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Abstract

Brazil ranks among the world's top four agricultural producers and exporters, and continued growth is important for domestic and global food security. Sustained productivity growth is essential to support this expansion. This study estimates a stochastic frontier production function and calculates total factor productivity (TFP) growth in Brazilian agriculture. TFP is decomposed into components related to technology, weather (growing degree days), policy variables, and other factors. The analysis uses municipal Agricultural Census data from 1985 to 2017. TFP increased at 1.56% per year, accounting for 60% of output growth. The decomposition highlights the slowing effect of climatic factors, alongside the accelerating influence of investments in R&D and education. A key finding is the pronounced divergence in outcomes across many dimensions. Output and TFP growth were fastest in the Cerrado biome, characterized by large farms, and slowest in the Caatinga. Output became increasingly concentrated in a small number of municipalities, which tended to exhibit faster TFP growth and specialization in annual crops such as soybeans. Conversely, about one-third of municipalities experienced decline in output and TFP. The findings have significant policy implications for addressing climate change, guiding investments in R&D, and managing the growing divergence of outcomes.

Keywords: Total Factor Productivity, Climate Change, Agriculture, R&D, Brazil.

JEL Codes: Q10, Q16, Q54, O13.

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1. Introduction

Studying agricultural productivity growth in Brazil is of considerable importance for both Brazil and the international community. Brazil is among the top four agricultural producers and exporters in the world (FAO, 2021) and continued growth of its production—largely driven by productivity growth—can have a significant impact on domestic and international food security. Generating income for a large share of agricultural producers, and contributing to maintaining food prices low, are also essential elements of a poverty reduction strategy for the country. Another important role for the agricultural sector relates to the generation of foreign exchange, which can be critical for economic development. In the first two decades of the twenty first century, agrifood exports in Brazil rose from 23% to 37% of total exports, thus underscoring the sector's relevance. The agricultural sector was also responsible for over 40% of the country's greenhouse gas emissions (GHG) around 2021—due to deforestation of the Amazon, extensive cattle production, fertilizer use, and other sources—bestowing upon it a potentially important role in the fight against global warming.[1] Recognizing the agricultural sector's broad economic, social and environmental importance, the main objective of this paper is to investigate the determinants of agricultural productivity growth in Brazil. Among the determinants that we prioritize, we seek to understand the extent to which climate change presents an obstacle to growth and to identify the policy levers, including education and agricultural R&D, that can contribute to a sustained high rate of productivity growth.

Research on TFP growth in Brazilian agriculture is rich in some ways and lacking in others. There are many papers on TFP growth at the national level since the 1970s. Gasques and co-authors, for example, have produced numerous studies that estimate TFP growth for Brazil and its states using a Törnqvist index number approach. Few studies, however, utilize econometric techniques with rich panel data that permit going beneath the state level and estimating inefficiency. One example is Rada et al. (2019) who estimated TFP growth with municipal data for different farm size groups, but their study ends in 2006. Another is Spolador and Danelon (2024) who used microregional data for the period 1996-2017, but only focused on crop output. We seek to fill this gap by providing a novel analysis of TFP growth based on municipal data from over 30 years. Relative to previous econometric studies, we include all of agricultural output, use highly disaggregated data, and cover a longer period. The extended time frame is especially important for studying the effects of climate change.

[1] The trade and GHG data come from OECD (2023).

The paper estimates a stochastic frontier production function to calculate total factor productivity (TFP) growth using municipal data drawn from four waves of the Agricultural Census for the period 1985 to 2017. We then decompose TFP growth following O'Donnell (2018) and several other papers. Our decomposition first shows the relative importance of the growth of inputs and TFP in explaining output growth. It then decomposes TFP growth into components related to a) unobserved heterogeneity, b) technology, c) weather, d) scale, e) policy (education and agricultural R&D), f) technical efficiency, and g) statistical noise. The results provide a novel description of TFP growth between 1985 and 2017 and have important implications for public policy. Key findings highlight the significant role of extreme heat in slowing TFP growth during this period, alongside the positive impact of investments in education and public agricultural R&D in promoting it. Another important finding relates to heterogeneity. We document a strong divergence of productivity growth across biomes, scale of municipal output, and types of specialization, and show how a small share of municipalities has been responsible for an increasing share of output and TFP growth.

The paper is organized as follows. Section 2 reviews key agricultural policies and the literature on TFP growth in Brazil. Section 3 describes the methodology, while Section 4 defines the study variables and presents descriptive statistics. Section 5 reports the econometric results and the decomposition of TFP over time, examining heterogeneity by biome, scale, and rate of TFP growth. This section also provides a detailed description of municipal characteristics and their variation across these dimensions. Section 6 extends the analysis with a TFP transition matrix, enabling an examination of TFP levels in 1985 and 2017, and transitions across quintiles, offering further evidence of TFP divergence. It concludes with a discussion of municipalities exhibiting strongly divergent dynamics at the bottom and top of the transition matrix. Section 7 provides the concluding remarks.

2. Background on studies of TFP and agricultural policies in Brazil

Understanding the evolution of total factor productivity (TFP) in Brazil requires a review of existing studies and the agricultural policies that have shaped it. Gasques et al. (2020) estimated TFP for Brazil and its states using data from seven Agricultural Censuses, covering the period from 1970 to 2017. Applying a Tornqvist Index, they found an average annual TFP growth rate of 2.0%, alongside output growth of 3.2% over the same period. Among Brazil's regions, the Center-West recorded the fastest productivity gains, with an annual TFP growth of 3.8%. For the specific period analyzed in this study (1985-2017), the authors estimated TFP growth of 1.81% per year. In a subsequent study, Gasques et al. (2022), extended the analysis to Brazil and a broad set of countries between 1975 and 2020, again employing a Tornqvist Index. They reported that Brazil's TFP growth exceeded the world average of 1.66%. The authors associate this performance with investments in research, the development of new production systems, as well as the influence of agricultural policies implemented during this period. Rada et al. (2019) estimated TFP growth by farm size in Brazil using municipal data from the Agricultural Censuses of 1985, 1996 and 2006. They found an average annual TFP growth rate of 1.82%, with the smallest farms (0-5 ha) and the largest farms (500+ ha) achieving the highest gains. More recently, Spolador and Danelon (2024) estimated TFP growth using microregion-level[2] Agricultural Census data for Brazil and decomposed it following O'Donnell's (2018) methodology. Their results indicate an average annual growth of 1.96% between 1996 and 2017.

Drawing on data from the United States Department of Agriculture (USDA) and using a growth accounting framework based on index number theory, Salazar et al. (2024) estimate agricultural output growth in 25 Latin American and Caribbean countries from 1961 to 2021, decomposing output growth into contributions from inputs and TFP. They find that the expansion of Brazil's agricultural sector over the past six decades has been driven by sustained growth in both productivity and input use. According to their estimates, agricultural production grew at an average annual rate of 3.48% between 1961 and 2021, decomposed roughly equally into contributions from TFP, which increased at an average annual rate of 1.81%, and from the accumulation of inputs, which expanded at 1.64% per year. This performance positions Brazil as the country with the second-highest average annual agricultural growth rate in Latin America and the Caribbean, surpassed only by Chile (2.27% per year).

Regarding the role of public policies in TFP growth, Vieira Filho (2018) highlights the relevance of research investments in driving the expansion of the Brazilian agricultural sector in recent decades, particularly following the establishment of the Brazilian Agricultural Research Corporation (Embrapa) in 1973. The author emphasizes the technical transformations of production systems, the adoption and diffusion of new technologies, and the role of partnerships between public and private research institutions. Similarly, Buainain (2025) argues that public policies and technological innovations have been central to productivity gains in Brazilian agriculture. While Embrapa played a leading role in this process, state research institutions, universities, and—more recently—the private sector also made critical contributions. He cautions,

[2] In the Brazilian context, microregions are geographic subdivisions used primarily for statistical and planning purposes. There were around 550 microregions in 2017, equivalent to about 10% of the number of municipalities.

however, that many of these gains were concentrated among specific groups of producers and regions, especially those engaged in large-scale monoculture production for export.

In a similar vein, Mendes et al. (2009) analyzed the effects of research developed by Embrapa on TFP in Brazilian states, using number of researchers as a proxy for research investment. Drawing on data from 1985 to 2004 and employing the Generalized Method of Moments (GMM), the authors found that a 1% increase in research investment was associated with an average TFP growth of 0.43%. Nin-Pratt et al. (2023) investigated the effects of research and development (R&D) spending on agricultural productivity in Latin American countries between 2000 and 2020. Using a Cobb-Douglas production function with USDA data and incorporating lagged R&D expenditures as an explanatory variable for TFP growth, they found that in Brazil, public and private R&D investments accounted for approximately 0.5 percentage points of the estimated annual TFP growth of 2.2%.[3] Akerman et al. (2025) also contribute to the literature on Federal research spending, providing the best causal analysis to date of Embrapa's impact on agricultural research and TFP growth in Brazil. Their identification strategy is based on a time-invariant environmental similarity index of municipalities across space and the staggered creation of research centers over time. They find that Embrapa explains close to 40% of TFP growth between 1970 and 2010, and they calculate a benefit-cost ratio of 17, suggesting that this was an excellent use of public resources.

Buainain et al. (2014) also highlight the role of rural credit and extension in the technological development of Brazilian agriculture, especially by enabling the financing and acquisition of new technologies, in addition to facilitating the transfer of knowledge to producers. Subsidized rural credit has long been one of the main policy instruments for promoting agricultural development in Brazil, particularly following the creation of the National Rural Credit System (SNCR) in 1965. Although it significantly expanded the availability of resources for financing and modernizing production, its distribution primarily benefited specific groups of producers—large farms, regions specializing in monocultures, and units with greater capacity for technological adoption (Buainain, 2025).

The successive fiscal crises experienced by Brazil during the 1980s led to major transformations in rural credit policy, including a reduction in available funds, the elimination of subsidies, and the introduction of interest rate equalization mechanisms, among other measures (Helfand & Rezende, 2004; Gasques et al., 2010). Beginning in the 1990s, credit policy was reoriented with

[3] Lachaud (2025) also studied TFP growth in Latin American countries, including Brazil, and the role of R&D in contributing positively not just to TFP growth but to conditional convergence across countries.

the creation of new credit lines targeting specific purposes and types of producers. This included a renewed focus on family farming through the National Program to Strengthen Family Farming (Pronaf), support for medium-sized producers via National Program for Strengthening Medium-Sized Producers (Pronamp), in addition to credit lines aimed at modernizing and restructuring establishments, such as the Modernization of Agricultural Fleet Program (Moderfrota) and the Program for Modernization of Rural Infrastructure (Moderinfra), among others.

The relevance of rural credit for TFP growth was analyzed by Gasques et al. (2004). The authors estimated TFP growth using the Törnqvist index and analyzed its determinants employing a Vector Autoregressive Model (VAR). Their findings indicate that a 1% increase in government expenditure on rural credit is associated with a 0.06% increase in TFP growth. Rada and Valdez (2012), in turn, used rural credit as a determinant of the technical efficiency of Brazilian agriculture, employing microregional Agricultural Census data from 1985 to 2006. The authors identified a positive effect of credit on productive efficiency, suggesting that this instrument can contribute to reducing the productivity gap between the most and least efficient microregions.

Technical assistance and rural extension policy (ATER) followed a trajectory similar to that of rural credit. As Peixoto (2014) notes, this policy was deprioritized by the government due to the fiscal crises of the 1980s, a situation exacerbated by the dissolution of the Brazilian Technical Assistance and Rural Extension Company (Embrater) in the early 1990s. Embrater had coordinated the activities of the state technical assistance agencies (Ematers). This situation began to shift with the creation of Pronaf which provided renewed emphasis on the importance of technical assistance for family farms. However, the true restructuring of technical assistance in Brazil began in 2003, with the creation of the National Policy for Technical Assistance and Rural Extension (Pnater) and, in 2010, the National Program for Technical Assistance and Rural Extension (Pronater). Both were formulated by the Ministry of Agrarian Development and presented new objectives for extension services that went beyond the traditional production-based focus. These included the incorporation of sustainable development by promoting the adoption of ecologically-based agriculture, the generation of new agricultural jobs, and others. In addition, the new policy sought to promote partnerships between public and private institutions in the provision of extension services, recognizing the limited capacity of public extension services to provide quality services to the more than four million family farms that exist in Brazil.

Several studies have evaluated the effects of rural extension, considering different performance measures of the Brazilian agricultural sector. Freitas et al. (2021) identified positive effects of rural extension (public and private) on the levels of technical efficiency of Brazilian agricultural establishments. Using microdata from the Agricultural Census, the authors estimated stochastic frontiers with matching to address sample selection bias. Among the results, it was found that access to public and/or private extension was associated with gains of 1 to 2% in technical efficiency. Rada et al. (2019) estimated TFP growth considering five farm size classes, including technical assistance as one of the policy variables potentially associated with TFP growth. The authors identified positive effects of extension services on productivity growth, however this effect was limited to farms in 100-500ha size class.

3. Methods

We estimate a Cobb Douglas stochastic frontier production function (SFPF) with an output quantity index that uses fixed prices from 2017. This allows us to implement the O'Donnell (2018) transitive decomposition of TFP. The production function is estimated with municipal data that spans the period from 1985 to 2017, drawn from four rounds of the Agricultural Census in Brazil (1985, 1995-96, 2006, 2017). Thus, implicitly we assume that all activities share a technology. This is common in studies that use countries, states, or municipalities as the unit of analysis.[4] Municipalities are aggregated into consistently defined geographical units—called AMCs—that account for the growth of municipalities over time.[5] The model that we estimate is as follows:

$$y_{it} = \alpha_i + \sum_{k=1}^{K} \beta_k x_{kit} + \tau T + \sum_{j=1}^{J} \eta_j z_{jit} + v_{it} - u_{it} \qquad (1)$$

Where y_{it} is the natural log of the output quantity index in AMC i at time t, α_i are AMC fixed effects, x_{kit} are the log of k production inputs, *T* is a time trend that captures technological progress, z_{jit} are climatic variables as well as other determinants of TFP[6], v_{it} is a symmetric random error, u_{it} is an asymmetric error term that captures inefficiency, and $\alpha_i, \beta_k, \tau,$ and η_j are coefficients to be estimated. The climatic variables included in z_{jit} measure extreme heat in the form of growing degree days and total precipitation in the growing season, and the other determinants are proxies for the human capital of agricultural producers and the public knowledge stock that resulted from federal investments in agricultural R&D. We also explored modeling the variance of the inefficiency term as a function of technical assistance, credit, and irrigation, and

[4] In future research, we plan to explore technological heterogeneity by farm size, biome, and type of specialization.
[5] AMCs are the commonly used Portuguese acronym for "minimum comparable areas." The number of municipalities rose from around 4100 in 1985 to over 5500 in 2017. We use approximately 3800 AMCs in the econometric analysis.
[6] To be more precise, z_{jit} are determinants of output. Once we control for the vector of inputs x_{kit}, these can be interpreted as determinants of TFP.

heteroskedasticity in v_{it} as a function of scale, proxied by total agricultural land in each AMC.[7] All variables used in the empirical analysis will be defined in Section 4. If the variance of $u_{it}$is small in relation to the variance of v_{it}, then a frontier cannot be estimated and the model collapses to an average production function. In this case *T* would represent average rather than frontier shifts of the production function.

We implement the transitive TFP decomposition as in O'Donnell (2018), Njuki et al. (2018) and Lachaud et al. (2022). The decomposition compares any two locations (m,i) in any two periods (s,t):

$$TFPI_{msit} = \left[e^{(\alpha_i - \alpha_m)}\right] \times \left[\prod_{k=1}^{K} \left(\frac{x_{kit}}{x_{kms}}\right)^{\beta_k - b_k}\right] \times \left[e^{(\tau_t - \tau_s)}\right] \times \left[\frac{\exp\left(\sum_{j=1}^{J} \eta_j z_{jit}\right)}{\exp\left(\sum_{j=1}^{J} \eta_j z_{jms}\right)}\right]$$
$$\times \left[\frac{\exp\left(-u_{it}\right)}{\exp\left(-u_{ms}\right)}\right] \times \left[\frac{\exp\left(v_{it}\right)}{\exp\left(v_{ms}\right)}\right] \quad (2)$$

where all variables and coefficients are as defined above other than b_k, which are the estimated β_k normalized by the estimated returns to scale. More formally, $b_k = \widehat{\beta_k}/\sum_{k=1}^{K} \widehat{\beta_k}$. The terms in (2) represent the following components of the decomposition: 1) the difference in unobserved heterogeneity (the fixed effects), 2) a scale effect (which captures deviations from constant returns to scale), 3) technological change, 4) the effect of weather and other drivers of TFP, 5) technical efficiency, and 6) statistical noise.

Most of our analysis below focuses on AMC level changes over time rather than differences in TFP levels across space. Thus, the first term in the decomposition drops out. These changes permit us to explore heterogeneity of TFP growth across AMCs by biome, activity of specialization, and scale of output. We use the following equation to calculate the growth rate of TFP in each AMC:

$$\Delta \text{TFPI(i,s,t)} = (\text{TFPI(i,t)}/\ \text{TFPI(i,s)})^{(1/(t-s))} \quad (3)$$

We then calculate a production weighted average of growth rates across AMCs in order to approximate TFP growth at the national, biome or any other level.[8] The one case where we are

[7] See Hadri (1999) on the doubly heteroscedastic model which builds on Caudill et al. (1995). Attempts to model the mean of the inefficiency term as in Battese as Coelli (1995), rather than its variance, did not converge.
[8] When the scale of observations is correlated with their TFP growth rates, using a simple average of growth rates can be misleading. We present evidence of a strong positive correlation. In this case, a weighted average of growth

interested in differences in TFP levels across space and time—and thus the difference in time-invariant heterogeneity is important--is when we calculate a transition matrix that compares the TFP ranking of AMCs in 1985 relative to their ranking in 2017. This allows us to describe TFP transitions and to explore divergence/convergence of TFP levels over time.

4. Variable definitions and descriptive statistics

Table 1 defines the variables used in the empirical analysis. These are explained in more detail below. Table 2 shows the percentage change in the output quantity index and its components. The output index consists of four components: indices for annual crops, perennial crops, and animal products, and a deflated residual that captures products for which only value of output rather than prices and quantities was available.[9] The output index includes data on more than one hundred of the most important annual (40), perennial (50), and animal (15) products. Together these account for about 90% of the value of output.[10] The second column reports aggregate growth, with a limited expansion in the first decade, but a marked acceleration over the subsequent two. The two final rows of the table present the distribution of output across components. In 1985, annual crops accounted for 42% of production, animal products for 26%, perennials for 22%, and the residual for 10%. Between 1985 and 2017, output from annual crops (e.g., soybeans, corn, and cotton) increased by 197%, while animal products (principally cattle, poultry and hogs) rose by 170%. In contrast, perennials crops (e.g., coffee and oranges) declined by 12%. As a result, the relative shares of annual crops and animal products in total output increased.

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rates is preferable because it recovers aggregate TFP growth more accurately. The weights used reflect average production of each AMC over the four censuses. See Seker and Saliola (2018) eq. (5).

[9] The inflation index used to deflate the residual was calculated by the authors as the implicit deflator from the Agricultural Census data, using the identity: implicit deflator = growth in nominal output / growth in quantity index.

[10] Two points are worthy of note. First, the quantity index was constructed using 2017 prices. Comparable results were obtained when other prices were used. Second, in order to be consistent with our decision to exclude forest land, which accounted for nearly one quarter of all land in farms in 1985, we also excluded "vegetable extraction" products that come from these lands. These are defined by IBGE as native products that are not planted, including for example rubber tapping, açai, and other fruits, seeds, firewood, etc. They accounted for 2.1% of the value of output in 1985 and declined to 0.5% in 2017.

Table 1
Variables used in Empirical Analysis

Variable	Definition	Units
Output quantity index	Fixed price output quantity index (Covers approx. 98% of output.)	R$ of 2017
Land quantity index	Land quantity index (Aggregates crop and pasture land using relative rental rates.)	Hectares of pasture
Family Labor	Number of family members employed on farm weighted by age and gender: men=1, women=.75, children under 14=0.5	Full time equivalent men
Purchased Inputs	Expenditure on production inputs (Includes fertilizer, pesticides, seeds/seedlings, salt and feed for animals, hired labor, etc.)	R$ of 2017
Machine Capital	Total number of machines (Includes tractors, planters, harvesters, trucks and pickups. Tractors are aggregated by horsepower, and then PC weights are used to aggregate all machines.)	Tractors
Animal Capital	Proxy for the cattle equivalent stock of animals (Relative cattle prices from 2017 are used, as well as an adjustment factor that reflects the capital intensity of each type of production activity--large, medium and small animals--in the initial year 1985.)	Cattle equivalent
Tree Capital	Proxy for the tree capital stock in perennial production (Present discounted value of future stream of profits. For each type of tree, the approach uses number of trees, expected years of production, average productivites from each year, and prices from 2017.)	R$ of 2017
Growing Degree Days	Growing degree days above 8C in nine-month growing season from Oct. to June aggregated into three intervals: 8-28C; 28-32C; >32C.	Degree days (1000)
Precipitation	Milimeters of precipitation in nine-month growing season from Oct. to June.	Milimeters (1000)
R&D Public Knowledge Stock	Proxy for federal public stock of knowledge (Uses Embrapa actual and estimated investments accumulated from 1950 to 2016, trapezoidal weights, and a 35 year lag structure for each census round.)	R$ of 2017 (tens of millions)
Producer Education	Average years of schooling for employers/self-employed farmers	Years
Total Land	Total agricultural land in each AMC	Hectares (millions)
Tech. Assistance	Share of farms that accessed technical assistance	Share
Credit	Share of farms that accessed rural credit	Share
Irrigation	Share of farms that used irrigation	Share

Table 2
Percentage change of outputs: 1985–2006

	Output quantity index	Components of output index			
		Annuals	Animals	Perennials	Deflated Residual
1985-1996	4	4	40	-13	-51
1996-2006	44	72	25	-4	127
2006-2017	53	68	54	6	31
1985-2017	**129**	**197**	**170**	**-12**	**44**
Shares of output index					
1985	1.00	0.42	0.26	0.22	0.10
2017	1.00	0.54	0.31	0.09	0.06

Table 3 reports the percentage change of inputs and related variables over the study period. The land index aggregates pasture and cropland using relative rental rates from the Getúlio Vargas Foundation (FGV).[11] The family labor index uses weights of 1.0 for men, 0.75 for women, and 0.5 for children under the age of fourteen, based on hours worked reported in the national household survey PNAD (Moreira et al., 2007). Purchased inputs, deflated using the same inflation index as residual output, comprise fertilizers, pesticides, animal feed, hired labor, and other items. Three capital indices were also constructed: one for machinery primarily used in annual crop production, one for livestock, and one for tree stocks associated with perennial products. Table 3 shows that land use declined by 17% and family labor by 31% over the period, while purchased inputs increased by more than 240%. The stock of machinery increased by over 50%, largely in the final decade, the animal stock increased by around 20%, and the tree stock declined, consistent with the contraction in perennial crop production.

A notable feature of output growth in this period is that it occurred with less labor and agricultural land, in part a reflection of productivity growth. Total labor in agriculture (including both family and hired) grew throughout the 20th century until reaching a peak in the 1985 Agricultural Census. It has declined in every Census since then. Regarding land, although deforestation is an extremely important issue in Brazil, and the agricultural frontier expanded in this period first in the Center-West and then north up through the Cerrado biome, total land used for crops, pastures and timber

[11] The FGV gathered these data every June and December from 1977 through 2013. We extrapolated to 2017. See Bacha et al. (2016).

(e.g. eucalyptus) actually declined by around 2.5% between 1985 and 2017.[12] This reflects a decline of close to 60 million ha of natural pasture which was replaced by about 40 million ha of planted pasture and an additional 13.5 million ha of annual crops. Land in perennial crops declined by about 2 million ha while land used for timber increased by a similar amount.

Table 3
Percentage change of inputs and other variables: 1985–2017

	Panel A: Inputs					
Period	Land	Family labor	Purchased inputs	Capital Stocks		
				Machines	Animals	Trees
1985-1996	-14	-21	44	6	12	-14
1996-2006	-3	-1	82	0	10	-5
2006-2017	0	-12	31	49	-2	6
1985-2017	**-17**	**-31**	**243**	**57**	**21**	**-14**

	Panel B: Other variables					
	Growing degree days					
	DD	HD	VD	Precip.	R&D	Education
1985-2017	**5**	**39**	**329**	**-23**	**111**	**198**

In addition to outputs and inputs, several variables are included as determinants of technological change or inefficiency. First, to capture the effects of extreme heat, growing degree days (GDD) are constructed following Schlenker and Roberts (2009), Burke and Emerick (2016), and Aragón et al. (2021). Given Brazil's size and diversity, and the fact that the analysis covers all agricultural output, the growing season is defined as the nine months of the year excluding the winter quarter (the third quarter of the year). Recognizing that different crops may exhibit distinct temperature thresholds, a more flexible specification is adopted than is common in the literature by

[12] Here we refer to unweighted land rather than the land index used in the empirical analysis.

distinguishing three GDD intervals: normal (8-28°C), harmful (28-32°C), and very harmful (above 32°C).[13] These are defined as follows:

Normal degree days: $DD = \frac{1}{24}\left[\sum_{t=8}^{\tau_l}(h_t \; * (t-8)) + \sum_{\tau_l}^{T}(h_t \; * (\tau_l - 8)\right]$

Harmful degree days: $HD = \frac{1}{24}\left[\sum_{\tau_l}^{\tau_h}(h_t \; * (t-\tau_l) + \sum_{\tau_h}^{T}(h_t \; * (\tau_h - \tau_l))\right]$

Very harmful degree days: $VD = \frac{1}{24}\left[\sum_{\tau_h}^{T}(h_t \; * (t-\tau_h)\right]$

where h_t are the hours in each temperature interval t of 1°C above 8°C and with the final interval set at 38°C and above, τ_l is the lower threshold of 28°C, and τ_h is the upper threshold of 32°C. The use of hourly data permits accounting for partial degree days in different intervals. DD aggregates the temperature above 8°C and below 28°C, in addition to all hours above 28°C evaluated at 28°C. HD captures the marginal impact of temperatures above 28°C. Thus, 29°C counts as one additional degree, 30°C as two, etc., with all hours above 32°C evaluated at 32°C. Finally, VD captures the marginal impact of temperatures above 32°C. DD, HD, and VD are divided by 24 to convert the hourly data into daily measurements. Like Burke and Emrick (2016), and unlike Aragón et al. (2021), we use total degree days rather than average degree days. Daily data on minimum and maximum temperatures are drawn from Copernicus Climate Change Service (ERA5) and linearly interpolated to approximate hourly temperatures. Table 3 shows that GDD have increased across all three intervals, with a particularly notable rise of more than 300% in the very harmful range (above 32°C). The shift in the temperature distribution between 1985 and 2017 is further illustrated in Appendix Figure 2.

Second, growing-season precipitation and its square are included as covariates, with data obtained from the Climate Research Unit (CRU) at the University of East Anglia. As reported in Table 3, precipitation levels declined in 2017 relative to 1985. Third, building on related work by Helfand, Freitas, and Torres (in progress), we construct knowledge stocks to capture the influence of public-sector agricultural research and development. These are developed using data on Embrapa's federal government spending between 1973 and 2016, disaggregated into approximately 15 product groups and 15 geographical regions (ecoregions). Embrapa spending is taken as a proxy for the broader public-sector effort carried out through the National System of

[13] We tested models with different thresholds, exploring a binary model with thresholds of 26°C, 28°C,…, 38°C, and models with two thresholds set at 28-32°C and 29-33°C. The model with thresholds at 28-32°C had the lowest RMSE, but in practice all models exhibited very similar RMSE (see Appendix Figure 1). Estimated coefficients also told a consistent story of increasingly negative marginal effects as we moved above the "normal" GDD interval.

Agricultural Research (SNPA). Each line of spending is extrapolated back to 1950 and aggregated over the 35 years preceding each census, applying weights that reflect the time lags between research investments and their effects on productivity, as suggested in the literature.[14] In our specification, we assume that research investments have no effect during the first four years, with impacts rising over the subsequent eight years and reaching a maximum between 12 to 20 years post-investment, after which they gradually decline to zero by year 35.[15] Ecoregion-level knowledge stocks are allocated equally across all AMCs in the region, while product-level stocks are assigned to AMCs according to each AMC's output composition. As shown in Table 3, our proxy for the knowledge stock roughly doubled over the period.

Fourth, we include a measure of human capital, proxied by the average years of schooling of agricultural producers in each AMC. These data are drawn from the Demographic Censuses, which are lagged by about five years relative to each Agricultural Census.[16] Table 3 indicates that average years of schooling tripled during this period. Fifth, we explore three variables that may affect management practices and production efficiency in each AMC: the share of producers utilizing technical assistance, access to credit for working capital and marketing, and the use of irrigation. Finally, heteroskedasticity in the symmetric error term (v) is modeled as a function of total land in agricultural production within each AMC.

5. Results

5.1 Model estimation and testing

Table 4 presents the estimated coefficients from five models. The first four are average production functions, while the fifth —the reference model for TFP decomposition—is a SFPF with a half-normal distribution for the inefficiency term. Evidence indicates that the errors from the average production function are significantly skewed, supporting the use of a frontier model. Moreover, substantial TFP divergence over time is observed between the most productive municipalities and others, possibly suggesting rising inefficiency. Nonetheless, we were unable to estimate a frontier model in which the variance of inefficiency is large relative to the variance of the symmetric error term. Thus, even though the SFPF is estimated, the inefficiency term remains relatively small, and the model likely underrepresents its true significance.

[14] Our approach follows the methods described in Alston et al. (2010), Alston and Pardey (2021), Avila and Evenson (1995), and Rada and Valdes (2012).

[15] We intend to explore robustness to alternative lag structures in future research.

[16] Producers are defined as the self-employed and employers whose principal occupation is in the agricultural sector.

Columns 1-3 of Table 4 were estimated with panel data and AMC level fixed effects. The models employ data for all of Brazil, using approximately 3,800 AMCs and over 14,850 observations.[17] Column 1 shows the coefficients from an average production function that only includes the log of production inputs and a time trend, which are all statistically significant at the 1% level, with the largest elasticities coming from land (0.44) and purchased inputs (0.30). Increasing returns to scale—with the sum of the coefficients on inputs equal to 1.1—suggest that the rising scale of production has contributed to TFP as well. Concentration of output in a declining share of AMCs is documented below.

Column 2 of Table 4 presents estimations in which climatic variables were added to the model. The coefficient on DD is negative, which is similar to the finding in Burke et al. (2024) for soybeans and maize in Brazil as well as wheat in India, the U.S. and E.U. The effect of HD is almost twice as large, given that the two coefficients (-0.59 and -0.51) need to be combined in this interval. And, while the density of VD is not large, the negative effect on TFP is again almost twice as large as the effect in the previous interval.[18] For the case of maize and soybeans in Brazil, Burke et al. (2024) also show that marginal effects have become increasingly negative across decades since the 1970s for both normal and harmful GDD. They hypothesize that this might be due to increasing intensification of rainfed agriculture. In effect, higher mean output might be associated with a larger variance of output reflecting an increased gap in production between years with favorable and unfavorable weather. Finally, column 2 also indicates a nonlinear effect of precipitation, which is positive across the range of our data.

Column 3 introduces two key policy variables: federal government investments in agricultural R&D as well as the average years of schooling of agricultural producers. When initially included without lags, R&D was insignificant and education had a negative coefficient. However, once lags were applied—one period for education and one half a period for R&D—both variables exhibit positive and statistically significant coefficients, indicating that the effects of investments in education and R&D materialize only over time. The results in Table 4 suggest that improvements in average municipal years of schooling require a decade or more to positively impact TFP growth, while the effects of R&D investments also emerge more slowly than initially anticipated when constructing

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[17] AMCs from the state of Rondônia were removed due to missing data, and about 350 extreme observations were trimmed based on a Tukey procedure using three times the interquartile range and subtracting/adding this to the 25th and 75th percentiles. Depending on the variable, this approach identified between 0.3% and 1.2% of the observations as outliers. Robustness tests were conducted that a) removed no outliers, or b) removed more outliers by using two times the interquartile range. At a later stage, we also intend to remove observations where "vegetable extraction" was large.
[18] Holding inputs constant, it is appropriate to interpret these variables as having an effect on TFP.

this variable. The lags of education impacts may be related to the time needed for schooling to positively affect the adoption of new technologies. Regarding R&D, the longer lags relative to a country like the U.S. may reflect the comparatively weaker agricultural extension services in Brazil.[19]

With approximately 3,800 AMCs, it is not feasible to include dummy variables in a Green (2005) true fixed effects model. The fixed effects cannot be removed from a stochastic frontier model by first differencing or mean differencing as is standard in linear panel models (Kumbhakar, 2015).[20] Column 4 (and Appendix Table 2) demonstrates that virtually identical coefficients can be obtained by including twenty dummies instead of 3,800 fixed effects.

[19] The education variable is lagged by one period and the R&D variable is lagged by one half a period. For education, we backcasted data by one period in order to have initial values. In the case of R&D, we also backcasted the initial value and then interpolated each pair to move it forward 5 years. When lagged by a full period the effect was implausibly large. Because we had already built into the R&D variable an initial period of 4 years before impacts begins to occur, the lag implies that it takes about a decade before impacts begin. The time to reach maximum impact is now 17 years rather than 12, which is in the range of plausible lags tested by Alston et al. (2010). Depending on the functional form of the model and the parameters chosen for the gamma distribution which defined the weights used for lags, they selected preferred models with peak impacts between 13 and 24 years.

[20] Due to the extensive cross-sectional dimension of our panel, incorporating this many dummy variables is computationally impractical, which precludes the standard fixed-effects estimation approach typically implemented in Stata and other software.

Table 4
Estimated coefficients from average and frontier models

Variables	Average production function				SFPF
	Production inputs & trend	Col. 1 and climatic var.	Col. 2 and policy var.	Col. 3 w/ 20 dum.	Col. 4 w/ frontier
	(1)	(2)	(3)	(4)	(5)
Land	0.44	0.39	0.39	0.38	0.38
Family labor	0.13	0.14	0.14	0.14	0.15
Purchased inputs	0.30	0.32	0.31	0.32	0.32
Machine capital	0.07	0.07	0.07	0.07	0.06
Animal capital	0.13	0.12	0.12	0.11	0.12
Tree capital	0.04	0.04	0.04	0.04	0.04
Time trend	0.008	0.015	0.005	0.005	0.006
Growing degree days					
Normal (<28C)		-0.59	-0.47	-0.45	-0.43
Harmful (28-32C)		-0.51	-0.50	-0.48	-0.50
Very harmful (>32C)		-1.14	-1.47	-1.55	-1.70
Precipitation		0.21	0.10	0.10*	0.10
Precipitation^2		-0.08	-0.04	-0.04**	-0.04
R&D knowledge stock			1.73	1.70	1.63
Producer education			0.03	0.04	0.03
Determinants of var. of v					
Total land					-0.17
Constant					-2.27
Determinants of var. of u					
Tech. assistance					-0.65**
Credit					-5.91
Irrigation					-0.48#
Constant					-3.19
Constant	3.71	6.64	6.21	5.14	5.17
Returns to scale:	1.10	1.08	1.07	1.07	1.06
Observations	14,852	14,852	14,852	14,852	14,852
AMCs	3802	3802	3802	3802	3802
R-sq:					
within	0.43	0.46	0.46		
between	0.84	0.84	0.85		
overall	0.80	0.80	0.81	0.92	0.94

Notes: All coefficients significant at 1% unless noted as *=10%, **=5%, #=not significant.

To achieve this, fixed effects from Column 3 are saved, ranked by magnitude, and then grouped into twenty categories. This intermediate step was necessary prior to estimating the SFPF in Column 5, as direct estimation with 3,800 fixed effects proved infeasible. By using twenty dummies to capture unobserved heterogeneity, the stochastic frontier model can be successfully estimated.[21]

Prior to estimating the SFPF in Column 5, the skewness of the residuals from models 3 and 4 in Table 4 are explored using the test proposed by Schmidt and Lin (1984).[22] In both cases, at the 1% significance level, the test rejects the null hypothesis of no skewness, although the skewness is in the opposite direction of what is normally presumed. We thus proceed to estimate the SFPF in Column 5. The model employs a half-normal distribution for the inefficiency term and models the variance of inefficiency (*u)* as a function of several variables that plausibly influence management decisions and technical efficiency: the municipal share of producers accessing technical assistance, credit, and irrigation. Heteroskedasticity in the symmetric error term (*v*) is modeled as a function of scale, proxied by total agricultural land in each AMC.[23] The results in Column 5 indicate that most of the coefficients are similar to those estimated in Column 4, and that technical assistance and credit contribute to reducing the variance of inefficiency. The standard deviation of the symmetric error (*v)* is six times larger than that of the asymmetric inefficiency term (*u*),[24] which explains why changes in inefficiency account for only a small share of TFP changes in the decomposition below.

Additional testing was conducted to further confirm the robustness of the preferred model. Without including explanatory variables for inefficiency, an exponential distribution for the inefficiency term is shown to perform better than the half-normal. The ratio (λ) of the standard deviation of the asymmetric inefficiency term (*u*) to that of the symmetric error (*v)* is larger than with the half-normal and statistically different than zero, providing evidence in favor of a stochastic frontier, although λ equals only about one third. Furthermore, unlike the half-normal, the exponential model does not converge when explanatory variables for *v* or *u* are included. Fortunately, as shown in Appendix Table 2, the five models in Table 4 as well as the exponential model all

[21] Appendix Table 1 shows that this approach to creating 20 dummies far outperforms the use of 27 state dummies. With our approach, the coefficients in columns 3 and 4 are extremely similar, suggesting little bias, whereas this is not the case when state dummies are used. A t-test of the differences between the coefficients with our 20 dummies vs the panel model with 3800 municipal fixed effects shows that none of the coefficients are statistically different even at the 10% level of confidence. The same comparison for the models with municipal vs state fixed effects shows that all but three coefficients are different at the 1% level.
[22] See Kumbhakar (2015).
[23] See footnote 7 and Hadri (1999).
[24] 0.31 vs. 0.05.

produce extremely similar TFP decompositions, both for the overall TFP growth rate (between 1.53 and 1.66% per year) and for the growth of each component. Accordingly, results based on the half-normal specifications are presented at this stage of the research.

5.2 Decomposition of output growth and TFP for Brazil and by biome

Based on the preferred specification in Column 5 of Table 4, Table 5 reports average annual growth of output, inputs, TFP and the TFP decomposition as defined in (2). Inputs have been aggregated with b_k, which are the estimated β_k coefficients normalized by the estimated returns to scale. Thus, the aggregation assumes constant returns to scale (CRS). Deviations from CRS are then captured by the scale term in the TFP decomposition.

The TFP index number comparison shown in equation (3) of Lachaud et al. (2022), and its decomposition as presented above in equation (2), hold multiplicatively (not additively) at the AMC level. Many studies, such as Lachaud et al. (2022) and Spolador and Danelon (2024), then calculate an unweighted average across countries (in the case of Latin America), or states (in the case of Brazil) to represent growth at the continental or national levels, respectively. Following Seker and Saliola (2018) and the discussion in footnote 5, we consider it preferable to calculate a *weighted average* across the 3,800 AMCs, given the considerable correlation between output scale and TFP growth, as shown below in Table 7. This ensures that results are more comparable to national aggregate studies of TFP growth in Brazil by Gasques et al. (2020) and others. The output quantity index is used to calculate average weights for the entire study period. If a single AMC produces 5% of national output, and another produces 0.01%, these weights are employed to aggregate AMC level growth rates.[25] For this reason, the results at the national level do not hold additively or exactly.

Table 5 shows that output rose by 2.59%, inputs by 0.97%, and TFP by 1.56% per year over the entire period. Thus, TFP growth has been substantial, explaining around 60% of output growth. We capture the effect of technological change on TFP growth in three ways. The two policy variables together account for a substantial portion of TFP growth. Public investments in agricultural R&D are the most influential, contributing 0.67% per year to TFP growth, while human capital—reflecting public investments in education—adds an additional 0.27% per year. The remaining technological change is captured by the time trend, which represents an important component of TFP growth, accounting for 0.56% per year. Appendix Table 2 confirms that including these three variables together does not

[25] Without weights, for example, output grows by less than half of the weighted growth rate or Gasques et al. (2020). We do not view this as credible.

result in double counting of technological change. When the two policy variables are excluded, the entire effect of technology is captured by the time trend; when they are included, the total effect is distributed across the three variables. Table 5 further shows that the statistical noise component is large (0.57% per year). The scale effect is positive, but small, and changes in technical efficiency explain close to zero.

The large negative effect of the climatic variables represents one of the most important results of Table 5, as they are shown to slow TFP growth by 0.56% per year. The magnitude of this effect reflects the combined effect of the GDD variables, as well as the negligible effect of precipitation. While not shown in Table 5, growing degree days below 28°C (DD) have the largest negative effect on TFP growth (-0.29% per year), followed by HD between 28°C and 32°C (-0.21% per year), and VD above 32°C (-0.05% per year). The impact of these variables results from the joint effect of the coefficients in Table 4 (which are increasingly negative the higher the temperature interval), the changes in these variables over time, and the density in each temperature interval. The share of HD rose from 13% to 17% during the period, and the share of VD rose from 4% to 8%. As average annual temperatures in Brazil continue to increase, it is likely that the negative effects on TFP growth will rise, presenting a growing challenge to agricultural production and productivity. It is imperative that research efforts increase their focus on adapting to these changes, for example through improved heat and drought resistant seeds. Migration of production to more suitable areas and other forms of adaptation will likely be important as well.

Table 5
Average annual growth in output, inputs, TFP, and its components
Brazil, 1985-2017

				TFP components						
Period	Output	Inputs	TFP	Climatic	Education	R&D	Technology	Scale	Efficiency	Stat. Noise
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1985-1996	1.46	0.58	0.97	-1.22	0.23	0.84	0.56	0.03	0.11	0.44
1996-2006	3.72	1.13	2.21	0.27	0.37	0.86	0.56	0.07	-0.17	0.24
2006-2017	3.69	1.63	2.00	-0.84	0.26	0.43	0.56	0.10	0.03	1.46
1985-2017	**2.59**	**0.97**	**1.56**	**-0.56**	**0.27**	**0.67**	**0.56**	**0.06**	**-0.01**	**0.57**

Table 5 also presents the decomposition for each decade. Output and TFP exhibited the slowest growth rates in the first decade, partly due to the negative effects of hyperinflation and the dismantling of the previous policy framework in the late 1980s and early 1990s (Helfand & Rezende, 2004). Output growth accelerated to approximately 3.7% per year over the following two decades. The sources of growth, however, differ across decades. Between 1996 and 2006, TFP increased much more rapidly than inputs, whereas growth was more balanced in the final decade. Referring to Table 2, only purchased inputs grew rapidly in the second decade, while both purchased inputs and machinery expanded in the final decade. The growth in the machinery capital stock reflects increased investment credit for tractors and other equipment through the Moderfrota program, highlighting an important role of credit (Araújo et al., 2021). Expanding the machinery capital stock affects output both directly, by increasing measured inputs, and indirectly, by facilitating embodied technological change.

The decomposition further highlights pronounced differences in the sources of TFP growth across decades. The negative climatic effects were largest in the first decade, but remained substantial in the final decade. The importance of public agricultural R&D was greatest in the first two decades and then fell by half, suggesting that the effect of public sector innovations might be declining, which represents an ongoing challenge for Embrapa and other public sector actors. It could also reflect the increasing role of the private sector in R&D, which would be captured in the technology trend and the large unexplained residual (column 10) in the final decade.

Table 6 extends the analysis by examining TFP growth and its decomposition in the four largest biomes in Brazil. There is considerable heterogeneity across the biomes. In the two most important producing biomes in the country, output grew much faster than the national average in the Cerrado (4.29% per year) and considerably slower than average in the Atlantic Forest (1.7% per year).[26] TFP growth was also fastest in the Cerrado (2.43% per year), accounting for almost 60% of its output growth, and it similarly accounted for a high share in the Atlantic Forest, though at a much slower rate. In the Amazon, the impressive output growth was driven disproportionately by inputs rather than TFP. Lastly, the Caatinga performed the poorest among the major biomes, with slow output growth and virtually zero TFP growth. In terms of the decomposition, it is noteworthy that the negative climatic effects are far larger in the semi-arid Caatinga than in any other biome. It is also of relevance that the effect of education is larger in the Cerrado and Atlantic Forest, where education levels had historically already been higher than in the Amazon and Caatinga. Finally, we note the large effect of statistical noise in the Cerrado (column 10), which suggests that there are still many unexplained reasons for the rapid growth of TFP in this biome.

[26] The output share of the Cerrado rose from 23% to 36% over the period, while the share of the Atlantic Forest declined from 59% to 48%.

Table 6
Average annual growth in output, inputs, TFP, and its components
Brazil and biomes, 1985-2017

				TFP components						
Biome	Output	Inputs	TFP	Climatic	Education	R&D	Tech.	Scale	Effic.	Stat. Noise
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Amazon	3.56	2.47	1.02	-0.80	0.17	0.97	0.56	0.15	-0.05	0.01
Caatinga	0.51	0.39	0.07	-1.36	0.16	0.70	0.56	0.02	-0.01	0.01
Cerrado	4.29	1.61	2.43	-0.59	0.30	0.76	0.56	0.10	-0.08	1.36
Atl. Forest	1.70	0.51	1.25	-0.43	0.27	0.57	0.56	0.03	0.04	0.21
Brazil	**2.59**	**0.97**	**1.56**	**-0.56**	**0.27**	**0.67**	**0.56**	**0.06**	**-0.01**	**0.57**

An important area for future research is the disaggregation of these biomes into socioeconomically relevant subregions in order to estimate separate models. Farm size and many other important variables differ considerably across subregions. For example, the Cerrado can be divided into three subregions: (a) the more traditional areas in the Southeast (e.g. in Minas Gerais and São Paulo) where population pressure is relatively high; (b) the Center-West, which has served as the frontier for agricultural expansion since the 1960s, stimulated in part by the founding of Brasilia in 1960 and the post-1964 policy of the military to occupy the Center-West and North; and (c) the states of Maranhão, Tocantins, Piauí and Bahia (known as MATOPIBA), which have represented the most dynamic area of expansion in recent decades. Similarly, future research could disaggregate the Atlantic Forest into its northeastern portion, historically cultivated with sugarcane, cacao and other crops, and the remainder, largely in the Southeast and South. Differences in average farm size across these subregions provide initial insight into the importance of these differences. Using our land index, we observe that average farm size in the Caatinga, where TFP has stagnated, is only one third of the national average, whereas in the Center-West portion of the Cerrado, it exceeds three times the national average. Thus, many of the important differences across biomes also reflect differences across farm size.

5.3 TFP decomposition by classes of scale of output and TFP growth

The TFP decompositions presented in this section are motived by the finding that production has been increasingly concentrated in fewer and fewer AMCs, a phenomenon that tracks the growing concentration of production in a small share of farms (Helfand et al., 2014; Helfand et al., 2020). Figure 1 demonstrates the rising concentration of production in the top 200 AMCs (~5%), highlighting that they accounted for 30% of total agricultural production in 1985, with this share rising to 48% in 2017.[27] The three main components of production all became increasingly concentrated, with the top 200 AMCs in 2017 producing 63% of annual, 61% of perennial, and 47% of animal production.[28] The same pattern is observed for the top 40 AMCs (~1%), where the share of total production rose from 11% to 25% (see Appendix Figure 3).

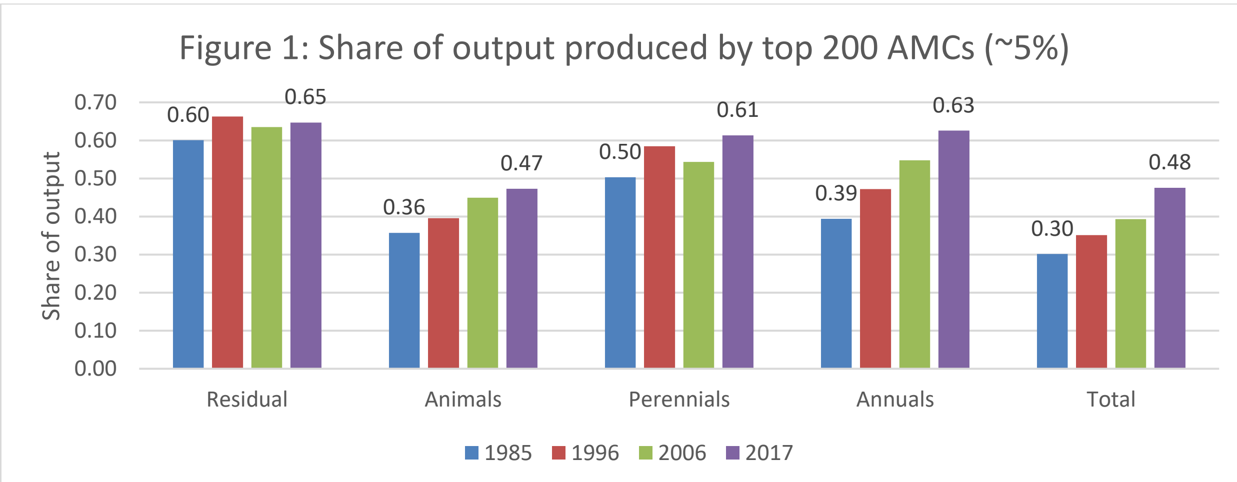


Table 7 shows the growth of output, inputs, and TFP for subgroups of AMCs based on the scale of production, where production is calculated as the average over the four censuses. The first row of the Table aggregates the 75% of AMCs that produced the least. This group only produced 28% of the country's agricultural output (Table 9), And the growth of outputs, inputs and TFP were much slower for this group than for the others. In fact, as seen in Columns 1 and 3 of the table, a strong positive relationship is observed between an AMC's scale of output and its growth rate of output and TFP. In essence, output and TFP grew slowly in the AMCs that produced very little, and much more rapidly in the AMCs that produced the most. In terms of the decomposition, negative climatic effects were slightly stronger for the AMCs that produced less, and the effect of increasing returns to scale rose with the scale of output. The classes with the largest output also exhibited the greatest statistical noise (Column 10), suggesting the presence of additional relevant factors beyond those included in the decomposition.

[27] The shares in Figure 1 are slightly different than in other tables because outliers have not been removed.
[28] Note that these are a different set of 200 AMCs for each variable.

Table 7
Average annual growth in output, inputs, TFP, and its components
Brazil and classes of scale of output, 1985-2017

Classes of scale of output	Output	Inputs	TFP	TFP components						
				Climatic	Education	R&D	Technology	Scale	Efficiency	Stat. Noise
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
< percentile 75	0.83	0.24	0.60	-0.72	0.23	0.60	0.56	0.02	0.02	-0.11
p75-p90	2.08	0.68	1.39	-0.49	0.28	0.64	0.56	0.04	0.02	0.33
p90-p95	2.97	1.13	1.79	-0.47	0.28	0.68	0.56	0.07	-0.01	0.66
p95-p99	3.68	1.37	2.20	-0.49	0.28	0.71	0.56	0.09	-0.03	1.06
>p99	5.23	2.28	2.67	-0.56	0.30	0.75	0.56	0.14	-0.08	1.55
Brazil	**2.59**	**0.97**	**1.56**	**-0.56**	**0.27**	**0.67**	**0.56**	**0.06**	**-0.01**	**0.57**

Table 8 extends the previous analysis by grouping AMCs according to their TFP growth rates. The bottom 25% of AMCs experienced negative TFP growth, with an average decline of 1.3% per year, while the next 25% of AMCs exhibited only marginally positive TFP growth. In contrast, the top 5% of AMCs achieved TFP growth of over 4.6% per year. TFP growth was strongly correlated with output growth, and climatic effects were more pronounced in AMCs with the slowest TFP growth. Conversely, AMCs with the fastest TFP growth displayed the largest unexplained residuals (Column 10). In sum, Tables 7 and 8 demonstrate strong positive correlations between scale and growth of both output and TFP.

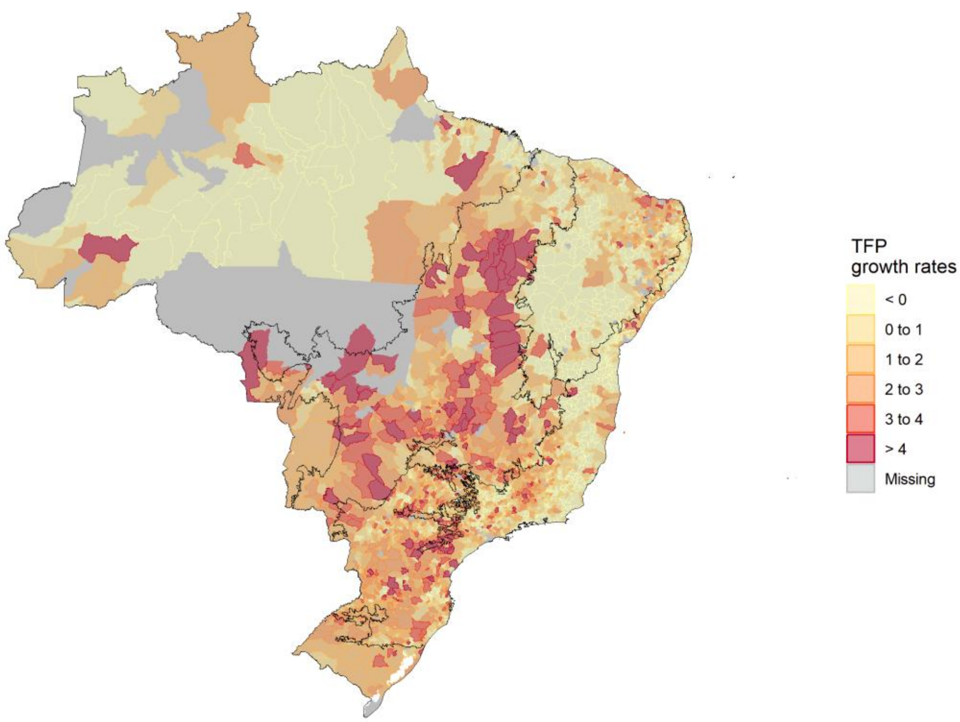
Table 8
Average annual growth in output, inputs, TFP, and its components
Brazil and classes of TFP growth, 1985-2017

Classes of TFP growth	Output	Inputs	TFP	TFP components						
				Climatic	Education	R&D	Technology	Scale	Efficiency	Stat. Noise
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
< percentile 25	-1.45	0.12	-1.30	-0.85	0.22	0.55	0.56	0.01	0.14	-1.91
p25-p50	0.57	0.48	0.20	-0.62	0.25	0.60	0.56	0.03	0.06	-0.68
p50-p75	1.99	0.72	1.26	-0.50	0.27	0.67	0.56	0.05	0.00	0.21
p75-p90	3.34	1.12	2.17	-0.41	0.28	0.72	0.56	0.07	-0.01	0.95
p90-p95	4.36	1.23	2.99	-0.44	0.29	0.70	0.56	0.08	-0.04	1.83
>p95	7.37	2.37	4.66	-0.65	0.29	0.72	0.56	0.15	-0.24	3.77
Brazil	**2.59**	**0.97**	**1.56**	**-0.56**	**0.27**	**0.67**	**0.56**	**0.06**	**-0.01**	**0.57**

5.4 Moving beyond the mean: Additional heterogeneity by production scale, TFP growth, biome, and specialization

This section was motivated by the observation that around one third of AMCs experienced declining output or TFP over the three decades (Figure 2). Our aim was to more fully characterize the *distributions* of output and TFP growth. In particular, we examine the extent to which differences in production scale, biome, average and initial specialization help explain these distributions.

Figure 2: Total factor productivity growth by municipality, 1985-2017



In Table 9, we describe selected characteristics of AMCs first for the full universe and then by classes of output scale. The first row of the table demonstrates that among all AMCs, 38% experienced declining output (Col. 2) and 32% declining TFP (Col. 3) between 1985 and 2017. The final four columns present the share of AMCs that were specialized in the production of animals, annual, and permanent crops, respectively, or had no specialization, applying a threshold of 60% of total output within each AMC over the entire period. Twenty-three percent of

AMCs were specialized in animal production, 21% in annual crops, 7% in permanent crops, and about half exhibited no dominant specialization.

Table 9
Characteristics of AMCs by classes of scale of output

Classes of scale	Share of	Share with declining		Share of specialized AMCs			
of output	Output	Output	TFP	Animal	Annual	Perennial	Not spec.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
All AMCs	1.00	0.38	0.32	0.23	0.21	0.07	0.49
< percentile 75	0.28	0.46	0.38	0.27	0.16	0.07	0.51
p75-p90	0.23	0.17	0.18	0.13	0.32	0.11	0.44
p90-p95	0.15	0.09	0.10	0.14	0.36	0.09	0.42
p95-p99	0.21	0.06	0.07	0.13	0.44	0.07	0.36
>p99	0.13	0.05	0.11	0.03	0.74	0.03	0.21

The lower portion of the table presents the same variables for AMCs grouped into classes based on percentiles of the output distribution. The 75% of AMCs that produced the least accounted for 28% of total output. Forty six percent of this group experienced declining output and 38% had declining TFP —a striking result. Half of these AMCs were not specialized in any one activity, but over a quarter were specialized in animal production. As scale of output increases, the share of AMCs with declining output or TFP falls, while the share specialized in annual crops rises. The final row of the table describes the 1% of AMCs that produced the most. This group accounted for 13% of total output (Col. 1), with 74% specialized in annual crops (Col. 5). Only a small share of these AMCs experienced declines in output or TFP, reflecting the boom of soybeans and other annual crops in recent decades. The *divergence* across AMCs is worth emphasizing: whereas nearly half of the bottom 75% of AMCs experienced declining output, the top 25% by scale produced over 70% of output and fewer than 15% had declining output or TFP over the thirty-year period. These patterns carry important policy implications that warrant further exploration.

Table 10 follows the same design as Table 9, with two key differences. First, AMCs are classified according to intervals of TFP growth rather than scale of output. Second, the share of specialized AMCs is reported for both the initial and final years, providing insight into changes over time. The first class of TFP growth represents the bottom 25% of AMCs, which account for 13% of output (Col. 1). These AMCs all experienced falling TFP (Col. 3) and close to 90% exhibited declining output (Col. 2). Relative to the national average, these AMCs were slightly more specialized in annual crop production in 1985, but substantially less so by 2017. The opposite is true for specialization in animal production. In the top 50% of the distribution, which accounted for about 70% of agricultural production (Col. 1), none experienced declining TFP and less than 10% exhibited declining output. When TFP growth rates increase as exhibited in descending order of rows, the share of AMCs specialized in annual production in 2017 rises. The bottom row, for example, represents the top 5% of AMCs. In 1985, only 21% of these AMCs were specialized in annual crops, consistent with the national average, but the share rose to 42% in 2017. In sum, there appears to be little correlation between specialization in 1985 and TFP growth over the next 30 years. However, by 2017, there was a positive correlation between specialization in annual crops and the growth rate of TFP over the previous 30 years.

Table 10
Characteristics of AMCs by classes of TFP growth

				Share of specialized AMCs			
Classes of	Share of	Share with declining		Animal		Annual	
TFP growth	Output	Output	TFP	1985	2017	1985	2017
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
All AMCs	1.00	0.38	0.32	0.16	0.38	0.23	0.23
< percentile 25	0.13	0.89	1.00	0.07	0.44	0.28	0.11
p25-p50	0.17	0.48	0.33	0.17	0.44	0.19	0.16
p50-p75	0.23	0.13	0.00	0.21	0.40	0.20	0.23
p75-p90	0.25	0.02	0.00	0.18	0.29	0.30	0.38
p90-p95	0.09	0.01	0.00	0.20	0.18	0.23	0.43
>p95	0.14	0.10	0.00	0.19	0.25	0.21	0.42

Table 11 extends the analysis by exploring differences across the principal biomes. The Table shows that AMCs in the Amazon and Caatinga only produced around 5% of output each and were much more likely to experience declining output and TFP. The Cerrado, in contrast, had the lowest share of AMCs with declining output or TFP. It is also important to keep in mind the differences in types of specialization across biomes. The Cerrado had the highest share of specialized AMCs, reaching 60% of the total. In the Caatinga, which is home to a high share of Brazil's poor and very small farmers, 57% of AMCs exhibited no specialization and approximately one third of AMCs were specialized in animal production. Perennial crops, such as coffee and oranges, are concentrated in the Atlantic Forest, making it the only biome with more than 10% of AMCs specialized in perennials.

Table 11
Characteristics of AMCs by biome

Biome	Share of	Share with declining		Share of specialized AMCs			
	Output	Output	TFP	Animal	Annual	Perennial	Not spec.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
All AMCs	1.00	0.38	0.32	0.23	0.21	0.07	0.49
Amazon	0.05	0.53	0.45	0.17	0.37	0.01	0.45
Caatinga	0.06	0.62	0.51	0.32	0.08	0.03	0.57
Cerrado	0.31	0.16	0.13	0.31	0.25	0.04	0.40
Atl. Forest	0.51	0.36	0.32	0.18	0.22	0.11	0.49

We conclude this section by presenting the same information as in previous tables, now categorized by classes of specialization. Two observations from Table 12 are particularly noteworthy. First, AMCs specialized in perennial crops exhibited a much higher share of declining output and TFP relative to other groups. Second, about 40% of agricultural output originates from non-specialized AMCs. Among the specialized groups, AMCs focused on annual crops account for a larger share of total annual production (61%) compared to those specialized in perennials (48%) and animals (33%).[29]

[29] These shares are calculated separately based on the data in in Column 1.

Table 12
Characteristics of AMCs by classes of specialization

Specialization	Share of Output	Share with declining Output	Share with declining TFP	Share of specialized AMCs: Animal	Annual	Perennial	Not spec.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
All AMCs	1.00	0.38	0.32	0.23	0.21	0.07	0.49
Animal	0.14	0.29	0.23	1	0	0	0
Annual	0.38	0.33	0.27	0	1	0	0
Perennial	0.08	0.58	0.65	0	0	1	0
Not specialized	0.41	0.41	0.34	0	0	0	1

6. Additional evidence on divergence: A TFP transition matrix

To shed additional light on divergence across AMCs, this section presents an AMC transition matrix for TFP levels between 1985 and 2017. The first row of Table 13 shows that over half (56%) of the AMCs located in the bottom quintile of productivity in 1985 remained there in 2017. Another quarter of these AMCs moved up to the second quintile. Furthermore, nearly a quarter (23%) of the AMCs that began in the second quintile moved down to the first. Thus, 79% of the AMCs that were in bottom quintile in 2017 came from the bottom two quintiles in 1985, suggesting a high degree of persistence perhaps akin to a "TFP trap." Similarly, 42% of the AMCs in the top quintile remained there, and 30% from the fourth quintile moved up. Thus 72% of the top quintile in 2017 came from the top two quintiles in 1985. In addition to the high degree of persistence at the top and bottom of the TFP ladder, results presented in the final column demonstrate that the top quintile is increasingly distancing itself from the rest.[30] The bottom two quintiles experienced declining TFP, which is consistent with the observation in previous tables that TFP declined in 32% of AMCs. The third and fourth quintiles witnessed stagnation or modest growth, and only the top quintile experienced rapid TFP growth over the period. The evidence in Table 13 suggests that inefficiency likely increased for a substantial share of AMCs, as they were unable to keep pace with the TFP growth of the most productive locations.

[30] Note that this is the growth rate in TFP levels of the top quintile. Different AMCs are in the top quintile in each year.

Table 13
TFP transition matrix: 1985-2017

1985 TFP quintiles	2017 TFP quintiles 1	2	3	4	5	% change in TFP levels
1	0.56	0.25	0.10	0.06	0.03	-23
2	0.23	0.31	0.26	0.13	0.07	-9
3	0.13	0.19	0.25	0.24	0.18	1
4	0.05	0.15	0.22	0.28	0.30	15
5	0.02	0.08	0.17	0.31	0.42	62

Another relevant question is the extent to which differences in TFP levels are explained by unobservable, time-invariant characteristics of AMCs. In other words, to what extent is fate destiny? One approach to address this question is to compare the percentage difference in TFP between the top and bottom quintiles with the corresponding difference in fixed effects across these quintiles. In 1985, the ratio of fixed effects accounted for 51% of the TFP gap, suggesting that unobserved, time-invariant spatial factors explained a substantial share of productivity differences. By 2017, this ratio declined to 33%, suggesting that technological changes —such as soil acidity correction in the Center-West, irrigation, and improved seed varieties — contributed to reducing the influence of time-invariant characteristics. This finding is encouraging, as it indicates that productivity is not entirely predetermined and that AMCs have the potential to influence their outcomes. This agency is reflected in movement of AMCs within the transition matrix over time.

Finally, Table 14 analyzes possible factors driving the divergent dynamics in the transition matrix. The table contrasts various characteristics of those AMCs that began and remained in the bottom quintile (Q1-Q1) with those that started in the bottom quintile in 1985 and moved up to the fourth or fifth quintiles in 2017 (Q1-Q45). Note that this latter group is somewhat small, containing around 80 AMCs. Similarly, the table contrasts those AMCs that began in the top quintile and remained there (Q5-Q5) with those that started there and ended in one of the bottom two quintiles (Q5-Q12). A striking finding is that 71% of the AMCs in the group that started and ended in the bottom quintile are located in the Caatinga. Over 60% of these AMCs experienced declining output and over 40% had declining TFP. Notably, 2017 falls in a period of extended drought in the Northeast of Brazil, which severely affected the Caatinga. Consequently, it is difficult to determine whether the observed TFP outcomes reflect a persistent TFP trap or are primarily driven by this large, idiosyncratic negative shock. Regardless, these findings carry important policy implications. By contrast, 59% of AMCs that started in the bottom quintile and moved into one of the top two quintiles were located in the Cerrado, with roughly half of this group situated in the new frontier region of MATOPIBA. Over half of these AMCs were specialized in annual crops, though they likely did not exhibit this specialization at the beginning of the study period. Interestingly, even in 1985, this group's output was already more than double that of the first group.

Turning to the group that started and ended with the highest TFP (Q5-Q5), they were much more likely to be specialized in annual crops than the national average, and more likely to be located in the Cerrado or Atlantic Forest. Interestingly, while a third experienced declining output, TFP declined in only 13% of these AMCs. In contrast, 73% of the group that started at the top and ended in the bottom two quintiles (Q5-Q12) were located in the Atlantic Forest. Of these AMCs, 30% were specialized in perennial crops, a much higher share than the national average of 8%. Over half of the AMCs in this group specialized in perennials was further specialized in cacao production.[31] This likely reflects the cacao production crisis in southern Bahia, caused by the onset of the "witch's broom" disease in the 1980s.

7. Farm size and the productivity of land and family labor

We conclude the discussion of results with a few comments on farm size and partial measures of productivity. In the Cerrado biome where TFP grew the fastest, average farm size is over two times the national average, and many farms are huge. Around two-thirds of land is in farms over 500ha and, in the Center-West which is largely Cerrado, over 50% of the land is in farms over 2,500ha. The productivity of land and family labor both grew about 40% faster in the Cerrado than the national average. In the Caatinga, where poverty is high, average farm size is about one

Table 14
Characteristics of transitions from bottom and top quintiles by degree of success

Transitions	Share in biome			Share with declining		Share of specialized AMCs				1985 Output
	Caat.	Cerr.	Mata Atl.	Output	TFP	Animal	Annual	Perennial	Not spec.	(10^6 2017 R$)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
All AMCs	0.17	0.18	0.58	0.35	0.32	0.23	0.20	0.08	0.50	50
Q1-Q1	0.71	0.15	0.11	0.61	0.43	0.43	0.03	0.02	0.53	14
Q1-Q45	0.05	0.59	0.30	0.00	0.00	0.04	0.53	0.01	0.42	33
Q5-Q12	0.16	0.04	0.73	0.96	1.00	0.02	0.30	0.30	0.38	57
Q5-Q5	0.02	0.29	0.66	0.31	0.13	0.09	0.43	0.08	0.40	108

[31] Specialization in perennials was defined above as 60% or more of total value of output coming from this group. Specialization in cacao is defined as 60% or more of perennial production coming solely from this one product.

third of the national average. Fifty-five percent of farms have less than 5ha and another 23% have between 5ha and 20ha.The productivity of land is only 40% of the national average and that of family labor is only 15%. Even starting from such a low level, the growth rate of both partial productivities was well below the national average. Finally, in the portion of the Mata Atlantica located in the South of Brazil, where there are many successful family farms, the productivity of land and family labor are around twice the national average, and both grew a little faster than the national average. Average farm size is around half of the national average in this portion of the biome. In contrast to the Caatinga, however, only a quarter of the farms have less than 5ha while 44% have between 5ha and 20ha.

8. Conclusion and discussion

In this paper we estimated a SFPF for Brazil and used the estimated coefficients to decompose output growth into contributions from inputs and TFP. We further decomposed TFP growth into several policy-relevant components. The results provide a novel characterization of TFP growth between 1985 and 2017 and carry important implications for public policy.

For Brazil as a whole, TFP growth explained around 60% of output growth in this period. By biome, output and TFP growth were fastest in the Cerrado, where farms tend to be much larger than the national average, and slowest in the Caatinga, home to many of the country's smallest farms. TFP growth was positively correlated with output growth, and both of these were correlated with the average scale of output in the period. Overall, output has become increasingly concentrated in a small share of AMCs, which also experienced faster TFP growth.

A key finding of this paper is the pronounced *divergence* of outcomes across many dimensions. We documented declining output and TFP in about a third of AMCs, with higher shares in the Amazon and Caatinga, in AMCs specialized in perennial crops, and in those AMCs with lower levels of production. This divergence led us to construct a transition matrix of TFP levels between 1985 and 2017, which revealed a high degree of persistence in both the bottom and top quintiles. Moreover, TFP grew much more rapidly in the top quintile than in any other group, widening the gap between the most productive AMCs and the rest. Public policy played an important role in driving TFP growth, but past achievements do not guarantee future success. Public investments in agricultural R&D were the single most important factor in our TFP decomposition, contributing 0.67% per year to TFP growth, or about 42% of the total.[32] Rising education levels among

[32] This is quite similar to Akerman et al. (2025) who calculate 39% for a slightly longer period.

agricultural producers—also a result of public investment—added 0.27% per year. In both cases, the lags between investments and impacts on TFP were longer than initially hypothesized. Future research should examine these lags more closely and explore whether they are unique to Brazil or common among developing countries, which may generally experience longer lags than high income countries. We also observed a reduction in the effect of public R&D on TFP growth in the final decade of our sample, coinciding with increased debates within Embrapa—and more broadly—about how to remain relevant and impactful in a context of increasing private sector R&D. What is clear is that continued generation of new knowledge and technologies, and their adoption by agricultural producers is critical to continued productivity growth. Embrapa plays a central role in the research ecosystem in Brazil by coordinating research efforts at the federal, state and university levels, as well as through partnerships with the private sector. Thus, adequate budgets, highly trained researchers, and strategic initiatives are critical. In terms of education, this likely played an important role in the adoption of new technologies and in the efficiency with which they were used. And even though our model identified a limited role for changes in inefficiency, credit and technical assistance were statistically significant in reducing differences in inefficiency.

To the extent that the rising scale and concentration of production contributes to output and productivity growth, this is important and should be supported because it contributes to food security, income in the sector, and export earnings. Brazil has a relatively neutral policy environment, having moved away from discrimination of the sector as of the late 1980s. But general support services are still small relative to the size of the agricultural sector (OECD, 2023) and infrastructure is precarious. This is an area where policy could be improved. But increasing concentration of production in a small share of municipalities also implies rising inequalities across space, with implications for employment and poverty. We documented a 30% decline in the use of family labor in this period, and there is abundant evidence of youth choosing to continue to exit from agriculture and rural areas. Average age of producers has risen, and many family farmers have difficulty finding a child who wants to take over the farm. Improving the accessibility and quality of schooling for the children of farmers should be a high priority. As demonstrated, it contributes to their productivity as farmers if they choose to remain in agriculture. It also improves the likelihood of a non-poor adulthood if they choose to migrate.

Another important result with considerable relevance for public policy relates to the negative effects of climate change over these three decades. We estimate that the climatic effects in this period slowed TFP growth by 0.56% per year. Our econometric model identified increasingly negative marginal effects for temperatures as they rose across our three intervals, while the TFP decomposition revealed that about half of the negative effect occurred below 28°C, more than one third between 28°C and 32°C, and close to 10% above 32°C. As Brazil continues to warm, these effects are likely to increase in magnitude and change in composition across intervals. Climatic impacts on the Caatinga, home to a high share of small farms and the rural poor, were more than double the national average, reflecting in part the effects of a prolonged drought in the 2010s. Overall, climate change poses a growing challenge to agricultural production and productivity in Brazil, underscoring the need for public policies—and public and private research efforts—to focus on adaptation. Possible strategies include developing drought- and heat-resistant seeds, expanding and improving irrigation, relocating production to more suitable areas, and other interventions.

The Caatinga biome in the Northeast of Brazil concentrates many of the most difficult challenges discussed above. Farm sizes are small, poverty is high, municipal output is low in most locations, and TFP growth was negative in half of them. It is also the region where climatic effects were most negative, with decadal TFP growth negative in the first and last decades. Policy for this biome requires an "all of the above" strategy. Investments in infrastructure, and especially irrigation, could reduce the effects of extreme events, including drought. Investments in developing new heat and drought resistant crop varieties could contribute to this goal as well. Crop insurance and social safety nets are also an important element of a strategy for dealing with shocks. And, finally, more accessible and higher quality education is important for youth, whether they remain in agriculture or decide that exit is their best strategy.

Future research should further explore the heterogeneity uncovered in this study. It would be fruitful, for example, to estimate separate models that allow for technologies to differ by farm size, specialization, and biome or sub-biome. Achieving this requires a database disaggregated in such a way that outputs can be appropriately attributed to inputs across these groups. Studies of this kind are underway as part of our research agenda.

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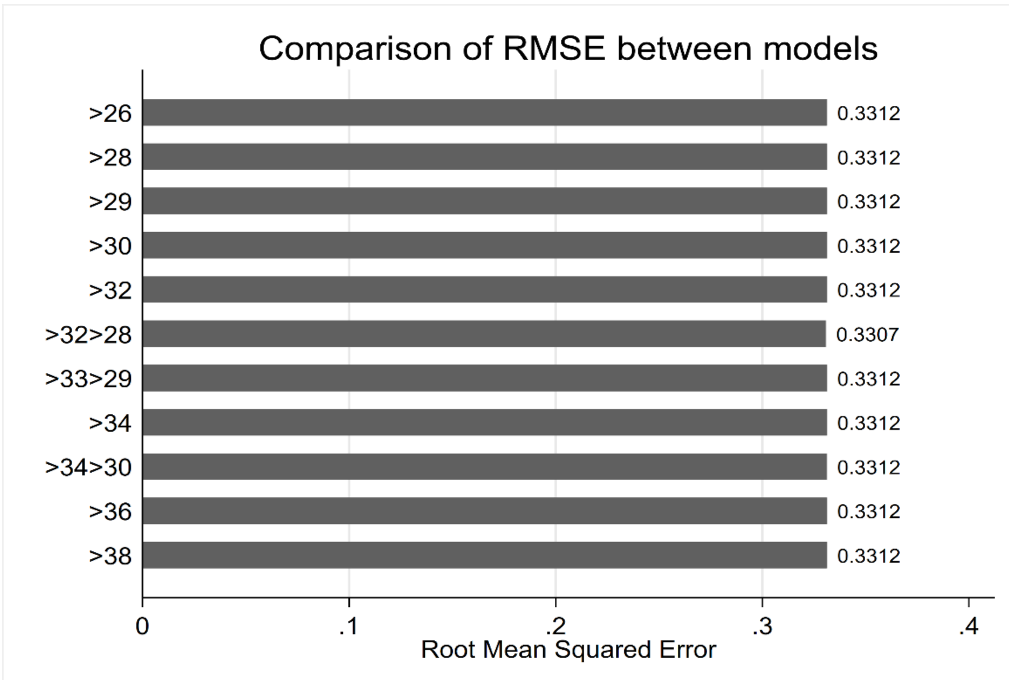
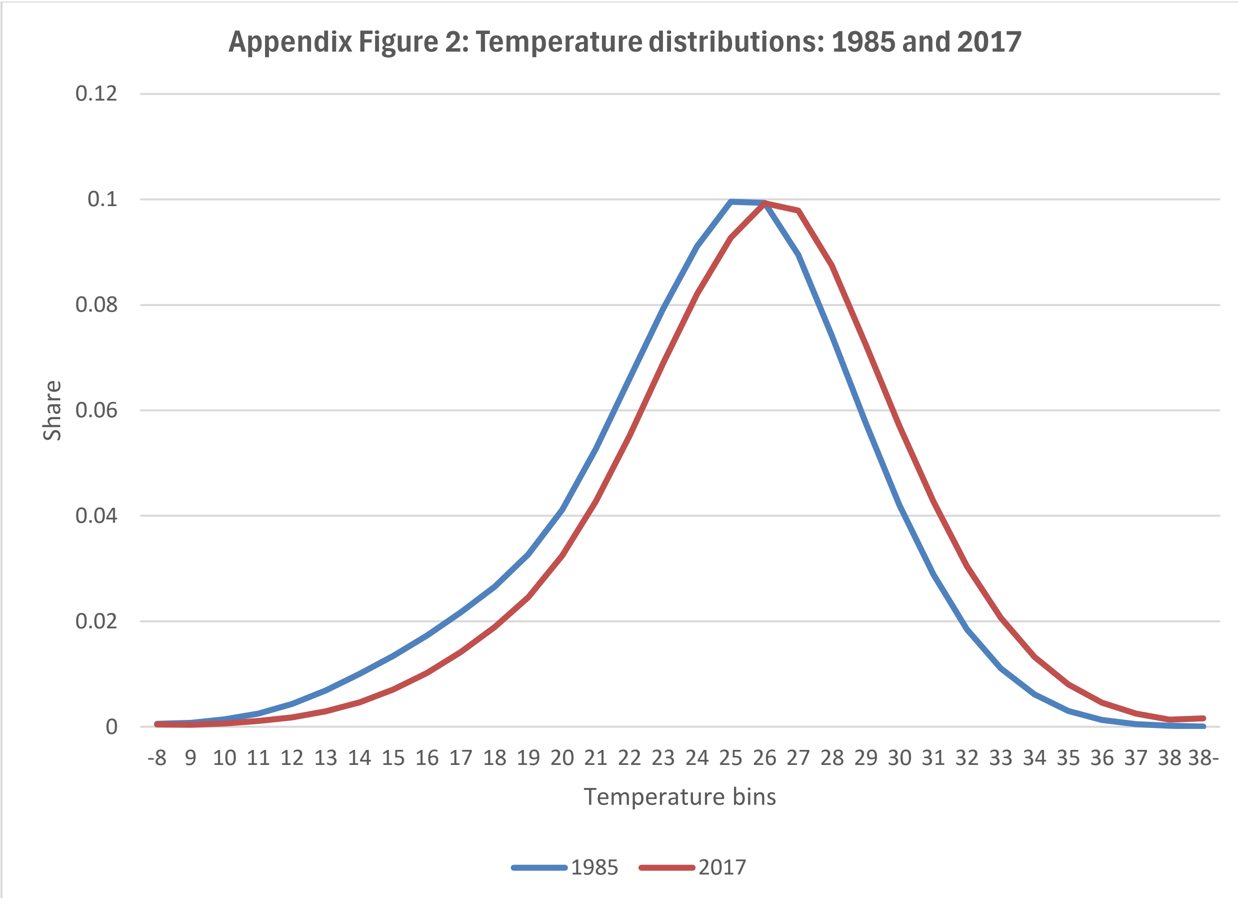
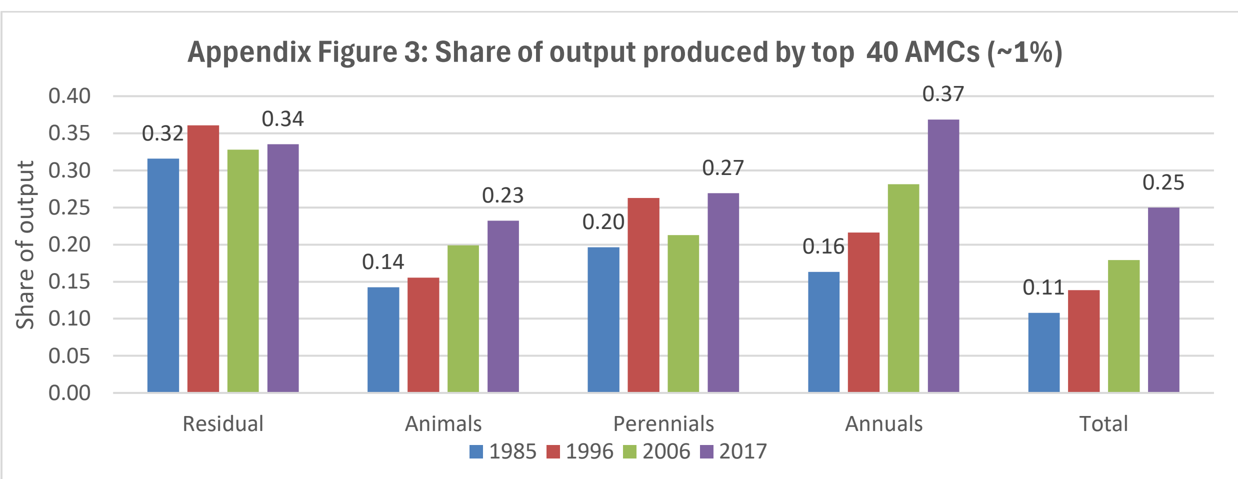
Appendix

Appendix Figure 1
RMSE from municipal panel fixed effects models with different temperature thresholds




Appendix Figure 2: Temperature distributions: 1985 and 2017
0.12
0.1
0.08
0.06
0.04
0.02
0
Share
-8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 38-
Temperature bins
1985
2017


Appendix Figure 3: Share of output produced by top 40 AMCs (~1%)
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
Share of output
0.32
0.34
0.14
0.23
0.20
0.27
0.16
0.37
0.11
0.25
Residual
Animals
Perennials
Annuals
Total
1985 1996 2006 2017

Appendix Table 1
Comparison of average production function coefficients from alternative models: AMC fixed effects, 20 groups, and 27 states

Variables	Regression results from Table 3		Comparison	T-test of dif. of coefficients	
	AMC fixed effects	20 dummies for groups of FEs	27 dummies for states	Col. 2 vs col. 1	Col. 3 vs col. 1
	(1)	(2)	(3)	(4)	(5)
Land	0.39	0.38	0.25	#	
Family labor	0.14	0.14	0.17	#	
Purchased inputs	0.31	0.32	0.45	#	
Machine capital	0.07	0.07	0.10	#	
Animal capital	0.12	0.11	-0.00#	#	
Tree capital	0.04	0.04	0.05	#	
Time trend	0.005	0.005	-0.00*	#	
Growing degree days					
Normal (<28C)	-0.47	-0.45	0.17	#	
Harmful (28-32C)	-0.50	-0.48	-0.19	#	
Very harmful (>32C)	-1.47	-1.55	-1.64	#	#
Precipitation	0.10	0.10*	0.25	#	**
Precipitation^2	-0.04	-0.04**	-0.07	#	#
R&D knowledge stock	1.73	1.70	-0.22	#	
Producer education	0.03	0.04	0.08	#	
Constant	6.21	5.14	3.70		
Returns to scale:	1.07	1.07	1.03		
Observations	14,852	14,852	14,852		
AMCs	3802	3802	3802		
R2:					
within	0.46				
between	0.85				
overall	0.81				
R2 adj.		0.94	0.89		

Notes: All coefficients significant at 1% unless noted as *=10%, **=5%, #=not significant.

Appendix Table 2
Average annual growth in output, inputs, TFP, and components by model in Table 4 and exponential
Brazil, 1985-2017

				TFP components						
Models from	Output	Inputs	TFP	Climatic	Education	R&D	Technology	Scale	Efficiency	Stat. Noise
Table 4 & Exp.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Col. 1	2.59	0.91	1.66				0.84	0.09		0.72
Col. 2	2.59	0.98	1.58	-0.67			1.52	0.08		0.65
Col. 3	2.59	0.96	1.60	-0.58	0.29	0.71	0.52	0.06		0.59
Col. 4	2.59	0.99	1.53	-0.56	0.30	0.70	0.47	0.06		0.55
Col. 5	2.59	0.97	1.56	-0.56	0.27	0.67	0.56	0.06	-0.01	0.57
Exponential	2.59	1.00	1.54	-0.56	0.30	0.70	0.47	0.06	-0.06	0.62