I Z A Institute of Labor Economics
Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 13682

# Smallholders, Market Failures, and Agricultural Production: Evidence from India

Joshua D. Merfeld

SEPTEMBER 2020

I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 13682

# Smallholders, Market Failures, and Agricultural Production: Evidence from India

**Joshua D. Merfeld**
*KDI School of Public Policy and Management and IZA*

SEPTEMBER 2020



ISSN: 2365-9793

**IZA – Institute of Labor Economics**

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

# ABSTRACT

## Smallholders, Market Failures, and Agricultural Production: Evidence from India*

Market completeness has important implications for household behavior. I firmly reject complete markets for smallholders but am unable to do so for non-smallholders. This leads to important differences in production behavior: smallholders reallocate labor across activities less in response to intra-seasonal crop price changes than do non-smallholders. A counterfactual exercise indicates smallholders could increase revenue by almost nine percent if they were to reallocate labor similarly to non-smallholders. The overall pattern of results is consistent with small-holders lacking sufficient wage employment opportunities. Since non-smallholders have to hire in for agricultural production, this lack of opportunities does not affect their decisions.

**JEL Classification:** J20, J43, O13, Q12, Q13
**Keywords:** markets, market failures, agriculture, labor

**Corresponding author:**
Joshua D. Merfeld
KDI School of Public Policy and Management
263 Namsejong-ro
Sejong-si
South Korea
E-mail: merfeld@kdis.ac.kr

* I am indebted to Leah Bevis, Marc Bellemare, Rajeev Dehejia, Alex Eble, Jonathan Morduch, Martin Rotemberg, and Debraj Ray for discussions and comments. Seminar participants at NYU, Columbia, and the KER conference provided helpful comments. All remaining errors are my own.

# 1 Introduction

Do households act as if markets are complete? While earlier research was less conclusive (Benjamin, 1992), the more recent papers in this body of literature consistently reject market completeness in a diverse set of circumstances, including sub-Saharan Africa (Dillon and Barrett, 2017; Dillon et al., 2019) and southeast Asia (LaFave and Thomas, 2016). However, while these results contribute to our understanding of market structure in these countries, little work has examined some of the implications of these specific findings of market (in)completeness.[1] This paper contributes to and extends this literature by empirically testing predictions for agricultural production in the face of market failures.[2] In addition, treating market failures as a household-specific phenomenon allows for a better understanding of exactly what kinds of markets appear to be failing and for which households.

An important feature of agricultural households is that they are both producers and consumers of the same good. This feature is described in the classical agricultural household model (Singh et al., 1986). In the canonical model under common assumptions, production and consumption decisions are separable. In other words, households are able to first make production decisions to maximize profits and then make consumption decisions. Importantly, this implies that production decisions are independent of consumption decisions and, thus, that household consumption preferences do not affect production decisions. This is a powerful simplification that underlies a number of influential studies into many different facets of household behavior. Both LaFave and Thomas (2016) and LaFave et al. (2018) enumerate a (non-exhaustive) list of some of these studies, which include: the operation of markets (Jayachandran, 2006; Kaur, 2019; Rosenzweig, 1980); nutrition, intrahousehold allocation of resources, and productivity (Strauss, 1984;

[1]Importantly, it is not a question of whether markets are incomplete, but rather whether household behave as if markets are incomplete.

[2]Previous theoretical and empirical research has examined the impacts of market failures on production decisions (de Janvry et al., 1991; Taylor and Adelman, 2003), including when labor markets are incomplete (Sadoulet et al., 1998).

Udry, 1996); technology adoption (de Janvry et al., 1991; Conley and Udry, 2010; Suri, 2011); risk (Townsend, 1994; Jacoby and Skoufias, 1997); and, perhaps most pertinent to the present study, wage determination and labor supply (Barnum and Squire, 1979; Strauss, 1986; Kochar, 1999).

However, the recursion property rests on a number of stringent assumptions, one of which is complete markets.[3] Yet, there is ample evidence that markets are not complete in developing countries. The most direct evidence comes directly from tests of the recursion property itself. Benjamin (1992) was the first to note that recursion implies production decisions should be independent of any household characteristics that affect only consumption, like demographic characteristics. As such, a straightforward test for market completeness is to regress total farm labor on household demographics; under the null hypothesis of complete markets, household demographics should not affect total farm labor demand and the vector of coefficients will be zero. Rejection of this hypothesis implies that markets are not complete. While Benjamin (1992) was unable to reject complete markets, more recent literature unequivocally challenges this finding; Dillon and Barrett (2017), Dillon et al. (2019), and LaFave and Thomas (2016) all strongly reject market completeness in multiple contexts.

Importantly, however, these results provide little intuition into what markets may be failing or why.[4] Moreover, this omnibus test does not yield any insight into how market failures may impact farmer decision-making. In this paper, I provide empirical evidence of some of the implications of market failures for agricultural production in India. In other words, I ask: what can we say about how markets – or the lack thereof – affect production decisions made by Indian households? While answering this question, I also provide one of the first direct tests of market failures in the Indian context and present additional evidence that market failures are a household-specific phenomenon; while I reject that

[3]For example, recursion also relies on perfect substitution of family and hired labor as well as no preferences for working on one's own farm.

[4]Dillon et al. (2019) is an exception. The authors explore asymmetric labor responses in an attempt to shed more light on the functioning of specific markets.

smallholders behave as if markets are complete, I am unable to reject this hypothesis for non-smallholders, consistent with recent evidence from Indonesia (LaFave et al., 2018).

Taking these results at face value, I then analyze whether smallholders and non-smallholders behave as predicted by economic theory. If smallholders behave as if markets are incomplete but non-smallholders do not, economic theory predicts that labor elasticity, with respect to crop prices, should be lower for smallholders. To test this prediction, I use five years of high-frequency data from ICRISAT's Village Dynamics in South Asia (VDSA) project. The data contain monthly data on labor allocation, wages, and crop prices. I first implement the classical test of Benjamin (1992) and LaFave and Thomas (2016) by regressing total farm labor on a vector of household demographic characteristics. Results strongly reject recursion – and, thus, that households behave as if markets are complete – for smallholders but fail to reject recursion for non-smallholders. I then empirically test the theoretical predictions. Identification comes from within-season reallocation of labor across different activities. I condition on all planting decisions and examine how households reallocate labor in response to price changes between planting and harvesting.

After first confirming that households do indeed reallocate labor in response to changes in crop prices within the agricultural season, I then test the the main theoretical prediction. The evidence clearly indicates that smallholder households respond less to intra-seasonal crop price changes than do non-smallholders. Moreover, the patterns suggest that smallholders have excess labor but may lack off-farm employment opportunities. I also perform a simple counterfactual exercise to estimate how much labor reallocation increases seasonal output. If smallholders were able to reallocate labor in response to price changes, like non-smallholders, revenue on the plots included in this study would be almost nine percent higher.

Additional results using labor allocated to non-agricultural activities provides additional evidence of how markets may fail for smallholders. In particular, an (unexpected) increase in crop price induces smallholders to report lower levels of involuntary unemployment but does not affect their allocation to wage employment. This is consistent with a story in which a decrease in crop prices leads smallholders to reallocate time to (unsuccessfully) search for off-farm wage labor. Importantly, non-smallholders do not reallocate labor to these two non-agricultural activities in response to changes in crop prices; the coefficients are not only insignificant but also small in magnitude. While none of the evidence comes from direct tests of which markets are failing, the overall evidence points to an environment in which smallholders overallocate labor to agricultural production. Consistent with this story, the number of acres-per-person is much higher for non-smallholders than smallholders. This is consistent with non-smallholders behaving as if markets are complete but with smallholders behaving as if they are not. In other words, it appears that non-smallholders may be able to hire in whenever they are in need of additional labor, but that smallholders are not always able to find wage employment, leading them to allocate their excess labor to agricultural production.

This paper contributes to several lines of literature. Most obviously, this paper extends the literature testing for market completeness using the agricultural household model (Benjamin, 1992; Dillon and Barrett, 2017; Dillon et al., 2019; LaFave and Thomas, 2016). In addition to providing evidence of market completeness in India in a more general sense, I also argue that market failures are a household-specific, not market-specific, phenomenon. This is consistent with other contemporaneous evidence from Indonesia (LaFave et al., 2018). While this is not a new argument, this paper offers clear empirical evidence of some of the implications of household-specific market failures.

Other research that does not explicitly test for market completeness nonetheless presents evidence consistent with incomplete markets. For example, findings that the shadow wage differs across activities is not consistent with the complete-markets case (Brummund and Merfeld, 2019; Jacoby, 1993; Skoufias, 1994). This paper extends earlier empirical and theoretical literature on the implications of market failures (de Janvry et al., 1991; Sadoulet et al., 1998; Taylor and Adelman, 2003) by leveraging arguably exogenous variations in prices between planting and harvest to examine how households respond when markets are incomplete.

The rest of this paper is organized as follows. The next section elaborates a theoretical model of how market completeness affects household production decisions. Section 3 discusses the data and methodology, including summary statistics. Section 4 presents the main results and Section 5 concludes.

# 2 Separation and Agricultural Production

Consider an agricultural household that maximizes its own utility, subject to agricultural production and a possible off-farm labor constraint. Consumption, $c$ and leisure $l$, are the arguments in the household's utility function. The household operates $i > 0$ plots and allocates its own labor to any of those plots, $L_i^F$, and wage labor, $L_w$, subject to possible constraint on total wage labor supplied off-farm, $\bar{L}_w$. Thus, the household's total time endowment is $\bar{L} = l + \sum_i L_i^F + L_w$. The household can also hire in labor, $L_i^H$, where $i$ again indexes different plots.

Thus, the household's problem is:

$$\max E\left[u(c, l|\ \gamma_i)\right], \text{subject to :} \tag{1}$$

$$c \leq \sum_i p_i f_i(L_i^F + L_i^H; A_i)\gamma_i + w(L_w - \sum_i L_i^H) \tag{2}$$

$$\bar{L} \geq l + \sum_i L_i^F + L_w \tag{3}$$

$$\bar{L}_w \geq L_w \tag{4}$$

$$0 \leq L_i^H, L_i^F, L_w, l, \tag{5}$$

where $\gamma_i$ is a multiplicative productivity shock, $p_i$ is the price of the crop grown on plot

$i$, and $w$ is the wage. The expectation is taken across $\gamma$. Due to my identification strategy, I model this as a static problem. The strategy focuses on *intra*seasonal labor reallocations across plots and, thus, land is fixed during the relevant period.

The assumption of complete markets is very useful analytically. As previously shown (Benjamin, 1992; Dillon et al., 2019; LaFave and Thomas, 2016), complete markets allow households to separate production decisions from consumption decisions. In effect, households first maximize farm profits before making consumption decisions. The household's production decisions can thus be modeled as:

$$\max E\left[\sum_i p_i f_i(L_i; A_i)\gamma_i + w(L_w - \sum_i L_i^H)\right] \equiv \pi^*. \tag{6}$$

Powerfully, this means that total farm labor, $L^{Total}$, is only a function of prices:

$$L^{Total*} = L^{Total*}(p_i, w \mid \gamma_i) \tag{7}$$

This prediction has formed the basis of most tests for complete markets. When markets are complete, total farm labor is uncorrelated with household consumption characteristics, such as household demographic variables. This is the basis for the first test in this paper, which follows LaFave and Thomas (2016) and which I describe in detail in section 3.

However, there are additional implications on the production side of market completness. In particular, the profit function itself implies a number of specific relationships across variables. First, consider the first-order conditions for total labor demand on a plot after the productivity shock has been realized[5]:

[5]This assumption is compatible with the identification strategy used in this paper, which I elaborate below.

$$p_i \frac{\partial f_i}{\partial L_i} \gamma_i = w. \tag{8}$$

Importantly, conditional on the price of crop $i$ and the market wage, the price of crop $j \neq i$ does not affect labor demanded on plot $i$. Intuitively, this is driven by the fact that each plot's labor choice is driven by equality of the marginal revenue product of labor (MRPL) with the market wage. A change in the price of crop $j$ will affect the MRPL of labor on plot $j$, but will not affect the MRPL of labor on plot $i$. Consider now a world in which the off-farm labor constraint (equation 4) is binding.[6] The first-order conditions are now,

$$p_i \frac{\partial f_i}{\partial L_i} \gamma_i = w^* = p_j \frac{\partial f_j}{\partial L_j} \gamma_j, \tag{9}$$

where $w^*$ is the household shadow wage, which need not equal the market wage. Unlike the market wage, the shadow wage is directly affected by labor reallocations across productive activities within a household.[7] Suppose $p_j$ increases, simultaneously increasing the MRPL of $L_j$. To bring the household back to an optimal allocation of labor, the household must increase $L_j$ in order to bring $MRPL_j$ back to equality with other labor uses. At the same time, given the market constraint – and the fact that households for whom $\bar{L}_w$ binds do not simultaneously hire labor – households must allocate labor *away* from other activities. In the current model, this would be $l$ and $L_i$. Thus, an increase in $p_j$ affects both $L_i$ and $l$, whereas neither is affected when markets are complete.

Figure 1 presents a graphical explanation of this. Panel A shows the change in $L_i$ when

[6] More generally, at least two markets are required to fail if we are to observe non-separation in the data.

[7] Indeed, the shadow wage is defined as being equal to the MRPL at the optimum. In the complete-market case, on the other hand, the optimal MRPL is determined by the market wage itself, and labor is only reallocated to bring the MRPL back into line with the wage.

$p_i$ changes and markets are complete. The increase in price induces an increase in MRPL, which in turn induces the household to increase $L_i$ through either an increase in $L_i^F$ – if the household supplies labor to the market – or by hiring in labor and increasing $L_i^H$ – if $L_w$ was already zero at the previous optimum. Again, however, labor allocated to other plots (or to household activities) should be unaffected. Panel B shows the same situation when markets are incomplete. A rise in $p_i$ induces an increase in $MRPL_i$, which then causes the household to increase labor allocated to plot $i$. However, given the labor constraint, this reallocation must come from a decrease in labor allocated to other activities, such as plot $j$. This reduction in labor allocated to plot $j$ causes a simultaneous increase in $MRPL_j$. This adjustment results in a smaller increase in $L_i$ in the incomplete markets case than in the complete markets case. In other words, the elasticity of labor with respect to crop price is lower when markets are incomplete. This is the key prediction tested in this paper.

## 2.1 Productivity Spillovers

One alternative explanation for the predictions above is productivity spillovers. For example, the total amount of labor a farmer allocates to her plots may directly affect productivity on plots, even conditional on total labor allocated to each plot individually. One possible explanation for such a relationship would be if input (or output) prices depend on the quantity purchased (sold). Importantly, any effects on output either directly or indirectly through labor productivity can impact the predictions made above.

As way of example, suppose the total amount of labor applied across all plots affects the marginal product on a plot, even conditional on that plot's labor allocation. Specifically, assume increasing total labor applied across plots also increases the marginal (revenue) product of labor on plot $i$. Then, an increase in the price of the crops planted on other plots will lead to an increase in labor applied to those other plots. In turn, this increase in labor application leads to an increase in the marginal revenue product of labor on plot $i$. In the complete market case, the household would then *increase* labor applied to plot $i$

to re-equate MRPL on that plot with the market wage. In the incomplete market case, on the other hand, this would lead to less of a reallocation of labor away from plot $i$. To test for these possibilities, I test for spillovers of this type in the results section below.

## 2.2 Efficiency of Family and Hired Labor

Another alternative, explicated in Benjamin (1992), is that family and hired labor have different prices. This could be driven, for example, by differing efficiencies of family and hired labor. There are two possibilities. First, consider a situation in which family labor is less efficient than hired labor. In this case, the household's profit-making labor allocation is to allocate family labor completely to the market, until the point that the marginal utility of an additional hour of work is equated with the marginal utility of an additional hour of leisure, with consumption being the relevant trade-off between the two. Importantly, the predictions above are unchanged, as separation still occurs: the household maximizes on-farm profits by allocating only hired labor to agricultural production, up to the point that the MRPL of that hired labor equals their wage.

The second case, in which family labor is more efficient than hired labor, is different. Following Benjamin (1992), assume family and hired labor are perfectly substitutable, but one hour of hired labor is equal to $\alpha$ hours of family labor. Thus, we can write total family labor-efficient units as:

$$L_e^F = L^F + \alpha L^H. \tag{10}$$

Importantly, the exact mix of family and hired labor will depend on household preferences; separation does not occur. However, the *total efficiency units of labor do not depend on household preferences*. Rather, they are determined by the first-order conditions (Benjamin, 1992). Thus, for a given $\alpha$ and a given $L_e^F$, the total amount of labor applied will be unchanged across plots, within the household.

This is a key point for this paper, as we can model profit-maximizing labor allocation decisions as plot-specific. In other words, a change in the price of a crop on plot $j \neq i$ does not change the first-order conditions for profit maximization on plot $i$. As such, the general predictions explicated above should hold here, as well.

# 3 Data and Empirical Strategy

This paper uses ICRISAT's Village Dynamics in South Asia (VDSA) data.[8] ICRISAT has been collecting longitudinal data in India for several decades, but I use the most recent longitudinal data, which spans the years 2010 to 2014. My final sample, which I describe in more detail below, comprises 1,089 different households across 17 districts in 8 different states. Importantly, the data contains monthly-level information on labor and resource allocation across agricultural plots for the entire five years of the panel. Data is collected monthly, so recall is minimized. In addition, the village data collects information on individual crop prices relevant for local farmers, also at monthly intervals, which plays an important role in the empirical strategy I employ. Finally, five separate years of data remove some concerns regarding the heterogeneity of effects when populations are subject to aggregate shocks (Rosenzweig and Udry, 2020).

## 3.1 Empirical Strategy and Identification

This paper approaches the question of separation and complete markets in several ways, making use of the rich panel data. Since I use household-level fixed effects, all regressions cluster standard errors at the household level unless otherwise reported. First, I borrow specifications from prior literature and analyze whether household demographics predict farm-level labor demand (Benjamin, 1992; Dillon and Barrett, 2017; Dillon et al., 2019; LaFave and Thomas, 2016). I diverge from the prior literature in two key ways. First, five

[8] http://vdsa.icrisat.ac.in/vdsa-index.htm

years of panel data allow me to employ fixed effects at much lower levels of aggregation than other literature. In particular, I am able to estimate regressions using household-plot-crop fixed effects, which restricts attention only to plots planted with the same crop in multiple years. Second, much of the previous literature has used data from Africa (Dillon and Barrett, 2017; Dillon et al., 2019) or Indonesia (Benjamin, 1992; LaFave and Thomas, 2016), whereas the ICRISAT VDSA data was collected in India.

I first explore the relationship between household demographics and plot-level labor demand:

$$logL_{ikt} = \alpha_{cik} + \gamma_{vtdc} + X_{ikt} + rain_{vt} + \beta(\Sigma_{g=1}^{G}\delta_{gkt}) + \varepsilon_{ikt}, \tag{11}$$

where $logL_{ikt}$ is log of total labor applied to plot $i$ in household $k$ in season $t$, $\alpha_{cik}$ is household-plot-crop fixed effects, $\gamma_{vtdc}$ is village-wave-season-crop fixed effects, $X_{ikt}$ is a vector of time-variant plot characteristics – area planted and area irrigated – $rain_{vt}$ is total rainfall in village $v$ in season $t$, $\delta_{gkt}$ is a group of variables indicating the number of household members that reside in the household in each demographic group $g$, and $\varepsilon_{ikt}$ is a mean-zero error term. Following previous literature, the assumption of complete markets implies that $\beta$ is a vector of zeros, that is, that demographic variables do not belong in the labor-demand equation. Thus, the null hypothesis is that $\beta = 0$, and F is the appropriate test statistic. I split household members into five separate demographic groups: prime-age males (15-59), prime-age females, elderly males (60+), elderly females, and children (<15). The main specifications include log of household size along with shares of four of the five demographic groups, with children being the omitted category. I also test robustness to alternative demographic definitions.

Identification here relies on there being no unobserved time-variant variables correlated with the error term and the demographic variables. The village-wave-season-crop fixed effects help alleviate any concerns that crop-specific aggregate village shocks in a given season are correlated with household size and total labor allocation. This could be the case if, for example, shocks lead to changes in migration. Household-plot-crop fixed effects alleviate additional concerns related to the endogeneity of household size, crop choice, and area planted. For example, if changes in household size are correlated with planting decisions – perhaps a larger household will decide to plant a larger area – then controlling for area planted may actually lead to biased demographic coefficients. While this would be a clear rejection of the separation hypothesis, if the effect of demographics on labor demand operates completely through area planted, then the bias might lead to a failure to reject the null hypothesis if we control for area planted. The fixed effects help alleviate this concern.

While the previous literature on separation and market failures has pooled all households, market failures are in fact a household-specific phenomenon. Just because one household has access to credit, for example, does not imply that other households in the immediate vicinity also have access to credit. As such, pooling all households may give a misleading picture of the context of household behavior. One variable that may be correlated with access to markets is landholdings. As such, I estimate Equation 11 separately for smallholders and non-smallholders, as defined by the survey. Smallholders are defined as landholders in the lowest two brackets of the landholding distribution. demogsums1 presents summary statistics of some of the differences between smallholders and non-smallholders in the VDSA data.

The predictions of the model relate to how households respond to changes in prices. It is difficult to find exogenous variation in prices with respect to household labor allocation and output at an aggregate level. As such, I focus on individual households and how they reallocate labor across plots *within* the agricultural season. In particular, I focus on monocropped plots – plots planted with just a single crop – and examine how households reallocate labor when the price of one crop changes relative to the price of another crop on that household's own plots. Before testing the predictions of the model, I first verify that households do indeed reallocate labor across plots in response to changes in crop prices. I estimate:

$$logL_{ikmy} = \alpha_{cik} + \gamma_{dymc} + X_{ikmy} + Z_{ikt} + rain_{vmy} + \beta logP_{ymvc} + \varepsilon_{ikmy}, \qquad (12)$$

where $logL_{ikmy}$ is log of non-planting and non-harvest labor allocated to plot $i$ in household $k$ in month $m$ in year $y$, $\alpha_{cik}$ is household-plot-cropped fixed effects, $\gamma_{dymc}$ is district-year-month-crop fixed effects, $X_{ikmy}$ is a vector of characteristics that vary by month (specifically, the amount of labor and materials that had been allocated to that plot in that season up to that point), $Z_{ikt}$ is a vector of planting hours and planting materials in that season, and $logP_{ymvc}$ is the monthly price of the crop planted on that plot, which is defined at the village level. In some specifications, I allow the effects of $X$, $Y$, and $rain$ to vary by the month of the year. In this specification, the coefficient of interest is $\beta$; it shows the effect of a change in the crop price on labor allocation at the plot level. For labor, note that this includes both family labor and hired labor. Perhaps unsurprisingly, hired labor is much more common for non-smallholder households.

The main hypotheses relate to how households respond to changes in crop price, similar to the specification in Equation 12. To this end, many of the specifications are simple variations on Equation 12. For prediction one, I restrict attention to households with just two separate crops. I add an additional variable to the specification, which is the price of the second crop grown by the household (that is, the price of the crop that is not grown on plot $i$). For the other two predictions, I interact the crop price dummy ($logP_{cvmy}$) with a dummy for smallholder (prediction two) or with both a dummy for smallholder and the number of crops grown by the household (prediction three).

## 3.2 Identification

This paper explores how households respond to change in crop prices *within* the agricultural season. One advantage of this strategy is that area planted is necessarily fixed after the planting season, avoiding one complication. However, the key drawback is that household labor allocation and crop prices may be endogenous. Most obviously, they may both be responding to (expected) temporal changes in the agricultural season or a shared cause, like rainfall. What my empirical strategy needs to accomplish is to purge any expected changes in crop prices, as well as any spurious causation caused by other variables. In essence, I need the crop price variable to represent *unexpected* changes in the crop price for any given household.

To accomplish this, the identification strategy relies heavily on fixed effects. Within variation comes from district-year-month-crop fixed effects. Since all households in a district will be similarly affected by aggregate shocks for a given crop, identification comes from unexpected differences in the price for a single crop across villages within a district. This helps purge any possibility that households change plots based on pre-planting signals – like weather forecasts (Rosenzweig and Udry, 2014, 2019). Also note that permanent differences in prices for a given crop in different villages within the same district are swept out by the household-plot-crop fixed effects.[9]

Since identification comes from within-season variation in crop prices, I control for all previous plot-level decisions. This includes the number of hours and materials used during planting as well as the sum of all previous hours and materials allocated to the plot between planting and the month of observation. Controlling for previous decisions should help alleviate any concerns that cyclical patterns are driving decisions, in addition to the fixed effects. In most specifications, the effect of previous hours and materials are

[9]The district-year-month-crop fixed effects are also important to sweep out aggregate correlations in prices, output, and labor allocation driven by weather. Table A1 shows that in a simple cross-section regression total output, at the plot level, is highly negatively correlated with harvest price. This is likely driven by the fact that poor output driven by weather shocks often leads to higher crop prices. However, once we include the district-year-month-crop fixed effects, this negative correlation disappears.

allowed to vary by the month of the year. I also include monthly rainfall totals, which are also allowed to vary by the month of the year, since the timing of rainfall is especially important in rain-fed agriculture.

Since crop prices vary at the village-crop level and both smallholders and non-smallholders reside in each village, it is unlikely that differences in the predictive power of crop prices alone can explain the results. Nonetheless, if there is heterogeneity in the make-up of each village, this is possible. Appendix Table A2 shows that, at the plot level, lagged crop prices are equally predictive of current crop prices for both smallholders and non-smallholders. In other words, any differential reactions to price changes are not driven by differences in the predictive power of prices for different households.

A short discussion of what actually drives the (unexpected) crop price changes is warranted. At first glance, one might wonder whether this is simply noise. However, certain households in the sample, non-smallholders, respond very strongly to these signals, suggesting noise cannot alone explain the variation. Within-country price variation persists in developing countries (Osborne, 2004; Chatterjee and Kapur, 2016; Zant, 2018), even in countries like India, which has invested significant amounts of money in improving infrastructure (Bellemare et al., 2013; Chatterjee and Kapur, 2016). In India, specifically, much of this variation may be driven by strict laws governing where farmers are able to market their agricultural output; farmers are generally only allowed to market output in the state in which they live, leading to cross-border discontinuities in prices, despite geographic proximity (Chatterjee, 2019). This does not, however, explain intra-state variation in prices. Instead, a look towards infrastructure may provide a partial answer. Though I control for village-specific rainfall, I do not control for rainfall and general agricultural productivity conditions in areas to which a given village is connected. Idiosyncratic changes in connected villages may drive similarly idiosyncratic changes in a given village. In fact, previous research has shown that just how one village is connected to other areas plays an important roll in price variation (Zant, 2018).

### 3.3 Summary Statistics

Table 1 presents summary statistics for a number of different variables, broken down by smallholder status. Note that observations are at the household-plot level, the same level at which Equation 11 is estimated. First, note that non-smallholders actually have larger households, on average, than smallholders. The demographic breakdown of the households are somewhat similar, though it appears that non-smallholders have slightly more prime-age female and smallholders have slightly more children.

On average, actual plots are larger, in terms of area planted, for non-smallholders, though they do not appear more likely to be irrigated, at least as a percentage of the plot. Consistent with this, non-smallholders also allocate more hours to these large plots. However, hours do not increase as much as area when comparing non-smallholders and smallholders, suggesting smallholder plots may be cultivated more intensively than non-smallholder plots, consistent with previous research. While individual plots are approximately 65 percent larger for non-smallholders, overall area planted is even higher, approximately three times larger than smallholder area planted.

Crop choice is somewhat similar across household types, though there are some differences. The highest average price per kg is highest for green gram, and non-smallholder plots are slightly more likely to be planted with green gram. Chickpea and pigeonpea are also higher-priced crops, and non-smallholder plots are more likely to grow the former, but not the latter. However, the most commonly grown crops, paddy and wheat – which together make up more than half of all plots – are equally likely to be grown on a plot across the two household types.

Table 2 presents summary statistics, at the plot level, for five different "months" of the year: one month prior to harvest, two months prior to harvest, three months prior to harvest, four months prior to harvest, and five months prior to harvest. The first thing to note is that total non-planting hours show modest differences by month, with total hours increasing by approximately 30 percent from one month prior to harvest to three months prior to harvest. Though the overall pattern for hired labor is similar, the magnitude of the change is much greater for hired labor than for total labor. Total materials used (in rupees), on the other hand, does not show similar patterns. Rather, materials appear to be increasing up until one month prior to harvest, at which point they decrease markedly. Crop prices appear to be increasing as we approach harvest – consistent with the months just before harvest being the leanest time of the year – other than five months prior to harvest. However, there are relatively few observations five months prior, so it is difficult to draw any firm conclusions.

# 4 Results

## 4.1 Testing for Separation Using Household Demographics

The results begin with the household separation regression in Equation 11. Table 3 presents these results. The first column is a cross-section regression of total plot-level labor on household demographics. The F-test at the bottom of the table strongly rejects the null hypothesis for the first column. However, since this is a cross-section regression, differences in households may be driving the results. Recall that non-smallholder households tend to be larger than smallholders. Since non-smallholder plots are also larger, the correlation between household size – though not necessarily household demographic make-up – and labor demand could be explained by these differences. Consistent with this, column two – which adds household-plot fixed effects – and column three – which adds household-plot-crop fixed effects – suggest a much different conclusion. In neither column do we reject the null hypothesis that all demographic variable coefficients equal zero.

However, the first three columns assume all households face similar conditions. Since market failures and separation are household-specific, we may be missing the bigger picture. Columns four through six allow the effects of the demographic variables to differ across household types.[10] It appears that the results do not reject separation for non-smallholder households, but do reject separation for smallholder households. This is consistent across the three columns, including when we allow for two-way clustering at both the household level and the village-season level.[11] In other words, it appears that smallholder households do not act as if markets are complete, as consumption characteristics are predictors of production decisions. We are unable to reject no correlation for non-smallholders, however.[12]

The correlation between demographics and labor demand for smallholders appears to be driven by prime females. Since the four demographic groups are share variables and household size is included as a covariate, the share variables are interpreted as changing the make-up of the household, but not changing the household. The omitted category is children, so the coefficients are interpreted as increasing each group relative to (i.e. decreasing) children. For smallholders, apparently having more women and fewer children leads to an increase in labor demand. One possibility is that women have more trouble finding outside work than men and, as such, the excess labor is applied to household production. In this case, to household agricultural production.

## 4.2 Labor Allocation and Crop Prices

The rest of this paper takes this result at face value and assumes separation holds for non-smallholders but not for smallholders. Before digging into the key predictions of differences in price-labor elasticities, I first present evidence that mid-season hours are

[10]They are estimated in a single regression, however.

[11]Since household-plot fixed effects are included in all columns, area planted is not necessarily a required covariate. Moreover, as shown in Table A3, household size is strongly correlated with area planted on individual plots. Nonetheless, column six adds area planted and area irrigated as additional covariates. Qualitative conclusions are unchanged.

[12]Table A4 presents robustness checks of varying demographic definitions. We consistently reject the null for smallholders but not for non-smallholders.

productive and that there are no obvious cross-plot spillovers due to total labor allocation. I then show that households respond to changes in crop prices by reallocating labor across plots based on these price changes.

First, Table 4 explores the productivity of mid-season hours – those hours between planting and harvest. The table presents results from a simple Cobb-Douglas production function, with log of output, in rupees, as the dependent variable and total mid-season labor hours (log plus one) as the key independent variable. Additional covariates also include planting decisions, which are likely correlated with both output and mid-season hours. Columns one through four show that mid-season hours are significant predictors of total output at the end of the season. One percent higher mid-season labor hours is associated with an increase in output of somewhere between 0.04 and 0.06 percent. In other words, these hours are indeed productive and, as such, farmers may reallocate their hours in response to changes in expected revenue driven by changes in crop prices.

Since the key prediction this article tests is that market failures lead to a linkage across plots, we must first rule out spillovers across plots due to other reasons. One possibility is that there are productivity spillovers due to labor allocation. Perhaps an increase in hours allocated to plots increases productivity due to bulk purchase discounts, for example. Columns five and six test this possibility. Column five adds as a covariate total mid-season hours on other plots. The coefficient is small – less than one-third the size of the mid-season hours coefficient – and not significantly different from zero. In column six, I include an additional interaction between mid-season hours on the plot and total mid-season hours on other plots. Again, there do not appear to be any spillovers related to mid-season labor allocation, at least not conditional on the other covariates included in the model.

Next, Table 5 asks whether households reallocate their labor in response to price changes. These regressions are at the household-plot-year-month level. The key covariate is now the price of the crop planted on that plot and, as such, I am no longer able to include village-by-crop-by-year-by-month fixed effects since this is the same level of variation as crop prices. As such, I move the fixed effect up to the district level instead fo the village level. As discussed above, I am isolating differences in crop prices across villages within the same district, conditional on household-plot-crop fixed effects, which should absorb any permanent differences in crop prices across these same villages. Column one again presents simple cross-sectional estimates. In the cross-section, there does not appear to be a correlation between the price of a crop in a specific month and the amount of labor a household allocates to a plot planted with that crop. Column two adds household-plot fixed effects and the coefficient increases markedly, by about five times. Column three then adds planting decisions – labor and materials. Although the coefficient is now marginally significant, substantive qualitative conclusions are no different between columns two and three; there appears to be a slight positive relationship between crop prices and labor allocation.

Columns one through three include total previous labor and materials allocated to the plot as well as monthly rainfall totals. However, it seems likely that the effect of these variables will depend on the month of the year. For example, rainfall during certain months may be much more important if it increases productivity more than in other months. As such, column four allows the effects of these covariates to vary by month of the year. This leads to an increase in the effect of crop price. It appears that households do indeed reallocate labor in response to changes in crop prices, with an implied elasticity of approximately 0.3. This elasticity is substantively unchanged if we add household-plot-crop fixed effects (column five) or the wage rate (column six). We also see an association between crop price and materials, though the coefficient is very imprecisely estimated. As we will see shortly, these estimates belie important heterogeneity.

Additional specifications are presented in Table A5. For labor, I test an additional specification adding village-month-crop fixed effects, which removes any village-level shared variation in the same month of the year for the same crop. This essentially treats seasonal patterns more explicitly, looking at within-village variation in the same month to the same crop across different years. The second column tests this possibility even more stringently, by including household-month-crop, instead of village-month-crop, fixed effects. The coefficients for the labor models actually increase quite markedly, suggesting even larger price responses. For materials, the household-month-crop fixed effects specification in column three results in an attenuated coefficient. As such, the labor results are quite robust, but the materials results are a bit less so.

Recall that when households act as if markets are complete, the relevant labor trade-off for each plot is between the productivity on that plot and wage employment. If a household is working both for a wage and on one's own farm, then when a crop price increases, the household will shift family labor away from wage work and towards that crop. On the other hand, if the crop price decreases, the household will shift labor away from that crop and towards wage employment. Importantly, since households are price takers, this additional labor allocation to wage employment does not affect the wage.

If markets are not complete, however, this is not the case. For a household that faces a wage labor constraint, they are not able to shift additional labor towards wage employment. This means any additional labor allocated to or from a plot must be from/to other places: leisure, domestic production, or other plots. Unlike with wage employment, this shift in labor also affects marginal productivity of labor in said tasks. This leads to a smaller labor reallocation response for these households than for households that are able to reallocate labor towards or away from wage employment.

Table 6 tests this prediction with four different dependent variables: total mid-season hours, family mid-season hours, hired mid-season hours, and mid-season materials. Column one presents the results for all labor. Consistent with economic theory, the elasticity of labor (re)allocation with respect to the crop price is significantly lower for smallholders than non-smallholders. For non-smallholders, a one-percent change in the crop price leads to a change in labor allocation of approximately 0.4 percent. For smallholders, on the other hand, it is just 0.15 percent.

Columns two and three present results for family and hired labor, respectively. While smallholders and non-smallholders reallocate family labor similarly, non-smallholders respond to crop price changes with hired labor much more than do smallholders. This is consistent with a world in which non-smallholder households need to hire in additional wage labor to meet their labor requirements, but smallholder households have what amounts to excess labor. Excess labor in this sense refers to smallholders having MRPLs on their plots lower than the market wage if they were to allocate all of their available labor to own agricultural production. Non-smallholders, on the other hand, would have MRPLs *higher* than the market wage, leading to them hiring additional labor. If true, smallholders would, on average, hire much less labor than non-smallholders, which is exactly what we see in the data. Moreover, the average seasonal total planted area per person – across the crops used in this study – is 2.27 acres per person for non-smallholders but just 0.77 acres per person for smallholders. We also see a difference in elasticities for materials, though the estimate for non-smallholders is quite imprecisely estimated.

The appendix presents several different robustness checks. First, Table A6 relaxes identifying assumptions by including village-year-month-crop fixed effects instead of district-year-month-crop fixed effects. The level effect of crop price is no longer identified, but the difference in its effect across household types is. All four specifications yield identical conclusions. Additionally, column five, including village-year-month-crop-fixed effects, also adds next month's crop price and its interaction with smallholder as an additional covariate. This is included to insure predicted price changes are not driving results. Column six instead includes district-year-month-crop fixed effects, the same specification as those in Table 6, as well as the following month's crop price, for a more apples-to-apples comparison to the results listed here in the main text. Qualitative conclusions are unchanged. In other words, it does not appear to be expected seasonal patterns driving the reallocation of labor.

Finally, all specifications in Table 6 include planting variables and the sum of all previous input choices as covariates. While these are not lagged variables in the traditional sense, it nonetheless raises some concerns regarding serial correlation and panel data. Table A7 presents results removing all planting and previous input allocation decisions from the regression. Conclusions are again unchanged.

### 4.3 Quantifying the Effects of Reallocation on Agricultural Output

If non-smallholder farmers do indeed reallocate labor in response to crop price changes more than smallholders, this suggests non-smallholders are more able to increase overall revenue output by responding to unexpected intra-season crop price changes. This section attempts to quantify this amount. An important caveat is required: these results take several coefficients at face value and ignore uncertainty in the estimation. As such, the point estimate should be taken with a grain of salt.

I quantify the effects of labor reallocation in several steps. First, I estimate total mid-season hours based on the planting and harvest price of the crop, at the household-plot-year-season level. I estimate this separately for both smallholders and non-smallholders. Consistent with the main results, non-smallholders appear to respond to harvest price but smallholders do not. These results are presented in Table A9. I then predict labor allocation for *all* households based on each regression, under the assumption that non-smallholders do not respond to harvest prices. Then, I estimate the effects of mid-season labor allocation for smallholders and non-smallholders on total output. Using the predicted labor allocations based on the price change from the first step, I then compute two separate predicted outputs for each household: one in which they respond to price signals (like non-smallholders), denoted $\hat{y}_{NS}$, and one in which they do not respond to price signals (like smallholders), denoted $\hat{y}_S$.

For each household, I then compute the difference between these two, or $\phi_{diff} = \hat{y}_{NS} - \hat{y}_S$. In other words, for every household, $\phi_{diff}$ is the difference in total predicted output based on whether they reallocate labor in response to price changes or not. The distribution of $\phi_{diff}$ is presented in Figure 2, separately for smallholders and non-smallholders. The point estimate suggests smallholders could increase their total output by almost 9 percent if they responded to price changes like non-smallholders. Non-smallholders, on the other hand, would have total output approximately 16 percent lower if they did not respond to price changes. Note that this does not include any additional income that might come from, for example, additional wage employment if it were available. This estimate pertains only to a reallocation of labor across plots.

### 4.4 Accounting for Changes in the Time Use of Household Members

The dataset also collects information on monthly labor allocation of individual household members. We can use this information to further explore some aspects of the theory and perhaps better understand the nature of agricultural production in rural India. To do this, I look at changes in individual-level time allocation to different productive activities based on changes in crop prices. One big issue with this is that most households grow more than one crop. As such, I create a price variable that is a weighted average of all crops grown by a household, weighted by the percentage of area in a given season allocated to each crop. In other words, for each household, I look at their total acreage in a season. I then take the percentage of that total acreage devoted to each individual crop and use that percentage to weight crop prices. Variation then comes from the changes in these prices throughout the season. While this is an admittedly imperfect measure, there is no obvious "price" to use for households that grow more than one crop.

Regressions include district-year-month-crop fixed effects and individual-crop fixed effects, where crop is defined not as individual crops, but as the exact combination of crops grown. In other words, identification comes from comparing individuals with the same combination of crops but with different percentages of land allocated to each crop.

The first set of results are in Table 7. I look at five separate types of activities: own farm days, wage days, other (productive) days, involuntary unemployment days, and non-farm work days (which are defined as the sum of wage and other days). I include all individuals in the dataset and also include age and age squared as covariates. Since there are a lot of zeros – only 25 percent of individual-month observations have non-zero wage days, for example – I transform all of the time-use variables using an inverse hyperbolic sine transformation (Bellemare and Wichman, 2020).[13] The first column is own farm days. As we would expect, we see a positive relationship between monthly (weighted) crop price and own farm days for both smallholder and non-smallholder households.

Column two presents result for wage labor. There appears to be no relationship between individual wage employment and crop price. However, this is additional evidence that many smallholders may face a wage labor constraint; if that constraint is already binding, then smallholders will not be reallocating any labor to or away from wage employment unless the MRPL on that household's plots is only slightly below the market wage, such that an increase in price would lead them to again equate MRPLs and the market wage. The negative coefficient is consistent with some households facing such a situation, but the coefficient is nowhere near significance, so caution is warranted interpreting even the sign. For non-smallholders, on the other hand, if they need to hire in labor for agricultural production, we would not expect them to also work on the market. A null effect is consistent with this.

We see no movement of other days, a relatively ill-defined category. The most interesting results are for involuntary unemployment days. There is a strong negative correlation between weighted crop price and involuntary unemployment days for smallholders. One possible interpretation for involuntary unemployment is when an individual searches for wage employment but fails to find any for a day, resulting in a day of (involuntary) unemployment. While an increase in one's own crop price(s) should not affect the probability

[13]Using logs is preferred because it allows for a straightforward elasticity interpretation. As such, in the main results presented above, I use logs as there are many more non-zero observations. Crop price, for example, is never zero, while mid-season hours has many more non-zero observations. Table A8 presents these same time-use results in levels. Qualitative conclusions are unchanged.

of finding outside employment conditional on searching, it could affect the probability an individual searches for outside unemployment. A negative coefficient for smallholders suggests higher own crop prices makes individuals less likely to search for wage employment. Again, we see no relationship for non-smallholders, as we would expect.

# 5 Conclusion

The overall evidence suggests that smallholders and non-smallholders respond much differently to price changes. These results are especially pertinent in a country like India, where the government is heavily involved in setting agricultural prices. The Indian government directly affects prices on both the consumption and production sides, through its public distribution system (PDS) and minimum support price (MSP) policies, respectively. Indirectly, other policies can also impact prices. For example, legislation that restricts farmers' sales to only markets within that farmer's state may artificially depress prices received by farmers (Chatterjee, 2019).

The policy implications of these findings can be substantial. First and foremost, any policy changes that affect agricultural prices – like the PDS and MSP – are likely to have different impacts on agricultural output in different areas. In other words, different households will respond differently to the same change in price driven by an agricultural policy. Production may remain relatively constant for a given crop in areas with more smallholders but may change significantly in areas with more large landholders. Similarly, the results on number of crops grown and the *increase* in elasticity for smallholders suggests districts with environments more amenable to diverse production may see larger changes in crop production than districts that are less suitable for diverse production if price of that crop changes.

Second, but related, changes to crop prices will have larger impacts on non-agricultural production and production of other crops for different types of households. Theory and results show that in order to increase production of a crop, smallholders must reallocate labor away from some other type of household production. Non-smallholders, however, do not. This implies that if, for example, the price of paddy increases, smallholders will have to decrease labor to production of other crops – if they grow other crops – decreasing production of those crops. Similarly, they may decrease time spent on other household production activities, as well. It is not clear from the present results exactly what type of domestic production decreases, but if less time is spent on human capital accumulation – time spent with children, for example – then there could be longer term knock-on effects. This is an interesting avenue for future research.

Third, the overall evidence points to providing off-farm wage employment to smallholder households as a potential way to increase economy-wide efficiency and improve the welfare of smallholders. Overallocation of labor to agricultural production leaves "money on the table" for smallholders. Interestingly, one possible policy intervention in this area is a public works program, like the Mahatma Gandhi National Rural Employment Guarantee Scheme (NREGS). NREGS has been found to provide households with alternative employment opportunities, allowing them to possibly allocate more labor to riskier productive activities (Gehrke, 2019; Merfeld, 2019). However, it is noteworthy that the data used in this paper come from after implementation of NREGS. As such, while it is possible that NREGS "improved" the overallocation of labor seen in smallholders, it clearly did not completely alleviate the problem.

An important takeaway from these results is that the market context in which a household operates can drive the household's behavioral responses to market signals. In other words, if we were to transplant the smallholder households into an environment in which they had ample access to off-farm wage labor opportunities, we might see them respond differently. This argument suggests that it is not necessarily differences in production technologies, per se, which drive differences in labor supply (and demand) responses. Instead, market structure itself can be a defining feature of these responses. This, of course, does not imply that production technologies do not also influence these decisions. How underlying production characteristics interact with market failures remains an interesting avenue for future research.

## References

Barnum, H. N. and Squire, L. (1979). An econometric application of the theory of the farm-household. *Journal of Development Economics*, 6(1):79–102.

Bellemare, M. F., Barrett, C. B., and Just, D. R. (2013). The welfare impacts of commodity price volatility: evidence from rural Ethiopia. *American Journal of Agricultural Economics*, 95(4):877–899.

Bellemare, M. F. and Wichman, C. J. (2020). Elasticities and the inverse hyperbolic sine transformation. *Oxford Bulletin of Economics and Statistics*, 82(1):50–61.

Benjamin, D. (1992). Household composition, labor markets, and labor demand: testing for separation in agricultural household models. *Econometrica*, pages 287–322.

Breza, E., Kaur, S., and Shamdasani, Y. (2020). Labor Rationing: A Revealed Preference Approach from Hiring Shocks.

Brummund, P. and Merfeld, J. (2019). Should farmers farm more? Comparing marginal products within Malawian households. *Working paper*.

Chakrabarti, S., Kishore, A., and Roy, D. (2018). Effectiveness of food subsidies in raising healthy food consumption: public distribution of pulses in India. *American Journal of Agricultural Economics*, 100(5):1427–1449.

Chatterjee, S. (2019). Market power and spatial competition in rural india. *Working paper*.

Chatterjee, S. and Kapur, D. (2016). Understanding Price Variation in Agricultural Commodities in India: MSP, Government Procurement, and Agriculture Markets. In *India Policy Forum July*, volume 12, page 2016.

Chatterjee, S. and Kapur, D. (2017). Six puzzles in Indian agriculture. In *India Policy Forum 2016*, volume 17, page 13.

Conley, T. G. and Udry, C. R. (2010). Learning about a new technology: Pineapple in Ghana. *American Economic Review*, 100(1):35–69.

de Janvry, A., Fafchamps, M., and Sadoulet, E. (1991). Peasant Household Behaviour with Missing Markets: Some Paradoxes Explained. *Economic Journal*, 101(409):1400–417.

Dillon, B. and Barrett, C. B. (2017). Agricultural factor markets in Sub-Saharan Africa: An updated view with formal tests for market failure. *Food Policy*, 67:64–77.

Dillon, B., Brummund, P., and Mwabu, G. (2019). Asymmetric non-separation and rural labor markets. *Journal of Development Economics*, 139:78–96.

Gehrke, E. (2019). An Employment Guarantee as Risk Insurance? Assessing the Effects of the NREGS on Agricultural Production Decisions. *The World Bank Economic Review*, 33:413–435.

Jacoby, H. G. (1993). Shadow wages and peasant family labour supply: an econometric application to the Peruvian Sierra. *The Review of Economic Studies*, 60(4):903–921.

Jacoby, H. G. and Skoufias, E. (1997). Risk, financial markets, and human capital in a developing country. *The Review of Economic Studies*, 64(3):311–335.

Jayachandran, S. (2006). Selling labor low: Wage responses to productivity shocks in developing countries. *Journal of Political Economy*, 114(3):538–575.

Jha, R., Bhattacharyya, S., and Gaiha, R. (2011). Social safety nets and nutrient deprivation: An analysis of the National Rural Employment Guarantee Program and the Public Distribution System in India. *Journal of Asian Economics*, 22(2):189–201.

Kaur, S. (2019). Nominal wage rigidity in village labor markets. *American Economic Review, forthcoming*.

Kochar, A. (1999). Smoothing consumption by smoothing income: hours-of-work responses to idiosyncratic agricultural shocks in rural India. *Review of Economics and Statistics*, 81(1):50–61.

LaFave, D., Peet, E., and Thomas, D. (2018). Who behaves as if rural markets are complete? *Colby College Working Paper*.

LaFave, D. and Thomas, D. (2016). Farms, families, and markets: New evidence on completeness of markets in agricultural settings. *Econometrica*, 84(5):1917–1960.

Meenakshi, J. and Banerji, A. (2005). The unsupportable support price: an analysis of collusion and government intervention in paddy auction markets in North India. *Journal of Development Economics*, 76(2):377–403.

Merfeld, J. D. (2019). Moving up or Just Surviving? Non-Farm Self-Employment in India. *American Journal of Agricultural Economics, forthcoming*.

Osborne, T. (2004). Market news in commodity price theory: Application to the Ethiopian grain market. *The Review of Economic Studies*, 71(1):133–164.

Rosenzweig, M. R. (1980). Neoclassical theory and the optimizing peasant: An econometric analysis of market family labor supply in a developing country. *The Quarterly Journal of Economics*, 94(1):31–55.

Rosenzweig, M. R. and Udry, C. (2014). Rainfall forecasts, weather, and wages over the agricultural production cycle. *American Economic Review*, 104(5):278–83.

Rosenzweig, M. R. and Udry, C. (2020). External validity in a stochastic world: Evidence from low-income countries. *The Review of Economic Studies*, 87(1):343–381.

Rosenzweig, M. R. and Udry, C. R. (2019). Assessing the Benefits of Long-Run Weather Forecasting for the Rural Poor: Farmer Investments and Worker Migration in a Dynamic Equilibrium Model. *National Bureau of Economic Research No. w25894*.

Sadoulet, E., De Janvry, A., and Benjamin, C. (1998). Household behavior with imperfect labor markets. *Industrial Relations: A Journal of Economy and Society*, 37(1):85–108.

Singh, I., Squire, L., and Strauss, J. (1986). *The basic model: theory, empirical results, and policy conclusions*, pages 17–47.

Skoufias, E. (1994). Using shadow wages to estimate labor supply of agricultural households. *American Journal of Agricultural Economics*, 76(2):215–227.

Strauss, J. (1984). Joint determination of food consumption and production in rural Sierra Leone: Estimates of a household-firm model. *Journal of Development Economics*, 14(1):77–103.

Strauss, J. (1986). Does better nutrition raise farm productivity? *Journal of Political Economy*, 94(2):297–320.

Suri, T. (2011). Selection and comparative advantage in technology adoption. *Econometrica*, 79(1):159–209.

Taylor, J. E. and Adelman, I. (2003). Agricultural household models: genesis, evolution, and extensions. *Review of Economics of the Household*, 1(1-2):33–58.

Townsend, R. M. (1994). Risk and Insurance in Village India. *Econometrica*, 62(3):539–591.

Udry, C. (1996). Gender, agricultural production, and the theory of the household. *Journal of Political Economy*, 104(5):1010–1046.

Zant, W. (2018). Trains, trade, and transaction costs: How does domestic trade by rail affect market prices of Malawi agricultural commodities? *The World Bank Economic Review*, 32(2):334–356.

# Tables

Figure 1: Agricultural Production and Market Failures

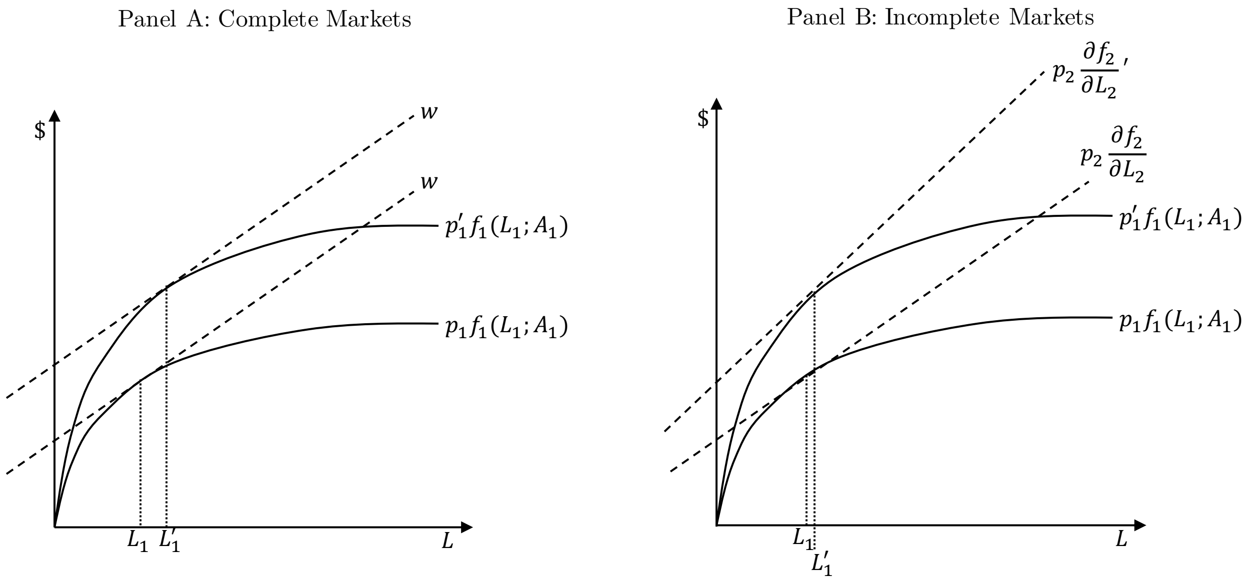
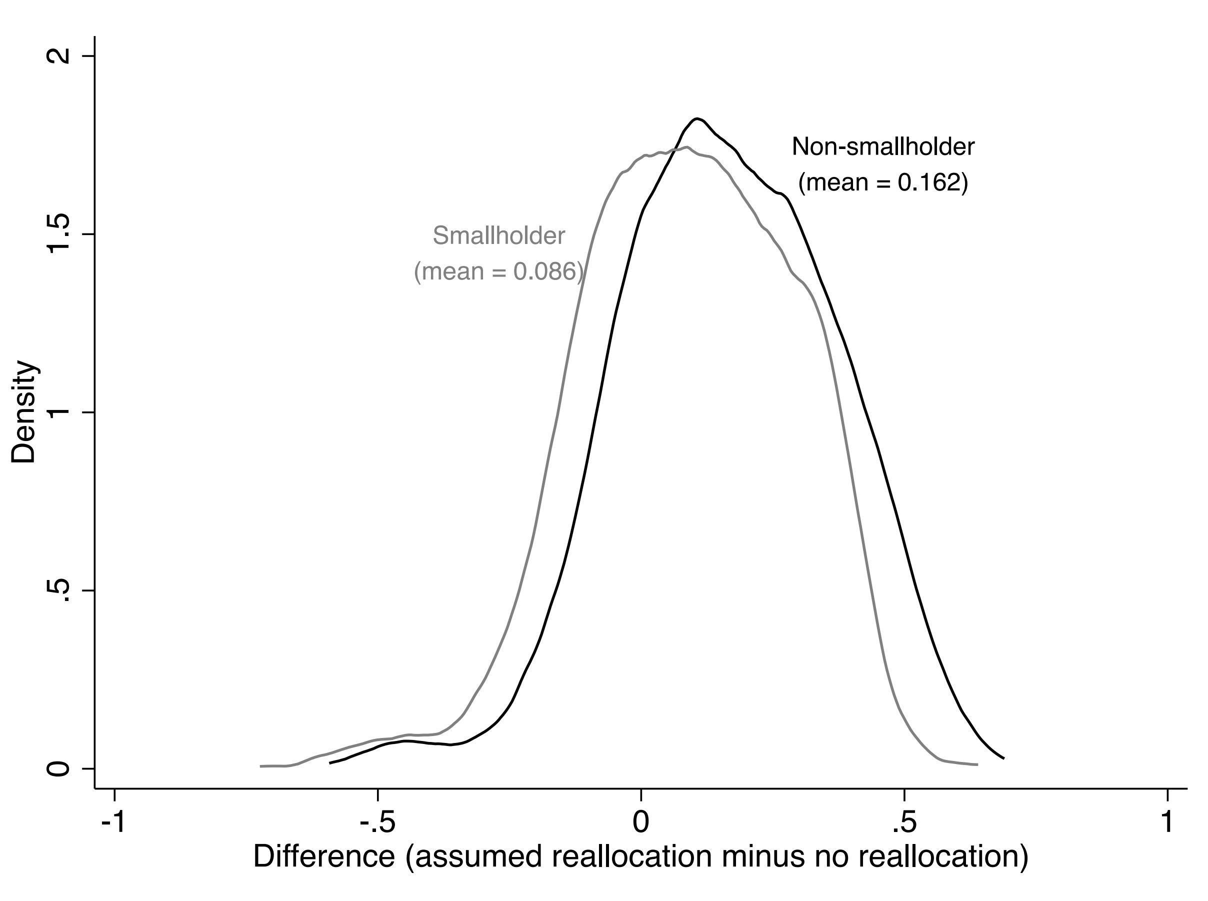


Figure 2: Effects of Labor Reallocation on Total Output




The figure shows the predict difference in output for households that reallocate labor in response to price changes relative to households that do not reallocate labor in response to price changes.

Table 1: Demography and Plot Summary Statistics

| | (1)<br>Non-smallholders | (2)<br>Smallholders | (3)<br>Diff (1-2) | (4)<br>p-value |
|---|---|---|---|---|
| Household size | 6.983 | 5.698 | 1.285 | 0.000 |
| | (3.488) | (2.260) | | |
| Elderly male percent | 0.110 | 0.102 | 0.008 | 0.439 |
| | (0.145) | (0.158) | | |
| Elderly female percent | 0.027 | 0.019 | 0.008 | 0.092 |
| | (0.079) | (0.065) | | |
| Prime male percent | 0.493 | 0.473 | 0.020 | 0.287 |
| | (0.241) | (0.240) | | |
| Prime female percent | 0.146 | 0.148 | −0.001 | 0.924 |
| | (0.179) | (0.176) | | |
| Child percent | 0.223 | 0.258 | −0.034 | 0.025 |
| | (0.187) | (0.199) | | |
| Plot area planted (log acres) | −0.393 | −0.893 | 0.501 | 0.000 |
| | (1.219) | (1.148) | | |
| Plot area irrigated (percent) | 0.581 | 0.540 | 0.041 | 0.218 |
| | (0.492) | (0.497) | | |
| Total plot non-harvest labor (log hours) | 3.390 | 3.073 | 0.317 | 0.005 |
| | (1.847) | (1.766) | | |
| Total area, all plots (log acres) | 1.802 | 0.674 | 1.128 | 0.000 |
| | (1.201) | (1.043) | | |
| Total non-harvest labor, all plots | 3.186 | 2.165 | 1.021 | 0.000 |
| (log hours) | (2.331) | (2.139) | | |
| Blackgram | 0.023 | 0.020 | 0.004 | 0.467 |
| | (0.151) | (0.140) | | |
| Chickpea | 0.085 | 0.054 | 0.031 | 0.003 |
| | (0.278) | (0.225) | | |
| Greengram | 0.011 | 0.006 | 0.005 | 0.036 |
| | (0.103) | (0.078) | | |
| Groundnut | 0.045 | 0.037 | 0.008 | 0.424 |
| | (0.207) | (0.188) | | |
| Lentil | 0.034 | 0.026 | 0.008 | 0.196 |
| | (0.180) | (0.158) | | |
| Maize | 0.050 | 0.073 | −0.023 | 0.025 |
| | (0.219) | (0.261) | | |
| Paddy | 0.303 | 0.296 | 0.007 | 0.806 |
| | (0.460) | (0.457) | | |
| Pigeonpea | 0.101 | 0.103 | −0.002 | 0.908 |
| | (0.302) | (0.304) | | |
| Sorghum | 0.069 | 0.120 | −0.051 | 0.001 |
| | (0.253) | (0.325) | | |
| Wheat | 0.279 | 0.265 | 0.014 | 0.532 |
| | (0.448) | (0.442) | | |
| Observations | 6,957 | 3,577 | | |

Statistics are at the household-year-season-plot level, the same level and sample used in Table 3. The first column presents means and standard deviations for non-smallholders, as defined by the survey, while the second column presents the same statistics for smallholders. The third column presents the difference between (1) and (2) and the fourth column presents the p-value for that difference, calculated using a regression and clustering standard errors at the household level.

Table 2: Monthly Summary Statistics

| | Months until harvest | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | One | Two | Three | Four | Five |
| Non-planting hours (log) | 2.619 | 2.697 | 2.892 | 2.807 | 2.719 |
| | (1.222) | (1.320) | (1.262) | (1.091) | (1.266) |
| Non-planting hired hours (log) | 0.888 | 1.183 | 1.528 | 1.254 | 1.258 |
| | (1.463) | (1.618) | (1.696) | (1.590) | (1.604) |
| Materials used (log Rs) | 4.574 | 4.864 | 4.349 | 4.087 | 3.273 |
| | (2.586) | (2.452) | (2.760) | (2.547) | (3.201) |
| Monthly crop price (log Rs) | 3.250 | 3.154 | 3.050 | 2.908 | 3.341 |
| | (0.701) | (0.718) | (0.705) | (0.627) | (0.971) |
| Total previous non-planting hours (log) | 4.289 | 3.436 | 2.643 | 2.298 | 1.795 |
| | (1.505) | (1.777) | (1.793) | (1.793) | (1.737) |
| Total previous materials (log Rs) | 6.832 | 5.580 | 4.626 | 4.565 | 3.003 |
| | (2.347) | (3.048) | (3.264) | (3.173) | (3.426) |
| Observations | 3,534 | 5,178 | 4,483 | 2,037 | 326 |

Statistics are at the household-year-month-plot level, the same level and sample used in Table 5 and Table 6. The statistics are broken down by months until harvest at the plot level, with five including any months greater than five, as well.

Table 3: Labor Allocation and Household Demographics

| | (1) All labor | (2) All labor | (3) All labor | (4) All labor | (5) All labor | (6) All labor |
|---|---|---|---|---|---|---|
| | | | | | Non-smallholders | |
| Household size | 0.036*** | −0.002 | 0.000 | −0.012 | −0.012 | −0.021 |
| | (0.009) | (0.014) | (0.014) | (0.017) | (0.019) | (0.019) |
| Prime male percent | 0.417*** | −0.154 | −0.039 | 0.004 | 0.004 | 0.034 |
| | (0.107) | (0.167) | (0.184) | (0.257) | (0.281) | (0.266) |
| Prime female percent | 0.486** | 0.378 | 0.351 | −0.329 | −0.329 | −0.219 |
| | (0.190) | (0.250) | (0.280) | (0.384) | (0.385) | (0.383) |
| Elderly male percent | 0.352*** | −0.111 | −0.004 | −0.123 | −0.123 | 0.019 |
| | (0.132) | (0.187) | (0.205) | (0.314) | (0.300) | (0.281) |
| Elderly female percent | 0.583** | 0.342 | 0.206 | 0.299 | 0.299 | 0.108 |
| | (0.245) | (0.540) | (0.640) | (0.558) | (0.532) | (0.495) |
| | | | | | Smallholders | |
| Household size | | | | 0.015 | 0.015 | 0.014 |
| | | | | (0.015) | (0.014) | (0.015) |
| Prime male percent | | | | −0.183 | −0.183 | −0.163 |
| | | | | (0.246) | (0.230) | (0.226) |
| Prime female percent | | | | 1.161*** | 1.161*** | 1.140** |
| | | | | (0.411) | (0.440) | (0.440) |
| Elderly male percent | | | | 0.031 | 0.031 | 0.063 |
| | | | | (0.239) | (0.222) | (0.218) |
| Elderly female percent | | | | −0.517 | −0.517 | −0.482 |
| | | | | (1.309) | (1.313) | (1.122) |
| **Clustering:** | | | | | | |
| Household | X | X | X | X | X | X |
| Village-season | | | | | X | X |
| **Fixed Effects:** | | | | | | |
| Village-Wave-Season-Crop | X | X | X | X | X | X |
| Household-Plot | | X | | | | |
| Household-Plot-Crop | | | X | X | X | X |
| **F-tests (all demographics = 0):** | | | | | Non-smallholders | |
| F | 5.936*** | 0.860 | 0.427 | 0.697 | 0.496 | 0.531 |
| (p-value) | (0.000) | (0.508) | (0.830) | (0.626) | (0.779) | (0.753) |
| | | | | | Smallholders | |
| F | | | | 2.338** | 2.065* | 1.959* |
| (p-value) | | | | (0.040) | (0.070) | (0.085) |
| Observations | 10,524 | 10,524 | 10,524 | 10,524 | 10,524 | 10,524 |

In all columns, the dependent variable is the total number of hours allocated to agricultural production, including hired and family labor but excluding harvest labor. Observations are at the household-year-season-plot level. Regressions also control for total rainfall and rainfall squared.

* p<0.1 ** p<0.05 *** p<0.01

Table 4: Productivity of Mid-Season Hours

| | (1) All | (2) All | (3) All | (4) By month | (5) Spillovers | (6) Spillovers |
|---|---|---|---|---|---|---|
| Mid-season hours (log) | 0.062*** | 0.048** | 0.042** | | 0.046** | 0.038* |
| | (0.020) | (0.020) | (0.020) | | (0.021) | (0.022) |
| Total harvest labor (log) | | | 0.210*** | | | |
| | | | (0.038) | | | |
| Hours one month before harvest (log) | | | | 0.015 | | |
| | | | | (0.026) | | |
| Hours two months before harvest (log) | | | | 0.043** | | |
| | | | | (0.017) | | |
| Hours three months before harvest (log) | | | | 0.036** | | |
| | | | | (0.017) | | |
| Hours four months before harvest (log) | | | | −0.008 | | |
| | | | | (0.012) | | |
| Hours five+ months before harvest (log) | | | | 0.037** | | |
| | | | | (0.018) | | |
| Mid-season hours on other plots | | | | | 0.014 | 0.007 |
| | | | | | (0.009) | (0.014) |
| Mid-season hours times hours on other plots | | | | | | 0.002 |
| | | | | | | (0.005) |
| Planting hours (log) | −0.008 | −0.013 | −0.015 | −0.016 | −0.013 | −0.013 |
| | (0.031) | (0.031) | (0.028) | (0.031) | (0.031) | (0.031) |
| Planting mats (log) | 0.019 | 0.009 | 0.017 | 0.007 | 0.009 | 0.009 |
| | (0.013) | (0.013) | (0.014) | (0.014) | (0.013) | (0.013) |
| **Fixed Effects:** | | | | | | |
| Village-Wave-Season-Crop | X | X | X | X | X | X |
| Household-Plot | X | | | | | |
| Household-Plot-Crop | | X | X | X | X | X |
| Observations | 10,534 | 10,534 | 10,534 | 10,534 | 10,534 | 10,534 |

Observations are at the household-year-season-plot level. The dependent variable in all columns is the log of total output (Rs). Mid-season labor is defined as any labor between planting and harvest. Regressions also control for total rainfall, rainfall squared, area planted, area irrigated, total planting materials used, and total planting hours.

* p<0.1 ** p<0.05 *** p<0.01

## Table 5: Plot-Level Monthly Labor Allocation and Crop Prices

| | (1) Labor | (2) Labor | (3) Labor | (4) Labor | (5) Labor | (6) Labor | (7) Materials |
|---|---|---|---|---|---|---|---|
| Monthly crop price (log R) | 0.023 | 0.139 | 0.145* | 0.293*** | 0.343*** | 0.369*** | 0.342 |
| | (0.077) | (0.087) | (0.087) | (0.092) | (0.104) | (0.111) | (0.513) |
| Planting hours (log) | | | 0.047*** | 0.055*** | 0.019 | 0.019 | 0.088*** |
| | | | (0.016) | (0.016) | (0.018) | (0.018) | (0.034) |
| Planting materials (log) | | | −0.010 | 0.004 | −0.015** | −0.015** | −0.035** |
| | | | (0.007) | (0.007) | (0.007) | (0.007) | (0.016) |
| **Fixed Effects:** | | | | | | | |
| District-Year-Month-Crop | X | X | X | X | X | X | X |
| Household-Crop | | X | X | X | | | |
| Household-Plot-Crop | | | | | X | X | X |
| **Previous labor, previous materials, and rainfall:** | | | | | | | |
| By month | | | | X | X | X | X |
| Observations | 24,318 | 24,318 | 24,318 | 24,318 | 24,318 | 24,318 | 24,318 |

Observations are at the household-year-month-plot level. The dependent variable in columns one through six is the log (plus one) of total mid-season labor hours, defined as any labor between planting and harvest. The dependent variable in column seven is the total amount of materials (log Rs) allocated to the plot in a given month. Regressions also control for total rainfall, rainfall squared, area planted, area irrigated, total planting materials used, total planting hours, total materials used in all months prior, and total labor allocated in all months prior. In columns four, five, six, and seven, the effects of these variables are allowed to vary by month of the year.

* $p<0.1$ ** $p<0.05$ *** $p<0.01$

Table 6: Input Allocation and Crop Price Elasticities

| | (1) All | (2) Family | (3) Hired | (4) Materials |
|---|---|---|---|---|
| Monthly crop price (log R) | 0.408*** | 0.311** | 0.450*** | 0.580 |
| | (0.117) | (0.131) | (0.137) | (0.468) |
| Monthly crop price times Smallholder | −0.250** | −0.020 | −0.294** | −0.659*** |
| | (0.104) | (0.102) | (0.123) | (0.184) |
| **Fixed Effects:** | | | | |
| District-Year-Month-Crop | X | X | X | X |
| Household-Plot-Crop | X | X | X | X |
| **Previous labor, previous materials, and rainfall:** | | | | |
| By month | X | X | X | X |
| Observations | 24,318 | 24,318 | 24,318 | 24,318 |

Observations are at the household-year-month-plot level. In column one, the dependent variable is log (plus one) of all mid-season labor hours, defined as any labor between planting and harvest in each month. In column two, the dependent variable is log (plus one) of mid-season family hours. In column three, the dependent variable is log (plus one) of mid-season hired hours. In column four, the dependent variable is log (plus one) of total materials (Rs) allocated to the plot in that month. Regressions also control for total rainfall, rainfall squared, area planted, area irrigated, total planting materials used, total planting hours, total materials used in all months prior, and total labor allocated in all months prior. In all columns, the effects of these variables are allowed to vary by month of the year.

* $p<0.1$ ** $p<0.05$ *** $p<0.01$

Table 7: Accounting for Changes in Time Use of Household Members

| | Own farm days | | Wage days | | Other days | | Inv. Unemp days | | NF work days (wage + other) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| | S | N | S | N | S | N | S | N | S | N |
| Monthly weighted crop price (log R) | 0.028*** | 0.006* | −0.006 | 0.003 | 0.001 | 0.002 | −0.012** | 0.003 | −0.006 | 0.004 |
| | (0.010) | (0.003) | (0.009) | (0.003) | (0.003) | (0.001) | (0.006) | (0.002) | (0.009) | (0.003) |
| Age | 0.102*** | 0.054** | 0.078*** | 0.047*** | 0.014 | 0.015*** | 0.055*** | 0.010 | 0.088*** | 0.061*** |
| | (0.024) | (0.022) | (0.030) | (0.015) | (0.012) | (0.004) | (0.020) | (0.007) | (0.031) | (0.015) |
| Age squared | −0.001*** | −0.001*** | −0.001*** | 0.000*** | 0.000*** | 0.000*** | −0.001** | 0.000 | −0.001*** | −0.001*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| **Fixed Effects:** | | | | | | | | | | |
| District-year-month-crop | X | X | X | X | X | X | X | X | X | X |
| Individual-crop | X | X | X | X | X | X | X | X | X | X |
| **Previous labor, previous materials, and rainfall:** | | | | | | | | | | |
| By month | X | X | X | X | X | X | X | X | X | X |
| Observations | 14,128 | 30,746 | 14,128 | 30,746 | 14,128 | 30,746 | 14,128 | 30,746 | 14,128 | 30,746 |

Observations are at the individual-month level and standard errors are clustered at the individual level. The dependent variable in each column is transformed using an inverse hyperbolic sine transformation. Odd-numbered columns are individuals in smallholder households and even-numbered columns are individuals in non-smallholder households. The dependent variable in each column is indicated in the column title. The main dependent variable, *monthly weighted crop price*, is average crop price faced by the household, weighted by the amount of land allocated to each crop. Regressions also control for total rainfall, rainfall squared, area planted, area irrigated, total planting materials used, total planting hours, total materials used in all months prior, and total labor allocated in all months prior. In all columns, the effects of these variables are allowed to vary by month of the year. In all columns, age and age squared are additional covariates.

# Appendix A

Table A1: Cross-Section vs. Within Variation - Prices and Output

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Harvest price (log Rs) | −0.429*** | −0.390*** | −0.250*** | −0.042 |
| | (0.070) | (0.071) | (0.069) | (0.080) |
| Planting price (log Rs) | −0.026 | −0.024 | 0.009 | −0.004 |
| | (0.072) | (0.071) | (0.073) | (0.095) |
| Wave-season FE | | X | | |
| District-wave-season FE | | | X | |
| District-wave-season-crop FE | | | | X |
| Observations | 10,534 | 10,534 | 10,534 | 10,534 |

Observations are at the household-plot-crop-season level. Regressions also control for total rainfall, rainfall squared, area planted, area irrigated, total planting materials used, and total planting hours.

* p<0.1 ** p<0.05 *** p<0.01

Table A2: Household Type and Predictive Power of Lagged Prices

| | (1) Non Smallholders | (2) Smallholders | (3) All | (4) All |
|---|---|---|---|---|
| | | | Non-smallholders | |
| Lagged (x1) monthly crop price (log R) | 0.280*** | 0.342*** | 0.317*** | 0.352*** |
| | (0.037) | (0.033) | (0.028) | (0.022) |
| Lagged (x2) monthly crop price (log R) | | | | 0.103*** |
| | | | | (0.020) |
| | | | Smallholders | |
| Lagged (x1) monthly crop price (log R) | | | 0.325*** | 0.361*** |
| | | | (0.028) | (0.024) |
| Lagged (x2) monthly crop price (log R) | | | | 0.098*** |
| | | | | (0.020) |
| **Fixed Effects:** | | | | |
| District-year-month-crop | X | X | X | X |
| Household-Plot-Crop | X | X | X | X |
| Inputs and rain by month | X | X | X | X |
| **F-test (non-smallholder = lag smallholder):** | | | Lag (x1) | |
| F | | | 0.740 | 1.100 |
| (p-value) | | | (0.390) | (0.295) |
| **F-test (non-smallholder = lag smallholder):** | | | Lag (x2) | |
| F | | | | 0.528 |
| (p-value) | | | | (0.468) |
| Observations | 13,324 | 6,743 | 20,067 | 19,320 |

In all columns, the dependent variable is the current crop price of the crop planted on the plot. "Lagged (x1)" indicates the price of that same crop in the previous month and "Lagged (x2)" indicates the price of that same crop two months prior. The F-tests test the null hypothesis that lagged crop prices predict current crop prices the same for both smallholders and non-smallholders.

* p<0.1 ** p<0.05 *** p<0.01

Table A3: Household Size and Planted Plot Area

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Household size | 0.038*** | 0.016* | 0.018*** | 0.013* |
| | (0.010) | (0.009) | (0.007) | (0.006) |
| **Fixed Effects:** | | | | |
| Wave-Crop-Season-Village FE | X | X | X | X |
| Household FE | | X | | |
| Household-Plot FE | | | X | |
| Household-Plot-Crop FE | | | | X |
| Observations | 10,534 | 10,534 | 10,534 | 10,534 |

The dependent variable in all columns is the log of planted area on the individual plot.

* p<0.1 ** p<0.05 *** p<0.01

Table A4: Labor Allocation and Household Demographics

| | (1) Log hhsize (with pcts) | (2) Logs (All) | (3) IHS (All) |
|---|---|---|---|
| | | Non-smallholders | |
| Household size/child | −0.005 | −0.039 | −0.027 |
| | (0.111) | (0.066) | (0.051) |
| Prime male | 0.058 | 0.151 | 0.115 |
| | (0.252) | (0.117) | (0.093) |
| Prime female | −0.278 | −0.340** | −0.252** |
| | (0.383) | (0.147) | (0.111) |
| Elderly male | −0.090 | −0.004 | −0.002 |
| | (0.310) | (0.070) | (0.054) |
| Elderly female | 0.403 | −0.021 | −0.017 |
| | (0.579) | (0.158) | (0.124) |
| | | Smallholders | |
| Household size/child | 0.027 | 0.067 | 0.052 |
| | (0.132) | (0.072) | (0.056) |
| Prime male | −0.227 | 0.040 | 0.033 |
| | (0.246) | (0.127) | (0.098) |
| Prime female | 1.144*** | 0.531*** | 0.395*** |
| | (0.414) | (0.191) | (0.144) |
| Elderly male | 0.014 | 0.094 | 0.074 |
| | (0.238) | (0.072) | (0.057) |
| Elderly female | −0.557 | −0.134 | −0.105 |
| | (1.317) | (0.426) | (0.336) |
| **F-tests (all demographics = 0):** | | Non-smallholders | |
| F | 0.580 | 1.372 | 1.300 |
| p-value | (0.715) | (0.232) | (0.262) |
| | | Smallholders | |
| F | 2.161* | 1.999* | 1.942* |
| p-value | (0.056) | (0.076) | (0.085) |
| Observations | 10,524 | 10,524 | 10,524 |

In all columns, the dependent variable is the total number of hours allocated to agricultural production, including hired and family labor but excluding harvest labor. Observations are at the household-year-season-plot level. In column one, household size is defined as the log of total household size and each demographic variable is defined as a percentage of the household, with children being the omitted category. In columns two and three, the household size coefficient refers to the coefficient on children only. In column two, all demographic variables are defined as the natural log of the number of persons plus one. In column three, all demographic variables are defined as the inverse hyperbolic sine transformation ($ln(x + \sqrt{x^2 + 1})$) of persons.

* p<0.1 ** p<0.05 *** p<0.01

Table A5: Plot-Level Monthly Labor Allocation and Crop Prices - Additional Specifications

| | (1)<br>Labor | (2)<br>Labor | (3)<br>Materials |
|---|---|---|---|
| Monthly crop price (log R) | 0.786*** | 1.032*** | 0.100 |
| | (0.149) | (0.171) | (0.328) |
| Planting hours (log) | 0.020 | 0.033 | 0.103*** |
| | (0.018) | (0.020) | (0.035) |
| Planting materials (log) | −0.007 | −0.002 | −0.016 |
| | (0.007) | (0.008) | (0.016) |
| **Fixed Effects:** | | | |
| District-year-month-crop | X | X | X |
| Household-Plot-Crop | X | X | X |
| Village-month-crop | X | | |
| Household-month-crop | | X | X |
| **Previous labor, previous materials, and rainfall:** | | | |
| Inputs and rain by month | X | X | X |
| Observations | 24,318 | 24,318 | 24,318 |

The table presents additional specifications for Table 5. All three columns include district-year-month-crop fixed effects. Column one also includes village-month-crop fixed effects, identifying effects from changes in crop prices in the same month across different years. Columns two and three instead add household-month-crop fixed effects, identifying effects from changes in crop prices in the same month across different years, but at the household-crop level.

* $p<0.1$ ** $p<0.05$ *** $p<0.01$

Table A6: Plot-Level Monthly Labor Allocation and Village Fixed Effects

| | (1) All | (2) Family | (3) Hired | (4) Materials | (5) All | (6) All |
|---|---|---|---|---|---|---|
| Monthly crop price times Smallholder | −0.168* | 0.086 | −0.248** | −0.451*** | −0.246 | −0.357* |
| | (0.098) | (0.096) | (0.125) | (0.162) | (0.177) | (0.190) |
| Next month's crop price times Smallholder | | | | | 0.057 | 0.072 |
| | | | | | (0.106) | (0.116) |
| **Fixed Effects:** | | | | | | |
| Village-year-month-crop | X | X | X | X | X | |
| District-year-month-crop | | | | | | X |
| Household-Plot-Crop | X | X | X | X | X | X |
| Inputs and rain by month | X | X | X | X | X | X |
| **Previous labor, previous materials, and rainfall:** | | | | | | |
| By month | X | X | X | X | X | X |
| Observations | 24,318 | 24,318 | 24,318 | 24,318 | 18,297 | 18,297 |

The table presents additional specifications for Table 6. Instead of district-year-month-crop fixed effects, however, the specifications include village-year-month-crop fixed effects in columns one through five. The level effect of month crop price is thus not identified, but the difference across household types is. In columns five and six, the specification also includes next month's crop price.

* $p<0.1$ ** $p<0.05$ *** $p<0.01$

Table A7: Plot-Level Monthly Labor Allocation - No Lagged/Planting Variables

| | (1) All | (2) Family | (3) Hired | (4) Materials |
|---|---|---|---|---|
| Monthly crop price (log R) | 0.320*** | 0.233** | 0.496*** | 1.041*** |
| | (0.100) | (0.115) | (0.149) | (0.335) |
| Monthly crop price times Smallholder | −0.210** | 0.014 | −0.262** | −0.682*** |
| | (0.104) | (0.102) | (0.127) | (0.185) |
| **Fixed Effects:** | | | | |
| District-Year-Month-Crop | X | X | X | X |
| Household-Plot-Crop | X | X | X | X |
| **Previous labor, previous materials, and rainfall:** | | | | |
| By month | X | X | X | X |
| Observations | 24,318 | 24,318 | 24,318 | 24,318 |

The table presents additional specifications for Table 6. All planting and lagged input variables are removed in all columns.
* p<0.1 ** p<0.05 *** p<0.01

Table A8: Accounting for Changes in Time Use of Household Members - Levels

| | Own farm days | | Wage days | | Other days | | Inv. Unemp days | | NF work days (wage + other) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| | S | N | S | N | S | N | S | N | S | N |
| Monthly weighted crop price (log R) | 0.131*** | 0.023 | −0.039 | 0.021 | −0.002 | 0.004 | −0.045** | 0.014 | −0.041 | 0.025 |
| | (0.041) | (0.014) | (0.057) | (0.019) | (0.009) | (0.003) | (0.022) | (0.010) | (0.056) | (0.020) |
| Age | 0.513*** | 0.313*** | 0.465** | 0.324*** | 0.020 | 0.034*** | 0.207** | 0.035 | 0.485** | 0.358*** |
| | (0.118) | (0.105) | (0.201) | (0.097) | (0.038) | (0.010) | (0.083) | (0.029) | (0.202) | (0.098) |
| Age squared | −0.007*** | −0.006*** | −0.007*** | −0.003*** | −0.001** | −0.001*** | −0.002** | 0.000 | −0.008*** | −0.003*** |
| | (0.001) | (0.001) | (0.002) | (0.001) | (0.000) | (0.000) | (0.001) | (0.000) | (0.002) | (0.001) |
| **Fixed Effects:** | | | | | | | | | | |
| District-year-month-crop | X | X | X | X | X | X | X | X | X | X |
| Individual-crop | X | X | X | X | X | X | X | X | X | X |
| **Previous labor, previous materials, and rainfall:** | | | | | | | | | | |
| By month | X | X | X | X | X | X | X | X | X | X |
| Observations | 14,128 | 30,746 | 14,128 | 30,746 | 14,128 | 30,746 | 14,128 | 30,746 | 14,128 | 30,746 |

Observations are at the individual-month level and standard errors are clustered at the individual level. Odd-numbered columns are individuals in smallholder households and even-numbered columns are individuals in non-smallholder households. The dependent variable in each column is indicated in the column title. The main dependent variable, *monthly weighted crop price*, is average crop price faced by the household, weighted by the amount of land allocated to each crop. Regressions also control for total rainfall, rainfall squared, area planted, area irrigated, total planting materials used, total planting hours, total materials used in all months prior, and total labor allocated in all months prior. In all columns, the effects of these variables are allowed to vary by month of the year. In all columns, age and age squared are additional covariates.

Table A9: Season Price Changes, Output, and Labor Allocation

| | Non-smallholder | | | Smallholder | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Labor | Labor | Output | Labor | Labor | Output |
| Harvest price (log Rs) | 0.272* | 0.209 | | 0.062 | 0.019 | |
| | (0.159) | (0.171) | | (0.133) | (0.144) | |
| Planting price (log Rs) | | 0.226 | | | 0.236 | |
| | | (0.188) | | | (0.166) | |
| Mid-season hours (log) | | | 0.030* | | | 0.070 |
| | | | (0.018) | | | (0.050) |
| District-wave-season-crop FE | X | X | | X | X | |
| Village-wave-season-crop FE | | | X | | | X |
| Household-Plot-Crop FE | X | X | X | X | X | X |
| Observations | 6,957 | 6,957 | 6,957 | 3,577 | 3,577 | 3,577 |

NOTES

* p<0.1 ** p<0.05 *** p<0.01