Agricultural productivity growth in Brazil: Large and small farms excel

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\textbf{A R T I C L E  I N F O}

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\textbf{A B S T R A C T}

The long-standing debate on the relationship between farm size and productivity has been generally limited by the range of farm sizes evaluated and the definition of productivity. In this paper we use data from three Brazilian agricultural censuses to address these issues. In particular, we introduce a wider distribution of farm sizes than presently available from the literature and we employ total factor productivity (TFP) as our performance measure. In doing so, we test which farm size class had the highest TFP levels in 1985 and 2006, how factor productivity growth varied within and across farm size classes between those years, and which policy or factor had the greatest productivity enhancing effect. When examining TFP growth, we move beyond the common decomposition into technical and efficiency changes by identifying the complete distribution of farm productivity performances. We find that by 2006 a U-shaped distribution of productivity over farm sizes had emerged. Considerable 1985–2006 TFP growth differences are prevalent; positive rates for the majority accompany stagnant or negative rates for some. Public education investments were associated with faster productivity growth regardless of farm size, while technical assistance’s positive effect and credit’s negative effect were associated with larger farm sizes. The role of specialization varied by size.

1. Introduction

Brazil ranks as the world’s fourth largest in terms of agricultural land use and production value (FAO, 2017). Unlike other top producers in the world, Brazil combines large, capital-intensive and export-oriented farms typical of developed agricultural economies with a high share of small, labor-intensive and subsistence-oriented farms emblematic of developing economies. In Brazil’s latest (2006) agricultural census, 36% of its 5.17 million farms operated less than 5 hectares (ha) and produced only 7% of total agricultural output value. Conversely, 2% of farms operated over 500 ha and produced 36% of agricultural output value. From this one might surmise that Brazil’s large agricultural operations are its most productive. The purpose of the present analysis is to test that proposition drawing on three rounds of agricultural census data in Brazil.

Comparing agricultural productivity across farm sizes typically involves estimating crop yield (quantity of output per ha) or land productivity (value of output per ha) for a single crop or multiple products. In Brazil, Fisher et al. (2016) find 1980 and 1996 maize yields higher for larger farms than for smaller ones. Filho and Vian (2016) examine a broader set of products in 2006 and conclude that most of them exhibit rising yields up to farms operating at least 500 ha. Yet crop yields account for only a single factor of production, namely land. Any conclusion about agricultural performance drawn from comparing yields fails to account for how farms of differing sizes utilize labor, capital, and intermediate inputs.

To capture the labor-intensive nature of Brazil’s small farms and land-intensive nature of its large ones we adopt total factor productivity (TFP), or output per unit of aggregate conventional inputs, as our comparative farm performance measure.\textsuperscript{1} Equally important, we allow the agricultural technology characterizing productivity growth to differ across farm sizes. By separately estimating the factor proportions that underpin TFP growth we control for the influence of scale economies and market imperfections in our comparative assessment. Scale is often used to explain rising productivity across farm sizes in developed agricultural economies (Paul et al., 2004; Key et al., 2008; Rasmussen, 2010), while the presence of market imperfections is a common explanation of the inverse productivity-farm size relationship in developing economies (Feder, 1985; Lamb, 2003; Barrett et al., 2010).

Agricultural TFP studies of Brazil are not uncommon (Avila and Evenson, 1995; Pereira et al., 2002; Avila et al., 2010; Gasques et al., 2010; Bragagnolo et al., 2010; Rada and Buccola, 2012; Rada, 2013;...

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\footnote{\textsuperscript{1} See Helfand and Taylor (2016) for a conceptual discussion of the implications of using partial measures of productivity rather than TFP.}

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Helfand et al., 2017). Yet only Helfand et al. (2017) estimated agricultural TFP growth across farm sizes. We extend Helfand et al. by (1) testing which farm size class had the highest TFP levels in 1985 and in 2006, (2) evaluating how the distribution of 1985–2006 factor productivity growth varied within and between sizes, (3) and identifying observable factors or policies that help explain respective farm-size productivity. To these ends, we utilize a pseudo-panel of 1985, 1995/96, and 2006 agricultural census data that is aggregated into 5 farm-size classes (0–5 ha, 5–20 ha, 20–100 ha, 100–500 ha, and 500+ ha) and approximately 3,800 Minimum Comparable Areas (MCAs) at the municipal (county) level.2

When separately evaluating Brazil’s 1985–2006 factor productivity growth for each size class we move beyond decomposing that growth into technical progress and efficiency change components and examine the full distribution of productivity performances. In this way we provide insight into the productivity growth laggards whose performances are typically lost to the average growth estimate of factor productivity relative to the best-practice technological frontier, i.e., technical efficiency change. We then assess how output specialization, capital intensity, access to technical assistance and agricultural credit, and public education may have lifted each size class’s farm productivity. In doing so, we provide insight into how Brazil’s policymakers may leverage and design policy to further accelerate inclusive agricultural growth.

In Section 2 of the present paper we provide background information by farm size, and in Section 3 we present our approach to TFP measurement and model selection. We present our variable definitions in Section 4, our empirical findings in Section 5, and our summary remarks in Section 6.

2. Brazilian agriculture by size

Based on FAO data from the 1990s, Eastwood et al. (2010) report that the overwhelming majority of farms in developing countries were smaller than 2 ha, including 92% in East Asia, 78% in South Asia, and 69% in Sub-Saharan Africa. The average farm size in China, for example, was 0.68 ha in 2013 (Ji et al., 2016). On the other end of the spectrum are the very large farms in Australia, the U.S., Canada, Russia, and the Ukraine where producers typically operate hundreds if not thousands of hectares. In order to facilitate comparisons between Brazil and the diverse agrarian structures around the world, we characterize Brazilian farms as very-small (0–5 ha), small (5–20 ha), small-to-medium (20–100 ha), medium-to-large (100–500 ha), and large (500+ ha).

Brazil in 2006 used over 330 million hectares to produce R$164 billion (US$75 billion) of output (Table 1).3,4 Brazil’s very-small, small, and small-to-medium farms operated less than 100 ha each in 2006 and accounted for 86% of the farms, 21% of the agricultural land, and 43% of the value of production. Since the mid-1990s many of these farms benefitted from public policies such as the PRONAF (National Program to Strengthen Family Farming) credit program under the authority of the Ministry of Agrarian Development. PRONAF is aimed at family farmers and, among other things, combines credit, new technology, and other investment to overcome transaction costs that limit their ability to access markets and increase income.5 In light of their substantial number, it is of little surprise that Brazil’s policymakers have honed policy specifically to family farms as a way to both alleviate poverty and bolster food production for the domestic market.

Brazil’s medium-to-large farms—those operating 100–500 ha—had less government support designed specifically for them. One policy that did target this group is the National Program to Support Medium Agricultural Producers (PRONAMP), which was created in the early 2000s but does not appear to have evolved beyond a special line of credit. Despite this class of farms utilizing 23% of the country’s farmland to produce 20% of its agricultural output in 2006, they have not received policy support to the same extent as smaller or larger size classes.

Brazil’s large commercial ‘agribusiness’ enterprises have relied on a combination of public (from the Ministry of Agriculture) and private investments to overcome market failures and inadequate public goods. These large farms—defined here as operating more than 500 ha—accounted for just 2% of producers in 2006, the majority of agricultural land, and around one-third of output. As with the small farms, it is predictable that these farms received public policy support given their role in generating important commodities and scarce foreign exchange.

Brazil’s large farms not only produced the highest share of output in 2006, they also achieved the fastest 1985–2006 output growth (Table 2).6 Output growth was realized through a dramatic increase in the use of purchased inputs and a modest increase in capital; land and family labor changed little over the period. In a departure from Table 1, where the very-small size class had the lowest share of 2006 output, these smallest producers had the second fastest 1985–2006 output growth. Between 1985 and 2006, Brazil’s 0–5 ha farms doubled output by doubling the use of purchased inputs and capital while reducing the use of land and family labor.

There is little indication from Table 2 as to which size class achieved the highest 1985–2006 total factor productivity growth. Steep growth in purchased inputs dampens expectations surrounding the largest size

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2 AMCs are temporally consistent spatial units that control for Brazil’s proliferating political boundaries. The number of AMCs is smaller than the baseline number of municipalities because some new municipalities were created from several previously existing ones. The number of municipalities grew from 4,107 in 1985 to 5,948 in 2006. From these municipalities, 3,861 AMCs were created. For simplicity, AMCs will be referred to as municipalities.

3 At an average annual commercial exchange rate of R$1.82 per US$1 (http://www. ipedata.gov.br/).

4 There were 255,000 farms (5%) classified by the Brazilian agricultural census in 2006 as “producers without area.” As a group they generated less than 1% of national output value. This category did not exist in previous censuses and is excluded from the present analysis in order to ensure temporal data consistency. For this reason Table 1 farm size shares do not sum to unity.

5 Family farms in Brazil are defined by law according to a number of criteria, including farm size, relying principally on their own off-farm income, and utilizing more family than hired labor. The criterion of size varies from one municipality to another and is related to achieving a minimum farm income. According to Brazilian law, farms of only a few hectares could be excluded if they rely heavily on hired labor, while a portion of the 100–500 ha could be included. All told, 84% of Brazil’s farms are legally defined as family farms, which includes the overwhelming majority of farms under 100 ha.

6 In contrast to FAO data, Brazilian data sources show declining land in agriculture. Raw data from the Agricultural Censuses and our index in Table 2 show declining land trends, consistent with Rada and Buccola (2012) and Gasques (2012). The difference between the FAO and Brazilian land data is largely due to pasture; since 1985, the FAO shows rising land in pasture while Brazilian sources show declining land in pasture. Notably, FAO pasture data have remained invariant post-2005, suggesting greater reliability of Brazilian land sources. The decline in family labor shown in Table 2 is the result of an exit of farm labor, but not necessarily of farm establishments. The number of farms was remarkably stable between 1970 and 2006 in the neighborhood of 5 million farms, with the exception of 1985. The raw data for total agricultural employment, in contrast, show a decline from 23.4 million people in 1985 to 16.6 million in 2006, with most of the reduction coming from family rather than hired labor. Family labor fell from 17.6 million in 1985 to 12.8 million in 2006.

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Table 1

<table>
<thead>
<tr>
<th>Farm size class (ha)</th>
<th>Farms</th>
<th>Area (ha)</th>
<th>Output (1000s of R$)</th>
<th>Share of Brazil</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-5</td>
<td>1,840,807</td>
<td>3,313,885</td>
<td>11,434,903</td>
<td>0.36 0.01 0.07</td>
</tr>
<tr>
<td>5-20</td>
<td>1,373,142</td>
<td>14,774,650</td>
<td>23,470,730</td>
<td>0.27 0.04 0.14</td>
</tr>
<tr>
<td>20-100</td>
<td>1,234,802</td>
<td>52,604,220</td>
<td>36,170,441</td>
<td>0.24 0.16 0.22</td>
</tr>
<tr>
<td>100-500</td>
<td>370,130</td>
<td>75,603,795</td>
<td>32,286,484</td>
<td>0.07 0.23 0.20</td>
</tr>
<tr>
<td>500-</td>
<td>101,763</td>
<td>187,383,487</td>
<td>59,584,360</td>
<td>0.02 0.56 0.36</td>
</tr>
<tr>
<td>Brazil</td>
<td>5,175,636</td>
<td>333,680,037</td>
<td>163,986,295</td>
<td>1.00 1.00 1.00</td>
</tr>
</tbody>
</table>

Source: Calculated from Brazil’s 2006 Agricultural Census.
Table 2
Percentage change of outputs and inputs by farm size class: Brazil, 1985–2006.

<table>
<thead>
<tr>
<th>Farm size class (ha)</th>
<th>Output</th>
<th>Land</th>
<th>Family labor</th>
<th>Purchased inputs</th>
<th>Capital stock</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Machines</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Animals</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Trees</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Total</td>
</tr>
<tr>
<td>0-5</td>
<td>100</td>
<td>-37</td>
<td>-24</td>
<td>104</td>
<td>113</td>
</tr>
<tr>
<td>5-20</td>
<td>76</td>
<td>-27</td>
<td>-28</td>
<td>90</td>
<td>45</td>
</tr>
<tr>
<td>20-100</td>
<td>53</td>
<td>-23</td>
<td>-26</td>
<td>61</td>
<td>1</td>
</tr>
<tr>
<td>100–500</td>
<td>43</td>
<td>-21</td>
<td>-31</td>
<td>96</td>
<td>-10</td>
</tr>
<tr>
<td>500</td>
<td>174</td>
<td>-4</td>
<td>7</td>
<td>306</td>
<td>16</td>
</tr>
<tr>
<td>Brazil</td>
<td>85</td>
<td>-15</td>
<td>-26</td>
<td>149</td>
<td>10</td>
</tr>
</tbody>
</table>

Note: Output is defined as the value of output deflated to RS2006; land is composed of cropland and pasture aggregated by relative rental rates; family labor is defined as male-adult equivalents; purchased inputs include expenditures on fertilizer, pesticide, hired labor, feed, fuel, electricity, seed, and major tools; total capital stock is the weighted aggregate of machinery, animal, and tree capital stocks. Complete variable descriptions are provided below.

Table 3

<table>
<thead>
<tr>
<th>Null hypothesis $H_0$</th>
<th>$\chi^2$ statistic</th>
<th>$\chi^2$ 0.95 value (df)</th>
<th>Decision</th>
<th>Choice</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pooled CD vs. pooled TL$^a$</td>
<td>4,285</td>
<td>25.00</td>
<td>Reject $H_0$</td>
<td>TL</td>
</tr>
<tr>
<td>Pooled TL with RE vs. Pooled TL with FE$^b$</td>
<td>5,878</td>
<td>67.50</td>
<td>Reject $H_0$</td>
<td>TL with FE</td>
</tr>
<tr>
<td>Pooled TL vs. farm-size TL with FE</td>
<td>3,631</td>
<td>246.97</td>
<td>Reject $H_0$</td>
<td>Farm-size TL with FE</td>
</tr>
</tbody>
</table>

Null hypothesis $H_0$

<table>
<thead>
<tr>
<th>Null hypothesis $H_0$</th>
<th>Observations</th>
<th>p-value</th>
<th>Decision</th>
<th>Choice</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normality distributed $\xi_i$ vs. skewed $\xi_i$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Size models (ha)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0-5</td>
<td>10,184</td>
<td>0.105</td>
<td>Fail to reject $H_0$</td>
<td>Normal $\xi_i$</td>
</tr>
<tr>
<td>5-20</td>
<td>10,517</td>
<td>0.399</td>
<td>Fail to reject $H_0$</td>
<td>Normal $\xi_i$</td>
</tr>
<tr>
<td>20-100</td>
<td>10,653</td>
<td>0.000</td>
<td>Reject $H_0$</td>
<td>Skewed $\xi_i$</td>
</tr>
<tr>
<td>100–500</td>
<td>10,071</td>
<td>0.000</td>
<td>Reject $H_0$</td>
<td>Skewed $\xi_i$</td>
</tr>
<tr>
<td>500 and more</td>
<td>6,101</td>
<td>0.898</td>
<td>Fail to reject $H_0$</td>
<td>Normal $\xi_i$</td>
</tr>
</tbody>
</table>

Notes:

$^a$ CD and TL are respectively Cobb-Douglas and translog production functions. Both average production functions have quarterly rainfall and temperature deviations from historical means.

$^b$ FE and RE refer respectively to fixed effects and random effects, and we used a Hausman test (H0: RE is appropriate).

3. Empirical models

Our empirical approach is to first estimate a base of relative 1985 total factor productivity levels to compare performance across farm size classes. We then estimate 1985–2006 TFP growth rates. These two are combined to generate 2006 TFP levels across farm size classes. Following an assessment of the role product specialization and capital intensity may have in raising TFP, we examine how public policy affects TFP growth.

We estimate 1985 TFP as follows:

$$\ln y_i = \alpha_i + \sum_{k=1}^{4} \beta_{ik} \ln x_{ik} + \frac{1}{2} \sum_{k=1}^{4} \sum_{l=1}^{4} \beta_{kl} \ln x_{ik} \ln x_{il} + \sum_{c=1}^{3} \beta_{ic} \ln D_c + \epsilon_i$$

where $y_i$ is a scalar output in municipality $i = 1,...,3861$ and size class $c = 1,...,5$; $x_{ik}$ is a vector of $K = 1,...,4$ inputs (land, labor, capital, and purchased inputs); $D_c$ are farm size class dummies; $\xi_i$ is a municipality dummy; $\alpha_i$, $\beta_{ik}$, $\beta_{kl}$, and $\beta_{ic}$ are parameters to be estimated; and $\epsilon_i$ is an independently and identically distributed normal econometric error. We impose on (1) a constant returns to scale technology which requires that the land, labor, purchased inputs, and capital linear parameters sum to unity ($\sum_{k=1}^{K} \beta_{ik} = 1$) and all cross-product terms sum to zero ($\sum_{k=1}^{K} \sum_{l=1}^{L} \beta_{kl} = 0$). Relative TFP levels are obtained from (1) via the size dummies $D_c$; that is, the difference in output after controlling for conventional inputs and unsolved municipal heterogeneity. Note that the size TFP estimates are expressed relative to the (excluded) smallest size class which is later normalized to equal 1.0 in 1985.

3.1. Estimating TFP growth

Prior to estimating 1985–2006 TFP growth, we conduct four econometric model selection tests on a specification similar to (1) but with the addition of a time dimension. The first is a test of Cobb-Douglas versus translog functional forms. Second, we apply the Hausman test of whether a fixed or random effects model is more appropriate with these data to capture unobserved and time-variant heterogeneity. Our third test is for skew in the econometric error to determine the presence of relative factor productivity differences (i.e., technical inefficiency) that may be modeled by a stochastic frontier. Finally, we test for differences in production technologies across farm sizes in the 1985–2006 period. Our expectation is a stochastic translog frontier that accounts for unobserved time-invariant heterogeneity, along the lines of Greene’s (2005) true fixed effects model.

Specification test statistics in Table 3 confirm the appropriateness of a translog with fixed effects and separate farm-size class production technologies for estimating TFP growth in 1985–2006. However, to our surprise, we find a lack of skew in three of five size classes at a 5% confidence level. Thus only two size classes appear to lend themselves to stochastic frontier estimation.

Stochastic frontier models rely on statistical skew to partition the composed econometric error into technical efficiency and idiosyncratic errors. Unfortunately, not only are we unable to estimate a stochastic frontier for all size classes, even those classes with statistical skew
Table 3 were econometrically intractable using stochastic frontier methods. TFP growth in 1985–2006 is therefore estimated separately for each farm size class from a translog production function:

\[
\ln y_{it} = \alpha_i + \sum_{k=1}^{N} \beta_{i,k} \ln x_{ik,t} + \frac{1}{2} \sum_{k=1}^{N} \sum_{l=1}^{N} \beta_{i,k,l} \ln x_{ik,t} \ln x_{il,t} + \beta_i t + \frac{1}{2} \gamma_i t^2 + \sum_{k=1}^{N} \beta_{i,k} \ln y_{ik,t} + \epsilon_{it},
\]

(2)

where \( \epsilon_{it} \) are fixed effects in municipality \( i \). Composed econometric error \( \epsilon_{it} \) is a two-sided independent and identically distributed normal that varies over space and time \( t \), as do environmental shocks \( u_{ik,t} \), \( l = 1,2 \). Eq. (2) summarizes the production technology – that is, the maximum output technically feasible given available inputs – of the average producer for a given size. A shift of that technology – measured as the derivative of output \( y \) with respect to time \( t \) while controlling for conventional inputs, environmental shocks, and unobserved and time-invariant heterogeneity – is defined here as TFP growth. Moreover, by virtue of input combinations \( x_{ik,t} \), TFP growth estimates from (2) are specific to observation \( i \):

\[
\delta \ln TFP_{it}/\delta t = \beta_i + \beta_i t + \sum_{k=1}^{N} \beta_{i,k} \ln y_{ik,t}.
\]

(3)

Growth estimates from (3) are applied to the 1985 TFP levels from (1) to achieve a 2006 comparison of factor productivity levels among farm size classes.

3.2. Decomposing TFP growth

Despite statistical evidence suggesting no relative factor productivity differences across representative-farms, we are unconvinced that all producers within any size class are operating at the same level of technical efficiency. Technical inefficiency in Brazilian agriculture has been documented in the literature (Bragagnolo et al., 2010; Rada and Buccola, 2012). We therefore replicate the TFP decomposition typical of the stochastic frontier literature into technical and efficiency changes using estimates from Eq. (3). To this end, we first trim the top 1% to account for possible outliers and assume that the 99th-percentile of TFP performances reflects the best-practice frontier in 1985 and in 2006. Change is thus defined here as the estimated shift in that frontier. Technical efficiency change is imputed as the difference between that measure of technical change and mean TFP growth estimated by (3). The agricultural productivity literature typically utilizes this type of decomposition to identify the technological leaders.

However, we believe too much information is lost to the average estimate of technical efficiency change. We therefore also examine the full dispersion of TFP growth performances to, in part, identify productivity growth laggards.

3.3. Accounting for policy

Abramovitz (1956) argued that TFP is the “measure of our ignorance.” That is, if we could account for all the factors, policies, and characteristics that explain agricultural output growth then our measure of TFP growth would be, in the limit, zero. However, one of our purposes is to calculate a measure of performance that is comparable to other work in the productivity literature, especially index number approaches that are commonly used to analyze aggregate agricultural supply. To this end, our approach in Eq. (2) has been to include only environmental shocks as conditioning variables for the TFP growth estimates in (3). Later, in a separate specification, we add to (2) three policy variables: years of agricultural education, access to technical assistance, and access to agricultural credit. In doing so, we not only analyze how these policies affect marginal TFP levels but also their effect on our measured rate of TFP growth.

4. Data

The agricultural output, input, environmental, and policy variables used to measure and evaluate Brazil’s farm performance across size classes are detailed below. Data aggregation requires that we assume homogeneity within each aggregate observation (for example, farms with 5–20 ha in the municipality of Vicosa). We call these “representative-farms”, as they reflect the average behavior of a given size in a given municipality. The econometric analysis thus explores variation between representative-farms across space and over time, but due to aggregation we cannot examine variation within them. We frequently refer to these representative-farms simply as producers.

4.1. Output and input indexes

Output is defined as the total value of agricultural output deflated by an implicit price deflator calculated from the data in Gasques et al. (2010). The implicit price index, for each census year, is the log difference between the growth of the total value of output and that of a Tornqvist quantity index covering 367 products.

Quantity indexes are constructed for four types of inputs: land, family labor, capital stock, and purchased inputs. The capital stock includes trees, animals, and machinery; purchased inputs include, among other items, hired labor. These variables, as well as the environmental shock and policy variables, are described below.

Land area provided by the censuses are specified in hectares by type: annual cropland, perennial cropland, natural pasture, and planted pasture. However, land price data from the censuses needed to aggregate each type into a single, constant quality series are not reported. We therefore apply the ratio of crop to pasture land rental rates at the macro region reported by the Getulio Vargas Foundation (FGV). One limitation of our approach is the assumed land-quality homogeneity between annual and perennial cropland, and between natural and planted pasture. However, we do separately account for the value of tree stocks in permanent cropland in our measure of agricultural capital.

Unlike hired labor, which is provided in the census as total expenditures, family labor is provided by counts of men, women, and children working in agriculture. Following Helfand et al. (2011) we use

[7] A challenge to adopting Greene’s TFP model – an approach that separates unobserved heterogeneity from time-varying inefficiency - is that the number of cross-sectional observations in the panel equals the number of fixed effects (Greene, 2005). As a result, many researchers are faced with the ‘incidental parameter’ problem; that is, inconsistent estimates when the number of cross-sectional units \( i \) is large relative to the number of time periods \( t \) in the panel. Model convergence also becomes an issue as the number of fixed effects grows. Standard techniques of mean- or first-differencing typically used to eliminate fixed effects in linear models do not apply in the stochastic frontier setting (Kumbhakar et al., 2015). The short time dimension of the present analysis (3 units), and large cross-sectional dimension (15,842 units), thus preclude our adoption of the TFP model (Bieleti and Barili, 2018; Bieleti et al., 2013). We therefore tested a Correlated Random Effects stochastic production frontier to complement the estimates presented in the present analysis. Maximum likelihood non-convergence and implausible results plagued the frontier models. None of the likelihood functions converged when a translog was adopted. In all cases the idiosyncratic error variance swamped the value of the inefficiency error variance, suggesting the likelihood function was unable to statistically parse inefficiency from heterogeneity. Convergence was only achieved for the largest class when adopting a Cobb-Douglas specification. But even here the results were implausible, with essentially no relative factor productivity differences and a uniform rate of technical progress across observations.

[8] The TFP growth decomposition results presented below are qualitatively equivalent to defining the best-practice frontier as the top 1 percentile of TFP performances. Because the top 1% likely includes some observations with positive measurement error, using the 99th-percentile helps to avoid this problem.

[9] An additional modeling decision designed to make our estimates more comparable to the aggregate TFP literature on Brazil is to weight by output while estimating the production functions. This issue is discussed further in Section 5.
weights of 1.00 for men, 0.75 for women, and 0.50 for children under the age of 14 to construct a measure of family labor in male adult equivalents. Note that in 2006, 92% of family members occupied on the farm were 14 years or older, and 65% of the total were men. Purchased inputs include expenditures on: hired-labor, fertilizers, pesticides, feed, fuel, electricity, soil correction, animal vaccines, seeds, transportation and other items. Labor (18%), fertilizers (16%), and pesticides (12%) are the most important components of the purchased input variable. All remaining purchased inputs account for less than 10% each. Lacking prices or quantities of these from the census, they are aggregated and deflated over time in the same manner as output.

We follow Moreira et al. (2007) and Butzer et al. (2012) to create an index of the capital stock in machines, animals, and tree crops. The machinery capital stock is the total horse-power of farm machinery in-use on Brazilian farms. This quantity includes tractors (available in five horsepower classes), trucks, pick-up trucks, planters, and harvesters multiplied by machinery- and horsepower-specific sale prices that are set relative to the largest horsepower tractor class (> 100 hp). The 1985 and 1995 censuses provide tractor data in five horsepower classes (< 10, 10–20, 20–50, 50–100, > 100), but the 2006 census only provide these data in two classes (< 100 hp and > 100 hp). We therefore calculated the 1985 and 1995 shares of tractors in each size class and projected them forward to 2006. Machinery sale prices are from the Institute of Agricultural Economics and are specific to the state of São Paulo in 1996, which has the most comprehensive data.

We include the stock of animal capital to account for animal inventories and to proxy for unmeasurable capital in farm structures such as barns and fences. Typically one would aggregate animal inventories using weights that reflect relative prices, such as those provided in Hayami and Ruttan (1985). Adopting such an approach in our case would produce a cattle-equivalent stock that is dominated (>90%) by large animals (cattle). However, much of the cattle in Brazil is produced extensively on pasture, and chicken meat accounted for 20% of total 1985 meat output.10 We therefore multiply each animal’s price weights by 1985 cattle, pig, and chicken slaughter ratios—that is, the number of slaughtered animals per total animal inventory—so that each animal’s share of the capital stock is roughly proportionate with its share of 1985 output.11 In doing so, we assume that on average each animal type requires the same capital intensity. In the end, our animal capital stock is comprised of 68% large animals, 12% medium sized animals, and 20% small animals. Time-invariant 1985 slaughter ratios allow all technological gains made in the production of each animal (weight, breeding times, etc.) in 1985–2006 to be captured by TFP.

The tree-crop capital stock is specified as the present discounted value generated from thirteen perennial crops. Drawing on the approach of Butzer et al. (2012), we utilize data on the quantity of trees, expected years of production, and average regional productivities and prices to calculate the present discounted value of the future stream of profits expected from Brazil’s stock of tree crops. Following Butzer et al., we assume that 65% of total revenues are required for production costs, leaving a 35% profit stream for estimating the present discounted value.

We aggregate the quantity stock of machinery capital, the value service flow of animal capital, and the present discounted value of tree-crop capital into a single capital index. Because the three sub-indices have different units, aggregation weights are estimated from a discounted 1985 regression of the value of output on the three 1985 capital stock sub-indices. To allow additional flexibility of our capital variable, we estimate weights at the regional level.12 Machines were the most important component of capital in all regions but the North where animals dominated. The weight on machines varied between 0.50 and 0.59 in the Southeast, South, and Center-West, and dropped to 0.39 and 0.15 in the Northeast and North.

4.2. Environmental controls and policy variables

The environmental variables employed in the present analysis control for droughts, extreme rainfall, and other environmental shocks to the agricultural production process. Using monthly data described in Wilmott and Matsuura (2001), we construct deviations from a 25-year moving average of quarterly rainfall and temperature. The 25-year window ends one year prior to each agricultural census, and the shocks are the observed temperature and rainfall levels in the census year relative to historical means. We describe the deviations from historical means with dummy variables that reflect whether rainfall or temperature for a given municipality, quarter and year were below the 10th percentile of shocks, in the 10th–30th, 30th–70th, 70th–90th, or above the 90th percentile of the distribution. Because deviations in the middle of the distribution reflect normal years for rainfall and temperature, we omit the 30th–70th category.

Education is defined as the average years of schooling in each municipality for adults employed in agriculture. The data are drawn from Brazil’s demographic censuses of 1980, 1991, and 2000, and are thus lagged by about five years in relation to each agricultural census. We further de-trended the change in education to reduce multicollinearity with the time trend by regressing years of education against time and adopting the residual as our variable of interest. The estimated coefficient of the detrended education variable was identical to that of the trending variable but the subsequent productivity growth estimates were more stable.

The number of establishments that use technical assistance by size class is available from the agricultural censuses. However, we avoid the potentially endogenous relationship between productivity and the choice to utilize technical assistance by instrumenting for the endogenous variable in the agricultural census—use of technical assistance—with a variable that broadly reflects the supply of technical services. This instrument is defined at the municipal level as the number of people working in technical agricultural jobs per 1,000 farms, and is constructed from 1980, 1991, and 2000 demographic census data.13 In the instrumenting equation the use of technical assistance by farm size is regressed on the instrument, dummies for year, region, farm size, and an interaction of the instrument and farm size dummies. The number of establishments that use credit by size class is available from the agricultural census, and may also be an endogenous variable. Similar to technical assistance, we create an instrument that reflects the availability of credit in each location. This variable is the number of public banks per municipality. Public banks, such as the Banco do Brasil, are more involved in providing rural credit than private banks. The data on bank branches come from the Central Bank, and are lagged one year relative to each agricultural census. As with technical assistance, predicted use of credit by size class and municipality is calculated from the first stage regression of credit by farm size

10 Hayami and Ruttan’s (1985) cattle-equivalent aggregation weights reflect that 1 cow equals 4 pigs and 80 chicken. Adopting weights reflecting Brazilian prices we find similarly that 1 cow equals 4 pigs and 138 chicken.
11 Note that a dairy cow would require more capital than a beef cow feeding on pasture. However, the total share of milk cows to the total cattle inventory in 1985 Brazil was only 10% (FAO, 2017).
12 Slaughter ratios in 1985 for large animals was 0.27, for medium sized animals was 0.63, and for small animals was 4.12.
13 Each variable was standardized prior to estimation by subtracting its mean and dividing by its standard deviation. The regressions fit the data well, with adjusted coefficients of determination (Adj. R²) between 0.55 and 0.85. The weights are normalized to sum to one for a given region, and for machinery, animals and trees, respectively, they are: North (0.15, 0.49, 0.36), Northeast (0.39, 0.29, 0.32), Southeast (0.30, 0.23, 0.27), South (0.31, 0.34, 0.15), and Center-West (0.95, 0.35, 0.05). Parameter estimates available upon request.
14 Details on the construction of this variable are available from the authors.
15 We thank Juliano Anunção for sharing this data with us.
on the instrument, dummies for year, region, farm size, and an interaction of the instrument and farm-size dummies.

5. Results

Because most of the literature on agricultural TFP growth in Brazil uses index numbers and is national in scope, all models estimated here use weights that reflect the value of output across representative-farms. Our objective is that the parameter estimates are influenced by those areas that produce more of the output. In this way our TFP estimates will be broadly comparable with the productivity literature that seeks to explain aggregate agricultural output growth with total input growth in Brazil. An alternative to our approach would be to weight by the number of farms within a given representative-farm. This would have generated parameter estimates that are influenced by where more farms are located, rather than more output, and thus less comparable with the literature on national supply performance.16

Under the assumption that the marginal elasticities, evaluated at the mean, from the estimation of Eqs. (1) and (2) reveal the cost structure associated with Brazilian agriculture, we find in 1985 that purchased inputs generated the highest cost share (0.51), with much lower shares for land (0.17), family labor (0.13), and capital (0.20).17 Our 1985–2006 TFP growth model indicates that purchased inputs generated the highest cost share of all inputs across all farm sizes (Table 4). This is consistent with estimates from the 1985 model and with the robust growth in purchased inputs presented in Table 2. Among all farm sizes, on Brazil’s smallest farms family labor had the highest cost share and capital had the smallest, while on its largest farms capital had the highest cost share and family labor the smallest. The goodness of fit measures in Table 4 illustrate that model (2) explains a considerable portion of the variation in output.

Fig. 1 combines results from Eqs. (1)–(3). The lower curve in the figure shows that output produced in the 5–20 ha and 20–100 ha size classes was done with TFP levels that were 8% higher than on the smallest farms in 1985. TFP levels in the 100–500 ha and 500–ha classes were respectively 16% and 20% higher. By 2006, the smallest class had achieved the second-highest level of factor productivity, being, however, only the largest. The 76% TFP growth achieved in 1985–2006 by the 0.5–ha class succeeded in lowering its relative productivity disadvantage with the 500–ha class from 20% in 1985 to 9% by 2006 (see the top horizontal line in Fig. 1).18 Farms in the middle three size classes were the least productive by 2006.


We now turn to analyzing whether the TFP growth exhibited in Fig. 1 is uniform over all representative-farms within each size class. To that end, we decompose TFP growth from Eq. (3) by defining the technological best-practice frontier as the 99th percentile of TFP observations in 1985 and in 2006. Technical change is the measured shift of that frontier, whereas technical efficiency change is, as in a stochastic frontier approach, the difference between shifts of the frontier technology and shifts of mean factor productivity relative to those best-practice producers.

16 The two weighting schemes provide very similar patterns of TFP over the first three size classes in 1985. However, TFP is considerably lower in the two larger size classes when weighting by the number of farms rather than by output. With output weights we observe a gradually increasing relationship between TFP and farm size in 1985, but with farm weights we observe a decreasing relationship. Applying farm weights would have resulted in farms over 500 ha being 17% less productive than the smallest farms. For the largest two size classes, those areas that produce a lot are not the ones where more farms are located.

17 Parameter estimates are available upon request.

18 The U-shaped pattern of TFP growth over size classes is nearly identical regardless of whether output or the number of farms is used as weights when estimating Eq. (2). The principal difference is that the magnitude of TFP growth is higher when output weights are used.

Table 4

<table>
<thead>
<tr>
<th></th>
<th>Brazil 0–5 ha</th>
<th>5–20 ha</th>
<th>20–100 ha</th>
<th>100–500 ha</th>
<th>500 ha +</th>
</tr>
</thead>
<tbody>
<tr>
<td>Land</td>
<td>0.25</td>
<td>0.44</td>
<td>0.09</td>
<td>0.07</td>
<td>0.05</td>
</tr>
<tr>
<td>Family labor</td>
<td>0.14</td>
<td>0.38</td>
<td>0.05</td>
<td>0.11</td>
<td>0.18</td>
</tr>
<tr>
<td>Purchased Inputs</td>
<td>0.47</td>
<td>0.49</td>
<td>0.41</td>
<td>0.45</td>
<td>0.51</td>
</tr>
<tr>
<td>Capital</td>
<td>0.27</td>
<td>0.09</td>
<td>0.27</td>
<td>0.31</td>
<td>0.42</td>
</tr>
<tr>
<td>R2 within</td>
<td>0.56</td>
<td>0.57</td>
<td>0.54</td>
<td>0.53</td>
<td>0.46</td>
</tr>
<tr>
<td>R2 between</td>
<td>0.93</td>
<td>0.77</td>
<td>0.79</td>
<td>0.88</td>
<td>0.87</td>
</tr>
<tr>
<td>R2 overall</td>
<td>0.88</td>
<td>0.65</td>
<td>0.67</td>
<td>0.77</td>
<td>0.77</td>
</tr>
<tr>
<td>N</td>
<td>47,526</td>
<td>10,184</td>
<td>10,517</td>
<td>10,653</td>
<td>10,071</td>
</tr>
</tbody>
</table>

Note: Parameter estimates for each regression are available upon request.

Unlike Brazil’s 1985–2006 agricultural TFP growth which has a U-shape distribution over farm size classes, we find that the fastest best-practice technical progress occurred in the 100–500 ha size class, which expanded by 4.9% each year in 1985–2006 (Fig. 2). Thus a subset of representative-farms in this size class were achieving very rapid rates of factor productivity growth. Yet that fast rate of progress was concentrated among a few producers; mean TFP growth was an extremely low 1.3% each year, the slowest among Brazil’s size classes. The rapid productivity growth by some and near-stagnant or negative growth by others is notable given the limited institutional policy support to this size class highlighted in Section 2.

Brazil’s smallest and largest size classes also achieved robust annual average technical change of over 4%, but that growth was more broadly realized by producers in these classes and respective TFP growth rates were 2.7% and 2.2%. Producers in the 5–20 ha group generated the least technical change; its most efficient producers were annually improving productivity by only about 3%. Yet with slower frontier growth came fewer efficiency losses and annual average TFP growth was close to the national mean of 1.8%.

Brazil’s national 1985–2006 factor productivity growth estimate is provided for comparison to the literature. The annual average 1.8% TFP growth rate is lower than the 3.1% estimated by Braggagno et al. (2010) for a slightly longer period, the 2.6% estimated by Rada and Buccola (2012), and the 2.2% estimated by Gasques et al. (2010), but very similar to the 1.7% estimated by Helfand et al. (2017). It is likely that our results are lower than what Braggagno et al., Rada and Buccola, and Gasques et al. estimated due the highly disaggregated nature of our data and the inclusion of fixed effects to account for unobserved heterogeneity. While the farm-size specific TFP growth rates estimated by Helfand et al. are close to those estimated here, the present estimates are likely more precise due to our improved approach of separating heterogeneity from productivity.

An important drawback of Fig. 2 is that we only learn by how much the most efficient producers are outpacing the average. While helpful in elucidating growth leaders, such an approach does little to improve our understanding of the performance of all producers, and in particular of the growth laggards. We therefore compute the full distribution of TFP performances for each size class.

The medium-to-large and large size classes had a number of producers with negative productivity change in 1985–2006 (Fig. 3). Notably, TFP growth of the 10th percentile performer in the 100–500 ha class was nearly zero. Thus of the 370,130 farms operating in this size class, close to 37,000 of them experienced input growth that exceeded or equaled output growth, resulting in no or negative factor productivity shifts. The large size class also had poor performers, but fewer in number.

The smallest size class achieved the highest rates of TFP growth at nearly every percentile of the distribution. It is only at the very top, above the 95th percentile, when the smallest producers cede position to the largest size class. The smallest producers substantially outperform...
the middle three size classes. For example, 75% of the representative-farms in the 0–5 ha size class had TFP growth above 2%, whereas at most 25% of those in the middle size classes achieve that growth rate.

The performance of the largest size class falls in between that of the smallest and the three middle size classes, though it is more closely aligned with the smallest class’s distribution. The 5–20 ha and 20–100 ha sized classes have steeper distributions, suggesting a higher concentration of growth rates in a narrow range of relatively poor performance.

5.2. Product specialization as a source of 1985–2006 TFP growth

In this subsection we investigate the extent to which there is heterogeneity of product specialization within each size class. A priori, we expect that agricultural productivity growth should have been higher for those small producers specializing in high-value horticultural or chicken and hog products. These have been dynamic sectors in Brazil, and producers could have achieved relatively high productivity growth using capital intensive processes and little land. For larger producers, we expect that specialization in mechanizable crops is likely to be associated with faster TFP growth.

Table 5 presents, for each farm size class, TFP growth rates by activity and degree of output specialization, defined here by the proportion of total agricultural output value accounted for by a given commodity group. For each farm size we compare productivity growth rates for those producers with 40–60%, 60–80%, 80–90%, and 90–100% of farm output value sourcing from perennial crops, non-horticultural annual crops, horticulture crops, chickens and hogs, and large animals (cattle).

Our expectation that small representative-farms achieved above average TFP growth in 1985–2006 by specializing in horticulture or chickens and hogs finds only mixed support. For the three smallest size classes, specialization in the range of 40–80% in chickens and hogs is associated with modestly higher productivity growth, but that advantage disappears with higher degrees of specialization. In fact, producers with 90–100% of output coming from these products have growth rates that are substantially lower than the mean. In the case of horticulture, producers in the 40–60% range have similar TFP growth to the mean, and growth rates decline with higher degrees of specialization. In the 0–5 ha class, the highest productivity growth rates are observed for producers fully specialized in perennial and annual crops.
For the large and medium-to-large size classes, we observe a clear positive relationship between TFP growth and higher degrees of specialization in annual crops. Representative-farms in the 500-1000 ha class that are completely specialized in annual crops achieve TFP growth that is 0.8 percentage points above the mean growth rate, whereas for these producers in 100-500 ha class the growth rate is 0.5 percentage points above the mean rate. For producers of this size, complete specialization in large animals also generates performance that is significantly above the mean.

Connected to output specialization is capital intensity. Assessing correlations between 1985 and 2006 TFP growth and average capital intensity levels (aggregate capital stock per ha) in that same period indicates more machinery, livestock, and tree-crop capital per hectare is negatively correlated with TFP growth in all size classes. The largest correlations are those related to farms operating between 5 and 100 ha; −0.93 for farms in the 5–20 ha size class and −0.88 in the 20–100 ha size class. These strong negative correlations suggest that those producers with more on-farm capital per hectare in 1985–2006 were not the same ones achieving the highest TFP growth. Note that all other correlations were less than −0.46.

### 5.3. Policy explanations of 1985–2006 TFP

Last, we investigate how farms of different sizes might be targeted by policy to improve their productivity, and how much of the TFP growth rate is explained by policy. Specifically, we evaluate the marginal effects of investments in agricultural technical assistance, credit, and education on TFP levels. We also assess how the introduction of the package of policy variables changed the TFP growth rate. To this end we re-specify Eq. (2) to include the technical assistance, agricultural credit, and agricultural education variables and re-estimate (3).

Table 6 provides each policy’s marginal effect on TFP levels, as well as their combined effect on the overall TFP growth rate. We find that a 1% increase in the predicted share of farms receiving technical assistance boosted TFP levels by 0.51% per year, but only for those producers operating between 100 and 500 ha. The effect was statistically insignificant for the other size classes. Similarly, agricultural credit was only statistically significant for the larger farm sizes, those over 100 ha.
Table 6

<table>
<thead>
<tr>
<th>Farm size class (ha)</th>
<th>Technical assistance</th>
<th>Agricultural credit</th>
<th>Agricultural education</th>
<th>Percent of TFP growth explained by policy</th>
<th>All policies included</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-5</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>15.9%</td>
<td>1.47%</td>
</tr>
<tr>
<td>5-20</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>11.4%</td>
<td>0.59%</td>
</tr>
<tr>
<td>20-100</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>2.67%</td>
<td></td>
</tr>
<tr>
<td>100-500</td>
<td>0.505</td>
<td>–</td>
<td>–0.303</td>
<td>10.4%</td>
<td>38.89%</td>
</tr>
<tr>
<td>500+</td>
<td>–</td>
<td>–</td>
<td>–0.238</td>
<td>17.8%</td>
<td>6.25%</td>
</tr>
</tbody>
</table>

Notes: – indicates the estimated parameter value from Appendix Tables A2–A6 was not statistically significant at the 5-percent level. Marginal effects on TFP levels are drawn from introducing these variables into Eq. (2). The total effect on the growth rate is drawn from comparing Eq. (3) estimates with and without the policy variables.

For both the 100–500 ha and 500-ha size classes, an increase in the predicted share of farms using agricultural credit lowered TFP; a 1% increase in credit access lowered the productivity level by 0.30% per year for the medium-to-large producers, and by 0.24% per year for the large producers. Education has a large and positive effect on TFP levels in all sizes except for the 20–100 ha class. A one-year increase in average years of schooling of the people working in agriculture raised TFP between 10% per year in the medium-to-large size class and 18% per year in the largest size class.

The marginal policy effects on TFP shown in Table 6 are very similar to the positive technical efficiency effects induced by more schooling infrastructure and public agricultural research investments found by Rada and Buccola (2012). However Rada and Buccola estimated a positive effect from agricultural credit, as did Gasques (2012). That credit has a negative effect on TFP is counter to our expectations and findings from the literature, but was robust to all model specifications. This result could, in fact, reflect overuse of credit, as those farms which obtained credit may have over-expended on inputs, lifting input growth more rapidly than output growth and thus reducing TFP growth. Alternatively, it might result from limitations in the way we constructed the credit variable, capturing access to credit without taking into consideration the quality of credit utilized. Moreover, it could be a result of mixing all types of credit together. Relative to production credit which is used to finance variable input expenditures and is more abundant, investment credit is more likely to have a positive relationship with long-term TFP growth. This is an issue that would benefit from additional research.

Table 5 further shows in column 5 the change in our TFP growth estimates once we re-estimate Eqs. (2) and (3) with the inclusion of all three policy variables. This exercise is helpful for demonstrating the difference between policy’s marginal effects on TFP levels and its overall contribution to explaining TFP growth. Despite the strong marginal effects from education and technical assistance policies, accounting for their combined contribution explained at most 6.25% of TFP growth in most size classes. In the 100–500 ha size class, though, the combined effect explained close to 40% of TFP growth—with the estimated annual average TFP growth rate declining from 1.5% in 1985–2006 to 0.8% as the result of the inclusion of the policy variables. If these results are accurate, then all other factors and policies, such as learning by doing and investments in agricultural research and extension, likely account for the remaining 0.8% TFP growth.

6. Conclusions

Unlike previous analyses of Brazilian agricultural productivity, we ask here how agricultural TFP has varied within and between farms of different sizes and what might explain those productivity differences.

Critical to our approach was separating time-invariant, unobserved heterogeneity from productivity, and allowing for different technologies for each farm size class to minimize distortions from returns to scale or market imperfections. We examined how marginal improvements in technical assistance, credit, and education affect TFP levels, as well as their cumulative effect on the rate of TFP growth. We also showed how output specialization and capital intensity are related to size-specific productivity performances.

The large (500-ha) size class achieved the highest TFP levels in 1985 and 2006, whereas the greatest TFP growth was achieved by the very-small (0–5 ha) size class. A broad characterization of these findings—withstanding the heterogeneity that exists within size classes—is that the smallest class represents a low-input, low-outcome model; the largest class represents a high-input, high-outcome model; and both have operated at very high levels of productive efficiency. The TFP-growth distribution over farm size classes is U-shaped, seemingly combining the inverse productivity relationship documented in developing economics with the rising productivity relationship found in developed economies. Concealed by the average rates of productivity growth are exceptional performances by some and very poor performances by others. The medium-large size class contained the most farms with negative productivity growth, but the largest size class contained the widest overall productivity dispersion, though substantial TFP gaps were prevalent in all size classes.

Of the farm size classes evaluated here, the medium-large class (100–500 ha) stands apart. First, this size achieved the slowest output growth in 1985–2006 among classes, reduced input use across all factors of production except purchased inputs, and received the least institutional support. This class realized the fastest 1985–2006 technical change, but also the lowest TFP growth among size classes. We examined a number of factors to investigate how Brazilian policymakers might lift growth in this (and other) size classes. Technical assistance and more education are two policies that raised TFP for this group, as did specialization in large animals and annual crops. But we also show access to public agricultural credit lowered TFP, that capital intensity is not associated with faster TFP growth, and that the complex of policies evaluated explained a substantial portion of the class’ TFP growth rate. This class requires further research, particularly with respect to identifying constraints that have resulted in stagnant or deteriorating farm performance. The negative correlation between TFP growth and capital intensity is one area deserving of additional future research.

Other future research should address whether public policies would have a larger impact if targeted to the growth laggards, the middle of the TFP growth distribution, or producers closer to the frontier. Given the substantial number of poor performances identified in the present analysis, would lifting the growth laggards improve aggregate TFP more than further extending the best-practice frontier? Another important question relates to how farm entry and exit may have affected the TFP performances. Does the limited change in the number of farm establishments over time reflect stability in the number of farms in each size class, or is it masking substantial farm entry and exit which could further elucidate the TFP estimates presented here?

Acknowledgements

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.foodpol.2018.03.014.
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