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ORIGINAL ARTICLE

Should farmers farm more? Comparing marginal products within Malawian households

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Abstract

According to standard economic theory, households should equate the marginal revenue product of an input across activities within the household. However, this prediction may not hold in the presence of risk. Using data on farm plots and non-farm enterprises in Malawi, we examine the impact of risk on the allocation decisions of agricultural households as they allocate labor across farm and non-farm production. We control for many household and production characteristics, including household fixed effects, and find farm marginal revenue product of labor (MRPL) to be consistently higher than non-farm MRPL. These results are consistent with farm production being riskier than non-farm production for most households in Malawi. These findings suggest that improved access to insurance of farming activities and wage employment opportunities could increase total household income.

KEYWORDS
agriculture, efficiency, labor productivity, non-farm production, risk

JEL CLASSIFICATION
J24, J43, O13, Q12, R23

1 | INTRODUCTION

A stylized fact of the development process is that agriculture's share of GDP decreases as a country develops (Lewis, 1954; Ranis & Fei, 1961). This relationship holds in the cross-section, with relatively more developed countries deriving a smaller percentage of GDP from agricultural sources (Chenery et al., 1975; Gollin et al., 2014). Moreover, even within countries, the non-farm sector tends to be more productive—as measured by the average revenue product of labor—than the agricultural sector (Gollin et al., 2014; McCullough, 2017; Young, 2013). Given these persistent empirical patterns, it is perhaps no surprise that many development policies focus on promoting non-farm growth; the recent microfinance revolution is but one example of this (Armendáriz & Morduch, 2010).

At the household level, however, a higher average revenue product in the non-farm sector does not necessarily imply a reallocation of labor is warranted, since theory predicts households should be equating marginal revenue products of labor (MRPL), not average revenue products. Whether the marginal revenue product suggests the same depends on the reasons that households operate non-farm and agricultural enterprises simultaneously and the shape of the production functions. If households operate non-farm enterprises to protect themselves against agricultural production risk, for example, MRPL equality need not hold, even in rational households. A large body of research shows that agricultural households diversify into non-farm self-employment for a number of reasons, including to insure against production or household shocks, or to accommodate agricultural seasonality or missing markets (Barrett et al., 2001; Gindling & Newhouse, 2014; Haggblade et al., 2010; Lanjouw & Lanjouw, 2001; Merfeld, 2020; Nagler & Naudé, 2014). In addition, diversification seems to be the norm, not the exception (Davis et al., 2017). Under these scenarios, households may not be moving into the non-farm sector chasing profits. Rather, they may instead be pushed into the sector due to a lack of more remunerative options and a desire to mitigate risk, leading to a lower MRPL in non-farm production. This article revisits the question of allocative efficiency, focusing on the impact of risk on the production choices.

Regardless of the exact motivation for diversification, standard economic theory of profit maximization predicts the equality of the MRPL across productive activities—in the current context, farm and non-farm production—as well as the equality of MRPL with the market wage. However, this result also generally relies on the assumption of complete and competitive markets, which recent work has shown to not hold across many developing countries (e.g., Dillon et al., 2019; LaFave and Thomas, 2016), as well as the assumption of a collective household model, which is also questionable (McPeak & Doss, 2006; Guirkinger et al., 2015; Udry, 1996; Walther, 2018). As such, whether households equate marginal revenue products across productive activities is an empirical question. Moreover, the answer to this question is not only interesting in its own right, but also is integral to labor supply estimation (Abdulai & Regmi, 2000; Barrett et al., 2008; Jacoby, 1993; Seshan, 2014; Skoufias, 1994) and can even shed light on some of the underlying market conditions which characterize production in rural areas of developing countries. This, in turn, may help us better understand why households diversify into non-farm production and develop more appropriate development interventions.

In particular, differing risk profiles of production can lead to deviations from MRPL equality (Barrett et al., 2008; Stiglitz, 1974). If production risk differs across activities, households optimize by equalizing their expected marginal utilities across activities. Additionally, price risk—uncertainty over the market price for a good—can also affect MRPL equality. Barrett (1996) shows that price risk can affect households differently since it is likely to be correlated with production risk. In particular, households are predicted to behave differently depending on whether they are net buyers or net sellers of crops, with net sellers more likely to exhibit what we traditionally associate with risk: an under-allocation of labor to the risky activity. In this article, we investigate the impact of risk on the allocation decisions of agricultural households across farm and non-farm production using household survey data from Malawi. At first glance, our results show that farming is more productive, at the margin, for the median household, and that incomes could increase if households farmed more. However, we go on to show that production risk and price risk both help explain why households make the allocation decisions we observe in the data.

To test this assumption of equality of the MRPL across household activities (similar in spirit to Chavas et al. (2005) and Le (2009)), we use three waves of the Malawi Integrated Household Survey (IHS). Without making further assumptions regarding market completeness, equality is only predicted for households that operate both farm and non-farm enterprises simultaneously. As such, we begin with summary statistics comparing households that operate both types of enterprises in the same wave to all households. The results do show the relevant subsample to be statistically different from the overall sample, limiting the external validity of the analysis. Nonetheless, this is the only group of households for which equality is theoretically predicted.[1]

We then examine whether MRPL, estimated using translog production functions, is equal across farm and non-farm production within a household. Our results show that farm MRPL is consistently higher than non-farm MRPL. This result holds under a variety of specification choices and sample restrictions. Further analysis indicates that bias in the production function estimates is unlikely to be responsible for the large deviations from equality that we observe.

However, we find evidence that price and production risk play an important role in household labor allocation. In particular, deviations from equality are much higher for plots planted with tobacco and cotton, two pure cash crops, than for plots planted with maize, a common subsistence crop in Malawi. This is consistent with households dealing with price risk by over allocating labor to crops of which they are net buyers and under allocating labor to crops of which they are net sellers (Barrett, 1996).

We also examine the role of price risk in allocation decisions by using revenue, acreage, and crop sales as proxies for market access. For all three variables, households above the median value show substantially larger MRPL

[1] One advantage of focusing on these households is that, theoretically, they should equate MRPL across household activities with similar risk profiles even if markets are incomplete. This also extends to differences in, for example, technology across households (Adom and Adams, 2020; Bravo-Ureta et al., 2020).

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deviations than households below the median. For revenue, we are unable to reject the null hypothesis of MRPL equality for households with below median total revenue. Similarly, the MRPL difference is around twice as large for the upper half of the distribution (relative to the lower half) of both acreage and crop sales. Insofar as these variables are proxies for market access, this evidence is consistent with price risk influencing allocation decisions if access to markets is correlated with the probability of being net sellers of crops (Barrett, 1996). Households that hire labor from the market are also more sensitive to fluctuations in output prices and should therefore have higher MRPLs than households that do not hire labor from the market. We find exactly this pattern for households that hire for farm production. Households that hire for non-farm production have much higher MRPL in that activity, to the point that their non-farm MRPL is actually higher than their farm MRPL. This is the only subsample in this article for which we find this pattern.

Consistent with production risk, we also find evidence that rainfall variability is associated with higher farm MRPL and deviations from equality. Overall, these results reinforce the commonly held belief that farming is risky and that farmers may deviate from profit-maximizing conditions to deal with this risk. In other words, reducing the risk faced by households could theoretically increase their expected (mean) incomes.

The rest of this article is organized as follows. In Section 2, we present the theory that informs our study. We discuss methodology and summary statistics in Section 3. We present results of our analyses and discuss policy implications in Section 4 before concluding in Section 5.

2 | THEORY

Our theoretical analysis combines two standard results in the literature on production functions. First, when considering how to allocate a resource across two different productive activities, it is well known that the optimal choice occurs when the marginal (revenue) products of the input for each activity are equal. Simply put, if both production process A and B use labor (L) as an input, the efficient allocation of labor implies ${MP_L}^A = {MP_L}^B$. This result has led to many articles testing for efficient allocation of resources. Two such articles related to our setting are by Udry (1996) and Linde-Rahr (2005). Udry tests for the efficient allocation of resources across plots within a household across genders and Linde-Rahr tests for efficiency across different types of crops within a household.

One limitation of this result is that it assumes both production processes are risk-free. The second strand of literature that we build on was started to address this limitation. If producers face risk in the production process, producers will under-allocate resources to that activity (in an agricultural context, this is similar to underinvestment driven by risk, e.g., Goldstein & Udry (2008)). Sandmo (1971) finds a similar result showing that if producers face uncertainty over the price of their output, risk-averse firms will use fewer inputs, thereby reducing their output. Barrett (1996) extends this analysis to consider the impact of price risk on a household model of production, in which households can sell and consume the agricultural goods they produce. His main result is that households that are net consumers of the staple good will over-allocate resources to its production in the presence of price risk. Barrett (1996) also shows that households that are net sellers of the staple good behave similarly to the producers in Sandmo (1971), and so under-allocate labor to production in the presence of price risk.

We combine these two strands of the literature by incorporating risk into the test of efficient allocation of resources across different productive activities. To accomplish this, we first switch from output to revenue to allow each production process to produce different kinds of output. The efficient allocation is then over marginal revenue products (*MRPL*), not marginal products. Next, we note that the results in Sandmo (1971) and for production risk imply *MRPL* is higher than the risk-free optimum because the producer is not using enough labor. Barrett (1996)'s result for households who are net consumers of the good implies the *MRPL* is lower than optimal because the household is using too much labor. Taken together, it is evident that responses to price risk can drive deviations in the equality of marginal revenue products.

In this article, we consider how risk affects the allocation of labor in households that conduct both farm (f) and non-farm (nf) production activities. If there were no risk, then the efficient allocation of labor would entail:

$$MRPL_f = MRPL_{nf} \tag{1}$$

However, in the presence of risk, this condition may not hold. Given that both farm and non-farm production may face price risk, and that it matters whether the household is a net seller or consumer of the staple good, there are six combinations to consider. We outline these in Table 1.[2]

The left-hand side of Table 1 indicates whether the farm output price is risky or risk-free. The top of the table indicates whether the non-farm output is risky or risk-free. So, if both output prices are risk-free, the household should

[2] We ignore the knife's edge case of households who sell the exact same amount they consume.

TABLE 1 Summary of Risk Combinations

		Non-farm output price is:	
Farm output price is:		Risk-free	Risky
	Risk-free	$MRPL_f = MRPL_{nf}$	$MRPL_f < MRPL_{nf}$
	Risky, HH is net consumer	$MRPL_f < MRPL_{nf}$	$MRPL_f < MRPL_{nf}$
	Risky, HH is net seller	$MRPL_f > MRPL_{nf}$	Ambiguous

"HH" is household, the f subscript denotes the household farm enterprise, and the nf subscript denotes the household non-farm enterprises.

allocate labor to the point where $MRPL_f = MRPL_{nf}$. However, as shown in the last column of the first row, if only the non-farm output is risky, then the household will under-allocate labor to the non-farm production activity, and $MRPL_f < MRPL_{nf}$. The second row shows that for net consumers of the staple good, if the farm output price is risky, then $MRPL_f$ will be less than $MRPL_{nf}$, whether the non-farm output price is risky or not. The last row shows that for net sellers of the staple good, $MRPL_f$ will be greater than the $MRPL_{nf}$ if the staple good price is risky but the non-farm output price is risk-free. However, if both output prices are risky and the household is a net seller, then the predicted relationship between the MRPLs is ambiguous, as it depends on the relative risk of each activity.

Lastly, we note that if households are not limited in their participation in the market for paid labor, then the efficient allocation of labor predicts the MRPL for risk-free household production should equal the market wage rate, w. If the relevant labor market constraint they face is on hiring out their own labor, then estimated MRPLs will be lower than the market wage, whereas if the relevant labor market constraint they face is on hiring in labor, then estimated MRPLs will be higher than the market wage (Merfeld, 2021).

3 | METHODS AND DATA

The basic steps involved in testing MRPL equality are as follows and are similar to those in Linde-Rahr (2005), who studies allocative efficiency across plots planted with different crops. First, we estimate production functions for both farm and non-farm enterprises. Second, we compute the MRPL across these two activities within the household. With these MRPL estimates, we then explicitly test whether MRPL—or shadow wages—are equal across activities within the household.

We present production function results using both a Cobb-Douglas production function and a translog production function. However, given that we reject the nested Cobb-Douglas within the translog production function, we present MRPL results only for translog production function estimates. The translog specification we estimate is:

$$\begin{aligned}\ln R_{iht} = {} & \alpha_h + I(Farm = 1) \\ & \times \left(\sum_j \beta_j ln\gamma_{jiht} + \frac{1}{2}\sum_j \sum_k \beta_{jk} ln\gamma_{jiht} ln\gamma_{kiht} + \delta C_{iht} + D_{dt} + \eta_m \right) \\ & + \sum_j \beta_j ln\gamma_{jiht} + \frac{1}{2}\sum_j \sum_k \beta_{jk} ln\gamma_{jiht} ln\gamma_{kiht} \\ & + \delta C_{iht} + D_{dt} + \eta_m + I(Farm = 1) + \varepsilon_{iht} \end{aligned} \tag{2}$$

where R_{iht} is revenue for enterprise i in household h in wave t, α_h is an intercept that varies by household (household fixed effects); $I(Farm = 1)$ is a dummy variable equal to one if the observation is a farm plot and equal to zero if the observation is a non-farm enterprise; γ_{jiht} and γ_{kiht} are inputs j and k; C_{iht} is a vector of controls that may affect revenue and which differ depending on whether the enterprise is (non-)farm; D_{dt} is district-by-wave fixed effects; η_m is a set of dummy variables indicating the month of interview; and ε_{iht} is a conditional mean-zero error term. We include labor (log of days), acres (log), and fertilizer (log of kg) as productive inputs in the farm production functions and labor (log of days) and total costs (log of MWK) as productive inputs in the non-farm production functions. We set land and fertilizer to zero for all non-farm enterprises and non-farm costs to zero for all farm plots.[3] We use revenue as the dependent variable in the production function estimation because the data on nonfarm enterprises only reports revenue—not physical output—and in order to compare across activities with different types of output. This could bias the estimates if the output prices are correlated with farm productivity. We include district-by-wave fixed effects to help alleviate both regional and temporal differences in output prices.

For farm plots, we restrict attention to plots planted with a select number of crops in order to construct prices for the farm output. We construct these prices by taking medians at the lowest administrative level of aggregation with a sufficient number of observations.[4] The crops we use have a sufficient number of observations with which

[3] Since we are fully interacting the model, this does not affect the estimation of the relevant farm or non-farm coefficients.

[4] Using different cutoffs for "sufficient" does not affect conclusions.

to create median prices. In contrast, we do not need to restrict estimation in a similar way for non-farm enterprises; entrepreneurs are directly asked about their total revenue. Finally, we drop the top one percent of farm and non-farm revenue and labor before estimating production functions.[5]

For both the Cobb-Douglas and translog specifications, we pool the data and estimate a single production function for both farm and non-farm enterprises, but we allow the effect of all variables—other than the household fixed effect—to vary by type of enterprise. Since the identifying assumptions for a pooled sample are more restrictive, we also estimate separate farm and non-farm production functions. The qualitative conclusions do not change, but the pooled specification greatly increases precision.

After estimating the production functions, we then calculate the MRPL for each activity. Using the translog specification, we construct our MRPL estimates for farm plots as

$$\frac{\partial R}{\partial L} = \frac{\hat{R}_{iht}}{L_{iht}} \left[\beta_L + \beta_{LL} \log L_{iht} + \beta_{LA} \log A_{iht} + \beta_{LF} \log F_{iht}\right] \tag{3}$$

where $\hat{R}_{iht}$ is predicted revenue, β_{LL} is the coefficient on the labor squared term, β_{LA} is the coefficient on the interaction between labor and acreage, and β_{LF} is the coefficient on the interaction between labor and fertilizer use. We use predicted revenue as it is the best estimate we have of the farmer's expected revenue. In other words, predicted revenue removes idiosyncratic risk and is the target farmers use when making labor allocation decisions.[6]

We calculate the MRPL for non-farm enterprises as

$$\frac{\partial R}{\partial L} = \frac{\hat{R}_{iht}}{L_{iht}} \left[\beta_L + \beta_{LL} \log L_{iht} + \beta_{LC} \log C_{iht}\right] \tag{4}$$

where β_{LC} is the coefficient on the interaction between labor and cost.

The production function in Equation (2) is at the plot/enterprise level. However, after estimating MRPLs, we need to aggregate to the household level in order to compare MRPLs across productive activities. This raises questions about the best way to aggregate multiple MRPLs, since many households operate more than one plot and some operate more than one enterprise in the same wave. We aggregate MRPLs to the household level in two ways. First, we take the simple median across plots within each household. If a household operates an even number of plots, we use the mean of the two middle plots to construct a household average MRPL. We construct the household average MRPL similarly for nonfarm enterprises, though most households operate only one in a given year. Second, we compute the household's weighted average MRPL, weighting by labor allocation across plots or enterprises.

Since it is not clear what the "correct" aggregation method is, and due to issues with recall bias raised by Arthi et al. (2018),[7] we also estimate production functions in which we aggregate (separately) all plots and all enterprises to the household level. We sum revenue, labor, acreage, fertilizer, and non-farm costs to the household level. For crop dummies, we collapse the data and leave these as indicator variables for whether the household grew that crop in that wave. For the plot characteristics, we include continuous variables for the percent of total household land with each characteristic. We then estimate production functions at the household level, leading to one MRPL for each household enterprise.

The theoretical prediction of MRPL equality holds only for households that operate both types of enterprises if households are constrained in their access to the local labor market. Therefore, we only use households that operate both non-farm and farm enterprises in the same wave to construct MRPL estimates. However, we present estimates of production functions using these households as well as separate estimates using all households in order to examine the external validity of our final sample.

Finally, in order to conduct inference over a multi-step estimator, we bootstrap the standard errors with 1000 replications. Since we employ household fixed effects, we set up the bootstrap to draw households, including all non-farm and farm enterprises operated by that household, across all waves.

4 | DATA

We use the Malawi IHS in this article, collected by the Malawi National Statistics Office. The IHS is part of the World Bank's Living Standards Measurement Study (LSMS) program. The IHS data consists of three waves: the first wave was collected from 2010 to 2011, the second in 2013, and the third in 2016 to 2017. There is a common panel sample in all three waves, such that we are able to follow some households across three separate years. However, the first and third waves also have large cross-section components, which dwarf the panel component in size. After restricting our sample and looking only at households that

[5] We report non-trimmed results in Table A5 in the appendix. Results are unchanged.

[6] As a robustness check, we use actual revenue in the calculation of MRPLs and do not find significantly different results. We present these results in Table A6 of the Appendix.

[7] Arthi et al. (2018) find that reported labor allocation is mismeasured at the plot level. However, when labor is aggregated to the household, this mismeasurement largely disappears.

operate both types of enterprises in the same wave, we are left with 3,827 household/wave observations. These numbers correspond to 10,593 individual observations, of which 6,490 observations are individual plots and 4,121 observations are individual non-farm enterprises.

Many of the variables used in estimation come from different modules in the IHS. As such, certain variables are at different levels of aggregation (i.e., household, household-plot, or household-plot-crop). For example, although crop output is reported at the plot-crop level, labor is only reported at the plot level. Thus, missing plot-crop observations require that we drop the entire plot from the sample. Additionally, we drop any nonfarm enterprises that were in operation for less than 6 months in the previous year—purposefully excluding possible seasonal enterprises that may be operated specifically in response to market failures and seasonality—and any non-farm enterprises that were not in operation in the month prior to data collection.[8] In the following sub-sections, we document some of these idiosyncrasies and the resulting decisions.

4.1 | Revenue

The key dependent variable in the production functions is revenue. The Malawi IHS, like many household surveys, asks farmers for agricultural output in weight, not in value. Since our methodology is designed to estimate the MRPL, we must construct crop prices to value output. We construct prices from sales information collected from households that sold crops.

However, most households do not report selling crops. As such, we impute prices based on the most local median price possible. We construct aggregate prices at four separate levels—the enumeration area, the traditional authority, the district, and the region—by taking the median crop price at each level of aggregation separately. We then assign prices to households using the lowest level of aggregation at which there are at least five valid price observations.[9] If any regions have less than five price observations for any given price, we assign a missing price value for all observations of that crop in that district. In this way, we are able to construct prices for 13 crops: maize, tobacco, groundnut, rice, sweet potato, potato, beans, soya, pigeon peas, cotton, sunflower, pumpkin leaves, and tomato.

4.2 | Labor and selection of Plots

We use days of labor as the independent variable of interest. This variable includes both family and hired labor, which we aggregate into a single variable. However, family labor generally predominates, as is clear in the summary statistics below. A major issue is that labor is reported at the plot level, while crop output is reported at the plot-crop level. This means that the labor inputs we observe on a given plot are applied to all crops on that plot and, as such, we are unable to disaggregate that labor by crop. As such, after constructing price observations, we also drop any plots that are planted with at least one crop with a missing price value. In this way, the entirety of labor allocated to the plot is applicable to the entirety of the output value we construct. In other words, we include only plots for which we have full information on inputs and outputs. This restriction drops less than ten percent of plots in each wave.

4.3 | Other controls

In addition to the productive inputs, we also control for a number of agriculture variables, including plot quality (as reported by the farmer), plot type, plot erosion, plot slope, and whether the plot is located in a swamp or wetland. In farm regressions, in addition to days of labor, we include the size of the plot (log of acres) and amount of fertilizer applied to the plot (log of kilograms) as productive inputs. In non-farm regressions, we include one separate productive input in addition to labor: log of total costs. This variable is directly asked of all households with a non-farm enterprise. The use of monetary values for a productive input could bias the coefficients in our production functions if input prices vary by region and/or household (Jacoby, 1993). We include district/wave fixed effects to help alleviate both regional and temporal differences in input prices. The mean total costs was equivalent to just 15 USD in 2010, while almost nine percent of non-farm enterprises reported zero non-labor costs in the previous month. Additional industry controls include indicator variables for industry and a single indicator variable for whether the non-farm enterprise has electricity.

Finally, the dependent variable for non-farm production is constructed using a single survey question, which asks respondents for total revenue in the 30 days prior to the interview. We include month of interview fixed effects in order to control for any seasonality in labor allocation across the year. However, we also estimate production functions on separate subsamples, depending on month of interview, and present these results below.

[8] Including non-farm enterprises who were in operation less than six months in the previous year does not affect our qualitative conclusions.

[9] In the appendix, we report results requiring at least ten valid price observations and without any price requirements. Our conclusions are unchanged.

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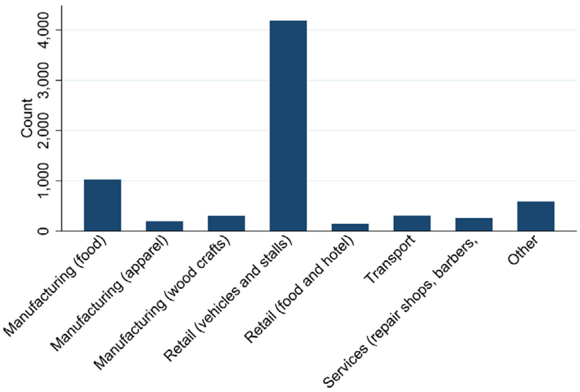

FIGURE 1 Non-farm business industries. Counts are based on the number of non-farm enterprises across all three waves of the survey

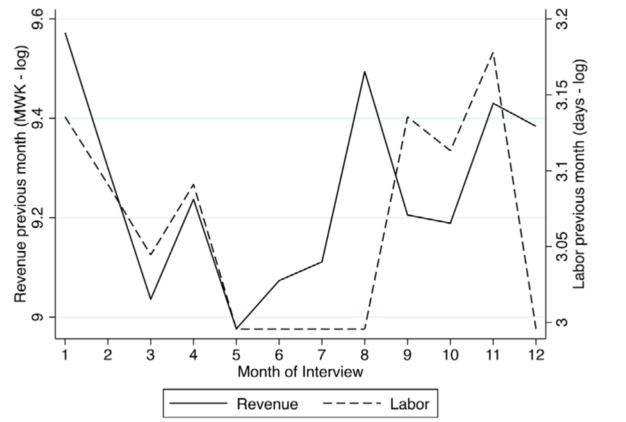

FIGURE 2 Month of interview and non-farm production characteristics. Revenue and labor are for non-farm production only

4.4 | Summary statistics and sample restrictions

Summary statistics at the household/wave level are shown in Table 2. To calculate these statistics, we collapse all farm and non-farm statistics to the household level. The first column presents statistics for all households that are in the Malawi IHS data and meet our criteria for calculating plot revenue but are not in the final sample because they do not operate both types of enterprises in the same wave. The second column includes all households that are in the final sample. The third column presents the *P*-value of tests for equality across the two samples.[10] Of the households not in the final sample, approximately 86 percent of them have plots but no non-farm enterprise while 14 percent operated non-farm enterprises but had no valid plot observation.[11] Overall, the statistics suggest there are some differences between the two samples, which may limit the external validity of our results.

Figure 1 presents the broad industry classifications of the non-farm enterprises in our sample. These are all generally small firms, with only the owner providing any labor. The vast majority of these enterprises are people engaging in petty retail, including owning a kiosk or stall. Services, on the other hand, make up a relatively small proportion of enterprises.

We present additional statistics in Table A1. Specifically, we look at variables related to a household's capacity to undertake certain kinds of activities. We group households into three groups: those that only engage in non-farm self-employment, those that only engage in farm self-employment, and those that engage in both in a given wave. We see that households that only engage in non-farm self-employment have much higher consumption per capita, are much less likely to be poor, and have much higher levels of education. The distance to the nearest bus stop and commercial bank suggest, however, that many of these households are likely more urban. Farm households appear to be the worst off, with those engaged in both activities simultaneously somewhere in-between. This suggests that this final group that engages in both activities might be on its way to growth and, as such, is an especially pertinent group of households to study.

One concern with our estimation method is that labor is seasonal, and thus we may not be making the proper temporal comparison across productive activities. This concern is compounded by the fact that the survey captures farm labor for the whole season whereas non-farm labor is only reported for the last 30 days. To help examine whether this is affecting our results, we present a graph of median non-farm revenue and labor by month of interview in Figure 2. In Malawi, there appears to be clear seasonality in labor allocation to non-farm production. In particular, both labor allocation and revenue appear to be lowest from February to around July, and then increase between August and January. Given that there does appear to be some seasonality in labor allocation and revenue, we will explore this further below, though we control for month of interview in all production function estimates.

[10] We construct these p-values by regressing each variable on a dummy variable indicating whether a household/wave observation is in the final sample, clustering the standard errors at the household level.

[11] Since non-farm enterprises are never dropped due to restrictions on revenue – unlike farm plots – a household only appearing in the non-farm statistics does not imply the household does not operate any plots. Rather, it is possible that the household operates plots that get dropped in our price-creation procedure explained above.

TABLE 2 Summary statistics

	(1) All mean/sd	(2) Both types mean/sd	(3) Diff (p) mean/sd
Household has plot in sample	.863	1.000	.000
	(.344)	(.000)	(.000)
Ag output (2010 MWK - log + 1)	10.003	10.209	.000
	(1.258)	(1.239)	(.000)
Total labor (log)	4.350	4.253	.000
	(.832)	(.899)	(.000)
Total family labor (log + 1)	4.256	4.066	.000
	(.974)	(1.139)	(.000)
Total hired labor (log + 1)	.423	.793	.000
	(.997)	(1.272)	(.000)
Household hired for ag	.179	.325	.000
production (yes = 1)	(.384)	(.468)	(.000)
Fertilizer (kg - log + 1)	1.386	1.470	.003
	(1.599)	(1.590)	(.000)
Acres in sample	1.736	2.217	.295
	(18.573)	(27.010)	(.000)
Maize in sample	.930	.922	.111
	(.256)	(.268)	(.000)
Tobacco in sample	.101	.072	.000
	(.302)	(.259)	(.000)
Household has non-farm ent. in	.137	1.000	.000
sample	(.344)	(.000)	(.000)
NF output (2010 MWK - log + 1)	9.632	9.112	.000
	(1.509)	(1.384)	(.000)
Total labor (log)	3.101	2.885	.000
	(.799)	(.848)	(.000)
Total family labor (log + 1)	2.971	2.806	.000
	(.789)	(.841)	(.000)
Total hired labor (log + 1)	.403	.244	.000
	(1.118)	(.861)	(.000)
Last monthly costs (2010 MWK -	8.517	7.802	.000
log + 1)	(2.755)	(2.854)	(.000)
Household hired for NF	.126	.083	.000
production (yes = 1)	(.331)	(.275)	(.000)
Male household head (yes = 1)	.736	.804	.000
	(.441)	(.397)	(.000)
Household size	4.677	5.141	.000
	(2.144)	(2.120)	(.000)
Total acres owned	3.660	7.748	.004
	(65.262)	(83.247)	(.000)
N	19,317	3,835	23,152

Standard deviations are in parentheses. Statistics are at the household/wave level. Farm and non-farm statistics were collapsed to the household/wave level before taking logs. The "All" column includes all households with at least one enterprise that meets our data criteria. The "Both types" column includes households with at least one farm and one non-farm enterprise in a given wave.

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TABLE 3 Production function estimates

	All households		Final sample	
	(1)	(2)	(3)	(4)
	C-D	Translog	C-D	Translog
Farm labor (L_f)	.255***	.152*	.281***	.076
	(.018)	(.091)	(.029)	(.146)
Acres (A)	.364***	.448***	.337***	.401***
	(.017)	(.090)	(.030)	(.152)
Fertilizer (F)	.083***	.249***	.079***	.210**
	(.008)	(.051)	(.015)	(.092)
$L_f \times L_f$		.012		.020
		(.012)		(.018)
$A \times A$		.008		−.008
		(.015)		(.022)
$F \times F$		−.026***		-.026*
		(.008)		(.014)
$L_f \times A$		−.017		-.010
		(.018)		(.031)
$L_f \times F$		-.011		.003
		(.009)		(.015)
$F \times A$		.001		.001
		(.010)		(.019)
NF Labor (L_{nf})	.201***	.298***	.210***	.303***
	(.029)	(.110)	(.029)	(.116)
Costs (C)	.229***	-.292***	.228***	-.293***
	(.012)	*.034)	(.011)	(.034)
$L_{nf} \times L_{nf}$		.015		.012
		(.020)		(.020)
$C \times C$		.057***		.057***
		(.002)		(.002)
$L_{nf} \times C$		-.037***		-.037***
		(.010)		(.010)
Test for nested Cobb-Douglas (*P*-value)				
Farm		.009		.399
Non-farm		.000		.000
R-squared	.786	.802	.710	.754
Observations	41,340	41,340	10,593	10,593

Standard errors clustered at the household level are in parentheses. Household fixed effects are included in all regressions. Also included are month of interview fixed effects and wave/district fixed effects. Month of interview and wave/district fixed effects are allowed to vary by type of production. In addition, we include crop dummies, plot quality variables, non-farm industry dummies, and a dummy indicating whether the non-farm industry has access to electricity. The F-tests present tests for a nested Cobb- Douglas production function in each translog; the P-value is constructed by testing whether all squared and interaction terms are simultaneously zero. The "All Households" columns include all households that operate at least one plot or at least one enterprise across all three waves of the Malawi LSMS. The "Final Sample" column includes the sample of households we use to calculate MRPL: those that operate at least one plot and at least one enterprise in the same wave. Revenue and non-farm costs are in (March) 2010 MWK.

*$P < .10$.

**$P < .05$.

***$P < .01$.

5 | RESULTS

We begin our discussion of the results with the pooled production function estimates in Table 3. We present results for both the Cobb-Douglas and translog specifications as well as for all households (first two columns) and for households that operate both enterprises in the same wave (last two columns). Comparing the Cobb-Douglas results

TABLE 4 MRPL Estimates

	Separate production functions		Pooled production function		Collapsed
	(1)	(2)	(3)	(4)	(5)
	Simple median	Weighted by labor	Simple median	Weighted by labor	Collapsed
Farm MRPL	115.306***	116.474***	82.548***	82.227***	102.068***
	(14.401)	(14.600)	(8.614)	(8.766)	(10.551)
Non-farm MRPL	6.959	6.881	24.377**	24.123**	37.352***
	(17.531)	(17.428)	(11.250)	(11.240)	(13.700)
Difference	112.610**	113.669***	54.051***	53.720***	63.434***
	(32.006)	(32.135)	(15.382)	(15.509)	(18.774)
N (household/wave)	3,827	3,827	3,827	3,827	3,827

Standard errors are constructed through bootstrapping the MRPL construction 1000 times. The bootstrap is set to draw households. MPRL estimates are in 2010 MWK. MRPL difference is constructed as farm MRPL minus non-farm MRPL. The MRPLs in the first and second columns are constructed by estimating a single production function but allowing the effects of all variables (except household fixed effects) to vary by enterprise type. MRPLs in the third and fourth columns are constructed by estimating separate production functions for farm and non-farm production. In the fifth column, MRPL is constructed by collapsing across plots and enterprises to the household/wave level and estimating a single production function, again allowing the effects of all variables (except household fixed effects) to vary by enterprise type.

*$P < .10$.

**$P < .05$.

***$P < .01$.

for all households (column 1) to final sample households (column 3) suggests the production technology is relatively similar. While labor appears slightly more productive—for both farm and nonfarm production—for the select subsample of households, the opposite is true for land. The coefficients on fertilizer and non-farm costs, however, are relatively similar.

The translog results are harder to interpret given the large number of interaction terms. Moreover, it is clear moving from column two to column four that we lose a substantial amount of precision in our estimates. This is especially true for farming. However, the translog coefficients for non-farm production are again remarkably similar for both groups of households. We formally test for the nested Cobb-Douglas in the translog specifications and present these results at the bottom of the table. We reject the Cobb-Douglas specification for farming for all households but fail to reject for our final sample. However, the *F*-test strongly rejects the Cobb-Douglas specification for non-farm production, with an F-statistic of 232 for column four. Given these results, we use the translog specification in the main results that follow.

We present the MRPL estimates in Table 4. Since MRPL equality is only theoretically predicted for households that operate both types of activities, we present MRPL results for only this subset of households. All MRPL estimates are in (March) 2010 Malawi Kwacha (MWK). We present the least restrictive estimates first in columns one and two, which are produced by estimating the farm and non-farm production functions separately, allowing the fixed effect to affect farm and non-farm production differently. Recall that we construct household MRPL estimates in two ways: taking the simple median across plots/enterprises and by weighting MRPLs across plots/enterprises based on labor allocation. The simple median suggests an average farm MRPL of about 115 MWK. In March 2010, the exchange rate was approximately 150 MWK to USD, so this MRPL translates to slightly less than one US dollar per worker-day. The average non-farm MRPL, on the other hand, is significantly smaller, at just 7 MWK. Finally, the difference, approximately 113 MWK, is highly significant. We come to identical conclusions when we aggregate MRPLs using labor allocation weights.

In column three, we construct MRPL estimates using the production function in column four of Table 3 (which pools the estimation for the households that operate both enterprises simultaneously). The fourth column of Table 4 presents results using the same base production function as the third column, but by aggregating MRPLs across plots/enterprises within a household using labor allocation weights. All three MRPL estimates—farm, non-farm, and the difference—are substantially more precisely estimated than the separate production functions. Moreover, the point estimates for farm MRPL are substantially smaller in magnitude while the estimates for non-farm MRPL are higher. Despite the difference being less than half as large as in the first two columns, it remains highly significant.

Taken at face value, these numbers point to possible costs from encouraging a reallocation of labor away from farm production and towards non-farm production. At the margin, reallocating a single day of labor in this

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direction is estimated to *decrease* income for the median household by around 56 Kwacha, which is a substantial percentage of average income in Malawi. If it is the case that the non-farm sector is indeed more productive than the farm sector, then our results suggest that the margin of adjustment is not within the household, but instead made by people completely switching sectors.

Given the evidence that disaggregated labor statistics are more prone to bias than are aggregated labor statistics (Arthi et al., 2018), we present another set of results in column 5 in which we aggregate all productive inputs to the household level *prior* to estimating production functions. We still pool these results and we present these MRPL estimates in column 5. Again, the results are completely consistent with the previous four columns. Taking these results together, we interpret this as evidence that farm MRPL tends to be higher than non-farm MRPL for the median household.

Given that our group of households is a selected sample, we estimate MRPLs for the sample of households that operate at least one farm or one non-farm enterprise in a given wave and present these results in columns one and two of Table A3. Overall, MRPL estimates present a similar picture to the summary statistics: farm MRPL is slightly higher for our final sample households, but non-farm MRPL is lower. The large difference between both enterprise and one non-farm enterprise MRPL is a bit misleading, as the one-enterprise MRPL estimate is imprecisely estimated; the upper bound of the 95% confidence interval of the distance indicates the difference could be as small as 20. Moreover, the median nonfarm MRPL when combining the two groups is just 22. In other words, the median MRPL across all households in the data is just 16 Kwacha higher than the median MRPL in our final sample of households.

Finally, we present daily wage estimates in column three of Table A3. The daily wages are substantially higher than MRPL in both the non-farm and farm sectors, suggesting the median household is not fully integrated into the local labor market. In other words, these households appear to be over allocating labor to household production—in both farm and non-farm enterprises—suggesting that increasing access to wage employment opportunities would increase household incomes.

5.1 | Bias in the production function estimates

We rely on fixed effects for identification. However, fixed effects do not control for time-variant omitted variables that may be correlated with both labor allocation and output, such as unobserved period-specific productivity shocks. As such, there are valid concerns that both labor coefficients may be biased. We believe the most likely direction of any possible bias in MRPLs is upwards. If true, then focusing on possible bias in the farm production functions is sufficient to determine whether bias plausibly drives our results.

A focus on the farm production function is helpful for two additional reasons. First, we are unable to reject the nested Cobb-Douglas for farm in our sample households (Table 3). Second, and related, using the Cobb-Douglas means we can focus on just a single coefficient. The translog production functions include labor in four different independent variables making discussion of bias complicated.[12]

For bias to be responsible for our results in Table 4, our estimated MRPL would have to be three or four times higher than the true MRPL. Median MRPL calculated from a single Cobb-Douglas production function for agriculture is 156.9, which is slightly higher than our main estimate. We present the corresponding production function estimates in column one of Table 9. The coefficient on labor is .429. For bias to be completely responsible for differences in MRPL, this coefficient would need to be more than three times too high (i.e., the true coefficient would need to be approximately .130, using the MRPL ratio from Table 4).

We use an instrumental variables strategy similar to that in Gollin & Udry (2020). We instrument for both land and labor using the interactions of rainfall with the share of other land in the village[13] planted with plots of the same crop and of the same characteristics. The idea here is that, controlling for own plot characteristics, these village-level variables affect labor allocation only through the shadow wage. The corresponding 2SLS estimate for labor is .332, or a decrease only one-third as large as the actual decrease needed for bias to explain the entire difference. However, these estimates are quite imprecise. Moreover, the F-stat of a joint test of significance for the instruments on both labor and land are between just five and six. In other words, these estimates may suffer from a weak instrument problem and not help our argument about the impact of bias.

There are two things worth noting which, we believe, reinforce our belief that bias is unlikely to be responsible for the estimated MRPL differences.[14] First, in both Tanzania and Uganda—two similar countries in sub-Saharan Africa—Gollin and Udry find a decrease in the labor coefficient of just six percent and 16 percent, respectively. In other words, in their contexts where the instruments

[12] Farm MRPL can be calculated as $\frac{\partial R}{\partial L} = \frac{\hat{R}_{iht}}{L_{iht}} \beta_L$.

[13] We really use the enumeration area, but call it village for simplicity.

[14] For this section, we contacted the authors of Gollin and Udry (2020) and asked them to share their uninstrumented production function estimates with us, which are not in the published paper. The authors kindly agreed.

appear to be better predictors of both land and labor, the authors do not find evidence of bias being very large. Second, the coefficient on labor across their countries and Malawi in this article are quite similar: .281 for Tanzania, .223 for Uganda, and .332 here in Malawi. Even if we used their lowest estimate of .223 for Uganda—that is, if we assumed the actual coefficient on labor in our own Cobb-Douglas results were .223—the estimated median MRPL using predicted output and labor allocation of the households in our sample would still be over 80. This is similar to the main results presented in Table 4, though is not directly comparable because results in Table 4 use the translog production function estimates.[15]

5.2 | Possible explanations for deviations from equality

While the above results show farm MRPL to be consistently higher than non-farm MRPL, there may be important factors of the environment in which these households operate that influence their allocation decisions. In this section, we first show that substantial heterogeneity in MRPLs exists, and then examine the role of price and production risk in explaining the allocation decisions we observe, consistent with the predictions in Table 1. Given the relative consistency across specifications and the fact that weighting by labor and pooling production functions (column four of Table 4) is not only the most precisely estimated but also the most conservative estimate of MRPL difference, we use this specification as the basis for all analyses that follow. We begin with a simple kernel density estimate of MRPL difference in Figure 3. For ease of presentation, we drop the top and bottom one percent of the sample. Consistent with our empirical results, the vast majority of the distribution lies to the right of zero, with the highest density around 50 MWK. While there is a wide distribution of MRPL differences, almost 86 percent of household/wave observations have a positive difference, which underscores the empirical results.

We next examine whether price and production risk help explain the allocation decisions we have observed. Tables 5 and 6 examine the role of price risk in allocation decisions.

[15] As additional evidence that the production function results are similar, the coefficients on land also react in identical ways when comparing 2SLS to OLS. In our results, the coefficient on land increases markedly. Gollin and Udry find the exact same pattern, supporting the contention that in their context, production functions appear similar to the production functions in our context. In other words, in their paper, 2SLS results do not support the argument that bias is driving our results, just like the results presented here, and the context appears to be quite similar.

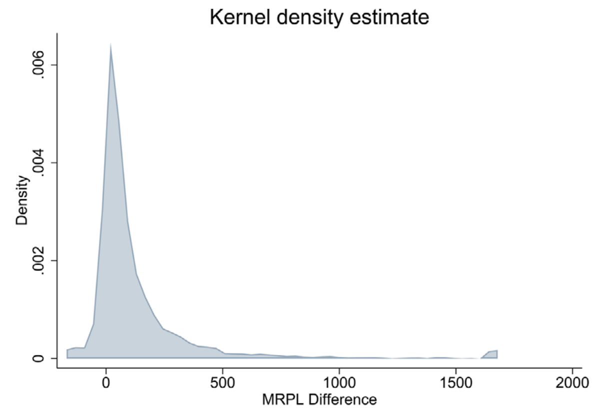

FIGURE 3 MRPL distribution - Pooled production function. MRPL estimates are constructed as in column four of Table 4. MRPL difference is constructed as farm MRPL minus non-farm MRPL. The top and bottom one percent are dropped for ease of presentation

In Table 5, we split the sample by crop choice and hiring, corresponding to the bottom two rows of Table 1. In Panel A, we look at households that grow maize (column one) and households that grow tobacco and/or cotton (column two). Maize is a common subsistence crop—and is thus more likely to be consumed, not sold, by our households (i.e., row two of Table 1)—and tobacco and cotton are common cash crops—and households, by definition, are net sellers of these crops (i.e., row three of Table 1). As shown by Barrett (1996), we expect larger deviations from equality for cash crops than subsistence crops when price risk affects decision-making. Consistent with this hypothesis, the observed MRPL difference is more than twice as large for households that grow tobacco and/or cotton than for households that grow maize. However, given the small sample size for cash crops, there is substantial imprecision. Nonetheless, the pattern supports the hypothesis.

In Panel B and Panel C, we split the sample by households that hire for farming (Panel B) and for non-farm (Panel C) and estimate MRPL separately for each group. Households that hire labor from the market may have higher productivity for the activity in which they hire for two reasons. First, the households may have higher productivity levels in order to afford hiring the outside labor. Second, households that hire labor are more exposed to price risk—in the sense of Sandmo (1971), that is, they are more likely to be net sellers—and therefore will under allocate labor to that activity and have a higher MRPL. Barrett (1996) shows that households that hire labor for farm production are more likely to be net sellers. Since all non-farm production is sold on the market, households that hire for non-farm production are more exposed to price risk for that activity. The results in Panels B and C of Table 5

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TABLE 5 MRPL, Crop Choice, and Hiring

	(1)	(2)
Panel A: Crop choice	**Subsistence (maize)**	**Cash (tobacco/cotton)**
Farm	72.127***	126.555**
	(12.707)	(56.512)
Non-farm	11.659	13.783
	(14.913)	(32.725)
Difference	50.033**	126.304*
	(21.744)	(72.375)
N (Household/wave)	2,254	362
Panel B: Hires for farm	**Yes**	**No**
Farm	130.832***	74.193***
	(25.301)	(8.552)
Non-farm	17.409	36.788***
	(22.931)	(13.338)
Difference	118.610***	33.970**
	(42.654)	(16.093)
N (Household/wave)	1,367	2,468
Panel C: Hires for non-farm	**Yes**	**No**
Farm	91.096**	81.051***
	(41.973)	(9.013)
Non-farm	127.762*	15.529
	(66.980)	(10.509)
Difference	−18.708	58.187***
	(79.980)	(15.464)
N (Household/wave)	362	3,473

A separate pooled production function is estimated for each column in each panel. Panel A splits the sample by crop choice, Panel B splits the sample by whether the household hires for farm production, and Panel C splits the sample by whether the household hires for non-farm production. Standard errors are constructed through bootstrapping the process 1000 times. The bootstrap is set to draw households.
*$P < .10$.
**$P < .05$.
***$P < .01$.

support these predictions, showing higher MRPLs in the activities for which households hire outside labor.

We also study MRPL heterogeneity using proxies for market access in order to test the importance of price risk. We now split households based on the median of three separate variables: total revenue, total acreage, and total crop sales in Panel A, Panel B, and Panel C, respectively, of Table 6. We assume households in the upper half of the distribution of these three variables have better access to markets. Column one presents MRPL estimates for all households above the median of the respective variable while column two presents estimates for all households below the median. If these variables are correlated with marketable surplus, we expect larger MRPL differences for households above the median than below if price risk appreciably affects labor allocation decisions. In fact, this is exactly what we see. When splitting the sample by revenue, households above the median show a median MRPL difference of more than 100 MWK, while households below the median show a difference of just seven MWK. We see a similar, though less pronounced, pattern for both acreage and crop sales. This is again consistent with the idea that price risk is an important component of agricultural decision-making.

Having established that price risk appears to be an important predictor of deviations from MRPL equality, we now move to rainfall and production risk. To examine the relationship between MRPL and production risk, we estimate MRPL using our main results in Table 4. We then estimate quantile (median) regressions of MRPL on both current rainfall and the rainy season precipitation coefficient of variation.[16] We do not split the sample as in Tables 5 and 6 in order to be able to include both

[16] The rainy season (November to April) precipitation coefficient of variation is defined using the previous 15 years (McCarthy and Kilic, 2015).

TABLE 6 MRPL and production characteristics

	(1) Above median	(2) Below median
Panel A: Revenue		
Farm	138.955***	42.473***
	(24.073)	(6.218)
Non-farm	41.700**	31.445***
	(20.125)	(11.303)
Difference	104.682**	7.471
	(35.819)	(10.384)
N (Household/wave)	1,909	1,918
Panel B: Acreage		
Farm	80.619***	77.049***
	(11.577)	(14.795)
Non-farm	11.954	31.617*
	(13.663)	(16.301)
Difference	63.403***	39.873*
	(21.654)	(22.318)
N (Household/wave)	1,909	1,918
Panel C: Crop Sales		
Farm	89.679***	73.451***
	(14.141)	(11.781)
Non-farm	11.521	37.302**
	(12.259)	(15.125)
Difference	75.981***	31.044
	(22.139)	(20.602)
N (Household/wave)	1,973	2,124

A separate pooled production function is estimated for each column in each panel. Panel A splits the sample by median of total revenue, Panel B splits the sample by median total acreage, and Panel C splits the sample by median of crop sales (gross). However, the median is zero, so this simply splits the sample by whether they sell or not. Standard errors are constructed through bootstrapping the process 1000 times. The bootstrap is set to draw households.
*$P < .10$.
**$P < .05$.
***$P < .01$.

rainfall variables simultaneously. We present these results in Table 7. In the table, there are three separate regressions. We only have both variables for waves one and two, so results are restricted to these waves.[17] When including both rainfall variables in each regression, a clear pattern emerges. Rainfall CV—the coefficient of variation, or the standard deviation divided by the mean, which we use as a proxy of production risk—is positively correlated with both farm MRPL and MRPL difference. The results are indicative of production risk affecting labor allocation significantly.

[17] We are able to match CV for some wave three households in the panel component of the data, under the assumption that rainfall CV is mostly unchanged between waves two and three.

TABLE 7 Median regression—MRPL and rainfall

MRPL:	(1) Farm	(2) Non-farm	(3) Difference
Current rainfall (mm)	−.010	−.001	−.012*
	(.008)	(.006)	(.015)
Rainfall CV	.377*	.039	.476*
	(.203)	(.161)	(.280)

The results are from three separate quantile (median) regressions using the different MRPL estimates as dependent variables. MRPL estimates come from column two of Table 3. Only waves one and two are included. Standard errors are constructed through bootstrapping the process 1000 times. The bootstrap is set to draw households.
*$P < .10$.
** $P < .05$.
*** $P < .01$.

Additional splits by household characteristics appear in Table A4. Specifically, we compare MRPL differences based on education of the household head, gender of the household head, and household size. Interestingly, across all different characteristics, non-farm MRPL is surprisingly consistent (the lowest is 19.1 and the highest is 25.6). Instead, any differences manifest themselves completely in agricultural production. Farm MRPL is higher for male-headed households than female-headed households, leading to a higher MRPL difference, and is higher for smaller households than larger households, also leading to higher differences. It is hard to draw too many conclusions due to effects pulling in different directions across household characteristics, but these MRPL differences are consistent with male-headed households planting more cash crops—which is empirically true—leading to higher agricultural MRPL under risk, and with larger households being more concerned about price risk—that is, with larger households being more likely to be net buyers—leading to lower agricultural MRPL.

5.3 | Robustness checks

One concern already documented is seasonality. Our specific concern is that although we restrict estimation to households that operate both non-farm enterprises and farm plots in the same year, it may still be the case that households allocate labor seasonally within the year, such that marginal revenue products in non-farm production come only from labor allocation in the farming slack season (either between planting and harvest or in the off-season). To check this possibility, we can estimate production functions and construct MRPL estimates based on month of interview. If seasonality is affecting our results, then we are likely to see substantially different

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TABLE 8 MRPL by months of interview

	August to January		February to July	
	(1)	(2)	(3)	(4)
	Simple median	Weighted by labor	Simple median	Weighted by labor
Farm MRPL	68.884***	68.280***	93.417***	95.648***
	(13.432)	(13.879)	(13.366)	(13.181)
Non-farm MRPL	24.973	24.821	34.934**	34.903**
	(15.650)	(15.586)	(15.233)	(15.204)
Difference	36.160*	35.015*	55.615***	57.082***
	(20.931)	(21.125)	(20.769)	(28.885)
Observations	1,778	1,778	2,053	2,053

Standard errors are constructed through bootstrapping the process 1000 times. The bootstrap is set to draw households. The results re-estimate the results from columns one and two of Table 4, restricting estimation only to households surveyed during the “high” non-farm season of August to January (columns one and two) or the “low” non-farm season of February to July (columns three and four).

*$P < .10$.

**$P < .05$.

***$P < .01$.

MRPL differences during planting and harvest seasons, especially since these two seasons apparently show large differences in non-farm labor allocation. Households that are interviewed during this time are simultaneously allocating labor to both types of production.[18]

Fortunately, the Malawi IHS allows us to examine whether seasonality may be affecting our results. Panel households were enumerated twice in every wave for the Malawi IHS. In general, approximately half of households responded to the non-farm module during the first visit—which tended to be during or just after the planting season—while approximately half of panel households responded to the non-farm module during the second visit, just after harvest.[19] Importantly, only panel households are visited twice. Moreover, panel households are the minority of our sample, as there are large cross-section components of waves one and three. As such, a large portion of households responded to the farm and non-farm modules during the same visit, during or immediately following harvest.

We estimate production functions separately for the subsample of households that were interviewed during the “low non-farm revenue” season, which we define as February to July[20], and the subsample of households that were interviewed during times of higher nonfarm labor allocation and revenue, from August to January. We present these results in Table 8. The first two columns restrict estimation to only non-farm enterprises that were interviewed from August to January, while the last two columns restrict estimation to only households interviewed from February to July. It appears that farm MRPL is slightly higher for those households interviewed from February to July, as is non-farm MRPL. Regardless of season, however, the difference remains positive and significant across the year. We interpret this as suggestive evidence that temporal variations in labor allocation and survey timing are unlikely to be driving our results.

A related explanation comes from possible differences in non-pecuniary benefits. Specifically, one concern with farm labor is that returns are not immediately realized. Non-farm labor, on the other hand, presumably results in more immediate cash. If households find themselves in need of cash immediately, they may have no choice but to allocate their time to non-farm self-employment, even if farm self-employment would net them more money overall. This could be the case if, for example, households need cash to pay for medical bills or school uniforms. We do not think this explains the entirety of our findings, however, for two reasons. First, we believe this effect will be seasonal. Specifically, following harvest when there is more cash on hand—and more crops to sell—this effect should be muted. Yet, we see differences in MRPL across production activities regardless of timing (Table 8). Second, our main results include cross-section households, which make up a much larger proportion of our sample than panel households, the latter of which identify the effects in Table 8. Most cross-section households, however, were interviewed after harvest, where we might not expect this effect to dominate.

Another possible explanation is that rainfall happened to be very good in the three survey years, which might induce an increase in MRPL over what was expected by

[18] Table A2 in the appendix presents summary statistics for month of interview across all three waves.

[19] All panel households should have reported agricultural output during the harvest visit.

[20] This only refers to the non-farm module. The farm statistics still come from the post-harvest questionnaire.

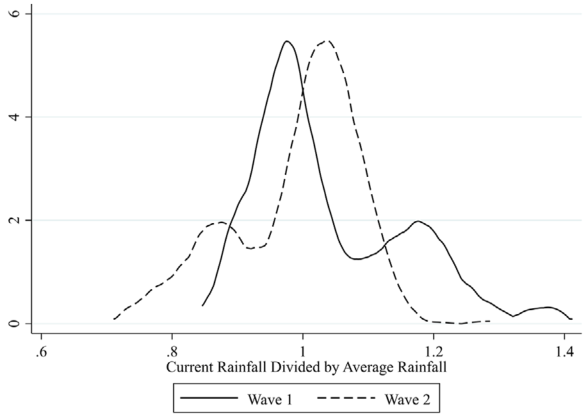

FIGURE 4 Yearly rainfall in waves one and two

farmers.[21] Figure 4 presents kernel density estimates of rainfall in waves one and two (the only waves for which we have rainfall CV data). The figure shows that rainfall was relatively higher than the 10-year average in wave one but relatively lower in wave two. While we do not have rainfall for wave three, we can look at other proxies for rainfall. Whenever farmers report area harvested lower than area planted, they are asked for the cause. In wave three, around 60 percent of plot-crop observations report lower area harvest than area planted. Of these, between 80 and 90 percent (depending on whether we use the cross-section or panel subsample) blame drought or irregular rains. In other words, it appears that wave three was actually a relatively poor rainfall year in Malawi. Based on these facts, we conclude above average rainfall is unlikely to be driving our high farm MRPL estimates.

In the appendix, we also explore the robustness of MRPL estimates to several variations in specifications. In Table A5, we present MRPL estimates when not trimming the top one percent of revenue and labor. We also estimate MRPL when using a minimum of 10 prices observations instead of five to construct aggregate crop prices (Table A7) as well as no minimum number of price observations (Table A8). Finally, in Table A6, we estimate MRPL using actual revenue instead of predicted revenue. Our conclusions are unchanged and farm MRPL remains higher than non-farm MRPL in all models/specifications.

5.4 | Policy implications

There are three main policy implications from this research. First, many people have rightfully highlighted the importance of insurance in improving the livelihoods of rural households in developing economies. The main finding of this article is that the MRPL in non-farm production is less than the MRPL in farm production. This is consistent with farm production being riskier than non-farm production. In terms of efficient allocation of labor, insurance which reduces the risks associated with farm production would allow households to allocate more labor to farm production, thereby both increasing the allocative efficiency of labor, and increasing the overall income of the household. As such, efficacious development policies that aim at increasing household income might include ways to help households mitigate and/or manage agricultural risks, whether that be the expansion of affordable credit, through agricultural extension services, or through other policies. While this type of focus might lead to households actually intensifying their agricultural production, it might nonetheless allow them to increase their incomes.

Second, wages are substantially higher than estimated MRPL in both farm and nonfarm production. While the first point argues that households are under allocating labor to farm production relative to non-farm production, the results with respect to wages also suggest that households are over allocating labor to household production relative to wage employment. It is clear that households are not fully integrated into the local labor market, with the most likely explanation being that households face a binding demand constraint. This is consistent with recent results for Malawi in Dillon et al. (2019).

The third primary policy implication of this research is that for these Malawian households, farm production has higher returns than non-farm production. This result is not consistent with the conventional wisdom that structural transformation out of agriculture is a necessary condition for development to occur. However, this does not imply the conventional wisdom is wrong altogether. It could be that the process of development happens when households completely switch from agriculture to non-farm sectors—historically manufacturing, but more and more commonly services—and does not apply to the types of activities that agricultural households conduct alongside their farming activities, as analyzed in this article. Policies aimed at promoting structural transformation should therefore be more focused on these discrete shifts in activity and less on the advancement of non-farm enterprises amongst agricultural households, at least in Malawi.

6 | CONCLUSION

In this article, we examine allocative efficiency across farm and non-farm production in rural households. At first glance, we present evidence of labor misallocation in

[21] Recall that we use predicted revenue to construct our main MRPL estimates, which is likely a better predictor of households' ex ante expectations. However, results in the appendix also show that the use of actual revenue instead of predicted revenue does not affect our results.

Malawi, though in a surprising direction; across a number of specifications, farm MRPL is consistently *higher* than non-farm MRPL. However, we show that risk plays an important role in labor allocation, suggesting that deviations from profit-maximizing conditions are not inconsistent with rationality. Our results suggest that removing risk—or, similarly, insuring farmers against risk—might result in higher incomes.

There are some important caveats to our findings. First, our sample is a relatively select group of households from just a single country. Previous research has shown that research findings may differ substantially across countries in sub-Saharan Africa (Dillon et al., 2019). Second, our estimation strategy requires a specific set of identification assumptions and, as such, omitted variables are a very real possibility. As with all such assumptions, additional studies that rely on different identification assumptions are required.

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SUPPORTING INFORMATION

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