Differential Disequilibrium Dynamics: A Schultzian Perspective on Producer Response to a Policy Shock

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A Schultzian Perspective on Producer Response to a Policy Shock

Abstract: Little empirical work has quantified the transitory effects of macroeconomic shocks on farm production behavior or on interhousehold differences in response to disruptions. We develop a simple analytical model to explain how macroeconomic shocks might temporarily divert managerial attention, thereby affecting farm-level productivity, but perhaps to different degrees and for different durations across production units. We then successfully test hypotheses from that model using panel data bracketing massive currency devaluation in Côte d’Ivoire. We find a sharp, transitory increase in mean plot-level technical inefficiency among Ivorian rice producers and considerable variation in the magnitude and persistence of this effect, attributable largely to \textit{ex ante} complexity of operations, and the gender and educational attainment of the manager.
I. Introduction

Although economies rarely move instantly from one long-term equilibrium to another, most empirical and theoretical analysis focuses on comparative statics and the long-term general equilibrium effects of macroeconomic shocks. Relatively little attention has been paid to the response paths followed by individual producers as they adjust from one equilibrium to another, and particularly not to empirical assessment of the dynamic response of small farmers responding to major policy shocks in low-income economies. Yet smallholders’ response to potentially long periods of disequilibrium may have important aggregate effects on output and rural poverty in low-income agrarian economies undertaking major macroeconomic reforms.

There may also be predictable variation in dynamic responses across individuals. Schultz (1964, 1975) hypothesized that the ability to deal with disequilibrium induced by economic shocks is largely a function of education, with better educated individuals adjusting more successfully than less educated agents. The basic idea is simple and intuitive; appropriate adjustment to shocks requires the collection and processing of new information, and better educated individuals would be expected, on average, to excel at such tasks. Schultz’s primary interest was technological shocks, but his point applies more broadly. Yet, despite the plethora of macroeconomic adjustment programs in low- and middle-income economies over the past two decades, we are unaware of any studies of interhousehold differences in the rate or extent of recovery from producer-level disequilibria induced by macroeconomic shocks.

An obvious reason for the dearth of empirical testing of the Schultzian hypothesis or of the effects of macro shocks on producer behavior more broadly has been a lack of panel production data straddling a major shock. One must be able to identify cross-sectional differences in
observational units’ intertemporal changes in behavior and performance. In this paper we use a 1993-95 panel data set of rice farmers in the west African nation of Côte d’Ivoire, straddling the massive devaluation of that country’s currency in 1994, to test (i) whether the macroeconomic shock is manifest at the microeconomic level in the plot-level technical efficiency of producers, (ii) whether there exist identifiable cross-sectional differences in the immediate impact of the shock, and (iii) whether the Schultzian hypothesis holds, that education is an important determinant of cross-sectional differences in subsequent recovery.

Our strategy in this paper is to start, in section II, by building a simple analytical model wherein a sharp change in the external economic environment (e.g., product and factor price ratios) diverts managerial attention from directly productive tasks to make sense of what is taking place around him or her, and this diversion may have a measurable effect on productivity. To implement the model econometrically, we then, in section III, estimate time-invariant production frontiers, using two different methods as a check on the robustness of our findings, derive plot-specific estimates of technical inefficiency, and then test whether mean technical inefficiency changed in the wake of the macroeconomic shock. In order to prevent misunderstanding, it is important to make plain from the outset that we are not suggesting currency devaluation generally hurt the rice sector or rice producers in Côte d’Ivoire. Indeed, section III shows that devaluation proved broadly stimulative to the sector. The section then goes on to draw out implications from our results, including an alternative way to understand differences between short- and long-run price elasticities of supply. In section IV, we then test for predictable cross-sectional variation in estimated technical inefficiency changes, and whether education is an important predictor of such cross-sectional variation, particularly in recovery from the shock. Section V concludes.
II. A Model of Farm Manager Response to Macroeconomic Shock

First we construct a simple model of producer behavior in which exogenous shocks may temporarily divert managerial attention, thereby reducing unobservable labor quality and yielding an increase in estimated technical inefficiency on the farm. The shock’s immediate impact and intertemporal propagation is conditional on individuals’ exposure to the shock and on their capacity to deal with disequilibrium, hence the possibility of cross-sectional differences in the initial impact of the shock and in the rate of recovery from any shock-induced effects. The structural model yields testable hypotheses with respect to (i) the effects of a uniform exogenous (e.g., macroeconomic or technological) shock on mean producer technical inefficiency, as commonly estimated using labor allocation data that cannot control for unobservable managerial attention, (ii) characteristics that will cause cross-sectional variation in the extent of the disruptions manifest as increased estimated technical inefficiency, and (iii) the effects of human capital, education in particular, on the extent and pace of recovery from temporary efficiency disruptions. The next two sections test those hypotheses econometrically.

We start with a standard, basic model of a household that maximizes utility subject to a budget constraint, a time availability constraint, and a technology constraint. The latter is the focus of attention in this paper. Let the variables $y$, $a$, $l$, and $x$ represent output, area, labor, and variable non-labor inputs, respectively, with the function $f(.)$ mapping the latter three into the former such that $y = f(a,l,x)$ with $f(.)$ monotone in each argument. In theory this constraint binds at all optima, so that in long-run equilibrium, optimizing producers should exhibit perfect technical efficiency, $y = f(a,l,x)$. Nonetheless, most empirical studies find evidence of technical inefficiency,
In this construction, \( y_i \theta_i = f(a_i, l_i, x_i) \) with \( \theta_i \), the plot-specific technical efficiency parameter,\(^1\) greater than one for most plots (Ali and Byerlee 1991).\(^2\)

In distinguishing between managers and manual laborers, economists have long implicitly recognized that managerial labor effort is a composite of two distinct concepts: physical work (\( w \)) and managerial attention (\( m \)). Manual labor demands mainly (or solely) the former, while managerial labor in an enterprise such as farming requires both. Let us represent this relationship by the function \( l(w, m) \), which is strictly monotonically increasing in both arguments. While undertaking the physical work required on a plot, a farmer may spend his measurable labor time focused either on the particular chores at hand or on other things that affect the farm. The imperfect relationship between time expended in physical work, \( w \), and effective labor effort, \( l \), underpins the vast literature on moral hazard in agricultural labor markets, in which hired workers are understood as able to reduce their effective labor effort without reducing the time they spend working, i.e., to shirk.

We apply the same basic concept with a somewhat different twist. Rather than shirking voluntarily, as hired laborers might, managers may have their attention temporarily diverted by exogenous events that require concentrated thought that can nonetheless be undertaken, perhaps at an efficiency cost, while performing other, more menial tasks. Macroeconomic or sectoral reforms that cause substantial swings in relative price ratios would be a good candidate, as would

\(^{1}\) In this construction, \( \theta_i \) can be interpreted as the output expansion that could be achieved given input allocations if the producer were technically efficient. Therefore \( \theta_i \geq 1 \).

\(^{2}\) There is, however, some reason to suspect that econometric error may substantially overstate smallholder technical inefficiency in much of the literature (Ali and Byerlee 1991, Barrett 1997, Sherlund et al. 1998). The problem of interpreting estimated technical inefficiency parameters lies at the heart of this paper since our model ultimately revolves around the unobservability of managerial attention.
the introduction of a new technology, the classic Schultzian scenario. This issue of partial
diversion of attention becomes important because only the physical work time of the farmer is
directly measurable, so empirical studies almost always use w to proxy for l. Since w and m are
highly correlated with one another in owner-operated businesses like smallholder agriculture, and
since both increase effective labor power, econometric estimates of the parameters of the
production frontier estimated using w in place of l(w,m) will be susceptible to omitted relevant
variables bias. For present purposes, however, the point on which we wish to focus is that when
something distracts managerial attention, perhaps a macroeconomic shock, effective labor input
decreases and output falls holding physical work time constant. So when w proxies for l(w,m),
this reduction in output will appear as a deviation from the production frontier, i.e., as an increase
in estimated technical inefficiency, θ. Given inability to measure directly m or its effect on
output, we can understand θ(m) as a weakly monotonically decreasing function of m.3

If exogenous shocks divert decision-makers’ attention from productive activities as they
collect and process information, weigh alternative courses of action, search for new buyers or
suppliers, or some combination of these, then shocks may have adverse effects on productivity.
We can formalize this idea by representing the farm-level supply of managerial attention by the
function m(ϕit, cit, bit, hit). The individual-specific shock effect felt by decision-maker i at time t, ϕit,
is nonnegative. The nonnegativity of ϕit is arbitrary; one could equally make it nonpositive.
The key is that the measure allows for no effect and that any shock effect, whether it increases or
decreases welfare, requires some attention. It is important not to confuse welfare effects with the
shock’s force in inducing behavioral response. The variable c is a nonnegative measure of the

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3 θ(m) is weakly monotone because θ is bounded from below at one.
complexity of the manager’s operations (e.g., the number of crops grown or the number of plots cultivated), \( b \) is a measure of the extramural burdens (i.e., for example, child care responsibilities) borne by the decision-maker, and \( h \) is a measure of the manager’s human capital endowment. Assume managerial attention is increasing in \( h \) and decreasing in the other three arguments.

Because women are the primary food producers in Sub-Saharan African agriculture, extramural burdens that may weigh on a farmer-manager deserve some attention. In the Ivorien rice systems we study, young children typically accompany their mother in the fields as she works, and there may be economies of scope in coupling child care with agricultural production (Udry 1996). When studying only the agricultural part of that joint production process, monotonicity then implies that output might appear less than it would if all resources, including the farmer-manager’s attention, were concentrated exclusively on agricultural activities and properly accounted for.\(^4\) Rural Ivorien women are also less educated than men. Only 4.6 percent of the women in our sample had even elementary school education, while almost 18 percent of the men had secondary level education or beyond. Partly as a consequence, women rice farmers are far less likely to speak French, the language of the national market information service. So when price shocks come along, women may have to invest more effort in acquiring and processing information not directly accessible to them, especially because the extension system in Côte d’Ivoire exhibits considerable bias against women (Adesina and Djato 1997).

The magnitude of the unobservable, individual-specific shock, \( \phi_u \), is itself a function of the complexity of the operation being managed and of the human capital of the manager. In the case

\(^4\) This is consistent with Adesina and Djato’s (1997) finding that while women rice farmers exhibit lower yields in Côte d’Ivoire, once one accounts properly for access to information, inputs, etc., the gender difference in efficiency vanishes.
of agriculture, for example, as the number of crops or plots under the manager’s control increases, so does the dimensionality of the information collection and processing and contracting tasks faced by the smallholder, so a shock should have greater effect on those managing more complex enterprises. The effect of human capital, especially education, is qualitatively different in that it doesn’t affect the magnitude of the immediate shock but rather the rate at which the shock’s effects dissipate. Literacy, numeracy, and logical abilities are no shield against disruption, but they certainly help individuals respond quickly and effectively to shocks by gathering and processing information efficiently and accurately.

These relationships can be captured in the linear state equation,

$$\phi_i = \rho \phi_{i-1} + \alpha h_i \phi_{i-1} + c_i \epsilon_i$$

where $\rho$ is a positive first-order autoregressive parameter capturing the intertemporal propagation of the shock conditional on $i$’s human capital endowment, $\alpha$ captures the effect of human capital on the shock’s propagation, and $\epsilon_i \geq 0$ is a cross-sectionally uniform exogenous shock, like a macroeconomic policy reform or the introduction of a new production technology. The Schultzian hypothesis suggests $\alpha < 0$, that human capital accelerates recovery from the distraction caused by an exogenous shock. In this framework, $\rho + \alpha h_i = 0$ implies full recovery after one period.

The effects of a common shock, $\epsilon_i$, on the managerial attention of the $i^{th}$ operator at time $t$, $m_{it}$, may therefore vary over time. The effects may emerge through any of several parallel transmission channels:

$$\frac{\partial m_{it}}{\partial \epsilon_i} = \frac{\partial m}{\partial \phi_i} c_i + \frac{\partial m}{\partial c_i} \frac{\partial c_i}{\partial \epsilon_i} + \frac{\partial m}{\partial b_i} \frac{\partial b_i}{\partial \epsilon_i} + \frac{\partial m}{\partial h_i} \frac{\partial h_i}{\partial \epsilon_i}$$

$$\frac{\partial m_{it+1}}{\partial \epsilon_i} = \frac{\partial m}{\partial \phi_i} c_i (\rho + \alpha h_i) + \frac{\partial m}{\partial c_i} \frac{\partial c_i}{\partial \epsilon_i} + \frac{\partial m}{\partial b_i} \frac{\partial b_i}{\partial \epsilon_i} + \frac{\partial m}{\partial h_i} \frac{\partial h_i}{\partial \epsilon_i}$$

$$\frac{\partial m_{it+1}}{\partial \epsilon_i} = \frac{\partial m}{\partial \phi_i} c_i (\rho + \alpha h_i) + \frac{\partial m}{\partial c_i} \frac{\partial c_i}{\partial \epsilon_i} + \frac{\partial m}{\partial b_i} \frac{\partial b_i}{\partial \epsilon_i} + \frac{\partial m}{\partial h_i} \frac{\partial h_i}{\partial \epsilon_i}$$
By the weak monotonicity of $\theta$ in $m$, the effect of the common shock, $\epsilon_i$, on plot- and period-specific technical inefficiency will be

$$\frac{\partial \theta_i}{\partial \epsilon_i} = \frac{\partial \theta}{\partial m} \left[ \frac{\partial m}{\partial \phi_u c_u} + \frac{\partial m}{\partial c_u} \frac{\partial c_u}{\partial \epsilon_i} + \frac{\partial m}{\partial b_u} \frac{\partial b_u}{\partial \epsilon_i} + \frac{\partial m}{\partial h_u} \frac{\partial h_u}{\partial \epsilon_i} \right]$$  \hspace{1cm} (4)

$$\frac{\partial \theta_{it+1}}{\partial \epsilon_i} = \frac{\partial \theta}{\partial m} \left[ \frac{\partial m}{\partial \phi c_u (\rho + \alpha h_u)} + \frac{\partial m}{\partial c_u} \frac{\partial c_{it+1}}{\partial \epsilon_i} + \frac{\partial m}{\partial b_u} \frac{\partial b_{it+1}}{\partial \epsilon_i} + \frac{\partial m}{\partial h_u} \frac{\partial h_{it+1}}{\partial \epsilon_i} \right]$$  \hspace{1cm} (5)

Under the assumptions that $\frac{\partial h_u}{\partial \epsilon_i} = \frac{\partial c_u}{\partial \epsilon_i} = 0$, i.e., that neither the manager’s stock of human capital nor the complexity of her operations change instantaneously, and that $\frac{\partial b_u}{\partial \epsilon_i} \geq 0$, i.e., that the shock fails to reduce the manager’s extramural burdens, the effect of a uniform common shock, $\epsilon_i$, on contemporaneous estimated technical inefficiency should be positive because it reduces managerial attention and therefore labor productivity. That effect should be greater for managers overseeing more complex operations and for managers who experience a greater increase in extramural burdens.

How might a farmer-manager’s extramural burdens increase? Just as exogenous shocks to relative prices or production technologies may force reevaluation and reallocation of agricultural production activities by a farm manager, so too might relative price shocks force reconsideration of domestic activities, e.g., what foods to purchase and where. Moreover, if shocks create stress and this “bad” is allocated within a household much as goods are, then the least powerful adults in the household may shoulder a disproportionately large share of the stress just as they commonly enjoy a disproportionately small share of the goods consumption (Haddad et al. 1997). So there may be transitory increases in burdens due to either increased demands for information collection and processing with respect to domestic responsibilities, intrahousehold redistribution of burdens, or both.

The difference of equations (5)-(4) identifies what factors affect plot-level recovery in
technical inefficiency (i.e., in output or yields, *ceteris paribus*):

\[
\left( \frac{\partial \theta_{it}}{\partial \epsilon_i} - \frac{\partial \theta_{i+1}}{\partial \epsilon_i} \right) = \frac{\partial \phi_m}{\partial c_m} \left( \frac{M_{it}}{M_{i+1}} \right) \left( \frac{M_{i+1}}{M_i} \right) + \frac{\partial m}{\partial c_m} \left( \frac{\partial c_{i+1}}{\partial \epsilon_i} - \frac{\partial c_i}{\partial \epsilon_i} \right) + \frac{\partial m}{\partial b_m} \left( \frac{\partial b_{i+1}}{\partial \epsilon_i} - \frac{\partial b_i}{\partial \epsilon_i} \right) + \frac{\partial m}{\partial h_m} \left( \frac{\partial h_{i+1}}{\partial \epsilon_i} - \frac{\partial h_i}{\partial \epsilon_i} \right) \right] (6)
\]

Assume the shock has no effect on human capital, so the last parenthetical expression in (6) equals zero, and that \( \alpha \) is negative, as predicted by Schultz. Then next period recovery is greatest (i.e., the value of (6) is lower) for managers with relatively more human capital or whose increase in extramural burdens in the immediate aftermath of the shock (period \( t \)) dissipates more by the next period, as reflected in the first and third parenthetical expressions, respectively, on the righthand side of equation (6). If the shock induces an increase (decrease) in the complexity of the operation, technical inefficiency will increase (decrease). This simple structural model yields several hypotheses which we test in section III.

This line of reasoning builds on a literature on the “human capital approach to allocative efficiency” that emerged in the 1970s among Chicago students of Becker, Griliches and Schultz. That literature emphasized the central role of education in achieving allocative efficiency, above all in agriculture (Griliches 1963, Welch 1970, 1978; Fane 1975; Huffman 1975, 1977; Ram 1980). Its focus was on the role of education in an environment of technological change, as was appropriate in post-war United States agriculture and during the Green Revolution abroad. More recently, technology shocks have been less common than policy shocks in low-income agriculture, so our focus differs because the context of disequilibrium has changed. The earlier literature also generally assumed technical efficiency and introduced education directly into the production function as an input. Our approach accommodates the empirical regularity of estimated technical inefficiency. More importantly, it allows us to identify education’s period-specific value in helping
producers adjust to shocks. As Schultz (1964, 1975) famously posited, human capital probably matters little to stable, traditional production, but becomes valuable to those dealing with disequilibrium. So we opt to estimate instead producers’ technical inefficiency and then check whether human capital has an effect on the magnitude of the initial shock, the recovery from the shock, or both.

III. Transitory Technical Inefficiency in Ivorien Rice Production

We use data from the farm management and household survey (FMHS) fielded by the West Africa Rice Development Association (WARDA) to test the hypotheses developed in section II. The WARDA FMHS tracked 120 randomly selected rice-producing households in Côte d’Ivoire, 1993-95, encompassing 1,218 individual plots, 589 of which were planted in rice. Surveys consisting of 22 different questionnaire modules were administered annually and are described in detail in WARDA (1997). Due to nonsystematically missing data or mechanization (we study only traditional rice farmers), 464 rice plots are used in estimation here.

The WARDA FMHS coincided with a significant macroeconomic shock that might induce microeconomic agents to respond as posited in the model developed above. After 46 years’ unchanged 50:1 parity against the French franc, the 14 members of the Communauté Financière Africaine devalued their common currency, the CFA franc (FCFA), by 100 percent in January 1994. While devaluation was widely anticipated, the extent and timing of the event were nonetheless a substantial shock to residents of the FCFA economies. For some months thereafter, there was considerable uncertainty as to how prices would change and what implications this had for farmers’ livelihood strategies. In short, the shock seems to have distracted Ivorien farmers,
but to what effect?

Rice yields among traditional Ivorien farmers in the sample declined sharply after the
devaluation, from a mean (median) of 2.16 metric tons/hectare (1.86 t/ha) in 1993 to 1.75 t/ha
(1.66 t/ha) in 1994. Yields recovered somewhat in 1995, to a mean of 1.99 t/ha (and a median of
1.95 t/ha). These unconditional statistics suggest a sharp, temporary decline in rice productivity
coincident with the macroeconomic shock of devaluation.5

The output effect of a shock obviously extends beyond its effects on technical inefficiency
or yields. In general, a shock could also stimulate a shift in the technology frontier or in variable
input use volumes. In our case of a massive currency devaluation, there is no reason to believe
that a discrete change to relative prices would fundamentally change the production technology,
and thus the production frontier. Following this logic, we estimate a time-invariant production
frontier in the next section.

A relative price shock would indeed be expected to induce change in input and output
choices. That was explicitly an aim of FCFA devaluation aimed at correcting price distortions
caused by currency overvaluation. In the FMHS survey regions, the nominal local market price of
local variety (as distinct from imported) rice increased 47.9 percent from 1993 to 1995 (Table 1).
This reflected a real increase in the rice price, as manifest by a 49.2 percent increase in the ratio of
the rice price to the price of yams, a locally nontradable food. Since nontradable labor and land
are the major costs of rice production in Côte d’Ivoire, devaluation led to increased incentive for

5 Of course, parts of the country experienced significantly lower rainfall in 1994 than in either 1993 or
1995, so natural, rather than policy shocks could be to blame. But when we control for a broader set of natural
variables (pests, plant disease, rainfall, etc.), qualitatively identical findings persist (Sherlund et al. 1999), so the
shock indeed seems to have temporarily adversely affected rice yields.
We compare 1995 against 1993 because stickiness in price adjustments and asynchronous agricultural calendars – some farms made irreversible production decisions before the price effects of devaluation had played out fully – make comparison of 1994 to 1993 somewhat suspect. That said, the qualitative result holds for the 1994/1993 comparison as well: nominal and real rice prices and input application rates increased.

It could conceivably still be consistent with the transitory drop in yields if land expansion preceded the observed increase in application of other (yield-increasing) inputs, but that wasn’t the case. The data show the pace of input expansion was roughly equiproportional across measured inputs 1993-94 and 1994-95.

What we hypothesize, in keeping with the model of the preceding section, is that devaluation induced a sharp adjustment in relative prices, depicted in stylized form in Figure 1 as a pivoting of the price line about the production frontier. But the diversion of managerial attention caused producers to move from the old equilibrium at $E^0$ to the new long-run equilibrium at $E^L$ in two or more steps, depending on how they dealt with the temporary disequilibrium induced by

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devaluation. Omitting, for the sake of brevity, the possibility of temporary allocative inefficiency, the response path of our stylized producer to the common exogenous shock, would involve an intermediate step to a point of disequilibrium within the production frontier, such as $D^1$. The location of $D^1$ relative to the production frontier and the rate at which the producer thereafter approaches $E^L$ – in other words the magnitude and persistence of induced transitory technical inefficiency – depend on the characteristics discussed in section II: human capital and the rate at which the manager learns about new conditions, changes in extramural burdens, and the complexity of the operation. The implication is that output will steadily increase as the producer moves from $Y^0$ to $Y^L$, but yield (reflected in the slope of the line segment connecting the origin to the production point) initially falls before recovering. This is exactly what was observed in Côte d’Ivoire in the wake of the FCFA devaluation.

The claim that exchange rate devaluation can induce temporary uncertainty that might divert managerial attention finds support in the price data. Figure 2 shows the evolution of 13-month centered moving average prices for locally produced rice as well as the time path of the coefficient of variation of those prices. One sees a clear shock to the relative (much less absolute) variation of the rice price series, beginning with devaluation in early 1994. The coefficient of variation in rice prices increased sharply for a period of almost a year before settling

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8 In Figure 1, allocative inefficiency would appear as selection of a point on the production frontier other than the point of tangency with the relative price line.

9 The underlying data are series for each of the three survey regions (Boundiali, Gagnoa, and Waninou). The figure depicts the unweighted arithmetic average of the series. The qualitative point holds for the series individually, as well.
down at a new, higher level.\textsuperscript{10} Our own casual conversations with African smallholders reveal that they indeed spend much time mulling over the implications of such shocks and the resulting uncertainty. So while it cannot be corroborated empirically, the sort of managerial attention diversion that we model indeed appears plausible.

By way of a brief tangent, we note that this model also offers an alternative way to understand the empirical regularity of short-run price elasticities of crop supply that are significantly lower than the corresponding long-run price elasticities (Askari and Cummings 1976, Rao 1989). Typically, the deviation of short-run from long-run elasticities is attributed to quasi-fixed factors of production (e.g., land), adaptive expectations formation, or unspecified convex adjustment costs. We do not challenge these other, quite sensible explanations. Because it explicitly introduces adjustment dynamics, however, the present model offers another, complementary explanation of the oft-observed phenomenon.\textsuperscript{11} In our model, there are no expectations, no quasi-fixed factors, and convention is not imposed on the explicitly identified source of the adjustment costs.

In order to test the hypotheses developed earlier, we must first estimate the time-invariant production frontier for Ivorien rice and then derive plot-specific estimates of technical

\textsuperscript{10} This pattern is consistent with theory and empirical evidence that devaluation increases the variance of stochastic price series more than the mean when devaluation induces a shift in the underlying market equilibrium condition from an importable to a nontradable (Barrett 1999).

\textsuperscript{11} One could presumably test the extent to which the present explanation prevails by checking the symmetry of the short-run/long-run differential to positive and negative price shocks. Conventional models would predict symmetric differentials, while ours would predict asymmetric differentials, with output overshooting the downward adjustment in response to a fall in relative output prices. Since the FMHS data include only price increases, we leave exploration of this possibility to future research.
inefficiency.\textsuperscript{1213} The literature on frontier production function estimation offers two broad classes of methods. The first method uses a stochastic parametric frontier (SPF) based on maximum likelihood estimation of $y = f(a,l,x)-u+v$, where $v$ is a symmetric independent and identically distributed normal error term and the nonnegative technical inefficiency parameter, $u$,\textsuperscript{14} is assumed to follow a particular, assumed statistical distribution. The second method uses a nonstochastic, nonparametric frontier based on data envelopment analysis (DEA), estimating the same function by mathematical programming as a piecewise linear frontier without the error term, $v$, and without any parameteric assumptions imposed on $f(.)$ or distributional assumptions imposed on $u$, just restricting $f(.)$ to be monotone and concave. Färe et al. (1994) offer a rich discussion of the relative merits of each technique. Here we report results based on SPF estimation assuming a truncated normal distribution for $u$ and DEA estimation allowing for variable returns to scale because we reject the constant returns to scale hypothesis in these data using Banker’s (1996)

\textsuperscript{12} Because managers may be aware of their technical inefficiency and adjust input applications accordingly, estimating the primal production function may introduce simultaneity bias. For this reason, some researchers prefer to estimate the dual cost or profit frontiers instead in estimating producer inefficiency. However, if the price data available are likely weakly related to the true shadow prices guiding decisions in an environment of considerable transactions costs, risk, quality variation, etc., then price observations will generally serve as poor instruments for inputs and the inefficiency of the dual method may be worse, on a mean squared error basis, than the bias of the primal method. Since price recordation occurred only at regional level in the FMHS data set and many plots’ inputs (e.g., child labor, adult family labor, land, animal traction, soil quality, slope) were not purchased and so have no observed prices associated with them, we opt for the primal method in the present analysis.

\textsuperscript{13} We employ a time-invariant frontier for two reasons. First, since we study only traditional, not mechanized, smallholder producers, there is little chance of an appreciable change in the underlying production technology over the course of three consecutive years. Second, in order to study intertemporal change in technical inefficiency one needs a common reference point in order to make meaningful comparisons across periods.

\textsuperscript{14} We use $u$ here for the sake of consistency with the established literature. We will shortly return to using $\theta(u,Y)$. 


The results are qualitatively identical for other SPF distributions such as the half normal and for DEA with constant returns to scale imposed. Full details of the estimated frontiers— including elasticity estimates, tests of monotonicity and concavity, etc.— are available from the authors by request or can be found in Sherlund et al. (1999). The estimated functional form is \( Y^{1/3} = \alpha_0 + \sum_{k=1}^K \beta_k \left( X_{jk} \right)^{1/3} + \sum_{k=1}^K \sum_{j=1}^K \gamma_{jk} \left( X_{jk} \right)^{1/3} + \varepsilon \). We use cube roots rather than square roots in order to satisfy regularity conditions violated by the traditional form. Technical details on the production frontier estimation are reported in Sherlund et al. (1999).

Since \( \theta \) is a radial measure of inefficiency, our estimation method assumes that inefficiencies appear equiproportionally in all inputs. However, current observers of these rice systems argue that labor constraints are the chief obstacles to productivity improvements (Dalton 1999). Therefore, a useful extension would apply nonradial measures to explore whether the inefficiencies apparent in the data are indeed attributable mainly to...
 DEA, the technical inefficiency parameters, \( \theta_{it} \), are the solutions to a linear programming problem in which each plot is compared to the estimated frontier.

With these \( \theta_{it} \) estimates in hand, the first question to address is whether estimated plot-specific technical inefficiency increased from 1993 to 1994 and whether it subsequently recovered in 1995, i.e., whether there were any shock-induced inefficiencies, and if so, whether they were transitory or permanent. By either frontier estimation method, more than three-quarters of plots exhibiting any change in estimated technical inefficiency from 1993 to 1994 showed increased inefficiency, and more than two-thirds exhibited a subsequent fall (at least partial recovery) from 1994 to 1995 (Table 2). Under DEA, the median plot lies on the production frontier each year (i.e., a majority of plots have \( \theta_{it}=1 \)). But the proportion of technically efficient plots fell from 75 percent in 1993 to 58 percent in 1994 before recovering to 67 percent in 1995. Frequency data therefore strongly support the hypothesis of devaluation-induced transitory plot-level technical inefficiency with incomplete recovery by the second year.

We explore this hypothesis further by bootstrapping the mean year-specific technical inefficiency parameter estimate in order to test for a statistically significant difference across years.\(^{18}\) Using 10,000 replicates of the mean of bootstrapped year- and plot-specific technical inefficiency estimates, we computed the mean and centered 95 percent confidence interval bounds for each year's distribution (Table 3). The mean technical inefficiency distribution shifts up significantly in 1994, then settles back in 1995, substantially under the SPF approach, more

\(^{18}\)For this, we adjusted the technical inefficiency estimates for potential small sample bias following Atkinson and Wilson (1995).
Moreover, since the macroeconomic shock (currency devaluation) affected only prices, there is no particular reason to expect an effect on the primal production function or the technologies it represents. Recall this sample includes only traditional, nonmechanized plots.

It thus appears that the story of Ivorien rice’s response to massive FCFA devaluation involves at least a transitory productivity decline, possibly due to the sort of managerial attention diversion we posited in section II. We now test explicitly to see whether the time path of plot-specific technical efficiency can be explained by our model.

IV. Education, Complexity, Gender, and the Ability to Deal with Disequilibrium

19 Moreover, since the macroeconomic shock (currency devaluation) affected only prices, there is no particular reason to expect an effect on the primal production function or the technologies it represents. Recall this sample includes only traditional, nonmechanized plots.
Our model not only predicts a temporary increase (decrease) in estimated technical inefficiency (output), it also hypothesizes predictable cross-sectional differences in changes in inefficiency. In particular, the adverse managerial diversion effects of the shock should be felt most acutely on plots managed by operators experiencing an increase in extramural burdens, and by those supervising relatively more complex operations. Given considerable evidence from low-income economies that household demands on women generally increase sharply in periods of macroeconomic disequilibrium (Elson 1991) and with the number of young children in the household, and in light of the literature on intrahousehold allocation, we use the number of young children (age five or younger) in the household and dummy variables for married women and unmarried women plot managers to proxy for the change in the manager’s extramural burdens. We use the number of rice plots (plots), the number of different crops under the control of the plot manager (crops), and the proportion of the plot planted in modern rice varieties (modern) to capture operational complexity. Most operators did not change the complexity of their operations during the survey period. So although our model suggests that the effect of the shock on complexity should itself affect the magnitude of the common shock’s effect on plot-and-period-specific technical inefficiency, we omit the change in complexity variable because it is clearly endogenous and we haven’t suitable instruments for predicting such changes. We use the operator’s highest level of schooling completed to proxy for human capital, and assume no change

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20 The November 1995 issue of World Development includes a special section on the topic of “Gender, Adjustment and Macroeconomics” that speaks directly to this issue.

21 As a check, we also ran regressions including change in crops, in plots, and in the proportion planted in modern varieties as regressors. This specification, which likely suffers endogeneity bias, returned qualitatively identical results as the specification we report, which may suffer (modest) omitted relevant variables bias from the omission of these change variables. The consistency of the results suggests the qualitative findings are robust.
in these adults’ education levels in the wake of FCFA devaluation.\textsuperscript{22}

We regressed the initial change in technical efficiency, $(\theta_{194} - \theta_{193})$, using both the DEA and SPF results, on dummy variables for education levels, married and unmarried women, and on operator age, experience in farming the cultivated rice variety (both in years), and the first year levels of the complexity variables, all entered quadratically,\textsuperscript{23} the number of young children in the household, as well as on multiplicative interactions between the complexity variables (crops, modern, and plots) and the education dummy variables. Because some plots are put in or brought out of fallow or are combined or subdivided across years, we do not have an even panel at plot level. So while we can use all 464 plot-level observations in estimating the time-invariant production frontier, the number of plots available for intertemporal comparisons varies across the pairs of years in question.

OLS estimates reported in Table 4 largely confirm our hypotheses regarding the initial effect of the macroeconomic shock on plot-level technical inefficiency. Education doesn’t shield people from the shock, as is apparent in the statistically insignificant estimates for the education variables and for the regressors interacting education and complexity. Female operators exhibit a far greater increase in technical inefficiency than do male operators, indeed the coefficient point estimates suggest operator gender had by far the greatest effect on initial increase in technical

\textsuperscript{22} In these data, almost 80 percent of plots were operated by farmers who had not completed elementary school. Only 15 percent had completed secondary school, and fewer than 2 percent had completed college. If higher education leads to self-selection out of agriculture, so that farmers with higher educational attainment may actually possess below-average ability or work ethic for individuals of their education level, then there may be some bias in the estimated effect of education on technical inefficiency. Our results may therefore err somewhat on the conservative side in making our point.

\textsuperscript{23} Because only 3 of the 464 total plots in the data set used modern varieties on other than all or none of the plot, a quadratic relationship would be uninformative, so the variable modern enters the model only linearly.
inefficiency. The effect is more pronounced for married women than for unmarried women, almost all of whom are single heads of household. The greater the number of young children in the household the greater the expected increase in plot-level technical inefficiency, although the effect is only marginally significant in either statistical or economic terms. While unable to explore this further in these data, these results appear to signal that added pressures facing women in periods of disequilibrium indeed take a toll on their productivity. Finally, estimated inefficiency is increasing in operational complexity, particularly as captured by the number of plots and crops cultivated by the smallholder.\textsuperscript{24} The expected change in technical inefficiency for the mean farmer – a 47 year old male without young children or an elementary education, with six years’ experience with the cultivated rice variety, two rice plots and three different crops – was 0.452 for the frontier estimated by DEA and 0.661 for the stochastic parametric frontier, implying a 35-55 percent increase in mean technical inefficiency from 1993 to 1994.

Our model also suggests that subsequent recovery from a shock will be greater for more educated operators. OLS regression results for the recovery in technical efficiency, \((\theta^*_{94} - \theta^*_{93})\), support this Schultzian hypothesis. As shown in Table 5, technical inefficiency decreases sharply for those who have completed at least primary (elementary) education, with the effects greatest for those with training through secondary level (the base for comparison is managers who have not completed elementary education). Education is most valuable for those with more complex operations, as indicated by the statistically significant positive estimates for interaction terms between education and operation complexity (crops in the case of the DEA estimates, plots in the

\textsuperscript{24} No manager operated more than four rice plots or six crops, so estimated technical inefficiency is increasing over the full range of the data.
case of the stochastic parametric frontier estimates). Both the magnitude and sign of the point estimates and the statistical significance of these estimates support the Schultzian claim that education facilitates more rapid and substantial recovery. The mean uneducated farmer would be expected to show no improvement in technical inefficiency (the point estimates are -0.090 for the DEA frontier and -0.026 for the SPF, respectively) in the year following the shock. By contrast, the same farmer with a secondary school degree would be expected to exhibit considerable, almost complete recovery (0.447 for the DEA frontier and 0.578 for the SPF). Much of the difference comes from the interaction of education with ex ante operation complexity, highlighting that educated managers deal better with disequilibrium, particularly when the decision making tasks confronting them are relatively complex. Point estimates suggest that women also exhibit some recovery, although the weak statistical significance and low magnitudes of the coefficient estimates, as compared to those in Table 4, suggest recovery is at best incomplete. The apparent increase in women’s domestic burdens induced by macroeconomic disequilibrium does not appear to subside rapidly. The complexity variables on their own (i.e., not interacted with education) are jointly statistically insignificant, suggesting that while this factor affects the initial impact of the shock, it has relatively little effect on subsequent recovery save for increasing the marginal value of education. While there appear to be a common adverse initial effect of macroeconomic disequilibrium on all operators’ efficiency (but not output), recovery experiences appear to vary more in cross-section, with education playing an especially important role.25

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25 We considered the possibility that these latter results might capture instead plot-specific learning by doing effects, especially if devaluation brought new plots into rice cultivation in 1994. But a Chow test failed to reject the null hypothesis of equality of parameters between those plots cultivated only in 1994 and 1995 (for which learning by doing could be an issue) and those cultivated in 1993, 1994, and 1995, returning a test statistic of 27.4, well below any reasonable critical value from the asymptotic $\chi^2(20)$ distribution.
Overall, the estimation results support the hypotheses advanced by our simple model. The macroeconomic shock of currency devaluation appears to have had a significant transitory effect on technical inefficiency felt most acutely among female farmers also bearing increased familial burdens and by smallholders managing relatively complex operations. The rate and extent of recovery, however, depends primarily on operator human capital endowments, especially secondary level education in this sample.

The point that being educated hastens one’s response to shocks but doesn’t shield one from them is a more nuanced finding than appears in the existing literature. For example, Glewwe and Hall (1998), using 1985 and 1990 panel data from Peru, found that households with better educated heads were less vulnerable to the adverse effects of macroeconomic shocks. But their data did not permit them to establish whether it was the relatively more rapid speed of *ex post* adaptation or less initial exposure to the shock that accounted for the superior performance over five years among households with better educated heads. Similarly, the “human capital approach to allocative efficiency” literature consistently found that education positively affects agricultural output, the allocative efficiency of farmers, or both (Griliches 1963, Welch 1970, 1978; Fane 1975; Huffman 1975, 1977; Ram 1980). But that literature failed to identify the context-dependent returns to education. Education seems to pay off most in the wake of substantial disruptions to the economic environment and when the operation managed is relatively more complex. Our analysis brings out these important refinements, offering empirical support to Schultz’s seminal claim that human capital enhances one’s ability to adapt to changing economic circumstances (Schultz 1964, 1975). Of course we cannot tell in these data whether people who go far in school are inherently more adaptable or whether they learned something there that helps
them adapt. So while our results suggest education is important, one must keep in mind that education might merely proxy for unobserved human capital more generally.

V. Conclusions

Macroeconomic shocks affect microeconomic decision-makers. The short-run burden of collecting and processing information on which operators base resource reallocation decisions, and of finding new trading partners and negotiating new contracts may divert managerial attention from directly productive activities, leading to transitory increases in technical inefficiency and therefore to (perhaps temporary) deviations of output below its potential. The disruption of the shock costs the economy aggregate output, but the effect is not uniformly experienced. Rather, there are predictable cross-sectional differences across operators in the extent to which the shock diverts managerial attention and therefore in induced transitory inefficiency. The pace and extent of subsequent recovery depends heavily on managerial human capital, especially education. Managers with greater cognitive abilities process information more quickly and more accurately, enabling faster recovery from the initial impact of a shock. So investment in universal education might bear dividends in the form of reduced foregone output in the wake of disruptive shocks, reinforcing the Schultzian argument that the returns to education increase as dynamic changes in the economy become greater or more frequent.

We tested these hypotheses using a panel of plot-level data on rice farmers in Côte d’Ivoire spanning a three-year period during which the currency underwent massive devaluation. The empirical evidence is consistent with the model. Education is no shield against the initial adverse effects of a shock, but aids greatly in recovery. The magnitude of the initial adverse
shock appears greatest for those managing more complex operations and for married women farmers with young children, presumably because their domestic burdens increase during periods of macroeconomic disequilibrium. But because women are both generally less powerful in controlling intrahousehold resource allocation, and thus more likely to bear extra burdens in times of stress, and far less likely then men to be educated in this setting, and thus less well equipped to collect and process information so as to recover quickly, women rice farmers face a more serious and protracted challenge in dealing with disequilibrium. Our results support arguments in favor of the relatively greater economic importance of educating women, albeit not at all due to the usual arguments about investments in children’s health or education.

The literature on producer response to macroeconomic and sectoral shocks has yet to address these issues although they surely matter to short-run sectoral and macroeconomic performance and to the welfare of poor smallholder subpopulations. Less well-educated smallholders and those who bear the domestic burdens of disequilibrium, chiefly women, fall behind their better-educated and less-encumbered counterparts. These effects may help explain the sluggish response of output – especially food output, which is disproportionately dependent on poorly educated female producers in Sub-Saharan Africa – to policy shocks over the past two decades in much of the low-income world (Barrett and Carter 1999).
Table 1: Observed Changes in Prices and Input Applications

(Percent change, 1993 to 1995)

<table>
<thead>
<tr>
<th>Prices (FMHS survey regions monthly average series)</th>
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<tbody>
<tr>
<td>Nominal local rice variety price</td>
<td>47.9</td>
</tr>
<tr>
<td>Local rice/yam price ratio</td>
<td>49.2</td>
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<td>Local rice price/wage ratio</td>
<td>16.8</td>
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<table>
<thead>
<tr>
<th>Input volumes (FMHS survey households)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Area in rice</td>
<td>39.7</td>
</tr>
<tr>
<td>Average plot size</td>
<td>12.8</td>
</tr>
<tr>
<td>Adult family labor hours</td>
<td>28.0</td>
</tr>
<tr>
<td>Hired labor hours</td>
<td>21.1</td>
</tr>
<tr>
<td>Child labor hours</td>
<td>54.8</td>
</tr>
<tr>
<td>Chemical inputs</td>
<td>5.0</td>
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Table 2: Year-on-Year Changes in Plot-Specific Estimated Technical Inefficiency

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<tr>
<td></td>
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<td>SPF</td>
<td>DEA</td>
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<td>$\theta_i$ increased</td>
<td>32.7</td>
<td>81.4</td>
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<td>$\theta_i$ decreased</td>
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<td>18.6</td>
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<tr>
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<td>47.2</td>
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Table 3: Temporal Bootstrap Results
(using 10,000 replicates)

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<th></th>
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<th>97.5% Bound*</th>
<th>Standard Deviation</th>
<th>n</th>
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<td>1.035</td>
<td>1.108</td>
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<td>DEA 1994</td>
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<td>1.139</td>
<td>1.372</td>
<td>0.051</td>
<td>176</td>
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<td>DEA 1995</td>
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<td>1.107</td>
<td>1.315</td>
<td>0.049</td>
<td>173</td>
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<td>Parametric 1993</td>
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<td>1.165</td>
<td>0.008</td>
<td>115</td>
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*= centered 95% confidence band
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<th>Parametric</th>
<th>Regressand:</th>
<th>DEA</th>
<th>Parametric</th>
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<td>($\theta_{a2}-\theta_{a3}$)</td>
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<td>Modern*Ele</td>
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<td>0.045</td>
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<td>(0.052)</td>
<td>m</td>
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<td>(0.094)</td>
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</tbody>
</table>

$r^2$ 0.492 0.586

***,**,* = statistically significant at the 99, 95, and 90 percent confidence levels, respectively

N=80

standard errors in parentheses
Table 5: Technical Inefficiency Recovery After Macroeconomic Shock

<table>
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<tr>
<th>Regressand:</th>
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<th>Regressand:</th>
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<td>Plots²</td>
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<td>(0.030)</td>
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<td></td>
<td>(0.032)</td>
<td>(0.024)</td>
</tr>
<tr>
<td>Modern</td>
<td>0.033</td>
<td>-0.003</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.092)</td>
<td>(0.004)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\(r^2\) | 0.342   | 0.361 |

***,**,* = statistically significant at the 99, 95, and 90 percent confidence levels, respectively

N=141

standard errors in parentheses
Figure 1: Hypothesized Response Path to a Discrete Relative Price Shock
Figure 2: Evolution of stochastic rice prices
(13-month centered moving average of regional series)
References


