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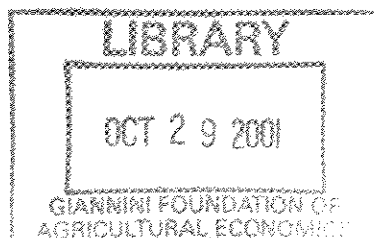
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ENVIRONMENTAL INDICES FOR THE CHINESE GRAIN SECTOR

by

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Environmental Indices for the Chinese Grain Sector*

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Abstract

Increased population pressure and political decisions have led to more intensive agricultural practices in China. As in other regions of the world, these practices can damage natural capital. We use the Kalman filter and Chinese panel data to estimate an index of environmental productivity (natural capital), together with the parameters of environmental dynamics and the production function. These estimates show that intensive practices are likely to have had persistent, substantial, and statistically significant negative effects on productivity. Ignoring these effects can cause substantial misallocation of resources. The results illustrate the possibility of estimating sectoral environmental indices using data commonly available.

Key Words: Chinese agriculture, dynamic production, environmental indices, sustainability, Kalman filter.

JEL Classification numbers: Q01, Q21, C32, C43

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1 Introduction

Remnants of Mao's policy of agricultural self-sufficiency persist in China. This policy has been criticized as being costly and inefficient, and it may have serious consequences if attempts to meet short-run production targets degrade land quality. We estimate the relation between Chinese agricultural practices and long-term productivity changes. Our approach uses the Kalman filter to estimate an index of agricultural productivity, jointly with an equation of motion for this index, and a production function that includes the index along with the usual inputs such as land and labor.

As with standard dynamic production functions, this model enables us to measure the short and long-run effects of changing inputs. The added advantage of this approach is that it yields an estimate of an unobserved state variable that we interpret as an index of environmentally-related agricultural productivity, i.e., a measure of natural capital. We use this index to assess the sustainability of agricultural practices, and to simulate the effects of moving from a myopic to a forward-looking policy.

Problems of decreased land productivity due to more intensive agriculture arise throughout the world. Overgrazing by livestock, harmful agricultural practices, and deforestation have degraded more than 1.2 billion hectares of land around the world in the past 45 years (World Resources Institute 1993). The affected areas account for 11 percent of the earth's vegetated surface, the combined size of China and India. This degradation has impaired biological productivity, making land reclamation costly or impractical. Despite the green revolution of the 1960's and 1970's, when the use of fertilizers and hybrid grains led to huge increases in food production, the per-capita food production has declined in 80 countries. Soil degradation contributed to this decline. The increased application of fertilizers may mitigate the loss in productivity in the short run, but exacerbate long-run losses.

The FAO's list of major land-use concerns include: decline in the quality of soils as a rooting environment; erosion and loss of topsoil by wind and water; loss of vegetation cover, including woody perennials; acidification, soil fertility decline and plant nutrient depletion; and salinity and salinization, particularly in irrigated systems (Food and Agriculture Organization 1996). Better measures of the effects of human activities on natural resources can help to improve agricultural practices, making it easier to increase food production and rural welfare. These measures should recognize that agricultural practices may have long-term and cumulative effects. The lack of data or the poor quality of data complicates the measurement problem

(Department of Agriculture 1994). Our approach recognizes that natural resource problems are dynamic, and it uses data that are widely available.

Intensive agricultural practices have helped China to increase its food production, but may result in long-term environmental problems that reduce future productivity. The application of chemical fertilizer has been steadily rising, marginal lands have been brought into production, and the length of the production season has been extended. These more intensive practices have produced a new generation of environmental threats that may eventually reduce productivity (Xu, Lu, and Zhu 1980), (World Bank 1997). The intensive practices create deficiencies in micronutrients, change the balance of nutrients, alter the structure of the soil, and lower resistance to pests (Casman and Pingali 1993). Runoff from fertilized fields contribute to water pollution, and inefficient irrigation exacerbates water shortages and has salinized large tracts of lands. Efforts to bring marginal lands under cultivation have worsened soil erosion and desertification, threatening China's fragile wetlands and grasslands. Microlevel studies document the loss of productivity due to intensive agricultural practices in the subtropical zones of China (Stoop 1993).

We use province-level panel data of Chinese grain production to measure the importance of environmental changes. Our two basic hypotheses are: (i) grain production depends on "environmental quality" – a measure of natural capital – in addition to standard inputs, such as labor, land, fertilizer and machinery; (ii) some agricultural decisions affect environmental quality and therefore affect future as well as current production.

The model consists of two equations. The first equation is a production function that includes standard inputs in addition to an unobserved state variable that we refer to as an index of environmental quality (or natural capital). This index measures only agricultural productivity. It excludes other environmental considerations, e.g. those related to health, biodiversity, or aesthetics. The second equation describes the change in this index, as a function of its current value and of current agricultural decisions that affect environmental quality. We estimate three sets of parameters: the production elasticities, the parameters of the dynamic equation for the environmental index, and the values of the unobserved environmental index.

These estimates enable us to assess whether agricultural practices lead to important changes in agricultural productivity. The persistence of the environmental index determines whether the effects of agricultural practices are long-lasting or transitory. Since we estimate the model using panel data, we can compare the indices across provinces. The time-series of the index for a

specific province indicates the direction of change of environmental quality, thus providing an informal measure of sustainability of agricultural practices. We also use the parameter estimates to illustrate the extent to which forward-looking behavior might change agricultural practices. Forward-looking behavior increases the shadow price of activities that damage the environment, thus reducing the level of these activities.

The problem of estimating an index of environmental quality differs from the problem of calculating more familiar indices, such as for capital and labor. We can observe the components of those indices (e.g. the type of capital, or the category of worker) and we can aggregate the components using prices. In the case of the environment, we seldom have good data on the components of the index, and we do not have reliable aggregators.

Ideally, an index of environmentally-related agricultural productivity includes measures of water and soil quality such as salinity, topsoil depth, and micronutrients. We do not have this kind of data for China. Even in the rare cases where good data exists, there is no generally accepted method of aggregation. For example, Jaenicke and Lengnick (1999) apply a particular method of constructing a static index of soil quality, using detailed data from US experimental plots. Transforming their (or some other) static index into a dynamic measure would not be straightforward, and would require still more data. This kind of detailed data does not exist on a large scale, and it is unlikely to become available – at least for developing countries where the environmental dangers are greatest.

Even though it is not feasible to construct an ideal index, it is important to have some measure of sustainability. Policymakers find it difficult to respond to problems which they cannot measure. Efforts to construct a “Green National Account” are a response to this need to measure environmental and natural resource changes. The Green National Accounts attempt to measure economy-wide changes. In contrast, our use of the Kalman filter enables us to estimate a dynamic environmental index at the sectoral level.

The next section reviews relevant literature, and the subsequent section explains our model. We then describe the data, our empirical results, and the implications of these results.

2 Literature Review

Increases in Chinese agricultural output have been attributed to institutional reforms, agricultural research and development, and the rapid increase of modern inputs. Stone (1988) em-

phasizes the expansion of China's irrigation system and the development and extension of new agricultural technology. Fan (1991) studies the effects of technological change and institutional reform on production growth. Lin (1992) and McMillan, Whalley, and Zhu (1989) also emphasize the improved production incentives resulting from institutional reform.

Huang and Rozelle (1995) study the role of intensified use of land, water and labor in increasing yields. They find that environmental factors contributed to the decline in the rate of increase of yields during the late 1980s. Erosion and salinization had a small, negative effect on yields. They use four measures of environmental stress in rural China: soil erosion, area "easily flooded and drought damaged", salinization, and a measure of intensity known as the Multi-Cropping Index (MCI), which we define below. The data on environmental stress are infrequent or of poor quality in China. For example, salinization data are updated every 5 years, and therefore cannot be used with annual production data.

We estimate a model using the Kalman filter (Hamilton 1994). This econometric technique has been widely used in economics. (A search in JSTOR with "Kalman filter" as keyword yields more than 100 results.) However, we found only one natural resource application of this estimation method. Berck and Johns (1991) use it to estimate the unobserved biomass of Pacific halibut, and the parameters of the growth equation. Golan, Judge, and Karp (1996) explain that the type of agricultural model that we use can be estimated using Maximum Entropy (ME) rather than the Kalman filter. They illustrate the ME estimation using Monte Carlo studies. Our attempts to use ME resulted in unstable parameter estimates, so we report only results of Kalman filter estimation.

3 The model

We first describe the general form of the model and then explain the specific model that we estimate. We have panel data; the time index is t and the province index is i . We estimate a log-linear model in order to be able to use the linear Kalman filter. Upper case letters denote variables in levels, and lower case letters denote the natural log of these variables. The model contains two equations, a production function and an equation of motion for the unobserved environmental index.

We have four types of data: y_{it} is output (the log of grain production); $z_{1,it}$ is a vector of variables that affect the environmental productivity index, but not agricultural production di-

rectly; $z_{2,it}$ is a vector of inputs that enter the production function but not the dynamic equation; and $z_{3,it}$ is a vector of inputs that enter both the production function and the equation of motion. We assume that $z_{j,it}$ is exogenous. The log of the environmental productivity index in province i at time t is γ_{it} , an unobserved state variable.

3.1 The General Specification

The model consists of the following equations

$$y_{it} = \beta_{0i} + \beta_1 \gamma_{it} + B_2 z_{2,it} + B_3 z_{3,it} + e_{it} \quad (1)$$

$$\gamma_{it+1} = \alpha_{0i} + \delta \gamma_{it} + A_1 z_{1,it} + A_3 z_{3,it} + v_{it}. \quad (2)$$

Equation (1), a production function, is the measurement equation, and equation (2) is the state equation.

The dimensions of the vectors of parameters, B_j and A_j , are conformable to the vectors z_j ; v_{it} and e_{it} are random errors. We assume that the errors are distributed normally, that they are homoskedastic and uncorrelated across time and province, and that e and v are uncorrelated.

Equation (1), the production function, is standard except for the inclusion of the environmental index. The elasticity of output with respect to the index is β_1 ; B_2 and B_3 are vectors of elasticities of output with respect to inputs z_2 and z_3 . The province-specific effect, β_{0i} , accounts for differences in, for example, irrigation or transportation systems. All other parameters in equation (1) are constant across both time and provinces.

Equation (2) describes the change in the environmental index in province i . The parameter α_{0i} measures the exogenous flow of environmental quality in province i . By making this parameter province-specific, we allow for the possibility that the environment evolves differently, and has different steady states, in the various provinces. These differences may be caused by a variety of factors including differences in climate or soil type. We also allow the initial value of the index, γ_{i0} , to be different across provinces. The parameter δ measures the persistence of the environmental index. The parameters A_1 and A_3 are the vectors of elasticities of the index with respect to z_1 and z_3 .

Parameter estimates enable us to assess the importance of and the persistence of agricultural practices on future productivity. Current practices are important to future productivity if and only if both A_3 and β_1 are non-negligible. Current practices have long-lasting effects if and

only if A_3 and δ are non-negligible. Thus, questions of the persistence and the importance of environmental impacts in production are related, but not identical.

We can write the model in a more familiar form by performing the following manipulations. Advance equation (1) by one period (replace t with $t + 1$) and multiply equation (1) by δ . Subtract one of the resulting equations from the other and then use equation (2) to eliminate $\gamma_{it+1} - \delta\gamma_{it}$. Rearranging the resulting equation and lagging it gives

$$y_{it} = \delta y_{it-1} + [(1 - \delta)\beta_{0i} + \beta_1\alpha_{0i}] + \beta_1 A_1 z_{1,it-1} + B_2 z_{2,it} - B_2 \delta z_{2,it-1} \quad (3)$$

$$+ B_3 z_{3,it} + (\beta_1 A_3 - \delta B_3) z_{3,it-1} + w_{it}$$

$$w_{it} \equiv e_{it} - \delta e_{it-1} + \beta_1 v_{it-1}. \quad (4)$$

Equation (3) is a fairly standard panel-data model with a fixed or random effect, except for the special covariance structure created by the definition of the random variable w_{it} .¹ Estimation by traditional methods requires the use of instrumental variables to deal with the correlation of lagged y and w . From equation (3) it is clear that our model includes familiar models as special cases. If $\delta = A_1 = B_3 = 0$ we obtain: (i) the standard fixed effect model if the distribution of v_{it} is degenerate; (ii) the standard random effects model if $\alpha_{0i} = \alpha_0$, $\beta_{0i} = \beta_0$, and $v_{it} = v_i$.

Estimation of equations (3) and (4) does not enable us to identify the distinct fixed effects in the dynamic equation and the production function, α_{0i} and β_{0i} , or to recover estimates of the environmental index, γ . The parameters δ and B_2 are over-identified; they can be estimated using the coefficients of y_{it-1} , $z_{2,it}$, and $z_{2,it-1}$ in equation (3). The parameter B_3 can be estimated using the coefficient of $z_{3,it}$. The remaining coefficient estimate (of $z_{3,it-1}$) cannot be used to estimate both β_1 and A_3 . However, the latter parameters can be identified using information on the covariance structure of the error, implicit in the definition of w_{it} .

There are several advantages of using the Kalman filter to estimate equations (1) and (2), rather than using panel-data methods to estimate equations (3) and (4). The Kalman filter provides estimates of the values of the environmental index, which measure environmental differences across provinces and over time. We use the estimates of the parameters of the production function and the equation of motion, together with the estimate of the current index, to compare the benefits of different agricultural policies. By using the Kalman filter, we also

¹An extensive literature on dynamic production functions estimates reduced form equations similar to equation (3). A related literature estimates dynamic supply functions. The supply function approach is probably not appropriate for China, where agricultural decisions have not been determined by competitive markets, and it is probably not feasible because of the lack of price data.

avoid some technical econometric problems. For example, we avoid having to choose a particular instrumental variable technique to deal with the correlation between lagged y and w in equation (3), and we avoid having to use the covariance structure implicit in the definition of w_{it} to identify β_1 and A_3 .

Regardless of which estimation method we use, this model has an inherent limitation. There are many unobserved (and therefore excluded) variables that affect production, so we cannot be certain that the state variable γ is an index of environmental productivity, rather than a composite of other excluded factors. An analogous problem arises in any estimation problem where omitted variables create the risk of ascribing the wrong meaning to parameter estimates.

Another problem involves the allocation of observed variables across the vectors $z_i, i = 1, 2, 3$. We have to decide whether a variable affects only the environmental index (z_1), only current production (z_2), or both (z_3). An argument could be made for putting most variables in the third category. The next sub-section describes a particular allocation that uses prior beliefs to distinguish among the three types of variables. For comparison we also estimate a more general model in which all of the inputs appear in both equations.

3.2 Definition of variables

It is important that z_1 and z_3 , which appear in the dynamic equation, effect future productivity via their effect on the environment, rather than via some other mechanism (e.g., improved marketing infrastructure). It is important that z_2 , which appears in the production function but not in the dynamic equation, include as many other production-related variables which are unlikely to have environmental effects.

The vector z_1 (which appears only in the dynamic equation) consists of the Multi-Cropping Index (*MCI*), defined as the ratio of the area sown during a season to the amount of cultivated land.² For example, if half of the cultivated land is sown twice in a season, the *MCI* for the region is 1.5. If some of the land that is usually cultivated is left fallow, the *MCI* can be less than 1 (as it is for some of our data). The *MCI* measures the intensity of cultivation; it is both a decision variable and is also influenced by geographic location and technology. Southern regions tend to have a longer growing season and therefore can plant more than one crop in a year. New crop varieties that are more resistant to cold weather can extend the growing season.

²“Cultivated land” refers to land that is “typically cultivated”, rather than the land that is actually cultivated in a year: otherwise, it would not be possible for $MCI < 1$.

The vector z_3 (which appears in both the production function and in the dynamic equation) consists of chemical fertilizer. Fertilizer obviously has a direct effect on current production, and it may also alter future productivity by affecting the soil condition. The dynamic effect could be positive or negative, depending on the sign of $\beta_1 A_3$. For example, the application of chemical fertilizer may increase future production by increasing nitrogen stocks. However, since chemical and organic fertilizers are substitutes, increased use of the former is associated with diminished use of organic fertilizers. This change can lead to lower soil quality. More generally, we think that fertilizer use is a good proxy for the intensity of agricultural production. Data on other variables that affect soil productivity, such as irrigation (which is associated with increased salinization) are not available at the provincial level.

The vector z_2 (which appears only in the production function) contains measures of draft animals, farm machinery, and labor, major inputs in production. The vector also includes the total area sown to grain, A . Since A appears in the definition of MCI (z_3), the two explanatory variables are imperfectly correlated. We include a time trend and a time trend squared in the vector z_2 in the production function to capture the effect of institutional changes and technological progress. These kinds of changes do not directly effect the environmental index, so the time trends do not appear in the dynamic equation.

We also estimate a more general model in order to assess the robustness of the model described above. In this more general model we include the other inputs (draft animal, machinery and labor) in the vector z_3 , so that they appear in both the production function and the state equation. We do not include A as a separate variable in z_3 since A enters via MCI .

4 Data

We have data for all 29 Chinese provinces from 1981-95, published by China's State Statistical Bureau (ZGTJNJ) (China Statistics Yearbook 1996). The categories of grain consist of rice, wheat, maize, soybeans, barley, sorghum, millet, potatoes and sweet potatoes. As in Huang and Rozelle (1995), we obtain the total quantity of grain (in units of 1000 tons) by summing the individual quantities, except that a ton of potatoes and sweet potatoes are valued at one fifth of a ton of other types of "grain" because of their lower caloric content.

The data on the agricultural inputs are not separated by production categories. To obtain measures for the grain production inputs we multiply the total agricultural inputs of chemical

variables	unit	mean	sd	min	max
chemical fertilizer	1,000 tons	778.20	690.57	2	3623
draft animal	1,000 heads	2426.99	1796.86	6	9858
total grain production	1,000 tons	13929.81	10627.45	370	43650
total grain area	1,000 hectares	3863.381	2624.01	187	10545
farm machine power	1,000 KW	8583.23	7223.86	243	43364
sown area for all crops	1,000 hectares	5046.265	3383.32	210	12839
cultivated area	1,000 hectares	3331.56	2228.10	221	8995
gross value of rural indu. output	million Yuan	33857.9	86071.4	5	799552
gross value of ag output	million Yuan	23074.68	28074.96	0	185748
total rural labor	1,000 persons	1351.18	1125.35	81.8	5177.7
grain output (y)		9.102405	1.11	5.91	10.68
grain area (a)		7.88	1.04	5.23	9.26
grain labor (l)		5.95	1.17	2.71	7.99
chemical fertilizer (f)		5.82	1.281	.589	7.90
draft animal (d)		7.05	1.32	1.33	8.87
machinery (m)		8.42	.93	5.38	10.43
MCI		1.54	.49	.86	2.575757

Table 1: Summary of Data

fertilizer, machine power, and draft animal by the ratio of total area sown in grain to the total area in other crops.

Rural industrial enterprises have become important in the rural economy, and a major employer of rural labor since the 1980s. We have data on total rural labor, but not on agricultural labor devoted to grain production. To obtain an estimate of labor used in grain, we multiply total rural labor by

$$\left(\frac{\text{gross value of ag output}}{\text{gross value of ag + rural industrial output}} \right) \left(\frac{\text{total area sown in grain}}{\text{total area sown}} \right).$$

If labor is more productive in industry than in agriculture, our measure understates the actual amount of labor in grain production. The measure overstates the actual amount if grain is less labor intensive than other farming activities.

We obtain MCI by taking the ratio of total area sown for all crops and the amount of cultivated area. Thus, MCI is a measure of intensity in the entire agricultural sector, not merely in the grain sector. If land is shifted from non-grain to grain use, total grain area increases without increasing the intensity of grain production. If total grain area increases without an offsetting decrease in non-grain area (e.g., due to the cultivation of marginal lands), then the intensity of grain production increases.

The first 10 rows of Table 1 give the units and the summary statistics of the raw data. The next 7 rows of the table give the summary statistics of the data that we used in estimation, after making the conversions described above. All of the data at the bottom half of the table are in natural logs, except for MCI , which is expressed as a fraction.

5 Results

We denote $\log(MCI) = mci$. Using this and the variable definitions in Table 1, we repeat the definitions of z_j : $z_1 = mci$; $z_2 = (a, l, d, m, t, t^2)$; and $z_3 = f$. We estimate the following specialization of equations 1 and 2:

$$\gamma_{it+1} = \alpha_{0i} + \delta\gamma_{it} + \alpha_1 mci_{it} + \alpha_3 f_{it} + v_{it} \quad (5)$$

$$y_{it} = \beta_{0i} + \beta_1 \gamma_{it} + \beta_{21} a_{it} + \beta_{22} d_{it} + \beta_{23} m_{it} + \beta_{24} l_{it} + \beta_{25} t + \beta_{26} t^2 + \beta_3 f_{it} + e_{it}. \quad (6)$$

We use our parameter estimates to measure the short- and long-run effects of more intensive agricultural practices. We then illustrate the trends of the environmental index for several provinces. Finally, we use the model to determine how production decisions might change if environmental effects are taken into account.

5.1 Parameter Estimates

Table 2 presents the Kalman filter estimates of equations (5) and (6). The first column gives the variable symbol, its name, and the associated coefficient. Since all dependent and explanatory variables (except time) are in logs, their coefficients are elasticity estimates. Columns 2 and 3 give, respectively, the coefficient estimates for the production function and for the equation of motion of the land productivity index. In order to test the significance of individual coefficients, we use the difference between the unrestricted and restricted log-likelihoods – a χ -squared

variable symbol, name, coefficient	production function	state equation	fixed effect OLS
γ , index, (β_1 and δ)	0.0577*	0.8538*	
a , area (β_{21})	0.5902*		0.5841**
d , draft animal (β_{22})	0.0570		0.078**
m , machinery (β_{23})	0.0131*		-0.028
l , labor (β_{24})	0.0327*		0.029
t , time (β_{25})	0.0102*		0.026**
t^2 , time squared (β_{26})	-0.0002		-0.0007**
f , chemical fertilizer (β_3 and α_3)	0.2546*	-0.9501*	0.1972**
mci , MCI (α_1)		-0.2311*	

* * 95% confidence level * 90% confidence level

Table 2: Estimation results of preferred model

statistic. These tests show that all parameter coefficients except for the square of the time trend and draft animal are significant at the 90% confidence level.

Area cultivated and chemical fertilizer have the largest elasticities of output. The point estimate of the elasticity of output with respect to the environmental index ($\beta_1 = 0.0577$) is statistically significant at the 10% level and it is larger than the elasticity estimates of draft animal, machinery, or labor. This comparison suggests that a change in the land productivity index has a non-negligible effect on agricultural output. The point estimate of the persistence parameter δ in equation (5) is large ($\delta = 0.85$), so changes in the environmental index are long-lasting. This estimate of δ , together with the elasticities of the index with respect to both chemical fertilizer and MCI , suggests that more intensive agricultural practices (more chemical fertilizer or a higher MCI) have significant and long-lasting negative effects on future land productivity.

The fourth column of Table 2 gives the coefficient estimates of a static model (no lagged variables), including a fixed effect, estimated using OLS. The output elasticities with respect to area are similar. The elasticity estimate for draft animal is higher under OLS and is significant at the 5% level, but the elasticity estimates for machinery and labor are not significant even at the 10% level under OLS. The elasticity level for fertilizer is about 20% lower under OLS, and is significant at the 5% level.

We emphasize the parameter estimates in Table 2 in the following subsections. In order

variable symbol, name	production function	state equation
γ , index	0.0577*	0.6090*
a , area	0.5902*	
d , draft animal	0.0570	0.0648*
m , machinery	0.0131*	-0.012
l , labor	0.0418*	0.05828
t , time	0.0091*	
t^2 , time squared	-0.0002	
f , chemical fertilizer	0.2424*	-0.8702*
mci , MCI		-0.2770*

* * 95% confidence level *90% confidence level

Table 3: Estimation results of general model

to assess the robustness of this model, we also present the Kalman filter estimates of a more general model in which all agricultural inputs other than area appear in the equation of motion for the environmental index. Table 3 presents these estimates. The estimated coefficients in the production function change very little. Estimates of the persistence parameter, δ , and of the elasticity of the index with respect to fertilizer are smaller, but of the same order of magnitude, as in the restricted model. The elasticity of the index with respect to draft animal is significant and positive, but small. Greater use of draft animal is probably associated with less intensive agricultural practices, leading to an improvement in the environmental index. The coefficients for machinery and labor have the expected sign (less environmentally damaging practices use more labor and less machinery) but these variables are not significant.

5.2 Dynamic Elasticities

In order to discuss the dynamic elasticities, we introduce additional notation. Define the vector $x_t \equiv (z_{1t-1}, z_{2t}, z_{2t-1}, z_{3t}, z_{3t-1})'$, the contemporaneous and lagged values of z_j in equation (3). Using this definition, and equation (3), we can write the expected value of the log of output at time $\tau > 0$, conditional on information available at $t = 0$, as

$$y_t = \delta^t y_0 + \mu \sum_{s=0}^{t-1} \delta^s x_{t-s}. \quad (7)$$

We suppress the province index i and the expectation operator, and we use the convention $\sum_{s=0}^{t-1} \delta^s x_{t-s} = 0$ for $t = 0$. The row vector μ contains the coefficients corresponding to elements of x appearing in equation (7).

We want to distinguish between the elements of x_t that enter both the observation and state equations, and all other elements of x_t (including the constant and the time trends). We denote the first set x_1 and the second set x_2 , so $x_t = \begin{pmatrix} x'_{1t} : x'_{2t} \end{pmatrix}'$. The conformable separation of the parameter vector is $\mu = \begin{pmatrix} \mu_1 : \mu_2 \end{pmatrix}$. Using the definitions of variables in Table 1, and the identification of parameters in Table 2, we have:

$$x'_{1\tau} = (f_t, f_{t-1}, mci_{t-1}, a_t, a_{t-1}).$$

Chemical fertilizer, f directly affects both the environment and agricultural production; mci directly affects the environmental variable, and land used in grain production, a , directly affects production. Since $MCI = \frac{A+NG}{L}$, where $NG = (\text{non-grain sown area})$ and $L = (\text{total "cultivated area"})$, we have $mci = a + \ln(NG) - \ln(L)$. Therefore, we include both a and mci in x_1 .

Using these definitions, and some algebraic manipulation to simplify the summation, we can rewrite equation (7) as

$$y_t = H(t) + \sum_{s=1}^{t-1} \delta^{s-1} (\beta_1 \alpha_1 mci_{t-s} + \beta_1 \alpha_3 f_{t-s}) + \beta_3 f_t + \beta_{21} a_t, \quad (8)$$

where $H(t) \equiv G(t) + \delta^{t-1} (\beta_1 \alpha_1 mci_0 + (\beta_1 \alpha_3 - \delta \beta_3) f_0 - \beta_{21} \delta a_0)$; the function $G(t)$ depends on the initial value of y (at time $t = 0$) and on the trajectories of the other inputs (labor, machinery, draft animals, the constant, and the time trend) between time 0 and t . Thus, $H(t)$ consists of variables that are predetermined at time $t = 1$ and of variables that have no dynamic effect.

We use equation (8) to compare the impact and the intermediate effect of changing environmental practices. For example, a temporary increase (at time $t = 1$) of chemical fertilizer causes an initial increase in output due to the direct effect of fertilizer on production, and a subsequent decrease in output due to the indirect effect, via the land productivity index γ . The impact multiplier is β_3 . The intermediate elasticity at time $t \geq 2$ caused by this one-time change is $\delta^{t-2} \beta_1 \alpha_3$.

If the increase in fertilizer use is maintained at the higher level indefinitely, the direct positive effect remains constant, but the indirect negative effect accumulates, as the environment is

degraded. Denote the elasticity of output at time $t \geq 1$ with respect to the sustained change in fertilizer as $\eta(t)$. Using equation (8) we have

$$\eta(t) = \beta_3 + \beta_1 \alpha_3 \sum_{s=1}^{t-1} \delta^{s-1} = \beta_3 + \beta_1 \alpha_3 \frac{1 - \delta^{t-1}}{1 - \delta}.$$

The impact elasticity is $\eta(1) = \beta_3$ and the long-run elasticity is $\eta(\infty) = \beta_3 + \beta_1 \frac{\alpha_3}{1 - \delta}$. For our point estimates in Table 2 we have $\eta(t) = .43918 \exp(-.15806t) - .12$, so $\eta(1) = \beta_3 = 0.2546$ and $\eta(\infty) = -0.12$. The elasticity becomes negative in 8.2 years and it travels half of the distance between its initial and steady state level in approximately 4.4 years.³ For the parameter values in Table 3, $\eta(t) = .21 \exp(-.49594t) + 0.114$, so $\eta(\infty) = 0.114$. For both sets of parameter values the elasticity diminishes over time because of the environmental feedback. The parameter estimates in Table 2 imply that a sustained increase in fertilizer use eventually decreases output; the estimates in Table 3 imply that the sustained increase in fertilizer eventually leads to very small output increases.

Grain production can be increased by increasing the area sown to grain (A). The effect of a change in A on future values of the environmental index depends on the manner in which MCI changes. If the increase in A is offset by a decrease in area sown to non-grain crops, (NG), there is no change in MCI and no environmental effect. To examine the effect of more intensive practices, we assume that A increases due to the use of plant varieties that permit an additional harvest, or to some other method of extending the growing season. We also assume that NG and cultivatable land, L , remain constant. (With these definitions, $MCI = \frac{A+NG}{L}$.) Using these assumptions and the definition $\phi \equiv \frac{A}{A+NG}$, we have $\frac{d(mci)}{da} = \phi$.

A temporary increase in area sown to grain (holding L and NG fixed) has an impact elasticity on output of β_{21} . The intermediate elasticity of output at $t \geq 2$ due to a change in A at time $t = 1$ is $\delta^{t-2} \beta_1 \alpha_1 \phi$. For the parameter estimates in Table 2, the impact elasticity is $\beta_{21} = .5902$ and the intermediate elasticity is $\alpha_1 \phi \beta_1 \delta^{t-2} = -.0183 \phi \exp(-.15806t)$.

A sustained increase in the area sown to grain crops has an intermediate elasticity of output of

$$\varepsilon(t) = \beta_{21} + \beta_1 \alpha_1 \frac{\phi}{1 - \delta} - \beta_1 \alpha_1 \phi \frac{\delta^{t-1}}{1 - \delta}.$$

³Define the deviation between $\eta(t)$ and its steady state value as $\theta(t)$, so $\theta(t)$ obeys $\theta(t+1) = \delta \theta(t)$. The half-life of θ – the amount of time it takes the elasticity η to travel half the distance between its initial value and its steady state – is $\frac{\ln 0.5}{\ln \delta}$. For our point estimate, this half-life is 4.4 years.

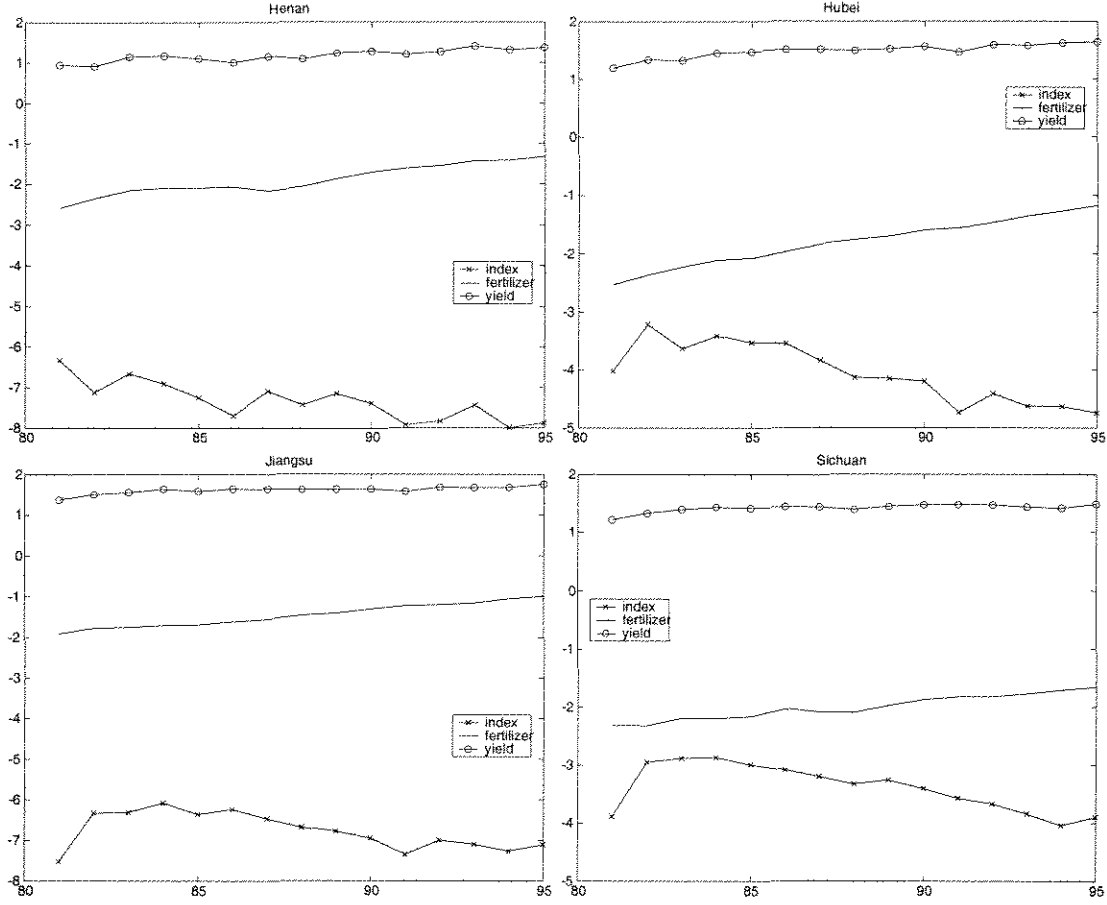
The long-run elasticity is $\beta_{21} + \beta_1 \alpha_1 \frac{\phi}{1-\delta}$. For our parameter estimates in Table 2, $\varepsilon(t) = 0.5902 - .091\phi(1 - 1.1712 \exp(-.15806t))$ and the long-run elasticity is $0.5902 - .091\phi$. Since $\phi \leq 1$, the minimum long-run elasticity is 0.499, approximately 85% of the impact elasticity. For the parameter estimates in Table 3, $\varepsilon(t) = .5902 - .0409\phi(1 - 1.642 \exp(-.49594t))$; in this case, the minimum long-run elasticity is 0.55, or 93% of the impact multiplier.

In summary, our point estimates suggest that more intensive practices – either an increase in fertilizer use or in area planted (with an attendant increase in *MCI*) – increase grain production in the short run. The long-run productivity effect, via the change in the environmental index, is fairly small for a change in area planted; for this variable, the environmental channel decreases the impact effect by less than 15% in the long run. For fertilizer, however, the environmental channel is significant: sustained increases in fertilizer (a proxy for more intensive agricultural practices) may reduce output.

5.3 Environmental Indices

The following figures graph the time series between 1980 and 1995 of yield per hectare and fertilizer per hectare and of the estimates of the (log of) the environmental index in four large agricultural provinces, Sichuan, Henan, Hubei, Jiangsu, and Sichuan. These environmental indices correspond to the model from Table 2. (We present these four provinces because their graphs are representative of the types of results that we obtained for the 29 provinces.)

The time series on yield has a slight upward trend; the upward trend for fertilizer is more obvious. There is considerably more variation in the time series for the environmental index, and the trend is distinctly negative. These graphs provide informal evidence that increased yields in China have been achieved at the expense of environmental degradation.



5.4 Policy Simulation

Our parameter estimates suggest that the environmental feedback may be significant, and that it may make the increase in yields unsustainable. This section presents another perspective of the importance of the environmental feedback. Using the parameter estimates and associated indices from Table 2, we show how the recognition of these feedback effects could change agricultural inputs and yield.

In order to perform this simulation, we consider the simplest scenario that is consistent with our model. We suppose that observed input choices were the result of the solution to a sequence of static optimization problems. The decision-maker knew the parameters of the production function, including the value of the environmental index in each period, but failed to recognize that current decisions have dynamic consequences. That is, the decision-maker treated γ_{it} as a sequence of exogenous variables, rather than a state variable whose evolution

could be influenced. With these beliefs, it is rational to choose inputs in each period by solving a static problem. When the decision-maker recognizes the endogeneity of γ_{it} , the optimization problem is dynamic, although the single period payoff function does not change.⁴

We do not know the single period objective function that led to observed input levels, so we assume that the decision-maker maximized the value of output minus the cost of inputs in each period. In a competitive market, we would calculate the value of output and of inputs using prices, but in the Chinese context the weights are the shadow prices of output and inputs. These shadow prices might differ from world prices for many reasons, including exchange rate constraints, the desire for self-sufficiency, or employment objectives. If Y is output, Z is the vector of inputs, and the corresponding shadow prices are p and \tilde{W} , the static maximand is simply $pY - \tilde{W}Z$. For example, p may be the shadow value of foreign currency times the price of imported grains. We divide by p to write the static maximand as $Y - WZ$, with $W \equiv \frac{\tilde{W}}{p}$, the relative shadow price of inputs.

As we noted above, the dynamic effect of area planted to grain, operating through the *MCI*, is small relative to the dynamic effect of fertilizer. In the interests of simplicity, we therefore treat A as a constant, and focus on the choice of fertilizer and other inputs. The other inputs – draft animal, machinery and labor (D, M, L) – have no dynamic effect in the model whose estimates are reported in Table 2. In the absence of contrary information, we assume that the ratios of relative shadow prices, $\frac{W(i)}{W(j)}$, remain constant. This assumption and the Cobb Douglas functional form enable us to aggregate these variable inputs using the index $N \equiv (D^{\beta_{22}} M^{\beta_{23}} L^{\beta_{24}})^{\frac{1}{\theta}}$, with $\theta \equiv \beta_{22} + \beta_{23} + \beta_{24}$. We write output (dropping the province index) as $Y_t = C_1 N_t^\theta F_t^{\beta_3} \Gamma_t^{\beta_1}$ where $\Gamma_t = \exp(\gamma_t)$ and the constant C incorporates the province-specific effect, the value of A (which we assume is constant) and the expectation of the random shock. With these definitions, we write the static maximand as

$$\max_{F_t, N_t} C_1 N_t^\theta F_t^{\beta_3} \Gamma_t^{\beta_1} - W_F F_t - W_N N_t, \quad (9)$$

where W_F and W_N are the shadow prices of N and F , normalized by the shadow value of

⁴Carlson, Zilberman, and Miranowski (1993) describe a variety of market failures that might lead to excessive use of natural capital. These include the absence of futures markets and other risk-reducing markets, common property problems, imperfect credit markets and insecure tenancy rights. All of these failures, in addition to inefficiencies arising from central planning, might contribute to the misallocation of resources in Chinese agriculture.

output. The first order conditions to problem (9) imply:

$$W_F = \beta_3 C_1 N_t^\theta F_t^{\beta_3-1} \Gamma_t^{\beta_1} \quad (10)$$

$$W_N = \theta C_1 N_t^{\theta-1} F_t^{\beta_3} \Gamma_t^{\beta_1}. \quad (11)$$

We use these equations, the average values of inputs, and our point estimates of the elasticities and the environmental indices for the last five years of our sample to estimate the values of W_F and W_N .

Setting the random term equal to 0, the deterministic version of the dynamic equation for the environmental index is

$$\Gamma_{t+1} = \Gamma_t^\delta F_t^{\alpha_3} C_2, \quad \Gamma_0 \text{ given} \quad (12)$$

where C_2 includes the province specific effect and MCI , which we treat as constant. The deterministic version of the dynamic problem, when the regulator recognizes the environmental feedback effects, is

$$\max_{\{F_t, N_t\}} \sum_{t=0}^{\infty} \rho^t (C_1 N_t^\theta F_t^{\beta_3} \Gamma_t^{\beta_1} - W_F F_t - W_N N_t) \quad (13)$$

subject to equation (12), where ρ is the discount factor. In solving this problem, we use our point estimates for the parameters and the initial condition, and our estimates of W_F and W_N .

The Hamiltonian to this problem is

$$H_t = \rho^t (C_1 N_t^\theta F_t^{\beta_3} \Gamma_t^{\beta_1} - W_F F_t - W_N N_t) + \rho^{t+1} \lambda_{t+1} (\Gamma_t^\delta F_t^{\alpha_3} C_2 - \Gamma_{t+1})$$

where λ_t is the costate variable for the state Γ_t . The first and second order conditions for an interior value of F_t include

$$\beta_3 C_1 N_t^\theta F_t^{\beta_3-1} \Gamma_t^{\beta_1} - W_F + \rho \alpha_3 \lambda_{t+1} \Gamma_t^\delta F_t^{\alpha_3-1} C_2 = 0 \quad (14)$$

$$\beta_3 (\beta_3 - 1) C_1 N_t^\theta F_t^{\beta_3-2} \Gamma_t^{\beta_1} + \lambda_{t+1} \rho \alpha_3 (\alpha_3 - 1) \Gamma_t^\delta F_t^{\alpha_3-2} C_2 < 0. \quad (15)$$

When $\rho = 0$ the solutions to the dynamic and static problems are obviously identical; in this case, the problem is concave and the optimal value of F_t is interior. However, for positive values of ρ , the shadow value of the index is positive, and the second term in equation (15) is positive: $\lambda_{t+1} \rho \alpha_3 (\alpha_3 - 1) > 0$. For sufficiently large values of ρ , the shadow value is large,

ρ	F	N	Γ	output	dynamic/static shadow price of fertilizer
0	1179.8	2134.2	0.0609	22880	1
0.1	1152.3	2141.0	0.0710	22953	1.0272
0.2	1108.3	2152.2	0.0914	23073	1.0735
0.3	1027.1	2174.3	0.1499	23310	1.1703

Table 4: Steady State Simulation Results

and the second order condition (15) does not hold. In this case, the problem is convex in F . A convex problem is reasonable only if we have bounds on the control variable F . With such bounds and a convex Hamiltonian, it is optimal to set F at one of its extreme values.

This type of solution means that it is optimal to exploit the environment as intensively as possible, and then to let it recover as quickly as possible. Intensive cultivation interrupted by periods when the field is left fallow may be a reasonable description of farm-level behavior, but it is not a reasonable description of aggregate province-level behavior.

For our parameter values, we found that the Hamiltonian is convex even when ρ is quite small – slightly greater than 0.3. This outcome is due to the log-linear functional forms (which we adopt in order to use the linear Kalman filter) together with the assumption that the ratios of static shadow prices are constant (which we adopt for lack of additional information). We report results only for small values of ρ , where the optimization problem is concave. These results correspond to a moderate degree of forward looking behavior. Since it makes sense to use our point estimates only to investigate the effects of small changes in attitudes, this restriction to small values of ρ is not troubling.

We solve problem (13) as a non-linear programming problem, using Matlab, replacing the upper limit ∞ by a finite horizon T . We choose T to be large enough so that the first period decision is insensitive to changes in T . Since ρ is small, $T = 20$ is sufficiently large. In order to obtain the steady state, we take the first period decision rule from this finite horizon problem; that is, we solve a “rolling time horizon” problem. Table 4 reports steady state values for four values of ρ , using parameter values from Shandong province, one of the largest grain producers in China. Columns 2 through 5 give the steady state values of fertilizer, the index of other inputs, N , the environmental index, and output.

A moderate degree of forward-looking behavior (an increase in ρ from 0 to 0.3) causes the optimal steady state level of F to decrease by about 13%, and the level of aggregate index of

other inputs (N) to increase by about 2%. The less intensive method of production (associated with $\rho = 0.3$ rather than $\rho = 0$) more than doubles the steady state value of the environmental index. The net effect of less intensive production and higher natural capital (i.e., a better environmental condition) is an increase in steady state output of about 2%.

The final column of Table 3 shows the ratio of the marginal cost of using an additional unit of F in the dynamic and the static setting. This ratio is

$$\frac{W_F - \rho\alpha_3\lambda_{t+1}\Gamma_t^\delta F_t^{\alpha_3-1}C_2}{W_F},$$

evaluated at the steady state. The numerator of this ratio is the static shadow price of fertilizer (W_F) plus the shadow value of the environmental index (λ) times the marginal effect on the fertilizer on the index. This ratio provides a steady state measure of the increase in the shadow marginal cost of fertilizer when the effect of fertilizer on the environment is taken into account. With a discount factor of $\rho = 0.3$ rather than $\rho = 0$, the shadow marginal cost of fertilizer increases by about 17%.

6 Conclusion

Agricultural practices that lead to short-run increases in output may damage long-term land productivity. When this damage occurs, the benefit of more intensive practices diminishes over time, and may become negative. We estimated a dynamic model of Chinese agriculture using province-level data. Using the Kalman filter, we obtained indices of natural capital and estimates of the parameters that determine the short- and long-run output elasticities.

Our estimates suggest that the long-run effects of some agricultural practices are both important and persistent. Using a parsimonious model, our point estimate of the impact elasticity of an increase in chemical fertilizer is 0.25, but the long-run elasticity of a sustained increase is -0.12 . Using a slightly more general model, the point estimates of the impact and of the long-run elasticities are 0.24 and 0.11. These estimates suggest that more intensive practices, proxied by higher fertilizer use, have diminishing benefits and may even reduce output. The impact elasticity of an increase in area is 0.59. If this increase in area is achieved by more intensive land use, the Multi-Cropping Index increases. The resulting greater stress on the land reduces the elasticity by as much as 15% in our parsimonious model, and 7% in the more general model.

The usual caveats for empirical work are appropriate here. We do not have data on several variables that affect the land productivity and/or current yield. The category “grains” includes

several crops, which ideally should be studied individually. In addition, most of our production data is for categories broader than “grains”; to use this data we made assumptions about shares of inputs devoted to grains and other activities.

Despite these caveats, this study is important for at least two reasons. First, we have found evidence for China, at an aggregate level, that the long-term consequences of agricultural practices may reduce future productivity. This evidence complements previous micro-level studies, and provides a sense of the magnitude of one dimension of environmental problems in China. Second, we have shown the practicality of estimating a land productivity index. In the past this index has been either a purely theoretical construction, or it has been measured using fairly narrow proxies.

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