INTERNATIONAL FOOD
POLICY RESEARCH INSTITUTE
sustainable solutions for ending hunger and poverty
Supported by the CGIAR

IFPRI Discussion Paper 00857

April 2009

Productivity Convergence in Brazil

The Case of Grain Production

Eduardo Magalhaes

Xinshen Diao

Development Strategy and Governance Division

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

The International Food Policy Research Institute (IFPRI) was established in 1975. IFPRI is one of 15 agricultural research centers that receive principal funding from governments, private foundations, and international and regional organizations, most of which are members of the Consultative Group on International Agricultural Research (CGIAR).

FINANCIAL CONTRIBUTORS AND PARTNERS

IFPRI's research, capacity strengthening, and communications work is made possible by its financial contributors and partners. IFPRI gratefully acknowledges generous unrestricted funding from Australia, Canada, China, Denmark, Finland, France, Germany, India, Ireland, Italy, Japan, the Netherlands, Norway, the Philippines, Sweden, Switzerland, the United Kingdom, the United States, and the World Bank.

AUTHORS

Eduardo Magalhaes, Datalyze Consulting Corporation

Xinshen Diao, International Food Policy Research Institute
Senior Research Fellow, Development Strategy and Governance Division
Email: x.diao@cgiar.org

Notices

[1] Effective January 2007, the Discussion Paper series within each division and the Director General's Office of IFPRI were merged into one IFPRI–wide Discussion Paper series. The new series begins with number 00689, reflecting the prior publication of 688 discussion papers within the dispersed series. The earlier series are available on IFPRI's website at www.ifpri.org/pubs/otherpubs.htm#dp.

[2] IFPRI Discussion Papers contain preliminary material and research results, and have been peer reviewed by at least two reviewers—internal and/or external. They are circulated in order to stimulate discussion and critical comment.

Contents

List of Tables

List of Figures

ACKNOWLEDGMENTS

This study is part of joint research project between IFPRI and Embrapa, Brazil. We are grateful to the research team led by Dr. Antonio Flavio Dias Avila at Embrapa for a series of brainstorming meetings and seminars held at Embrapa and IFPRI to initiate this project. Researchers from Embrapa, including Geraldo Souza, Eliseu Alves, Bernardo Melo, Fernando Garagorry and Eliane Gomes have provided excellent comments and suggestions during the research process of this paper. We thank Xiaobo Zhang and Liangzhi You from IFPRI for their help in the use of the generalized entropy methodology and Shenggen Fan for his suggestion at the early stage of the research. We also benefit from the suggestions and comments received from the IFPRI's anonymous reviewer of the early version of this paper. Embrapa has also provided part of research funding for this study.

ABSTRACT

In recent years, Brazil has become a considerable player in agricultural markets for a number of commodities. Such agricultural growth in Brazil has largely been the result of gains in productivity over the last several decades. Still, there remain some sub-national regions and states that lag behind in both agricultural productivity and levels of per capita income. In this paper, we investigate whether technological spillovers in agriculture have reached the poorer or less productive regions with focus on the evolution and patterns of land productivity. To assess such spillovers, we examine three cereal crops: maize, rice and wheat, as these crops are grown by commercial and subsistence farmers throughout the country. We first apply a generalized entropy (GE) method to assess whether inequality in productivity has changed over time. The entropy analysis indicates that the trends for overall entropy did not increase over time for all three crops. Moreover, declining trends in between-group inequality were observed for maize and wheat and remained constant for rice. This result suggests that yields in less productive micro-regions, indeed, have grown faster than yields in more productive micro-regions, at least in the case of maize and wheat. Next, two types of econometric estimations are used to measure whether convergence has occurred in yields of the three crops. The econometric findings are consistent with the GE results and suggest that conditional convergence has occurred in all three crops, which demonstrates that yields in less productive regions converge to those in productive regions, given the control of other factors. However, the process has been rather slow.

Keywords: productivity, convergence, spillovers, Brazil

1. INTRODUCTION

Over the last several decades, Brazil has achieved significant agricultural growth and become a key player in world agricultural markets. Highly valued crops such as coffee, soybeans, and sugarcane have reached record-high production levels, which has turned Brazil into one of the largest producers in the world for these commodities. Gains in staple food crops, such as maize, beans, rice, and wheat have also been significant. Such impressive gains in production are naturally derived from improvements in productivity, which are often the result of agricultural research and development (R&D) that has taken place in the country over decades. It is well known that the creation of the Brazilian Corporation for Agricultural Research (Embrapa) in the early 1970s, in conjunction with local and state research institutions, has helped increase crop yields dramatically in the country and expanded a number of crops to regions that were previously not suitable to produce them. Much of the spread and increased production of soybeans, for instance, has been directly linked to Embrapa's research results.

National levels of productivity and production growth, however, may mask dramatic differences in agricultural productivity across regions, given the huge size of the country and differences in agricultural and other natural resource conditions among regions. On the other hand, with long-term and intensive research activities conducted by agricultural research institutions, one would expect that the technology and know-how initially developed for advanced regions would have spilled over to other regions over time. Indeed, vast literature on spillovers of technology derived from R&D exists for both agricultural and nonagricultural sectors (see, e.g., Alston 2002 for a good review on R&D in agriculture). Such technological spillovers are expected to narrow the productivity gap and help regions lagging behind to catch up with more advanced regions in levels of productivity. Moreover, lagging regions often have disproportionately high poverty rates in the rural areas. Technological spillover effects will allow research institutes to contribute more to poverty reduction in these regions by promoting (and generating) agricultural productivity growth.

The purpose of this study is to assess the patterns and the magnitude of spatial or cross-regional technological spillovers in Brazil's agriculture. We focus on three main grain crops for this study, as these crops are broadly grown by both commercial and subsistence farmers throughout the country. More specifically, we focus on the land productivity dynamics of maize, rice, and wheat, and microregions are the primary units of analysis. Constrained by the lack of information about other factors (labor, capital, and purchased inputs) at a highly spatially disaggregated level for a relatively long time period, we have to ignore the productivity changes driven by the other factors. Brazil has 558 microregions, which encompass over 5,500 municipalities. The advantage of using microregions lies in the fact that their spatial boundaries are relatively stable over time and are not subjected to political redistricting policies, which have often caused changes both in population numbers and boundaries in municipalities over time. We also analyze patterns of land productivity at the subnational (also referred to as regional) and state levels by aggregating data from the microregions (also referred to as MIR). Data[1] used in the analysis of productivity came from Embrapa, which systematically collects and analyzes data originated from the Brazilian Bureau of Geography and Statistics.

The rest of this paper is organized as follows: Section 2 contains two parts. The first part presents a brief overview of the importance of maize, rice, and wheat in Brazil, looking at production and trade-related issues, as well as key policies. It also summarizes the key elements of the history of R&D in the country as it pertains to these crops. The second part of this section begins with a descriptive overview of land productivity in Brazil. Starting at the national level, it looks at trends in land productivity over time for these crops. Not surprisingly, productivity has grown considerably for the three crops, but has this growth been uniform across the country? To answer this question, we apply measures of generalized entropy (GE) to analyze patterns of spatial or regional inequality for each crop. From the national level

[1] Authors are grateful to Flavio Avila, Geraldo Souza, and particularly Fernando L. Garragory for providing access to the data and especially for their time and dedication in assisting with the data transfer and providing details on the organization of the data set.

analysis together with the results of the GE analysis, we further discuss the results at regional and state levels, with the goal of identifying less productive regions. To complement and likely help clarify the findings from the entropy analysis, we also present an analysis of yield gaps, which follows a methodology similar to the poverty gap indicator. Section 3 focuses on the measurement of technological spillovers across microregions for the three grains. The section starts with an overview and the rationale of the methods used in the analysis. We used two models of convergence to measure the existence and magnitude of spillovers in grain productivity, both of which have been described and tested in the convergence literature. Section 4 describes and discusses the results, and the final section provides a conclusion.

2. AN OVERVIEW OF THE GRAIN SECTOR IN BRAZIL

Maize, rice, and wheat have long been key crops in the Brazilian agricultural landscape and livelihood, both in terms of their nutritional value in consumption and their production revenue. Numbers drawn from the current levels of production reflect in part the importance of these crops for Brazilian agriculture. For instance, in 2007 Brazil produced 52 million, 11 million and 4 million tons of maize, rice, and wheat, respectively.[2] These three grains together account for 97 percent of total cereal production, of which maize is the most important, accounting for 75 percent of cereal production.

To gain perspective on the meaning of these numbers, one can evaluate how Brazil compares to other countries and regions of the world in terms of scale of production of these crops. For rice, Brazil is the largest producer in Latin America, accounting for 46 percent of the region's production, and the ninth-largest producer in the world, second only to the Asian countries as a group. Maize also ranks high in terms of production, both in Latin America and worldwide, accounting for 47 and 7 percent of Latin America and world production, respectively. In Latin America, Brazil is the second most important wheat producer, responsible for 17 percent of the region's production.

While Brazil is a large producer of the three grain crops, it is not a large exporter. In fact, Brazil is a net importer of rice and wheat and has become a net exporter of maize only in recent years (see figure 1a). Most of the wheat consumed domestically comes from abroad and imports are generally greater than national production. Brazil was a net exporting country for rice in the 1960s and 1970s, but this changed during and after the economic crisis in the 1980s. Even as Brazil has continued to export some rice in recent years, the amount of imported rice is much greater than that exported. However, compared with domestic production, imported rice accounts for a minimal share of domestic consumption. In recent years, exports of maize have increased significantly, as shown in figure 1a, and in some years (e.g., 2003 and 2004), exports have been as high as 7–12 percent of domestic production.

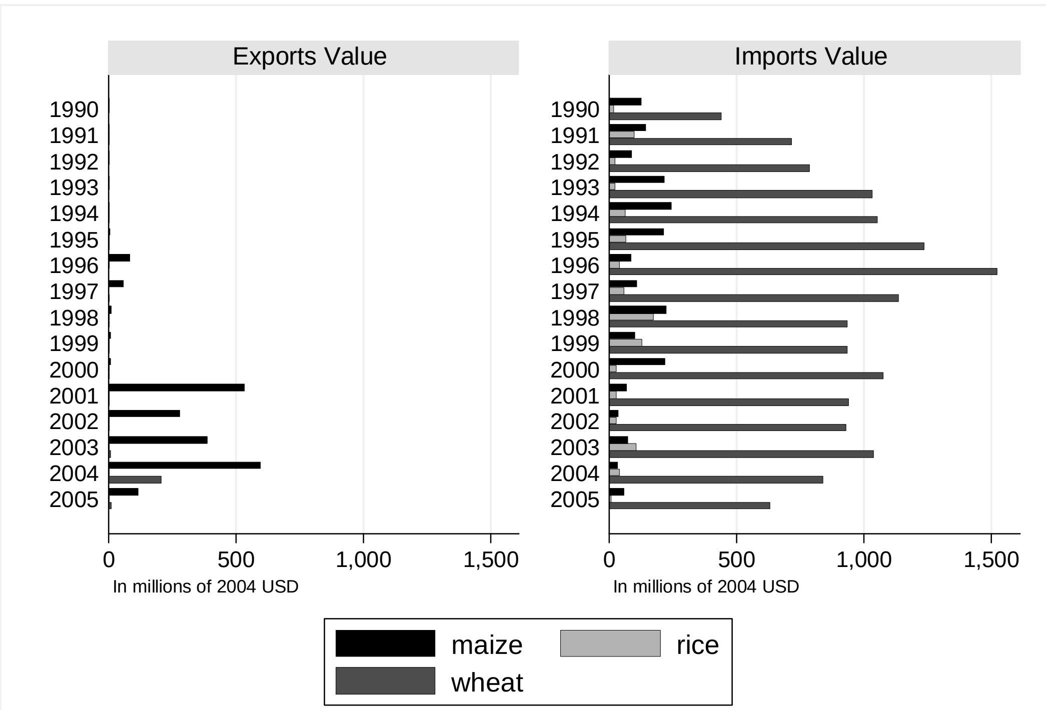
Though Brazil seems not to have a comparative advantage in world grain markets, it is one of the biggest exporters for soybeans and coffee in the world (figure 1b). Underpinning the differences in these figures are completely different production systems. For the grain crops shown in figure 1a, one typically observes relatively smaller plots, with production spread out in the country (though wheat does not fall in that pattern). The two export crops in figure 1b often require large-scale commercial farming in Brazil in order to achieve a high degree of both production and market efficiencies.[3]

Differences in production systems help explain the dramatic differences in foreign trade between rice, maize, and wheat, and coffee and soybeans. At the same time, macroeconomic policies have also played an important role in forming such production systems. Until the early 1990s, Brazil underwent a range of policies that attempted to protect the local economy through import substitution policies. With the reinstatement of democracy in the mid to late 1980s, more export-oriented policies were implemented, and this has been reflected in the performance of high-value export commodities, like soybeans and coffee[4]. Also noteworthy and particularly relevant for this study is the fact that rice and maize occupy much larger shares of area in the northern and northeastern regions of the country, where rural poverty tends to concentrate. For the country as whole, rice, wheat, and maize occupied, respectively, 6.2 percent, 3.7 percent, and 18.0 percent of the total agricultural area harvested in 2005. Within these totals, nearly a third of the rice area and slightly over 40 percent of maize area were in the north and northeastern regions[5]. This fact further justifies the purpose of this study, as it suggests that these crops are highly relevant for the poor.

[2] Comparative production and trade statistics came from Faostat (http://faostat.fao.org/, accessed August, 2008).
[3] This is the other reason for us to focus on grain production for our analysis in this paper.
[4] During the 1960s and 1970 the Brazilian government started a program to deliberately increase production of soybeans. A similar program for wheat was also started, but proven to expensive and soon canceled. Wheat has played an important role in the initial expansion of soybean as an inter-crop. For an excellent discussion see Schnepf, Dohlman and Bolling, 2001
[5] Data taken from Ipeadata (http://www.ipeadata.gov.br, accessed July 2008)

Naturally, such high levels of production are in part the result of considerable research efforts, both on the part of local and state research institutions, and particularly from Embrapa for some crops. Research on these three crops dates back to the 19th century, when agricultural research officially started in Brazil in 1887 (with the creation of institutes such as the Agronomic Institute of Campinas).[6] Even at the very early stages of agricultural research, these crops were already an important part of the research portfolio. Over the years, Brazil went through a number of economic crises, including the world crisis in the 1930s, which inevitably affected the way the economy functioned and put Brazil on the path to industrialization. Still, a number of institutes specializing in one or more of these crops were created both before and during the crisis, for example, the Institute of Irrigated Rice in the southern part of the country. State research institutes were originally located mostly in southern states, and the bulk of these centers focused on export crops such as cotton and sugarcane. Being export oriented and located in the south often meant unequal access to new technologies for the poorest parts of the country, that is, the north and northeast. In addition, there was little integration among and within the various institutes that had been created, which, compounded by economic crises, led to inefficient and often counterproductive research efforts (Beintema, Pardey, and Avila 2001).

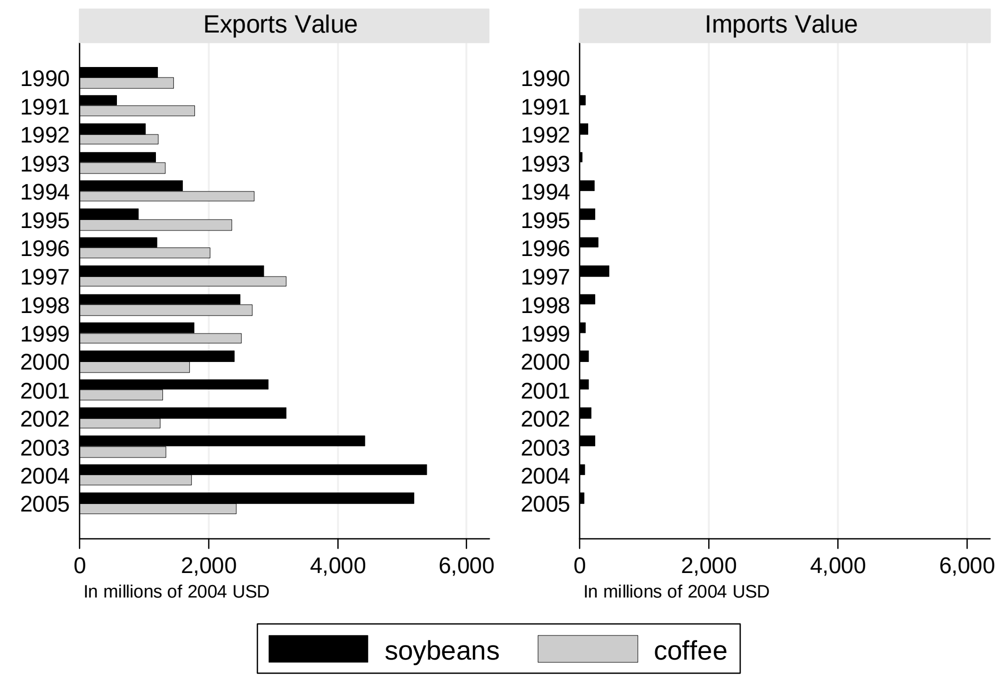
Figure 1a. Import and export values of rice, wheat, and maize in Brazil



Source: FAO trade statistics, accessed on August 2008

[6] This section draws heavily from Beintema, Pardey, and Avila 2001 and Beintema, Pardey, and Avila 2006.

Figure 1b. Import and export values of coffee and soybeans in Brazil



Source: FAO trade statistics, accessed on August 2008

In the early 1970s, the government established the Brazilian Corporation of Agricultural Research (Embrapa) with the goal of organizing and promoting agricultural research throughout the country, as an attempt to allow the entire country to benefit from agricultural research. Today, with 41 research centers and an annual budget of more than $600 million, Embrapa is present in nearly every state. Crop-specific centers such as those for rice and beans, for maize and sorghum, and for wheat were among the first to be created. Each of these centers focuses almost exclusively on these different crops. Since their inception, these crop-specific centers have released a number of varieties with either higher yields or improved quality. The newly developed varieties also address changes in consumer preferences (in the case of rice varieties). Of the $1.4 billion (in 1999 U.S. dollars) spent on public research in 1996, Embrapa accounted for 58 percent; the remainder was divided among states, nonprofit organizations, and higher education agencies (Beintema, Pardey, and Avila 2001).

Land Productivity—A Generalized Entropy Analysis

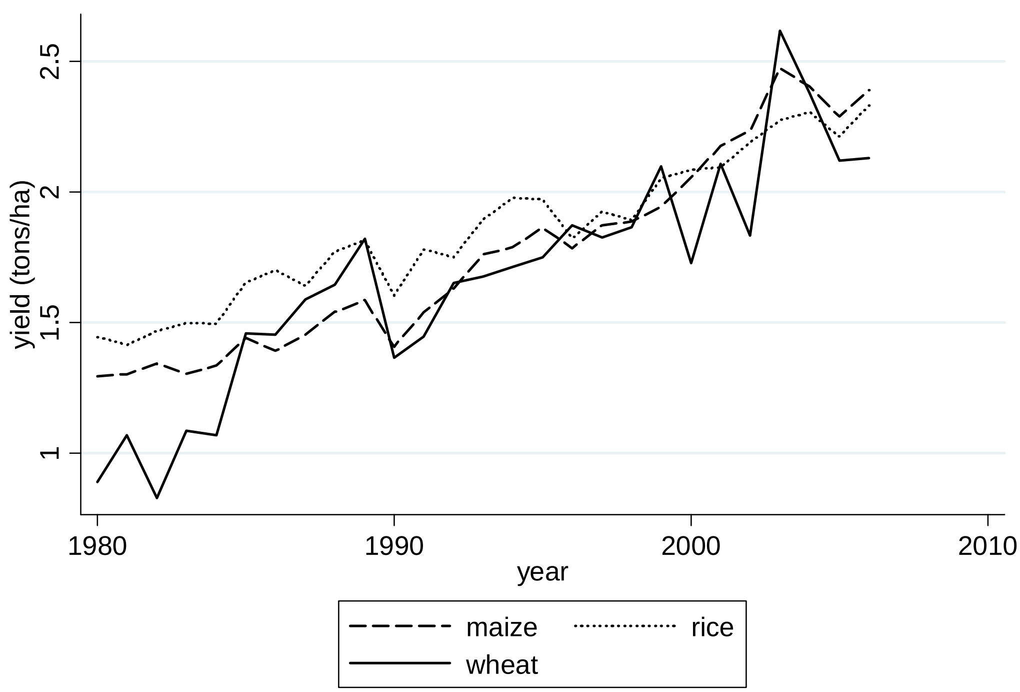
Increased production levels can be the result of land expansion, given that Brazil is a land-abundant economy at the aggregate level. Land abundance, however, may not always translate into land expansion for individual crops. To illustrate this point, Figure A.1 in the appendix shows trends in land allocation shares over the last 50 years, such as the share of agricultural land over total land; the share of cropland (for both arable and permanent crops) over agricultural land; and shares of some individual crops (soybeans and sugarcane) over total cropland. A few striking patterns emerge from figure A1. First, overall agricultural land has been increasing over time at a very low rate of 1.1 percent per year. In addition, while cropland area has increased relative to total agricultural land, its share in total agricultural land remains considerably below other land uses, such as pastures and meadows (though these have been decreasing). In terms of land allocated to crops, the largest increase is for those crops with significant economies of scale, such as soybeans and sugarcane. The shares of these two crops in total cropland have grown, respectively, by 7.34 and 1.51 percent annually. In contrast, the share of cropland allocated to the three cereals declined, though the absolute level of their area has modestly increased over time. In some parts of Brazil (e.g., the midwest), soybean and sugarcane production has replaced grain production, and the cereal area has declined over time (Schnepf, Dohlman, and Bolling 2001). Recently soybean production has started to expand to some states in the north, indicating that continuous land expansion may not be a choice for grain production. This further shows that growth in grain production has become more intensively dependent on productivity growth. Hence, it becomes increasingly important to understand how land productivity has led to growth in grain production at both national and regional levels.

Measures of land productivity account for both changes in land use patterns and increases in the level of yields for each individual crop. For a country as large as Brazil, it is expected that significant variation in land productivity takes place due to a number of reasons. First, Brazil is home to various agro-ecological zones, each of which contains different patterns of rainfall, soil quality, temperatures, and a number of other biophysical aspects. At the same time, these biophysical differences are augmented by significant levels of regional income inequality, as evidenced by the much higher share of poverty in the north and northeast, vis-à-vis other regions. To better understand how inequality takes place in land productivity, its changes over time, and more specifically, to document and measure the levels of inequality, it is often useful to analyze the main trends of agricultural productivity in Brazil according to different geographical breakdowns, in particular, nation, regions, and states.

National levels of land productivity in grain production have increased considerably since 1980, with annual yield growth rates of 2.65 percent, 1.85 percent, and 3.26 percent for maize, rice, and wheat, respectively. The steeply upslope trends in crop yields of these three crops shown in Figure 2 reflect this fact. Studies for other countries, as well as for Brazil, however, have shown that impressive growth rates at highly aggregated levels rarely translate into uniform growth patterns within countries (see, for example, You 2008 in the case of Brazil and China). In fact, many studies find significant levels of inequalities in productivity growth within regions or states of a country (see, for instance, Wan 2001; Wan and Zhou 2005).

To aid in the assessment of whether this is indeed the case for Brazil's grain sector, we have applied a generalized entropy (GE) measure to assess whether levels of productivity growth have varied across regions in Brazil. The advantage of using GE methods is that they are additively decomposable, that is, it is possible to identify the different contributions to total (national) inequality coming from either between sub-groups (which can be defined according to the desired analysis) or within each of the sub-groups. From the generalized entropy formula described in appendix A1, we note that a number of specifications can be obtained depending on the choice of parameter c. In particular, the choice of c has a direct implication on whether the entropy measure is sensitive to transfers between groups. Sensitivity to transfers takes place when c equals 1 or 0. The equations derived from choosing c=1 or c=0 are the well-known inequality measures popularized by Theil. Since we are interested in capturing transfers occurring between groups, we have selected to use Theil's indicators (c=1 and c=0). Results using the two distinct values of *c* differed across crops. For maize, the only difference took place in the within-group inequality for the below-average group, in which the slope for c=0 was not significant while the slope for c=1 was significant and positive. Slopes for rice also differed for the below-average group (positive and significant when c=1) and for the between-group's measure, which declined for c=1 and remained non-significant for c=0. Wheat differed for the overall measure (with a positive and significant slope for c=1, and a non-significant slope for c=0), and the below average within-group inequality for which the slope was positive c=1 (non-significant for c=0). The main difference between the two measures of *c* seems to rest in the slopes of the below-average groups. From this discussion, we can see that when c=1, inequality in the below-average group tends to be higher than when c=0. Interestingly, these higher within-group inequalities only affected the between-group inequality for rice, prompting a decline in the gap between groups. Given the similarity in results for between-group inequality, which is the most important measure for our purposes, we will to continue to discuss the results for the most conservative case, i.e. c=0. The basic measure of GE (c=0) is essentially a difference of logged means between the actual yield and a reference yield (typically the average for the sample), weighted by the share of that sample in the total population (see Kanbur and Zhang, 1999 for methodological details and Mishra, Moss and Erickson, 2006 for an application of this method). In this particular case, land productivity for the three crops in a given micro-region was weighted by the area harvested with that crop in that particular micro-region.

Figure 2. Average yields for maize, rice and wheat



Source: Authors' calculations based on data provided by Embrapa

As a starting point to understanding patterns of inequality in Brazil, we divided the data into two groups: microregions whose land productivity was above the national mean and microregions that fell below the national mean. The national mean of yield for each crop is an average between 1980 and 1985, which allows us to avoid any possible abnormalities in performance in a specific year. However, in doing so, some microregions performed above the average in some years and below the average in the other years during the same initial period, which made the classification confusing and defied the purpose of identification. To address this issue, we used the mean yields of the first five years (1980–1985) for each microregion in which classification was ambiguous (i.e., those with averages below and above the national for the initial period) and compared these means to the national yield average. This, in turn, allowed us to properly classify each of the microregions into either the below- or above-average group. Another issue was that some microregions did not produce one or all of the crops in the first period, and as such, could not be tagged according to the procedure above. In these cases we compared the means of these "newcomer" microregions during the first period in which production began against the national average of that period. If the means of the newcomers were above the national average, we defined them in above-average group. If they were below the national average, we placed them in the below-average group. By tagging regions with the appropriate classification, we were able to calculate within- and between-group inequalities in addition to overall inequality. The overall breakdown of microregions by crop was as follows: In the first period, there were 261, 315, and 91 MIRs below average for maize, rice, and wheat, respectively. Further, 290, 185, and 66 MIRs were classified as above average.

Results from the entropy are encouraging and point to a diminishing tendency in spatial inequality over time (see complete results in Table A.1 in the appendix). The first encouraging aspect of the entropy results is that trends for overall entropy did not increase over time for any of the three crops, as indicated by the nonsignificant slope. Moreover, declining trends in between-group inequality were observed for maize and wheat. For rice, between-group inequality remained constant (i.e., slopes were not significant). A reduction in between-group inequality points to the fact that yields in less productive microregions have indeed grown faster than yields in more productive ones (See Table A.2). While yields in poor regions are catching up, there is still a considerable gap from the more productive regions, despite the positive results from the yield-gap analysis.

Perhaps a more intuitive way of understanding patterns of inequality, and particularly the between-group inequality, in Brazil is to look at the evolution over time of yield gaps[7] between less and more productive regions. To do so, we constructed a yield-gap index, which follows the same rationale of the poverty gap but only applies to yields.[8] The index was calculated by taking the average of the distances between the average yields in the north and northeast regions (this is the baseline yield) and yields below the baseline yield in other regions. These distances are then divided by the reference yield (average of north and northeast regions) so as to enable us to visualize how other regions have performed relative to these poorer regions. Figures 3a and 3b present the findings. Since wheat is not produced in the north and northeast, we only present these findings for maize and rice. The results show decreasing gaps for both rice and maize in nearly all regions. We note in figures 3a and 3b that the midwest has shown a nearly zero gap for all but one period. This may seem encouraging but most likely reflects the possibility that no microregions in the midwest were below the baseline for most periods, and thus the gap could not be measured. For other regions (south and southeast), the gap has decreased over time, as suggested by the negative slopes, indicating that there has been recovery in the two poorest regions. Rice displayed decreasing gaps over time for the southern region and a stationary (zero slope) for the midwest and southeastern regions relative to the north and northeastern regions. An important result that emerges from figures 3a and 3b is that the yield-gap trends generally support the findings for between-group inequality, showing negative slopes for most regions for maize and zero slope for most regions for rice, even if these two measures were calculated in very different forms (between groups looks at groups below and above average, and the yield gap looks at groups below the baseline yield, defined as the average yield of the north and northeast regions).

[7] We are grateful to the anonymous IFPRI reviewer for suggesting this measure.

[8] Specifically, for a given crop, the formula of the yield gap is given by $\frac{1}{n}\sum_{i=1}^{q}\left(\frac{z-y_i}{z}\right)$ where z is the baseline yield, y is the yield in other regions (that fall below the baseline), and q is the number of microregions in other regions that produce the crop and whose yields were below the baseline (UNDG).

Figure 3a. Entropy and yield-gap plots for maize

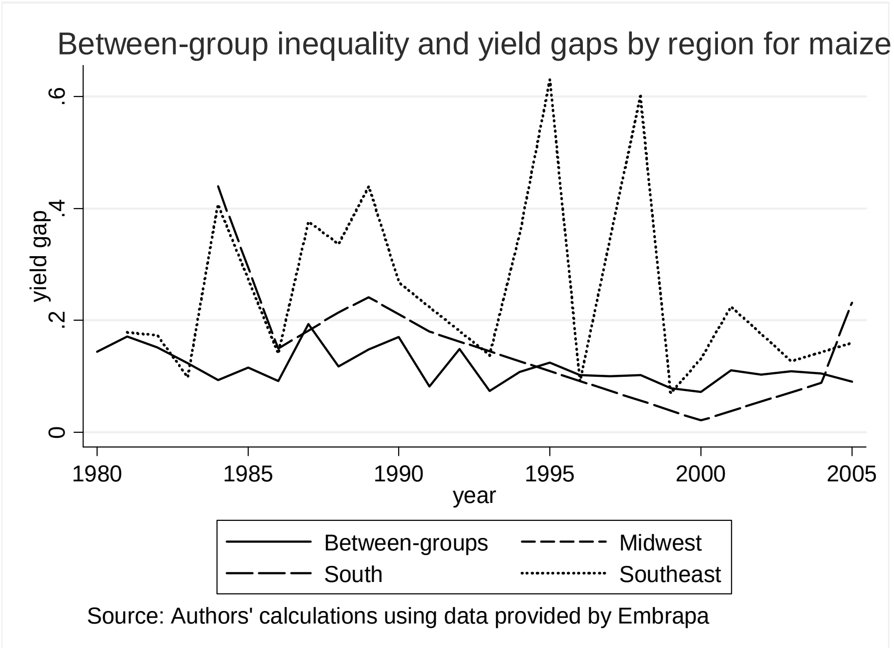
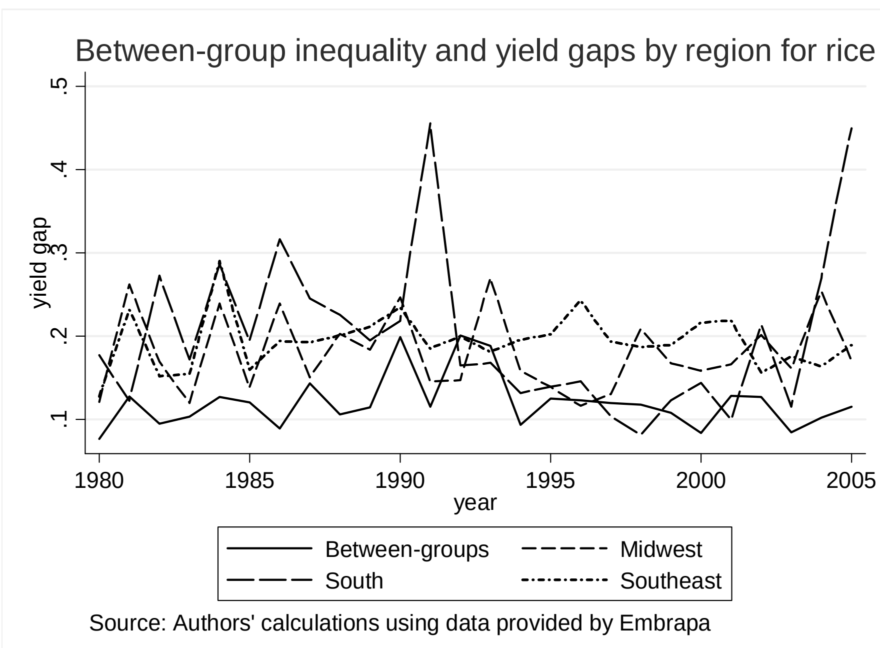


Figure 3b. Entropy and yield-gap plots for rice



The entropy analysis provided above points to generally stationary or decreasing trends in inequality for the three crops, though some of the within-group inequalities have increased (see Table A.1 and Figures A.2a–A.2c in the appendix). For example, inequality grew for the above-average group for maize and wheat and for the below-average group for rice. These findings, while somewhat optimistic, do not imply that the spatial inequality in grain yields has disappeared after two decades; they only indicate decline or stability of trends of such inequality. For a country as large as Brazil, it would be expected that considerable yield variation still exists today, especially given its geographical complexity. In the next section, we provide a more disaggregated analysis, looking first at regional trends in land productivity, then expanding the analysis to the state level for the worse-performing regions (as these are home to most of the poor in the country).

Land Productivity across Regions

The 558 MIRs are actually scattered into five spatially distinguished subnational regions: the midwest, the north, the northeast, the south, and the southeast, as well as 27 states, including the Federal District. As a starting point to understanding such extensive geography, Table 1 presents descriptive information on the five regions of the country. In particular, it contains five-year averages of land productivity as well as the standard deviation and coefficient of variation. The first aspect to note is that, following the national trend, yields have increased over time across all regions for all three crops. However, yields for rice and maize in the north and northeast were systematically below other regions and also fell below the national average. Moreover, measured by standard deviation (STD), the low level of yields seems to be predominant within the two northern regions, as the value of STD is much lower in these two regions than in the other regions in the initial period.

Table 1 also shows that values of STD and coefficient of variation (CV) increase over time and become the highest among the northern regions in most recent periods. This result indicates increased yield volatility and hence more inequality within the region.

The picture painted in Table 1 is one in which there are clear differences across regions in Brazil. In the first period, the southern region had the highest yields across all crops. For rice and wheat, the south continues to lead for most periods. Maize yields, however, show a different dynamic with the growing importance of the Midwest and the de facto leadership in yields for all remaining periods. For the three crops, with the exception of the notorious outlier in the northeast, wheat yields seem to be the most uniform across regions.

The lower yields and increased volatility in the yield within regions for the two north regions compelled us to look beyond regional averages for the north and northeast regions in an effort to gain a more accurate view of the yield dynamics within these lagging regions. To do so, we looked at the yield performance at the state level within these two lagging regions. For this analysis, we focused on maize, as rice shows a similar dynamic to maize, and data for wheat are spotty for these regions. While both regions have lagged behind the others, between them, it is clear that the northeast performs worse than the north in the case of maize (see figures 4a and 4b). The low average regional yield in the northeast is associated with low yields in a large number of states. States such as Alagoas (AL), Paraiba (PB), Pernambuco (PE), and Rio Grande do Norte (RN) have only reached the regional 1980–1985 average level in recent years, that is, more than 25 years later than other regions. Few states, including Bahia (BA), Sergipe (SE), and more recently, Maranhao (MA) have surpassed the regional 1980–1985 average yields by fairly significant levels.

The northern region, as well as many states in the region, has higher initial yield levels than the northeast region and most states in the northeast. The most important observation of figure 4b is that the yield growth among the northern states is relatively faster than those in the northeast region, as almost all northern states managed to eventually reach that initial regional average in the following periods, with the exception of Amapa (AP). However, one has to keep in mind that while some progress has been achieved by selected states in both regions, the benchmark yield chosen for the comparison was achieved 25 years ago for the region as whole, which suggests that progress has been slow, at best.

Table 1. Five-year averages of crop yield and selected statistics by region

		Region					
Period	**Statistic**	**Midwest**	**North**	**Northeast**	**South**	**Southeast**	***National***
Maize							
1980–1985	*mean*	1.79	1.13	0.42	2.07	1.86	***1.34***
	STD	0.44	0.43	0.29	0.62	0.63	***0.85***
	CV	24.45	37.97	68.94	29.65	34.01	***63.46***
1986–1990	*mean*	2.24	1.23	0.49	2.17	2.06	***1.48***
	STD	0.74	0.55	0.29	0.75	0.70	***0.96***
	CV	32.82	44.34	59.96	34.29	34.04	***64.83***
1990–1995	*mean*	2.66	1.30	0.59	2.59	2.34	***1.72***
	STD	0.85	0.54	0.51	0.87	0.76	***1.12***
	CV	32.01	41.22	86.23	33.44	32.46	***65.18***
1996–2000	*mean*	2.97	1.34	0.69	2.90	2.64	***1.91***
	STD	0.94	0.63	0.63	0.93	0.92	***1.27***
	CV	31.61	47.36	91.52	31.99	35.01	***66.56***
2000–2006	*mean*	3.64	1.56	0.78	3.63	3.26	***2.33***
	STD	1.13	0.68	0.73	1.45	1.27	***1.66***
	CV	31.13	43.74	92.90	39.96	38.79	***71.08***
Rice							
1980–1985	*mean*	1.18	1.24	1.21	2.14	1.54	***1.50***
	STD	0.28	0.54	0.85	1.14	0.63	***0.86***
	CV	23.50	43.59	70.75	53.33	40.96	***57.28***
1986–1990	*mean*	1.32	1.30	1.46	2.37	1.79	***1.71***
	STD	0.38	0.56	1.05	1.34	0.77	***1.01***
	CV	28.63	42.85	71.53	56.67	43.11	***58.88***
1990–1995	*mean*	1.55	1.43	1.56	2.70	1.90	***1.88***
	STD	0.50	0.69	1.22	1.51	0.74	***1.13***
	CV	32.01	47.90	78.28	56.10	38.89	***60.07***
1996–2000	*mean*	1.94	1.39	1.51	3.04	1.85	***1.96***
	STD	0.74	0.62	1.07	1.64	0.72	***1.19***
	CV	38.39	44.70	70.90	53.79	38.82	***60.88***
2000–2006	*mean*	2.36	1.69	1.63	3.36	2.13	***2.23***
	STD	0.99	0.98	1.23	2.12	0.82	***1.46***
	CV	41.75	58.23	75.85	63.25	38.65	***65.39***
Wheat							
1980–1985	*mean*	1.08	1.00		1.01	1.25	***1.08***
	STD	0.66			0.38	0.50	***0.46***
	CV	61.40			37.55	39.80	***42.36***
1986–1990	*mean*	1.46		0.90	1.48	1.83	***1.58***
	STD	0.82		0.42	0.42	0.69	***0.59***
	CV	56.41		47.14	28.66	37.62	***37.56***
1990–1995	*mean*	2.04			1.49	2.07	***1.64***
	STD	1.39			0.37	1.04	***0.74***
	CV	68.40			24.66	49.91	***45.07***
1996–2000	*mean*	2.45			1.66	2.54	***1.88***
	STD	1.56			0.43	1.34	***0.90***
	CV	63.54			26.05	52.59	***47.87***
2000–2006	*mean*	2.70		5.19	1.90	2.96	***2.20***
	STD	1.60		0.34	0.54	1.30	***1.04***
	CV	59.32		6.48	28.43	44.08	***47.37***

Source: Authors' calculations based on Embrapa's data
Note: CV = coefficient of variation.

Figure 4a. Maize yields in northeastern states, relative to 1980-1985 regional average

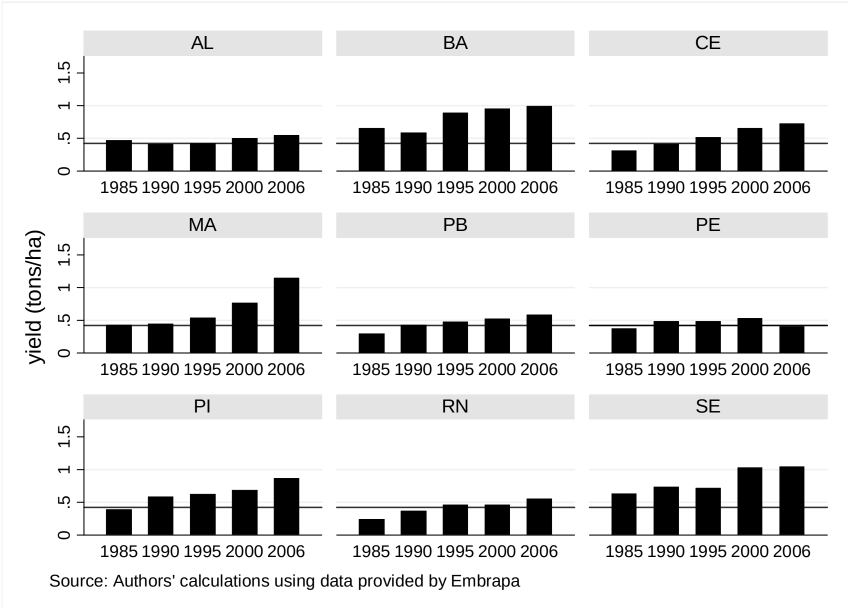
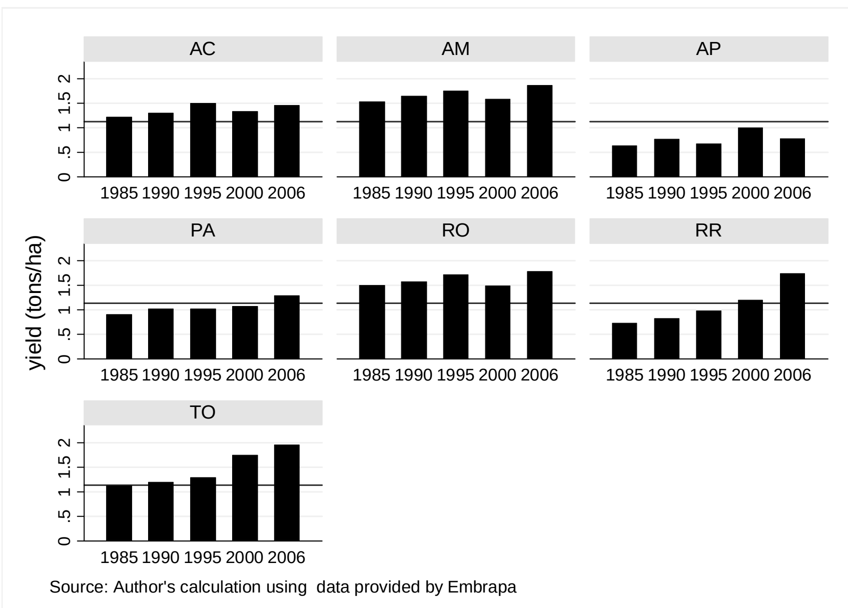


Figure 4b. Maize yields in northern states relative to 1980-1985 regional average



The above discussion describes the evolution of cropland productivity at the three levels: national, regional, and states (within the lagging regions). While we observe significant productivity growth at all levels, large differences in the levels of yields still exist across and within regions. With this fact as a background, the question about the existence of technology spillovers and catching-up still needs to be addressed using more rigorous methods. Specifically, despite the existence of regional and state differences, have less productive regions been able to catch up with more productive ones? Further, what are the main factors that have helped or hindered this process?

3. ANALYZING YIELD CATCH-UP USING CONVERGENCE METHODS

To answer the questions raised at the end of Section 2, it is important to first assess the significance of poorer or less productive regions catching up with more productive ones. Catch-up in productivity is often the outcome of spillovers, as predicted in theory and briefly outlined in the introduction. New technology that eventually leads to spillovers across regions originates from R&D in agriculture. Brazil has invested quite significantly in agricultural research over the last few decades. A sizeable share of this investment was made by Embrapa, an institution that has not only focused on promoting agricultural productivity growth as a mandate but has also emphasized poverty alleviation through enhancing broad productivity growth across the country. Combining the theory behind spillovers with the significant efforts of Embrapa to enhance productivity and reach the poor through productivity growth, we should expect the level of crop yields in poorer regions to grow faster and eventually approach that of the richer regions. It is important to highlight that productivity catch-up also depends on many factors that are beyond what a research institution can do. These factors include general infrastructure conditions in the lagging regions, which translate into higher associated costs such as transportation costs, lower educational levels for the poor and lower access to inputs and knowledge. Combined, these factors can hinder or block spillovers from reaching poorer or less-developed areas (see, for example, Johnson and Evenson 2000). While keeping these other structural factors in mind, we do not attempt to explain the reasons for catching up or not in the following analysis, due to limited data on infrastructural variables at the microregional level.

There are two types of potential catching up: The first occurs when less productive regions reach the same level of output as more advanced regions, which means that inequality among regions no longer exists. The second type occurs when the yield gap still exists between advanced and less-advanced regions within a country, but the gap becomes smaller over time. The first type of catch-up in yield is called absolute convergence, while the second is referred to as conditional convergence, which implies that convergence will occur if certain factors are controlled for (such as R&D and education). Conditional convergence does not necessarily imply the end of inequality, since regions do not converge to the same level of yield for a given crop, and thus, it is possible that some regions still grow faster than others and in doing so, create or maintain inequality (Lei and Yao 2008).

Analytic Methods

We address convergence by resorting to two econometric methods. The methods we apply in this paper focus on whether yields in poorer areas have converged or caught up with yields in richer areas. These two methods are often referred to as beta convergence.[9]

The first measure of beta convergence tests whether the convergence exists, and if so, whether it is conditional or unconditional. This approach follows the methodology developed by Bernard and Jones (1996) and used by Lusigi, Piesse, and Thirtle (1998) and others. This test takes advantage of the panel nature of the data and has the added benefit of testing for convergence without requiring conditioning variables (in case of conditional convergence). On the other hand, a drawback of the Bernard and Jones method is that it does not provide an explanation as to what has led to convergence.

[9] Some authors (such as Lei and Yao 2008) also present an additional measure of convergence, which aims to assess whether inequality has increased or decreased over time. Often authors use the coefficient of variation or the natural log of the standard deviation of the variable of interest to analyze trends in inequality. Decreasing trends imply convergence, and increasing trends suggest divergence. Achieving convergence while at the same time decreasing inequality is often called sigma convergence (see, for instance, Lei and Yao 2008). Since we have resorted to generalized entropy measures to assess trends in inequality, we do not use any additional measures of sigma convergence in this paper.

Using a fixed-effect estimator for panel data,[10] we have estimated the following equation:[11]

$$\ln Yld_{it} = (\delta_r - \delta_i) + (1-\lambda)\ln Yld_{it\text{-}1} + \varepsilon_{it} \tag{1}$$

where $\ln Yld_{it} = \ln Yld_r - \ln Yld_i$.

The left-hand side variable is a measure of the growth rate of yields and is expressed as the logged difference between the reference yield *r* in year *t* minus the yield of microregion *i* in the same year *t*. The right-hand side of the equation contains a drift (or trend) term ($\delta_r - \delta_i$) and a lagged term of the left-hand side variable. The λ shown in the coefficient of the lagged term is an estimate of the rate of convergence. For this analysis, we have used two different types of reference yields. The first one is a slight adaptation of Bernard and Jones (1996) and consists of using the yield of the fastest-growing microregion in year *t*.[12] The second measure follows Lusigi, Piesse, and Thirtle (1998) and is simply the national yield average for every year.

The model estimated in equation (1) tests the hypothesis that differences in productivity relative to the benchmark yield are generated by a non-stationary process with a non-zero drift term ($\delta_r - \delta_i$). If the hypothesis cannot be rejected, convergence is not observed. Unconditional convergence occurs when the coefficient ($1-\lambda$) is significant and the drift term equals zero, suggesting the regions will not only converge but will do so to the same level. A non-zero drift term accompanied by a significant coefficient indicates that convergence is conditional on other factors, which in turn suggests that regions will converge but not to the same level of productivity. The magnitude of the drift term will influence the speed at which regions converge.

Equation (1) resembles a typical dynamic model equation in which the dependent variable is regressed against itself lagged. It is natural to expect that in doing so, we are introducing a bias caused by the lack of strict exogeneity, derived from the correlation between the dependent variable and its lagged term (Wooldridge 2002). Our choice for using this method originated from the lack of potential explanatory variables for convergence, combined with the fact that this method, put forward by Bernard and Jones (1996), allows for testing the presence or absence of convergence, as well as its type, without requiring additional variables. However, we must exercise caution in estimation of the variance-covariance matrix of these regressions so as to minimize or eliminate any bias caused by the correlation described above[13]. To deal with this bias, we have estimated equation (1) using a robust variance-covariance matrix, as suggested by Wooldridge (2002), as well as by obtaining standard errors derived from a clustered estimation, in which the panel identification is used as a cluster. This second method generates a variance-covariance matrix that is robust to both serial correlation and heteroskedasticity, and is in fact equivalent to the estimator described in Arellano (1987). In addition, we have also estimated equation (1) by assuming that disturbances are heteroskedastic and first-order auto-regressive (see Baltagi and Wu 1999). Reassuringly, while the magnitude of the convergence term may change (in the case of heteroskedastic auto-regressive estimation), the findings obtained by simply estimating equation (1) as a fixed-effect model held up to the various specifications of variance. Given that the new estimations did not alter the results, we only report and discuss results for the fixed-effects estimation. Other results are available at request.

The second convergence test we used was adapted from Baumol (1986) and resembles more closely the approach followed by Barro and others, which in turn stemmed out of the growth models originally proposed by Solow and later complemented by Mankiw (Mankiw, G, N. et al 1992) and a

[10] The decision to use fixed effects was based on the results of the Hausman test, which strongly rejected the hypothesis that nonobservable fixed effects are uncorrelated with the right-hand side variables.

[11] All estimations and data management tasks were performed using Stata 10 MP.

[12] In constructing the reference yields for the fastest-growing microregion, we were able to identify the microregions and the regions in which they belonged. Table A.3 in the appendix shows the maximum yields reached by leading regions as well as the total number of times leading microregions fell into each region. We were pleasantly surprised to see that a number of leading microregions for rice were in the Northeast.

[13] We thank our anonymous reviewer for emphasizing the need to deal with this problem more explicitly.

number of other economists. Unlike the Bernard and Jones (1996) method, this method uses cross-sectional data (as opposed to panel) and is estimated by regressing the growth rate of yields (between end and initial years) on the initial level of productivity. This allows us to see whether dispersion has diminished between final and initial years. In addition, Baumol's model also allows for the inclusion of conditioning variables that may influence the ability of countries or regions to converge. Some authors, such as McCunn and Huffman (2000), argue correctly that one potential drawback of this method is that the choice of initial and final years may influence the output, depending on whether these years were typical or atypical. In many cases, authors use averages of a few years to address this problem. In this paper, we have addressed this issue by estimating a number of regressions, including various subperiods between 1980 and 2006.

To apply Baumol's model (1986), we have estimated equation (2) using ordinary least square regression.

$$\ln Yld_{ic} = \alpha + \beta \ln Yld_{i0} + \varepsilon \tag{2}$$

where $\ln Yld_{ic} = \ln Yld_{if} - \ln Yld_{i0}$, $\beta = (1 - e^{\lambda t})$ and λ represents the rate of convergence.

The left-hand side of equation (2) is simply the logged difference between the yields in the end year *f* in microregion *i* and the yield in the first year *0* of analysis. The right-hand side of the equation contains the natural log of yield in the first year *0* for microregion *i*, as well as a constant α and an error term. For convergence to occur, β must be negative and significantly different from zero. Obtaining a negative and significant coefficient for the initial yield is an indication of convergence but does not rule out the possibility of conditional convergence. To ensure unconditional convergence, other relevant conditioning factors (such as education, investment, R&D, and share of agriculture in the economy) that can be added to equation (2) have to be jointly insignificant.

To date and to the best of our knowledge, data on the possible conditioning variables just described are not available at the microregional level. Hence, we do not attempt to further explain convergence using the aforementioned variables. However, we have noted from Section 2 that regions in Brazil differ significantly in terms of yield performance. A number of factors may help explain these differences, some of which are listed in the previous paragraph, while some are purely biophysical. However, there may be other unidentified aspects particular to these regions that help explain the heterogeneity observed in Section 2.[14] We attempt to capture some of this heterogeneity by adding dummy variables to equation (2) and estimating equation (3), following McCunn and Huffman (2000). Given that data for wheat are spotty in the poorest regions, we have only estimated equation (3) for maize and rice.

$$\ln Yld_{ic} = \alpha + \beta \ln Yld_{i0} + \delta D_V + \varepsilon \tag{3}$$

Equation (3) differs from equation (2) only in the δD_v term, which contains a vector of dichotomous dummy variables for four out of the five regions in Brazil. The fifth dummy variable was excluded to avoid multicollinearity. Addressing multicollinearity, however, gave us another tool with which to analyze patterns of convergence in Brazil. By excluding one region, we were able to choose a region against which to assess the performance of other regions. We have chosen the southern region as the reference region because it performed considerably better than other regions during the initial periods (see Table1). Negative and significant values of δ suggest that a given region is on a slower path of

[14] For instance, beyond biophysical differences in the pool of resources (soil, weather, and temperature), local policies and even policies originating from the federal government may affect agriculture (and thereby productivity) locally if efforts are directed to certain regions more than others. In technical terms, regional dummy variables control for the presence of unobserved fixed effects and thereby provide a more accurate picture of convergence, as these unobserved fixed effects could potentially influence the estimates of convergence.

growth than the south. Conversely, a positive $\hat{\delta}$ indicates that a region has outpaced the south. The magnitude of $\hat{\delta}$ is an indication of how much the region lags behind or is ahead of the south.

Results and Discussion

Given the large number of microregions and years present in our data set, we provided a descriptive table in the appendix, which outlines a few basic statistics regarding the structure of the overall panel data set by crop (see Table A.4). In particular, it presents the mean and the standard deviation for the two dependent variables used in the Bernard and Jones (1996) method (growth rates relative to the fastest-growing microregion and growth rates relative to the average yield of all microregions in a given year) The first thing to note is the large number of observations present for all three crops, as indicated by the *N* in Table A.4. In addition, especially for maize and rice, nearly all microregions were included as panels (see the *n* in Table A.4). More interesting, however, is to note the decomposition of the standard deviations into within and between panels. The three crops show fairly different degrees of variation for the between and within panels, with maize presenting the highest difference between the two measures (within and between), while wheat shows very small differences. The small difference for wheat (especially in the case of the first measure of growth rate) indicates that the variation in growth rates between microregions was nearly the same as the variation of growth rates within a given microregion over time. In practical terms, this means that randomly selecting two microregions would provide a similar variation in growth rates as choosing a single microregion in two different time periods. In simpler terms, this amounts to a much smaller variation in the growth rates of wheat vis-à-vis the other two crops, which probably is reflected in the goodness of fit of the regressions presented in Table 3 (in which we regress the growth rates between two years against the initial level of yield).

The estimations obtained from equation (1) and based on the method outlined by Bernard and Jones (1996) are presented in Table 2. We note that conditional convergence has occurred for the three crops, as the coefficients of the lagged productivities as well as the drift terms are significantly different from zero. These results indicate that individual microregions converge to their own steady states, which can be different across regions. In large enough samples, convergence (in this case, conditional) takes place regardless of the choice of reference yield (Bernard and Jones 1996). Indeed, even the point estimates of the lagged coefficients were almost the same for the three crops under the two different reference yields, reinforcing the point made by Bernard and Jones. These findings, therefore, suggest that less productive regions have indeed caught up with more productive regions for all the three crops, as long as other factors are controlled for. It is worth emphasizing the meaning of conditional convergence. Convergence theory suggests that when convergence takes place, yields in poorer regions grow faster than yields in richer regions. However, the theory also says that poorer regions will grow at a lower growth path than richer regions and that the gap between rich and poor remains, though it may diminish over time. For the gap to diminish, other factors have to be accounted for. It is important to keep this in mind as one compares the results from the econometrics with the descriptive information provided in the previous section.

The speed of the catch-up (indicated by the lambda in Table 2) was the highest for maize or wheat (depending on the choice of reference yield) and the slowest for rice. These differences and the speed of convergence are particularly relevant for maize and rice, since wheat is not planted in the poorest regions of the country (north and northeast). For maize and rice, we note that these results provide support to the findings obtained in the yield-gap and between-group entropy analyses discussed previously. Maize observed more pronounced decreases (two regions out of three) in the yield-gap and a statistically significant decrease in the between-group inequality. Results for rice were not as pronounced or as statistically significant (only one region showed a negative slope in the yield-gap analysis), which is reflected in the different speeds of convergence.

Table 2. Bernard-Jones test for the presence of convergence (derived from a fixed-effect estimator for panel data)

Variable	Maize	Rice	Wheat	Maize	Rice	Wheat
Reference yield	*Simple average of all microregions*			*Fastest microregion in year t*		
Yield growth rate	0.15***	0.24***	0.16***	0.16***	0.26***	0.15***
Constant	0.27***	0.12***	0.07***	1.24***	1.06***	0.86***
Implied λ	0.85	0.76	0.84	0.84	0.74	0.85
N	13,990	12,123	2,845	13,990	12,123	2,845

Note: * p<.1; ** p<.05; *** p<.01

The results above are reinforced by the evidence provided by the cross-sectional estimations, that is, estimating equation (2) for selected different starting and ending years between 1980 and 2006. The cross-sectional estimation results in Table 3 (panel a) indicate that all three crops converged during the period between 1980 and 2006, as well as for all but one subperiod (2000–06) in between. Rice and maize failed to converge in the subperiod of 2000–2006. The lack of significance for the last period was most likely attributed to low variability in the yields between the beginning and ending periods. In most cases, wheat converged at a faster rate than rice and maize, but at the same time, the goodness of fit of the wheat regressions was considerably lower, suggesting that little variation in the yield growth rates can be explained by initial yield levels.

Overall, however, it is encouraging that yields in less advanced microregions have generally shown signs of catching up with more productive microregions. However, these results do not necessarily imply absent or low regional inequalities. In fact, as Table 2 indicates, there are significant differences in yield performance across regions, particularly for rice and maize, which are planted throughout the country. To account for these differences in yield performance across regions, we estimated equation (3) for rice and maize. Results are presented in Table 3, panel b.

As indicated in the methodological section, a negative and significant coefficient on a regional dummy variable indicates that this region is on a lower steady state growth path (implying that it will catch up more slowly) than that of the reference region—the south—which again reinforces the notion of conditional convergence, as regions will converge to different levels. From Table 3 (panel b), we note that for maize, in all regions except for the midwest, dummy variables show negative and significant signs for most periods (the southeast had a nonsignificant rate in the 1990–2000 period). It is also noticeable that the northeast has the highest negative coefficients, confirming the descriptive analysis in Section 2, in which the northeast seemed to be the worst performer. For rice, however, the magnitudes of the coefficients among the different regions oscillated considerably, making it more difficult to single out the worst performer. The midwest outperformed other regions, as indicated by the fact that its dummy variables were not significant for most periods. With the exception of the period of 2000–2006 for rice, dummy variables were jointly significant and different from zero at less than 1 percent level of significance, according to Wald tests.

The use of regional dummy variables increases significantly the magnitude of λ, indicating that controlling for regional fixed effects indeed helps speed up convergence. The higher value of λ is reflecting regional differences in levels of unspecified fixed effects. For the entire period, maize yields grew at a pace of 2.0 percent annually in the first estimation (without regional dummies) and at 2.8 percent in the second estimation. Within subperiods, the gains were even more pronounced, more than doubling in 1980–1990 and nearly doubling between 1990 and 2000. Rice too improved, albeit not as much, from 2.2 percent to 2.5 percent. Subperiod improvements were also considerably lower than for maize.

Table 3. Cross-sectional regressions for land productivity for selected periods, by crop and panel

Variable	1980–2006	1980–1990	1990–2000	2000–2006	1980–2006	1980–1990	1990–2000	2000–2006
	Initial-final period				***Initial-final period***			
	Panel a, equation (2)				***Panel b, equation (3)***			
Maize								
Yield growth rate	-0.48***	-0.24***	-0.47***	-0.03	-0.77***	-0.61***	-0.84***	-0.19***
Dummy MW	na	na	na	na	*0.13*	*-0.15**	*0.08*	*0.05*
Dummy N	na	na	na	na	-0.69***	-0.51***	-0.66***	-0.18***
Dummy NE	na	na	na	na	-0.93***	-1.21***	-0.97***	-0.39***
Dummy SE	na	na	na	na	-0.15**	-0.26***	0.020	-0.17***
Constant	0.68***	0.09***	0.50***	0.12***	1.05***	0.58***	0.88***	0.39***
Implied λ	0.020	0.021	0.038	0.005	0.028	0.048	0.061	0.029
N	515	520	539	540	515	520	539	540
R squared	0.47	0.17	0.46	0.003	*0.59*	*0.38*	*0.63*	*0.08*
Rice								
Yield growth rate	-0.58***	-0.44***	-0.50***	-0.08	-0.63***	-0.58***	-0.52***	-0.08**
Dummy MW	na	na	na	na	0	-0.49***	0.09	0.03
Dummy N	na	na	na	na	-0.44***	-0.42***	-0.43***	0.03
Dummy NE	na	na	na	na	-0.18**	-0.48***	-0.12**	-0.03
Dummy SE	na	na	na	na	-0.18***	-0.25***	-0.26***	0.09*
Constant	0.58***	0.16***	0.47***	0.11***	0.74***	0.49***	0.63***	0.08
Implied λ	0.023	0.037	0.041	0.013	0.025	0.045	0.042	0.012
N	429	455	459	439	429	455	459	439
R squared	0.35	0.22	0.43	0.01	0.39	0.29	0.53	0.03
Wheat								
Yield growth rate	-0.96***	-0.74***	-0.55***	-0.28**	na	na	na	na
Constant	0.54***	0.24***	0.37***	0.21***	na	na	na	na
Implied λ	0.034	0.055	0.044	0.041	na	na	na	na
N	97	103	96	97	na	na	na	na
R squared	0.03	0.06	0.04	0.06	na	na	na	na

Note: $\beta = 1-e^{\lambda t}$, where λ = rate of convergence; na = not applicable

Observation: Please note that in these estimations the reference yield is the yield in the first year.

Legend: * p<.1; ** p<.05; *** p<.01

These findings suggest that while some catching-up has been happening, there are still very dramatic cross-regional differences, which have slowed down the effectiveness of spillovers to poorer regions. It is hard to speculate whether spillovers will eventually lead to a significant reduction in regional differences. From our analysis of the two lagging regions—north and northeast—this reduction does not seem to have occurred in a substantial form, as these two regions have progressed very slowly in catching up to the national and even regional yield levels. In fairness, however, we must acknowledge that we have not controlled for all the other relevant factors that may contribute to the overall spillover effect. These factors include the regional share of agriculture to gross domestic product, educational levels, and a number of other factors that may not be directly related to yields but still can affect the estimation results. We are aware of the importance of these factors but have not included them in the analysis due to lack of data.

4. CONCLUSIONS

This paper provides a comprehensive analysis of spatial patterns and their evolution over time for land productivity of maize, rice, and wheat in Brazil. From the outset, we posed the question of whether the efforts in R&D and the effects of spillovers have led less productive regions to catch up with more productive ones. In more technical terms, our goals are to find out whether spatial inequality in yields has declined and convergence has occurred in Brazil.

To analyze the evolution of spatial patterns of grain productivity, it was first necessary to get a sense of how land productivity has evolved. Looking at national trends, we observed that grain yields have grown dramatically since 1980. However, analyzing growth at the national level incurs the possibility of masking regional and state inequalities. To get a better sense of whether the spatial or regional gaps between productivity in the three grain crops have reduced over time, we used the generalized entropy (GE) measure to track the productivity inequality over time. GE analysis shows that overall inequality displayed a declining trend in maize and wheat and did not increase for rice. Decomposition of the overall inequality into between and within groups shows that trends for between-group inequalities also declined for maize and wheat and remained constant for rice. On the other hand, a positive slope was observed for within-group inequality. In the case of maize and wheat, increased within-group inequality occurs in the group with above-average yields, while it occurs in the below-average group in the case of rice. Despite decreasing yield inequality, the spatial and regional productivity gap is still significant. Thus, we calculated a yield-gap measure similar to the poverty gap indicator, which compares yields across regions that fall below a baseline yield (defined to be the average yield for the north and northeast regions). We found that yield gaps have typically decreased (relative to the baseline yield) for all but one region for maize and decreased for one region for rice.

We then applied two econometric models of convergence to further assess whether less productive microregions have caught up with more productive ones. Both models indicate that conditional convergence in land productivity has indeed taken place for all three crops. The second test, however, pointed to significant differences in the speed of convergence among regions, and the northeast fell considerably behind other regions.

While the results from these tests confirmed the existence of productivity catch-up by less productive regions with more productive ones, there still remains a gap between the two types of regions, as established by the fact that convergence only occurs in the presence of other controlling factors. Even in the presence of controlling factors, the level that poorer regions will eventually reach will not be the same as richer regions, since poorer regions are on a lower growth path than richer ones. Constrained by the data we currently have, we cannot conduct quantitative analysis to explain the reasons (controlling factors) for catching-up in technology as well as the still-existent yield gap. Plausible explanations include the existence of considerable socioeconomic differences among these regions, caused in part by policies that generally tended to benefit regions other than the northeast and north regions. Other heterogeneous regional conditions, including much harsher climates and other agro-ecological conditions in the two lagging regions, combined with delayed access to R&D, may have also played a role. These factors, together with many other factors beyond the three crops in particular and the agricultural sector in general (e.g., lower levels of education and limited access to nonfarm job opportunities) have created barriers for technology spillovers and resulted in a much larger concentration of poverty in these regions. Obviously, more research with more data is needed to properly identify whether and how these socioeconomic factors have affected the ability to increase productivity among the lagging regions in Brazil.

APPENDIX: SUPPLEMENTARY FORMULAS, TABLES, AND FIGURES

Formula A1 (extracted and adapted from Kanbur and Zhang 1999).

$$I(y)=\begin{cases} \sum_{i=1}^{K} f(y_i)\left\{\left(\frac{y_i}{\mu}\right)^c - 1\right\} & c \neq 0,1 \\ \sum_{i=1}^{K} f(y_i)\left\{\left(\frac{y_i}{\mu}\right)\log\frac{y_i}{\mu}\right\} & c = 1 \\ \sum_{i=1}^{K} f(y_i)\log\left(\frac{\mu}{y_i}\right) & c = 0 \end{cases}$$

In the above equation, y_i is the *i*th yield of microregions measured in kg/ha, μ is the total sample mean, $f(y_i)$ is the population share of y_i in the total population, and *n* is total population.

Table A.1. Results of general entropy analysis using the 1980–1985 average as reference

a. Maize

Year	**All**	**<**	**>**	**Between**	**All**	**<**	**>**	**Between**
	c = 0				***c = 1***			
1980	26.71	39.70	3.36	0.14	15.51	27.94	3.37	0.06
1981	29.59	43.70	3.04	0.17	16.44	36.76	3.03	0.06
1982	26.21	31.82	3.25	0.15	16.11	22.87	3.29	0.07
1983	25.45	57.35	3.13	0.12	13.50	45.11	3.20	0.03
1984	13.64	9.29	2.61	0.09	10.50	8.30	2.58	0.06
1985	17.51	14.18	2.82	0.12	12.75	12.47	2.79	0.07
1986	16.31	11.34	5.40	0.09	13.34	11.01	5.06	0.07
1987	32.55	46.17	3.25	0.19	17.63	42.76	3.11	0.05
1988	20.02	16.84	4.69	0.12	14.56	12.95	4.29	0.08
1989	23.00	18.81	3.98	0.15	16.15	17.51	3.74	0.08
1990	28.41	35.06	4.04	0.17	16.90	31.31	3.74	0.07
1991	19.00	16.48	8.75	0.08	15.89	18.63	8.03	0.05
1992	26.02	36.34	3.36	0.15	15.79	35.13	3.26	0.05
1993	19.12	53.15	3.14	0.07	11.12	46.48	3.01	0.01
1994	17.89	15.91	3.71	0.11	13.62	19.43	3.39	0.06
1995	21.18	22.85	3.69	0.12	14.72	24.83	3.35	0.06
1996	18.31	19.13	4.37	0.10	13.90	24.20	4.11	0.05
1997	20.21	30.11	3.85	0.10	13.97	33.30	3.60	0.03
1998	24.08	55.62	3.60	0.10	13.63	50.74	3.30	0.01
1999	17.54	28.61	4.16	0.08	12.58	31.23	3.92	0.03
2000	18.85	23.29	7.41	0.07	15.16	27.51	6.60	0.03
2001	24.43	49.16	3.97	0.11	14.27	46.10	3.55	0.02
2002	23.31	34.99	5.83	0.10	16.12	34.75	5.58	0.03
2003	20.84	29.64	3.70	0.11	13.78	29.63	3.35	0.04
2004	26.06	44.79	5.29	0.11	16.80	44.37	4.73	0.02
2005	25.94	37.47	9.11	0.09	18.87	39.07	7.90	0.02
Slope			++	---		++	++	---

Table A.1. Continued

b.Rice

Year	**All**	**<**	**>**	**Between**	**All**	**<**	**>**	**Between**
	c = 0				***c = 1***			
1980	12.48	3.72	8.42	0.08	13.43	2.71	8.15	0.09
1981	21.19	8.13	9.37	0.13	21.85	6.73	9.01	0.15
1982	13.84	2.48	10.07	0.09	15.85	1.96	9.52	0.12
1983	18.00	8.04	6.82	0.10	17.06	5.57	6.45	0.11
1984	17.71	2.91	10.07	0.13	19.60	2.56	9.20	0.15
1985	16.89	1.77	10.85	0.12	18.73	1.57	9.89	0.14
1986	13.22	2.13	9.48	0.09	14.72	2.11	8.40	0.11
1987	24.52	10.18	10.36	0.14	23.77	8.30	9.03	0.15
1988	15.84	2.36	11.96	0.11	17.64	2.25	10.17	0.13
1989	18.18	4.17	11.87	0.11	19.30	3.80	10.26	0.13
1990	31.37	11.28	11.90	0.20	29.47	10.24	10.07	0.19
1991	17.81	3.08	11.61	0.12	18.29	2.97	9.10	0.13
1992	35.15	17.10	11.43	0.20	30.64	13.55	9.44	0.19
1993	29.36	11.10	9.72	0.19	26.61	9.61	7.96	0.18
1994	14.03	2.94	7.31	0.09	14.32	3.19	6.11	0.10
1995	18.56	4.10	9.09	0.12	18.50	4.14	7.37	0.13
1996	19.04	4.04	10.24	0.12	18.70	4.45	8.06	0.13
1997	19.39	5.61	9.78	0.12	18.55	5.70	7.74	0.12
1998	23.18	14.55	7.63	0.12	19.66	13.07	6.34	0.10
1999	18.71	6.19	10.23	0.11	17.94	6.29	8.03	0.11
2000	15.79	5.96	9.47	0.08	15.00	5.90	7.25	0.09
2001	22.06	10.99	7.12	0.13	19.13	10.18	5.54	0.11
2002	23.57	14.29	6.88	0.13	19.51	12.36	5.46	0.10
2003	16.32	9.14	6.37	0.08	14.87	9.39	5.23	0.07
2004	18.51	9.39	6.87	0.10	16.50	8.70	5.27	0.09
2005	20.53	10.00	7.59	0.11	18.19	8.69	5.66	0.11
Slope			--			+++	---	--

Table A.1. Continued

c. Wheat

Year	All	<	>	Between	All	<	>	Between
	c = 0				***c = 1***			
1980	2.05	0.59	0.39	0.02	2.04	0.59	0.39	0.02
1981	2.05	0.52	0.43	0.02	2.05	0.52	0.43	0.02
1982	4.22	3.81	0.41	0.02	3.40	2.75	0.41	0.02
1983	2.02	0.66	0.38	0.02	1.98	0.66	0.37	0.01
1984	2.01	0.62	0.52	0.01	1.98	0.61	0.53	0.01
1985	2.31	0.70	0.93	0.01	2.37	0.69	1.03	0.02
1986	2.08	2.09	1.39	0.00	1.95	1.87	1.40	0.00
1987	2.20	2.54	0.52	0.01	1.99	2.37	0.50	0.01
1988	2.64	2.04	1.36	0.01	2.54	1.88	1.40	0.01
1989	2.24	2.29	1.42	0.00	2.23	2.29	1.48	0.00
1990	2.17	1.28	2.91	0.00	2.20	1.27	2.90	0.00
1991	2.83	2.22	0.90	0.01	2.68	2.14	0.90	0.01
1992	4.39	5.43	3.57	0.00	4.35	5.07	3.78	0.00
1993	3.66	1.91	5.30	0.00	3.71	1.89	5.22	0.00
1994	2.22	1.24	2.52	0.00	2.30	1.36	2.45	0.00
1995	2.77	2.85	0.98	0.01	2.70	2.89	1.09	0.01
1996	3.83	2.29	5.04	0.00	3.68	2.21	4.71	0.00
1997	2.88	2.17	1.90	0.01	2.87	2.16	1.94	0.01
1998	3.46	2.65	2.11	0.01	3.46	2.73	2.18	0.01
1999	2.02	2.05	1.41	0.00	1.98	2.08	1.37	0.00
2000	4.50	1.83	7.92	0.00	4.35	1.82	7.52	0.00
2001	3.75	2.09	3.38	0.01	3.67	1.95	3.20	0.01
2002	3.18	3.50	2.71	0.00	3.37	3.63	2.98	0.00
2003	1.47	0.81	1.36	0.00	1.54	0.84	1.42	0.00
2004	2.56	2.59	1.55	0.00	2.64	2.69	1.71	0.00
2005	2.87	2.83	1.34	0.01	2.92	3.03	1.46	0.01
Slope			++	---	+	++	++	---

Table A.2. Average yields for microregions below and above the national average

Year	Maize		Rice		Wheat	
	Below	**Above**	**Below**	**Above**	**Below**	**Above**
	(ton per hectare)					
1980	0.56	1.93	1.09	2.05	0.76	1.12
1981	0.52	1.97	0.98	2.16	0.95	1.28
1982	0.62	1.99	1.08	2.13	0.67	1.09
1983	0.49	1.99	1.02	2.28	0.92	1.31
1984	0.65	1.96	1.07	2.21	0.88	1.35
1985	0.72	2.09	1.21	2.41	1.13	1.91
1986	0.76	1.97	1.3	2.4	1.23	1.74
1987	0.53	2.27	1.16	2.45	1.4	1.85
1988	0.76	2.25	1.34	2.5	1.39	1.98
1989	0.72	2.37	1.33	2.65	1.66	2.06
1990	0.6	2.11	1.11	2.47	1.19	1.65
1991	0.82	2.19	1.37	2.5	1.27	1.75
1992	0.68	2.48	1.24	2.63	1.5	1.9
1993	0.74	2.57	1.39	2.73	1.45	2.05
1994	0.9	2.59	1.56	2.7	1.52	2.04
1995	0.86	2.77	1.54	2.72	1.51	2.11
1996	0.87	2.63	1.4	2.57	1.74	2.1
1997	0.88	2.78	1.46	2.73	1.62	2.18
1998	0.81	2.85	1.39	2.71	1.6	2.28
1999	0.91	2.88	1.56	2.87	1.88	2.46
2000	1.09	2.92	1.63	2.87	1.62	1.9
2001	0.89	3.32	1.53	3.09	1.85	2.53
2002	1.01	3.33	1.65	3.13	1.63	2.15
2003	1.08	3.73	1.76	3.16	2.24	3.13
2004	1.04	3.62	1.74	3.29	2.09	2.8
2005	1.07	3.38	1.67	3.17	1.81	2.58
2006	1.13	3.53	1.78	3.28	1.94	2.37
1980–1985 average	*1.34*		*1.50*		*1.08*	
Growth rates (%)	***2.81***	***2.65***	***2.12***	***1.66***	***3.52***	***2.98***

Table A.3. Maximum yield and number of leading microregions by region

	Maize					Rice			Wheat			
Year	**MW**	**N**	**NE**	**S**	**SE**	**NE**	**S**	**SE**	**MW**	**NE**	**S**	**SE**
	(ton per hectare)											
1980				4.43		4.2					1.8	
1981				4.19			4.49					2.49
1982				4.32		5.77			1.79			
1983				3.93		5.94						2.44
1984				3.83		5.39			2.5			
1985				4.56				4.99	3.96			
1986	4.1					5.41			3			
1987				4.57		5.48						3.66
1988		6.2					5.39					4.75
1989				4.91			6.44					4.26
1990				4.35		5.28						3.59
1991	5.12						5.95					3.21
1992				4.94		7			4.05			
1993	5.11					8			4.93			
1994			5.13				6.32		5.04			
1995				5.57		6.24			5.35			
1996		6.8					5.87					4.78
1997				5.59			6		5			
1998				5.91			6.72		5			
1999	6.1						7.47					5.23
2000				6.15			7.36		5			
2001				6.96			8.16		5.4			
2002				7.74			8.64					6
2003				7.82			8.96					5.4
2004				7.57			8.62					5.19
2005					7.93		8.18			5.58		
2006				8.1			8.18		5.2			
Count	4	2	1	19	1	10	16	1	14	1	1	12

Table A.4. Descriptive statistics of panel data set

Variable		Mean	STD	Min	Max	Observations
	Maize					
Growth rates using maximum yields as reference	Overall	1.48	0.94	0.00	7.21	N = 14,660
	Between		0.84	0.12	3.45	n = 558
	Within		0.44	-0.82	6.31	T-bar = 26.27
	Rice					
	Overall	1.41	0.60	0.00	5.64	N = 12,770
	Between		0.48	0.12	2.50	n = 519
	Within		0.37	-0.39	4.78	T-bar = 24.61
	Wheat					
	Overall	0.99	0.42	0.00	4.24	N = 3,170
	Between		0.34	0.00	2.37	n = 182
	Within		0.32	-0.32	3.60	T-bar = 17.42
	Maize					
Growth rates using average yields as reference	Overall	0.32	0.94	-1.39	6.15	N = 14,660
	Between		0.84	-1.04	2.29	n = 558
	Within		0.43	-1.98	5.17	T-bar = 26.27
	Rice					
	Overall	0.16	0.59	-1.44	4.26	N = 12,770
	Between		0.48	-1.13	1.29	n = 519
	Within		0.35	-1.82	3.39	T-bar = 24.61
	Wheat					
	Overall	0.08	0.40	-1.19	3.24	N = 3,170
	Between		0.33	-0.85	1.50	n = 182
	Within		0.29	-1.14	2.56	T-bar = 17.42

Source: Authors' calculation using data provided by Embrapa.

Figure A.1. Land use patterns in Brazil

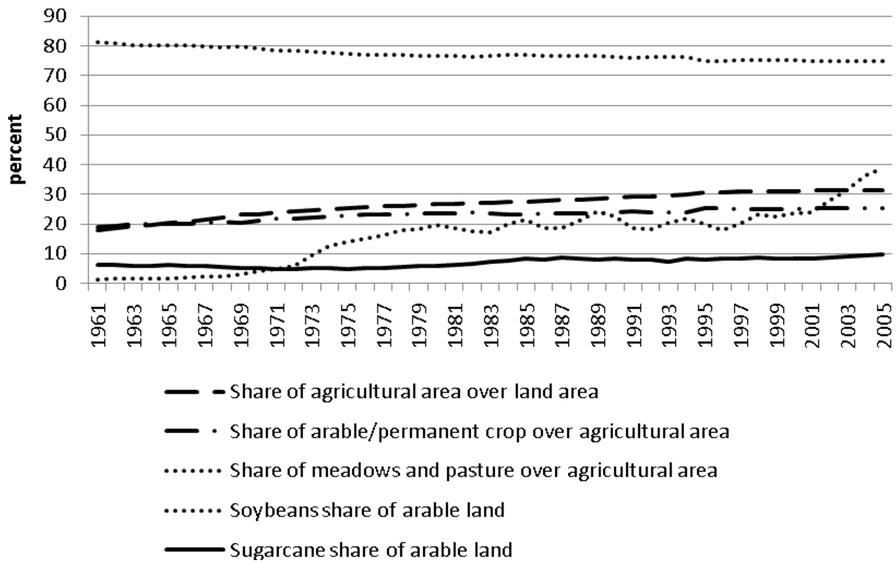


Figure A.2. Generalized entropy patterns

a. Maize

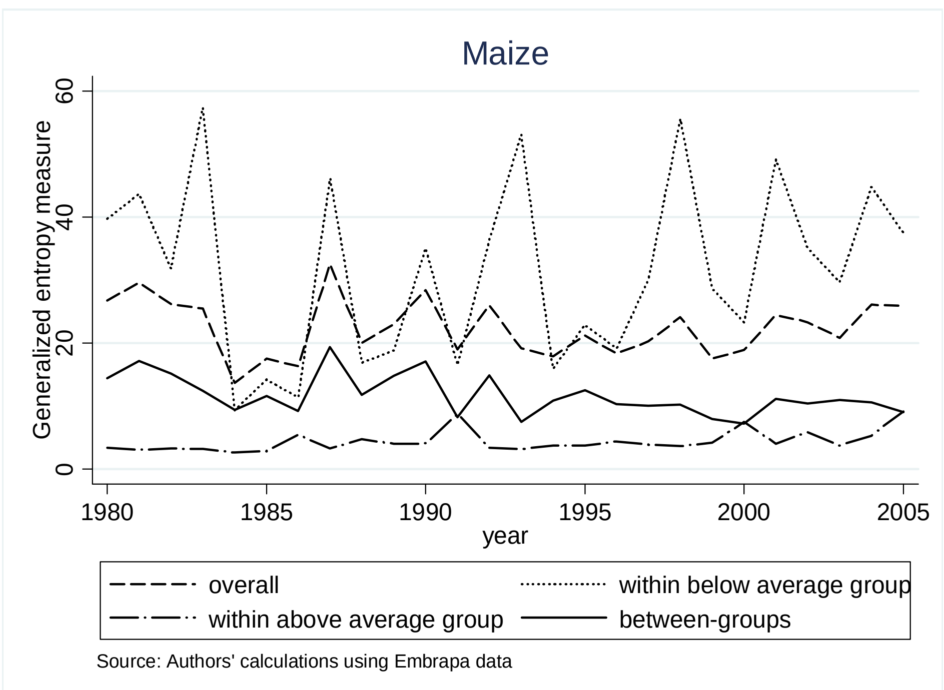


Figure A.2. Continued

b. Rice

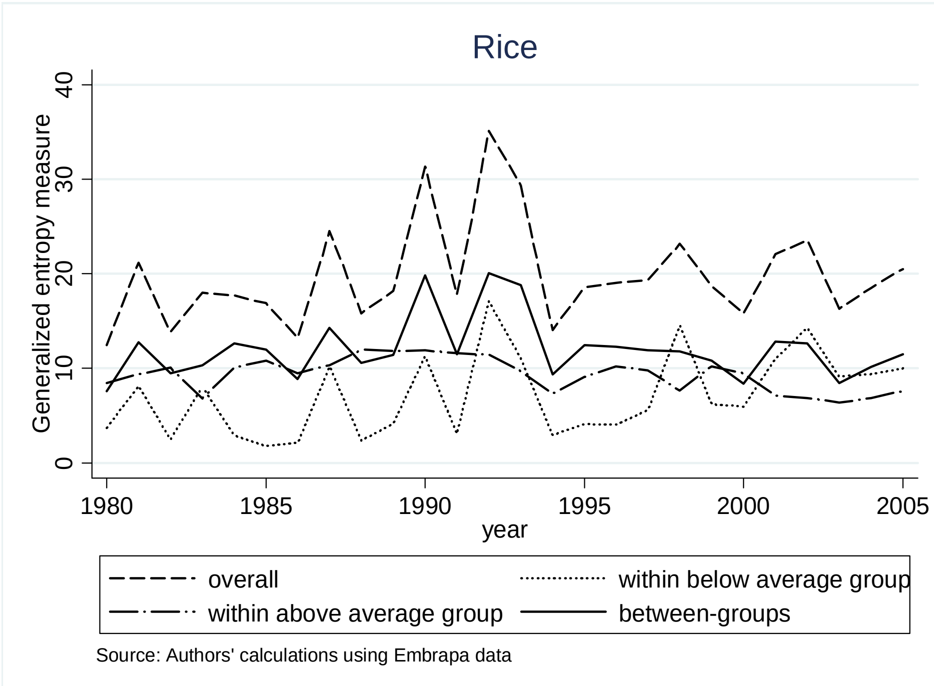
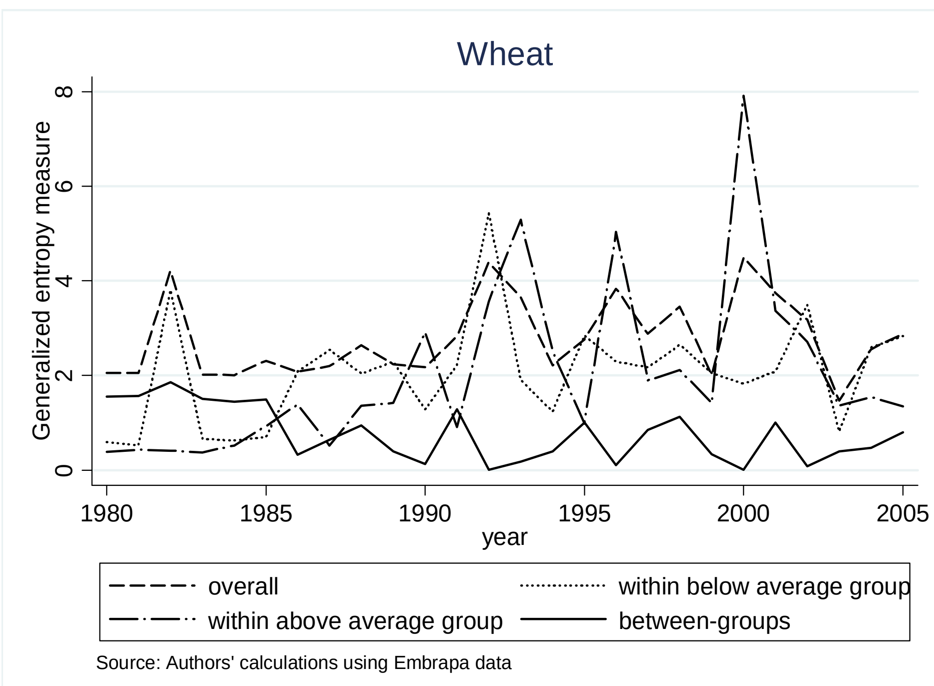


Figure A.2.Continued

c. Wheat



REFERENCES

Alston, J.M. 2002. Spillovers. The Australian Journal of Agricultural and Resource Economics 46 (3): 315–46.

Arellano, M. 1987. Computing robust standard errors for within groups] estimators. Oxford Bulletin of Economics and Statistics 49:431–34.

Baltagi, B.H., & Wu, P.X. 1999. Unequally spaced panel data regressions with AR(1) disturbances. Econometric Theor, Vol.15: 814-23.

Baumol, W.J. 1986. Productivity growth, convergence, and welfare: What the long-run data show. American Economic Review 76: 1072–85.

Beintema, N.M., Pardey, P.G., and Avila, F. 2001. Agricultural R&D in Brazil: Policy, investments and institutional profile. Washington, DC: International Food Policy Research Institute, Embrapa, and Fontagro.

Beintema, N.M., Pardey, P.G., and Avila, F. 2006. Brazil: Maintaining the momentum. In Agricultural R&D in the developing world: Too little, too late? ed P.G. Pardey, J.M. Alston & R.R. Piggott (257–81). Washington, DC: International Food Policy Research Institute.

Bernard, A.B., and Jones, C.I. 1996. Productivity across industries and countries: Time series theory and evidence. Empirical Economics 21:135–46.

Johnson, D.K.N., and Evenson, R.E. 2000. How far away is Africa? Technological spillovers to agriculture and productivity. American Journal of Agricultural Economics 82 (3): 743–49.

Kanbur, R., and Zhang, X. 1999. Which regional inequality: Rural–urban or coast–inland? An application to China. Journal of Comparative Economics 27: 686–701.

Lei, C.K., and Yao, S. 2008. On income convergence among China, Hong Kong and Macau. World Economy 31 (3): 345–66.

Lusigi, A., Piesse, J., and Thirtle, C. 1998. Convergence of per capita incomes and agricultural productivity in Africa. Journal of International Development 10 (1): 105–15.

Mankiw, Gregory N., Romer, David and Weil, David N. 1992. A Contribution to the Empirics of Economic Growth. The Quarterly Journal of Economics. Vol. 107(2): 407-437.

McCunn, A., and Huffman, W.E. 2000. Convergence in U.S. productivity growth for agriculture: Implications of interstate research spillovers for funding agricultural research. American Journal of Agricultural Economics 82 (2): 370–88.

Mishra, A.K., Moss, C.B., and Erickson, K.W. 2006. Farm wealth inequality within and across states in the United States. Agricultural and Resource Economics Review 35 (2): 251–64.

Schnepf, R.D., Dohlman, E., and Bolling, C. 2001. Agriculture in Brazil and Argentina: Developments and prospects for major field crops. Agriculture and Trade Report WRS-01-3. Washington, DC: Market and Trade Economics Division, Economic Research Service, U.S. Department of Agriculture.

You, L. 2008. A tale of two countries: Spatial and temporal patterns of rice productivity in China and Brazil. IFPRI Discussion Paper 758. Washington, DC: International Food Policy Research Institute.

Wan, G. 2001. Changes in regional inequality in rural China: Decomposing the Gini index by income sources. Australian Journal of Agricultural and Resource Economics 45 (3): 361–82.

Wan, G., and Zhou, Z. 2005. Income inequality in rural China: Regression-based decomposition using household data. Review of Development Economics 9: 107–20.

Wooldridge, J.M. 2002. Econometric analysis of cross section and panel data.

Cambridge, MA: MIT Press.

RECENT IFPRI DISCUSSION PAPERS

For earlier discussion papers, please go to www.ifpri.org/pubs/pubs.htm#dp.
All discussion papers can be downloaded free of charge.

856. *Dynamics of structural transformation: An empirical characterization in the case of China, Malaysia, and Ghana.* Thaddee Badibanga, Xinshen Diao, Terry Roe, and Agapi Somwaru, 2009.

855. *Do institutions limit clientelism? A study of the district assemblies common fund in Ghana*. Afua Branoah Banful, 2009.

854. *The evolution of Chinese entrepreneurial firms: Township-village enterprises revisited*. Chenggang Xu and Xiaobo Zhang, 2009.

853. *Evaluating the impact of land tenure and titling on access to credit in Uganda*. Carly K. Petracco and John Pender, 2009.

852. *Participation by men and women in off-farm activities: An empirical analysis in rural northern Ghana*. Nancy McCarthy and Yan Sun, 2009.

851. *Measuring agricultural innovation system properties and performance: Illustrations from Ethiopia and Vietnam.* David J. Spielman and Dawit Kelemework, 2009.

850. *Are returns to mothers' human capital realized in the next generation?: The impact of mothers' intellectual human capital and long-run nutritional status on children's human capital in Guatemala*. Jere R. Behrman, Alexis Murphy, Agnes R. Quisumbing, and Kathryn Yount, 2009.

849. *Understanding Farmers' Perceptions and Adaptations to Climate Change and Variability: The Case of the Limpopo Basin, South Africa*. Glwadys Aymone Gbetibouo, 2009.

848. *Agglomeration, migration, and regional growth: A CGE analysis for Uganda*. Paul Dorosh and James Thurlow, 2009.

847. *Biosafety decisions and perceived commercial risks: The role of GM-free private standards.* Guillaume Gruère and Debdatta Sengupta, 2009.

846. *Impact of soaring food price in Ethiopia: does location matter?* John M. Ulimwenju, Sindu Workneh, and Zelekawork Paulos, 2009.

845. A*ggregate effects of imperfect tax enforcement*. Miguel Robles, 2009.

844. *Agricultural strategy development in West Africa: The false promise of participation?* Danielle Resnick and Regina Birner, 2008.

843. *Climate variability and maize yield in South Africa: Results from GME and MELE methods*. Wisdom Akpalu, Rashid M. Hassan, and Claudia Ringler, 2008.

842. *Local impacts of a global crisis: Food price transmission and poverty impacts in Ghana*. Godsway Cudjoe, Clemens Breisinger, and Xinshen Diao, 2008.

841. *Technology transfer, policies, and the role of the private sector in the global poultry revolution*. Clare A. Narrod, Carl E. Pray, and Marites Tiongco, 2008.

840. *The impact of agricultural extension and roads on poverty and consumption growth in fifteen Ethiopian villages*. Stefan Dercon, Daniel O. Gilligan, John Hoddinott, and Tassew Woldehanna, 2008.

839. *The impact of Ethiopia's Productive Safety Net Programme and its linkages*. Daniel O. Gilligan, John Hoddinott, and Alemayehu Seyoum Taffesse, 2008.

838. *Aid effectiveness and capacity development: Implications for economic growth in developing countries*. Prabuddha Sanyal and Suresh Babu, 2008.

837. *A two-dimensional measure of polarization*. Tewodaj Mogues, 2008.

836. *Higher fuel and food prices: Economic impacts and responses for Mozambique*. Channing Arndt, Rui Benfica, Nelson Maximiano, Antonio M.D. Nucifora, and James T. Thurlow, 2008

835. *Accelerating innovation with prize rewards: History and typology of technology prizes and a new contest design for innovation in African agriculture.* William A. Masters and Benoit Delbecq, 2008.

834. *Local politics, political institutions, and public resource allocation*. Nethra Palaniswamy and Nandini Krishnan, 2008.

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

www.ifpri.org

IFPRI HEADQUARTERS

2033 K Street, NW
Washington, DC 20006-1002 USA
Tel.: +1-202-862-5600
Fax: +1-202-467-4439
Email: ifpri@cgiar.org

IFPRI ADDIS ABABA

P. O. Box 5689
Addis Ababa, Ethiopia
Tel.: +251 11 6463215
Fax: +251 11 6462927
Email: ifpri-addisababa@cgiar.org

IFPRI NEW DELHI

CG Block, NASC Complex, PUSA
New Delhi 110-012 India
Tel.: 91 11 2584-6565
Fax: 91 11 2584-8008 / 2584-6572
Email: ifpri-newdelhi@cgiar.org