IS LATE REALLY BETTER THAN NEVER? THE FARMER WELFARE EFFECTS OF PINEAPPLE ADOPTION IN GHANA[1]

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Abstract:
Export agriculture offers potentially high returns to smallholder farmers in developing countries, but also carries substantial market risk. In this paper we examine the intertemporal welfare impact of the timing of a farmer's entry into the export pineapple market in southern Ghana. We examine whether farmers who never cultivated pineapple are better or worse off than farmers who decided to adopt pineapple earlier or later relative to their peers and experienced a significant adverse market shock several years prior to our endline survey. We use a two stage least squares model to estimate the causal effect of duration of pineapple farming on farmer welfare. Consistent with economic theory, we find that earlier adoption of the new crop brings greater welfare gains than does later uptake. But we find that the gains to later uptake of pineapple – just before the market shock – are small in magnitude, just 0.1 standard deviations of a comprehensive asset index, indicating that the gains to adoption may be precarious and depend on the context, in particular on the severity of prospective market shocks.

Keywords: smallholder welfare, cash crops, market access, pineapple, technology adoption and disadoption

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1. Introduction

There has been much optimism about the prospects for development through agricultural exports in low-income countries (World Bank 2008). Several studies examine the increased market opportunities of smallholders due to the proliferation of supermarkets in low- to middle-income countries, the increase in exports due to liberalized rules of trade and foreign direct investment, and improvements in logistics and infrastructure (Reardon *et al.* 2009). Most careful evidence to date finds that, even controlling for the initial advantages often enjoyed by those who participate in modern agrifood value chains, smallholder suppliers tend to enjoy higher net earnings per hectare or per unit of output marketed, although this is by no means universal or uniform (Michelson 2013, Barrett *et al.* 2012).

In response to these generally positive effects for smallholders, aid agencies have invested heavily in efforts to train and equip farmers in developing countries to grow cash crops such as pineapple for export. They have recognized and attempted to alleviate some of the various constraints farmers face in entering these markets, for example, by providing access to credit, technical and institutional training, and appropriate certification.

Crucial questions remain, however, about the ability of smallholders to succeed or even benefit from export agricultural market opportunities. Indeed, supplying modern value chains exposes producers to significant new market risks, especially if farmers reallocate land and other scarce inputs to the export crop, becoming vulnerable to disruptions outside local market control, such as changing foreign consumer preferences, exchange rates, or trade barriers (Maertens and Swinnen 2009). For example, the epilogue in Ashraf *et al.* (2009) studying the effects of Kenyan smallholders growing baby corn and French beans describes the catastrophic effect that farmers faced when their crop no longer met the revised Euro-Retailer Produce Working Group Good Agricultural Practices (EurepGAP) 2005 requirements.

The case we study is similarly cautionary. European demand for fresh pineapple from Ghana grew rapidly over the course of the 1990s and early 2000s, abetted by expanded sea freight capacity (FAOStat 2013, Fold and Gough 2008). From 2005, after almost a decade of rapid growth in pineapple production and exports, demand for Ghana's pineapples suddenly fell sharply (Figure 1). The main explanation for the drop in demand was a sudden shift among European consumers' taste from the variety of pineapple most commonly grown in Ghana, Smooth Cayenne, to a new variety called MD2 (Fold and Gough 2008). This paper studies the welfare consequences of the timing of farmers' pineapple adoption in the face of this exogenous market shock. We use original data from four communities in the Akwapim South district of Southern Ghana, where the returns to pineapple adoption were initially extremely high (Conley and Udry 2010, Udry and Goldstein 1999). Because the onset and effects of the shock were fully exogenous to the farmers in this study, we can treat the demand shock as a natural experiment.

More specifically, this study compares the implications for smallholder farmers' long-term household welfare of the timing of a farmer's decision to grow pineapple, in particular whether to adopt early, late or not at all. In the canonical model of the farmer welfare effects of technology adoption (Cochrane 1958), early adopters systematically benefit most from the introduction of a new and lower-cost farm technology, while nonadopters lose, and late adopters fall somewhere in between, perhaps benefitting, perhaps suffering some losses, although not as large as those endured by non-adopters who face lower prices without enjoying lower costs. But that theory relies on a strong assumption that the new technology is unambiguously and permanently superior for the farmer. Although analysts commonly use technology adoption models to explain patterns of uptake of new products – such as pineapple in Ghana (Conley and Udry 2010, Udry and Goldstein 1999), sunflower in Mozambique (Bandiera and Rasul 2006), or horticultural crops in Kenya (Ashraf *et al*. 2009) – a new crop is more profitable only conditional on consumer demand. If market demand for the new crop suddenly collapses, due to shifting standards (Ashraf *et al*. 2009), consumer tastes (Fold and Gough 2008), or if the market price collapses due to excessive aggregate supply expansion in the face of price inelastic demand (McKay *et al*. 1997), then adoption no longer unambiguously dominates non-adoption. In that case, the timing of entry into and exit from the market matters. And in the case of perennial crops, like pineapple, non-trivial sunk costs create frictions that can cause predictable delays in entry and/or exit that can then prove costly. This basic insight has been overlooked to date in the literature on smallholder crop choice and technology adoption. In this paper, we explore whether those southern Ghanaian farmers who never cultivated pineapple are better or worse off than farmers who decided to adopt the technology and subsequently suffered an exogenous market shock, and whether the long-term welfare effects vary by whether farmers adopted pineapple earlier or later.

The remainder of this paper is structured as follows. Section 2 provides some background on pineapple cultivation in Ghana. Section 3 then explains the data. Section 4 describes the empirical strategy, section 5 discusses the results, and section 6 concludes.

2. Background

Pineapple (*Ananas comosus*) is a unique crop for multiple reasons. Pineapple is a perennial grown not from seed, but rather from vegetative propagation from ‘suckers’, the side shoots from the plant’s main stem. Each plant bears a single fruit and multiple suckers, which can subsequently generate fruit themselves. It takes some time before a farmer can harvest, typically 10-20 months after suckers are planted. And if a farmer decides to discontinue pineapple, s/he must dig up and remove the plants. Pineapple cultivation also does not follow a seasonal calendar. In the Akwapim South region of Ghana, pineapples can be grown at any time of the year. Entry into the pineapple market thus involves a longer-term investment and greater sunk entry and exit costs than does the seasonal cultivation of grains, roots and tubers that has been customary in Akwapim South. These characteristics create frictions that impede both entry and exit (Dixit and Pindyck 1994, Chavas 1994), impeding the sort of easy and regular transition between adoption and disadoption that is feasible with respect to farmers’ seed and fertilizer choices, for example (Suri 2011). The timing of entry into and exit from an industry like pineapple farming can therefore matter a great deal in the face of stochastic market conditions.

Pineapples grow best in slightly more acidic soils, with an optimum pH ranging between 4.5 and 6.5, which is lower than for most other crops. Maize, for example, grows best in soils with a pH of 6.0-7.0. Furthermore, pineapples can survive long dry periods, although sufficient water is important during flowering and fruiting (FAO, http://www.fao.org/nr/water/cropinfo_pineapple.html).

Smooth Cayenne, a variety that originated in Hawaii, is one of the most common pineapple varieties. It is sweet, juicy and especially well suited to canning and processing. Coastal West Africa's climate and relative proximity to ports and to Europe gave it both cost and quality advantages in the export market for fresh Smooth Cayenne pineapple. In the 1990s, as transport bottlenecks that had previously limited fresh fruit export volumes relaxed, Ghana's pineapple production increased significantly. Farmers who entered the pineapple market in the 1990s enjoyed significant increases in farm profits relative to the maize-cassava intercropping that had prevailed for many years (Conley and Udry 2010, 2001). Udry and Goldstein (1999) estimated that farmers in Ghana could achieve returns ten times higher growing pineapple for export than maize or cassava for semi-subsistence or local trading. The strong reported profits and abundant technical assistance available to southern Ghanaian smallholders from the late 1990s through the mid-2000s attracted many new entrants into pineapple production.

A competing variety, MD2, was aggressively propagated by Del Monte in Costa Rica and marketed in Europe in the early 2000s to meet consumer demand for sweet, juicy and yellow pineapples (Fold and Gough 2008). MD2 pineapples are slightly smaller and have a more square shape than Smooth Cayenne, thereby lending themselves better to packing and stacking on supermarket and refrigerator shelves. Enjoying ideal growing conditions and significant economies of scale, from the early 2000s Costa Rica's lower cost of MD2 production began significantly undercutting Smooth Cayenne in the competition for European retail markets, gutting Côte d'Ivoire's once-dominant market share and significantly diverting demand from Ghana too (Fold and Gough 2008, http://developeconomies.com/development-economics/a-brief-history-of-fresh-pineapple-exports-in-ghana/).[2]

The demand for Smooth Cayenne pineapple decreased as early as the end of 2003, and was noticed by major players in the industry in Ghana at that time (Ghanaian Chronicle 2004). The fall in demand became more pronounced during 2004, the point at which it was reported by most farmers in our sample. When describing the market shock to us, farmers recounted having to leave their entire crop to rot in the fields when the buyers stopped coming. Some reported losing thousands of dollars in revenue, more than the total assets of the median household in the survey communities. While farmers previously had informal agreements to sell to certain buyers, they quickly learned to demand written contracts from buyers and they formed cooperatives to provide legal support in the event that the contracts were not honored. While government, aid donors and large pineapple processing companies introduced initiatives to equip farmers to shift to the new variety, MD2, (GNA 2004), many smallholder farmers decided to leave the pineapple industry entirely in the wake of this market shock.

The industry consolidated in the wake of the collapse of the European export market for Smooth Cayenne, with large farms supplying the bulk of Ghana's MD2 for export. Smallholder farmers who continued to farm as of 2009-10 concentrated mainly on supplying Smooth Cayenne to local factories for canning and juicing, with only a limited amount of Smooth Cayenne being exported from Ghana. Ghana's pineapple producers'

[2] Ghanaian farmers might also have lost their ability to export to Europe because of the widespread adoption of a new and demanding certification standard, EurepGAP, in Europe around the same time. However, focus group discussions with farmers in Akwapim South suggest the new certification standards were of minor concern. Farmers reported being offered timely support from NGOs to adopt the standards and pass the required audits.

experience with the rise and fall of an export market offers uncommon insights into the welfare impacts of the timing of market entry and exit when producers face significant sunk costs that create frictions in these transitions.

3. Data

The data come from two panel surveys of four communities in the Akwapim South district in southern Ghana. The first survey, conducted in 1997 and 1998 by a team led by Chris Udry and Markus Goldstein, interviewed approximately 250 couples (500 spouses in each of 250 households), collecting extensive data on respondents' farming practices, social networks and household characteristics, including a 15-month panel of data on household consumption and wealth[3]. Soil samples were also collected during the 1998 survey from each plot owned by a respondent. In 2009, 70 households in each of those same four villages were resurveyed using a nearly identical questionnaire to the 1997-98 survey instrument. Approximately half of the households surveyed in 2009 were part of the initial 1997-98 sample.[4] Five survey rounds were conducted (one round every two months), covering a wide range of subjects, including personal income, farming and non-farm business activities, gifts, transfers and loans, household consumption expenditures and respondents' in-sample social networks.[5] These data were supplemented with focus group discussions conducted in September 2009 and July 2010 in the two main pineapple farming villages, Pokrom and Oboadaka.

[3] Further details can be found in Udry and Goldstein (1999).
[4] In the original sample, and in the 2009 re-sampling, we selected only from the pool of households headed by a resident married couple. However, we retained households from the 1997-98 sample even if only one of the spouses remained. These 'single-headed households' account for between 7 and 15 of the sample households in each community.
[5] Details and questionnaire can be found in Walker (2011).

4. Econometric strategy

We are interested in measuring and comparing the change in welfare experienced by different categories of farmers: those who never take up pineapple ('nonadopters') and those who enter the market ('adopt') early or late, as well as those entrants who exit the market ('disadopt') early or late. The central prediction of the canonical farm technology adoption model (Levins and Cochrane 1996, Cochrane 1958) is that early adopters gain relative to late adopters, who in turn fare better than nonadopters. The adage 'better late than never' follows directly. Allowing for the possibility that the new 'technology' subsequently becomes relatively unprofitable, the same logic holds that early disadopters – those who abandon the new crop soon after it becomes less profitable – would fare better than late disadopters. This logic yields a clear prediction of the ordering of the welfare effects between early adopters/early disadopters and late adopters/late disadopters. But for new crop adoption – as distinct from the adoption of a new production technology that is unambiguously and permanently superior if replaced (Foster and Rosenzweig 1996, Cochrane 1958) – it becomes ambiguous whether the 'better late than never' prediction holds. This requires empirical exploration that, to the best of our knowledge, has not previously been undertaken.

Because the decision and timing of adoption is a choice variable that cannot be randomly assigned, observed outcomes are likely correlated with both time-invariant and time-varying unobserved variables causing the point estimates of duration of pineapple cultivation to be biased in a standard ordinary least squares estimation framework. We therefore employ an instrumental variables strategy to account for the prospective selection bias in the timing of pineapple cultivation. We estimate a tobit model to predict how many years a household cultivates pineapple before the demand shock, taking into account the censoring of duration at zero for nonadopters. We use exogenous soil conditions, pH and soil organic matter, as instruments, explained in more detail below. Unfortunately we were unable to find a convincing instrument for disadoption which is likely correlated with a farmer's ability, social networks and assets that likely also affect changes in well-being over time. Therefore, we do not examine the timing of disadoption, but rather focus on the effect and magnitude of timing of adoption before the exogenous market shock. In the second stage estimation, we use a fixed effects panel data estimator to control for time-invariant unobservables and estimate the effect of instrumented pineapple cultivation duration, pre- and post-shock, and farmer category on household welfare in 2009, proxied by an asset index.

More specifically, in the first stage, we first estimate the duration (in years) that a farmer cultivated pineapple before the export market shock hit, roughly in January 2004. A tobit model accounts for the left-censoring of duration at zero that occurs for farmers who never farmed pineapple[6]. Therefore, we have,

$$\begin{gathered} y_i^* = \boldsymbol{X}_i\gamma_1' + \boldsymbol{Z}_i\gamma_2' + \varepsilon_i \\ y_i = 0 \; if \; y_i^* \leq 0 \\ y_i = y_i^* \; if \; y_i^* > 0 \end{gathered} \tag{1}$$

where the variable y represents the observed duration measured in years for individual i. The latent variable is $y^* \sim N(\mu, \sigma^2)$ and the Prob$(y^* \leq 0) = \Phi(-\mu/\sigma)$ where $\Phi(.)$ is the normal cumulative distribution function. The matrix $\boldsymbol{X'}$ contains individual- and

[6] 55 percent of the sample farmers never cultivated pineapple.

community-level explanatory variables while the matrix $\boldsymbol{Z'}$ contains individual-level instrumental variables. We cluster errors to allow for correlation at the village level.

As shown in Figure 1, the value and quantity of pineapples exported from Ghana decreased significantly from 2004 to 2005. We therefore use January 1, 2004 as the "shock" date, measuring the years before January 2004 to determine the duration a farmer cultivated pineapple before the shock.[7] The duration variables were constructed using data collected in the 2009 survey, asking farmers whether they farmed pineapple and the dates they started and ended farming it. The median adoption date conditional on adoption pre-shock was March 1996.

The first stage explanatory variables were taken from the 1998 surveys and include age and age squared to control for life cycle effects, gender of the household head, dummy variables for whether the respondent attended primary, secondary or high school, number of household members, number of working age household members (ages 18-60 years), number of years having resided in the village, and a social network variable indicating the number of people a person knows[8]. Table 1 shows summary statistics for the variables used in the first stage estimation. 46 percent of the sample is female with a mean age of 40, a mean household size of 8 of which on average 3.7 are of working age. 53 percent of respondents received schooling through middle school.

Our ability to identify the welfare effects of adoption and timing of pineapple adoption rests on the challenging task of finding an instrument, z, that is correlated with

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[7] Below we repeat the estimation to allow for changes to timing of the market shock. The qualitative results are unchanged.

[8] Respondents were asked about their relationship with other villagers, including how well they knew the other villagers, how long they had known them and how often they had spoken to them. Here we simply control for the number of villagers a respondent knows.

the decision and duration of cultivating pineapple, but not independently with changes in farmers' welfare status. We use two instruments, the respondents' mean 1998 soil organic matter (SOM) and acidity (pH) levels observed among the plots a farmer cultivated. Pineapple thrives in low pH and high SOM soils, so the likelihood that a farmer adopts and the duration s/he cultivates pineapple should be related to one or both of these variables. Meanwhile, high acidity (i.e., low pH) lowers the productivity of virtually all other crops grown in Akwapim South, while high SOM has the opposite effect. We would therefore not expect these variables to jointly affect change in farmer asset holdings independently of their effect on pineapple cultivation. The most acidic soil recorded had a pH of 5.4 with a mean pH of 6.4. The mean soil organic matter was 3.18 percent. We test the exclusionary restriction (in the second stage) necessary for these variables to serve as suitable instruments for pineapple cultivation and confirm the statistical defensibility of this instrumental variables estimation strategy.

Given the first stage tobit estimates, we predict the number of years that a household cultivated pineapple pre-shock. Figure 2 shows the close fit between observed and predicted duration (years). The correlation coefficient between observed and predicted duration pre- shock is 0.59. We use these predicted values to estimate the effect of duration on welfare using a fixed effects model. Specifically, we estimate

$$\Delta w_i = \alpha_0 \hat{y}_i + \Delta \boldsymbol{X}_i \beta' + u_i \qquad (2)$$

where Δw_i is the change in welfare for individual i between 1998 and 2009, $\hat{y}_i$ is the predicted duration pre- and post-shock from the first stage, $\Delta \boldsymbol{X}_i'$ is a matrix of time-varying control variables, and u_i is the error term, which captures any remaining individual- and time-varying unobservables that we assume to be i.i.d and have mean zero. Table 2 shows summary statistics for the controls included in the second stage tobit estimation.

We proxy welfare with an asset index. The use of assets and asset indices to measure household welfare has become more common over the last decade, providing some advantages over other more common welfare measures, e.g., consumption, income and expenditures. Because assets are accumulated over time and last longer, they tend to better reflect a household's permanent income or longer-term living standards than income, for example, which often suffers from seasonal variation and/or a large share of non-remunerated self-employment (Moser and Felton 2007, Sahn and Stifel 2000) or even expenditures, which are subject to liquidity constraints and greater measurement error than easily-observed assets (Carter and Barrett 2006, Filmer and Pritchett 2001, Sahn and Stifel 2000). Several studies have indeed shown a strong link between household productive assets and subsequent poverty rates (Adato *et al*. 2006, Barrett *et al*. 2006).

In constructing an asset index, one must choose a set of weights to assign to each asset within an asset category. The weights are multiplied to the asset and summed over the different assets within a category to create the index. Commonly used weights include prices, unit values, or parameter estimates from principal components analysis, factor analysis, multiple correspondence analysis or polychoric principle components analysis (Moser and Felton 2007). Obtaining asset prices can be difficult in the context of low-income rural communities where secondary markets for assets are thin and market prices may not accurately reflect the quality of an asset. Another method involves assigning each asset a binary value of one or zero if it is owned or not and summing the number of assets within a category. While such a method is simple, it does not differentiate among assets with radically different values. Filmer and Pritchett (2001) recommend using principle components analysis (PCA) to aggregate several binary asset ownership variables into a single dimension. Sahn and Stifel (2000) use factor analysis (FA) instead of PCA, arguing that FA offers more flexibility because it does not force all the components to explain the correlation structure between the assets. We follow the Sahn and Stifel (2000) FA method to create an asset index.

We generate four asset indices, one each representing durable goods (bicycle, car, fan generator, radio, television, etc.), livestock (goats, lambs, sheep, ducks, etc.), productive goods (barrel, chain saw, pick axe, pump, etc.) and finally an overall asset index encompassing all of the preceding three categories. Summary statistics for each good owned by respondents comprising the asset indices are reported in Appendix A. Estimated factor loadings are reported in Appendix B. Summary statistics for the asset indices are reported in Table 3 by wealth percentile and by year. As expected, the mean value of the asset index increases by percentile group across all asset indices for both years.

A total of 508 individuals were surveyed in 2009. A large number of these individuals – 291 or approximately 57% – were also surveyed in 1998. Approximately 224 individuals were surveyed in 1998 but not in 2009 because they were no longer found for various reasons (e.g., death, moved away, etc.). Because attrited households may systematically differ from those households who remain in the survey, failure to account for these possibly systematic correlations may bias results. We correct for the resulting potential attrition bias using inverse probability weights, following the procedure explained in Baulch and Quisumbing (2011). We create weights for each observation by estimating two probit equations – one with variables associated with attrition and the other without. Intuitively, their ratio creates weights giving households that have similar initial characteristics but subsequently attrit more weight.

There exists one additional source of prospective bias that has not yet been addressed: supplier-side bias, whereby suppliers might select to purchase pineapples from farmers who have certain skills, access to resources, or have plots closer to roads. In our discussions with pineapple grower groups, farmers explained that buyers would visit their village, often unannounced, and would purchase pineapples from any farmer whose pineapples were ready for harvest. We therefore assume no supplier-side selection effects exist in this particular setting.

5. Results and Discussion

Results for the tobit model (equation 1) are reported in Table 4. As expected, farmers with high school level education are statistically significantly more likely to have adopted pineapple earlier (i.e., longer duration of pre-shock cultivation). Women are strongly and significantly less likely to have adopted pineapple, and much less early. Crucial to our identification strategy, an increase in soil pH level has a strong negative and statistically significant effect on the duration of pineapple cultivation pre-shock. This is exactly as expected given that pineapples grow better on more acidic soils. SOM, however, does not have a statistically significant independent effect on pineapple cultivation duration.

Given the estimated tobit model, we can predict the duration a household farmed pineapple before January 1, 2004. The predicted values are censored at zero such that all predicted values are non-negative. The censored mean values are shown in Table 5.

Using the predicted values from the tobit model, we estimate the fixed effects model (equation 2) of the effect of duration before the shock on change in the comprehensive asset index. Results are shown in Table 6 using different specifications as a check on the robustness and stability of our core parameter estimates of interest. The number of years a farmer has grown pineapple before the shock has a positive estimated effect on household wealth under all specifications and is statistically significant when controlling for age, change in household size, change in household members of working age and whether they attended high school (Models I-III). Models IV and V modify our preferred IV specification, Model III, by including the square of the pineapple cultivation duration or a dummy variable for nonadopters, respectively, to allow for prospective nonlinearities in the effect of duration on wealth accumulation. Neither of those coefficient estimates is statistically significant, but they reduce the precision of our estimate of the impact of pineapple cultivation duration on wealth accumulation because of the small sample size and their collinearity with the primary variable of interest. The instrumented results are roughly six times larger in magnitude and more precisely estimated but qualitatively consistent with the ordinary least squares estimation result (Table 6, column 'OLS').

We also test how sensitive our results are to changing the shock date. Indeed, given that pineapple in Akwapim can be cultivated throughout the year, the shock might have been experienced at different times for different farmers depending on their harvest date. Table 7 shows model III estimated at different cut off dates. Defining the shock date at January 2004 or January 2005 does not affect our interpretation of results. Cut-off dates after 2005 are increasingly likely to suffer from endogeneity due to the propensity for better off farmers to weather the market shock.

We also estimate model III from Table 6 using the different asset indices as the welfare measure, as shown in Table 8. Pineapple cultivation duration before January 2004 only has a positive and statistically significant effect on the all-encompassing and productive asset indices, indicating that the earlier a farmer adopted pineapple, the greater the household's overall wealth in 2009 and the more she has accumulated in the way of productive assets used to generate income. By contrast, duration of pineapple cultivation pre-January 2004 has a slight negative but not statistically significant effect on the durable and livestock asset indices.

Finally, given the coefficient estimates reported in model III of Table 6, we plot how the timing of a farmer's entry into pineapple cultivation affected his/her 2009 welfare, as measured by the overall asset index. As seen in Figure 3, early adopters benefit significantly relative to late adopters and nonadopters. Indeed, late adopters are only 0.1 standard deviations better off than nonadopters. So while we find that late adopters are statistically significantly better off than nonadopters, the gains do not appear economically significant, unlike the gains from early adoption. The ordering between these groups obviously depends on the magnitude of the market shock, if any, experienced by new entrants. But these results clearly call into question the longstanding assumption that 'better late than never' applies to entry into new product markets, as well as to the uptake of unambiguously and irreversibly superior production technologies.

6. Conclusions

Timing market entry and exit optimally is notoriously difficult, especially in the face of sunk costs and market frictions. But as our results show, the timing of entry into a new product market matters to the intertemporal welfare effects of farmer uptake of a new, currently profitable crop. The familiar adage 'better late than never' may not necessarily hold. As in the case of southern Ghanaian pineapple producers, those who never converted to the new crop fared almost as well off as late adopters, without having to bear the risk of potentially more damaging losses.

These results carry important policy implications. The introduction of new cash crops, especially those that may not have a domestic market and thus are subject to added market risk associated with exchange rates, foreign market access standards and unfamiliar consumer tastes, must be undertaken with caution. Under the best of circumstances, some adopters – especially early adopters – will benefit from increased profits associated with new products. However, the adoption of new technologies may expose smallholders to new and heightened market risks. Producers and those who promote new products must remain attuned to shifting market conditions and be prepared to facilitate orderly exit from the subsector if and when demand patterns shift adversely. In product markets with significant risk and high entry and exit costs, financial instruments may also be warranted to protect small farmers against the consequences like those faced by farmers in Akwapim South.

8. References

Adato M, Carter M and May J (2006). "Exploring poverty traps and social exclusion in South Africa using qualitative and quantitative data". *Journal of Development Studies* 42(2): 226-247.

Ashraf N, Giné X and Karlan D (2009). "Finding missing markets (and a disturbing epilogue): Evidence from an export crop adoption and marketing intervention in Kenya". *American Journal of Agricultural Economics* 91(4): 973-990.

Barrett C, Marenya P, McPeak J, Minten B, Murithi F, Oluoch-Kosura W, Place F, Randrianarisoa J, Rasambainarivo J and Wangila J (2006). "Welfare dynamics in rural Kenya and Madagascar". *Journal of Development Studies* 42: 248-247.

Barrett C, Bachke M, Bellemare M, Michelson H, Narayanan S and Walker T (2012). "Smallholder participation in contract farming: comparative evidence from five countries". *World Development* 40(4): 715-730.

Baulch B and Quisumbing A (2011). "Testing and adjusting for attrition in household panel data". Chronic Poverty Research Center Toolkit Note. Available online at http://www.chronicpoverty.org/publications/details/testing-and-adjusting-for-attrition-in-household-panel-data

Carter M and Barrett C (2006). "The Economics of Poverty Traps and Persistent Poverty: An Asset-Based Approach". *Journal of Development Studies* 42(2): 178-199.

Chavas J (1994). "Production and Investment Decisions Under Sunk Cost and Temporal Uncertainty". *American Journal of Agricultural Economics* 76 (1): 114-127.

Cochrane W (1958). Farm Prices: Myth and Reality. St. Paul: University of Minnesota Press.

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

Conley T and Udry C (2001). "Social learning through networks: the adoption of new agricultural technologies in Ghana". *American Journal of Agricultural Economics* 83(3): 668-673.

Dixit A and Pindyck R (1994). Investment under Uncertainty. UK: Princeton University Press, Chichester, West Sussex.

FAO: http://www.fao.org/nr/water/cropinfo_pineapple.html, last accessed July 2013.

FAOSTAT: http://faostat.fao.org checked July 2013.

Filmer D and Pritchett L (2001). "Estimating wealth effects without expenditure data or tears: an application to educational enrollments in states of India". *Demography* 38(1): 155-132.

Fold N and Gough K (2008). "From smallholders to transnationals: the impact of changing consumer preferences in the EU on Ghana's pineapple sector". *Geoforum* 39(5): 1687–1697.

Foster A and Rosenzweig M (1996). "Technical change and human-capital returns and investments: evidence from the Green Revolution". *Journal of Political Economy* 86(4): 931-953.

Ghanaian Chronicle (2004), 'Pineapple exporters face stiff competition.' March 4, 2004 news article, accessed from http://www.modernghana.com/news/50702/1/pineapple-exporters-face-stiff-competition.html on January 13, 2011.

GNA (2004), 'Ghana to Produce MD2 Pineapple Suckers.' September 10, 2004 news article, accessed from http://www.modernghana.com/news/62783/1/ghana-to-produce-md2-pineapple-suckers.html on January 13, 2011.

http://developeconomies.com/development-economics/a-brief-history-of-fresh-pineapple-exports-in-ghana/ last accessed August 2013.

Levins R and Cochrane W (1996). "The treadmill revisited". *Land Economics* 72(4): 550-553.

Maertens M and Swinnen J (2009). "Trade, standards, and poverty: evidence from Senegal". *World Development* 37(1): 161-178.

McKay A, Morrissey O and Vaillant C (2007). "Trade liberalization and agricultural supply response: issues and some lessons". *European Journal of Development Research* 9(2): 129-147.

Michelson H (2013). "Small farmers, NGOs, and a Walmart world: welfare effects of supermarkets operating in Nicaragua". *Amercian Journal of Agricultural Economics* 95(3): 628-649.

Moser C and Felton A (2007). "The construction of an asset index measuring asset accumulation in Ecuador". The Brookings Institution: CPRC Working Paper 87.

Reardon T, Barrett C, Berdegue J and Swinnen J (2009). "Agrifood Industry Transformation and Small Farmers in Developing Countries." *World Development* 37(11): 1717-1727.

Sahn D and Stifel (2000). "Poverty comparisons over time and across countries in Africa". *World Development* 28(12): 2123-2155.

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

Udry C and M Goldstein (1999). "Agricultural innovation and resource management in Ghana." Unpublished final report to IFPRI under MP17.

Walker, T F (2011). "Risk Coping, Social Networks and Investment in Rural Ghana." Ph.D. Dissertation, Cornell University.

World Bank (2008). *World Development Report*. Washington DC: World Bank.

9. Figures

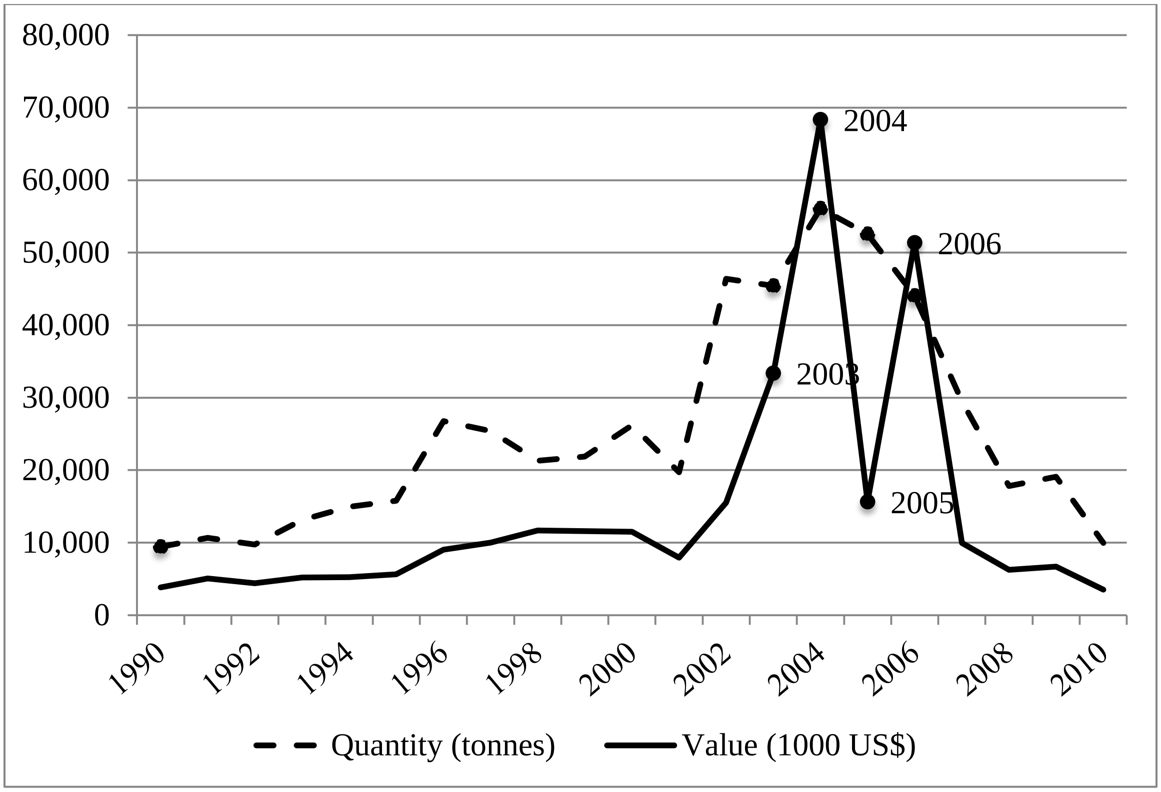

Figure 1. Pineapple quantity and pricesvalue exported from Ghana (FAOSTAT, 2013)

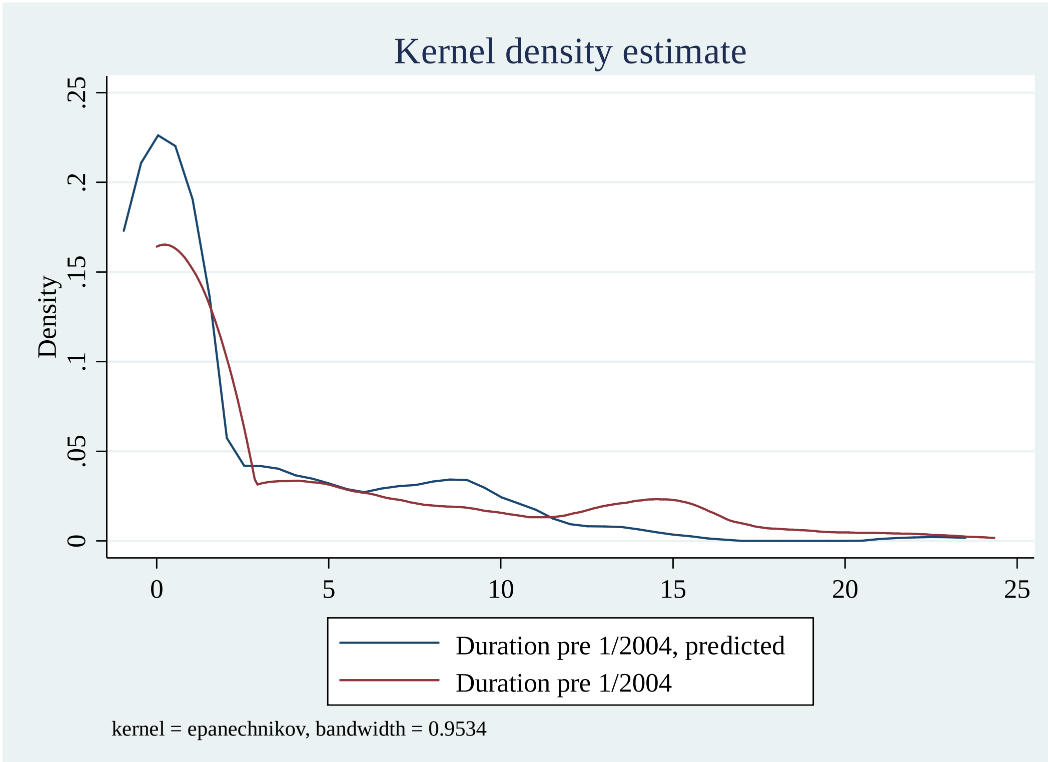

Figure 2. Observed and predicted pre-2004 duration variables (months)

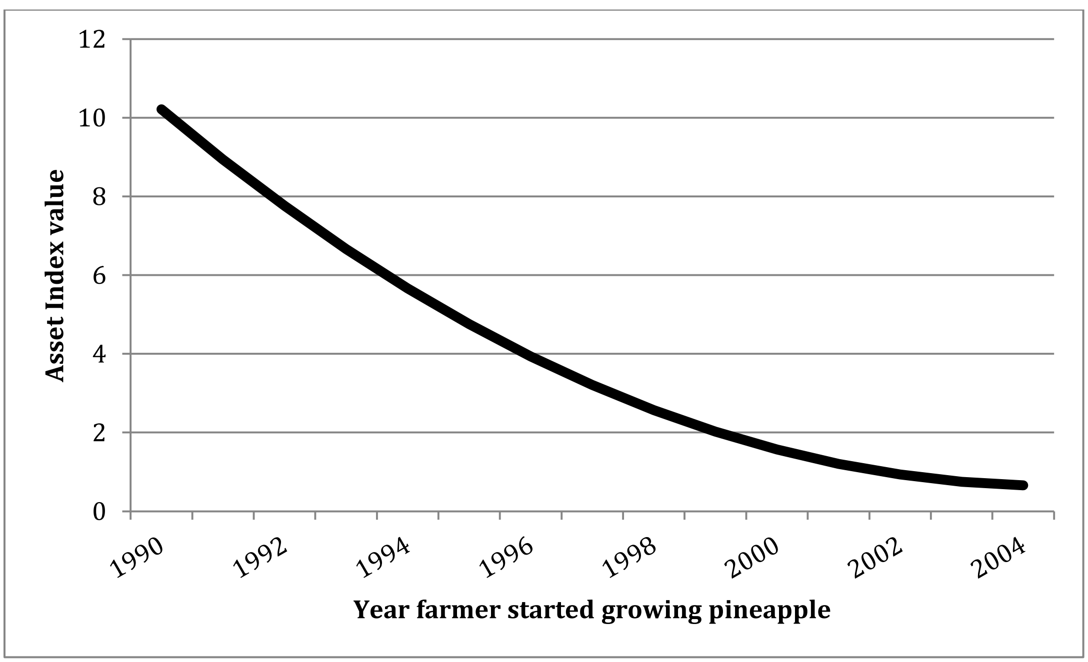

Figure 3. Estimated 2009 wealth level of farmers as a function of the year a farmer began to grow pineapples relative to nonadopters.

10. Tables

	Mean	**Std. Dev.**	**Min.**	**Max.**
Pineapple cultivation duration pre-2004 (years)	3.61	5.73	0.00	24.33
Age (years)	40.07	11.27	18.00	75.00
Age, squared	1731.89	1008.28	324.00	5625.00
Gender (female=1)	0.46	0.50	0.00	1.00
Highest level of schooling = primary school	0.16	0.36	0.00	1.00
Highest level of schooling = middle	0.53	0.50	0.00	1.00
Highest level of schooling = high	0.15	0.36	0.00	1.00
Household number (headcount)	8.39	4.51	2.00	24.00
Household number of working age	3.68	2.77	2.00	15.00
Years in village	67.48	65.86	1.50	400.00
Social network index	3.97	2.32	1.00	11.00
Pokrom resident	0.18	0.39	0.00	1.00
Darmang resident	0.29	0.46	0.00	1.00
Oboadaka resident	0.31	0.46	0.00	1.00
Average soil pH	6.42	0.59	5.36	7.60
Average soil organic matter	3.18	0.86	1.22	5.30
pH, squared	41.60	7.64	28.73	57.76

Table 1. Summary statistics for variables used in first stage (n = 161) (1998 data)

	Mean	Std. Dev.	Min.	Max.
Pineapple cultivation duration pre-2004	3.87	5.92	0.00	24.33
Age	39.89	11.23	18.00	75.00
Age, squared	1716.31	1011.76	324.00	5625.00
Δ household members	-0.59	3.85	-14.00	6.00
Δ household members of working age (18-50)	1.02	2.61	-8.00	9.00
Number in social network	4.06	2.39	1.00	11.00
Highest level of schooling = high school	0.15			
Gender	0.45			
Nonadopter	0.58			
Farmed pineapple during on or after 1/2004	0.21			

Table 2. Summary statistics for controls used in the second stage (n = 142)

		1998				2009			
	percentile	mean	std.dev.	min	max	mean	std.dev.	min	max
Asset index	0-25th	-0.564	0.041	-0.774	-0.529	-0.549	0.006	-0.563	-0.540
	26-50th	-0.493	0.033	-0.528	-0.404	-0.464	0.037	-0.526	-0.405
	51-75th	-0.220	0.130	-0.397	0.067	-0.166	0.161	-0.397	0.121
	76-100th	0.465	0.279	0.132	1.067	1.281	1.395	0.125	8.783
Durables asset index	0-25th	-0.523	0.055	-0.718	-0.490	-0.490	0.010	-0.525	-0.473
	51-75th	-0.441	0.107	-0.468	0.062	-0.282	0.177	-0.468	0.046
	76-100th	0.484	0.419	0.072	1.300	1.322	1.411	0.069	7.952
Livestock asset index	0-25th	-0.565	0.052	-0.821	-0.473	-0.563	0.048	-0.635	-0.473
	26-50th	-0.353	0.069	-0.472	-0.221	-0.349	0.076	-0.472	-0.219
	51-75th	-0.073	0.089	-0.211	0.091	-0.072	0.095	-0.218	0.091
	76-100th	1.017	0.990	0.092	4.983	0.945	2.342	0.092	16.374
Productive asset index	0-25th	-0.543	0.061	-1.116	-0.523	-0.523	0.000	-0.523	-0.523
	26-50th	-0.463	0.016	-0.495	-0.456	-0.466	0.012	-0.476	-0.453
	51-75th	-0.074	0.157	-0.287	0.088	-0.213	0.127	-0.440	0.080
	76-100th	0.763	0.508	0.169	1.880	1.356	1.366	0.099	7.565

Table 3. Asset index summary statistics, by percentile and year

Age of respondent	0.548
	(0.723)
Age, squared	-0.005
	(0.007)
Gender	-9.751
	(2.315)***
Highest level of schooling: primary school	5.648
	(1.561)***
Highest level of schooling: middle school	4.337
	(0.925)***
Highest level of schooling: high school	5.758
	(1.928)***
Household members	0.274
	(0.519)
Household members of working age (18-50)	-0.680
	(0.581)
Years of residence in village	0.021
	(0.014)
Social network	0.896
	(0.414)**
Pokrom	10.586
	(2.060)***
Darmang	9.968
	(0.990)***
Oboadaka	11.032
	(0.822)***
pH	-81.009
	(14.652)***
Organic matter	0.440
	(1.404)
pH, squared	6.117
	(1.191)***
Constant	235.293
	(35.897)***
	161
	0.15

Table 4. First stage - tobit model with village clustered standard errors (in parentheses). Pre-shock duration is left censored at zero. Dependent variable is duration of pineapple cultivation in years pre-2004.

Notes: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

	N	Mean	Std. Dev.	Min.	Max.
duration pre 1/2004 (months)	161	3.607	5.726	0.000	24.333
duration pre 1/2004 (months), predicted	167	2.445	3.983	0.000	22.539

Table 5. Summary statistics of observed and predicted pre-shock pineapple cultivation duration variables (years) (six additional values were predicted given the availability of the explanatory variables)

	I	II	III	IV	V	OLS
Duration pre 1/2004 (years)	0.092**	0.092**	0.091**	0.078	0.101	0.015
	(0.041)	(0.045)	(0.046)	(0.181)	(0.097)	(0.015)
Gender	-0.654***	-0.690***	-0.691***	-0.713*	-0.765	-1.060***
	(0.198)	(0.235)	(0.234)	(0.387)	(0.707)	(0.139)
Age of respondent	-0.002	0.024	0.023	0.022	0.020	0.032
	(0.033)	(0.032)	(0.032)	(0.032)	(0.040)	(0.029)
Δ household members		0.016	0.016	0.016	0.016	-0.010
		(0.031)	(0.031)	(0.030)	(0.031)	(0.023)
Δ household members of working age (18-50)		-0.049	-0.048	-0.048	-0.048	-0.029
		(0.038)	(0.037)	(0.038)	(0.038)	(0.030)
Highest level of schooling: high school			0.077	0.081	0.063	0.221
			(0.260)	(0.266)	(0.297)	(0.230)
Duration pre 1/2004 (years), squared				0.001		
				(0.009)		
Nonadopter					0.198	
					(1.756)	
Constant	1.133	0.658	0.673	0.728	0.661	0.876
	(0.701)	(0.684)	(0.679)	(0.875)	(0.726)	(0.646)
N	157	142	142	142	142	142
Adjusted R^2	0.17	0.16	0.16	0.15	0.13	0.31

Table 6. Effect of instrumented duration pre-shock, pre-shock squared and nonadopter on asset indices

Notes: Δ Variable = Variable (2009) – Variable (1998). The difference in age squared is included as a control but is not statistically significant from zero, so is omitted from the table above. Clustered standard errors reported in parentheses. * $p<0.1$; ** $p<0.05$; *** $p<0.01$

	2009	2008	2007	2006	2005
Duration pre 1/XXXX (years)	0.101**	0.106**	0.108**	0.103**	0.097**
	(0.041)	(0.044)	(0.045)	(0.046)	(0.045)
Gender	-0.331	-0.360	-0.409	-0.504*	-0.603**
	(0.335)	(0.324)	(0.309)	(0.283)	(0.254)
Age of respondent	0.029	0.027	0.026	0.024	0.024
	(0.035)	(0.035)	(0.035)	(0.034)	(0.033)
Age, squared	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ household members	0.026	0.027	0.026	0.023	0.019
	(0.035)	(0.035)	(0.034)	(0.033)	(0.031)
Δ household members of working age (18-50)	-0.058	-0.058	-0.057	-0.055	-0.051
	(0.042)	(0.042)	(0.042)	(0.040)	(0.039)
Highest level of schooling: high school	0.030	0.024	0.023	0.037	0.056
	(0.275)	(0.278)	(0.280)	(0.275)	(0.267)
Constant	0.120	0.200	0.303	0.442	0.569
	(0.757)	(0.753)	(0.741)	(0.714)	(0.694)
N	142	142	142	142	142
Adjusted R2	0.01	0.00	0.02	0.07	0.12

Table 7. Effect of instrumented duration pre-shock, pre-shock squared and nonadopter on asset indices

	Δ Index, all	**Δ Index, Livestock**	**Δ Index, Durables**	**Δ Index, Productive**
Duration pre 1/2004 (years)	0.091**	-0.020	-0.006	0.199***
	(0.046)	(0.028)	(0.048)	(0.066)
Gender	-0.691***	0.388**	-1.168***	-0.089
	(0.234)	(0.194)	(0.248)	(0.314)
Age of respondent	0.023	0.012	0.043	-0.003
	(0.032)	(0.029)	(0.034)	(0.042)
Δ household members	0.016	0.021	-0.002	0.042
	(0.031)	(0.026)	(0.029)	(0.045)
Δ household members of working age (18-50)	-0.048	-0.050	-0.035	-0.065
	(0.037)	(0.034)	(0.032)	(0.057)
Highest level of schooling: high school	0.077	-0.077	0.256	-0.019
	(0.260)	(0.230)	(0.254)	(0.345)
Constant	0.673	-0.599	0.700	0.652
	(0.679)	(0.700)	(0.796)	(0.878)
N	142	142	142	142
Adjusted R2	0.16	0.05	0.28	.

Table 8. Effect of instrumented duration pre-shock, pre-shock squared and nonadopter on comprehensive asset index, livestock asset index, durables asset index and productive asset index.

Notes: Δ Variable = Variable (2009) – Variable (1998). The difference in age squared is included as a control but is not statistically significant from 0, so is omitted from the table above. Clustered standard errors reported in parentheses. * p<0.1; ** p<0.05; *** p<0.01

11. Appendices

A. Factor summary statistics

	Mean	Std. Dev.	Max
Productive:			
Barrel	0.314	1.032	9.25
Chain saw	0.017	0.174	3
Corn mill	0.006	0.085	1.5
Cutlass	0.795	1.138	8.4
Gallon container	0.007	0.130	3
Hammer	0.155	0.427	2.8
Hoe	0.235	0.671	6.4
Knapsack	0.046	0.302	4
Mattock	0.027	0.200	2
Mist blower	0.160	0.525	4
Pick axe	0.056	1.237	30
Pump	0.005	0.092	2
Rake	0.007	0.101	2
Saw	0.007	0.165	4
Shovel	0.008	0.109	2
Sprayer	0.092	0.370	5
Livestock:			
Cows	0.041	0.578	11
Chicken	7.612	14.546	268.67
Goats	3.121	5.446	53
Pigs	0.132	1.129	23
Sheep	1.858	4.303	33
Guinea Pigs	0.095	0.940	15
Rabbits	0.089	1.069	18
Ducks	0.467	2.516	34
Durables:			
Bicycle	0.060	0.253	2
Car	0.050	0.263	3
Fan	0.117	0.436	4.33
Generator	0.088	0.454	4.75
Gun	0.040	0.207	2
Radio	0.386	0.638	4.375
Refrigerator	0.101	0.330	3
Sewing machine	0.280	0.459	2.625
Television	0.211	0.485	4.5

B. Estimated factor loadings

	All	Productive	Livestock	Durables
Barrel	0.681	0.820		
Chain saw	0.249	0.200		
Corn mill	-0.015	-0.008		
Cutlass	0.717	0.820		
Gallon container	0.037	0.029		
Hammer	0.578	0.541		
Hoe	0.687	0.769		
Knapsack	0.243	0.328		
Mattock	0.001	0.041		
Mist blower	0.663	0.728		
Pick axe	0.088	0.106		
Pump	0.281	0.183		
Rake	0.085	0.211		
Saw	0.011	0.056		
Shovel	0.109	0.179		
Sprayer	-0.102	-0.134		
Cows	0.510		0.687	
Chicken	0.337		0.814	
Goats	0.067		0.561	
Pigs	-0.036		-0.003	
Sheep	-0.003		0.485	
GuineaPigs	0.030		0.147	
Rabbits	-0.026		-0.024	
Ducks	-0.027		0.296	
Bicycle	0.465			0.510
Car	0.363			0.480
Fan	0.604			0.788
Generator	0.715			0.497
Gun	-0.078			-0.087
Radio	0.751			0.779
Refrigerator	0.694			0.805
Sewing machine	-0.051			-0.034
Television	0.700			0.867