JAE Journal of Agricultural Economics

Journal of Agricultural Economics, Vol. 71, No. 2, 2020, 287–304
doi: 10.1111/1477-9552.12363

The Evolving Structure of Chinese R&D Funding and its Implications for the Productivity of Agricultural Biotechnology Research

Jinyang Cai, Weiqiong Chen, Jikun Huang, Ruifa Hu and Carl E. Pray[1]

(Original submitted October 2018, revision received March 2019, accepted July 2019.)

Abstract

China's research and development (R&D) policy has changed considerably over recent decades, and great changes occurred in 2006 when the main programme objective of China's R&D changed from the 863 Programme and 973 Programme to the National Science and Technology Major Project. One topic that has drawn extensive attention is whether the investment reform improved R&D productivity in China. Using a unique panel dataset from 160 universities, this paper examines the effect of the investment reform on productivity improvement in China's agricultural biotechnology sector. We use a panel count data model with a dynamic feedback mechanism to model the knowledge production process. Strong evidence indicates that the investment reform greatly contributes to knowledge output production in China's agricultural biotechnology sector. We also find that the input quality is more important than the absolute quantity; human research capacity exhibits the greatest contribution to the output of patents; past knowledge accumulation helps produce more patents; and entry barriers to patent production exist in China's agricultural biotechnology sector. Moreover, the patent explosion in China may have been largely caused by improvements in the human capital input quality.

[1]Jinyang Cai, Weiqiong Chen and Ruifa Hu are all in the School of Management and Economics, Beijing Institute of Technology, Beijing, China and Sustainable Development Research Institute for Economy and Society of Beijing, Beijing, China. Email: ruifa@bit.edu.cn for correspondence. Jikun Huang is at the China Centre for Agricultural Policy, School of Advanced Agricultural Sciences, Peking University, Beijing, China. Carl E. Pray is in the School of Environmental and Biological Sciences, Rutgers University, New Jersey, USA. This research was supported by National Natural Science Foundation of China [71973011, 71661147002], the National Key Programme on GM New Varieties [2018ZX0815-001], and the Joint Development Programme of Beijing Municipal Commission of Education. We thank Huang Lu and Wang Yuguang for their help with the patent data collection, and anonymous referees for their constructive comments on an earlier draft.

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Keywords: *Agricultural biotechnology*; *dynamic feedback*; *human capital*; *investment reform*; *patents*; *research and development*; *research input quantity and quality*.

JEL classifications: *Q16, Q18*.

1. Introduction

The Chinese government has implemented a series of national research and development (R&D) programmes to realise its development objectives since the middle of the 1980s. Before 1986, when the government wanted to launch a research programme – such as the atomic bomb or the Artemisia annual programme – the government would draft researchers from throughout the entire country to form a research group or even a research institute and would then provide funding. In 1986, based on some prominent scientists' suggestions, the Chinese government launched its first national R&D programme, i.e. the National High Technology Research and Development Programme (Rozelle *et al*., 1997; Gilmour *et al*., 2015). Because the programme started in March 1986, it was named the 863 Programme. The objectives of the 863 Programme were to boost the innovation capacity in high-tech sectors, achieve 'leap-frog' development in key high-tech fields and gain a foothold in the world arena. Agricultural biotechnology (agbiotech) research was one of the important fields in the programme.

However, after the 863 Programme ran for several years, the government and scientists realised that it was difficult to achieve breakthroughs in some high technology fields without the support of key basic research. Subsequently, the National Key Basic Research and Development Programme (973 Programme) was proposed by scientists and approved by the government in 1997 and established in 1998. This programme aims to support key basic research and development (Rozelle *et al*., 1997; Gilmour *et al*., 2015). The objective of the 973 Programme was to enhance the independent innovation ability of basic research in China and provide a source of innovation for the formation of high-tech in the future. Basic agbiotech research was also an important objective of the 973 Programme.

Since 2006, the government has launched another new National R&D programme, the National Science and Technology Major Project (STMP). Based on the 'National Medium and Long-term Science and Technology Development Plan Outline (2006–2020)', the programme supported 16 major projects – objective of these projects being to generate national major strategic products and key common technologies and promote the formation of critical projects. The National Genetically Modified Variety Development Special Programme (GMSP), which was established in 2008, is one of the major projects. In contrast to the 863 Programme, which focused only on high technology, and the 973 Programme, which focused only on basic research, the GMSP aims to develop and commercialise new biotechnology as well as to conduct key basic research. The aim of the GMSP is to spur the growth of patents and new genetically modified (GM) varieties in the agricultural biotech research sector.

Both the amount and structure of government funding can be important for the productivity of government research institutes. However, does the reform of the recent technological programmes improve R&D productivity in China? In particular, is knowledge output generated as expected under different research funding mechanisms? China files the largest number of patent applications in the world (Hu *et al*., 2017). To some extent, patents have always been used as a measure of innovation,

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and the patent surge in China seems paradoxical given China's weak record of protecting intellectual property rights (Hu and Jefferson, 2009). In addition to R&D investment and foreign direct investment mentioned in the existing literature, we investigate whether any other factors contribute to the patent boom in China. In other words, do the investment objectives change and does the improvement in researcher quality contribute to the patent surge in China?

Furthermore, in contrast to other countries, where genetically modified (GM) technologies are mainly developed by the private sector, most GM technologies and products in China are developed by public research institutes (Huang *et al.*, 2002; Pray *et al.*, 2002; Cai *et al.*, 2017). Is there any difference between China's public-dominated agbiotech R&D and international private-dominated agbiotech R&D? Foltz *et al.* (2003) find there are no barriers to entry in agbiotech production in the United States, but are there any entry barriers in China's public sector-led GM technology production? These issues have not been examined in the literature to date.

To answer these questions, we focus on patents and published articles as measures of China's agbiotech R&D output. We examine whether the national programmes increased the productivity of agbiotech R&D and whether the programmes realised their policy objectives. Because patents work best in applied research and are less effective in stimulating fundamental research, we use patents as the main output of high technology research, and research papers as the main output of basic research. We use the number and quality of patents and research papers to measure the success of the 863 Programme and 973 Programme, respectively, and also measure the productivity of GMSP by both patents and research papers.

The process of technological innovation is dynamic, and prior success could have an impact on the probability of current success in technological innovations (Blundell *et al.*, 1995), creating significant challenges for empirical analyses. We use unique panel data and provide an explicit examination of the dynamic feedback. This approach captures the inherently dynamic and nonlinear process of innovative activities and examines both observed and unobserved heterogeneity across universities in terms of knowledge output production (Blundell *et al.*, 1995; Foltz *et al.*, 2003). Existing research indicates that the university research production process is typically time consuming (Pakes and Griliches, 1980; Hall *et al.*, 1986; Foltz *et al.*, 2012). Based on consultation with experts in the agbiotech field, we use lagged inputs of three years for patents and two years for published articles in the modeling process.

The econometric model of knowledge output production described below combines a negative binomial count model with a random effects panel data model. More specifically, the empirical modelling effort tests five hypotheses regarding the impact of the changing investment systems on knowledge output production. The five hypotheses are listed as follows.

Hypothesis 1: Different programmes have objective effects, wherein the investment of the 863 Programme and the GMSP should significantly influence the output of patents, while that of the 973 Programme and the GMSP should significantly influence the output of published papers.

Hypothesis 2: Investment reform effects occur, wherein GMSP funding should lead to a significant increase in the knowledge outputs compared with those of the 863 and 973 programmes.

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Hypothesis 3: High-quality input effects occur, wherein the inputs associated with higher quality (e.g. higher percentage of researchers with PhD degrees) should have a greater impact on knowledge output production, suggesting that the quality of the inputs for a scientific production function may have greater importance than the absolute quantity.

Hypothesis 4: The most crucial factor for output in agbiotech is human research capacity improvements, rather than the amount of investment, wherein human research capacity improvements are a critical determinant of agbiotech research output in China.

Hypothesis 5: Correlated dynamic effects and patenting culture effects occur, wherein agbiotech patent production is positively influenced by past knowledge accumulation (i.e. path dependence), which suggests that individuals with a history of more patents should also have more agbiotech patents and implies that entry barriers occur in agbiotech research output production.

The remainder of this paper is organised as follows. Section 2 presents the methodology and data sources. Section 3 provides the descriptive analysis and summary statistics of the inputs and outputs of agbiotech research in China. Section 4 describes the results of the econometric models, and Section 5 provides the conclusions and implications.

2. Methodology

2.1. Theoretical framework for modelling university research output

The primary aim of this paper is to determine whether the recently developed funding system in China has a greater impact on the knowledge output of universities and research institutes as measured by patents and published articles (Foltz *et al.*, 2007; Weber and Xia, 2011; Foltz *et al.*, 2012). Following Blundell *et al.* (1999) and Foltz *et al.* (2003), a classical research production model is specified as follows:

$$Y_{it} = f(X_{it}, u_{it}) = f(L_{it-\tau}, K_{it-\tau}, O_{it}, u_{it}) \qquad \begin{array}{l} \text{for } i = 1, \ldots N \\ t = 1, \ldots T \end{array} \tag{1}$$

where Y_{it} is a measure of research output and includes 1) patent applications or patents authorized, and 2) research articles published, with i indexing universities and t indexing years in our application; X_{it} is a vector of the characteristics of the universities, including human capital inputs, capital and other factors, e.g. the research history of the university; L represents human capital and includes both the quality and quantity of researchers; and K represents capital and includes research funds from the 863 and 973 programmes, the GMSP and other funding sources. Earlier work found that human capital and capital inputs have a significant lagged effect on research output (Pakes and Griliches, 1980; Hall *et al.*, 1986). We also use a lagged form of human capital and capital input to reflect the fact that research leading to research output could take time. The determination of this lag, i.e. the value of τ, is driven by the time spent on research. Here, we use 3 for the value of τ for patent production and 2 for published research articles based on consultations with experts in the agbiotech field.[2] In addition, O_{it} describes other contemporaneous impact factors, and u_{it} represents unobservable university differences.

[2]Other lag lengths did not improve the empirical performance of our models.

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Patents are an important measure of technological innovation. Because technological innovation is always described as an inherently dynamic and nonlinear process and evidence suggests that historical dependence exists in innovation activities (Blundell *et al.*, 1995; Foltz *et al.*, 2003), we also focus on modelling the importance of unobserved heterogeneity with dynamic feedback mechanisms for patent production. The patent production equation is respecified as follows:

$$Y_{it} = f(X_{it}, u_{it}) = f(L_{it-\tau}, K_{it-\tau}, G_{it-1}, O_{it}, u_{it}) \qquad \begin{array}{l}\text{for } i = 1, \ldots N \\ t = 1, \ldots T\end{array} \tag{2}$$

where G_{it-1} represents a university's patenting culture and accumulated patent knowledge stock. We assume that previous patents provide experience and knowledge about the patenting process, but past innovations depreciate over time; thus, the contribution of older experience and knowledge becomes less valuable as time passes (Hall *et al.*, 1986; Blundell *et al.*, 1995). More specifically, G_{it-1} is defined as follows to reflect a dynamic feedback effect:

$$G_{it-1} = Y_{it-1} + (1 - \sigma)G_{it-2}, \tag{3}$$

where σ is the depreciation rate. Following Blundell *et al.* (1995) and Foltz *et al.* (2003), we take the depreciation rate to be 30%, 20% and 10% to reflect the diminishing contribution of old experience and knowledge.

2.2. *Specification of the empirical model*

The dependent variable in our models is either the number of patents produced or the number of articles published, which are count (non-negative integer) variables. It is well known that the classical linear model is inadequate in modelling a discrete variable because the predicted probabilities may be higher than unity (Blundell *et al.*, 1995; Cai *et al.*, 2016). The most frequently used models for count data are the Poisson and negative binomial models (Hausman *et al.*, 1984; Miaou, 1994; Jansakul and Hinde, 2002; Yang *et al.*, 2009). The common first moment condition for these models is as follows:

$$E(Y_{it}) = \mathrm{e}^{X'_{it}\beta}, \tag{4}$$

where Y_{it} represents the research output. Accordingly, the research output model presented above can be parameterised by the following linear equation:

$$\begin{aligned} X'_{it}\beta = {} & \theta_0 + \theta_1 invest\_T_{it-\tau} + \theta_2 per\_863_{it-\tau} + \theta_3 per\_973_{it-\tau} + \theta_4 per\_GMSP_{it-\tau} \\ & + \theta_5 per\_phd_{it-\tau} + \theta_6 per\_master_{it-\tau} + \theta_7 national_i + \theta_8 G_{it-1} + \eta_i + \upsilon_t \end{aligned} \tag{5}$$

where *Invest_T* is the total investment, and the next three variables denote the research funding resources: *per_863* is the percent of investment from the 863 Programme, *per_973* is the percent of investment from the 973 Programme, *per_GMSP* is the percent of investment from the GMSP, and the comparison group is funding from other sources, including international funding. The following two variables represent the quality of the human capital input, with *per_phd* representing the percentage of faculty with a PhD degree and *per_master* representing the percentage of faculty with a master's degree, and the comparison group comprises faculty with a maximum of a bachelor's degree. *National* is a dummy variable representing a strong research capacity. Our national university designation includes national research institutes (such as

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the research institutes included in the Chinese Academy of Sciences) and the universities included in the '985' project, which aims to build world-class universities in China.G_{it-1} is the dynamic feedback effect of accumulated patent experience and knowledge. The variables η_i and υ_t denote the university-specific fixed effect and time-specific effect, respectively.

Although G_{it-1} can be used to parameterise unobservable heterogeneity, Blundell *et al.* (1995) also proposed using search activities in a pre-sample to parameterise unobservable heterogeneity. Following Blundell *et al.* (1995), we consider a fully observed latent variable, i.e. S_{it}, which represents a university's patent search activities as a function of previous search activities, university characteristics, and unobservable variables as follows:

$$S_{it} = \gamma_1 S_{it-1} + \gamma_2 x_{it-1} + \eta_i + \varepsilon_{it}, \tag{6}$$

where η_i is the university-specific fixed effect, and ε_{it} is the disturbance. Because a university that received more funding and developed more patents during a previous period is more likely to receive funding, we assume that the university characteristics, which are represented by x_{it}, follow the following feedback mechanism:

$$x_{it} = \varphi_1 x_{it-1} + \varphi_2 S_{it-1} + \upsilon_{it}. \tag{7}$$

Equation (7) can be rewritten as follows:

$$x_{it} = (1 - \varphi_1 L)^{-1}(\varphi_2 S_{it-1} + \upsilon_{it}), \tag{8}$$

where L is the lag operator. Substituting x_{it} into equation (6) and assuming stationarity of S_{it}, we obtain the following:

$$(1 - \gamma_1 L)(1 - \varphi_1 L)S_{it} = \gamma_2 \varphi_2 L^2 S_{it} + \gamma_2 L v_{it} + \eta_i + \varepsilon_{it}. \tag{9}$$

Taking expectations over time t and assuming that $E(\varepsilon_{it}) = E(v_{it}) = 0$, we find that search activities are proportional to the unobservable university-specific fixed effect as follows:

$$\overline{S}_i = \eta_i[(1 - \gamma_1)(1 - \varphi_1) - \gamma_2 \varphi_2]^{-1}, \tag{10}$$

where $\overline{S}_i$=$E(S_{it})$. Although the observed count of patent Y_{it} is not search activity S_{it}, it could be a reasonable proxy for S_{it} over a long enough time span (Foltz *et al.*, 2003). We also use pre-sample received patents ($BEFORE_i$) as another proxy for the university unobservable heterogeneity and estimate the following model:

$$\begin{aligned} X'_{it}\beta = {} & \partial_0 + \partial_1 invest\_T_{it-\tau} + \partial_2 per\_863_{it-\tau} + \partial_3 per\_973_{it-\tau} + \partial_4 per\_GMSP_{it-\tau} \\ & + \partial_5 per\_phd_{it-\tau} + \partial_6 per\_master_{it-\tau} + \partial_7 national_i + \partial_8 BEFORE_i + \eta_i + \upsilon_t \end{aligned} \tag{11}$$

All the variables are the same as those in equation (5), except $BEFORE_i$ is used instead of G_{it-1}. The variable $BEFORE_i$ represents the number of patents applied for or received before the start of the GM special programme in 2008, and ∂ represents the parameters to be estimated.

2.3. *Poisson model vs. negative binomial model*

Poisson and negative binomial models are commonly used to model the number of patents or published articles for firms or universities (Hausman *et al.*, 1984; Foltz *et al.*, 2007). It is often assumed that the number of patents or published articles follows a Poisson distribution with a conditional mean (u_{it}) depending upon a set of

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regressors (x_{it}) and corresponding parameters (Rose *et al.*, 2006). Following Wooldridge (2003), the Poisson probability distribution for the research output (Y_{it}) equal to y_{it} and conditional on x_{it} can be expressed as follows:

$$\Pr(Y_{it} = y_{it}x007C; x_{it}) = \frac{e^{-\exp(x_{it}\beta)}[\exp(x_{it}\beta)]^{y_{it}}}{y_{it}!}, y_{it} = 0, 1, 2\ldots$$

where x_{it} is a vector of potential research input for university i in year t, and β is a vector of the parameters to be estimated.

One limitation of the Poisson regression is that the variance of the data is restricted to be equal to the mean as follows: $E(y_{it}x007C; x_{it}) = Var(y_{it}x007C; x_{it}) = u_{it}$. In many empirical applications of the model, it is not uncommon to find that the variance of y_{it} is larger than the mean (Wedderburn, 1974; Cox, 1983; Dean and Lawless, 1989; Lambert, 1992; Gurmu and Trivedi, 1996), implying 'overdispersion' in the data. Ignoring the extra variations would lead to the underestimation of the variance of the estimated parameters (Miaou, 1994). To address this problem, we can relax the variance assumption of the Poisson model and allow for an over-dispersion parameter by using the negative binomial model (Rose *et al.*, 2006). We code the variance of y_{it} as φu_{it} instead, where $\varphi \geq 1$ is an overdispersion parameter. We find evidence that the variance is larger than the mean in our data, so we use a negative binomial model rather than a Poisson model to address the overdispersion problem in our data.

The panel data allow us to control for university-specific effects. Following Foltz *et al.* (2003) we also use a random effects formulation to control for the unobserved university-specific effect. The random effects model is selected rather than the fixed effects model because a substantial proportion of the variables, such as the percentage of all types of funding and the proportion of faculty with a PhD, are slow moving in our sample. The use of a fixed effects model, which mainly focuses on year-by-year variations, could produce noisy results rather than the desired information.

2.4. Data sources

The data used in this paper comprise two parts. The first part includes survey data collected in 2010 by mail and followed up with telephone calls. We surveyed all 200 colleges or research institutes that engaged in the National GM Variety Development Special Programme in China. The colleges or research institutes were selected on the basis of their involvement in the GMSP because this programme is the largest agricultural biotechnology R&D programme in China (Hu *et al.*, 2013). To implement the survey, we sent the survey forms to and worked closely with the research management division of each college or institute. In each institution, the division head was responsible for completing and returning the survey forms. All participants were informed that all information would be used only for the research purpose and that in the final dataset, their affiliations and names would be eliminated, with their survey information identified only with the aid of a confidential identifier code. As a result of this anonymity and the support of the Ministry of Agriculture, our survey response rate was 100%. To ensure high-quality data, phone calls were made to the division head of each university or institute to clarify missing or inconsistent data. The survey data represent a unique panel dataset of multiple inputs and outputs from 200 institutes among 28 of 31 provinces in China covering the 2005–2010 period. The collected data included detailed information related to the research capacity, including the number

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of agricultural researchers separated by different education degrees and positional titles, all types of research funding and the number of published articles from 2005–2010.[3]

The second part included all agricultural biotechnology patent data collected from the Derwent Innovations Index from 1985–2013. To avoid confounding the effects of different lengths between application and acceptance, we used the date of the application rather than the date of the award as the date of a patent. One problem with the two data parts is that in our survey data, we treated a college as a research institute, whereas the patent data from the Derwent Innovations are collected within a university. We could hardly separate the patent data of a university into several colleges; therefore, we merged the survey data of the colleges if they were from the same university. For instance, in the Chinese Agricultural University, the survey data of the College of Biological Sciences and the College of Agronomy and Biotechnology were merged into the Chinese Agricultural University. After adjusting our data, we finally obtain 160 universities or research institutes (hereafter, university) in our sample dataset.

3. Descriptive Analysis and Summary Statistics

3.1. Inputs: Human capital and capital

Table 1 shows the number and percentage of agbiotech researchers with different levels of education across 160 universities engaged in the GMSP. Although the total number of agricultural researchers decreased during the 2005–2010 period (Huang *et al*., 2012), the total number of agbiotech researchers increased from 10,239 in 2005 to 13,626 in 2010. It is worth noting that the credentials of the researchers in China's agbiotech research sector substantially improved. The share of researchers with a master's degree remained almost the same, whereas the share of researchers with a maximum of a bachelor's degree continued to decrease. In contrast, the percentage of agbiotech researchers with a PhD degree, which is a measure of the high quality of human capital input, increased from 33.4% in 2005 to 44.6% in 2010, suggesting that the quality of China's agbiotech research base substantially improved.

The agbiotech research fund sources can be divided into the following four categories: the 863 Programme, the 973 Programme, the GMSP and other sources, including funds from international programmes and the National Natural Science Foundation of China. As shown in Table 2, the total amount of agbiotech funds continued to increase from 2005 to 2010, except for the funds from the 863 Programme, which increased from 2005 to 2008 and then slightly decreased. The proportion of funds from both the 863 and 973 programmes continued to decrease from 2005, whereas that from the GMSP continued to increase with a high growth rate since its establishment in 2008. This is mainly because the arrangement of funding changed in 2008, after which important research projects were funded by the GM special programme.

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[3]The research funding data were deflated using 2010 as the base year. The survey data from 2010 included data only until the end of August. We assume that the funding received and the articles published by a university are evenly distributed throughout the year; therefore, we multiplied the funding and article data from 2010 by a factor of 1.5. This action did not measurably change the results compared with those obtained using the unchanged data.

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Table 1

Number and percentage of agbiotech researchers with different levels of education

	Total number	PhD degree (%)	Master's degree (%)	Bachelor's degree (%)	Other (%)
2005	10,239	33.4	27.1	26.1	13.4
2006	10,717	36.0	27.3	25.0	11.8
2007	11,378	38.0	27.8	22.9	11.2
2008	12,161	41.1	28.0	21.1	9.8
2009	13,052	43.4	27.9	19.6	9.1
2010	13,626	44.6	27.7	19.2	8.4

***Data source*:** Authors' survey.

3.2. Outputs: Patents and article production

As mentioned above, university knowledge outputs in agbiotech mainly include patents and publications in scientific journals. Patents and articles are important components of intellectual property and important measures of innovative activities. In this section, we describe the development of patents and articles to determine R&D in the agbiotech field in China.

3.2.1. Agbiotech patents of all universities engaged in the GMSP from 1986 to 2013

Figure 1 presents the number of agbiotech patents of all universities in our sample from 1986 to 2013. The trends of the patents that were applied for and authorised presented in Figure 1 indicate that there has been a rapid increase in Chinese agbiotech patent production. Across all 160 universities, the first agbiotech patent was applied for in 1986, and the first agbiotech patent was authorised in 1991. During the 1986–2013 period, a total of 138 universities applied for 10,060 agbiotech patents, and 132 universities received 5,718 agbiotech patents. The vast majority of patenting activity occurred between 2006 and 2013, and during this period, 86% of the patents were

Table 2

Funds for agbiotech research from different sources (2005–2010)

	Agbiotech funds (million)					Proportion of funding sources (%)			
	Total	863	973	GMSP	Other	863	973	GMSP	Other
2005	916	235	223	0	458	25.7	24.3	0.0	50.0
2006	1,044	237	239	0	569	22.7	22.9	0.0	54.4
2007	1,308	311	279	0	718	23.8	21.3	0.0	54.9
2008	2,270	418	335	780	737	18.4	14.7	34.4	32.5
2009	2,932	398	452	1,306	775	13.6	15.4	44.6	26.4
2010 (Jan–Aug)	3,278	326	441	1,793	718	9.9	13.4	54.7	21.9
2010 (estimated)	4,916	489	661	2,689	1,077	9.9	13.4	54.7	21.9

Note: The research funding data were deflated using 2010 as the base year.
***Data source*:** Authors' survey.

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applied for, and 90% of the patents were granted. Before the commercialisation of transgenic crops in 1996, there were only 11 agbiotech patents across all these universities. However, after the commercialisation of transgenic crops, the number of authorised agbiotech patents increased from 4 in 1996 to 926 in 2013, with an average annual growth rate of up to 37.7%.

The top twenty universities, ranked by the number of accepted agbiotech patents since the start of the GMSP programme from 2008 to 2013, are shown in Table 3. Overall, the patent holders are moderately concentrated among 160 universities. The top twenty universities accounted for 56% of the total over the period 2008–2016 (Table 3). During this period, the top five holders accounted for 25% of the total number of patents, while the top ten patent holders accounted for 37%. In the pre-sample data, these twenty universities had 62% (the top twenty universities had 72%) of the total number of patents. The decreasing percentage in the top twenty holders indicates that competition in Chinese agbiotech R&D has becoming increasingly fierce.

The top two producers before 2008 remained in the top three after the start of the GMSP, and fifteen of the top twenty producers remained in the top twenty, showing some persistence between the two time periods. However, Sichuan Agricultural University presents a striking contrast from having zero patents during the pre-sample period to being the eleventh producer in patent production during the latest period. The persistence in agbiotech patent production suggests that innovation histories and knowledge accumulation are important factors for the production of patents, justifying the use of G_{it-1} and $BEFORE_i$ to control for unobserved university heterogeneity.

Comparing patent production between the national universities and non-national universities during 1991–2007 (Table S1, in the online Appendix). Fifty-five national universities had an acceptance rate per university per year of 2.6, against 1.0 for the

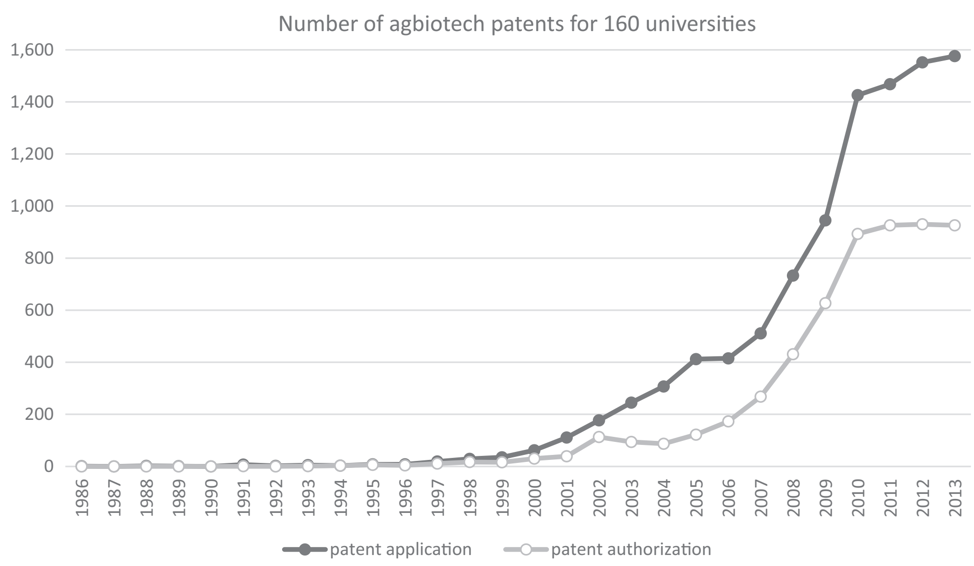

Fig. 1. Number of agbiotech patents across 160 universities from 1986 to 2013
***Data source*:** Patent data were retrieved from the Derwent Innovations Index.

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non-nationals. Separating the entire period into several different periods (we set the time points as 1996 and 2008). Since the commercialisation of transgenic crops, which started in 1996 and 2007, the average annual rates were 1.1 vs. 0.2, respectively, which dramatically increased to 8.0 vs. 3.3 between 2008, the GMSP start, and 2013. This suggests that national universities with a strong research capacity also generate more agbiotech patents, and that the variable *national* could have a positive effect on agbiotech patent production.

3.2.2. Number of articles published by 160 universities from 2005 to 2010

The number of agricultural and agbiotech articles published by agricultural researchers at 160 universities showed a steady growth trend during the 2005–2010 period (Table S2 in the online Appendix). From 2005 to 2009, the average annual growth rate of agricultural articles was 7.3%, while that for agbiotech articles was even higher at 9.1%. The structure of agricultural articles shows that the proportion of agbiotech articles increased from 34.7% in 2005 to 37.3% in 2010. The above analysis suggests that China's agricultural research gradually shifted towards transgenic biotechnology.

Table 3

University rankings of agbiotech patent production from 1986 to 2013

University	Rank 08–13	Patents 08–13	Pre-sample rank 86–07	Pre-sample patents 86–07
Huazhong Agricultural University	1	297	2	68
China Agricultural University	2	258	4	57
Zhejiang University	3	255	1	77
Nanjing Agricultural University	4	213	14	26
Shanghai Jiaotong University	5	155	9	36
Institute of Crop Sciences, CAAS	6	144	20	14
Northwest A&F University	7	117	27	8
Jiangsu Province Academy of Agricultural Sciences	8	116	25	11
Institute of Botany, CAS	9	99	12	28
South China Agricultural University	10	97	21	14
Sichuan Agricultural University	11	96	NA	0
Fudan University	12	95	13	27
Sun Yat-sen University	13	94	3	59
Shandong University	14	93	16	19
Institute of Microbiology, CAS	15	92	7	39
Tsinghua University	16	86	5	45
Biotechnology Research Institute, CAAS	17	86	15	26
Chinese Academy of Inspection and Quarantine	18	85	29	7
Southwest University	19	84	43	5
Shanghai Institutes for Biological Sciences, CAS	20	80	6	41
Total of the above twenty universities		2,642		607
Total of the top twenty universities		2,642		708
Total of 160 universities		4,733		985

***Data source*:** Patent data were retrieved from the Derwent Innovations Index.

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Based on the high quality of scientific research, the number of agricultural and agbiotech SCI articles presented an even faster growth rate, at 16.7% and 19.3% respectively, suggesting that the agricultural research quality in China continued to improve.

3.2.3. Summary statistics of the model variables

The variables used in the econometric analysis are summarised in Table 4. On average, the 160 universities applied for approximately 8 and received nearly 5 patents per year from 2008 to 2013. In 2010, Zhejiang University applied for the most agbiotech patents, 94. However, Huazhong Agricultural University received the most agbiotech patents (59 patents) in 2012.

4. Results

4.1. Impact of changing the investment system on agbiotech research output – patent applications

The results obtained from maximum likelihood estimations using a random effects negative binomial model are shown in Table 5. The following three models were estimated: (a) a base model without controlling for the pre-sample measurements of heterogeneity and with no dynamic effects; (b) a model using $before_i\_apply$ as a proxy for the average past search activities (we used the number of patents applied for before 2007), which measures a part of the individual unobservable heterogeneity and to reflect the potential barriers to entry over time in agbiotech patent production (Blundell *et al.*, 1995; Foltz *et al.*, 2003); and (c) a dynamic model using the continuous dynamic patent effects, G_{it-1}_apply, where columns (3)–(5) use different depreciation rates for patents that were previously applied for. In column (3), the depreciation rate σ is set at 30%, and in columns (4) and (5), the depreciation rate σ equals 20%

Table 4

Summary statistics of the model variables

Variable	Definition	Mean	SD	Min	Max
$patent\_apply_{it}$	Number of patents applied for	8.02	13.55	0	94
$patent\_award_{it}$	Number of patents received	4.93	8.88	0	59
$invest\_T_{it-3}$	Total agbiotech funding (million yuan)	1.39	4.59	0	90.75
per_863_{it-3}	Percent of funding from 863	0.19	0.29	0	1
per_973_{it-3}	Percent of funding from 973	0.11	0.21	0	1
per_GMSP_{it-3}	Percent of funding from GMSP	0.22	0.35	0	1
per_phd_{it-3}	Percent of researchers with a PhD degree	0.39	0.27	0	1
per_master_{it-3}	Percent of researchers with a master's degree	0.29	0.16	0	0.87
national	National university = 1; otherwise = 0	0.34	0.48	0	1
$before_i\_apply$	Number of patents applied for before 2007	14.75	30.19	0	214
$before_i\_award$	Number of patents received before 2007	6.16	12.98	0	77
$paper\_T_{it}$	Number of agbiotech articles	100.85	215.15	0	2,670
$paper\_SCI_{it}$	Number of agbiotech SCI articles	21.98	59.74	0	823

Note: The total number of observations is 960. Number of universities = 160. Funding is measured in million yuan.
Data source: Authors' survey.

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and 10%, respectively. All models produce estimates of dispersion, which are significantly different from zero. Additionally, the likelihood ratio test of all models is significant at the 1% significance level, suggesting that the random effects model is more appropriate than a pooled data model.

The signs of the coefficients in all models are generally as we expected. The results suggest that the investments of the 863 Programme and GMSP significantly influence the output of patents compared with other investments (Hypothesis 1). In addition, in all models shown in Table 5, the coefficient of per_GMSP_{it-3} is larger than the corresponding coefficient of per_863_{it-3}, which supports our hypothesis Hypothesis 2: research investment in China is becoming more efficient. This may be because compared with the 863 and 973 programmes, the GMSP lasts for a longer period; thus, scientists do not have to waste time applying for programmes and can focus on their research. The coefficient of per_973_{it-3} in all models is not significant, which may be because the 973 Programme only aims at key basic R&D, with the assessment objective of research papers (Hypothesis 1).

As shown in column (1), the 10% increase in the proportion of researchers with PhD and master's degrees is associated with an increase in the expected number of

Table 5

Random effects negative binomial estimate of agbiotech research output: patent application

	(1)	(2)	(3)	(4)	(5)
			Continuous dynamic effects		
	Comparison model	Pre-sample dynamic effects	$\sigma = 30\%$	$\sigma = 20\%$	$\sigma = 10\%$
$invest\_T_{it-3}$	0.006	0.002	–0.004	–0.003	–0.002
	(0.004)	(0.003)	(0.005)	(0.005)	(0.005)
per_863_{it-3}	0.335***	0.290***	0.336***	0.341***	0.345***
	(0.117)	(0.111)	(0.117)	(0.117)	(0.117)
per_973_{it-3}	0.177	0.137	0.180	0.187	0.193
	(0.143)	(0.133)	(0.144)	(0.144)	(0.144)
per_GMSP_{it-3}	0.468***	0.373***	0.361***	0.369***	0.382***
	(0.082)	(0.082)	(0.088)	(0.088)	(0.087)
per_phd_{it-3}	2.513***	2.106***	2.253***	2.275***	2.308***
	(0.325)	(0.309)	(0.327)	(0.327)	(0.328)
per_master_{it-3}	1.441***	1.162***	1.421***	1.439***	1.457***
	(0.438)	(0.387)	(0.428)	(0.429)	(0.430)
national	0.501***	0.167	0.472***	0.472***	0.470***
	(0.181)	(0.173)	(0.175)	(0.175)	(0.176)
$before_i\_apply$		0.020***			
		(0.003)			
G_{it-1}_apply			0.005***	0.004***	0.003***
			(0.001)	(0.001)	(0.001)
Constant	–0.564**	–0.597**	–0.548**	–0.554**	–0.559**
	(0.269)	(0.244)	(0.265)	(0.266)	(0.266)
Observations	960	960	960	960	960
Number of groups	160	160	160	160	160

Note: Standard errors are shown in parentheses, ***, **, and * indicate statistically significant differences at the 1%, 5% and 10% levels, respectively. Research funding data were converted into constant 2010 yuan using the consumer price index.

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patent applications by 25.1% and 14.4%, respectively, suggesting that the quality of the inputs is more important than the absolute quantity (Hypothesis 3). As mentioned above, from 2005 to 2010, the percentage of researchers with a doctoral degree increased by 11.2% (from 33.4% in 2005 to 44.6% in 2010), and that of researchers with a master's degree increased by 0.6% (from 27.1% in 2005 to 27.7% in 2010), implying that the improvement in the quality of researchers accounted for 29% (29% =2.513*11.2%+1.441*0.6%) of the patent boom in China. Moreover, compared with the coefficients of investment, a 10% increase in the proportion of funding from the 863 Programme and GMSP only increases the expected number of patent applications by 3.35% and 4.68%, respectively. Because the proportion of GMSP funding increased by 54.7% (from 0% in 2005 to 54.7% in 2010) and the proportion of 863 funding decreased by 15.8% (from 25.7% in 2005 to 9.9% in 2010) during the 2005–2010 period, the contribution of the programme objective change to the patent boom in China was approximately 20% (20%=0.468*54.7%+0.335*(–15.8%)), which is lower than the contribution of human research capacity improvements. This result also offers support for Hypothesis 4: the most important factor for output in agbiotech is human research capacity improvements rather than the investment amount.

In column (2), we use $before_i\_apply$ to determine whether there are barriers to entry over time in agbiotech patent production. Compared with the findings of Foltz *et al.* (2003), we find that there are entry barriers in agbiotech patent production. The measure of the search levels, $before_i\_apply$, is significant, suggesting that the agbiotech patent production levels prior to 2007 were important in explaining patent production during the sample period (2008–2013). Except for the coefficient shown in column (2), which may be due to the correlation with the variable $before_i\_apply$, the coefficient of *national* is significant in the remaining models, suggesting that a university with a strong research capacity will definitely have more agbiotech patents.

In columns (3)–(5), we use the dynamic effects, G_{it-1}_apply, to proxy the knowledge accumulation and patenting culture effects in the patenting process. Consistent with the findings reported by Foltz *et al.* (2003) and Blundell *et al.* (1995), our results also suggest that path dependence occurs in innovation activities. The coefficients of the dynamic effects in all models are significant at the 1% level, thus providing evidence of persistence in agbiotech patent production and suggesting that patent experience helps scholars produce more patents (Hypothesis 5). It is also worth noting that as the depreciation rate σ decreases from 30% to 10% (columns (3)–(5)), the weight of past knowledge increases and the coefficient of the dynamic effects decreases, providing evidence that as time passes, the contribution of previous experience and knowledge becomes less valuable.[4]

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[4]One concern is that researchers may only make patent applications due to the assessment of a research project; therefore, using the number of patent applications may not be a good measure of research output and, thus, may bias the results. The number of patents awarded can be used as a measure of real research outputs with high quality. We also use the number of patents awarded as the dependent variable instead of the number of patents applied for to do the robustness check. The results are quite similar except that the coefficients of investment and human research capacity become smaller, but the coefficient of knowledge accumulation becomes larger. This finding suggests that there are even stronger barriers to entry and stronger path dependence for research outputs with higher quality. For more details, please see the supplementary materials in the online Appendix.

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4.2. Impact of a changing investment system on agbiotech research output: number of published articles

Using the number of articles published as a measure of agbiotech research output produces the results shown in Table 6. Our analysis of patent production above suggests that the addition of a dynamic effect does not measurably influence the results. Using article production as the output measure does not allow a dynamic feedback effect because we lack information on articles published prior to 2005.[5] In column (1), we use all published agbiotech articles, including those published in Chinese and English, as a measure of agbiotech research output. In column (2), we only use articles indexed by the SCI/SSCI to consider the quality of the articles published.

In column (1) of Table 6, the variables with a positive and significant effect on agbiotech article production include the total research budget, funding from the 863 Programme, funding from the 973 Programme, the GMSP, and the proportion of researchers with a doctoral degree. In general, the results suggest that the influence of the GMSP is larger than that of the 863 and 973 programmes (Hypothesis 2). The quality of the inputs appears to be more important than the absolute quantity (Hypothesis 3).

In column (2) of Table 6, when we use higher quality articles as a measure of agbiotech research output, the coefficient of the 863 Programme becomes insignificant, which may be because the 863 Programme only aimed to conduct high technology R&D, while the assessment objectives of the 863 Programme are patents and new technologies (Hypothesis 1). The coefficients of per_master_{it-2} are not significant in either model. The coefficients of *national* are also not significant in either model, suggesting that after controlling for research funding and human research capacity, significant differences are not observed between national research institutes and provincial research institutes with respect to their contribution to article production. The contribution of the programme objective change is 20% (20% =0.418*54.7%+0.224*(13.4%–24.3%), which is much lower than that of human research capacity improvements (32%=2.861*11.2%), thus providing evidence that the most important factor for output in agbiotech in China is the human research capacity rather than the investment amount (Hypothesis 4).

5. Conclusions

The R&D programme objective in China has changed considerably since 2006: R&D investments were initially dominated by the 863 and 973 programmes and then became dominated by the GMSP (as part of the more general STMP). In this paper, we use R&D in China's agbiotech research as an example to estimate whether the change in the programme objective has increased research productivity in China. Using a unique panel dataset based on 160 universities that participated in the GMSP programme during the 2005–2010 period, we model the knowledge production process by estimating several random effects negative binomial models. We find strong evidence that the investment reform greatly contributes to knowledge output production in China's agbiotech sector (Hypothesis 2). We also find that the input quality is

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[5] Millions of papers have been published by the 160 universities over time, and it is difficult to determine whether these papers were published by researchers engaged in the GMSP programme.

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Table 6

Random effects negative binomial estimate of agbiotech research output: number of articles published[a]

	(1) $paper\_T_{it}$	(2) $paper\_SCI_{it}$
$invest\_T_{it-2}$	0.015***	0.012**
	(0.005)	(0.006)
per_863_{it-2}	0.150**	0.054
	(0.066)	(0.095)
per_973_{it-2}	0.168**	0.224**
	(0.082)	(0.106)
per_GMSP_{it-2}	0.423***	0.418***
	(0.090)	(0.146)
per_phd_{it-2}	1.129***	2.861***
	(0.241)	(0.366)
per_master_{it-2}	0.124	0.037
	(0.315)	(0.489)
national	0.138	0.073
	(0.168)	(0.218)
Constant	2.049***	0.991***
	(0.192)	(0.291)
Observations	640	640
Number of groups	160	160

Note: Standard errors are shown in parentheses; ***, **, and * indicate statistically significant differences at the 1%, 5% and 10% levels, respectively. Research funding data were converted into constant 2010 yuan using the consumer price index.

[a]There might be substitute effects between patents and research papers for individual scientists. We drew several scatter diagrams of patents, including patents applied for and patents awarded, and research papers, including all research papers and SCI/SSCI research papers, and the results show that the relationship between patents and research papers is complementary rather than substitutional, which may be due to the dataset used, which includes data on the whole university rather than individuals. Within a particular university, some research teams focus on basic research, while other teams focus on applied research; thus, our data show no substitute effect between patents and research papers. The complementary effects between patents and research papers may be due to the research capacity of the university. In a better university, faculties engaged in basic research or applied research could have a stronger capacity than those in an inferior university. The effect of the research capacity of a university could be regarded as an unobserved fixed effect and can be controlled for by using panel data and a random effects model.

more important than the absolute quantity (Hypothesis 3) and that the objectives of different programmes exert various effects, suggesting that different assessment mechanisms have a strong impact on output production (Hypothesis 1) and that the improvement in human research capacity is crucial for the output of patents in China (Hypothesis 4). We find that past knowledge accumulation helps produce more patents and that there is evidence of entry barriers in China's agbiotech patent production (Hypothesis 5). We also find evidence that improvement in the quality of human capital inputs is a key factor behind China's patent explosion.

The productivity improvement in China's R&D sector may be partially due to the newly designed research funding system and the scale effect of funding, which avoids

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the problem of low-level repetitive research. Another reason may be that compared with the 863 and 973 Programmes, the funding of the GMSP is consistent and coherent. The funding of the GMSP always lasts for a longer period; thus, scientists do not have to waste time applying for new projects. The newly designed research funding system, the scale effect of funding and the consistency of funding could be the key factors explaining the improved productivity in China's R&D sector. We are pleased to observe that the outputs are consistently generated as expected by the programmes. Because the objective of the GMSP is to generate new varieties, we should set the assessment mechanism as a product instead of a patent or published paper. From the conclusions above, the continued training of a large number of scientists may be a good method for increasing innovation in China.

Although productivity has considerably improved in China's agbiotech sector, further studies are still needed to examine whether this type of effect also exists in other fields, such as the other 15 special programmes in the STMP. We should also notice that the dropout mechanism of the new funding system, such as the GMSP, is very weak (because these types of programmes always last for a long period). Some institutes may free riding after they participate in the programme. After a five-year period, an existing institute is prioritised with respect to continued participation in these programmes, leaving fewer opportunities for those not in the programmes. Further studies should also focus on the long-term effects of these special programmes in the GMSP or STMP.

Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Figure S1. Number of agbiotech patents in China from 1985 to 2013

Table S1. Patent production of national and non-national universities.

Table S2. Number of agricultural and agbiotech articles published from 2005 to 2010.

Table S3. Robustness check: Using awarded patents as a measure of agbiotech research output.

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