

(maize) crops for this part of Lao PDR, it asks how much land was allocated to rice and maize production in the previous seasons, how much was harvested of each crop, if other inputs to production were used, and if applicable, the achieved sales price.

Food security is assessed using two commonly employed metrics. The first is the Household Food Insecurity Access Scale (HFIAS), which measures household-level food access, developed under the Food and Nutrition Technical Assistance Project (Coates et al. 2007). HFIAS measures perceived food insecurity via a series of frequency of occurrence questions about feelings of anxiety over food supply as well as the quality and quantity of food consumed by the household over the past four weeks (see Appendix B for the list of questions asked).

As a second measure we use the food consumption score (FCS), which records and combines into a weighted score the quantity and frequency of all food types and groups eaten in the seven days leading up to the interview (INDDEX Project 2018). This method measures a household's food consumption relative to a fixed minimum caloric level, which has been calculated specifically for Lao PDR by Baumann et al. (2013). Because the FCS relies on a recall period of only seven days it likely overestimates food security in our setting, with the survey taking place during or just after the rice harvest, which is the most food-abundant period of the year. For this reason, and our own modelling focus on an endogenously determined minimum consumption threshold, we prefer the longer-term, perception-based HFIAS measure.[10]

At the end of the survey, we elicit risk attitudes in an incentivized risk task. The task is based on Eckel and Grossman (2008), where the participant is asked to pick one of ten gambles that are increasing in the expected return and risk, with the last two choices increasing in risk only and thus used to identify risk-loving preferences. As each household's consumption threshold is unobservable, risk preferences are computed based on the assumption that respondents are expected utility maximizers with $y = 0$. For each choice in the risk task, a relative risk aversion (RRA) parameter range is computed with the minimum and maximum set at -1.5 to 25, respectively. The risk tasks were incentivized financially such that depending on the decisions made, each respondent could earn up to $64,000$ Kip, equivalent to about 2 days of wages.[11] The risk tasks were explained visually with the instructions and payoffs provided in Appendix C.

3.2 Summary statistics

The sampling strategy described above and the diversity of the regions surveyed resulted in data being collected from a heterogeneous group of smallholder households and thus

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[10] In line with the HFIAS guidelines, we classified households that responded 'often' to questions E or F, or anything other than 'never' to questions G, H, or I (see Appendix B) as severely food insecure households. Using FCS to measure food insecurity yields qualitatively similar results.

[11] The Kip/USD exchange rate was 0.00013 at the time.

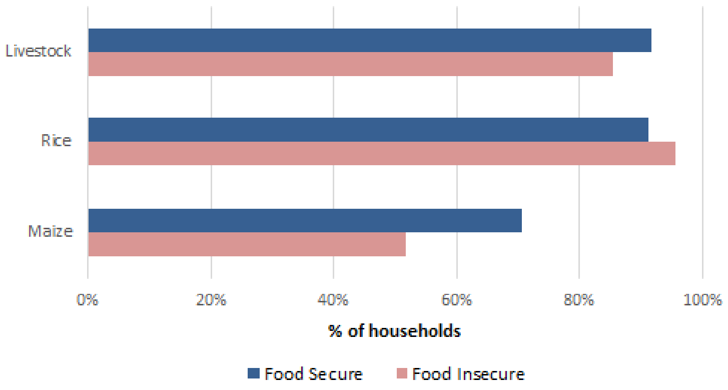

Figure 1: Percentage of sampled households that own livestock and grow rice and maize by food security status.

represents the perfect setting to investigate the relationship between livelihood portfolios and food security. In terms of land-based activities, we focus on rice and maize production as these are, respectively, the main subsistence and the most important cash crops in the region, as well as being the most common in the sample. Figure 1 gives an overview of the proportion of food secure and food insecure households in our sample that own livestock, and grow rice and maize. Most households in both categories own livestock, which is typically grazed on common land. Figure 1 also shows that most households grow rice, but a larger proportion of food secure than food insecure households grow maize.

The variables included in the empirical analysis are motivated by the theoretical model presented in Section 2, where the allocation of household resources across livelihood activities is shown to depend on the returns and risks of each activity, the risk attitude of the household as well as the salience of the minimum consumption threshold. The returns from rice and maize are computed for each household based on the household's allocated land areas, reported land values, harvests, and sales prices. The standard deviation represents the return risk. Other key variables in the empirical model are the share of total household land allocated to rice production (rice share) and the share of total land allocated to maize production (maize share). The returns and shares are computed for the wet season only as this is the principal growing season for rice and maize in the Northern Uplands of Lao PDR, and hence the season for which land is likely to be a limiting factor of production.

As shown in Table 1, surveyed households allocate on average 36% of their agricultural land towards the production of rice, with some households allocating none and others all of their land to rice. With a mean return of 0.04 and a standard deviation of 0.07 per hectare, growing rice achieves lower returns and lower risk than growing maize, which has returns on average of 0.09 and a standard deviation of 0.17. On average, households allocate 1/4 of their land to the production of maize.[12]

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[12] Missing observations of the return series are replaced by the minimum observed returns in the data.

Table 1: Summary statistics of households.

Variables	Definition	Unit	Mean	SD	Min.	Max
Household Level						
RiceShare	Proportion of land in rice production	$[0, 1]$	0.36	0.36	0	1
MaizeShare	Proportion of land in maize production	$[0, 1]$	0.25	0.31	0	1
ReturnRice	Return on land from rice production	unit free	0.04	0.07	0	0.44
ReturnMaize	Return on land from maize production	unit free	0.09	0.17	0	1
FoodInsecurity	HFIAS severe food insecurity measure	$0, 1$	0.33	0.47	0	1
FCS	Food consumption score	unit free	51.94	12.88	3.5	99.50
Livestock	Ratio of cattle and buffalo to total livestock	$[0, 1]$	0.61	0.41	0	1
RRA	Elicited relative risk attitude	unit free	3.76	7.82	-1.5	25.00
Village Level						
RoadAccess	Road access during the wet season	$0, 1$	0.70	0.46	0	1
Ricebank	Rice bank present in village	$0, 1$	0.40	0.50	0	1
Mktdist	Distance to nearest market	km	16	17.04	0	63.00
Elevation	Mean elevation within 5km radius of village	m	819.23	233.38	582.87	1354.12
Ethnic	Main ethnicity is Kmeu, Hmong or Phoutai	$0, 1$	073	0.44	0	1
Irrig	Share of irrigated agricultural land in village	%	12.56	19.76	0	75.87
Observations		269				

Based on our preferred HFIAS-based measure, about 1/3 of the sampled households classify as being severely food insecure. The average FCS is 51.94, with a score below 37.85 characterizing severe food insecurity (Baumann 2013). The risk preference elicitation task, using the mid-point of the implied RRA range for each choice, reveals that the average surveyed farmer is risk averse and has a RRA of 3.76. However, some household heads can be characterized as risk-lovers (RRA < 1), while others exhibit extremely risk averse behaviour (RRA=25).

Additional household and village-level characteristics that do not explicitly feature in the theoretical model but are found to be important predictors of livelihood choice in other studies, are also investigated. These include livestock assets owned by the household. The weighted share of cattle and buffalo owned relative to a household's total large livestock assets is computed by applying the recommended livestock weights for South East Asia (Chilonda and Otte 2006). On average, about 60% of the livestock owned by surveyed households is in the form of valuable cattle and buffalo.[13]

To address potential causal inference concerns, instrumental variables that exploit heterogeneity at the village level are introduced to the analysis in Section 4.1. In our sample, about 30% of households reside in villages that do not have year-round road access, 40% have a rice bank in their village, and the nearest market for buying and selling food is on average 16km away, ranging from 0km to 63km. Households reside in

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[13] Households in our sample also owned pigs and goats, and none owned sheep or horses.

villages that differ in their elevation, with mean elevations within a $5km$ radius ranging from $583m$ to $1354m$. *Ethnic* refers to a dummy variable that takes the value of one if the main ethnic group is either Keumu, Homong or Phoutai, which is the case for 73% of households, with a standard deviation of 44%.

The real risk free rate of interest, as represented by μ_3 in the theoretical model of Section 2, is computed as the difference between the nominal interest rate and the inflation rate as reported in the Bank of Lao Report (2017). The nominal rate is taken as the mid-range of the 12 months time deposit rates for Q2 2016, which is 4.315%. The inflation rate is 1.25%. The resulting real risk free rate is $\mu_3 = 3.07\%$ per annum.

4 Empirical model

The livelihood portfolio model of Section 2 is applied to studying the livelihood choices of $N = 269$ farmers in Laos using the data of Section 3. The parameters of the model are estimated using an iterative generalised method of moments (GMM) estimator.

4.1 GMM estimation and moment conditions

The set of moment conditions of the livelihood portfolio model combine the first and second moments of the returns on rice and maize, with the two share equations in (6) and (7). The respective expected returns on rice and maize from equation (38) of Appendix A.1 are

$$\begin{aligned} E\left[r_1\right] &= \mu_1 \\ E\left[r_2\right] &= \mu_2. \end{aligned} \tag{13}$$

As there are two risky assets the covariance matrix of returns consists of three moments

$$\begin{aligned} E\left[r_1^2 - \mu_1^2\right] &= \sigma_1^2 \\ E\left[r_2^2 - \mu_2^2\right] &= \sigma_2^2 \\ E\left[\left(r_1 - \mu_1\right)\left(r_2 - \mu_2\right)\right] &= \sigma_{12}, \end{aligned} \tag{14}$$

where the first two equations are the respective rice and maize returns variances and the third is the returns covariance between rice and maize.

The remaining two moments are the rice and maize share equations. Taking expectations of (6) and (7) gives the moment equations

$$\begin{aligned} E\left[w_1\right] &= \frac{a_1}{RRA}\left(1 + BE\left[\frac{y}{W}\right]\right) - \frac{\beta B}{\sigma_1} E\left[\frac{y}{W}\right] \\ E\left[w_2\right] &= \frac{a_2}{RRA}\left(1 + BE\left[\frac{y}{W}\right]\right), \end{aligned} \tag{15}$$

where RRA represents $1 - b$ in the theoretical model and is evaluated using data on the elicited relative risk aversion of the household as described Section 3.2, and

$$\begin{aligned} a_1 &= \frac{\sigma_2^2(\mu_1 - \mu_3) - \sigma_{12}(\mu_2 - \mu_3)}{\sigma_1^2\sigma_2^2 - \sigma_{12}^2} && (16) \\ a_2 &= \frac{\sigma_1^2(\mu_2 - \mu_3) - \sigma_{12}(\mu_1 - \mu_3)}{\sigma_1^2\sigma_2^2 - \sigma_{12}^2} && (17) \\ B^{-1} &= -\mu_3 + e - f - (\mu_1 - \mu_3)\beta/\sigma_1 && (18) \\ e &= \tau f. && (19) \end{aligned}$$

The use of data on household elicited RRA in the share moment equations in (15) has the advantage of circumventing the need to estimate the risk preference parameter b in the utility equation in (4), while providing important information on the heterogeneous attitudes to risk by households. To capture potential differences between the experimental risk aversion measure and the implied estimate from the data, a bias term is added and estimated in an extended version of the base model in Section 5.3.

The share moment equations in (15) are a function of expected vulnerability, which is treated as an unknown parameter given by

$$\nu = E\left[\frac{y}{W}\right]. \tag{20}$$

This parameterization of the stochastic vulnerability variable has the advantage of circumventing the latency issue that data are not available on minimum consumption levels of households, y, or their overall wealth, W.

From the properties of the y equation in (3) and the discussion in Section 2.3, the parameter τ in (19) represents the long-run equilibrium expected threshold-to-consumption ratio, y/c. To identify τ, we exploit data on the FCS collected for each household in conjunction with the Lao-specific consumption threshold of being food-poor of 37.85 (INDDEX Project 2018, Baumann 2013). From the data, this implies a long-run estimate of $y/c = \tau = 0.7288$. Finally, from the discussion of Section 3.2, the real risk free rate of interest is set at $\mu_3 = 0.0307$.

To construct the GMM estimator, we define the $J = 7$ moment vector for each household i, as

$$m_i = \begin{pmatrix} r_{1i} - \mu_1 \\ r_{2i} - \mu_2 \\ (r_{1i} - \mu_1)^2 - \sigma_1^2 \\ (r_{1i} - \mu_1)(r_{2i} - \mu_2) - \sigma_{12} \\ (r_{2i} - \mu_2)^2 - \sigma_2^2 \\ w_{1i} - a_1(1 + B\nu)/RRA_i + \beta B\nu/\sigma_1 \\ w_{2i} - a_2(1 + B\nu)/RRA_i \end{pmatrix}, \tag{21}$$

where the full set of unknown parameters is given by

$$\theta = \left(\mu_1, \mu_2, \sigma_1^2, \sigma_2^2, \sigma_{12}, \beta, \nu\right)'. \tag{22}$$

The moment conditions in (21) represent disturbance terms as in regression analysis, as they equal the difference between the observed and expected values of a variable for household i. For a sample of $N = 269$ households, the GMM estimator $\widehat{\theta}$, is the solution of (Martin et al. 2013)

$$\widehat{\theta} = \arg\min_{\theta} Q_N\left(\theta\right), \tag{23}$$

where

$$Q_N\left(\theta\right) = \frac{1}{2} M_N'\left(\theta\right) W_N^{-1}\left(\theta\right) M_N\left(\theta\right), \tag{24}$$

is the objective function and

$$M_N\left(\theta\right) = \frac{1}{N}\sum_{i=1}^{N} m_i, \tag{25}$$

is the mean of the $(J \times 1)$ moment conditions m_i, and

$$W_N\left(\theta\right) = \frac{1}{N}\sum_{i=1}^{N} m_i\left(\theta\right) m_i'\left(\theta\right), \tag{26}$$

is the $(J \times J)$ optimal weighting matrix.

The model is just identified as the number of unknown parameters and moment conditions match. The GMM estimator of the two expected returns on rice and maize are simply the respective sample means. The GMM estimators of σ_1^2 and σ_2^2 are the respective sample variances of the returns on rice and maize, and the estimator of σ_{12} is the sample covariance of the two returns. The β and ν GMM estimators are obtained from the last two moment conditions of (21), which represents a nonlinear system of two equations with β and ν entering both equations as B is a function of β from (18).

As the GMM objective function is a nonlinear function of θ in equation (22), an iterative gradient algorithm based on the BFGS algorithm is used to minimize the objective function in (23), where the gradients are computed numerically. The GMM standard errors of $\widehat{\theta}$ are computed jointly, being based on all $J = 7$ moment conditions in (21). All computations are performed using the MAXLIK optimizers available in GAUSS24.

4.2 Empirical results

The GMM parameter estimates of the livelihood portfolio model are given by Model 1 in Table 2 with p-values in parentheses. The estimate of the expected return on rice is 3.85% compared to maize, which is 8.62%. The corresponding risk estimates are $\widehat{\sigma}_1^2 = 0.0055$ for rice and $\widehat{\sigma}_2^2 = 0.0306$ for maize, providing evidence that the higher risk associated with producing maize is compensated by a higher expected return. The estimated covariance is positive with a value of $\widehat{\sigma}_{12} = 0.0010$, suggesting that rice and maize returns are jointly affected by similar factors, such as the weather, although this estimate is statistically insignificant. As the unrestricted model is just identified the value of the GMM objective function is $Q = 0$. From the first five moment conditions of (21), the expected returns and risk estimates of rice and maize equal their sample analogs, with the expected returns estimated by the returns sample means and the return risk estimates computed from the returns covariance matrix.

There is support for the livelihood portfolio model based on a utility function with an endogenously determined stochastic minimum consumption threshold. The utility risk estimate of β for Model 1 is positive and statistically significant with an estimate of 0.0181 and a p-value of 0.0168. The implied estimate of expected household vulnerability, ν, is just over 25%. This suggests that households are, on average, highly vulnerable, having to allocate one-quarter of household wealth to satisfy the minimum consumption threshold.

As discussed in Section 2.5, to understand the effect of vulnerability, y/W, on rice shares, it is necessary to identify the relative magnitudes of a_1/RRA and β/σ_1, where a_1 is based on (16) and RRA is computed at its sample mean. Using the maximum likelihood estimates in Table 2 for Model 1, the latter term equals 0.2441, dominating the first term, which equals 0.0063. This shows that, on average, an increase in y/W increases the share of land allocated to rice. Of course, as relative risk aversion does vary across households, the effects of changes in vulnerability on rice shares can impact households differently.

The β and ν estimates are based on the last two moment conditions of (21) corresponding to the rice and maize share equations. This is a nonlinear system of two equations with the GMM estimates of β and ν representing the solutions. Parameter identification is achieved by information on relative risk aversion of farmers as given by RRA_i. From the share moment conditions there is an inverse relationship between risk aversion and the rice and maize shares, w_{1i} and w_{2i}, respectively. The correlation between risk aversion and rice shares is -0.017 and -0.141 for maize shares. The negative correlation supports the theory that rice and maize are risky assets, resulting in reduced shares in these assets from increased risk aversion with the largest reduction for the riskier asset given by maize. The maize correlation is statistically significant at the 5% level with a p-value of 0.0205, whereas for rice, the correlation is insignificant with a p-value of 0.7724.

A feature of the unrestricted parameter estimates is the statistically insignificant covariance between rice and maize returns. Setting this parameter to $\sigma_{12} = 0$ (Model 2) does not qualitatively change the properties of the estimated model. The expected returns and risk estimates for rice and maize are similar to their unrestricted estimates. There are also minimal changes in the utility risk β parameter estimate, decreasing from 0.0181 to 0.0148, as well as the estimate of the household vulnerability parameter ν, which is still just over 25% as it is for Model 1. The imposition of the restriction results in the

Table 2: GMM parameter estimates of livelihood portfolio models, with p-values in parentheses.

Description	Param.	Model			
		1	2	3	4
Mean (rice)	μ_1	0.0385 (0.0000)	0.0384 (0.0000)	0.0470 (0.0000)	0.0463 (0.0000)
Mean (maize)	μ_2	0.0862 (0.0000)	0.0860 (0.0000)	0.0918 (0.0000)	0.0883 (0.0000)
Variance (rice)	σ_1^2	0.0055 (0.0000)	0.0057 (0.0000)	0.0066 (0.0000)	0.0066 (0.0000)
Variance (maize)	σ_2^2	0.0306 (0.0000)	0.0315 (0.0000)	0.0350 (0.0000)	0.0344 (0.0000)
Covariance (rice, maize)	σ_{12}	0.0010 (0.1556)	0.0000	0.0006 (0.4394)	0.0006 (0.4572)
Utility risk	β	0.0181 (0.0168)	0.0148 (0.0356)	0.0000	0.0000
Vulnerability (y/W)	ν	0.2539 (0.0000)	0.2528 (0.0000)	0.2499 (0.0000)	0.0000
Q		0.0000	0.0074	0.0220	0.0756
$J = NQ$		0.0000	2.0011	5.9284	20.3279
DOF		0 (n.a.)	1 (0.1572)	1 (0.0149)	2 (0.0000)

model being overidentified. A test of the over-identifying restriction is based on Hansen's J statistic, which has an asymptotic chi-square distribution under the null hypothesis that the model is correctly specified with 1 degree of freedom. The overidentification test shows that we fail to reject the null with a p-value of 0.1572.

By restricting the returns covariance to $\sigma_{12} = 0$ simplifies the share moment conditions in (21) to

$$w_{1i} = \frac{(\mu_1 - \mu_3)(1 + B\nu)}{\sigma_1^2 RRA_i} - \frac{\beta B\nu}{\sigma_1} \tag{27}$$

$$w_{2i} = \frac{(\mu_2 - \mu_3)(1 + B\nu)}{\sigma_2^2 RRA_i}. \tag{28}$$

The shares are a function of the risk adjusted excess returns on each asset where the risk adjustments are based on the (squared) returns risk on the asset, relative risk aversion and utility risk. As with Model 1, the GMM parameter estimates show that increases in vulnerability, ν, increase the share of land allocated to rice, while decreasing the share allocated to maize.

An important special case of the unrestricted model is where the minimum consumption threshold of the utility function is deterministic. As a test of this restriction the utility risk parameter is set to $\beta = 0$ (Model 3) resulting in an over identified model with 1 degree of freedom. The reported value of the J-statistic in Table 2 for Model 3 is 5.93 with a p-value of 0.015, providing evidence against a deterministic threshold at the 5% level.

As a further test of the model, the utility function is restricted to not have a threshold by setting the utility risk and vulnerability parameters to $\beta = 0$ and $\nu = 0$, respectively. The parameter estimates of the no-threshold model are given by Model 4. There are minimal changes to the expected returns estimates and the returns risk parameter estimates. A test of the joint restriction is given by the J statistic in Table 2 based on a chi-squared asymptotic distribution with 2 degrees of freedom. The value of the statistic is 20.33, which is a strong rejection of the null hypothesis that utility is maximized without regard to a minimum consumption threshold with a p-value of 0.0.

Overall, these results provide strong empirical support for the theoretical model, in particular, the importance of household vulnerability and exposure to utility risk in driving resource allocation decisions by households.

5 Extensions

A property of the estimated livelihood portfolio model presented in Table 2 is that household vulnerability, y_i/W_i, is represented by an unconditional distribution with a mean equal to ν. To relax this restriction, the model is extended by specifying vulnerability to be a function of a set of observed household characteristic variables, x_i, according to

$$\frac{y_i}{W_i} = (\nu^{1/2} + \phi' x_i)^2, \tag{29}$$

where ϕ is a vector of parameters. The choice of characteristic variables is motivated by previous work. The first is $FoodInsecure$, indicating if a household is severely food insecure based on the HFIAS measure. This variable is central to the question addressed in this paper. As reported in FAO (2020) for Lao PDR, it is hypothesized that $FoodInsecure$ has a parameter satisfying $\phi_1 > 0$, as food insecurity implies greater vulnerability, y/W, and therefore a reduction of land allocated to the cash crop maize, as shown in the share equation (7).

The second characteristic variable is $RoadAccess$ with parameter ϕ_2 and indicates if a household has road access to markets, including during the wet season. We expect $\phi_2 < 0$, as farm households in villages with all-year-round road access face fewer constraints in selling their outputs, enabling them to devote a greater share of land to cash crop production on average than villagers who are cut off from markets for part of the year (see, for example, Khandker et al. (2009)).

The final characteristic variable, $Livestock$, denotes the relative share of cattle and buffalo to all large livestock owned by the household. Owning valuable livestock such as cattle and buffalo has been shown to be a consumption-smoothing strategy in the absence of access to credit markets (Rosenzweig and Wolpin 1993). This practice is also widespread in Lao PDR (FAO 2020). The sign of the parameter on $Livestock$, ϕ_3, fundamentally depends on whether large livestock ownership is a complement or a substitute to income smoothing. In the case of $\phi_3 < 0$, livestock ownership reduces y/W, resulting in a greater share of land being allocated to maize. This would indicate that consumption smoothing reduces the need for income smoothing. When $\phi_3 > 0$, consumption and income-smoothing are complements, whereby ownership of large livestock is also associated with lower land allocations to the cash crop, maize.

By specifying (29) the unconditional distribution of household vulnerability is effectively replaced by a conditional distribution with unknown parameters ν, ϕ_1, ϕ_2, and ϕ_3. The choice of the square function in this equation ensures that y_i/W_i is non-negative for all households. A special case of (29) is where $\phi_1 = \phi_2 = \phi_3 = 0$, which results in the model presented in (20).

5.1 Instrument choice

Specifying y/W as a function of the characteristic variables in (29) raises a number of issues for causal inference. One is related to simultaneity, whereby the characteristic variables *FoodInsecure* and *Livestock* and the land shares for rice and maize are contained within the household's decision set and, therefore, potentially jointly determined. Another issue relates to measurement errors, especially in relation to the measurement of severe food insecurity, which is based on how individual households perceive their own food insecurity in the four weeks leading up to the survey. Finally, there may be unobserved confounders that determine land shares to rice and maize crops beyond the variables that are controlled for in the model.

To address the issues of endogeneity, measurement errors and omitted confounder variables, the GMM moment conditions are extended to include a set of instrumental variables. The instruments consist of road access ($RoadAccess$), which is its own instrument as it is included in the set of characteristics variables in equation (29), the existence of a rice bank in the village ($Ricebank$), the distance of the village to the nearest market used for buying and selling food ($Mktdist$), the mean elevation within a $5km$ radius of the village ($Elevation$), the main ethnicity in the village being either Keumu, Hmong or Phoutai ($Ethnic$), and the share of irrigated land ($Irrig$) at the village level, as well as a constant. The set of instruments for household i is summarized as

$$z_i = (Const, RoadAccess_i, Ricebank_i, Mktdist_i, Elevation_i, Ethnic_i, Irrig_i) \,. \qquad (30)$$

These village-level variables are exogenous to the extent that they all lie outside the immediate decision set of sampled households, a condition needed for instrument validity. Given their vulnerability, it is unlikely that any individual household has the ability to impact any of these village-level characteristics either by significantly influencing community investment decisions or by moving to a different location.

Besides the choice of variables satisfying the exogeneity condition for instrument validity, the instruments in (30) also satisfy the relevancy condition. In the case of the instrument $Ricebank$, having access to a rice bank affects the HFIAS measure of severe food insecurity, $FoodInsecure$, directly by allowing households to access rice via the rice bank in times of need. As such, contributions to a rice bank are another form of consumption smoothing and therefore correlated with other consumption smoothing strategies, notably investments in large livestock, as measured by the characteristic variable $Livestock$ in equation (29).

Closeness to a market for selling and buying food lowers barriers that vulnerable households face when it comes to accessing food. As a result, $Mktdistance$ is expected to be highly correlated with $FoodInsecure$. $Mktdistance$ is likely also a proxy for distance and ease of access to financial institutions and formal ex-post consumption smoothing strategies such as holding savings and credit accounts instead of $Livestock$.

$Elevation$ is a proxy of the suitability of the surrounding farmland used by villagers for agriculture. Land of high elevation is less suited for agricultural cultivation of rice and cash crops. In particular, upland rice cultivation is based on shifting cultivation that occurs on smaller plots and is characterized by lower and more variable yields than lowland rice cultivation. These practices are linked to reduced food availability and greater food insecurity (FAO 2020). Similarly, greater variability in yields should affect the need for ex-post consumption smoothing strategies and, therefore large livestock holdings.

Ethnic represents a dummy variable that takes the value of one if the main ethnicity in the village is from a minority group (Keumu, Hmong or Phoutai), zero otherwise. As food insecurity is more prevalent amongst these ethnic groups (FAO 2020), this instrument provides additional information on *FoodInsecure* that is exogenous to the determination of household level land shares in rice and maize.

The instrumental variable *Irrigation* measures the proportion of surrounding farmland that is irrigated and is a proxy for how sophisticated the local farming system is in general. Irrigation is directly related to achievable yields and the availability of food at the local level, which affects food security at the household level.

The additional moment conditions of the extended model are obtained by replacing the last two moment conditions in (21) corresponding to the two share equations, with

$$m_i^* = \begin{pmatrix} w_{1i} - \left(a_1 \left(1 + B(\nu^{1/2} + \phi' x_i)^2\right) \dfrac{1}{RRA_i} - \beta B(\nu^{1/2} + \phi' x_i)^2 \dfrac{1}{\sigma_1} \right) \\ w_{2i} - a_2 \left(1 + B(\nu^{1/2} + \phi' x_i)^2\right) \dfrac{1}{RRA_i} \end{pmatrix} \circ z_i', \qquad (31)$$

where $\phi' x_i = \phi_1 FoodInsecure_i + \phi_2 RoadAcess_i + \phi_3 Livestock_i$, z_i contains the 7 instruments in (30), and $\circ$ represents the Hadamard product. The full set of moment conditions for the extended empirical model consists of the 14 moment conditions in (31), together with the first 5 moment conditions in (21), for a total of 19 moment conditions. The number of unknown parameters is now 10, as given by

$$\theta = \left(\mu_1, \mu_2, \sigma_1^2, \sigma_2^2, \sigma_{12}, \beta, \nu, \phi_1, \phi_2, \phi_3\right)'. \qquad (32)$$

There are 9 over-identifying restrictions which are tested using the J statistic.

For the instruments z_i in (30) to be valid, they need to be correlated with the characteristic variables x_i in (29) they are instrumenting, as well as being uncorrelated with the share equation disturbances as defined by the first term on the right-hand side of (31). This latter condition further implies that the instruments are uncorrelated with any variables excluded from x_i (omitted variable bias) and any errors arising from deviations between correctly measured and observed variables in the model (measurement error). As a test of these assumptions instrument relevance and exogeneity tests are presented in the empirical extension of the model. The instrument relevance tests are constructed from a regression of the x_i variables in (29) on the z_i instruments in (30). These tests just apply to the characteristic variables *FoodInsecure* and *Livestock*, as *RoadAccess* acts as its own instrument given that it is also included in the set of z_i instruments. The exogeneity tests are constructed from a regression of the rice and maize share disturbances in (31)

Table 3: GMM parameter estimates of the extended livelihood portfolio models based on an alternative identification strategy, with p-values in parentheses.

Description	Param.	Model 1	Model 2	Model 3
Mean (Rice)	μ_1	0.0333	0.0333	0.0333
		(0.0000)	(0.0000)	(0.0000)
Mean (Maize)	μ_2	0.0881	0.0882	0.0884
		(0.0000)	(0.0000)	(0.0000)
Variance (Rice)	σ_1^2	0.0046	0.0046	0.0045
		(0.0000)	(0.0000)	(0.0000)
Variance (Maize)	σ_2^2	0.0312	0.0312	0.0318
		(0.0000)	(0.0000)	(0.0000)
Covariance (Rice,Maize)	σ_{12}	0.0014	0.0014	0.0014
		(0.0701)	(0.0700)	(0.0697)
Utility risk	β	0.0343	0.0338	0.0524
		(0.0043)	(0.0018)	(0.0470)
Vulnerability (y/W)				
Constant	ν	-2.4006		
		(0.8701)		
FoodInsecure	ϕ_1	0.1928	0.1850	0.1633
		(0.0319)	(0.0149)	(0.0210)
RoadAccess	ϕ_2	-0.1345	-0.1359	-0.1101
		(0.0473)	(0.0390)	(0.0293)
Livestock	ϕ_3	0.6954	0.6771	0.5375
		(0.0001)	(0.0000)	(0.0002)
Relative risk aversion bias	α			0.0422
				(0.1329)
Q		0.0547	0.0548	0.0490
$J = TQ$		14.7090	14.2425	13.1698
DOF		9	10	9
		(0.0992)	(0.1622)	(0.1551)

evaluated at the GMM estimator, on the z_i instruments.

5.2 Understanding household vulnerability

The results of estimating the livelihood portfolio model based on (29) and the instruments in (30), are given in Table 3. Model 1 gives the parameter estimates for the unrestricted model. The parameter estimate of ν in (29) is statistically insignificant with a p-value of 0.87. Imposing the restriction $\nu = 0$ yields the empirical results given by Model 2. A comparison of the parameter estimates of Model 1 and Model 2 reveals there are no qualitative changes in the point estimates.

Comparing Model 2 of Table 3 with the estimates presented in Table 2 shows no qualitative changes in the base estimates. The estimated utility risk parameter β is now larger in magnitude and estimated with much greater precision, with a p-value of 0.0018 versus p-values of 0.0168 and 0.0356 in Table 2.

Inspection of the coefficients on the household characteristic variables in equation (31) for Model 2 in Table 3, show that food insecurity ($FoodInsecurity$), road access ($RoadAccess$) and livestock ($Livestock$), are all statistically important determinants of household vulnerability y/W, and in turn, land allocations, with the parameter estimates satisfying the hypothesized signs discussed in Section 4.1. The implied estimates of y/W for each household are obtained by evaluating (29) based on the maximum likelihood estimates in Table 3 for Model 2. The average of the implied vulnerability ratio y/W is 22%, which is comparable to the estimate of 25% obtained in Table (2). The estimates of y/W range from a minimum of 0% to a high of 74%, with a standard deviation of 18%.

Diagnostic tests of the estimated models are given by Hansen's J statistic in the bottom block of Table 3. For all model specifications, the number of over-identifying restrictions is satisfied with p-values less than 5%. Additional diagnostic tests are given in Table 4, which provides instrument relevance and exogeneity tests. The instrument relevance tests are given in the first block of the Table with p-values in parentheses. The test statistic is computed as $(N-K)R^2$ where R^2 is the coefficient of determination from regressing the characteristic variables x_i on the instruments z_i, and K is a small sample correction equal to the number of instruments excluding the constant. The test statistic has an asymptotic chi-square distribution with 6 degrees of freedom. The instrument relevance test is satisfied for both $FoodInsecure$ and $Livestock$ with p-values showing that there is a significant correlation between the characteristic variables and the instruments.

The exogeneity tests are given in the second block of results in Table 4. The test statistic is computed as $(N-K)R^2$ where R^2 is the coefficient of determination from regressing the rice and maize share moment conditions on the instruments z_i, and K as before represents a small sample correction equal to the number of instruments in excluding the constant. The test statistic has an asymptotic chi-square distribution with 6 degrees of freedom. The exogeneity test is satisfied for both rice and maize share moment conditions evaluated at the GMM estimates, with both p-values exceeding the 5% level. A similar set of tests is applied to determine the exogeneity status of the risk aversion variable RRA_i by regressing the rice and maize share moments evaluated at the GMM estimates, on a constant and RRA_i. The results of these tests are given at the bottom of Table 4 and provide further support for the null hypothesis the risk aversion variable is exogenous.

5.3 Consistency of elicited relative risk aversion

An important feature of the empirical models is the use of data on household relative risk aversion, elicited from the incentivized risk task as described in Section 3. As a test of

Table 4: Instrument relevance and exogeneity tests of the extended portfolio models, with p-values in parentheses based on an asymptotic chi-square distribution with 6 degrees of freedom. Instrument relevance tests are constructed from a regression of the characteristic variables x_i in (29) on the instruments z_i in (30). Exogeneity tests are constructed from a regression of the rice and maize share disturbances in (31) evaluated at the GMM estimates, on the set of instruments z_i in (30).

Test	Statistic
Instrument relevance	
FoodInsecure	56.0020 (0.0000)
Livestock	32.4205 (0.0000
Exogeneity: Instruments	
Rice share moment	12.3492 (0.0546)
Maize share moment	4.5590 (0.6015)
Exogeneity: RRA	
Rice share moment	0.0017 (0.9669)
Maize share moment	0.0759 (0.7830)

the consistency of this measure of risk aversion and how it translates into optimal shares of rice and maize a bias term α, is introduced into the set of unknown parameters by redefining the relative risk aversion measure as

$$RRA_i + \alpha. \tag{33}$$

Values of $\alpha > 0$ $(\alpha < 0)$, suggest the experimental risk aversion measure underestimates (overestimates) the respondents' risk aversion on average, whereas if $\alpha = 0$, the observed allocation of rice and maize in the portfolio is consistent with the elicited risk attitude.

The moment conditions to allow for potential biasedness in the risk aversion measure according to (33), simply involves replacing RRA_i in (31) by $RRA_i + \alpha$, and extending the number of parameters in (32) to include α, for a total of 11 parameters and 8 over-identifying restrictions. The ability to identify the bias parameter α arises because of the additional over-identifying restrictions of the extended model. This property is not available for the configuration of the model based on the moment conditions in (31), which is just-identified.

The results of extending the model specification to allow for a bias in the experimental elicitation of risk attitudes based on (33) are given by Model 3 in Table 3. We find a positive but statistically insignificant coefficient on the bias parameter α, a result which is also supported by the over-identification test reported for Model 3. These results provide further support for Model 2 as the preferred specification.

6 Effects of food insecurity on livelihood portfolios

Three experiments are performed to analyse the effects of food insecurity on livelihood portfolios. The first experiment consists of evaluating the effects of vulnerability on livelihood portfolios from changes in household characteristic variables. The second experiment looks at the effects of a livelihood diversification program that seeks to address food insecurity by encouraging affected households to diversify into higher return activities. The final experiment compares the diversification program in the second experiment with three other policy experiments consisting of the establishment of a food safety net, infrastructure development, and insurance programs designed to mitigate the effects of consumption shocks.

6.1 Marginal effects of vulnerability characteristic variables

We evaluate the effect of vulnerability on livelihood portfolios from increases in the household characteristic variables $FoodInsecure$, $RoadAccess$ and $Livestock$ in (29). As $FoodInsecure$ and $RoadAccess$ are qualitative variables, the marginal effects of these variables are based on discrete derivatives of the portfolio share equations in (6) and (7).

The marginal effect of *FoodInsecure* is the difference between expected portfolio shares conditional on the data, and from assuming that no households are food insecure. From Table 1, this assumed change in food security status affects 33% of households. In the case of *RoadAccess*, the comparison is between the expected portfolio shares from assuming that all households have road access compared with conditioning on the data, which from Table 1 constitutes a 30% increase in households having road access. The *Livestock* marginal effect for a 10% increase in cattle and buffalo compares expected portfolio shares conditional on the data with expected shares assuming a 10% reduction in livestock holdings of households.

The estimates of the marginal effects of food insecurity are reported in the second column in Table 5. Food insecurity results in smallholder farmers allocating approximately 6% more land to rice production than their food secure counterparts. While this effect is moderate, Table 5 also shows that the diversification into cash crop production is more sensitive, with food insecurity being associated with 24% lower land allocation to maize.

Table 5: Effect of increased food insecurity, road access, and livestock ownership on rice shares (w_1) and maize shares (w_2).

Land share	FoodInsecure	RoadAccess	Livestock
Rice	0.0558	-0.0547	0.0673
Maize	-0.2443	0.1368	-0.2283

The marginal effects for *FoodInsecure* and *RoadAccess* are based on the discrete derivatives of (6) and (7) evaluated at the parameter estimates of Model 2 in Table 3. The same approach is taken for *Livestock*, but assuming a 10% increase in cattle and buffalo holdings.

Table 5 also shows that the effect of food insecurity on the livelihood portfolio is quantitatively more important than having all-year round road access, which is associated with 14% more land being allocated to maize on average. The marginal effect of *Livestock*, indicates that a 10% increase in the proportion of large livestock to total livestock is associated with a 7% increase in land allocated to rice and 23% less land being allocated to maize. This positive relationship is evidence that ex-ante income smoothing via the reduced allocation of land to the riskier cash crop and ex-post consumption smoothing are complementary strategies.

6.2 Marginal effects of a livelihood diversification program

The structural framework is used to gain insights into the relative expected effectiveness of livelihood diversification programs in encouraging diversification into high-return activities by more or less food-secure households. The ultimate objective of local livelihood diversification programs and their associated activities is to increase the returns and decrease the risk of high-return activities for participating farmers. This corresponds within

Table 6: Program effects on maize shares (w_2) by food security status

Program	Lever	Marginal effect on maize shares		
		Secure	Moderately insecure	Severely insecure
Livelihood diversification	Maize return	0.1762	0.0255	0.0043
	Maize risk	0.3293	0.0478	0.0081
Food safety net	Food security	n/a	0.0725	0.1172
Infrastructure	Road access	0.0689	0.0523	0.0462
Insurance	Consumption smoothing	0.1097	0.0577	0.0397

All marginal effects are computed using the parameter estimates of Model 2 in Table 3, based on the average risk aversion of each subgroup. The marginal effects from a livelihood diversification program are based on $\partial w_2/\partial \mu_2$ from (9) and $-\partial w_2/\partial \sigma_2^2$ from (10), evaluated for each food security group. The marginal effects of the remaining programs are based on discrete derivatives where the baseline and post policy maize shares are evaluated for each food security group.

the context of our model to increasing expected maize returns, μ_2, and decreasing maize variance, σ_2^2. To assess the marginal impact of livelihood diversification programs on the cash crop investment by food secure and food insecure households, we compute the partial derivatives $\partial w_2/\partial \mu_2$ from (9) and $-\partial w_2/\partial \sigma_2^2$ from (10) in Table 6 using the parameter estimates of Model 2 in Table 3.

The first two rows in Table 6 show the marginal effects on maize shares from livelihood diversification programs. These estimates reveal stark differences in how such programs benefit the average food secure versus food insecure household. In particular, the estimates reported in the first row show that increasing expected returns from maize by one percentage point induces food secure households to increase the land allocated to maize by 18%. In contrast, moderately and severely food insecure households increase their maize shares by only 3% and 0.5%, respectively. Similarly, the livelihood portfolio of food secure households is much more sensitive to a decrease in maize risk, with food secure households increasing their land allocation to maize by 33% for a 1% decrease in maize variance as compared with moderately and severely food insecure households that allocate only 5% and 1% more land to maize on average. These results imply that food insecure households in our sample are much less able to leverage the economic opportunities from livelihood diversification programs than their food secure counterparts.

6.3 Marginal effects of alternative programs

For illustration purposes, the anticipated livelihood diversification program outcomes are contrasted with the expected marginal effects on cash crop investment from other types of development programs commonly discussed in the literature. The first are food safety net programs, designed to elevate food insecure households to food security via the establishment of food banks, food voucher systems, or other food-focused social protection programs. The second are infrastructure type programs, providing all villages in our sample with all-year-round road access. Thirdly, we report the expected marginal effects of insurance programs that reduce the need for smallholder farmers to engage in ex-ante income smoothing and to hold buffalo and cattle to insure against consumption shocks. The marginal effects of these alternative programs are based on computing the discrete derivatives of (6) and (7), using the parameter estimates of Model 2 in Table 3. For example, in the case of a food safety net program, the predictions of the model based on observed levels of food insecurity are compared with the predictions of the model when all smallholder farmers in the sample are food secure. A similar approach is used for road access, while the case of insurance provision is evaluated for a 10% reduction in cattle and buffalo holdings. The results are reported in the last rows of Table 6.

In contrast to the comparatively weak response of food insecure smallholders to livelihood diversification incentives, our estimates suggest that when food safety net programs are successful, the moderately and severely food insecure farmers respond by increasing their respective maize shares on average by 7% and 12%. Similarly, our results indicate that infrastructure projects that provide year-round road access to villages result in greater livelihood diversification, with the severely and moderately food insecure groups increasing their land allocation to maize by about 5% each. This response is only marginally weaker than that of the food secure group, which increases their maize allocation by 7% on average.

The last row of Table 6 shows the diversification benefits to food insecure smallholder farmers from the provision of formal insurance. For example, offering formal insurance products that reduce the need for ex-ante income smoothing and informal ex-post consumption smoothing by 10% results in increased allocations to the cash crop by 6% and 4% respectively for moderately and severely food insecure smallholder households. However, access to formal insurance has the largest marginal effect on food secure smallholder farmers, who are expected to increase their cash crop land allocation by 11% on average.

Of all the program types discussed, our results suggest that road-building programs have an approximate uniform effect on livelihood diversification across the three food security groups. In contrast, livelihood diversification programs and those that provide formal insurance benefit primarily the food secure smallholder farmers. The program type that yields the greatest benefits for livelihood diversification and future earning opportunities among the food insecure is one that targets food insecurity directly at the consumer level by establishing a food safety net. It must be noted that the marginal effects reported in Table 6 are illustrative in that they assess hypothetical program outcomes for our specific study context. Nevertheless, the results have broader relevance as they reflect important differences in the relative effectiveness of the various program types in achieving livelihood diversification across target groups. These differences are a direct consequence of the interaction between smallholder farmers' vulnerability, their attitudes to risk, and the opportunities they are presented with.

7 Discussion

The empirical results presented in Section 4.2 provide strong support for the theoretical framework derived in Section 2. Importantly, the vulnerability estimate of y/W in the base case is 25%, which implies that households in our sample are on average highly vulnerable, having to allocate one-quarter of household wealth to satisfying the minimum consumption level. This results in the average household in our sample allocating more land to rice production than they otherwise would. Such resource allocation decisions allow households to smooth their income by reducing their exposure to cash crop production risk but come at the cost of foregoing higher net returns (Morduch 1995). Moreover, the empirical estimates show that the minimum threshold level is subject to significant variability. This added utility risk reinforces the tendency of vulnerable households to engage in income smoothing. Overall these results provide strong justification for a portfolio model with a stochastic minimum consumption threshold.

Our empirical framework also allows us to identify if households with certain characteristics are more vulnerable and, therefore, susceptible to adopting costly income-smoothing strategies. We find that food insecure households and those without all-year road access are much less likely to diversify into high-return cash crops, with vulnerable smallholder households allocating between 14% to 24% less land to the cash crop. To the extent that large livestock is used for consumption-smoothing purposes (Rosenzweig and Wolpin 1993), our results also show that ex-ante income smoothing and ex-post consumption smoothing strategies are complements: in our sample, vulnerable households that face significant production and utility risks diversify less into the high-return activity, while also using livestock as a hedge.

By focusing on income smoothing as a way for households to manage production and utility risk, we implicitly assume that credit and insurance markets or their informal alternatives are either missing or not readily accessible to households. Not allowing for credit markets formally in the model, when households are accessing them frequently for consumption smoothing purposes, would result in an empirical underestimation of household risk aversion (Morduch 1995). We have a two-fold strategy to address this concern. Firstly, we experimentally elicit household risk preferences outside of the model and use this data as input for the empirical estimation. The risk elicitation experiment yields relatively high levels of risk aversion among the households in our sample as compared with other studies (Eckel and Grossman 2008). Secondly, we allow for a bias term, α, when estimating overall risk aversion in Model 3 of Table 3. The positive and statistically insignificant coefficient on α combined with the elicited risk preferences suggest that credit and insurance markets are not commonly used by sampled households in our study in order to smooth their consumption and are therefore unlikely to be a concern for the present analysis.

It is common practice in the finance literature (see, for example, Dominitz and Manski 2007, Kimball et al. 2008, Ameriks et al. 2020) to fit cross-sectional data to a dynamic model. Following this literature, where beliefs about future returns and the riskiness of financial assets are elicited from wealthy investors using surveys, we also attempted to elicit expected crop returns and their riskiness in our rural, lower-middle income country setting. To implement this in the field we used tokens that respondents could place on a range of prices and yields for next season's crops, with more tokens placed representing a greater likelihood of the outcome occurring. However, with an average of just over five years of schooling and around 12% of illiteracy, we found the elicitation of households' expected crop returns and their associated risk too challenging. Instead, we approximated these by the observed mean returns and their variability in the village, as it is reasonable to assume that households inform their planting decisions by observing their neighbors' success in planting different crops.

An important property of the theoretical framework is that it is highly flexible and can accommodate a broad range of livelihood activities. While the riskier livelihood activity in our empirical application is maize, conceptually, the model could be extended to other activities that are characterized by higher returns but also higher production and or market risk than the subsistence crop, and that require household resources such as land or labor. The theoretical framework could, therefore, be used to characterize livelihoods in a variety of settings where food insecurity is a concern.

Overall, our results suggest that the very households that have been targeted for decades by market-based, production-side policies aimed at making the agricultural transformation inclusive of these households and improving their livelihoods through greater diversification and adoption of higher return activities (de Janvry and Sadoulet 2020), are also the households that are least in a position to benefit from these policies. Exposure to significant utility risk means that these households are less likely than their less vulnerable counterparts to invest in high-return market-based activities that also tend to be higher risk. Instead, such households resort to managing utility risk by investing more resources in low-return subsistence activities and miss out on the market opportunities that present themselves, thereby falling more and more behind less vulnerable households. Systematic reviews of impact evaluations of food and nutrition security interventions document a positive effect on agricultural productivity and incomes, and a weak evidence base when it comes to food security outcomes (van Vugt et al. 2023). This lack of clear impact on food security could be explained by such programs benefiting predominantly poor but relatively food secure smallholder farmers. Our findings are further supported by the increasing rates of severe food insecurity that have been observed globally despite significant investments in agricultural production systems to improve food security (FAO 2022).

In its recent State of Nutrition and Food Security Report (2022), the FAO advocates for a policy shift whereby governments and non-government organizations are urged to re-purpose resources previously spent on production side policies to tackle utility risk in the form of food insecurity directly at the consumer level. The key argument being put forward is that policies targeting the production side create market distortions that are detrimental to food insecure households. Our analysis provides another reason why food insecurity should be addressed at the consumer level first, namely that food insecurity represents an important barrier for households to adjust their livelihood portfolios in response to production-side policies. We are able to provide a quantitative estimate of the importance of this barrier, whereby the food insecure smallholder farmers' response to livelihood diversification programs is between 6 to 30 times weaker than that of their food secure counterparts. In contrast, social protection programs that benefit food insecure consumers via in kind or cash transfers have been shown to act as an insurance against utility risk (Gadenne et al. 2021). We show that insuring against utility risk in this way results in smallholder farmers being less inclined to smooth their income ex-ante, while allocating more of their resources to higher return activities that carry a greater future earnings potential. In particular, we compare the anticipated marginal effects of livelihood diversification, road construction, formal insurance and food safety net programs and find that the latter have the greatest potential to achieve livelihood diversification amongst the moderately and severely food insecure.

8 Conclusions

Food insecurity lags economic development in many low- and lower-middle-income countries. Over the past decade a key strategic focus in eradicating food insecurity has been the participation in high value markets and income generation by rural smallholder farmers with a high dependence on subsistence farming. This research sheds further light on the determinants of livelihood portfolio diversification amongst this group, particularly the role of food insecurity in livelihood choices. The results presented in this research demonstrate that vulnerability to an endogenous minimum consumption threshold impacts the portfolio choice of affected households, whereby food insecure households invest more resources in lower-risk, lower-return subsistence farming activities than their food secure counterparts. These insights are based on the theoretical results of a stochastic dynamic livelihood portfolio model whereby household consumption and resource allocation across livelihood activities are jointly optimized.

It is shown that livelihood portfolio choice is a function of a minimum consumption threshold that varies with past consumption and is subject to shocks. The parameters of the theoretical model are estimated by generalized method of moments, using highly granular data on the livelihood activities undertaken by poor smallholder households in Lao PDR. The results demonstrate that severely food insecure households allocate larger proportions of their land to subsistence crop production and significantly smaller proportions to cash crop production compared with food secure households. Moreover, food insecure households are shown to be much less responsive to market-based supply-side policies and programs that encourage smallholder farmers to diversify into higher-return, higher-risk activities. Our estimates show that these households' land allocations would barely change when presented with cash crop programs that increase the net cash crop returns and reduce their risk. These results imply that by not investing in high-return activities such as cash crops, food insecure households are less able to leverage the benefits of localized economic development and market integration.

Overall, this study contributes to the understanding of why food insecurity persists despite significant support for the agricultural sector through market-based, supply-side policies. Importantly, in contrast to many policies and interventions that target markets and value chain development as a means to improve food security, our results point to a need to tackle food insecurity directly at the consumer level. These measures could reduce the utility risk of households through food subsidies, food vouchers and food-focused social protection programs.

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A Model derivations

A.1 Derivation of dW

The starting point is a household endowed with productive resources, of which resource L is the limiting factor in production and a common input to all livelihood activities undertaken by the household. For smallholder households, the limiting factor is typically land or labor. The net revenue per unit from allocating L to livelihood activity j is given by P_j, which may represent the market value of the food generated from subsistence activities, the income generated from cash crop production, or the income (wages or rents) earned from leasing the resource to a third party.

Let the number of livelihood activities be n, with the total productive wealth of the household from all activities at time t, given by

$$W\left(t\right)=\sum_{j=1}^{n}L_j\left(t\right)P_j\left(t\right). \tag{34}$$

The dynamic wealth constraint, dW, is derived from first principles based on Leroux and Martin (2016), whereby the change in household productive wealth is given by

$$dW=\sum_{j=1}^{n}dP_jL_j+\sum_{j=1}^{n}P_jdL_j+\sum_{j=1}^{n}dP_jdL_j. \tag{35}$$

In this model, household investments in the limiting factor of production, represented by dL_j, are financed via reduced consumption ($-cdt$), which means that consumption has to be sacrificed in order to purchase additional land or hire additional labor. Acknowledging the existence of such a consumption-investment trade-off implies that

$$-cdt=\sum_{j=1}^{n}P_jdL_j+\sum_{j=1}^{n}dP_jdL_j. \tag{36}$$

Substituting this expression into equation (35) gives

$$dW=\sum_{j=1}^{n}dP_jL_j-cdt. \tag{37}$$

The return from livelihood activity j is time-varying and subject to risk. Formally, we model the return from allocating one unit of the limiting factor of production, L, to activity j as a Geometric Brownian motion with an expected return of μ_j, standard deviation of σ_j, and returns covariance between activities of σ_{ij}. Using the geometric representation of dP

$$dP_j = \mu_j P_j dt + \sigma_j P_j dz_j, \tag{38}$$

equation (37) is written in the case of $n = 3$ activities as

$$dW = \mu_1 P_1 L_1 dt + \sigma_1 P_1 L_1 dz_1 + \mu_2 P_2 L_2 dt + \sigma_2 P_2 L_2 dz_2 + \mu_3 P_3 L_3 dt - cdt, \tag{39}$$

with the restriction $\sigma_3 = 0$ as the third activity is treated as risk free.

Defining the share of productive household wealth allocated to activity j as $w_j \equiv P_j L_j / W$, imposing the adding up condition $w_3 = 1 - w_1 - w_2$, and substituting into (39) gives after collecting terms

$$dW = ((\mu_1 - \mu_3) w_1 W + (\mu_2 - \mu_3) w_2 W - c)\, dt + \sigma_1 w_1 W dz_1 + \sigma_2 w_2 W dz_2, \tag{40}$$

which is equation (2) in the paper.

A.2 Portfolio optimization

The household maximizes intertemporal utility by jointly choosing its consumption, c, relative to the endogenous minimum threshold, y, and the livelihood portfolio shares, w_1 and w_2, by solving the value function in equation (4), subject to the constraints (2) and (3) and the initial conditions $W(0) = W_0$ and $y(0) = y_0$, where r is the rate of discount. As this is an autonomous infinite horizon problem, the value function becomes (Kamien and Schwartz 1981, p.246)

$$\begin{aligned} rV\left(W,y\right) &= \max_{c,w_1,w_2}\left(\frac{\left(c-y\right)^b}{b}+\left(\left(\mu_1-\mu_3\right)w_1W+\left(\mu_2-\mu_3\right)w_2W+\mu_3W-c\right)V_W\right. \\ &\quad +\frac{1}{2}w_1^2W^2\sigma_1^2V_{WW}+\frac{1}{2}w_2^2W^2\sigma_2^2V_{WW} \\ &\quad +w_1w_2W^2\rho\sigma_1\sigma_2V_{WW}+\left(ec-fy\right)V_y \\ &\quad \left.+\frac{1}{2}\beta^2y^2V_{yy}+w_1W\sigma_1\beta yV_{Wy}+w_2Wy\rho\beta\sigma_2V_{Wy}\right), \end{aligned} \tag{41}$$

where V_W, V_{WW}, V_y and V_{yy} denote respectively the first and second derivatives of V with respect to W and y, and V_{Wy} denotes the cross-derivative.

Maximizing the right-hand side of (41) with respect to the control variables c, w_1 and w_2, yields the generic solutions for excess consumption

$$c-y=\left(V_W-eV_y\right)^{\frac{1}{b-1}}, \tag{42}$$

and the optimal portfolio shares

$$w_1=-\frac{\sigma_2^2\left(\mu_1-\mu_3\right)-\sigma_{12}\left(\mu_2-\mu_3\right)}{\left(\sigma_1\sigma_2\right)^2-\sigma_{12}^2}\frac{V_W}{WV_{WW}}-\frac{\beta y}{\sigma_1}\frac{V_{Wy}}{WV_{WW}} \tag{43}$$

and

$$w_2=-\frac{\sigma_1^2\left(\mu_2-\mu_3\right)-\sigma_{12}\left(\mu_1-\mu_3\right)}{\left(\sigma_1\sigma_2\right)^2-\sigma_{12}^2}\frac{V_W}{WV_{WW}}, \tag{44}$$

with $w_3=1-w_1-w_2$. As (42) to (44) are functions of W, with the solutions for c and w_1 being also functions of the minimum consumption threshold, y, it follows that the solution to V, must be a function of W and y. Following Nakagawa (2012), we propose (5) as a trial solution

$$V=A\left(W+By\right)^b. \tag{45}$$

where A and B are as yet unknown constants.

Substitution of (45) and its derivatives in (42) gives the optimal solution for consumption in excess of the threshold level, as

$$c - y = (Ab)^{1/(b-1)} (1 - eB)^{1/(b-1)} (W + By), \tag{46}$$

with expressions for the constant A and B given in Appendix A.3. Repeating these steps for the optimal portfolio shares in equations (43) and (44) gives

$$w_1 = \frac{\sigma_2^2 (\mu_1 - \mu_3) - \sigma_{12} (\mu_2 - \mu_3)}{\sigma_1^2 \sigma_2^2 - \sigma_{12}^2} \frac{1}{1-b} \left(1 + B\frac{y}{W}\right) - \frac{\beta}{\sigma_1} B \frac{y}{W} \tag{47}$$

and

$$w_2 = \frac{\sigma_1^2 (\mu_2 - \mu_3) - \sigma_{12} (\mu_1 - \mu_3)}{\sigma_1^2 \sigma_2^2 - \sigma_{12}^2} \frac{1}{1-b} \left(1 + B\frac{y}{W}\right), \tag{48}$$

which correspond to equations (6) and (7) in the paper.

A.3 Solution of unknown constants A and B

To generate solutions of the constants A and B, substituting the generic solutions (42) to (44) for c, w_1 and w_2 respectively, and making use of the derivatives $V_y = BV_W, V_{yy} = B^2 V_{WW}$, and $V_{Wy} = BV_{WW}$, allows equation (41) to be expressed as

$$\begin{aligned} rV \;=\; & \left(\frac{1-b}{b}\right) (1 - eB)^{b/(b-1)} V_W^{b/(b-1)} - y\,(1 - eB)\,V_W \\ & - \left(\frac{1}{2}\frac{\sigma_2^2 (\mu_1 - \mu_3)^2}{\sigma_1^2\sigma_2^2 - \sigma_{12}^2} + \frac{1}{2}\frac{\sigma_1^2 (\mu_2 - \mu_3)^2}{\sigma_1^2\sigma_2^2 - \sigma_{12}^2} - \frac{\sigma_{12} (\mu_1 - \mu_3)(\mu_2 - \mu_3)}{\sigma_1^2\sigma_2^2 - \sigma_{12}^2}\right) \frac{V_W^2}{V_{WW}} \\ & - (\mu_1 - \mu_3) \frac{\beta y}{\sigma_1} BV_W + \mu_3 W V_W - fyBV_W. \end{aligned}$$

As

$$V_W = bA\,(W + By)^{b-1} = b\frac{V}{W + By},$$

we can substitute $\left(\left(W+By\right)/b\right)V_W$ for V on the left hand side and simplify. Substituting the generic solution $V_W/V_{WW}=\left(W+By\right)/\left(b-1\right)$, yields

$$\begin{aligned} r\frac{\left(W+By\right)}{b} &= \left(\frac{1-b}{b}\right)\left(1-eB\right)^{b/(b-1)}\left(Ab\right)^{1/(b-1)}\left(W+By\right) \\ &\quad -\left(1-eB\right)y-fyB-\frac{\left(\mu_1-\mu_3\right)}{\sigma_1}\beta yB \\ &\quad -\left(\frac{1}{2}\frac{\sigma_2^2\left(\mu_1-\mu_3\right)^2}{\sigma_1^2\sigma_2^2-\sigma_{12}^2}+\frac{1}{2}\frac{\sigma_1^2\left(\mu_2-\mu_3\right)^2}{\sigma_1^2\sigma_2^2-\sigma_{12}^2}-\frac{\sigma_{12}\left(\mu_1-\mu_3\right)\left(\mu_2-\mu_3\right)}{\sigma_1^2\sigma_2^2-\sigma_{12}^2}\right)\frac{\left(W+By\right)}{\left(b-1\right)} \\ &\quad +\mu_3W. \end{aligned} \tag{49}$$

Collecting terms on the RHS associated with W and y enables us to solve by the method of undetermined coefficients, whereby equating terms in

$$\begin{aligned} \left(W+By\right) &= \Bigg(\left(\frac{1-b}{r}\right)\left(1-eB\right)^{b/(b-1)}\left(Ab\right)^{1/(b-1)}-\frac{1}{2}\frac{\sigma_2^2\left(\mu_1-\mu_3\right)^2}{\sigma_1^2\sigma_2^2-\sigma_{12}^2}\frac{b}{r\left(b-1\right)} \\ &\quad -\frac{1}{2}\frac{\sigma_1^2\left(\mu_2-\mu_3\right)^2}{\sigma_1^2\sigma_2^2-\sigma_{12}^2}\frac{b}{r\left(b-1\right)}+\frac{\sigma_{12}\left(\mu_1-\mu_3\right)\left(\mu_2-\mu_3\right)}{\sigma_1^2\sigma_2^2-\sigma_{12}^2}\frac{b}{r\left(b-1\right)}+\mu_3\frac{b}{r}\Bigg)W \\ &\quad +\Bigg(\Bigg(\left(\frac{1-b}{r}\right)\left(1-eB\right)^{b/(b-1)}\left(Ab\right)^{1/(b-1)}B-\frac{1}{2}\frac{\sigma_2^2\left(\mu_1-\mu_3\right)^2}{\sigma_1^2\sigma_2^2-\sigma_{12}^2}\frac{b}{r\left(b-1\right)} \\ &\quad -\frac{1}{2}\frac{\sigma_1^2\left(\mu_2-\mu_3\right)^2}{\sigma_1^2\sigma_2^2-\sigma_{12}^2}\frac{b}{r\left(b-1\right)}+\frac{\sigma_{12}\left(\mu_1-\mu_3\right)\left(\mu_2-\mu_3\right)}{\sigma_1^2\sigma_2^2-\sigma_{12}^2}\frac{b}{r\left(b-1\right)}\Bigg)B \\ &\quad -\frac{\left(\mu_1-\mu_3\right)}{\sigma_1}\beta B\frac{b}{r}-\frac{b}{r}+eB\frac{b}{r}-fB\frac{b}{r}\Bigg)y, \end{aligned}$$

implies that the following two conditions hold

$$\begin{aligned} 1 &= \frac{1-b}{r}\left(1-eB\right)^{b/(b-1)}\left(Ab\right)^{1/(b-1)}-\frac{1}{2}\frac{\sigma_2^2\left(\mu_1-\mu_3\right)^2}{\sigma_1^2\sigma_2^2-\sigma_{12}^2}\frac{b}{r\left(b-1\right)} \\ &\quad -\frac{1}{2}\frac{\sigma_1^2\left(\mu_2-\mu_3\right)^2}{\sigma_1^2\sigma_2^2-\sigma_{12}^2}\frac{b}{r\left(b-1\right)}+\frac{\sigma_{12}\left(\mu_1-\mu_3\right)\left(\mu_2-\mu_3\right)}{\sigma_1^2\sigma_2^2-\sigma_{12}^2}\frac{b}{r\left(b-1\right)}+\mu_3\frac{b}{r}, \end{aligned} \tag{50}$$

$$
\begin{aligned}
B \;=\; & \left(\frac{1-b}{r}\left(1-eB\right)^{b/(b-1)}\left(Ab\right)^{1/(b-1)} - \frac{1}{2}\frac{\sigma_2^2\left(\mu_1-\mu_3\right)^2}{\sigma_1^2\sigma_2^2-\sigma_{12}^2}\frac{b}{r\left(b-1\right)} \right. \\
& -\frac{1}{2}\frac{\sigma_1^2\left(\mu_2-\mu_3\right)^2}{\sigma_1^2\sigma_2^2-\sigma_{12}^2}\frac{b}{r\left(b-1\right)} \\
& \left. + \frac{\sigma_{12}\left(\mu_1-\mu_3\right)\left(\mu_2-\mu_3\right)}{\sigma_1^2\sigma_2^2-\sigma_{12}^2}\frac{b}{r\left(b-1\right)} \right) B \\
& -\frac{\left(\mu_1-\mu_3\right)}{\sigma_1}\beta_1 B\frac{b}{r} - \frac{b}{r} + \frac{b}{r}\left(e-f\right)B.
\end{aligned}
\tag{51}
$$

To derive an expression for B in (45), combine (50) and (51) and solve for B^{-1} to yield

$$
B^{-1} = -\mu_3 + e - f - \frac{\left(\mu_1-\mu_3\right)}{\sigma_1}\beta, \tag{52}
$$

which is the expression given in equation (8) of the paper. The constant B represents a continuous discounting rate which weights future threshold consumption y, with By representing the present value of future consumption thresholds. The consumption threshold discount rate is a function of the risk free rate μ_3, the consumption threshold adjustment parameters e and f, the expected excess return on rice per unit or risk $(\mu_1-\mu_3)/\sigma_1$, and the utility risk parameter β. As $B<0$, $W+By$ represents the difference between wealth and the present value of future consumption thresholds. Increases in the expected excess return on rice per unit and utility risk, result in future consumption thresholds being discounted more heavily, causing an increase in $W+By$.

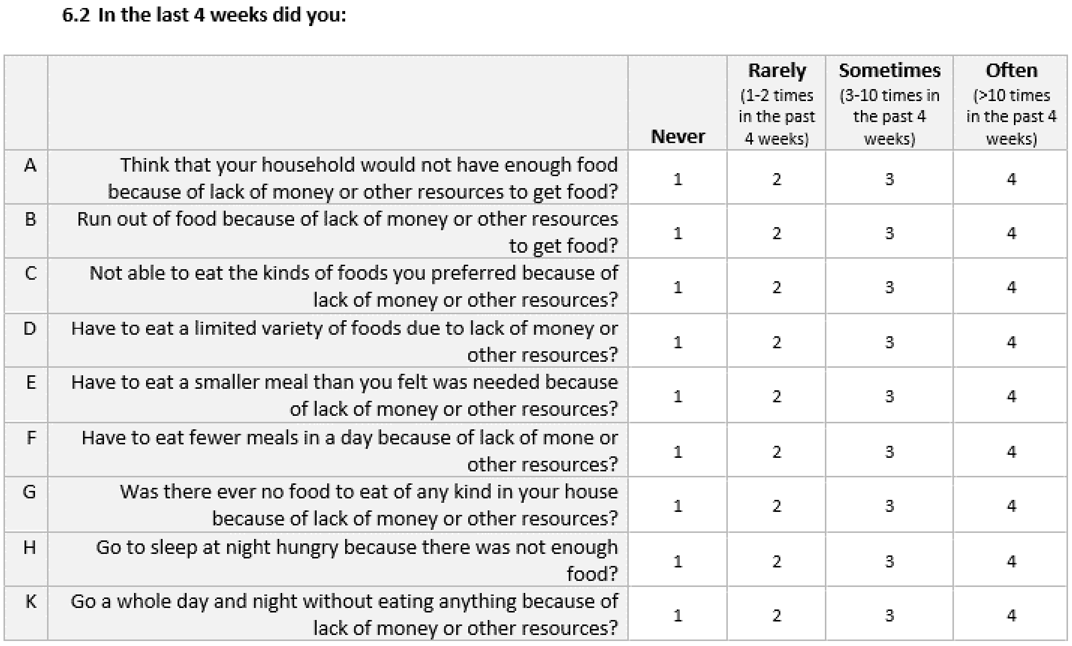
To generate an expression for A (45), solve for $(Ab)^{1/(b-1)}$ in (49) and substitute the result $f-e+(\mu_1-\mu_3)\beta/\sigma_1 = -\mu_3 - B^{-1}$ from the expression for B in equation (52), to give

$$
\begin{aligned}
\left(Ab\right)^{1/(b-1)} \;=\; & \left[r - \mu_3 b - \left(\frac{1}{2}\sigma_2^2\left(\mu_1-\mu_3\right)^2 + \frac{1}{2}\sigma_1^2\left(\mu_2-\mu_3\right)^2 \right.\right. \\
& \left.\left. - \;\sigma_{12}\left(\mu_1-\mu_3\right)\left(\mu_2-\mu_3\right) \right) \frac{1}{\left(\sigma_1\sigma_2\right)^2-\sigma_{12}^2}\left(\frac{b}{1-b}\right) \right] \frac{\left(1-eB\right)^{-b/(b-1)}}{1-b}.
\end{aligned}
\tag{53}
$$

The constant A contains all of the parameters in the model.

B HFIAS questions

Table B.1: Household food insecurity access score questions asked to measure perceived food insecurity over the past 4 weeks (adapted from Coates et al. 2007 and translated into Lao)

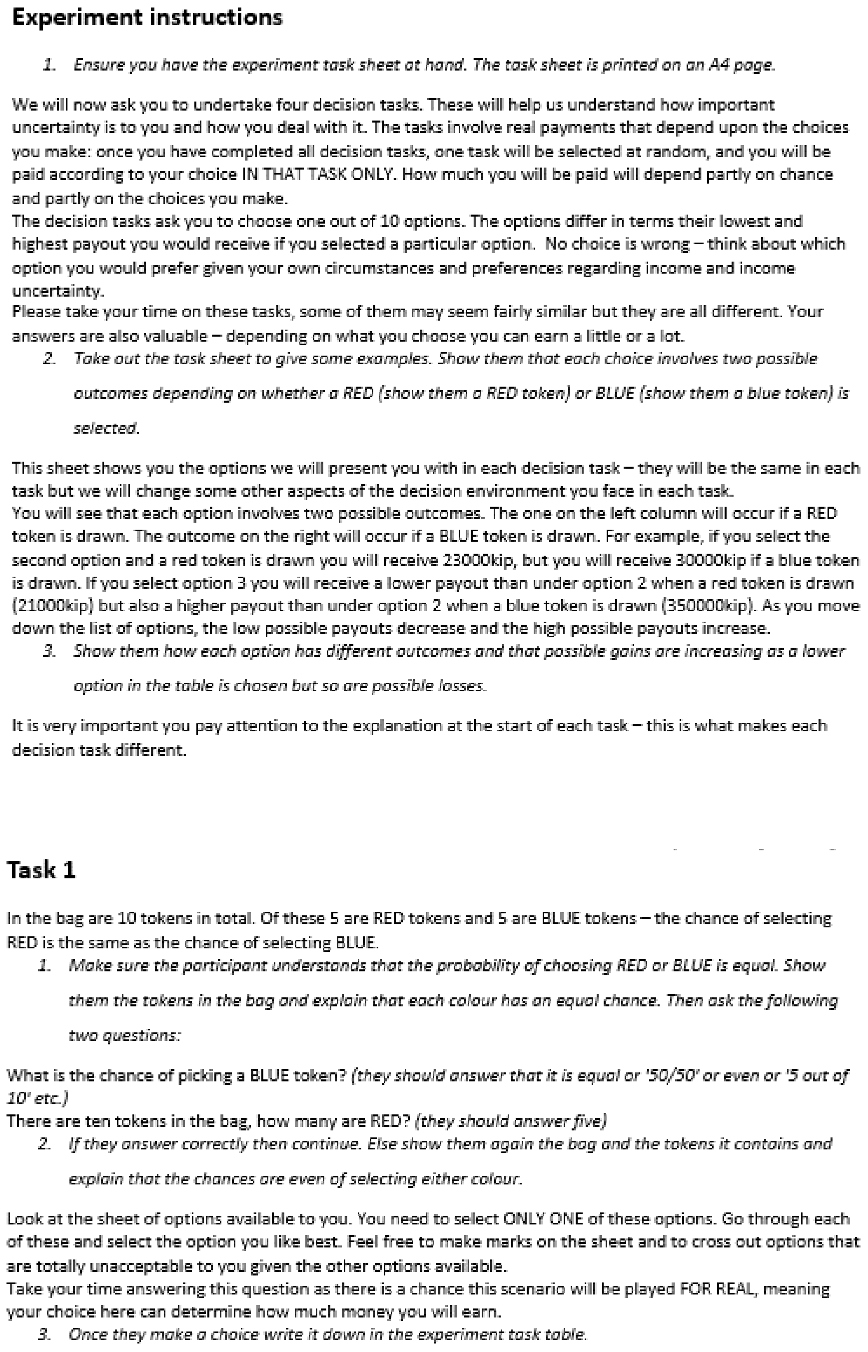


6.2 In the last 4 weeks did you:

		Never	**Rarely** (1-2 times in the past 4 weeks)	**Sometimes** (3-10 times in the past 4 weeks)	**Often** (>10 times in the past 4 weeks)
A	Think that your household would not have enough food because of lack of money or other resources to get food?	1	2	3	4
B	Run out of food because of lack of money or other resources to get food?	1	2	3	4
C	Not able to eat the kinds of foods you preferred because of lack of money or other resources?	1	2	3	4
D	Have to eat a limited variety of foods due to lack of money or other resources?	1	2	3	4
E	Have to eat a smaller meal than you felt was needed because of lack of money or other resources?	1	2	3	4
F	Have to eat fewer meals in a day because of lack of mone or other resources?	1	2	3	4
G	Was there ever no food to eat of any kind in your house because of lack of money or other resources?	1	2	3	4
H	Go to sleep at night hungry because there was not enough food?	1	2	3	4
K	Go a whole day and night without eating anything because of lack of money or other resources?	1	2	3	4

C Incentivized risk elicitation instructions

Table C.1: English translation from Lao



Experiment instructions

1. *Ensure you have the experiment task sheet at hand. The task sheet is printed on an A4 page.*

We will now ask you to undertake four decision tasks. These will help us understand how important uncertainty is to you and how you deal with it. The tasks involve real payments that depend upon the choices you make: once you have completed all decision tasks, one task will be selected at random, and you will be paid according to your choice IN THAT TASK ONLY. How much you will be paid will depend partly on chance and partly on the choices you make.
The decision tasks ask you to choose one out of 10 options. The options differ in terms their lowest and highest payout you would receive if you selected a particular option. No choice is wrong – think about which option you would prefer given your own circumstances and preferences regarding income and income uncertainty.
Please take your time on these tasks, some of them may seem fairly similar but they are all different. Your answers are also valuable – depending on what you choose you can earn a little or a lot.

2. *Take out the task sheet to give some examples. Show them that each choice involves two possible outcomes depending on whether a RED (show them a RED token) or BLUE (show them a blue token) is selected.*

This sheet shows you the options we will present you with in each decision task – they will be the same in each task but we will change some other aspects of the decision environment you face in each task.
You will see that each option involves two possible outcomes. The one on the left column will occur if a RED token is drawn. The outcome on the right will occur if a BLUE token is drawn. For example, if you select the second option and a red token is drawn you will receive 23000kip, but you will receive 30000kip if a blue token is drawn. If you select option 3 you will receive a lower payout than under option 2 when a red token is drawn (21000kip) but also a higher payout than under option 2 when a blue token is drawn (350000kip). As you move down the list of options, the low possible payouts decrease and the high possible payouts increase.

3. *Show them how each option has different outcomes and that possible gains are increasing as a lower option in the table is chosen but so are possible losses.*

It is very important you pay attention to the explanation at the start of each task – this is what makes each decision task different.

Task 1

In the bag are 10 tokens in total. Of these 5 are RED tokens and 5 are BLUE tokens – the chance of selecting RED is the same as the chance of selecting BLUE.

1. *Make sure the participant understands that the probability of choosing RED or BLUE is equal. Show them the tokens in the bag and explain that each colour has an equal chance. Then ask the following two questions:*

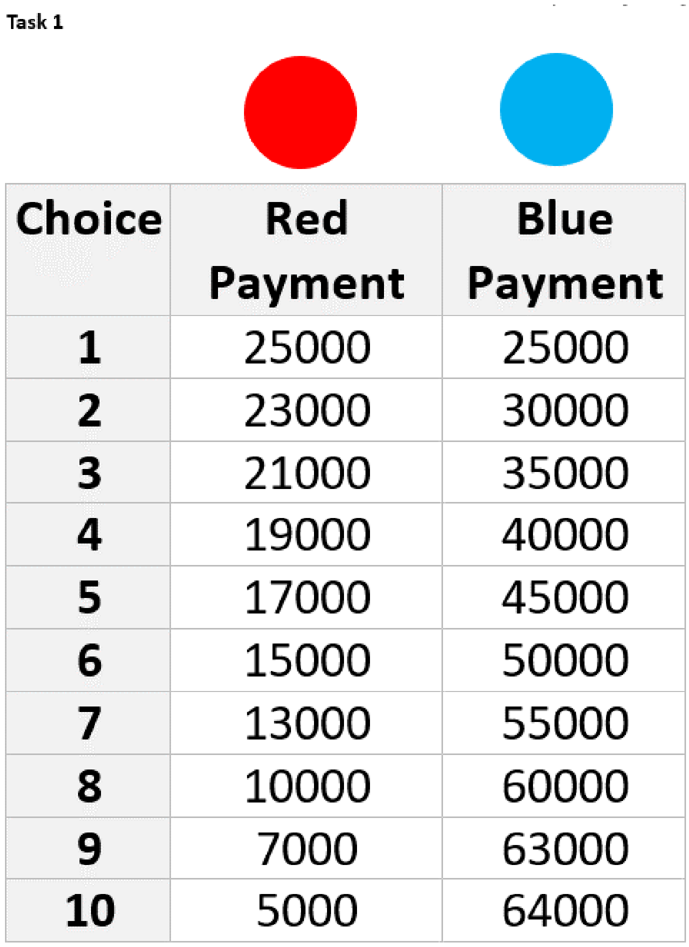
What is the chance of picking a BLUE token? *(they should answer that it is equal or '50/50' or even or '5 out of 10' etc.)*
There are ten tokens in the bag, how many are RED? *(they should answer five)*

2. *If they answer correctly then continue. Else show them again the bag and the tokens it contains and explain that the chances are even of selecting either colour.*

Look at the sheet of options available to you. You need to select ONLY ONE of these options. Go through each of these and select the option you like best. Feel free to make marks on the sheet and to cross out options that are totally unacceptable to you given the other options available.
Take your time answering this question as there is a chance this scenario will be played FOR REAL, meaning your choice here can determine how much money you will earn.

3. *Once they make a choice write it down in the experiment task table.*

Table C.2: Payoff table for the risk elicitation task in Kip.



Task 1

Choice	Red Payment	Blue Payment
1	25000	25000
2	23000	30000
3	21000	35000
4	19000	40000
5	17000	45000
6	15000	50000
7	13000	55000
8	10000	60000
9	7000	63000
10	5000	64000