Does storage technology affect adoption of improved maize varieties in Africa? Insights from Malawi's input subsidy program

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**Abstract**

To date there is limited knowledge of how having access to post-harvest storage technology affects a smallholder African farmer's decision to adopt higher-yielding improved maize varieties. This is a key issue because higher yielding varieties are known to be more susceptible to storage pests than lower-yielding traditional varieties. We address this question using panel data from Malawi, and incorporating panel estimation techniques to deal with unobserved heterogeneity. Our results indicate that acquiring chemical storage protectants after the previous harvest is associated with a statistically significant and modest positive impact on the probability of adopting improved maize, total area planted to improved maize varieties, and share of area planted to improved maize varieties in the next planting season. We also find that the storage chemical subsidy is associated with significant crowding out of commercial storage chemical purchases, as farmers who acquire subsidized chemicals are more than 50 percentage points less likely to purchase commercial chemicals on average. These findings have implications for maize adoption and input subsidy policies, and they indicate that researchers, extension staff, and policy makers should consider post-harvest issue when promoting adoption of improved varieties.

**Keywords:**

Storage, Food security, Improved maize seed adoption, Input subsidies, Malawi, Sub-Saharan Africa

**Introduction**

Increasing adoption of modern inputs such as improved seeds and chemical fertilizer is essential for boosting staple crop production and increasing smallholder food security in sub-Saharan Africa (SSA). Numerous studies in SSA find that adoption of improved maize varieties contributes to raising productivity which increases household income and food security (Smale, 1995; Katengeza et al., 2012; Mason and Smale, 2013; Bezu et al., 2014). However in addition to increasing productivity, it is essential to recognize that food security does not simply end at harvest because susceptibility to pests during storage can cause tremendous post-harvest dry weight (quantity) losses of up to 30% in six months of storage for grains (Boxall, 2002). In addition, previous work confirms common rural knowledge that higher yielding but softer dent hybrids, the most commonly promoted improved maize varieties in SSA, offer less natural protection against storage insects such as maize weevil and larger grain borer due to their softer husks, than do lower yielding but harder traditional flint varieties (Smale et al., 1995; Adda et al., 2002). Therefore farmers face a rational trade-off at planting time between choosing an improved variety that may boost production but where the harvested maize is more susceptible to pests when stored vs. choosing a traditional variety that is lower yielding but less vulnerable to pests in storage. Nevertheless, issues related to post harvest loss are often overlooked in studies that model smallholder improved seed adoption behavior.

With these considerations in mind, the first objective of this article is to determine how use of storage technology in the form of chemical protectants affects a smallholder's decision to adopt improved varieties of maize seed in Malawi. In doing so this study makes an empirical contribution to both the technology adoption literature.
erature and the input subsidy literature in SSA. Malawi has received wide-spread recognition for scaling up a large inorganic fertilizer subsidy program in 2005 and a subsidy for improved maize seeds in 2006 (Dugger, 2007). With the expansion of the seed subsidy program, by the 2008–2009 agricultural year almost 40% of smallholder households had received subsidized improved seed (Mason and Ricker-Gilbert, 2013). However less attention has been paid to the fact that Malawi implemented a subsidy for maize storage chemicals beginning after the 2009 harvest and running through 2012 harvest as a compliment to the fertilizer and seed subsidy. The storage chemical component was added to the subsidy program based on a recognition that post-harvest pests may undermine increases in maize production that are achieved by farmers who adopt improved varieties through the subsidy program.

Therefore, the second objective of this study is to test whether or not, and to what extent the storage chemical subsidy may crowd out or crowd in the commercial market for storage chemicals. This is an important issue because for the storage chemical component of the subsidy program to be successful it must increase the amount of storage chemicals that households use. If acquiring subsidized storage chemicals makes people more likely to buy commercial storage chemicals then the subsidy program crowds in commercial storage chemical use, and adds to the total quantity of storage chemicals applied to farmers’ maize. Conversely, if those who acquire subsidized storage chemicals use some or all of it in place of commercial purchases, then the effect of the subsidy on total chemical use will be reduced, causing crowding out of commercial chemicals, and undermining the effectiveness of the program.

The first wave of data from our study provide evidence on storage chemical use after the 2007/08 growing season, the year before the storage protectant subsidy was scaled up, but when the fertilizer and seed subsidy was in full swing. In the first wave all purchases of storage chemicals are from the commercial market. The second wave of data provide information on storage protectant use after the 2010 season when the storage chemical subsidy, the fertilizer subsidy, and the seed subsidy were all in full effect. During that season households could potentially purchase storage chemicals from either commercial or subsidized sources. As a result, this article should provide useful insights about acquisition to storage technology and how it potentially serves as a complimentary input to fertilizer and seed.

There is a growing literature measuring the impact of input subsidy programs on smallholder behavior and well-being in SSA. One related study in Malawi finds that households who acquire subsidized seed and fertilizer plant a significantly larger share of their land to maize and tobacco, the crops targeted by the country’s input subsidy program, than do other households (Chibwana et al., 2012). Another study uses household-level panel data from Malawi and Zambia and finds that in both countries households who acquire subsidized improved maize seed varieties purchase significantly less improved seed varieties on the commercial market (Mason and Ricker-Gilbert, 2013). The present study adds to the literature on input subsidies by estimating the impact of storage chemicals on a farmer’s improved seed adoption decision in the context of a large-scale input subsidy program.

To our knowledge, there is little research investigating the relationship between investment in storage technology and adoption of improved maize varieties. One previous study in Ghana (Gyasi et al., 2003) and one study in Zambia (Langyintuo and Mungoma, 2008) consider how a farmer’s perception of hybrid maize storability affects his or her decision to adopt it. Both studies estimate hybrid maize adoption and include “storability” as a dummy variable equal to one when a farmer perceives that hybrid maize stores better than local varieties and 0 otherwise. However, these studies do not consider a farmer’s ability to protect maize stores in their model. One limitation of the previous approach is that there is likely limited variation in the storability dummy, as evidence from Malawi suggests that most farmers believe local varieties to store better than hybrid (Smale, 1995; Lunduka et al., 2012). Therefore, the present article builds upon past work by considering how accessing storage protectants affects a farmer’s decision to adopt improved varieties of maize.

In this article we first set up a model of smallholder maize adoption decision making, where the farmer chooses whether or not to adopt improved maize varieties as a binary decision. Second we model the farmer’s decision of how much absolute area to plant to improved maize varieties. Third we estimate the farmer’s decision on the share of his or her area to plant to improved maize varieties. The key right hand side (RHS) variable of interest is whether or not the household used storage chemicals on their maize crop after the previous harvest. In doing so, we empirically test whether or not households who access storage chemicals are significantly more likely to adopt improved maize seed and also plant larger areas of land to improved maize varieties in the next growing season. Since the key RHS variable is whether or not the household uses storage chemicals after the previous harvest it is pre-determined when the household makes planting decisions the following season. This structure avoids possible concerns about reverse causality. In addition, we use several panel estimation techniques including first-differencing and the Mundlak-Chamberlain device to deal with potential correlation between covariates and unobservable factors that could potentially bias our coefficient estimates, particularly those variables that represent participation in the input subsidy program.

The rest of this article is organized as follows. In the next section we present a background of Malawian post-harvest challenges, improved maize adoption, and the input subsidy program. Then introduce the conceptual model, the empirical model, and the identification strategy. Subsequently, data, results, and conclusions are presented.

Background

Post-harvest losses in Malawi

Post-harvest storage losses in Southern Africa are predominately caused by molds, rodents, and insect pests (World Bank, 2011). The main harvest in Malawi is followed by a long dry season so mold damage to grain is not a significant storage problem for smallholders. Nevertheless, post-harvest grain damage due to insect pests is a major issue. While producers have always dealt with the maize weevil as a dominate pest, improving smallholder maize storage practices in Africa has become increasingly more important over the past thirty-five years since the larger grain borer (LGB) was accidentally introduced in Africa from Central America in the 1970s and 1980s (Golob, 2002). Lacking natural predators, LGB’s nearly simultaneous initial infestation in Tanzania and Togo have since expanded throughout both Eastern and Western Africa. As a result farmers have had to abruptly and fundamentally shift storage practices in this time to avoid inevitable stock destruction as the threat from LGB has increased (Addo et al., 2002). LGB supposedly entered Malawi in 1991/92 through trade shipments from Tanzania through the northern district of Chitipa. LGB is now prevalent in almost every district of Malawi and poses an enormous constraint on smallholder maize storage (Singano et al., 2008).

In the past many farmers throughout the continent preferred to store husked maize on cob, but the husk provides LGB with a more...
stable brace to penetrate grains. Shelled maize creates a less stable environment to somewhat mitigate losses, though admixing insecticides is universally recommended for medium to long term storage in LGB-infested zones (Golob, 2009). Previously, insecticides such as Actellic contained only a pirimiphos-methyl compound which effectively controls the maize weevil. Blends were found to best control LGB in long term storage, however, and heavy research investments led to the release of new products blended with permethrins or deltamethrins (Golob, 2002). The Actellic Super or Shumba Super labels are two widely available brands which combine the lethal chemicals for both pests, used in Malawi.

There is limited information about on-farm storage practices in Malawi. However, Jones (2012) uses data from the nationally representative Agricultural Input Support Survey conducted after the 2008/09 season in Malawi and finds that nationally 45% of households use storage chemicals. In addition, 54% of households store local varieties of maize in woven or plastic bags, while 78% of households store improved varieties of maize in woven or plastic bags. Jones also notes that farmers report losing 8.5% of their improved maize in storage, and 7.4% of their local maize in storage. This information is descriptive in nature, and does not account for the possibility that farmers storing improved maize may be more likely to treat it with chemicals than if they are storing local varieties. It does, however provide some useful prima facia evidence about on-farm storage practices among Malawian smallholders.

Use of improved maize varieties in Malawi

The spectrum of improved varieties available for Malawian farmers has changed greatly over the last several decades. Smale (1995) documents a structural shift in the 1990s as national research institutions began to push away from traditional improved dent varieties to improved semi-flint varieties. The flinty texture allowed farmers to increase yields while better maintaining desirable post-harvest qualities such as high flour-to-milling ratios, and better natural resistance to maize weevils. However this has evolved into a present-day reversion back to largely dent varieties, including selections from multi-national corporations like Pioneer and Monsanto. While the reasons driving this reversion to more storage susceptible varieties is not the subject of this study, the farmer is ultimately left with little choice outside of dent varieties when sourcing improved seed. Grain damage in storage is thus a large concern for all dent-growing producers who must later cope with pests like LGB and maize weevil. In fact a recent study, Lunduka et al. (2012) use data from the Mulanje district of Malawi and find that many farmers prefer local varieties of maize to improved varieties because of their storability, taste, ease of pounding, and high flour-to grain ratios, despite the fact that they know improved maize varieties have higher yields.

Storage chemical subsidies in Malawi

The Malawian government introduced subsidized storage chemicals in 2008/09 in acknowledgement of the growing constraint posed by storage pests. The maize storage chemical subsidy ran through the 2011/12 season. In the 2011/12 season, the price of subsidized storage chemicals was 100 Kwacha per 200 g bottle of actellic, as compared to prices of 250–350 MK per bottle in retail outlets (author’s observation). Following recommended application doses of 25 g/50 kg maize grain, each should protect 400 kg of maize. Unlike the improved seed and fertilizer subsidy program, no vouchers are required for the storage chemical subsidy. Any farmer is permitted to purchase as many subsidized bottles as he or she needs or can afford from the Extension Planning Area (EPA) offices while stocks remain, although extension agents have authority to regulate this quantity as they deem appropriate. Stock shortages are common and anecdotal evidence suggests that they vary by region since allocation is determined by district maize production.6

Fertilizer and seed subsidies in Malawi

Fertilizer subsidy programs have existed in almost every year for decades in Malawi. However, after a drought-affected poor harvest in the 2004/05 growing season, the government decided to greatly expand its subsidized fertilizer program and continue subsidizing improved maize seeds, under the Farm Input Support Program (FISP). The program uses vouchers to target farmers who meet certain criteria. These targeted farmers can then redeem the vouchers for inorganic fertilizer at a reduced price and improved maize seed for free. During the 2008/09 growing season (the first year of the data used in this study), the government of Malawi made 202,000 metric tons of subsidized fertilizer and 5365 tons of subsidized seed available to farmers. The program cost an estimated US $265 million (Dorward and Chiwara, 2011). The government paid greater than 90% of the commercial fertilizer cost for farmers who received the subsidy that year. Recipient farmers were officially required to pay the equivalent of US $5.33 for a 50 kg bag of fertilizer that cost between US $40 and $70 at commercial prices, while vouchers for improved maize seed could be redeemed at no charge. From 2008/09 to present, all subsidized fertilizer vouchers had to be redeemed at government depots, while households could redeem their maize seed vouchers at a wide range of large and small input suppliers’ stores. Officially each targeted household was supposed to receive two coupons good for two 50-kg bags of fertilizer at a discounted price, and one coupon for a 2 kg bag of hybrid maize seed or a 4 kg bag of OPV seed. In reality, the actual amount of subsidized fertilizer and seed acquired by households varied greatly.

Throughout the years of the subsidy’s implementation, the process of determining who received coupons for fertilizer and seed was subject to a great deal of local idiosyncrasies. In 2007/08 and afterward there was a shift in allocation from area under cultivation to allocation based on farm household population and hence as shift in relative allocations from the North and Central regions to the Southern region (Dorward and Chiwara, 2011). At the village level, subsidy program committees and the village heads were supposed to determine who was eligible for the program. In more recent years open community forums were held in some villages where community members could decide for themselves who should receive the subsidy. From about 2008 “vulnerable households” were officially supposed to be targeted with priority given to resource poor households, including disabled, elderly, female, and child-headed households. However, numerous unofficial criteria may have been used in subsidized seed and fertilizer application, such as a household’s relationship to village leaders, length of residence, and social and/or financial standing of the household in the village.

Methods

Conceptual framework

Consider a smallholder household’s decision whether or not to plant a piece of land with improved maize varieties that are higher

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6 Author’s observations through interactions with officials in Blantyre, Zomba, Thyolo, Lilongwe, Nkhotakota, and Mzimba offices in June/July 2011 and Jan/Feb 2012.
yielding, but offer less natural protection against insect pests when
stored, vs. planting a traditional maize variety that may be lower
yielding, but be less susceptible to damage from pests in storage.
Assume that the household will plant the improved variety if
\( \pi(I) \geq \pi(L) \), so that profits \( \pi \), from planting improved varieties \( I \),
are greater than or equal to the profits from planting local varieties, \( L \).
Assuming that other inputs besides storage chemicals are held
constant, the household understands that \( \pi(I) = P_m(X_I) - P_r(C_I) \),
where \( P_m \) represents the market price for the quantity of improved
maize produced \( X_I \) and \( P_r \) represents the price of a given quantity of
storage chemicals \( C_I \) applied to improved maize.\(^7\) The household
also understands that \( \pi(L) = P_m(X_L) - P_r(C_L) \) where \( X_L \) represents
the quantity of local maize produced, and \( C_L \) represents a quantity of
storage chemicals applied to local maize. If we assume that
\( X_I > X_L \), then the household produces more maize per area of land
with improved varieties than with local varieties. However, if \( C_I > C_L \),
then improved varieties require a greater quantity of storage
chemicals to be applied to a given quantity of maize than do local
varieties. Therefore, the household must decide between higher
revenue/higher cost improved varieties, and lower revenue/lower
cost local varieties.

In addition, it is widely known that maize prices in many parts of
SSA increase greatly after harvest. In fact market price data from the
Malawian Ministry of Agriculture and Food Security show that
real prices typically increase 50–100% within six months of the
harvest season (Government of Malawi, various years; Chapoto
and Jayne, 2010). Therefore, the household can increase profits if it
is able to hold stocks until later in the marketing year because \( P_m \)
will rise accordingly as maize becomes scarce. If the household
can hold stocks until \( P_m \) increases sufficiently, then improved vari-
eties will generate higher revenues than local varieties because
\( X_I > X_L \). However, the household must be able to overcome the
potential dry-weight loss caused by pests when grain is placed in
storage. This can be achieved through using storage chemicals on
improved maize, but this comes at an extra cost which reduces to
profitability of improved maize varieties because \( C_I > C_L \).

The presence of a subsidy for storage chemicals like the one in
Malawi beginning in 2008/09 reduces \( P_r \) to \( P_r^* \). This lowers the
input/output price ratio of \( P_r/P_m \), since \( P_r > P_r^* \). Therefore, the adop-
tion of improved maize varieties will become more attractive
under subsidization because \( P_r(C_I) \) will decline faster than \( P_r(C_L) \)
which will cause a larger increase in \( \pi(I) \) than in \( \pi(L) \).

In our model the farmer considers using 3 interrelated inputs:
storage chemicals, inorganic fertilizer, and improved maize seed.
The farmer’s decision making process is thus examined in accord-
ance with the sequential input adoption literature, which consid-
ers that theses inputs form a package that a farmer may choose to
adopt entirely at the same time (simultaneous adoption), or in
different components at different times (sequential adoption)
(Leathers and Smale, 1991; Ersado et al., 2004; Chavas and Di
Falco, 2012). The literature cites relative prices of the inputs, risk
aversion and understanding of the technology as reasons why
farmers may make sequential rather than simultaneous adoption
decisions. Leathers and Smale show that in the presence of incom-
plete information, farmers may make a rational decision to adopt
part of an input package, even when it would be more profitable
for them to adopt the package as a whole. Ersado et al. present
an empirical test of sequential vs. simultaneous adoption. The
authors use a likelihood ratio (LR) test to compare a restricted
model of simultaneous adoption where adoption of all inputs
occurs together, vs. an unrestricted model where the impact of
each of the technologies on adoption is considered separately in a
sequential adoption framework. We consider this test of sequential
vs. simultaneous adoption in the empirical model presented in the
next section.

**Empirical model**

**Improved maize adoption**

We operationalize the conceptual model presented above, where household \( i \) at time \( t \) must decide (i) whether or not to adopt
improved maize varieties, (ii) the total area to plant to improved
maize varieties, and (iii) the share of its land to plant to improved
maize varieties. These decisions are a function of the following
factors:

\[
I_i = \beta_0 + \beta_1 C_{i-1} + \beta_2 F_{i} + \beta_3 S_{i} + A_{ti} \beta_4 + X_{it} \beta_5 + W_{i} \beta_6 + R_{it} \beta_7 + D_{it} \beta_8 + a_i + \varepsilon_i \tag{1}
\]

where \( I \) again represents the household’s improved maize adoption
decision. The variable for whether or not the household acquired
storage chemicals after the previous harvest is represented by \( C \).
In the first wave of our data collected after the 2008 harvest, all
storage chemicals come from commercial sources, while in the sec-
ond wave households can purchase from subsidized or commercial
sources. We use a variable \( = 1 \) if the household used storage chem-
icals after the previous harvest and \( 0 \) otherwise.\(^8\) The coefficient \( \beta_1 \)
tests the key hypothesis of whether or not households who used
storage chemicals after the previous harvest are more likely to adopt
improved maize varieties. The impacts of this study are predicated
on the assumption that use of storage chemicals after one season
is associated with increased planting of improved maize varieties
the next season. Since a household makes the decision to acquire
storage chemicals after the harvest that occurs in May, that decision
is complete by planting time beginning the following October.\(^9\)

Kilograms of subsidized fertilizer that the household acquires in
year \( t \) is represented by \( F \) and the kilograms of subsidized
improved maize seed that the household acquires in year \( t \) is repres-
ented by \( S \). Their respective parameters are \( \beta_4 \) and \( \beta_3 \). (1) is
presented as a sequential adoption model, and including \( F \), and \( S \)
controls for the extent that use of other inputs affect the decision
to plant improved seed at time \( t \). However, we recognize that the
decision to adopt all three inputs may be made simultaneously,
so we conduct a LR test following Ersado et al. (2004) to compare
the model in Table 1 with a model where adoption of improved
maize is considered by a single decision where the RHS variable \( = 1 \)
if the farmer uses storage chemicals, or subsidized fertilizer, or
subsidized improved maize seed at time \( t \), and \( 0 \) otherwise. Results
of the LR test confirm that the simultaneous adoption model can be
strongly rejected (\( p\)-value = 0.000) in favor of the sequential adop-
tion model presented in Eq. (1). This finding provides evidence that
in our context, farmers in Malawi make decisions about storage
chemicals, fertilizer and improved seeds in a sequential manner.

In Eq. (1) credit and market access factors that may affect
a household’s decision to plant improved maize seed are represented
by the vector \( A \), while \( \beta_4 \) represents the corresponding parameter
vector. These factors include (1) distance to paved road in kilome-
ters, (2) distance to the main market in kilometers, (3) distance to

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\(^7\) Anecdotal evidence suggests that in Malawi local maize receives a higher price
per kg than improved varieties due to its desirable storage and consumption
characteristics. However, we set that aside for parsimony in the conceptual model.

\(^8\) We treat \( C \) as a binary variable rather than a continuous variable representing the
kilograms of storage chemicals acquired because thorough analysis of the data
combined with discussions in the field confirm that many households do not know
the quantity of storage chemicals that they acquire and apply. Furthermore some
households acquire storage chemicals in liquid form, while others acquire it in
powder form making it hard to convert to equivalent measures. Therefore to
eliminate measurement error we model storage chemical acquisition as a binary
decision.

\(^9\) Even if insect damage emerges 2–3 months after harvest and thus induces
treatment, this occurs well before the next planting season in Malawi.
extension services in kilometers, (4) number of input suppliers in the village, and (5) whether or not there is a farm credit organization in the village. Household demographics that affect improved seed adoption are represented by the vector X, while \( \beta_5 \) represents the corresponding parameter vector. These include (1) value of household assets, (2) household landholding, (3) adult equivalents, (4) if the household is female headed, (5) education of the household head. Factors such as assets, landholding and education of the household head proxy for household understanding and ability to take risks which also influence the adoption decision in a sequential adoption model. Prices that affect the decision to adopt improved seed are represented by the vector w. Relevant prices are (1) commercial price of fertilizer (NPK & urea), (2) agricultural wage rates in the community, (3) previous year hungry season maize price (May to July), while \( \beta_6 \) represents the corresponding parameter vector. Including the previous year’s maize price assumes that farmers have naïve expectations about maize prices, but it serves to proxy for the maize price farmers may expect in the coming year. Including prices controls for the exogenous changes that impact relative prices, which affect sequential adoption decisions. Average rainfall over the previous five growing seasons and the coefficient of variation on average rainfall over the previous 5 growing seasons are represented by R, while \( \beta_7 \) represents the corresponding parameter vector. These variables are lagged over 5 years in order to proxy for the naïve expectation of what a farmer expects rainfall to be in the coming year, when he or she makes decisions about seed varieties at planting.

Year and region fixed effects are represented by a vector of dummy variables denoted by D, while \( \beta_8 \) represents the corresponding parameter vector (see Table 1 for a full list of explanatory variables). The error term in Eq. (1) has two parts. The time constant-unobserved heterogeneity is represented by \( a_0 \), and the unobserved time-varying shocks are represented by \( e_{it} \).

**Crowding out of commercial storage chemicals by storage chemical subsidy**

In order to understand the impact that the storage chemical subsidy has on the probability of using commercial storage chemicals, it is important to understand how acquisition of subsidized chemicals may affect a farmer’s decision to use commercial storage chemicals. Following the work of Xu et al. (2009), Ricker-Gilbert et al. (2011), and Mason and Jayne (2013) who conceptualize crowding out in the context of subsidized fertilizer, consider the following equation for the probability that a farmer will use commercial storage chemicals, either subsidized or commercial:

\[
C_{it} = \frac{C_0 + x_i S_{it-1} + A_x x_2 + X_{it} x_3 + R_{it} x_4 + D_{it} x_5 + b_i + u_{it}}{1 + e^{R_{it} x_4 + D_{it} x_5 + b_i + u_{it}}}
\]

where C is a binary variable representing whether or not a household purchases storage chemicals on the commercial market, and S is a binary variable representing whether or not the household uses subsidized storage chemicals. The previous studies that have addressed crowding out in the context of input subsidy programs have done so for fertilizer, which is modeled as a continuous variable. Therefore, in this application we adapt the crowding out framework to the binary decision of whether or not to use storage chemicals.

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**Table 1**

Descriptive statistics of variables used in the analysis.

<table>
<thead>
<tr>
<th>Variables</th>
<th>2008/09</th>
<th>2010/11</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median</td>
</tr>
<tr>
<td>Dependent variables</td>
<td></td>
<td></td>
</tr>
<tr>
<td>=1 if household plants improved maize seed</td>
<td>0.69</td>
<td>0.80</td>
</tr>
<tr>
<td>Hectares of improved maize seed planted</td>
<td>0.32</td>
<td>0.20</td>
</tr>
<tr>
<td>Share of total area planted to improved maize seed</td>
<td>0.39</td>
<td>0.30</td>
</tr>
<tr>
<td>Share of total maize area planted to improved maize seed</td>
<td>0.44</td>
<td>0.33</td>
</tr>
<tr>
<td>=1 if HH used commercial storage chemicals after harvest</td>
<td>0.51</td>
<td></td>
</tr>
<tr>
<td>RHS variables</td>
<td></td>
<td></td>
</tr>
<tr>
<td>=1 if HH used subsidized storage chemicals after previous harvest</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>=1 if HH used storage chemicals after previous harvest (subsidized or commercial)</td>
<td>0.51</td>
<td>0.58</td>
</tr>
<tr>
<td>kgs. of subsidized seed acquired in current year</td>
<td>2.29</td>
<td>2.00</td>
</tr>
<tr>
<td>kgs. of subsidized fertilizer acquired in current year</td>
<td>65.88</td>
<td>50.00</td>
</tr>
<tr>
<td>=1 if farm credit organization in village</td>
<td>0.32</td>
<td></td>
</tr>
<tr>
<td>Distance to paved road (km)</td>
<td>16.92</td>
<td>12.00</td>
</tr>
<tr>
<td>Distance to main market (km)</td>
<td>39.53</td>
<td>32.00</td>
</tr>
<tr>
<td>Distance to extension services (km)</td>
<td>6.11</td>
<td>5.00</td>
</tr>
<tr>
<td>Number of dealers who sell subsidized inputs in village</td>
<td>0.60</td>
<td>0.00</td>
</tr>
<tr>
<td>Value of household assets (‘000 kwacha)</td>
<td>48.07</td>
<td>13.75</td>
</tr>
<tr>
<td>Area cultivated (ha)</td>
<td>0.96</td>
<td>0.81</td>
</tr>
<tr>
<td>Landholding (ha)</td>
<td>1.12</td>
<td>0.81</td>
</tr>
<tr>
<td>Age of household head in first survey year</td>
<td>44.78</td>
<td>42.00</td>
</tr>
<tr>
<td>Adult equivalents</td>
<td>4.16</td>
<td>3.92</td>
</tr>
<tr>
<td>=1 if death in the family over past two years</td>
<td>0.10</td>
<td></td>
</tr>
<tr>
<td>=1 if primary (grades 1–4)</td>
<td>0.25</td>
<td></td>
</tr>
<tr>
<td>=1 if upper primary (grades 5–8)</td>
<td>0.34</td>
<td></td>
</tr>
<tr>
<td>=1 if secondary (grades 8–12)</td>
<td>0.13</td>
<td></td>
</tr>
<tr>
<td>=1 if post-secondary</td>
<td>0.01</td>
<td></td>
</tr>
<tr>
<td>Past year hungry season maize price (kwacha/kg)</td>
<td>38.15</td>
<td>39.29</td>
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<tr>
<td>Past year harvest season maize price (kwacha/kg)</td>
<td>45.05</td>
<td>44.40</td>
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<tr>
<td>Price of NPK &amp; Urea fertilizer (kwacha/kg)</td>
<td>160.33</td>
<td>153.08</td>
</tr>
<tr>
<td>Agricultural wage rate (kwacha/day)</td>
<td>330.74</td>
<td>283.61</td>
</tr>
<tr>
<td>Average rainfall, past five growing seasons (in cm)</td>
<td>822.59</td>
<td>820.20</td>
</tr>
<tr>
<td>Coefficient of variation on past rainfall</td>
<td>0.11</td>
<td>0.12</td>
</tr>
</tbody>
</table>

---

* Regression results for share of maize area planted to improved maize varieties are not shown for space considerations, as they do not differ fundamentally from share of total area planted to improved maize varieties. These results are available from the authors upon request.

** Variable is converted to real 2011 kwacha. US $1.00 = 151.55 kwacha in 2010/11 (Chirwa and Dorward, 2013).
acquires storage chemicals from subsidized sources. The coefficient estimate, \( z_1 \), tells us the degree to which acquiring subsidized storage chemicals affects the probability that a household will purchase storage chemicals commercially (e.g. the crowd out or crowding in effect). If \( z_1 > 0 \), then acquiring subsidized storage chemicals is said to crowd in commercial chemical use. Conversely if \( z_1 < 0 \), then acquiring subsidized storage chemicals is said to crowd out commercial chemical use, and if \( z_1 = 0 \) there is no effect. Since \( C \) and \( S \) are both binary variables, \( z_1 \) is computed as the average partial effect (APE). The other variable vectors in Eq. (2) are the same as they are in Eq. (1), and the corresponding \( z \)'s represent the parameters to be estimated. The model in Eq. (2) excludes the vector of prices, denoted by \( w \) in Eq. (1), because the prices we have available are determined during the next agricultural season, after the storage chemical purchase decision from the past harvest has been made.

Identification strategy

Ideal identification strategy

In an ideal world we could identify the impacts of storage chemical use, subsidized seed use and subsidized fertilizer use via a randomized control trial (RCT) design where a randomly chosen group of farm households would be given the opportunity to obtain and apply these inputs on their farm. This RCT design would allow us to compare impacts from the treatment group with a control group of farm households who do not receive the inputs. RCTs are now considered the “gold standard” of impact evaluation in the development economics literature, because ideally they should allow us to obtain an unbiased average treatment effect (ATE) of using storage chemicals, subsidized seeds and subsidized fertilizer (Duflo et al., 2007). While it would have been ideal to have the ability to evaluate the effects of these inputs in an RCT framework in our context, given the fact that the government of Malawi rolled out the input subsidy programs without conducting any pilot program or considering the need to measure program impacts in an experimental framework, obtaining the “gold standard” is impossible.

Nevertheless, for evaluating the impact of storage chemicals on improved maize adoption, the panel dataset used in this study gives us the ability to measure before and after effects of the subsidy program and within household changes over time. Using panel methods with a well specified model can remove some of the endogeneity concerns related to using non-experimental methods (Wooldridge, 2010). Furthermore, RCT designs are subject to the critique of limited external validity, as the results obtained in one context may not be relevant in another context (Ravallion, 2009; Barrett and Carter, 2010). In addition, randomizing treatments in agricultural impact assessment has recently come under criticism for failure to control for the effort effect (Bulte et al., 2014). In this situation, participants who are randomly chosen to receive a treatment systematically adjust their level of effort to increase the impact above and beyond the effect of the treatment itself. Failure to account for this effort effect will bias the ATE and overestimate the impact of a treatment.

Current identification strategy

Ultimately given our context and data at hand we do the best possible job we can of identifying consistent impacts of storage chemical use on improved maize adoption in Malawi in a non-experimental context. We need to deal with several modeling challenges in our study to consistently estimate the impact of acquiring storage chemicals on a household’s improved maize adoption decision. The first issue is potential reverse causality between the key RHS variable and the dependent variable. The argument in this paper is that accessing storage chemicals affects the household decision to adopt improved maize varieties. However, one might argue that the relationship goes the other way because households who decide to grow improved varieties may be more likely to acquire storage chemicals if they believe the chemicals are necessary to prevent storage losses. The structure of our analysis should eliminate this concern because the RHS variable that we use is whether or not the household used storage chemicals after the previous harvest, which occurs around May in Malawi. Therefore, that decision is clearly pre-determined before the planting decision is made for the following season, which usually occurs sometime between October and December of the same calendar year in Malawi.

The second potential identification issue is that households are heterogeneous in their ability to acquire storage chemicals. In Malawi, households can go to the market and purchase the quantity of storage chemicals they need or can afford. With the advent of the storage chemical subsidy in 2008/09, any farmer in Malawi could visit an extension office and purchase as many bottles of protectant as they want or need for 100 Kwacha per bottle, subject to availability. To deal with potentially uneven access to storage chemicals by households we include variables such as household assets, distance to the local extension office, distance to roads, and number of dealers who sell subsidized inputs in the village in our empirical models.

The third issue is that even after controlling for observable household-level and community-level access factors, there could be left over unobserved heterogeneity that affects use of storage chemicals and also a households’ decision to adopt improved maize varieties. Other studies related to adoption of inputs in SSA have found different estimates when unobserved heterogeneity is controlled for and when it is not (Suri, 2011; Mason and Ricker-Gilbert, 2013). For example, some households may be more motivated to acquire storage chemicals because they are more aware of pest risk than other farmers. Other farmers could just be more talented and know how to manage pests without chemicals. Factors like motivation and talent are unobservable in our models of improved seed adoption and, if ignored, can cause bias coefficient estimates to the extent they are correlated with storage chemical use.

Fortunately, we have panel data that allows us to address the issue of unobserved heterogeneity. We first estimate all models as linear using a household-level first difference (FD) estimator, which measures the difference in the variables of interest between 2008/09 and 2010/11. As such we estimate Eq. (1) in FD form as follows:

\[
\Delta_i = \alpha_0 + \alpha_{1i}C_{it-1} + \alpha_{2i}F_{it} + \alpha_{3i}S_{it} + \alpha_{4i}D_{it} + \alpha_{5i}B_{it} + \Delta\beta_0 + \Delta\beta_1C_{it} + \Delta\beta_2F_{it} + \Delta\beta_3S_{it} + \Delta\beta_4D_{it} + \Delta\beta_5B_{it} + \Delta\gamma_{it}
\]

(3)

where \( \Delta \) represents the variables in FD form. Eq. (3) demonstrates that the FD estimator removes unobserved time constant heterogeneity, \( \alpha_i \) in Eq. (1), from the model. In this application the FD estimator is preferable to similar but simpler difference-in-differences (DID) estimator, because the DID only measures changes in the main variable \( C_{it-1} \), while the FD estimator measures changes for all RHS variables, and thus completely removes any correlation between \( \alpha_i \) and all RHS variables, including subsidized seed and subsidized fertilizer, from the model. Note that Eq. (2) is operation-alized in an analogous manner using the FD estimator.

The FD estimator offers consistent estimates when models are structured in linear form. However, the dependent variables in our analysis may have non-linear distributions. Unfortunately, FD generates inconsistent parameter estimates when applied to non-linear models due to the incidental parameters problem (Wooldridge, 2010). Fortunately, we can use the Mundlak–Chamberlin (MC) device following Mundlak (1978) and Chamberlain (1984) to deal
with correlation between unobserved heterogeneity and RHS variables in non-linear models. The MC device deals with potential correlation between unobserved heterogeneity and RHS variables by decomposing $a_i$ in the following way:

$$a_i = \varphi_{it} + X_{it} \xi + r_{it} \quad (4)$$

The MC device assumes that $r_{it} | X_i \sim \text{Normal}(0, \sigma^2_i)$; where $X_i$ is the household time average of all time-varying covariates in Eq. (1). Therefore, to operationalize the MC device, $X_i$ needs to be included as a covariate in all equations. This specification provides coefficient estimates that are analogous to FD or household fixed effects estimation (Wooldridge, 2010).

For the purposes of this paper the time varying shocks $\Delta_{it}$ are assumed to be uncorrelated with the covariates in our models. It may be possible that the quantity of subsidized fertilizer and/or subsidized seed acquired by the households may be correlated with time-varying shocks $\Delta_{it}$. The only way explicitly around this is via instrumental variables (IV), we would need 3 IVs in this context, or an exogenous treatment. However, a recent study in Malawi uses the MC device to deal with correlation between RHS variables and unobserved heterogeneity, along with the control function approach using IV to deal with correlation between subsidized inputs and time-varying shocks (Mason and Ricker-Gilbert, 2013). The study finds that controlling for unobserved heterogeneity affects coefficient estimates, but once unobserved heterogeneity is controlled for correlation between time-varying shocks and subsidized seed and fertilizer is found to not to have as statistically significant effect on the coefficients. Therefore, in the present study we assume that subsidized seed, subsidized fertilizer, and subsidized storage chemicals are uncorrelated with time-varying shocks. That being said, as with any study using observational data, our results cannot be considered fully causal.

**Functional form and estimator choice**

Adoption of improved maize varieties

The decision whether or not to adopt improved maize varieties is estimated as a binary decision where the dependent variable takes on a value of 1 if the household adopts improved maize varieties and 0 otherwise. We estimate this decision first as a linear probability model (LPM) using the FD estimator and then by a probit with the MC device. The LPM assumes that the marginal effects are linear and ignores any potential non-linear relationships. The probit estimator allows us to consider that the adoption response may be non-linear across the distribution of our data. These models are first estimated in a parsimonious manner only includes the key RHS variables of interest, if the household used storage chemicals, kilograms of subsidized fertilizer acquired, and kilograms of subsidized seed acquired, along with year and region dummies. Results from the parsimonious model are then compared with the full model that includes the entire set of controls presented in Eq. (1) on the RHS.

Area planted to improved maize varieties

The decision of how much area to plant to improved maize varieties potentially takes on the property of a corner solution variable, because a significant number of households do not grow improved varieties. However, beyond that the distribution of area planted is relatively continuous. Therefore, we compare results when the model is estimated linearly with results using a tobit estimator that accounts for the variable’s corner solution distribution. First the area planted model is estimated using linear FD and results are compared when the model is estimated via tobit with the MC device. Coefficient estimates using parsimonious models specifications are compared to full models specifications just as in the binary adoption model presented above.

Share of area planted to improved maize varieties

The decision of share of total area to plant to improved maize varieties can be captured in a fractional response because the total share must lie between the 0 to 1 range. We compare results using the linear FD model with results using a fractional probit with the MC device, which explicitly constrains the predicted value between 0 and 1. As in the above models, coefficient estimates using parsimonious models specifications are compared to full models specifications.

Crowding out/in of commercial storage chemicals

The decision whether or not to purchase commercial storage chemicals is estimated as a binary 0 or 1 decision. Therefore, the estimators used in this model are the same as the decision whether or not to adopt improved maize varieties. We estimate this decision first as a linear probability model (LPM) using the FD estimator and then by a probit with the MC device. Parsimonious model results are compared to the results of the full model.

Note that all coefficient estimates that are generated via probit, tobit, and fractional probit are reported as average partial effects (APE) using the ‘margins’ function in STATA.

Data

Data from this study come from two waves of surveys on smallholders in Malawi. The first round of data comes from the Agricultural Inputs Support Survey II (AISS2) which was conducted after the 2008/09 growing season in Malawi. The second round of data comes from the Agricultural Input Support Survey IV (AISS4) conducted after the 2010/11 growing season. The data were collected by Wadonda consulting and the two data sets give us a balanced panel of 462 households in 8 districts, across all 3 regions of Malawi. The sample represents 8 major maize growing livelihood zones covering 77% of all rural households (Wadonda Consulting, 2011).

The AISS2 and AISS4 build upon two earlier nationally representative surveys, the Second Integrated Household Survey (IHS2) in Malawi collected during the 2002/03 and 2003/04 growing seasons, and the 2007 Agricultural Inputs Support Survey (AISS1) conducted after the 2006/07 growing season. Unfortunately, questions related to household storage decisions were only asked during the AISS2 and AISS4 surveys and not in any of the earlier surveys. Therefore we have to treat the data as a two wave panel. However, we use inverse probability weights (IPW) multiplied by the survey weights to deal with household attrition and ensure that our sample which remains in the AISS2 and AISS4 are representative of Malawi’s smallholder population. The IPW technique involves three steps: (i) use probit to measure whether observable factors in one wave affect whether a household is re-interviewed in the next wave; (ii) obtain the predicted probabilities (Pr(1)) of being re-interviewed in the following wave; (iii) compute the IPW = (1/Pr(1)) and apply it to all models estimated. For households originally sampled in IHS2, the IPW for household 1 in AISS1 = 1/Pr(AISS1). The IPW in AISS2 = 1/(Pr(AISS1) * Pr(AISS2)), while the IPW for AISS4 is 1/(Pr(AISS1) * Pr(AISS2) * Pr(AISS4)). (For more information on IPW see Wooldridge, 2010). We multiply the IPW by the survey sampling weights in the first wave to control for the probability of

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11. The Mundlak–Chamberlin device is also sometimes referred to as the correlated random effects (CRE) estimator.

12. Results showing the coefficient estimates for the time averages of the covariates, obtained using the MC device are available in Appendix 1 online. Results using pooled estimation that does not control for unobserved heterogeneity are available in Appendix 2 online.
the household being selected for interview from the population. The models estimated by OLS, probit, and FD include the IPW × survey weights. The models estimated via tobit do not include this weighting because IPW is not valid in such models. However the results do not differ in any meaningful way when the IPW is used and when it is not, so attrition issues should not be a major concern in this application.

Landholding and area cultivated

The variables for landholding and area cultivated are constructed using the household survey data from farmer estimates of plot sizes. The RHS variable for landholding is based on the amount of land that farmers say that they have the right to cultivate. It is computed as the sum of crop land, fallow land, virgin land, orchards, and land rented out, but excludes land rented in. Landholding is used as a right-hand-side variable in this analysis to proxy for household wealth.

Area cultivated is constructed as the amount of land that a household cultivates for rainy season crop production during the corresponding year. This calculation includes land rented in but not land rented out.\(^\text{13}\) Area cultivated variable is used to create the dependent variable for area planted to improved maize and share of area planted to improved maize. Since many plots are intercropped in Malawi it is difficult to accurately aggregate exactly how much intercropped land is allocated specifically to maize, and not to other crops on the same intercropped plot. Therefore, for practicality the dependent variables for area planted to improved maize and share of area planted to improved maize should be thought of as area with improved maize cultivated on it.

Prices, wage rates, and rainfall variables

Fertilizer prices

Fertilizer prices used in the study are calculated from the survey as Malawian kwacha per kilogram of commercial maize fertilizer. The price is calculated as an average of urea and Nitrogen/Phosphorus/Potassium (NPK) prices, which are the primary fertilizers applied to maize in Malawi. These prices are based on what survey respondents say they pay for commercial fertilizer during the planting season, generally from October to December in Malawi. For those buying fertilizer commercially we use the observed price that they pay, while for those who do not buy commercially we use the district median price to proxy for the price that the household faces for the input.

Maize prices

Data for the variable representing the median hungry season maize price in the household’s district during the previous year, and the variable representing the median harvest season maize price in the household’s district during the previous year both come from district-level data on maize retail sales, collected by the Malawian Ministry of Agriculture.

Wage rate calculations

Agricultural wage rates are calculated as the price per day of hiring in labor from the household survey. We use the observed price for households who hire in labor, and for those who do not hire in labor, we use the district median wage rate to proxy for the price that they would face to hire workers. The top and bottom 5% of computed wage rates are replaced with district median wage rates to remove outliers.

Rainfall

Locally interpolated time-series data on rainfall come from the University of East Anglia’s Climate Research unit (CRU)-TS 3.1 Climate Database (Climate Research Unit, 2011; Mitchell and Jones, 2005).

These data are considered to be one of the most reliable sources of rainfall data that is available. They are geo-referenced to the household’s enumeration area. The average past rainfall and coefficient of variation on past rainfall variables are constructed as the average over the past 5 years in the enumeration area, and they vary by survey wave. The variables are season specific and is structured as T-J to represent a farmer’s naive expectation at the time of planting as to what he or she expects about the coming seasons rainfall.

All other explanatory variables are constructed from the household survey.

Results

Table 1 presents the means and medians of the variables used in the analysis. The descriptive statistics for the dependent variables indicate that the number of households planting improved varieties, hectares planted to improved varieties, and share of area planted to improved varieties have all increased between 2008/09 and 2010/11. In 2008/09, 51% of households purchase storage chemicals commercially, and 0% acquire storage chemicals through the subsidy program. In 2010/11, 58% of households acquire storage chemicals, with 11% of them acquiring the input through the subsidy program. Should the 11% of farmers who receive the subsidized storage chemicals be among those who ordinarily would not purchase storage chemicals in the absence of the subsidy, then one would not expect any impact on the commercial chemical market (in other words, no impact in crowding in or out of chemical retailers). In fact, further analysis of our data indicate that 154 of the 462 respondents in the survey (33% of the sample) bought commercial chemicals in both 2008/09 and 2010/11. Interestingly, 50 households obtained subsidized storage chemicals in 2010/11, and 27 of those households bought commercial chemicals in 2008/09. Since only 3 of those households also bought commercial chemicals in 2010/11 this suggest relatively significant prima facia evidence of crowding out (24/50 = 48%). However these numbers are descriptive and unconditional and do not control for other factors that could affect crowding out.\(^\text{14}\)

Kilograms of subsidized seed acquired by households also increased during that period from an average of 2.29 kgs per household in 2008/09 to 3.69 in 2010/11. At the same time the average amount of subsidized fertilizer acquired per household declined from 65.88 kg in 2008/09 to 54 kg in 2010/11. It is also interesting to note that the average value of household livestock and durable assets increased substantially from 48,070 Kwacha in 2008/09 to 65,940 in 2010/11, while the median value of assets actually declined during that period from 13,750 in 2008/09 to 13,500 in 2010/11. This may indicate that a select few individuals at the top of the distribution are improving their situation, while the vast majority of smallholders are not accumulating any meaningful quantity of wealth.

Table 2 presents the total kilograms of improved maize seed acquired by households in the sample, and the percentage of households acquiring storage chemicals, disaggregated by source (subsidized or commercial) and survey wave (2008/09 or 2010/11). The results suggest that from the first to the second wave of our survey the amount of commercial seed use goes down as the seed subsidy goes up. This provides some prima facia evidence

\(^{13}\) Note that the correlation between landholding and area cultivated is 0.61 in our dataset.

\(^{14}\) We thank an anonymous reviewer for making this point.
of crowding out from the seed subsidy, as we might expect. In addition, storage chemical use follows the same trend and also shows some evidence of crowding out. However, the table indicates that there is still a significant market for commercial improved seed, and for commercial storage chemicals in both years of the survey. In 2008/09 commercial seed purchases make up 39% of total seed purchases; a mean- 

Table 3 presents the results for factors affecting the probability that a household adopts improved maize varieties. Across the estimators used in columns 1–4 we can see that acquiring storage chemicals is associated with a positive effect on the probability that a household adopts improved maize varieties. The effect is statistically significant, with p-value < 0.10 in all four columns. The coefficient estimates on the RHS variables of interest in parsimonious model specifications are very similar to those in the corresponding fully specified models. This lends confidence in the stability and consistency of the estimates. The coefficient estimates are consistent and indicate that in the linear FD models presented in columns 1 and 2, acquiring storage chemicals is associated with an increased probability that a household plants improved maize seed by between 8.57 and 9.01 percentage points on average. The results using probit with the MC device in columns 3 and 4 which considers possible non-linear effects, indicate that acquiring storage chemicals is associated with an increased probability that a household plants improved maize varieties by between 6.60 and 6.88 percentage points on average. Looking across columns it is also evident that acquiring an additional kilogram of subsidized seed and subsidized fertilizer are significantly associated with an increased probability that a household plants improved maize varieties by a relatively small amount. The direction of the effect is what we would expect ex ante.
Table 4 presents factors affecting the total area in hectares that a household plants to improved maize varieties. Similar to the results in Table 3, Table 4 shows that across columns 1–4 acquiring storage chemicals is associated with a positive and statistically significant effect on the area that households plant to improved maize varieties (p-value < 0.10). Again coefficient estimates from the parsimonious models are very similar to the estimates in the fully specified models. When the model is estimated linearly using FD in columns 1 and 2, the average household who uses storage chemicals is associated with an increase in area planted to improved maize between 0.0848 and 0.0855 hectares. When potential nonlinearities are considered in the tobit with MC device estimation in columns 3 and 4, results indicate that using storage chemicals is associated with an increase in area planted to improved maize between 0.0754 and 0.0758 hectares on average. Considering the fact that the average landholding in our sample is only about 0.0754–0.0758 hectares on average. There is also evidence in columns 3 and 4 to suggest that an additional kilogram of subsidized seed and fertilizer is associated with a statistically significant and relatively small positive effect on area planted to improved maize varieties.

Table 5 shows the factors affecting share of total area that is planted to improved maize varieties. The results of Table 5 are consistent with those in Tables 3 and 4. They indicate that acquiring storage chemicals is associated with a statistically significant and positive effect on share of area that a household plants to improved maize varieties. Again parsimonious model results are similar to full model results for key RHS variables. They indicate that when the models are estimated linearly via FD in columns 1 and 2, using storage chemicals is found to be associated with an increase in the share of area planted to improved maize varieties by between 7.70 and 8.14 percentage points on average. There is also evidence in columns 3 and 4 to suggest that an additional kilogram of subsidized fertilizer is associated with a statistically significant and small increase the share of area planted to improved maize varieties by between 0.029 and 0.030 percentage points on average. When potential nonlinearities are considered in columns 3–4 using fractional probit estimator choice. They show that using storage chemicals after the previous harvest to associated with the household being statistically more likely to plant improved maize varieties, plant more area to improved maize varieties, and plant a larger share of area to improved maize varieties.

Table 6 presents the factors affecting whether or not a household acquires grain storage chemicals on the commercial market following the preceding harvest. The coefficient of the subsidized storage chemical variable provides the estimate of how storage chemicals...
crowd in or crowd out commercial chemical use. The results across model specifications indicate that acquiring subsidized storage chemicals has a statistically significant (p-value < 0.10) and economically meaningful association with crowding out of commercial storage chemicals. Parsimonious model results are similar to full model results. When the models are estimated linearly using FD LPM columns 1 and 2, access to subsidized storage chemicals is associated with a reduction in the probability that a household will purchase commercial storage chemicals by between 50.56 and 51.81 percentage points on average. When nonlinearities are considered using a probit estimator with the MC device in columns 3 and 4, use of subsidized storage chemicals is associated with a reduction in the probability that a household will purchase storage chemicals by about 49.50 percentage points. The results in columns 2 and 4 of Table 6 show that households where the head has some schooling are significantly more likely to purchase commercial storage chemicals on average, than are households where the head has never been to school. Column 4 also indicates that on average households with a higher value of livestock and durable assets are significantly more likely to purchase commercial storage chemicals on average.

The results section in this article concludes with a discussion of how the findings of storage chemicals’ impact on improved maize adoption can affect household income. In order to do so we use parameter estimates from Bezu et al. (2014) that use the IHS2, AISS1, and AISS2 data sets in Malawi. The findings in Bezu et al. indicate that a 1% increase in area under improved maize cultivation increases average household income by 0.261% per adult equivalent, with statistical significance at the 1% level. The study also finds that increases in improved maize adoption have progressive distributional impacts, as a 1% increase in improved maize area raises household income by 0.296% per adult equivalent on average for the poorest third of the sample, while the effect is not statistically significant for the richest third of the sample.

When we put the estimates from Bezu et al. in the context of our study, we find that when the results from column 4 of Table 4 in the present study are converted into elasticity form, a 1% increase in storage chemical is associated with an increase in area planted to improved maize of 0.1123%. When 0.1123 is multiplied by 0.261 from Bezu et al. we find that a one percent increase in storage chemical adoption is associated with an increase in area under improved maize cultivation by 0.261% per adult equivalent. The results in Bezu et al. are also significant for the poorest third of households, as a 1% increase in storage chemical use is associated with an increase in household income of 0.296% per adult equivalent on average for that sub-sample of the population. These results are not huge but are fairly meaningful for smallholder household income in Malawi. It is also important to note that since the crowding out rate of the storage chemical subsidy program is around 50%, then a 1% increase in subsidized storage chemical

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) FD LPM Parsimonious</th>
<th>(2) FD LPM Full</th>
<th>(3) Fractional Probit with MC device(^a) Parsimonious</th>
<th>(4) Fractional Probit with MC device(^a) Full</th>
</tr>
</thead>
<tbody>
<tr>
<td>=1 if HH used storage chemicals after previous harvest</td>
<td>0.0988** (0.015)</td>
<td>0.0906** (0.023)</td>
<td>0.0814** (0.025)</td>
<td>0.0770** (0.031)</td>
</tr>
<tr>
<td>kgs. of subsidized seed acquired</td>
<td>0.0075 (0.208)</td>
<td>0.0077 (0.168)</td>
<td>0.0073 (0.221)</td>
<td>0.0078 (0.174)</td>
</tr>
<tr>
<td>kgs. of subsidized fertilizer acquired</td>
<td>0.0006 (0.129)</td>
<td>0.0006 (0.131)</td>
<td>0.0007* (0.076)</td>
<td>0.0007* (0.054)</td>
</tr>
<tr>
<td>=1 if farm credit organization in village</td>
<td>0.022 (0.955)</td>
<td>0.0102 (0.773)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>distance to paved road (km)</td>
<td>-0.0017* (0.067)</td>
<td>0.0099** (0.042)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>distance to main market (km)</td>
<td>0.0084*** (0.001)</td>
<td>0.0070*** (0.001)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>distance to extension services (km)</td>
<td>0.0004 (0.849)</td>
<td>0.0005 (0.983)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>number of dealers who sell subsidized inputs in village</td>
<td>0.0025 (0.468)</td>
<td>0.0219 (0.269)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>log value of household assets</td>
<td>-0.0125 (0.333)</td>
<td>-0.139 (0.339)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>landholding (in ha)</td>
<td>-0.0106 (0.333)</td>
<td>-0.185 (0.146)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>age of household head in first survey year (^a)</td>
<td>0.0080 (0.457)</td>
<td>0.0091 (0.837)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>=1 if female headed household</td>
<td>0.0180 (0.774)</td>
<td>0.0091 (0.837)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>log of adult equivalents</td>
<td>-0.0165 (0.764)</td>
<td>-0.130 (0.768)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>=1 if primary (grades 1 to 4)</td>
<td>0.0376 (0.463)</td>
<td>0.0247 (0.593)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>=1 if upper primary (grades 5 to 8)</td>
<td>-0.0015 (0.982)</td>
<td>-0.0095 (0.868)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>=1 if secondary (grades 8 to 12)</td>
<td>0.0785 (0.362)</td>
<td>0.0611 (0.404)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>=1 if post-secondary</td>
<td>-0.4946*** (0.004)</td>
<td>-0.4758*** (0.003)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>past year hungry season maize price (kwacha/kg) (^a)</td>
<td>-0.0010 (0.884)</td>
<td>-0.0012 (0.840)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>past year harvest maize price (kwacha/kg) (^a)</td>
<td>-0.0034 (0.660)</td>
<td>-0.0021 (0.753)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>price of NPK &amp; Urea fertilizer (kwacha/kg) (^a)</td>
<td>0.0007 (0.152)</td>
<td>0.0005 (0.304)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>agricultural wage rate (kwacha/day) (^a)</td>
<td>0.0001* (0.082)</td>
<td>0.0001* (0.051)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>average rainfall, past five growing seasons (cm)</td>
<td>0.0029 (0.106)</td>
<td>0.0029* (0.063)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>coefficient of variation on past rainfall</td>
<td>-1.6175 (0.251)</td>
<td>-1.3689 (0.273)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>462</td>
<td>462</td>
<td>924</td>
<td>924</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.035</td>
<td>0.112</td>
<td>0.168</td>
<td>0.267</td>
</tr>
</tbody>
</table>

Coefficients in columns 3 and 4 are Average Partial Effects (APE) estimated via the margins command in Stata; all models include year and region dummy variables; standard errors clustered at the household level; FD = First Difference, LPM = linear probability model, MC = Mundlak-Chamberlain.

\(^a\) Statistically significant at the 10% level.

\(^b\) Statistically significant at the 5% level.

\(^c\) Statistically significant at the 1% level.

\(^d\) Corresponding coefficient is time constant and does not vary over time.
\(^e\) Variable is converted to real 2011 kwacha. US $1.00 = 151.55 kwacha in 2010/11 (Chirwa and Dorward, 2013).

\(^f\) Model includes time-averages of all time-varying covariates; R-squared is correlation-squared in columns 3 and 4.
use can be said to help increase household income by only 0.0145% per adult equivalent for all households, and by 0.0165% per adult equivalent for the poorest third of households. As is the case with all types of input subsidy programs, minimizing crowding out of subsidized storage chemicals can help increase total chemical use among smallholders.

Conclusions & policy implications

To date, the relationship between accessing post-harvest technologies and adoption of improved maize varieties in Africa is poorly understood. Using data from Malawi, this article estimates how use of storage chemicals affects a farmer's decision to adopt improved maize varieties, that while being higher yielding, are more susceptible to pest damage during storage than are traditional maize varieties. The article also estimates the extent to which acquiring subsidized storage chemicals crowds out commercial storage chemical acquisition. The implications of this article are important as food security does not end at harvest. With destructive pests like the larger grain borer changing the face of post-harvest grain management in many regions of sub-Saharan Africa, we provide evidence in this article that the consequences even extend to farmers' planting decisions.

The key findings from this article indicate that acquiring storage chemicals after the previous harvest is associated with a statistically significant increase in the probability that the average household will plant improved maize varieties, plant a larger area to improved maize varieties, and increase the share of total area that is planted to improved maize varieties. The magnitude of the effects are not large, but are meaningful for smallholders.

These results are what we might expect, given that Malawian farmers acknowledge available improved maize varieties to be more susceptible to insect pests than local varieties. Therefore, increased access to storage chemicals may increase households' willingness to adopt these higher yielding varieties. Increased adoption of improved maize varieties can have important economic effects for smallholders, because these varieties have the potential to increase yields, and thus household income and food security. Combining our results with findings in Bezu et al. (2014) indicate that an increase in storage chemical use is associated with a small positive effect on household income through its influence on adoption of improved maize varieties. Additional benefits may be also realized by smallholders by maintaining higher quality grain in storage, to sell later at higher prices.

In addition, this study finds that the storage chemical subsidy is significantly associated with crowding out commercial storage chemicals ceteris paribus. These effects are consistent with other studies in both Malawi and Zambia that measure crowding out of commercial fertilizer by subsidized fertilizer (Xu et al. 2009; Ricker-Gilbert et al., 2011; Mason and Jayne, 2013), and crowding out of commercial seed by subsidized seed (Mason and Ricker-Gilbert, 2013). The results from our study indicate that the lower bound crowding out estimate for the subsidy is a 50.56 percentage point reduction in the probability that a household buys storage chemicals commercially. This translates into the storage chemical subsidy only raising the probability that a household will use storage chemicals by about 49.50 percentage points on average.

Ultimately, results from this article demonstrate that policies and programs that facilitate access to storage inputs, chemical or otherwise, can advance the adoption of improved maize varieties that can enhance staple crop production and food security goals.
for smallholder producers. Failure to account for the production and post-harvest biological constraints which farmers face may result in sub-optimal input use among smallholders. This can undermine the effectiveness of input subsidy programs that seek to promote improved seed adoption by subsidizing seed and inorganic fertilizer. While subsidies for storage chemicals can increase adoption of the input and area planted to improved varieties, they need to be targeted to households who are unable to purchase them on the commercial market, in order to reduce crowding out of commercial inputs. In addition, the supply chain for storage chemical can be strengthened by distributing subsidized chemicals through private agro-dealers, just like the seed subsidy in Malawi, rather than through extension offices.

The goal of this article is to show that there is a clear relationship between access to storage technologies and adoption of improved maize varieties. However, results from this article should not necessarily be used to advocate for increasing storage chemical use among smallholders. Storage chemicals may have other health risks that have not been addressed here, and there are alternative post-harvest technologies such as hermetic (air tight) storage containers that can potentially reduce pest risk in a chemical-free environment. If the government wants to promote storage chemicals to protect against insect damage in the post-harvest season, farmers need to be trained on how to use these chemicals appropriately. While the evidence presented in this study applies to Malawian farmers, this relationship is relevant for smallholder farmers in many regions who face destructive storage pests like the larger grain borer. Our result also show that researchers, extension staff, and policy makers should consider post-harvest issues when promoting adoption of improved varieties.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version, at http://dx.doi.org/10.1016/j.foodpol.2014.10.015.

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