Agricultural policy and productivity: evidence from Brazilian censuses

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Abstract

Brazil's economic strategy has shifted hesitatingly during the last several decades from one of producer protection to trade competitiveness. Exploiting the variations these shifts have afforded, we use a sequence of decennial agricultural censuses to examine Brazilian policy implications for agricultural competitiveness and efficiency. Total factor productivity is decomposed into best-technology and efficiency elements, each subject to policy influence. We find technology growth, at 4.5% per annum, to have been extraordinarily high, particularly in the south. But because productivity among average producers has fallen rapidly behind that on the technical frontier, total productivity growth has been a much more modest 2.6% per year. Public agricultural research programs most benefit the country's technological leaders, widening the gap between frontier and average producer. Credit, education, and road construction policies instead narrow that gap. Credit and road programs especially enhance efficiency in the south, where efficiency losses have been greatest.

1. Introduction

In forging its economic development path, Brazilian governments have long balanced trade-promoting and protectionist economic policies. How these policies have affected farm productivity is central to evaluating agriculture's role in the economic development process. Brazil provides a unique example of such a role because, despite pronounced macroeconomic instability, it has emerged as an economic and agricultural powerhouse, reaching 3.6% real annual economic growth in the century's first decade, well beyond the 2.2% in the United States and other high-income countries (World Bank, 2010).[1] On the agricultural front, it was a globally top-five producer of 31 farm commodities in 2000, and of 36 commodities by 2008 (FAO, 2011).

In the present analysis we use a sequence of decennial agricultural censuses to help understand that success. In particular, we decompose Brazilian agricultural factor productivity growth into frontier technology and efficiency change and assess the policy impacts on these performance indicators. Census sequences offer substantial advantages for such an analysis. We choose the three censuses taken since Brazil's return to democracy in 1985 to focus on the consequences of its agricultural research and public infrastructure policies. We find that nationally focused agricultural research has greatly widened the productivity gap between best-practice and average producers, while regionally focused research has had little such influence. Public infrastructure and credit investments have, in contrast, narrowed the productivity gap. Technical progress in livestock production has exceeded than that in crops, but improvements among average producers have not kept pace with those on the technical frontier.

2. Brazilian development policy

Led by an emphasis on import substitution-industrialization (ISI) and export-favoring policies—aimed at boosting

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Data Appendix Available Online

A data appendix to replicate main results is available in the online version of this article. Please note: Wiley-Blackwell is not responsible for the content or functionality of any supporting information supplied by the authors. Any queries (other than missing material) should be directed to the corresponding author for the article.

[1] High-income countries here refer to the Organization for Economic Cooperation and Development's (OECD) definition.

domestic capital production and foreign currency reserves—Brazil's agriculture enjoyed rapid export-led growth in the 1970s, soybeans playing a central role (Graham et al., 1987). A looming debt crisis in the early 1980s initiated an economy-wide shift from an ISI to a liberalization strategy, one that intensified under the macroeconomic strain of the 1990s hyper-inflation (Helfand and Rezende, 2004).

A combination of the 1979 oil shock, rising international interest rates, and Mexican debt problems propelled Brazil's managed economy toward its own fiscal crisis. Rural credit contraction and minimum-support farm price programs were the primary 1980s policy levers for relieving the burden of inflation and foreign debt that, in 1979, constituted 28% of gross domestic product (GDP) (Helfand and Rezende, 2004; Schnepf et al., 2001). With the return of elected officials in 1985, policymakers looked to a variety of stabilization plans. The *Cruzado* (1986), *Bresser* (1987), and *Verao* (1989) plans, aimed at harnessing inflation, were unable to do so. The broader *Collor I* and *II* plans were introduced in 1990–1992 to stabilize prices, deregulate and modernize the economy, and facilitate trade. In a 1991 nod to international competitiveness, Brazil joined the *Southern Common Market* (Mercosul), eliminating most tariffs on Argentinean and Uruguayan imports.

Despite these steps, 1994 public debt reached 30% of GDP and annual inflation exceeded 5,000%, leading to the final *Real* plan (Oreiro and Paula, 2007; Schnepf et al., 2001). Its market-oriented reforms included a reduced state role in price, production, and trade and further contributed to agricultural modernization—particularly in pig, poultry, and dairy sectors (Helfand and Rezende, 2004).

We hypothesize that in spite of this macroeconomic instability, Brazil's public research and infrastructure policies have greatly enhanced farm technical efficiency. Judgments about efficiency depend on careful technology measurement. To this end we employ a stochastic input distance frontier approach—together with 1985, 1995/6, and 2006 microregion agricultural census data—to estimate technology growth by agricultural subsector and productive efficiency by microregion. We then gauge the influences of agricultural research and investment policies on that performance. To our knowledge, the only recent census-based evaluation of Brazilian farm productivity is Gasques et al. (2010), who rely on index number rather than econometric analysis.

3. Assessing Brazilian efficiency

Brazilian public agricultural research began in the early 19th century. By 1889 three research centers were in operation, focusing on coffee, sugarcane, and later cotton. The Department of Agriculture was re-established in 1909 and seven research institutes created in the 1920s (Ayer and Schuh, 1972; Beintema et al., 2001).

Table 1
Embrapa expenditure shares

Year	NC	RR	Thematic
Total expenditure shares			
1985	36%	41%	23%
1995	33%	41%	26%
2006	32%	41%	27%
Personnel expenditure shares			
1985	38%	46%	16%
1995	34%	44%	21%
2006	33%	43%	24%

3.1. Role of Embrapa

Although public research proliferated over the next 40 years, it was not until the 1964 military government that national emphasis was laid on farm modernization. Nonexport-crop research had until then been poorly managed, and human capital and extension investments deficient (Graham et al., 1987). Schuh and Alves (1970) note that appropriations to industrialization programs had decimated agricultural research capacity.

The national agricultural research agency, Embrapa, was created in 1973 as a cooperative arrangement between federal and state experiment stations. Its applied research model is decentralized—split among national commodity (NC), regional resource (RR), and "thematic" centers—allowing localized research in cooperation with private seed producers and farm organizations (Matthey et al., 2004). Regional-resource differs from national-commodity research in that it focuses on a state or region, biome, or climate rather than on a national-scope product. Thematic research is designed to support NC and RR work by examining such basic problems as soil conservation, satellite imagery, and genetics and biotechnology. The NC and RR centers accounted in 1985 for 77% of Embrapa's total and 84% of its personnel expenditure. These shares have slightly declined (Table 1).

By 2006, Brazil's agricultural research intensity—research expenditure per dollar of agricultural GDP—had fallen from Latin America's top to second behind Uruguay, despite more government spending on, and full-time staff for, research than in any other Latin American nation during the census periods we examine (Stads and Beintema, 2009). Embrapa accounted that year for 57% of spending in public agricultural research institutions. However, government support for it rose significantly in 2007–2009, no doubt helping it re-emerge as Latin America's leading public research entity (Beintema et al., 2010).

3.2. Rural credit

The National System of Rural Credit was created in 1965 to quicken capital formation in exportable farm products (Schnepf et al., 2001). The 1970s was a period of rapid rural credit growth—the most important lever at the time for raising short-run farm output—exacerbating inflationary pressures (Graham

et al., 1987). Real interest rates averaged -12.5% between 1970 and 1990 (Schnepf et al., 2001). Graham et al. (1987) note that the proportion of rural credit to agricultural GDP rose from 58% in 1971, peaked at an astounding 94% in 1976, and fell to 43% in 1981. By the 1990s, subsidized credit was funneled primarily to small farms, leaving larger producers to private credit sources (Mueller and Mueller, 2006). Rural credit volume declined throughout the 1980s and 1990s in the face first of international donor pressure, then stabilization efforts (Helfand and Rezende, 2004; Schnepf et al., 2001).

4. Measuring Brazilian agricultural progress

The productivity implications of these policy changes are usefully assessed in a stochastic frontier framework. Suppose $y_{jit}^o \in \mathbb{R}_+^M$, $j = 1 \ldots M$ are scalar outputs; $x_{kit} \in \mathbb{R}_+^K$, $k = 1 \ldots K$ are scalar inputs; $t = 1 \ldots S$ a technology indicator; and $i = 1 \ldots N$ a set of observations on technology $T = \{(x_{kit}, y_{jit}, t) : x_{kit} \text{ can produce } y_{jit}\} \in \mathbb{R}_+^{K+M}$. Our strategy is to characterize agricultural technology by way of its input requirement sets $L(y_{jit}^o) = \{x_{kit} \in \mathbb{R}_+^K : (y_{jit}^o, x_{kit}, t) \in T\}$, that is the inputs x_{kit} and technology T necessary to produce output set y_{jit}^o.

4.1. Input distance approach

Because deterministic input distance function

$$D_I(x_{kit}, y_{jit}, t) = \sup_\lambda \{\lambda > 0 : x_{kit}/\lambda \in L(y_{jit}^o, t)\} \quad \forall \, y_{jit} \in \mathbb{R}_+^M \tag{1}$$

can be mapped into and out of input set $L(y_{jit}^o, t)$, it is a faithful reflection of technology T. In particular if inputs are weakly disposable, Eq. (1) implies $D_I(\cdot) \geq 1$ if and only if $x_{kit} \in L(y_{jit}^o, t)$. When $D_I(\cdot) = 1$, λ obtains its minimum at unity and inputs x_{kit} are located on the boundary of the input requirement set, maximizing technical efficiency. Yet stochastic frontiers differ from their deterministic counterparts in that maximized technical efficiency is not constrained to unity. Central to releasing this restraint is to consider distance (1) as a random, negative departure from the technical frontier. Combining this error with the function's own error, and expressing them in exponential form, gives stochastic frontier (Aigner et al., 1977; Meeusen and Van den Broeck, 1977):

$$D_I(x_{kit}, y_{jit}, t; \boldsymbol{\beta}) = e^{v_{it} - u_{it}} \tag{2}$$

in which $\boldsymbol{\beta}$ is a parameter vector to be estimated; $u_{it} \sim N^+(\mu, \sigma^2)$ is a nonnegative, truncated normal error representing an observation's distance from the frontier; and $\boldsymbol{v}_{it}$ an independently and identically distributed (iid) random noise with mean zero and variance σ_v^2. Because of v_{it}'s distributional independence, $\sigma_{vu} = 0$.

Consider the exponential form $\exp[F(\ln x_{kit}, \ln y_{jit}, t; \boldsymbol{\beta})]$ of the left-hand side of (2), in which F is the technical frontier, a function of the productive inputs and outputs. Using Battese and
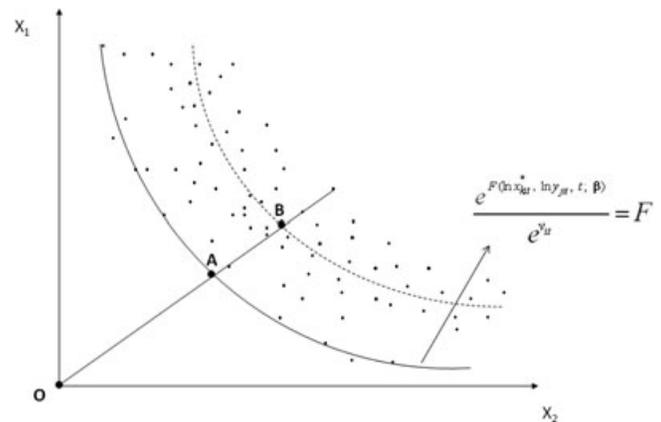

Figure 1. Assessing mean TFP from an input distance frontier.

Coelli's (1992) time-effect parameterization of the inefficiency error, $u_{it} = u_i \exp[-\eta(t - S_i)] = u_i \eta_{it}$, allows a stochastic technical-efficiency (*TE*) interpretation of the distance:[2]

$$D_{it} = e^{F(\ln x_{kit}, \ln y_{jit}, t; \boldsymbol{\beta})}/e^{v_{it}} = TE_{it} = e^{-u_i \eta_{it}}. \tag{3}$$

To impose the required linear homogeneity on (3), that is $D_I(\cdot) = \omega D_I(\cdot)$ for any $\omega > 0$ (Shephard, 1970), we let $x_{kit}^* = x_{kit}/x_{lit} \neq +\infty$, employing the lth input as numeraire (Lovell et al., 1994). Rearranging terms and taking logs brings,[3]

$$-\ln x_{lit} = F(\ln y_{jit}, \ln x_{kit}^*, t; \boldsymbol{\beta}) - v_{it} + u_i \eta_{it}. \tag{4}$$

Equation (4) allows a measure of total factor productivity (TFP) that can be decomposed into frontier productivity and technical efficiency. Fig. 1 shows the best-practice frontier F at which, along the given ray, point A employs the fewest inputs needed to produce y. Productivity at frontier point A then is

$$FP_A = \frac{y}{\overrightarrow{OA}} = e^{F(\ln x_{kit}^*, \ln y_{jit}, t; \boldsymbol{\beta})}, \tag{5}$$

namely mean output divided by inputs x_1 and x_2 represented in distance $\overrightarrow{OA}$. The average-efficiency farmer, at point B, produces the same output at higher input levels. Thus, we can write sample-mean TFP as

$$FP_B = \frac{y}{\overrightarrow{OB}} = e^{F(\ln x_{kit}^*, \ln y_{jit}, t; \boldsymbol{\beta}) - u_i \eta_{it}}. \tag{6}$$

Technical efficiency *TE* is the ratio of factor productivity at the average (FP_B) and frontier (FP_A) farm:

$$TE = \frac{FP_B}{FP_A} = \frac{\overrightarrow{OA}}{\overrightarrow{OB}} = \frac{e^{F(\cdot) - u_i \eta_{it}}}{e^{F(\ln x_{kit}^*, \ln y_{jit}, t; \boldsymbol{\beta})}} = e^{-u_i \eta_{it}}. \tag{7}$$

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[2] For computational purposes, Battese and Coelli (1992) specify random inefficiency as $u_{it} = u_i \exp[-\eta(t - S_i)]$, where S_i is a base inefficiency level and η a random parameter. In the final time period, $t = S_i$ and hence represents the reference point from which inefficiency in other periods is measured.

[3] Imposing linear homogeneity on frontier F implies substituting $1/x_{lit}$ for ω, such that $e^{F(\ln y_{jit}, \ln x_{kit}^*, t; \boldsymbol{\beta})} = 1/x_{lit} \cdot e^{F(\ln y_{jit}, \ln x_{kit}, t; \boldsymbol{\beta})}$. Noting from the text that $e^{F(\ln y_{jit}, \ln x_{kit}, t; \boldsymbol{\beta})} = e^{v_{it} - u_i \eta_{it}}$, we have $e^{F(\ln y_{jit}, \ln x_{kit}^*, t; \boldsymbol{\beta})} = e^{v_{it} - u_i \eta_{it}}/x_{lit}$. Taking logs and rearranging terms give $-\ln x_{lit} = F(\ln y_{jit}, \ln x_{kit}^*, t; \boldsymbol{\beta}) - v_{it} + u_i \eta_{it}$.

Solving for FP_B and taking logs gives

$$\ln FP_B = \ln FP_A + \ln TE = \ln FP_A - u_i \eta_{it}. \tag{8}$$

In proportional terms that is, factor productivity at the average farm is the sum of frontier productivity and average efficiency, namely frontier productivity less average inefficiency.

4.2. Econometric methods

We examine the productive efficiency impacts of three categories of Brazilian public policy: (i) infrastructure investment, proxied by road density (D) and primary school education (E); (ii) credit investment, represented by rural credit volume (C); and (iii) technology investment, represented by agricultural research stocks (R_z, $z = 1, \ldots, Z$). Roads are the primary means of reallocating physical capital and are strongly associated with general economic development in middle- and low-income nations (Calderón and Servén, 2004). Primary education correspondingly improves human capital and thus the ability to innovate. Credit provides the liquidity for exploiting those infrastructures and, in particular, for modernizing farm inputs. Agricultural research is, along with informal learning-by-doing, an important mechanism for expanding the space of input-output combinations on farms and therefore the technology frontier.

We express the log of Brazil's agricultural input distance frontier in generalized Cobb-Douglas form

$$F(\ln y_{jit}, \ln x_{kit}^*, t; \boldsymbol{\beta}) = \beta_0 + \sum_{j=1}^{M} \beta_j \ln y_{jit} + \sum_{k=1}^{K-1} \beta_k \ln x_{kit}^* + \beta_t t. \tag{9}$$

Output subscript j here successively indexes crops and livestock, and input subscript k indexes land, family labor, hired labor, and capital and materials; i indexes 558 Brazilian microregions, and t the time trend (1985, 1995/6, 2006). Because it is natural to think of input use on a per-hectare basis, land is used as the numeraire input.

Stochastic frontier models often represent fixed effects by way of inefficiency error u_{it}, a method that blends time-wise inefficiency variations with other sources of unobserved heterogeneity (Greene, 2005). We follow an alternative approach by specifying dummy variable M_h, $h = 1, \ldots, H$, to account for state-wise, time-invariant, unobserved heterogeneity and error u_{it} to account for any agricultural technical inefficiency. Rewriting the right-hand side of (9), inclusive of state dummies, as $F(M_h, \ln y_{jit}, \ln x_{kit}^*, t; \boldsymbol{\beta})$ and substituting into (4) gives[4]

$$-\ln x_{lit} = F(M_h, \ln y_{jit}, \ln x_{kit}^*, t; \boldsymbol{\beta}) - v_{it} + u_i \eta_{it}. \tag{10}$$

The Brazilian agricultural census is, as in most other countries, conducted decennially, leaving relatively few time-series sample points with which to measure technical change. That is, censuses are comparatively rich in cross-sectional and poor in time-series information. They thus are most useful for the questions and methods for which a cross-section is especially informative. A particular implication of this observation is that a small set of decennial censuses offers inadequate sample space for estimating either highly flexible functional forms or single-stage models of the factors influencing both technical change and technical efficiency. We respond to this situation in two ways. First, as indicated above, we employ the relatively restrictive generalized Cobb-Douglas functional form to specify the distance frontier.

Second, we pay special attention to policies influencing farm efficiency, variations of which can be examined just as well in cross-section as in time-series. We pursue a two-stage approach for estimating policies' farm efficiency effects: first using technology frontier (10) to estimate technical efficiencies, then a regression to gauge the policy impacts on these efficiencies.[5] Specifically, estimated error terms of technology frontier (10) provide the observation-specific mean technical efficiencies

$$E(TE_{it}) = E[e^{-u_i \eta_{it}}]. \tag{11}$$

The log of expected efficiency is then regressed against government research stocks R_{zit}, road densities D_{it}, one-period-lagged rural credit $C_{i,t-1}$, and education levels E_{it}. In as much as $\ln E(TE_{it}) = \ln TE_{it} + \varepsilon_{it}$, we have

$$\ln TE_{it} = f\left(\ln R_{zit}, \ln D_{it}, \ln C_{i,t-1}, \ln E_{it}; \delta\right) + \boldsymbol{\varepsilon}_{it}, \tag{12}$$

where $z = 1, 2, 3$ respectively represent agricultural research stocks at NC, RR, and thematic research centers; δ is the estimated parameter vector, and ε_{it} a normal error with mean zero and variance σ_ε^2.

5. Data

Sources of agricultural production and policy data are shown in Appendix Table A1. Farm-level survey data collected in Brazil's agricultural censuses are used here at two aggregation levels: microregion and state. Commodity output, arable land, and expenditures on fertilizer, feed, seed, pesticides, livestock vaccines, and electricity are microregion data. Labor, livestock, and farm machinery data employed are partly microregion and partly state-level aggregates. Infrastructure and rural credit policy data are obtained from Brazilian statistical yearbooks at the

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[4] Distance frontier estimates (10) account for agriculture's stochastic nature but may be biased to the extent inputs are endogenous. Normalizing inputs by a numeraire input generally succeeds in exogenizing them more than would normalizing through a Euclidean norm or leaving them unnormalized (Kumbhakar and Lovell 2000, p. 95).

[5] Coelli (1995) notes that one-stage productive-efficiency models have become popular because two-stage approaches are asymptotically inefficient. Buccola and McCarl (1986) introduce a third estimation stage to reduce that inefficiency in small samples. The large samples afforded by household census data render one- and three-stage approaches less compelling because second-stage estimates are consistent.

Table 2
Brazilian regions and states

Regions	States			
Northern	Rondônia	Acre	Amazonas	Roraíma
	Para	Amapá	Tocantins	Bahia
	Maranhão	Piaui	Ceará	Rio Grande do Norte
	Paraíba	Pernambuco	Alagoas	Sergipe
Southern	Minas Gerais	Espírito Santo	Rio de Janeiro	São Paulo
	Paraná	Santa Catarina	Rio Grande do Sul	Mato Grosso do Sul
	Mato Grosso	Goiás	Federal district	

Table 3
Brazilian agricultural commodities

Crops	Beans, cotton, maize, manioc, onion, groundnuts, rice, soybeans, wheat, tomato, bananas, cocoa, coffee, oranges, and sugar.
Livestock	Cattle meat, eggs, cow milk, poultry meat, and pig meat.

Table 4
Brazilian currencies

Economic plan	Currency	Period	Equivalence
	Cruzeiro (Cr$)	08/1984 to 02/1986	
Cruzado Plan I and II	Cruzado (Cz$)	02/1986 to 01/1989	Cz$1 = Cr$1,000
Verao Plan I and II	Cruzado Novo (NCz$)	01/1989 to 03/1990	NCz$1 = Cz$1,000
Collor Plan I and II	Cruzeiro (Cr$)	03/1990 to 08/1993	Cr$1 = NCz$1
Transition to *Real* Plan	Cruzeiro Real (CR$)	08/1993 to 05/1994	CR$1 = Cr$1,000
Real Plan	Real (R$)	05/1994 to Present	R$1 = CR$2,750

Source: Instituto Brasileiro de Geografia e Estatística (IBGE).

state level. Embrapa reports expenditures at each research establishment (Appendix Table A2). Our methods for imputing state-level data to the microregion level differ for each variable and are described below. Table 2 lists the 27 states involved, comprised of the 558 microregions in this study.

The strength of Brazil's agricultural census data lies in the stability of its structure across census years. With the same 20 outputs and 11 inputs, and 558 continuous observations on them across the 1985, 1995/6, and 2006 census years, it constitutes an intermittently time-aggregated panel data set. We aggregate the present study's 20 commodities into two revenue-share-weighted quantity indexes: crops and livestock (Table 3). Recorded inputs consist of agricultural land, labor, farm machinery, livestock, fertilizer, feed, seed, pesticide, animal vaccine, and electricity. As described below, some of these are quantity and others expenditure indexes. The Brazilian currency changed five times between 1984 and 1994 (see Table 4). Upon converting 1985 output and input prices to *Reais,* we use the Internal Availability General Price Index (IGP-DI)—capturing wholesale, consumer, and construction price

changes—to normalize 1985 and 1995/6 output and input prices to a 2006 basis (IBRE, 2010).

5.1. Labor

Labor inputs in the 1985 and 1995/6 censuses are from Avila and Evenson (1995) and available at the state level, while those in the 2006 census year are reported at the microregion level (IBGE, 2010). We construct two male-equivalent labor quantity indexes, one for hired and the other for family labor. The ILO-provided 1998–2002 mean Brazilian ratio of female to male wage rates is used to quality-adjust female labor to male-labor equivalents (International Labor Organization, 2010). Female agricultural labor wages were, on average, 92% of male wages during that time.

Labor counts in the 1985 and 1995/6 data are available by type (i.e., family, permanent-hired, and temporary-hired) and agricultural subsector (crop, livestock, and forestry). In interpolating labor counts to the microregion, we follow Avila and Evenson's (1995) method of weighting each labor type engaged in crop agriculture by the microregion's state share of total cropland. A similar approach is taken for each labor type in the livestock subsector except that the weight applied is the microregion's state-revenue share of livestock sold. Forestry labor weights are assumed equal in every microregion and state.[6]

We distinguish permanent and temporary from family labor, summing the former two into a hired-labor variable. Both hired and family labor are then multiplied by each state's agricultural-labor gender share to obtain the proportion of male and female laborers in that state. All labor data are then re-aggregated into male-equivalent quantity indexes using the ILO wage data. The 2006 census labor counts are available by gender and labor type at the microregion level and also are converted here to male-equivalent family and hired-labor quantity indexes.

5.2. Land

Land size is available in the censuses at the microregion level and quality differentiated into four groups: permanent cropland, temporary cropland, natural pasture, and planted pasture. Permanent croplands are those planted to perennials, and temporary croplands to annuals, forages, and flowers. Natural pastures may be partly cultivated; planted pasture may be degraded or improved. To obtain temporary-cropland-equivalent land quantities, we use Fuglie's (2010) method to estimate land weights for each land group and census period (Table 5). From those estimates, temporary cropland is assumed to be the most productive in 1985 and 2006, but perennial cropland the most productive in 1995/6. The precipitous decline in perennial cropland's weight between 1995/6 and 2006 may reflect extensification, as its planted hectares rose from 7.5 million to 11.6 million during that time.

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[6] Over the 1985–1995/6 census periods, forestry labor accounts for a very small (mean 4.1%) share of total labor.

Table 5
Estimated land weights

Land types	Years		
	1985	1995/6	2006
Permanent cropland	0.88	1.15	0.46
Temporary cropland	1.00	1.00	1.00
Artificial pastures	0.16	0.10	0.08
Natural pastures	0.03	0.04	0.05

5.3. Capital and materials

We express capital and material inputs as service expenditure indexes. Our capital service expenditure includes farm equipment and livestock, although data shortage in the 1985 census restricts the equipment measure to tractors. State-level tractor service prices are from Barros (1999). For 1985 and 1995/6 tractor service prices, Barros (1999) employs new and used 1997–98 prices of two Massey Fergusson tractor sizes, amortized over 21 years at a 7% depreciation rate and, after converting to *Reais*, deflated by the FGV's IGP-DI to a 2006 basis. Census reports on numbers of tractors-in-use are then multiplied by the corresponding service prices. Year 2006 tractor service expenditures are found by multiplying the 1995/6 annual service price by the IGP-DI conversion to 2006, then multiplying by tractors-in-use.

Livestock capital consists of on-farm stocks of bulls and steers, bovines, horses, asses, mules, pigs, goats, chickens, roosters, and hens. These data are available at the state level in 1985 and 1995/6 and the microregion level in 2006, and aggregated to bovine equivalents using Hayami and Ruttan's (1985, p. 450) cattle-normalized weights. We interpolate state bovine-equivalent animal stocks to every microregion by multiplying the state's stock by each microregion's state share of livestock sold. Bovine sale prices are available by state in 1985 and by microregion in 1995/6 and 2006. We amortize those prices over 10 years at a 10% discount rate to obtain a bovine-equivalent capital service price. Multiplying bovine-equivalent animal stocks by service price provides the livestock capital service rate.

Material service expenditures include those on fertilizer, seed, pesticides, animal vaccine, feed, and electricity. They are available at the microregion level for each census period. As with all other inputs, 1985 expenditures are converted to *Reais*, then deflated to a 2006 basis with the IGP-DI series.

5.4. Estimation strategy

Embrapa provides annual personnel expenditures (PE_{zit}) for each decentralized research unit. We then combine research unit expenditures into three research categories: national commodity-level research (NC), regional resource research, and thematic research centers (Appendix Table A2). Following Huffman and Evenson (1993) we construct an agricultural research stocks (R_{zit}) series to reflect the magnitude of research knowledge.

The process of decentralizing federal research expenditures to the NC, RR, and thematic centers did not begin until 1975. We avoid, as Evenson and Alves (1998) do, including a depreciation component in the research-stock lag structure. Rather, a geometric lag is assumed in which research's productivity impacts begin 10 years before the present, then rise geometrically:

$$R_{zit} = 0.000978(PE_{zi,t-1}) + 0.001955(PE_{zi,t-2})$$
$$+ 0.00391(PE_{zi,t-3}) + 0.00782(PE_{zi,t-4})$$
$$+ 0.01564(PE_{zi,t-5}) + 0.03128(PE_{zi,t-6}) \quad (13)$$
$$+ 0.06256(PE_{zi,t-7}) + 0.12512(PE_{zi,t-8})$$
$$+ 0.25024(PE_{zi,t-9}) + 0.50048(PE_{zi,t-10}).$$

Because national commodity centers focus on given farm products, and thematic centers on issues such as agro-biology and biotechnology that are potentially applicable to any producer, we assign NC and thematic expenditures to each microregion. Equation (13) is then used to compute the microregion's research stocks. Regional-resource research is, in contrast, generally constrained to particular states, biomes, or climates (Appendix Table A2). Research department expenditures with a state-wide focus are assigned to each microregion in that state. Uniquely, we employ geographic information systems (GIS) to assign expenditures of biome- or climate-focused centers to each microregion in which the centroid of observation lies within the biome or climate.

Rural credit is provided in annual statistical yearbooks by total value and number of credit contracts. Between 1995/6 and 2006, the aggregation at which rural credit contracts are recorded was changed: state-level credit data are available for the 1985 and 1995/6 censuses, but only national-level data for the 2006 census. We lag total credit per contract one year under the assumption that credit's production effects are noninstantaneous. For the first two census periods, a state's microregions are each assigned the state's credit-per-contract volumes; for the 2006 contract period, every microregion is assigned the national total per-contract volume. State-level road densities are measured as total kilometers of unpaved roads, expressed as a proportion of the state's geographic area (km^2), and assigned equally to each microregion in the state. State-level education is proxied by the number of primary schools per 1,000 persons, and assigned equally to each microregion.

Every Brazilian government since the 1964 military regime has emphasized the improvement of agricultural competitiveness. It seems reasonable, therefore, to focus on the productive efficiency only of farms that appear to have competitive potential. A number of factors, including urban and industry expansion and the recent growth of rural tourism, induce Brazilian farmers to exit agriculture. We dropped 13 microregions that seem, from a comparison of 2006 with 1985 production levels, to be leaving agriculture. An additional six were dropped on account of missing data.

Table 6
Brazilian annual technical progress, efficiency change, and TFP growth

	National	By region	
	Brazil	North	South
Crop technical progress	2.88%	3.41%	3.62%
Livestock technical progress	7.50%	5.81%	7.25%
Aggregate technical progress (ε_{Ft})	4.54%	4.26%	4.92%
Efficiency change (ε_{Et})	−1.92%	−2.30%	−3.63%
TFP growth rate ($\varepsilon_{TFP,t}$)	2.62%	1.96%	1.29%

Table 7
Determinants of Brazilian agricultural productive efficiency

Dep. Var.: TE	National	Regional	
	Brazil	Northern	Southern
NC ($\varepsilon_{ER_{nc}}$)	−0.213***	−0.283***	−0.340***
RR ($\varepsilon_{ER_{rr}}$)	−0.003***	−0.003	−0.004***
Road	0.076***	0.072***	0.129***
Rural Credit	0.063***	0.063***	0.170***
Schooling	0.101***	0.149***	0.105***
Constant	3.225***	4.515***	4.273***
Adj. R^2	0.405	0.429	0.706
N	1617	735	882

Note: All variables are in log form. *** Indicates statistical significance at the 1%-level.

Although this study emphasizes nationwide farm productivity, a national measure can mask regional variations, especially in large economies (Ball et al., 2004; Fan and Pardey, 1997; Fan and Zhang, 2002). Graham et al., (1987) argue in particular that regional disparities between the Brazilian north and south have been rooted in a policy bias toward the south. We, therefore, complement our national analysis by taking a regional perspective as well. Evenson and Alves (1998) note a significant north-south difference in soil quality, rainfall, temperature, and per capita income. Dillon and Scandizzo (1978), Finan and Nelson (2001), and Sietz et al. (2006) depict the Brazilian northeast as supporting predominately smallholder, rainfed and mixed cropping, and livestock ranching subject to frequent droughts. The south, in contrast, has been the epicenter of commercial crop and livestock production on account of its fertile soils, abundant water, and transportation infrastructure (Graham et al., 1987; Matthey et al., 2004). States we judge to comprise the northern and southern regions are listed in Table 2.[7]

6. Results

Models (10) and (12) were estimated with STATA 11. Our national and regional technology estimates—Eq. (10)—are provided in Appendix Tables A3–A5, the corresponding technology and efficiency change rates in Table 6, and estimates of efficiency determinants in Table 7. All distance frontier estimates exhibited monotonic technology. The Cobb-Douglas functional form maintains technology convexity.

A potential concern in estimating Eq. (10) is that we were forced to weight temporary and permanent labor equally in the hired-labor count construction. That concern was relieved by the high pair-wise correlation (0.83 in southern Brazil) between family and hired labor, obviating the need to specify both family and hired labor.[8] Because the number of male-equivalent family

labor units exceeded the corresponding number of hired labor units by a factor of three during the sample period, the family-labor variable was retained.

Research stocks at Brazil's thematic research centers have been nearly perfectly correlated (0.99) with national-commodity research stocks. Because, as mentioned above, thematic research centers support NC and RR research in areas such as soil conservation and biotechnology, thematic research effort was eliminated from the model. No pairwise correlation between efficiency determinants in Eq. (12) exceeded 0.51.

6.1. Technology, efficiency, and productivity

As Table 6 shows, mean annual Brazilian technical improvement in the livestock sector has been a very high 7.5%, far outstripping the 2.9% in the crop sector.[9] Weighting the two sectors by their mean share of agricultural revenue gives an aggregate national rate of technical improvement (ε_{Ft}) of 4.54% per annum. Producers did not share equally in that improvement because, as the aggregate annual efficiency change (ε_{Et}) in Table 6 indicates, the mean farmer has been falling further behind the technical frontier at the rate of 1.92% per annum. Combining technical change with mean efficiency change gives a 2.62% total factor productivity growth rate ($\varepsilon_{TFP,t}$) in Brazilian agriculture during the 1985–2006 period. Our national TFP growth estimate is close to Gasques et al. (2010), whose index-number approach yields a 2.87% TFP growth rate between 1985 and 2006.

The regional productivity estimates, highlighted also in Table 6, are revealing. Technical growth in the southern livestock and crop subsectors has been only moderately greater than in the north. At 3.62% per annum, crop technical shift in the south only slightly outpaced the 3.41% in the north; and the south's 7.25% annual livestock technical shift somewhat outpaced the north's 5.81%. Overall, the 4.92% annual

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[7] A reviewer argues that the internal diversities in the Brazilian North and South render them unsuitable as a basis for stratification when computing productivity and efficiency measures, exacerbating unobserved heterogeneity problems in our model. However, unobserved heterogeneity does not appear to be a serious issue, as dividing the data by Brazilian biome rather than political boundary provides aggregate productivity measures very similar to those in the present article.

[8] Including family labor does not change the national TFP estimate by more than 0.07 percentage points.

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[9] Given that recorded production data are decennial, we assume linear annual growth across a given decade. Thus, for example, the annual 2.88% rate of crop technical change in Table 6 corresponds to 28.81% per decade during the 1985–2006 period.

technical improvement in the more commercial south was 0.66% higher than in the mixed-crop-oriented north. The south's superior technology growth rate is remarkable, given that the mean value of its output—in reference to which percent growth is computed—has been four times greater than in the north.

But farm efficiency changes, namely trends in the gap between mean farm performance and a rapidly expanding frontier, have worked in the opposite direction. Technical efficiency fell at an annual 3.6% rate in the south—1.3% higher than in the north. Consequently, the north's total factor productivity rose 1.96% per annum, more than a half-point greater than the south's 1.29%. It is interesting that 1985 and 2006 mean efficiency *levels* in the north were, on a zero-one scale, 0.94 and 0.59, somewhat greater than the south's 0.82 and 0.40. That is consistent with the north's typically less-advanced production systems because a simpler technology ought, for the average farmer, to be financially and managerially easier to achieve than is a more complex one.

6.2. Efficiency determinants

Agricultural research effort typically is used as a determinant in technology growth models because research innovations expand production possibilities. But including it as a technology *efficiency* determinant can be just as useful, allowing us to depict the distribution of research benefits between the frontier and mean farm. In particular, any negative coefficients on research stocks in Eq. (12) imply that research effort expands frontier productive opportunity more than it expands mean farm performance. Research would in that case be widening the disparities among farm performances and thus reducing mean-farm efficiency as measured against the best-practice frontier.

6.2.1. Research policy

The model (12) estimates in Table 7 reveal this very phenomenon. They show in particular that a 1% rise in national-commodity research stocks has, while presumably benefitting both average and frontier farmers, pushed best-practice technology 0.21% further ahead of the mean producer. Relative to the frontier, that is, commodity research has impaired mean farm efficiency at the rate of $\partial \ln TE / \partial \ln R = \varepsilon_{ER} = -0.21\%$, widening the disparities among farm performances. Reasonably, that would have occurred only if commodity research programs had been designed for, or promulgated most energetically to, producers with the human and physical resources necessary to operate near the technical frontier.

This research-induced efficiency deterioration qualitatively mirrors the average *time*-induced farm efficiency deterioration shown in Table 6. Indeed, because the Table 6 estimates imply a trade-off between frontier and efficiency change in the average census year and hence for the average *source* of such tradeoffs, they can be used to draw approximate imputations for public

research's influence on frontier ε_{FR} and thus on TFP growth $\varepsilon_{TFP,R}$. In particular if $\varepsilon_{FR} / \varepsilon_{ER} \approx \varepsilon_{Ft} / \varepsilon_{Et}$, that is if, relative to their efficiency effects, the frontier shift induced by a 1% research expansion is the same as induced by a 1% expansion of the average piece of innovation-relevant information, we can approximate $\varepsilon_{TFP,R}$ by (Appendix B)

$$\varepsilon_{TFP,R} = \varepsilon_{ER} \left[\frac{\varepsilon_{Ft}}{\varepsilon_{Et}} + 1 \right]. \tag{14}$$

Under proportionality assumption $\varepsilon_{FR} \approx \varepsilon_{ER} \cdot [\varepsilon_{Ft} / \varepsilon_{Et}]$, a 1% boost in national commodity research stock has been associated with an approximately $(-0.21)(4.54/-1.92) = 0.50\%$ rise in the technical frontier. From (14), the corresponding rise in average-farm or Brazilian total factor productivity has been 0.29%. National commodity research under such reasoning likely has enhanced mean factor productivity even as it has heightened the productivity differences among individual microregions.

Table 7 shows that programs at regional resource (RR) centers have, however, not affected farm efficiency much at all. A 1% rise in RR stocks has impaired mean efficiency by a negligible (although statistically significant) 0.003%, implying such stocks have benefited the average as much as the frontier farmer. On the other hand, if Brazilian farmers have faced the same frontier/efficiency trade-offs in the presence of a fixed stock of RR research as they have in the presence of the average innovation source, then these resource centers have had little effect on TFP also. In particular, total factor productivity's elasticity with respect to RR research stocks would be only $(-0.003)(4.54/-1.92) = 0.01\%$.

Regional estimates of model (12) provide a picture of how policy impacts might have differed between the more commercial south and mixed-cropping north. Mirroring results from the national model, national-commodity research in both the northern and southern regions has improved productivity while exacerbating the performance spread between average and frontier farms. A 1% boost in commodity-oriented research pushes the technical frontier 0.28% further away from the mean northern producer and 0.34% away from the mean southern producer. The implication is that while commodity research has aided frontier producers more than it has average ones, the relative advantage to frontier operators has been no greater in the south than in the north. Similarly, regional-resource research in both the north and south has shared in the nonsignificant efficiency effects we observe at the national level.

6.2.2. Infrastructure & credit policy

In proportional terms, primary school education has had the greatest positive efficiency impact of any policy strategy examined. Every 1% expansion of the per capita number of schools has boosted national agricultural efficiency by 0.10%. Those effects have been greater in the north (0.15%) than in the south (0.10%). By comparison, unit percentage expansions in road density have brought only a 0.07%, and rural

credit a 0.06%, efficiency improvement. Infrastructure effects in northern Brazil mirror these national averages. However, road-density and rural-credit impacts on farm efficiency in the south are substantially higher than in the north. Indeed rural credit has in the south the strongest—and schooling the weakest—pro-efficiency effect of any of the three policy strategies. Expanding southern rural credit by 1% improves farm efficiency by 0.17%, the highest elasticity we encountered.

While a government-sponsored research program can influence the productivity of either ordinary or leading-edge farm managers—for example by focusing on simple agronomic improvements rather than engineered plant characteristics requiring close horticultural management—infrastructure policies such as school and road construction are inherently average-household oriented. Road networks and primary education affect dimensions of physical and human capital common to everyone, so their presumably positive influence on envelope technologies must be diffuse, lagged, and hard to measure. Our estimates here of infrastructures' positive effects on average efficiency should therefore be regarded as the lower bound of their effects on eventual mean productivity.

7. Conclusions

The Brazilian government's transition to a more liberalized development strategy offers important lessons about policies' implications for frontier and average agricultural performance and for the productivity gap separating them. Among the policies in which government has invested, commodity research has had the largest measured effect, broadening the productivity gap but likely enhancing total factor productivity. Education, transportation, and credit infrastructure have narrowed that gap although their diffuse nature allows one to demonstrate only a modest narrowing. For average farms to keep pace with frontier ones, substantially greater infrastructure and credit investments are required. Indeed, improved targeting of these investments may be just as important as any rise in their magnitude. In Brazil's south, for example, farm efficiency would benefit more from new transportation infrastructure and rural credit than it would from new education investments. Efficiency in the north would, in contrast, benefit more from school expansion. That may partly be because of the north's presently low literacy rates.[10]

Much of the attention paid in the literature to Brazilian agriculture is to its crop technology advances. But it is the livestock technology frontier that has expanded more quickly. Best-practice livestock possibilities likely have benefited from the liberalization reforms that have improved the competitiveness of the pig, poultry, and dairy sectors (Helfand and Rezende, 2004). The greater aggregate technology expansion in the south has led, by comparison, to greater inter-farm produc-

tivity dispersion and lower mean productivity growth, echoing the relation between growth and inequality voiced by Kuznets (1955).

Appendix A. Data and estimates

Table A1
Data sources

Series	Level of aggregation	Source
Commodity production	Microregion	IBGE
Agricultural land use	Microregion	IBGE
Persons employed primarily in agriculture	State & Microregion	Avila and Evenson (1995) & IBGE
Tractors in use	Microregion	IBGE
Livestock capital	Microregion	IBGE
Fertilizer expenditures	Microregion	IBGE
Pesticide expenditures	Microregion	IBGE
Feed expenditures	Microregion	IBGE
Seed expenditures	Microregion	IBGE
Livestock vaccine expenditures	Microregion	IBGE
Electricity expenditures	Microregion	IBGE
Tractor service prices	State	Barros (1999)
Farm animal prices	State & microregion	IBGE
Farm level commodity prices	Microregion	IBGE
Public agricultural R&D expenditures	Research establishment	Embrapa, personal communication (2011)
Rural credit	State	Annual Statistical Yearbooks[c]
Total primary schools per capita	State	Annual Statistical Yearbooks[a]
Road density (km/area)	State	Annual Statistical Yearbooks[b]

[a]1987–88, 1997, and 2007 Statistical Yearbooks.
[b]1985, 1986, 1990, 1995, 1997, 2006, and 2008 Statistical Yearbooks.
[c]1987–88, 1992, 1997, and 2007 Statistical Yearbooks.

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[10] 2008 mean illiteracy rates in the north (13.7%) were much greater than in the south (5.9%) (AEB, 2009).

Table A2
Embrapa research centers

Embrapa centers	Decentralized units		Unit focus
National commodity centers	CNPSO	Embrapa soy	National
	CNPA	Embrapa cotton	National
	CNPGL	Embrapa dairy cattle	National
	CNPGC	Embrapa beef cattle	National
	CNPMF	Embrapa manioc and fruit	National
	CNPMS	Embrapa corn and sorghum	National
	CNPSA	Embrapa pig and poultry	National
	CNPAF	Embrapa rice and beans	National
	CNPH	Embrapa horticulture	National
	CNPT	Embrapa wheat	National
Regional resource centers	CPAMN[a]	Embrapa middle-north	Piauí and Maranhão
	CPATSA	Embrapa tropical semiarid	Caatinga biome
	CPATC	Embrapa coastal tablelands	Ceará, Rio Grande do Norte, Paraíba, Pernambuco, Alagoas, Sergípe, and Bahia
	CPAP	Embrapa pantanal (marshlands)	Pantanal biome
	CPACT[b]	Embrapa temperate climate	Temperate climate
	CPAO[c]	Embrapa west	Paraná, Mato Grosso do Sul, Mato Grosso
	CPAC	Embrapa cerrados (Savannahs)	Cerrados biome
	CPPSE	Embrapa southeast livestock	Minas Gerais, Espírito Santo, Rio de Janeiro, and São Paulo
	CPPSUL	Embrapa south livestock	Paraná, Santa Catarina, Rio Grande do Sul
	CPAF-AC	Embrapa acre	Acre
	CPAF-RO	Embrapa Rondônia	Rondônia
	CPAF-RR	Embrapa Roraima	Roraima
	CPAF-AP	Embrapa Amapá	Amapá
	CPAA	Embrapa western Amazon	Amazonas
	CPATU	Embrapa eastern Amazon	Pará
Thematic centers	CNPS[d]	Embrapa soils	National
	CNPAB	Embrapa agro-biology	National
	CNPMA	Embrapa environmental	National
	CENARGEN	Embrapa genetic resources and biotechnology	National
	TechTransfer[e]	Embrapa technology transfer	National

Table A2
Continued

Embrapa centers	Decentralized units		Unit focus
	CNPDIA	Embrapa agricultural instrumentation	National
	CNPM	Embrapa satellite monitoring	National
	CNPTIA	Embrapa agricultural information	National
	CTAA	Embrapa agro-industrial food technology	National
	CNPAT	Embrapa tropical agro-industry	National

[a]CPAMN expenditures include UEPAE Teresina expenditures from 1974 to 1992.
[b]CPACT expenditures include CNPFT and CPATB expenditures from 1974 to 1992.
[c]CPAO expenditures include Uep-MT expenditures.
[d]CNPS expenditures include Uep Recife expenditures.
[e]TechTransfer expenditures include SNT and SCT expenditures.

Table A3
National-level distance (technology) frontier parameters

Dep. Var.: -Land	Coefficients	Standard error	Z	P > |Z|
t	0.0414873	0.0023787	17.44	0
Livestock	−0.0552626	0.0103686	−5.33	0
Crops	−0.144028	0.0072123	−19.97	0
Family labor	0.135269	0.0108102	12.51	0
Capital & materials	0.2352767	0.0124002	18.97	0
Rondônia	−0.0361817	0.0583754	−0.62	0.535
Acre	0.0220506	0.070803	0.31	0.755
Amazonas	0.1813674	0.0487384	3.72	0
Roraima	−0.1409069	0.0749873	−1.88	0.06
Para	0.0469247	0.0323922	1.45	0.147
Amapa	0.1480658	0.0791537	1.87	0.061
Tocantins	−0.016636	0.0520776	−0.32	0.749
Maranhão	0.1194625	0.0323072	3.7	0
Piauí	0.0310568	0.0366808	0.85	0.397
Ceará	0.0943866	0.0237729	3.97	0
Rio Grande do Norte	0.0591605	0.0311202	1.9	0.057
Paraiba	0.0806764	0.0282457	2.86	0.004
Pernambuco	0.0268908	0.0368521	0.73	0.466
Alagoas	−0.0114314	0.0399014	−0.29	0.775
Sergípe	−0.0559679	0.0395234	−1.42	0.157
Bahia	−0.0339284	0.0267066	−1.27	0.204
Minas Gerais	0.0159579	0.0192074	0.83	0.406
Espírito Santo	−0.0573202	0.0389124	−1.47	0.141
Rio de Janeiro	0.0929519	0.0327001	2.84	0.004
São Paulo	0.0625117	0.0209637	2.98	0.003
Parana	0.0463187	0.024587	1.88	0.06
Santa Catarina	−0.0212219	0.032422	−0.65	0.513
Rio Grande do Sul	−0.0126058	0.0280178	−0.45	0.653
Mato Grosso do Sul	0.0706086	0.0437481	1.61	0.107
Mato Grosso	0.026365	0.0347969	0.76	0.449
Goiás	0.0596324	0.0351847	1.69	0.09
Federal district	0.0561749	0.1555487	0.36	0.718
/mu	−0.242737	0.577148	−0.42	0.674
/eta	−0.0971649	0.0040501	−23.99	0

Table A3
Continued

Dep. Var.: -Land	Coefficients	Standard error	Z	P > |Z|
/lnsigma2	−0.5238277	0.4296355	−1.22	0.223
/ilgtgamma	3.000539	0.4350897	6.9	0
Sigma2	0.5922493	0.2544513		
Gamma	0.9525985	0.0196463		
Sigma_u2	0.5641757	0.2539607		
Sigma_v2	0.0280735	0.0013479		

Note: The model's log likelihood: 97.72; number of observations = 1,617. All production output and input variables except *t* are logged.

Table A4
Northern distance (technology) frontier parameters

Dep. Var.: -Land	Coefficients	Standard error	Z	P > |Z|
t	0.0459276	0.0035489	12.94	0
Livestock	−0.07911	0.0179251	−4.41	0
Crops	−0.1348272	0.0140415	−9.6	0
Family labor	0.1636855	0.0179689	9.11	0
Capital & materials	0.2922746	0.0210033	13.92	0
Rondônia	−0.0619692	0.0622412	−1	0.319
Acre	0.0118963	0.0730975	0.16	0.871
Amazonas	0.1431808	0.0519366	2.76	0.006
Roraima	−0.1471046	0.0793973	−1.85	0.064
Para	0.0244586	0.0355186	0.69	0.491
Amapa	0.0881847	0.0823824	1.07	0.284
Tocantins	−0.0284176	0.0560015	−0.51	0.612
Maranhão	0.0932357	0.0352467	2.65	0.008
Piauí	−0.0006166	0.0397583	−0.02	0.988
Ceará	0.0763581	0.0265198	2.88	0.004
Rio Grande do Norte	0.048042	0.0342775	1.4	0.161
Paraiba	0.0656565	0.030862	2.13	0.033
Pernambuco	0.0219454	0.0394252	0.56	0.578
Alagoas	−0.0149701	0.0433732	−0.35	0.73
Sergípe	−0.0646852	0.0428959	−1.51	0.132
Bahia	−0.0542761	0.0301411	−1.8	0.072
/mu	0.0320298	0.5171099	0.06	0.951
/eta	−0.1082521	0.0068702	−15.76	0
/lnsigma2	−0.5225577	0.4411413	−1.18	0.236
/ilgtgamma	2.866514	0.4548991	6.3	0
Sigma2	0.5930019	0.2615976		
Gamma	0.9461661	0.0231707		
Sigma_u2	0.5610782	0.2611019		
Sigma_v2	0.0319236	0.0021603		

Note: The model's log likelihood: −13.54; number of observations = 735. All production output and input variables except *t* are logged.

Table A5
Southern distance (technology) frontier parameters

Dep. Var.: -Land	Coefficients	Standard Error	Z	P > |Z|
t	0.0606387	0.0038148	15.9	0
Livestock	−0.0836522	0.0119978	−6.97	0
Crops	−0.1676636	0.0085866	−19.53	0
Family labor	0.109254	0.0128364	8.51	0
Capital & materials	0.1821401	0.0146371	12.44	0
Minas Gerais	0.1309768	0.032469	4.03	0
Espírito Santo	0.046278	0.0469615	0.99	0.324
Rio de Janeiro	0.1861043	0.0427864	4.35	0
São Paulo	0.1411202	0.033596	4.2	0

Table A5
Continued

Dep. Var.: -Land	Coefficients	Standard Error	Z	P > |Z|
Parana	0.16066	0.0339056	4.74	0
Santa Catarina	0.1090492	0.0415643	2.62	0.009
Rio Grande do Sul	0.1159032	0.0374952	3.09	0.002
Mato Grosso do Sul	0.1715614	0.0500478	3.43	0.001
Mato Grosso	0.1154483	0.0441733	2.61	0.009
Goiás	0.169128	0.0432321	3.91	0
Federal District	0.1756773	0.1409262	1.25	0.213
/mu	0.973265	0.0997064	9.76	0
/eta	−0.0757849	0.0038171	−19.85	0
/lnsigma2	−1.947924	0.0937097	−20.79	0
/ilgtgamma	1.779412	0.1336491	13.31	0
Sigma2	0.1425697	0.0133602		
Gamma	0.8556242	0.0165099		
Sigma_u2	0.1219861	0.0134901		
Sigma_v2	0.0205836	0.0012403		

Note: The model's log likelihood: 152.65; number of observations = 882. All production output and input variables except *t* are logged.

Appendix B. Approximate TFP elasticity of domestic public research

As shown in Eq. (2)–(8), innovation generally affects both the isoquant frontier and the mean farmer's divergence from the frontier. Differentiating (8) with respect to time—noting that total factor productivity refers to mean-farm performance, and letting frontier productivity be $FP_A = F$—serves to decompose sample-mean TFP change into a frontier effect and efficiency effect:

$$\frac{d\ln TFP}{dt} = \frac{d\ln F}{dt} + \frac{d\ln TE}{dt} \tag{B.1}$$

The factors affecting frontier productivity and mean efficiency can be regarded as arising from either formal research programs or informal sources, holding all noninnovation factors (e.g., infrastructure) constant:

$$\ln F = F[\ln R(t), \ln I(t)] \tag{B.2}$$

$$\ln TE = TE[\ln R(t), \ln I(t)] \tag{B.3}$$

where *R* are domestic public research stocks, and *I* are informal information sources such as from the private-sector and word-of-mouth. These expressions can be used to ascribe a time rate of change to a combination of public-research effect and informal-information effect. Differentiating (B.2) and (B.3) with respect to time *t*:

$$\frac{d\ln F}{dt} = \frac{\partial \ln F}{\partial \ln R}\frac{d\ln R}{dt} + \frac{\partial \ln F}{\partial \ln I}\frac{d\ln I}{dt}, \tag{B.4}$$

$$\frac{d\ln TE}{dt} = \frac{\partial \ln TE}{\partial \ln R}\frac{d\ln R}{dt} + \frac{\partial \ln TE}{\partial \ln I}\frac{d\ln I}{dt}. \tag{B.5}$$

Equations (B.4) and (B.5) show what would be obtained if F and TE were each regressed against the time trend while allowing other factors (i.e., inputs, outputs, and infrastructure policies) to vary. That is, they provide a schematic picture of the time-wise changes in information factors accounting for technical and efficiency change. Substituting (B.4) and (B.5) into (B.1) allows reasonable surmises about formal research's effects on mean and frontier productivity, even when—as in the present study—data are inadequate for direct estimates of those effects.

In particular, expressing (B.4) and (B.5) in elasticity symbols, we have

$$\varepsilon_{Ft} = \varepsilon_{FR}\varepsilon_{Rt} + \varepsilon_{FI}\varepsilon_{It} \qquad (B.6)$$

$$\varepsilon_{Et} = \varepsilon_{ER}\varepsilon_{Rt} + \varepsilon_{EI}\varepsilon_{It} \qquad (B.7)$$

where the E subscript refers to technical efficiency TE. Our dataset provides—in conjunction with Eq. (10) and (12) from the text—estimates of ε_{Ft} and ε_{Et} (Table 6) and ε_{ER} (Table 7), but not ε_{FR}. But observe that

$$\frac{\varepsilon_{FR}}{\varepsilon_{ER}} = \left.\frac{\partial \ln F}{\partial \ln E}\right|_{R^0} \text{ and } \frac{\varepsilon_{FI}}{\varepsilon_{EI}} = \left.\frac{\partial \ln F}{\partial \ln E}\right|_{I^0}. \qquad (B.8)$$

Now suppose

$$\left.\frac{\partial \ln F}{\partial \ln E}\right|_{R^0} \approx \left.\frac{\partial \ln F}{\partial \ln E}\right|_{I^0}. \qquad (B.9)$$

That is, suppose the proportional trade-off between frontier performance and efficiency afforded by a given public research stock R is approximated by the trade-off afforded by given levels of other innovation-relevant information I. Given (B.9), we can then write

$$\varepsilon_{FR}/\varepsilon_{ER} \approx \varepsilon_{FI}/\varepsilon_{EI} \qquad (B.10)$$

so that, from (B.6) and (B.7),

$$\varepsilon_{FR}/\varepsilon_{ER} \approx \varepsilon_{Ft}/\varepsilon_{Et}. \qquad (B.11)$$

However, analogously to (B.1), we can characterize public research stock's influence on total factor productivity growth ($\varepsilon_{TFP,R}$) as

$$\varepsilon_{TFP,R} = \varepsilon_{FR} + \varepsilon_{ER}, \qquad (B.12)$$

Solving (B.11) for ε_{FR} and substituting into (B.12) gives

$$\varepsilon_{TFP,R} = \varepsilon_{ER}\left[\frac{\varepsilon_{Ft}}{\varepsilon_{Et}} + 1\right], \qquad (B.13)$$

estimates of whose the right-hand-side elements are provided in Tables 6 and 7.

Diagrammatically, then, conditions (B.9) and thus (B.13) occur when the slope on the locus of frontier/efficiency combinations offered by the sample-mean research stock is, expressed in proportional changes, equal to the slope on the frontier/efficiency combinations offered by the average of all other innovation-relevant information. Expressed still another way, it occurs when the *ceteris paribus* frontier shift induced, at the sample mean, by a 1% research stock expansion bears the same proportion to the *ceteris paribus* efficiency shift induced by that expansion as it does when the sum of all other innovation-relevant information—rather than formal research alone–is rising. Public information's relevance for frontier-efficiency trade-offs is, in other words, assumed typical of other information's relevance.

That relationship, of course, need not hold in reality. Yet two arguments work in its favor. The first argument has a Taylor-series rationale: equation (B.11) and thus (B.13) constitute a first-order approximation of formal research's impact on the technical frontier because its proportional relationship to its efficiency effects corresponds to the mean proportional impact of all innovation-relevant information. The second argument appeals to the factors affecting technology rates. In a statistical context that corresponds to a situation in which the frontier/efficiency trade-off afforded by the given research stock is approximated by the trade-off afforded by the average of all other innovation-relevant information. By (B.9), formal research's comparative accessibility to the mean and the frontier farmer then is the same as informal information's comparative accessibility to those same farmers. This is a rather weak restriction. It requires only that a farmer's comparative willingness to employ new information is a function principally of her openness to information novelty itself.

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