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Contribution of Wheat Diversity to Total Factor Productivity in China

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The impact of wheat diversity on the productivity of wheat in China is examined using total factor productivity (TFP) and an instrumental variable approach. TFP in seven key wheat-producing provinces in China shows significant, though variable, growth for all provinces during the period 1982–1995. Analysis of the causes of TFP growth tests alternative taxonomies of wheat diversity (named varieties and morphological groups) and three measures of diversity. The analysis shows significant effects of diversity on TFP with results consistent across taxonomies and measures of diversity. Further decomposition of the estimation results confirms the relative magnitude of impact of wheat diversity on TFP growth.

Key words: agricultural productivity, China, crop diversity, diversity index, total factor productivity, wheat

Introduction

The determinants of crop diversity and the impacts of crop diversity on the socioeconomic and environmental landscape have been the focus of a growing body of literature at both the farm level and at aggregate levels of analysis. Crop diversity plays an important role in current production levels and in future production possibilities, and it is recognized that genetic resources are required for future use in improving yields and overcoming often unforeseen production constraints (Cassman et al., 2005). Insufficient levels of crop diversity can potentially compromise the ability of natural systems and of scientists and farmers to respond to new pests, pathogens, and adverse environmental conditions.

An increasingly large body of research highlights the successful utilization of genetic resources in crop improvement in achieving yield gains and increasing crop adaptability and productivity in heterogeneous environments (Day Rubenstein et al., 2005; Fowler, Smale, and Gaiji, 2001; Jana, 1999; Hoisington et al., 1999; Naeem et al., 1994). Diversity within the pool of varieties can also promote the maintenance of yields through better disease resistance and improved yield stability by retarding the spread of insects

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**Erika Meng, our colleague, coauthor, and close friend, passed away at the age of 46 on June 1, 2008. This was a deep shock, not only to us but to all of those who have been touched by Erika's enthusiasm for life, passion for research, and dedication to the study of economic development. But, while this may be the final paper that we publish with Erika's name next to ours, this will not be the last time that she touches our lives. Erika's spirit and memory live on as strong as ever. This paper is dedicated to that spirit and memory.*

and pests (Heal et al., 2004; Heisey et al., 1997; Priestley and Bayles, 1980). Access to diversity, for example, in the form of early, middle, and late maturing varieties, might also promote the more efficient use of fixed inputs (e.g., family labor) by allowing labor use to be spread out over time.

There may be circumstances, however, under which crop diversity could potentially reduce productivity. For instance, crop diversity in the form of additional species might reduce the productivity of the main crop through competition for nutrients, light, or other production factors (Tscharntke et al., 2005). A decline in productivity could also result if diversity cuts into the gains from specialization. In the absence of insurance markets for crop production or other means for reducing risk, farmers may choose to plant a basket of varieties in their fields rather than achieve the maximum potential yield by specializing in the variety with the highest expected yield.

Although several studies have attempted to quantify the impact of crop diversity on production and variability of production at community and regional levels using various measures of diversity, they have arrived at a number of different conclusions. Many of these studies reported a positive effect of crop diversity on production and reduction in production variability (Meng et al., 2003; Smale et al., 1998; Heisey et al., 1997). Using income rather than production as the focus of their analysis, Di Falco and Perrings (2003) also found evidence to support the positive effects of crop diversity. Widawsky and Rozelle (1998), however, found a negative correlation of genetic diversity of Chinese rice crops with both yield and the variation of yield. Omer, Pascual, and Russell (2007) theoretically derived and empirically tested the positive relationship between biodiversity and the optimal level of output under a more intensive agricultural system—a biodiversity-poor agricultural landscape. Using farm-level data, Di Falco and Chavas (2006) concluded the impact of biodiversity on productivity is strongly affected by pesticide use. Although the beneficial role of biodiversity on raising productivity and reduction of yield variability is strong under low pesticide use, the positive impact disappears when pesticide use is high.

While previous work on the subject has contributed to our understanding of the effect of diversity, it is possible that certain research-related decisions on the selection of variables (for use in the empirical modeling) and the nature of the samples may have influenced the findings. The assessment of the contribution of crop diversity on productivity is complicated by the existence of numerous factors, including agro-climatic, institutional, and economic measures that also affect productivity. Choices concerning the manner in which productivity and diversity are measured may also affect the outcomes of any analysis. In particular, none of the previously cited studies used total factor productivity (TFP) as the measure of productivity. TFP, a commonly used measure of technical efficiency for gauging sectoral performance, is arguably (in some cases) a better measure for assessing efficiency compared to yield or production. Small sample sizes and other methodological issues also may be limiting the understanding of the effect of diversity on productivity.

The objective of this paper is to undertake an analysis of the impact of wheat diversity on the efficiency of crop production at the national level in China during the period from 1982 to 1995. Specifically, we examine the effects of crop diversity on TFP utilizing a subset of spatial diversity indices constructed based on both variety names and morphological characteristics embodied by the set of cultivated varieties. The scope of the analysis focuses on the seven key wheat-producing provinces of Hebei, Shandong, Henan, Shanxi, Jiangsu, Anhui, and Sichuan. All of the provinces with the exception of Shanxi were in the top six wheat-producing provinces in China each year during the study period. In aggregate, the seven provinces accounted for an average of 63% of China's sown area and 71% of its output over the period of our investigation.

Methodology and Data

TFP Measures

We follow the approach of Jin et al. (2002) in creating our measure of TFP.[1] In briefest terms, changes in TFP are measured by comparing changes in an index of output relative to an index of input changes (Capalbo, Ball, and Denny, 1990; Ball et al., 1997, 1999). Increases in total output not accounted for by the increases in total inputs are attributed to technical advances. For a homogeneous commodity, TFP can be computed as a ratio of output to an aggregated index of inputs used in the production of the output.

In our study, a Turnquist-Theil index is applied to compute wheat TFP by province over time. Expressed in logarithmic form, the Tornquist-Theil TFP index is defined as:

$$\ln(TFP_t/TFP_{t-1}) = \ln(Q_t/Q_{t-1}) - ½\,\Sigma_j\,(S_{jt} + S_{jt-1})\ln(X_{jt}/X_{jt-1}), \tag{1}$$

where Q is defined as wheat production (output), S_{jt} is the share of input j in the total cost of wheat production, X_j is input j used in the production of wheat, and t indexes time (years). We compute the TFP index for wheat production in each province for each year.

TFP Data

Contributing to the debates and uncertainty associated with previous productivity studies in China are poor data and ad hoc weights. Data sources are numerous and not necessarily consistent. Researchers often warn their readers about the limited quality of many of the input and output series. For example, Stone and Rozelle (1995) cautioned those interested in China's agricultural productivity that the trends of all pre-reform TFP estimates depend heavily upon the nature of the assumed factor proportions used to aggregate inputs. Without a means of determining the most appropriate set of weights, Wen (1993) utilized sensitivity analysis, updating aggregate TFP until the early 1990s with all three sets of weights devised by earlier analysts.

Data used in calculating TFP measures are also described in detail in Jin et al. (2002). The data are based primarily on information included in a data set collected by China's State Price Bureau (SPB). Using the SPB data (SPB, 1982–1990, 1991–1995), we are able to address some of the difficulties faced by previous researchers. The sampling framework covers more than 20,000 households in each year of our sample, and the data include information on quantities and total expenditures of all major inputs, as well as expenditures on a large number of miscellaneous costs. Data on output and total revenues earned from the crop are also reported for each household. The household-level

[1] Our methodological approach for calculating TFP is also similar to that of Rosegrant and Evenson (1992) and Fan (1997) in utilizing standard Divisia index methods.

data set is supplemented by provincial surveys also conducted by the SPB, which provide information on unit labor inputs that reflect the opportunity cost of the daily wage foregone by farmers. As the TFP analysis focuses specifically on wheat, we calculate the output index only for wheat. Data on wheat production inputs used in the computation for wheat TFP include sown area, labor, seed, fertilizer, pesticide, farm plastic film, animal traction, machinery and equipment, and other material inputs. The data are typically thought to be of high quality and have been used extensively in the literature (e.g., Rae et al., 2006; Jin et al., 2002; Huang and Rozelle, 1996).

Although the data are of high quality, we nevertheless had to supplement the SPB data with information from an alternative data set. Specifically, in order to obtain estimates of land rental rates, the authors conducted a survey of 230 villages in seven provinces in China. During the survey, enumerators asked farmers to provide their estimates of the average per hectare rental rate they were willing to pay for cropland. These rates were elicited net of all other payments often associated with land transfer transactions in China (e.g., taxes), but which are incorporated as part of the regular cost-of-production survey.[2]

Spatial Diversity Indices and Data

In our study, spatial diversity is defined as the amount of variation found in a given geographical area—in this case each of our seven sample provinces. To examine the impact of diversity, we constructed six indices to capture different aspects of spatial diversity in the pool of wheat varieties cultivated in each of the provinces (Meng et al., 1998). The two sets of indices are based on two different taxonomies, or different means of distinguishing crop populations. The first taxonomy relies on *named varieties*. The second taxonomy utilizes variation among selected *morphological characteristics* as the basis for forming groups. Morphological traits are physically observable descriptors frequently used in the crop science literature to describe plant populations and to assess their diversity. These traits can be measured both quantitatively (e.g., height, wheat spike length, thousand kernel weight) and qualitatively (e.g., grain color, awn presence). The morphological groups for our analysis were formed by combining maximum-likelihood estimation with a clustering method to predict group membership based on plant characteristics obtained from experimental trials (Franco et al., 1998). The technique defines groups by minimizing the within-group variance and maximizing between-group variance. Specifically, the clustering is based on pairwise Gower distances among varieties measured on habit,[3] resistance to stem rust, time until maturity, plant height, and

[2] Ideally, we would like to obtain rental rates for all the years. But this was not possible because land rental markets were virtually nonexistent before 1990, and farmers were unable to provide the figures for the years before 1990. In our survey only the rental rate for 1991 was obtained. In the TFP calculation [equation (1)], the land rental rate and total wheat area in 1991 were used to obtain the total cost of land in wheat production in 1991, and the ratio of total cost of land to total cost of wheat production in 1991 gave the share of land in the total cost of wheat production for 1991. We then assume the share of land did not change over time.

[3] *Habit* refers to the natural tendencies of plants. Different habits are used to define different types of wheat varieties. Specifically, *spring habit* is a category of wheat varieties in which the farmer plants the seed in the spring (after the winter snows melt) and harvests in the late summer or early fall. Most spring wheat varieties in China are planted in the far northern reaches of the country. *Winter habit* is a category of wheat varieties in which the farmers plant the seed in the fall and harvest in the spring. Winter habit wheat requires extremely cold temperatures and a layer of snow to ensure high yields. *Facultative habit* is a category of spring wheat varieties that have been bred so they can be planted at the same time as winter habit wheat. Facultative varieties, however, typically do not require extreme cold during the winter.

kernel weight at time of release. These characteristics were found to be the most significant variables contributing to discrimination among groups.

Data for the construction of the diversity indices are drawn from a database of released major varieties and their sown areas, as well as information on a set of traits for each variety from experimental trials that was compiled from government publications (China Ministry of Agriculture, 1986–1997), databases and library materials, and communications with breeders in the seven selected provinces.[4] By using data from experimental trials designed to minimize the interaction between genotype and environment, we increase the certainty that the observed variation in traits reflects genetic differences.

The three indices calculated for each taxonomy-based set represent a different concept of spatial diversity as defined by Magurran (1988). A *richness* index (Margalef) captures the number of individuals encountered in a given sampling effort and can be most easily expressed by a simple count. A *dominance* index (Berger-Parker) provides information about the distribution of the sample. The *evenness* index (Shannon) combines elements of both richness and dominance in a measure of proportional representation with the number of individuals. The Shannon-evenness index reflects the degree of equality in the abundance of the individuals, or the relative uniformity of their distribution. The construction of each index is described in table 1.

TFP and Spatial Diversity Trends in Reform China

TFP Trends

When aggregating across provinces for an all-China index, we observe that the trend line traced out by our TFP measure has several distinct phases (top graph line, figure 1). During the early reform period, TFP for wheat rose more than 60%, resulting at least in part from incentives generated by the Household Responsibility System (Lin, 1992; McMillan, Whalley, and Zhu, 1989).[5] Huang and Rozelle (1996), however, demonstrate that public investment in research and irrigation also contributed heavily to supply increases during this period. We therefore expect these factors also contributed to the growth in TFP during the early 1980s.

TFP for wheat leveled off in the mid- to late 1980s (table 2). There have been a number of proposed hypotheses for the stagnation in productivity, including commodity pricing policies, land rights issues, and input availability (Jin et al., 2002). Decreasing levels of investment in research, water, and other public services also may have contributed to a slowdown in the turnover of new varieties, a fall in the release of varieties with higher

[4] Only "major" varieties with a cultivated area of at least 10,000 *mu* (667 hectares) in a province are counted in this calculation. While our database does not have full coverage of all varieties in each study province, the total planted area of the varieties included in the analysis accounts for approximately 85% of the total wheat area planted in each of the seven provinces. The set of traits for which data were assembled included location of variety release, average trial yield, variety yield ranking relative to other trial varieties, wheat type (winter, spring, facultative), number of tillers, average number of spikes per mu, thousand kernel weight, average number of kernels per spike, maturation period, plant height, protein content, grain hardness, stem rust resistance, leaf rust resistance, resistance to powdery mildew, and resistance to fusarium head blight.

[5] China's Household Responsibility System (HRS) was first implemented in late 1970s, and the reform was completed in more than 90% of rural areas by 1984, so 1984 is generally regarded as the cut point for land reform. In other words, reform period refers to the period from late 1970s to 1984, and non-reform period refers to the period after 1984.

Table 1. Spatial Diversity Indices

Index Name	Category	Mathematical Construction	Description	Adaptation in This Study
Margalef	Richness	$D_{mg} = (S - 1)/\ln(N)$	Number of classes weighted by the logarithm of the total number of samples	Number of crop populations per million hectares
Berger-Parker	Dominance	$D = 1/(N_{\max}/N)$	The less dominant the most abundant class, the higher the value of the index	Inverse of maximum area share occupied by any single crop population
Shannon	Evenness	$H' = -\Sigma p_i \ln(p_i)$	The term p_i represents proportion, or abundance, of a class	We define p_i as area share occupied by the ith crop population

Sources: Adapted from Aguirre, Bellon, and Smale (2000); mathematical construction as defined by Magurran (1988).

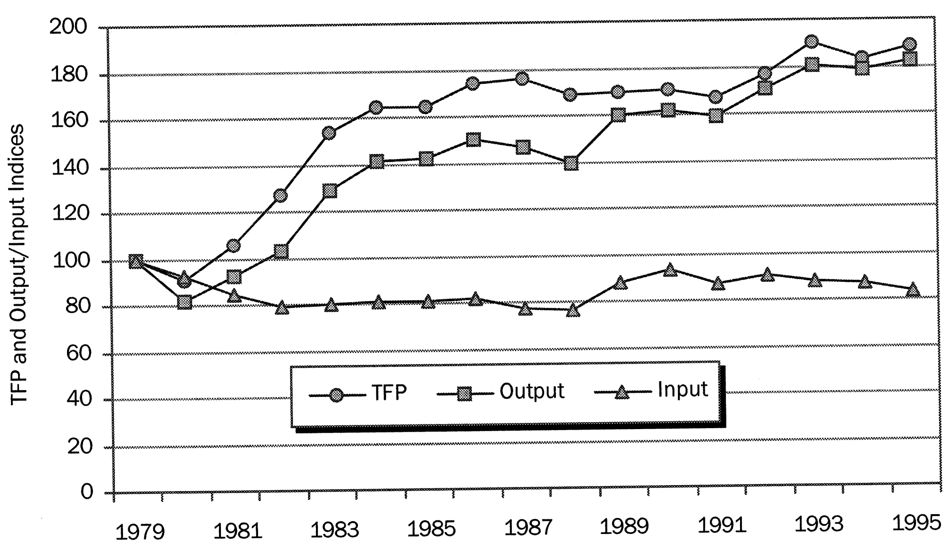

Figure 1. TFP and output/input indices for wheat in China, 1979–1995

Table 2. Total Factor Productivity of Chinese Wheat, 1982–1995

	Normalized National Mean[a] by Index[b]			Index 1 by Province						
Year	Index 1	Index 2	Index 3	Hebei	Shanxi	Jiangsu	Anhui	Shandong	Henan	Sichuan
1982	100	100	100	100	139	221	181	139	156	159
1983	121	128	124	146	171	230	189	188	191	183
1984	129	134	130	161	186	249	210	198	213	182
1985	129	139	133	188	190	244	202	217	197	178
1986	137	147	140	207	194	266	227	222	202	185
1987	139	148	140	193	154	284	233	221	219	189
1988	133	144	137	210	160	276	196	208	218	165
1989	134	150	142	223	197	245	193	203	211	205
1990	134	150	142	221	193	260	190	199	189	203
1991	132	150	141	221	186	230	89	229	206	205
1992	139	163	151	216	160	281	201	232	202	195
1993	150	167	157	215	205	278	240	246	238	191
1994	144	166	153	233	204	272	241	252	225	195
1995	148	170	157	244	183	285	219	290	227	218
Annual Growth Rate	0.018	0.029	0.024	0.047	0.013	0.013	0.002	0.033	0.016	0.015

[a] National mean is the weighted average of sown area for all wheat-growing provinces.

[b] Index 1 is calculated using a Tornquist-Divisia formula [text equation (1)]; Index 2 and Index 3 are fixed coefficient indices from Wen (1993).

yield potential, or a decline in the availability of varieties to meet new production, marketing, and environmental concerns (Jin et al., 1999). Huang and Rozelle (1995) conclude that environmental degradation may also have been a factor in slowed output growth during this period.

However, in contrast to the predictions in Wen's (1993) conclusions, wheat TFP resumed its positive growth in the 1990s. Productivity rose significantly between 1990 and 1995. In fact, compared to other commodities, wheat was the best performing crop in terms of TFP (Jin et al., 2002).

Several factors could account for the resumption of the growth of wheat TFP. Reforms resulting in greater market liberalization during this period may have allowed producers to move into crops in which they had a comparative advantage (de Brauw, Huang, and Rozelle, 2004). Leaders also refocused their efforts on investments in the research system (Rozelle, Pray, and Huang, 1997), although the level of activity differs sharply by province. With the resurgence of growth, the average annual growth rates of TFP range between 1.8% and 2.9%, depending on the measure used.

TFP growth across provinces varies sharply in terms of both levels and trends over time (table 2). At 4.7%, the annual growth rate in Hebei province was the highest, followed by 3.3% in Shandong and 1.6% in Henan. The lowest growth rate was observed in Anhui province with an annual growth rate of 0.2%. Except for Hebei and Shandong, all other provinces experienced stagnation or declines in TFP during 1985–1990, which in general continued through to 1995. The observed TFP trend across provinces also suggests evidence of TFP catch-up (table 2).

Wheat Spatial Diversity Trends

Spatial diversity indices based on named varieties grown in the seven major wheat-producing provinces of China between 1982 and 1995 are presented in figure 2. A comparison across the richness, dominance, and evenness indices calculated using the data set of named varieties shows, in general, Hebei and Henan provinces to be the most diverse throughout the study period, while Sichuan and Jiangsu provinces are among the least diverse across all the diversity indices. With respect to richness (figure 2a), we see that farmers in Hebei and Henan generally cultivated a larger pool of varieties, while farmers in Sichuan cultivated the smallest pool of varieties during most of the 1982–1995 period.

A peak in the Berger-Parker inverse dominance index indicates a low level of dominance of a single variety in the total pool of cultivated varieties (figure 2b). The inverse dominance index for each province shows a cyclical trend coinciding with the emergence and disappearance of popular varieties, a trend that is evident in all provinces over the study period. A wheat variety may disappear because it is replaced by new varieties in the pool, or because its seed sources gradually diminish, or some combination of both. Inadequate seed supplies relative to demand may also constrain the area planted to popular varieties. In examining levels of the Berger-Parker inverse dominance index, no province emerges as clearly more diverse than another, although the index reaches its lowest levels (associated with the greatest dominance by a single variety) in Sichuan and Jiangsu.

The contrast between Sichuan and other provinces becomes evident when examining the Shannon index of spatial evenness (figure 2c). Sichuan is the least "even" in the

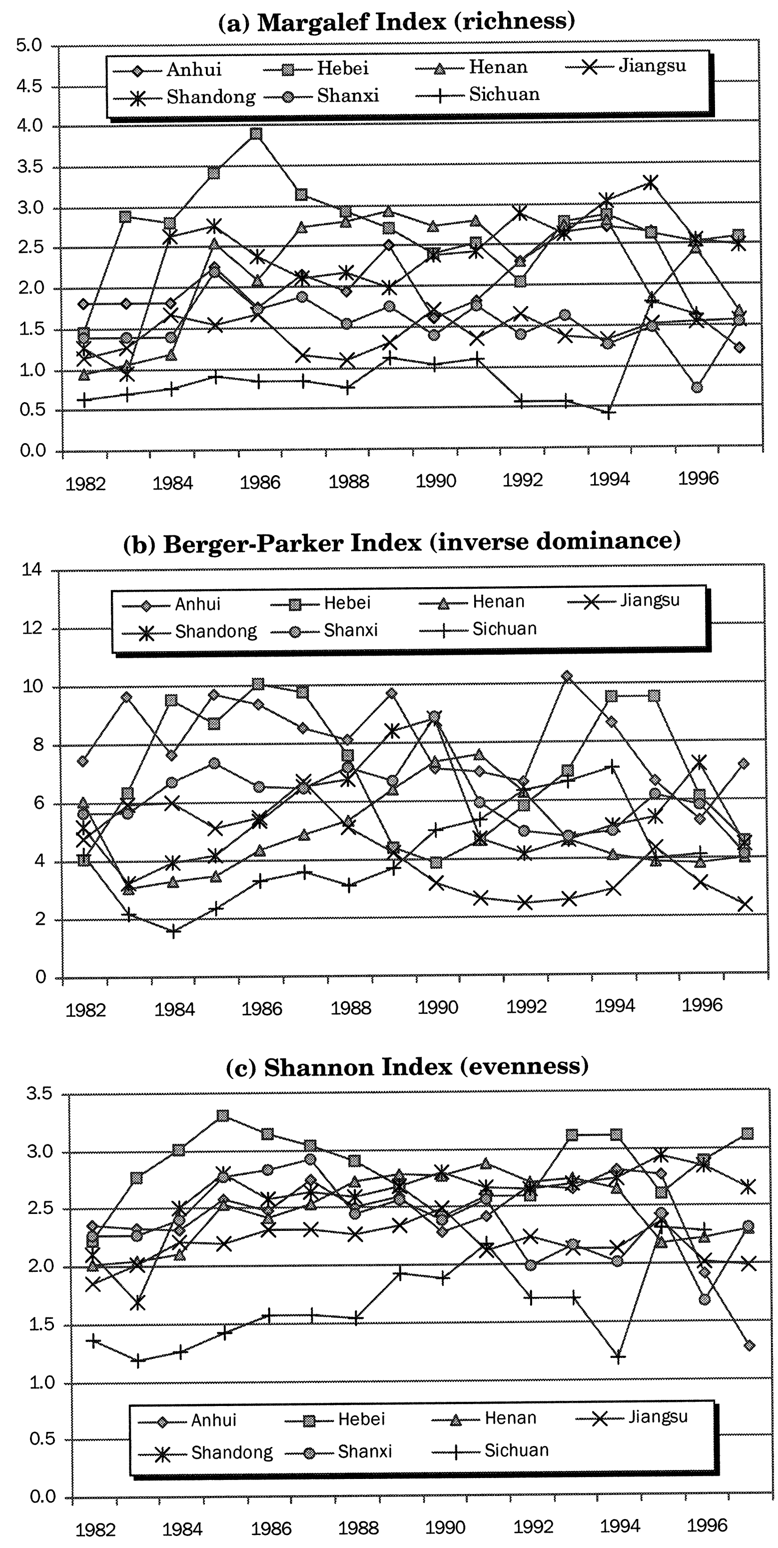

Figure 2. Spatial diversity indices, selected provinces, by named variety, 1982–1997

spatial distribution of its wheat diversity. The reasons for this relative lack of diversity are not immediately clear; however, wheat produced in Sichuan is exclusively fall-planted, spring-harvested (or spring-habit) wheat. In general, spring-habit wheat has been found to exhibit lower diversity levels in China than winter or facultative-habit wheat. Moreover, common characteristics of wheat varieties released in Sichuan include large, dense spikes and high thousand-kernel weight. The prevalence of these characteristics may be influenced by a combination of breeding decisions and specific requirements demanded in Sichuan's wheat-growing areas. Consequently, the effective supply of wheat varieties in Sichuan might also be a factor in determining observed patterns of diversity.

The highest evenness indices over the time period of the sample are generally found in Hebei province. A possible explanation for the relative evenness among wheat varieties in Hebei lies in its agro-ecological suitability for wheat varieties of all three growth habits—winter, spring, and facultative. A similar evenness among wheat varieties and agro-climatic diversity is found in Shanxi province, a neighboring province to Hebei. Note that all three growth habits are also present, but to a lesser extent than in Hebei.

A similar set of spatial diversity indices was calculated based on groups classified for each province using the morphological characteristics of varieties cultivated in the province (figure 3). In a number of ways the morphology-based indices are similar to those based on named varieties. According to the morphology-based indices, diversity levels in Hebei province also are consistently high relative to the other provinces. Likewise, diversity levels in Sichuan also rank the lowest of the seven provinces analyzed. In the case of Hebei, cultivated varieties were classified into six to seven morphological groups each year in the province, and only in one year did the area share for any one group rise above 60%. In contrast, Sichuan's cultivated varieties were classified into one or two morphological groups for most of the years analyzed. In each year, the predominant morphological group accounted for more than 90% of total cultivated area. Particularly with respect to the evenness of morphological groups, Hebei and Shanxi rank at the top of the set of provinces examined (figure 3c). Morphological groups in Henan and Sichuan provinces appear to be the least evenly distributed.

TFP and Spatial Diversity

A casual examination of changes in total factor productivity and spatial diversity over time reveals several interesting patterns. Hebei, the province with the largest growth rate in TFP (table 2), also exhibits high levels and overall positive trends in spatial diversity as measured by all of the different indices (figures 2 and 3). Provinces with slower growth in TFP, such as Jiangsu, also had lower levels and either slower rates of increase or stagnant measures of diversity.

Based on the correlations observed in the above descriptive analysis, it might be worthwhile to examine the relationship between diversity and TFP. A greater amount of diversity could provide farmers in heterogeneous agro-climatic environments with varieties better adapted for increasing yield potential in a range of soil and climatic conditions. A diverse set of varieties and/or varietal characteristics could contribute to the obstruction or halt of the spread of disease and insect infestations. In an area with poorly functioning markets, farmers with access to greater spatial diversity could maintain the option to adopt a number of different varieties with different planting times and

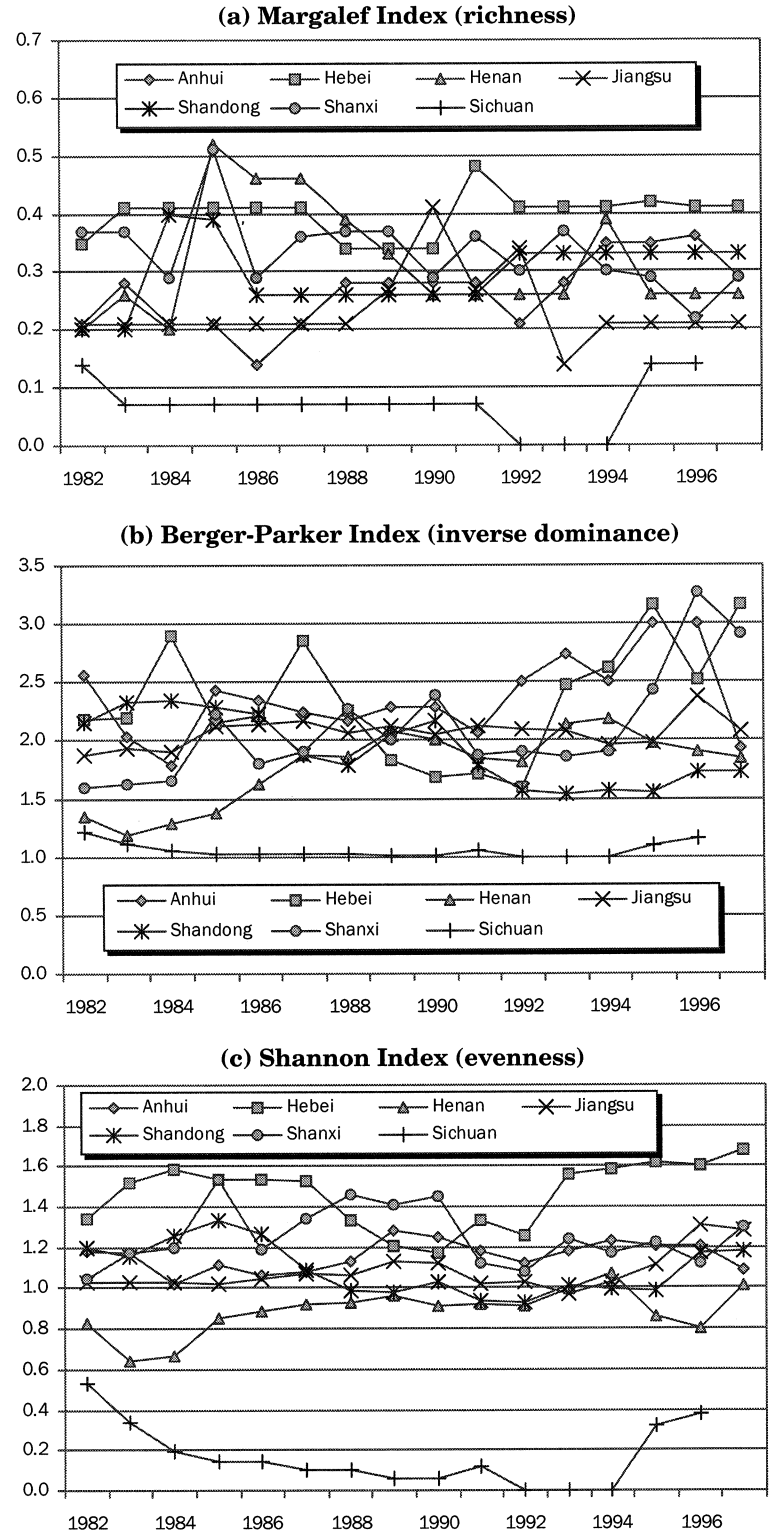

Figure 3. Spatial diversity indices, selected provinces, by morphological group, 1982–1997

maturing characteristics. This option could contribute to the more efficient use of fixed family labor and lead to higher levels of productivity. As discussed above, however, there are also reasons to suspect that a more diverse basket of varieties could potentially reduce total factor productivity. The apparent empirical correlation between TFP and spatial diversity aside, the causal relationship is likely to be more complicated. Moreover, many other factors may affect TFP in addition to diversity, and some of those factors may be correlated with diversity. It is for this reason that we need to shift to multivariate analysis.

TFP Model Specification

Wheat TFP in China is likely to be driven by factors other than the level of spatial diversity. Other factors that could account for variations in TFP include changes in technology, institutional reform, infrastructure development, and improvements to human capital. The need to incorporate changes in resource quality into TFP analyses has also been widely discussed (Murgai, 2001; Ali and Byerlee, 2002). Whether human capital should be included in the determinants of TFP depends on how the measure of labor is generated. For example, if current wages are used as a weight for labor input (as in this paper), human capital is generally assumed to have already been taken into account. Our framework for explaining TFP changes over time can be specified as:

$$TFP = f(Spatial\ Diversity, Technology, Infrastructure, Institutional\ Reforms, \mathbf{Z}), \quad (2)$$

where *TFP* is total factor productivity, *Spatial Diversity* is one of the six different measures of spatial diversity, *Technology* is defined in the next paragraph, the irrigation index (*Irrigation*) proxies for infrastructure and is measured as the ratio of irrigated land to cultivated land and accounts for changes in the availability of irrigation over time, *Institutional Reforms* (D_{90-95}) is an indicator variable equal to 1 for the period between 1990 and 1995 (and zero otherwise). This variable is included to measure the effect of period-varying factors on TFP during the period of market liberalization experienced by China in the early 1990s. **Z** is a vector of control variables whose elements represent weather, agro-climatic zones, and provincial dummies (to control for all fixed but unobserved factors that differ across provinces). In most countries, technology and infrastructure are believed to be the major factors that drive long-term TFP growth (Rosegrant and Evenson, 1992). Most other determinants contribute either to short-term fluctuations (i.e., weather) or represent one-time-only fixed shifts in TFP over time (i.e., the variables reflecting institutional change). The coefficients of interest in this analysis are those on the spatial diversity variables.

In addition to determining spatial diversity outcomes through their selection of varieties, farmers also choose the rate at which they adopt the new varieties embodying technological innovations. Here, we use a measure of change in seed technology in each province that is based on the rate of varietal turnover (*VT*).[6] The variable VT_{ht} is defined as:

[6] *Varietal turnover* is the measure of the time required for existing varieties to be replaced by new varieties in farmers' fields.

(3) $$VT_{ht} = 1, \text{ for } t = 1,$$

where h refers to province, t indicates time period, and $t = 1$ refers to the first year of the sample (e.g., 1982);

(4) $$VT_{ht} = VT_{ht-1} + \sum_k V_{hkt},$$

where

$$V_{hkt} = \begin{cases} W_{hkt} - W_{hkt-1} & \text{if } W_{hkt} - W_{hkt-1} > 0, \\ 0 & \text{otherwise,} \quad \text{for } t > 1. \end{cases}$$

In equation (4), V_{hkt} is the area share change (from $t - 1$ to t) for those varieties that are increasing in share of wheat acreage planted, and W_{hkt} is the area share of the kth variety in *total wheat sown area* in year t in province h (Jin et al., 2002). Equations (3) and (4) define seed technological change as the extent to which newly introduced varieties replace existing varieties. Assuming farmers are rational, the measure depends on the assumption that variety replacement by farmers occurs if and only if the new variety is of a higher "value" than the variety it is replacing. A value improvement can be cost-reducing, yield-enhancing, or one that incorporates important consumption characteristics.

Accounting for Endogeneity

Since the farmer may simultaneously make production decisions affecting TFP, diversity, and technology adoption, an OLS regression of TFP on diversity and varietal turnover is likely to be problematic due to correlation of the error term with these explanatory variables. To avoid the endogeneity of diversity and varietal turnover in the estimation of the *TFP* equation, we employ an instrumental variables approach. Our strategy for identifying the effects of technology on TFP assumes that the technology delivered by the national and international research systems affects adoption (and hence both varietal turnover and diversity), but does not affect TFP except through the seeds (or basket of seeds) that farmers adopt.

If these assumptions hold, we can follow Jin et al. (2002) and use the following three variables as instruments for varietal turnover: *Research Stock*—the investments made by the government in crop research (or more precisely, the country's stock of crop research);[7] *CG*—a measure of the germplasm flowing into each province from international agricultural research centers;[8] and *Yield Frontier*—a variable representing the

[7] Measuring the research stock is more complex, and takes into account the longer lags that exist between the time of an expenditure and the period when it affects production. The stock also depreciates over time. The research variable is estimated as:

$$z_r(t) = \sum_{t=1}^{n} \alpha(t)\dot{z}_r(t),$$

where $z_r(t)$ is the research stock in period t, $\dot{z}_r(t)$ is the current expenditure from the national budget on research, and $\alpha(t)$ is the timing weight for accumulation of new research expenditures to the stock of research. Since there is little theoretical guidance for determining these weights for China, a set of weights estimated by Pardey et al. (1992) in Indonesia is used.

[8] We define a variable that represents the proportion of genetic material in China's germplasm for wheat that comes from the Consultative Group on International Agricultural Research system (*CG* contribution). This variable is created using pedigree data for all varieties in the field in each period, and assigning geometric weights to parents (0.25/parent), grandparents (0.06/grandparents), and so on. The *CG* contribution represents the proportion of germplasm with ancestors that are identified as being from the International Maize and Wheat Improvement Center (CIMMYT).

yield-increasing potential of technology generated by the research system.[9] The variable *Yield Frontier* should also explain the adoption of new seed technology, but have no independent effect on TFP.

We also need to generate a strategy for identifying the effect of diversity on TFP. To do so, we take advantage of the fact that in production systems characterized by some amount of home consumption, as is the case for many of the regions in our study provinces, the consumption characteristics of the available varieties are often equally as important as the production traits in the variety choices of farm households (yet should not have an independent effect on TFP). Hence, diversity outcomes can be driven by both consumption and production considerations. We use the consumption/marketing-side factors as instrumental variables in the diversity equations. Accordingly, three additional instrumental variables are utilized in the diversity equation: *MktIntegration*, *PriceRatio*, and *PurchaseDiff*. *MktIntegration* is a variable created for each province and for each year using weekly wheat price data collected by the provincial Commercial Administration Office in all of China's major wheat-growing provinces. The data, which were available for multiple markets in different provinces, were used to measure the degree of integration of wheat prices in each province with the rest of the wheat-growing provinces. In other words, using standard empirical approaches, an integration statistic was generated for each year and each province.

The two variables *PriceRatio* and *PurchaseDiff* were created using data available from the Price Bureau of each province. The different price series measure the different types of grain sales farmers were required (and allowed) to make during the early reform era (between 1980 and 1995). During this time period, farmers were required to deliver a certain portion of their harvest to the state-run grain bureau (called the "quota sale") for a state-set, often below-market price (called the "quota price"). After the mandatory quota sales were completed, farmers then had two channels through which they were able to sell their wheat. They could sell to the grain bureau (at a price that was higher than the quota price—called the "state procurement price"), or they could sell their wheat on the market at a non-state procurement price. To measure how commercialized the wheat market was in each province (i.e., how much distortion the state created in state-set quota and state procurement prices relative to the market price or the non-state procurement price), we create two variables. *PriceRatio* equals the ratio of the non-state procurement price to the quota price. *PurchaseDiff* equals the state procurement price minus the non-state procurement price.

A simultaneous, three-stage least squares (3SLS) estimator is used to estimate the effect of diversity, technology, and other explanatory variables (e.g., infrastructure, institutional change, environmental factors) on TFP. The estimable empirical specifications of endogenously determined diversity and technology (VT), as well of the TFP model, are as follows:

$$(5)\qquad TFP_{ht} = f(VT_{ht}, Diversity_{ht}, Extension_t, Irrigation_{ht}, D_{90\text{-}95}, Weather\ Event\ Index_{ht}, Provincial\ Dummies) + e1_{ht};$$

[9] *Yield Frontier* is defined to be nondecreasing. If a given major variety has the highest yield in a province in one year, then *Yield Frontier* in that province is calculated using the yield level of that variety. It is assumed the yield frontier will not fall, even if farmers have stopped using that variety and all other varieties have lower certified yields in the following years.

(6) $$VT_{ht} = g_V(Extension_t, Irrigation_{ht}, D_{90\text{-}95}, Weather\ Event\ Index_{ht}, Provincial\ Dummies, Research\ Stock_t, CG_{ht}, Yield\ Frontier_{ht}) + e2_{ht};$$

(7) $$Diversity_{ht} = g_D(Extension_t, Irrigation_{ht}, D_{90\text{-}95}, Weather\ Event\ Index_{ht}, Provincial\ Dummies, CG_{ht}, Yield\ Frontier_{ht}, MktIntegration_{ht}, PriceRatio_{ht}, PurchaseDiff_{ht}) + e3_{ht}.$$

In the above system of equations, *h* indexes provinces and *t* indexes time, total factor productivity (*TFP*) is our main independent variable to be explained, *Diversity* is the right-hand-side variable of interest, and VT_{ht} and *Extension* are important control variables that account for technology (where *Extension* is a variable reflecting all expenditures made on the extension system and aggregated to the national level).[10] The impact of infrastructure on TFP is assumed to be captured by *Irrigation*. The impact of institutions on TFP is captured by $D_{90\text{-}95}$. To account for the other control variables (**Z**), we also include two environmental variables to allow for production fluctuations due to the effects of flood and drought (*Flood Index* and *Drought Index*), as well as provincial dummies to control for unobserved fixed effects associated with each province. Table 3 provides definitions of all variables included in the system of equations (5)–(7).

Equations (6) and (7) are, respectively, the varietal turnover equation and the diversity equation. As discussed above, the three "research supply" instrumental variables (*Research Stock*, *Yield Frontier*, and *CG*) are used to control for the endogeneity of VT. The three "consumption market-related" instrumental variables (*MktIntegration*, *PriceRatio*, and *PurchaseDiff*) are used to control for the endogeneity of diversity.[11] Other exogenous variables are included in both equations.

Given the fact that we have two right-hand-side endogenous variables (*VT* and *Diversity*) in the *TFP* equation and six instrumental variables (three each for *VT* and *Diversity*), we can perform an exclusion restriction or over-identification test for determining whether our IVs are exogenous (Wooldridge, 2006). As will be shown in the next section, the test results confirm that all six IVs are indeed exogenous.

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[10] Because the *Extension* variable was measured at the national level, there was concern that it could be affecting our results. Thus, we also ran our basic set of regressions with and without the *Extension* variable. As it turns out, the nature of the findings on the impact of diversity (and other variables) on TFP are largely consistent.

[11] Effective instrumental variables (IVs) have an effect on the endogenous, right-hand-side variable of interest (either *VT* or *Diversity*) and do not have an independent effect on the dependent variable of interest (*TFP*). Logically, our instrumental variables meet these conditions. In the case of the *VT* equation, our instrumental variables (*Yield Frontier*, *Research Stock*, and *CG*) are variables collected from research institutes and other agencies involved with the production of technology (e.g., the Ministry of Agriculture). Because of this, we believe the IVs have an effect on *VT* since they affect the generation of the technology. However, our *TFP* variable is measured from data on the producers, or those who demand the technology. Hence, our logic is that our supply-side IVs could not directly affect producer behavior (or efficiency) except through their adoption of the new technologies (*VT*). The same logic holds for the IVs in the diversity equation (*MktIntegration*, *PriceRatio*, and *PurchaseDiff*). These three variables measure behavior from the demand side of food markets (the demand of state grain bureau officials and traders). As long as these variables are related to diversity (as we see they are by looking at the *F*-test of their joint significance), we contend they can be considered as good IVs since there is no reason to believe these demand-side activities could have any direct effect on productivity (except through diversity). For all of these reasons, we conclude we have two valid sets of instrumental variables.

Table 3. Variable Names and Definitions for Dependent, Independent, and Instrumental Variables

Variable Name	Definition
Endogenous Dependent Variables:	
TFP	Total factor productivity indices
VT	Varietal turnover—a measure of change in seed technology
Diversity	Spatial diversity indices (as defined in table 1)
Exogenous Independent Variables:	
Extension	All expenditures on the extension system, aggregated at the national level
Irrigation	Measured as the ratio of irrigated land to total cultivated land in each province
Flood Index	A measure of susceptibility to flooding—"easily flooded" area normalized by sown area
Drought Index	A measure of susceptibility to drought—"drought damaged" area normalized by sown area
D90–95	Dummy variable for market reform: = 1 for any year between 1990–95, = 0 otherwise
Provincial Dummies	Dummy variable for each province to control for unobserved fixed effects in each province
Instrumental Variables for VT:	
Research Stock	Investment made by government in crop research (refer to footnote 7)
CG	Proportion of genetic germplasm for wheat that comes from overseas (see footnote 8)
Yield Frontier	Highest wheat yield in a province in one year
Instrumental Variables for Diversity:	
MktIntegration	A measure of market development generated for each year and each province using weekly wheat price data; measures the degree of integration of wheat prices in each province with the rest of the wheat-growing provinces
PriceRatio	A measure of market development defined as the ratio of the non-state procurement price to the quota price
PurchaseDiff	A measure of market development defined as the state procurement price minus the non-state procurement price

Estimation Results

The econometric estimates of our model (tables 4 and 5) perform well, and the parameter estimates are largely robust to specification changes. The system-weighted R^2 statistics are greater than 0.92 for all model specifications. Tests for exclusion restrictions that examine the validity of instruments confirm the choice of instruments used in the varietal turnover and diversity equations is statistically valid.[12] Statistically, our instruments have a high degree of explanatory power on varietal turnover and diversity, but do not affect TFP except through their influence on technology in the form of varietal turnover or spatial diversity.

[12] The exclusion restriction test statistics range from 0.845 to 5.831 depending on which type of diversity index is included in the *TFP* equation. Compared to 9.49, the critical value for rejection, the results indicate that the null hypotheses of no correlation between the exogenous instruments and the disturbance term from the *TFP* equation cannot be rejected.

Table 4. Results of TFP Analysis Using Named Variety-Based Diversity Indices ($N = 98$)

	Berger-Parker Index (inverse dominance)			Margalef Index (richness)			Shannon Index (evenness)		
	TFP Equation	VT Equation	Diversity Equation	TFP Equation	VT Equation	Diversity Equation	TFP Equation	VT Equation	Diversity Equation
Shanxi	13.318	0.084	–4.255**	–33.254*	0.099	–0.344	–27.427	0.072	–0.200
	(0.43)	(0.46)	(2.50)	(1.73)	(0.55)	(0.75)	(1.31)	(0.40)	(0.71)
Jiangsu	100.655***	–0.397**	–0.144	171.337***	–0.398**	–2.218***	147.637***	–0.398**	–0.820***
	(4.45)	(2.33)	(0.09)	(8.09)	(2.33)	(4.87)	(7.57)	(2.34)	(2.96)
Anhui	0.734	–0.020	1.015	36.259***	–0.013	–0.601***	35.275***	–0.030	–0.285***
	(0.08)	(0.27)	(1.54)	(4.68)	(0.18)	(3.34)	(4.44)	(0.40)	(2.61)
Shandong	45.024***	–0.166**	–0.863	58.028***	–0.165**	–0.764***	53.680***	–0.164**	–0.341***
	(4.13)	(2.08)	(1.11)	(6.10)	(2.07)	(3.66)	(5.56)	(2.06)	(2.68)
Henan	53.031***	–0.223***	–3.167***	22.044***	–0.213***	–0.412**	29.706***	–0.228***	–0.306***
	(3.72)	(2.81)	(4.41)	(2.84)	(2.69)	(2.14)	(3.37)	(2.90)	(2.63)
Sichuan	54.145***	–0.259**	–4.791***	42.694***	–0.241**	–1.641***	65.199***	–0.274**	–1.130***
	(2.60)	(2.18)	(4.68)	(2.82)	(2.02)	(5.92)	(3.46)	(2.33)	(6.76)
dtime3	2.941	–0.114	0.056	4.574	–0.111	–0.036	6.283	–0.125*	–0.023
	(0.28)	(1.55)	(0.07)	(0.56)	(1.51)	(0.17)	(0.70)	(1.71)	(0.19)
Flood	–105.695***	–0.060	–0.595	–103.198***	–0.059	–0.289	–115.611***	–0.055	0.032
	(4.88)	(0.38)	(0.39)	(5.96)	(0.38)	(0.71)	(6.24)	(0.35)	(0.13)
Drought	–33.191	–0.209	0.192	–42.874**	–0.208	0.237	–54.747***	–0.212	0.355
	(1.52)	(1.31)	(0.12)	(2.43)	(1.30)	(0.56)	(2.83)	(1.33)	(1.37)
Irrigation	60.186	–0.417	–11.751*	–216.426***	–0.393	3.502**	–146.713**	–0.420	0.880
	(0.59)	(0.62)	(1.81)	(3.23)	(0.58)	(1.97)	(2.09)	(0.63)	(0.81)
Extension	–0.007	0.001***	–0.003	0.003	0.001***	–0.002***	0.011	0.001***	–0.001***
	(0.34)	(4.83)	(1.38)	(0.19)	(4.87)	(2.66)	(0.64)	(4.76)	(2.88)
VT	17.200***			18.366***			13.368**		
	(2.82)			(4.20)			(2.49)		
Research Stock		0.013***			0.013***			0.013***	
		(19.49)			(19.31)			(20.17)	
CG		0.041	–0.234		0.044	–0.090		0.045*	–0.026
		(1.54)	(1.05)		(1.65)	(1.40)		(1.71)	(0.71)
Yield Frontier		0.003***	–0.004		0.003***	–0.002		0.003***	–0.000
		(2.71)	(0.45)		(2.87)	(0.70)		(2.58)	(0.33)
Diversity	14.624***			34.302***			68.418***		
	(3.80)			(4.50)			(4.77)		
MktIntegration			–0.602			–0.538			–0.134
			(0.35)			(1.04)			(0.44)
PriceRatio			–1.061**			–0.635***			–0.308***
			(2.25)			(4.23)			(3.47)
PurchaseDiff			0.126***			0.056***			0.034***
			(2.71)			(4.00)			(4.12)

Notes: Single, double, and triple asterisks (*) denote statistical significance at the 10%, 5%, and 1% levels, respectively. Values in parentheses are the absolute value of z-statistics.

Table 5. Results of TFP Analysis Using Morphological Characteristics-Based Diversity Indices (N = 98)

	Berger-Parker Index (inverse dominance)			Margalef Index (richness)			Shannon Index (evenness)		
	TFP Equation	VT Equation	Diversity Equation	TFP Equation	VT Equation	Diversity Equation	TFP Equation	VT Equation	Diversity Equation
Shanxi	−83.437***	0.107	0.802***	−86.873***	0.109	0.153**	−87.399***	0.100	0.419***
	(2.77)	(0.59)	(2.80)	(3.75)	(0.60)	(2.31)	(3.34)	(0.55)	(3.56)
Jiangsu	162.827***	−0.405**	−1.294***	200.583***	−0.402**	−0.404***	207.111***	−0.400**	−1.052***
	(4.42)	(2.38)	(4.69)	(6.20)	(2.36)	(6.10)	(4.71)	(2.34)	(8.99)
Anhui	11.190	−0.015	0.128	56.838***	−0.011	−0.174***	49.230***	−0.014	−0.341***
	(1.13)	(0.19)	(1.18)	(4.03)	(0.15)	(6.66)	(3.22)	(0.19)	(7.61)
Shandong	69.708***	−0.167**	−0.698***	85.405***	−0.167**	−0.194***	98.086***	−0.167**	−0.574***
	(3.30)	(2.10)	(5.37)	(5.07)	(2.09)	(6.39)	(3.72)	(2.09)	(10.85)
Henan	26.360**	−0.211***	−0.300**	23.092**	−0.209***	−0.050	63.879***	−0.214***	−0.458***
	(1.98)	(2.66)	(2.55)	(2.49)	(2.64)	(1.83)	(2.74)	(2.70)	(9.60)
Sichuan	30.266	−0.238**	−0.759***	62.119**	−0.233*	−0.286***	115.222**	−0.242**	−1.111***
	(1.12)	(1.99)	(4.57)	(2.53)	(1.95)	(7.33)	(2.18)	(2.03)	(16.55)
dtime3	9.394	−0.109	−0.135	6.691	−0.107	−0.034	11.875	−0.109	−0.098*
	(0.65)	(1.49)	(1.03)	(0.67)	(1.46)	(1.17)	(0.97)	(1.49)	(1.90)
Flood	−98.569***	−0.058	−0.262	−124.028***	−0.059	0.059	−115.406***	−0.060	0.071
	(3.95)	(0.37)	(1.02)	(6.08)	(0.38)	(1.00)	(5.45)	(0.38)	(0.68)
Drought	−34.646	−0.206	−0.097	−55.340**	−0.206	0.072	−34.751	−0.207	−0.031
	(1.43)	(1.29)	(0.36)	(2.57)	(1.29)	(1.17)	(1.62)	(1.30)	(0.29)
Irrigation	−308.592**	−0.359	4.428***	−320.825***	−0.368	0.967***	−341.900***	−0.387	2.666***
	(2.36)	(0.53)	(4.12)	(3.52)	(0.54)	(3.75)	(2.99)	(0.57)	(5.81)
Extension	−0.015	0.001***	−0.000	−0.008	0.001***	−0.000	−0.017	0.001***	−0.000
	(0.62)	(4.88)	(1.16)	(0.44)	(4.90)	(1.16)	(0.77)	(4.88)	(1.17)
VT	26.263***			28.578***			30.377***		
	(5.56)			(6.72)			(6.47)		
Research Stock		0.013***			0.013***			0.013***	
		(19.24)			(19.17)			(19.31)	
CG		0.046*	−0.012		0.045	0.001		0.043	0.018
		(1.71)	(0.40)		(1.67)	(0.09)		(1.61)	(1.20)
Yield Frontier		0.003***	−0.001		0.003***	−0.001***		0.003***	−0.002***
		(2.84)	(0.73)		(2.91)	(2.60)		(2.84)	(3.42)
Diversity	48.499			275.539***			113.124**		
	(1.70)			(3.28)			(2.42)		
MktIntegration			−0.941***			−0.085			−0.421***
			(2.74)			(1.25)			(3.41)
PriceRatio			−0.232***			−0.068***			−0.118***
			(3.39)			(3.41)			(3.72)
PurchaseDiff			0.019***			0.004**			0.007**
			(2.65)			(2.07)			(2.28)

Notes: Single, double, and triple asterisks (*) denote statistical significance at the 10%, 5%, and 1% levels, respectively. Values in parentheses are the absolute value of z-statistics.

Determinants of Varietal Turnover and Diversity

While the varietal turnover and diversity equations are mainly used to provide consistent estimates of the endogenous variables in the TFP equation, they also provide interesting insights into the process of technology and diversity creation in China.

The positive and significant sign on the *Research Stock* variable in the varietal turnover equations indicates that investments in the research system have been effective. Moreover, a higher level of national research stock accelerates the pace of varietal turnover. If technology is indeed a key factor in the growth of China's agriculture in the future (Huang and Rozelle, 1996), our findings emphasize the necessity of maintaining the level and growth of public investment in crop research and development. Unlike results obtained by Jin et al. (2002), our results indicate no significant impact from CIMMYT germplasm on technology development, likely due in large part to the lag in impacts from collaborative research efforts in wheat that began in earnest only in the latter part of the 1980s. The results from the diversity equations are also consistent with the expectation that a higher market demand leads to a greater diversification of wheat varieties.

Determinants of TFP

The signs of many of the estimated coefficients from the control variables of the TFP specification are also, for the most part, as expected and many have low standard errors (relative to the magnitudes of the coefficients). For example, the coefficient on the *Flood* variable is consistently negative and significant in all the TFP equations. The coefficient on the *Drought* variable also is negative, although it is significant in only half of the specifications. Similar to the results obtained by Rosegrant and Evenson (1992), parameter estimates for *Irrigation* are negative and significant, with the single exception of the variety-based dominance TFP equation result in table 4. The negative sign, while at first somewhat puzzling, is an intuitive result. The main irrigation infrastructure in rural China was already long established before the reform era (1980 to 2008). Not only was there massive construction during the Collective Era (before 1980), but many of China's most productive regions have been irrigated for thousands of years. Based on our data, by 1982, the share of area irrigated for the seven main wheat provinces was already 42%. During our study period, it increased by only six percentage points (42% to 48%).

So now the question becomes: Was the land that was irrigated later less inherently productive than the land that was irrigated earlier? Logically, it seems obvious that governments and individuals would bring the best land under irrigation first, since the returns to such investments would be highest. Gu (1999) describes one of the main policies during the 1980s as increasing the output of marginal lands by investing in irrigation. Hence, when this occurred, and marginal land was brought into production, it is entirely plausible that the measured coefficient on the irrigation variable would be negative.

Another finding from our TFP equation is the large and positive influence of technology on TFP. This result holds over all model specifications. The positive and highly significant coefficient on the rate of varietal turnover shows that TFP increases as new technology is adopted by farmers. Both the positive contributions of China's research system and its success in pushing out the yield frontier imply that domestic investments in agricultural R&D have positively influenced wheat TFP change.

Although *Extension* does not appear to have a significant direct effect on TFP, it has a significant impact on technology adoption. The impact of extension can occur through its role in disseminating new seed technologies, as measured by the coefficient on the *Extension* variable in the technology and diversity equations, and through its provision of other services that enhance farmer productivity, as measured by the coefficient on the *Extension* variable in the TFP equation. The positive and significant coefficients on the *Extension* variable in all of the varietal turnover equations demonstrate the importance of extension in facilitating farmer adoption of technology (tables 4 and 5). Extension, however, plays no role in increasing (or decreasing) spatial diversity and plays no independent role in increasing the yield potential of varieties that have been adopted by farmers. The latter result perhaps may not be completely unexpected given the reforms that have shifted extension from an advisory body to one that must be self-supporting, often through the sale of seed and other inputs (Huang et al., 1999).

Most importantly, the coefficients on the *Diversity* variables are robust and consistent across specifications. With only one exception, all representations of diversity used—i.e., those based on named varieties or morphological taxonomies—positively affect aggregate TFP. The pattern of the results suggests that diversity, whether measured in terms of named varieties or morphological characteristics, contributes to an increase in TFP. This finding seems to imply that support for the use of diverse materials in breeding research will have positive effects on future wheat productivity.

Decomposition Analysis

To interpret the relative magnitude of impact of each factor on TFP growth—and to determine how important diversity is—we conducted a decomposition analysis for the sources of TFP growth. The decomposition results are reported using elasticities calculated from the estimated coefficients from regressions that included the named variety-based diversity indices (table 6). Although not reported, the results using the elasticities calculated from the regressions using morphological characteristics-based diversity indices are similar.

The decomposition results reveal that technology is by far the most important factor influencing TFP growth. Technology improvement as measured by the varietal turnover would cause wheat TFP to grow by 1.68% to 2.31% per year, depending on the specifications, and accounts for 84% to 116% of the total growth rate.[13]

Consistent with the preceding discussion, spatial diversity also is potentially one of the most important contributors to TFP growth, as indicated by the large and positive TFP elasticity with respect to diversity. According to our findings, a 10% increase in spatial diversity as measured by the Margalef diversity index would lead to a 3.3% increase in aggregate TFP. However, compared to technology improvement, the overall contribution of diversity to TFP growth over the study period is more moderate and accounts for 12%, 37%, or 46% of the total TFP growth depending upon the diversity measure used.

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[13] More than 100% means that without other negative factors, the TFP growth rate would be higher than the observed growth rate.

Table 6. Decomposition of Sources of Wheat TFP Growth in China, 1980–1995

Variable	TFP Elasticities [a]	Factor Annual Growth Rate [b]	Sources of TFP Growth: Rate [c]	Sources of TFP Growth: Percent [d]
DIRECT [e]		— **Berger-Parker Index (inverse dominance)** —		
VT	0.22	9.90	2.16	108.21
Diversity	0.43	0.55	0.24	11.80
Extension	0.07	3.43	0.24	11.85
Flood	–0.04	0.26	–0.01	–0.46
Drought	–0.02	6.27	–0.14	–7.21
Irrigation	–0.31	2.80	–0.43	–21.51
INDIRECT [f]				
Research Stock	0.34	5.06	1.72	85.85
CG	0.00	–11.22	–0.01	–0.62
Yield Frontier	0.12	11.94	1.46	73.13
PriceRatio	–0.15	0.41	–0.06	–3.08
PurchaseDiff	0.14	14.56	2.02	100.79
DIRECT [e]		— **Margalef Index (richness)** —		
VT	0.23	9.90	2.31	115.57
Diversity	0.33	2.28	0.75	37.49
Extension	0.07	3.43	0.25	12.66
Flood	–0.03	0.26	–0.01	–0.45
Drought	–0.03	6.27	–0.19	–9.32
Irrigation	–0.27	2.80	–0.37	–18.57
INDIRECT [f]				
Research Stock	0.36	5.06	1.83	91.69
CG	0.00	–11.22	–0.01	–0.73
Yield Frontier	0.13	11.94	1.56	78.10
PriceRatio	–0.21	0.41	–0.09	–4.29
PurchaseDiff	0.14	14.56	2.04	101.86
DIRECT [e]		— **Shannon Index (evenness)** —		
VT	0.17	9.90	1.68	83.99
Diversity	0.82	1.12	0.92	45.96
Extension	0.05	3.43	0.18	9.20
Flood	–0.04	0.26	–0.01	–0.51
Drought	–0.04	6.27	–0.24	–11.90
Irrigation	–0.40	1.40	–0.57	–28.28
INDIRECT [f]				
Research Stock	0.26	5.06	1.33	66.64
CG	0.00	–11.22	–0.01	–0.48
Yield Frontier	0.10	11.94	1.14	56.76
PriceRatio	–0.20	0.41	–0.08	–4.20
PurchaseDiff	0.15	14.56	2.17	108.37

[a] TFP elasticity with respect to each factor is calculated on the basis of coefficients in table 4 (i.e., named variety-based diversity indices used in the regressions).
[b] Factor growth rate is computed by a least squares estimate.
[c] Growth rate contributed by each factor is calculated by multiplying factor growth rate (column 2) by elasticity (column 1).
[d] The percentage of TFP growth explained by each factor is the corresponding value in column 3, divided by the total growth rate of TFP (which is 2.01%).
[e] "Direct" refers to those factors included in the TFP equation, thus with direct effects on TFP.
[f] "Indirect" refers to those factors included either in the *VT* equation or *Diversity* index equation, thus with effects on TFP indirectly through their effects on the VT or Diversity index.

The main reason for the relatively small effect of diversity on TFP is explained by the low growth rate of the diversity indices. For example, the annual growth rate of the Berger-Parker diversity index is only 0.55% compared to a 9.90% annual growth rate for the technology improvement variable (*VT*). The fact that diversity has the largest elasticity but small growth rate implies a significant potential for the future—should leaders promote diversity. The positive contribution of technology and spatial diversity is counteracted by environmental factors such as flood, drought, and irrigation.

The decomposition analysis also identifies a few key factors that indirectly contribute to TFP growth through their effect either on technology or diversity [table 6, lower ("Indirect") panels]. While the direct interpretation is less straightforward because part of the effect has already been explained through technology and diversity, we can still use the decomposition results to illustrate the relative importance of these factors. Consistent with the previous findings, research stock and yield frontier are by far the two most important factors contributing to TFP growth through their effect on technology improvement. Market liberalization, as measured by the difference between non-state purchases and government purchases at a negotiated price, is the single largest contributor to TFP growth through its positive effect on spatial diversity. Somewhat surprisingly, the ratio of market price to quota price has little importance in determining spatial diversity, and hence TFP.

Discussion and Conclusions

Our results establish a significant analytical link between diversity and aggregate productivity. The significance of the impact was robust to changes in both the specific representation of spatial diversity (e.g., richness, inverse dominance, evenness) and the taxonomy used (e.g., named variety, morphological grouping). The results reinforce previous findings that underscored the importance of a continuing role of public investment in the agricultural research and extension system in order to maintain and increase productivity. Our findings also highlight a specific avenue through which productivity gains can be improved. Spatial crop diversity in the mix of cultivated varieties has positively impacted wheat productivity. Attention to maintaining and increasing levels of diversity in the development of wheat varieties can provide a means of improving productivity. The increasing market forces and the growing importance of wheat quality and other characteristics are the main factors for focus by wheat scientists to expand sources of diversity in developing new crop varieties.

Additional studies on other crops and in other countries are warranted in order to verify both the methodology used and the conclusions drawn. Productivity impacts of crop diversity have been explored in previous studies; however, as Smale, Lipper, and Koundouri (2006) note, due to mixed results, it is not clear how specific these results are to location and cropping system. More research is required to further clarify diversity-productivity relationships and the circumstances under which positive impacts take place. Regional-level studies should also be complemented with additional farm-level analyses to promote a better understanding of the conditions under which the different impacts of biodiversity are realized.

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