Old McDonald had a Microscope: The Impact of Research Spending on U.S. Agricultural Productivity

by
Benjamin Rietmann

A THESIS

submitted to

Oregon State University

Honors College

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the requirements for the
degree of

Honors Baccalaureate of Science in Agricultural Business Management and Agricultural Sciences
(Honors Scholar)

Presented November 28, 2018
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AN ABSTRACT OF THE THESIS OF

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Abstract approved:____

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The United States is a global leader in agricultural productivity. Much of its productivity growth can be attributed to public investments in agricultural research and development, starting in the 19th century and continuing until today. Past studies have shown high returns to agricultural research investments, but publicly funded agricultural research is a common target for politicians hoping to cut spending. As private research investments have grown while public investment has stagnated, there is some question about whether publicly funded research projects still have a significant impact on productivity. In order to answer this question, this study uses econometric models using Ordinary Least Squares (OLS) as an estimator to regress Total Factor Productivity (TFP) on total agricultural research spending as well as on the ratio of public spending to total spending, in conjunction with a set of other explanatory variables. It was found that increases in both total research spending and in the share of public spending were significantly correlated with increases in agricultural productivity. This adds to the evidence that overall agricultural research increases productivity and provides evidence that higher levels of public research spending specifically may have an impact on agricultural productivity.

Key Words: Agriculture, Research, R&D, Productivity, Total Factor Productivity

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I understand that my project will become part of the permanent collection of Oregon State University, Honors College. My signature below authorizes release of my project to any reader upon request.

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INTRODUCTION

In August of 2018 the Trump administration proposed a plan to move the USDA's Economic Research Service (ERS) and National Institute of Food and Agriculture (NIFA), two agencies tasked with food and agriculture research, out of the Washington, DC area. The move was seen by many as an attempt to stifle research and comes on top of earlier proposed spending cuts to the agencies. This action evokes questions regarding the value of federally funded agricultural research, and if it is a justifiable use for taxpayer dollars.

The farms and ranches of the United States are among the most productive in the world. In 2016, US agricultural output was the third highest globally, after India and China. In addition to providing food for its own people, the US is now the world's largest exporter of agricultural products (FAO, 2018). These high output levels can be explained in part by high levels of productivity. Many attribute the US's dominant position in agricultural productivity to public investment in research and development throughout the 19th and 20th centuries (Evenson, Waggoner, and Ruttan, 1979 and Alston et al., 2010). Research is often considered to be a public good that produces positive externalities and is underproduced in a market equilibrium.

Skeptics deem returns from agricultural research to have been overestimated (Alston et al., 2000 and Alston et al., 2011). Comin (2004) argues that across the entire economy, actual US R&D levels may be socially optimal, and that public R&D is not responsible for a large share of productivity growth in the US. Agricultural research remains a low political priority among many state and federal legislators (Dewey, 2018). Some suspect that the value of agriculture R&D is lower than its opportunity cost, and that among industries, agriculture has received unfair special treatment.

Others say that public agriculture research spending is redundant, as private entities do research in many of the same areas as private researchers.

I was inspired to work towards a better understanding of the value of publicly funded agricultural research as a result of two internships. The first was spent at NIFA in Washington, DC in the summer of 2017, where I assisted with congressional and stakeholder affairs. My primary duty was to support the education of congressional staff members on the impacts of research funded by the agency. This position allowed me to work in the area where my interests in both science and public policy intersect. In order to gain more exposure to natural sciences and to learn even more about the US agricultural research and extension system, I worked at the Columbia Basin Agricultural Research Center over the summer of 2018. My interest in research and its impacts has culminated in this thesis, in which I will seek to explain the relation between agricultural research and U.S. farm productivity.

Since 2000, US agricultural productivity growth has shown signs of slowing, and US public spending on agricultural research and development has stagnated. Meanwhile, in the same time period, private R&D spending has doubled (USDA, 2015). This study will work to better the understanding of what the role of publicly funded research and development has been in making gains in productivity since 1970. It will seek to understand if growing farm productivity comes as a result of this spending, and if there is any impact to changes in the ratio between public and private agricultural research spending.

1.1. MEASURING PRODUCTIVITY

Productivity is a measure of how efficiently producers can convert inputs into outputs. It is important to note the difference between production and productivity. Production is measured by the volume of output, whereas productivity measures the efficiency of production. Production can be influenced both by input use levels and by changes in productivity, while productivity is only influenced by changes in efficiency. Productivity is commonly defined as a ratio of a volume measure of output to a volume measure of input use. From this basic definition, there are several different measures of productivity used by economists. The Organisation for Economic Co-operation and Development (OECD) (2001) enumerates the five most commonly used measures of productivity as follows:

1. Labor productivity based on gross output:

$$\frac{Quantity\ index\ of\ gross\ output}{Quantity\ index\ of\ labor\ input}$$

2. Labor productivity based on value added:

$$\frac{Quantity\ index\ of\ value\ added}{Quantity\ index\ of\ labor\ input}$$

3. Capital-labor Multifactor Productivity based on value added:

$$\frac{Quantity\ index\ of\ value\ added}{Quantity\ index\ of\ combined\ labor\ and\ capital\ input}$$

4. Capital productivity based on value added:

$$\frac{Quantity\ index\ of\ value\ added}{Quantity\ index\ of\ capial\ input}$$

5. Capital-labor-energy-materials (KLEMS) Multifactor Productivity:

$$\frac{Quantity\ index\ of\ gross\ output}{Quantity\ index\ of\ combined\ inputs}$$

This study uses the fifth measure listed, which is often referenced in economic literature as Total Factor Productivity (TFP).[1] Total Factor Productivity, as defined by Diego Comin (2006), is "the portion of output not explained by the amount of inputs used in production. As such, its level is determined by how efficiently and intensely the inputs are utilized in production." Fuglie et al. (2012) define TFP as "the ratio of total output to total inputs in a production process. Let total output be given by Y and total inputs by X". This can be shown as:

$$TFP = \frac{Total\ output}{Total\ inputs} = Y/X$$

TFP was originally theorized by Solow as rising output with constant capital and labor input. Echevarria (1998) adapts Solow's (1957) method using the following equation to represent the relationship between outputs, inputs, and TFP:

$$Y_t = A_t f(K_t, L_t, N_t)$$

Where Y_t represents value added in the agricultural sector in year t, and A_t, K_t, L_t, and N_t denote TFP, capital, labor, and land, respectively. It is assumed that the production function is constant returns to scale. In the same model, TFP growth is estimated as:

$$\frac{\mathrm{dA}}{\mathrm{dt}}\frac{1}{\mathrm{A}} = \frac{\mathrm{dY}}{\mathrm{dt}}\frac{1}{\mathrm{Y}} - \alpha\frac{\mathrm{dK}}{\mathrm{dt}}\frac{1}{\mathrm{K}} - \beta\frac{\mathrm{dL}}{\mathrm{dt}}\frac{1}{\mathrm{L}} - \gamma\frac{\mathrm{dN}}{\mathrm{dt}}\frac{1}{\mathrm{N}}$$

Echevarria (1998) then goes on to find values for α, β, and γ in order to calculate total factor productivity growth.

[1] In the OECD manual referenced, Multifactor productivity (MFP) is used as a synonym for Total Factor Productivity. While these terms are not exact synonyms, they largely refer to the same idea. The manual uses the MFP acronym to "signal a certain modesty with respect to the capacity of capturing *all* factors' contribution to output growth" (OECD 2001).

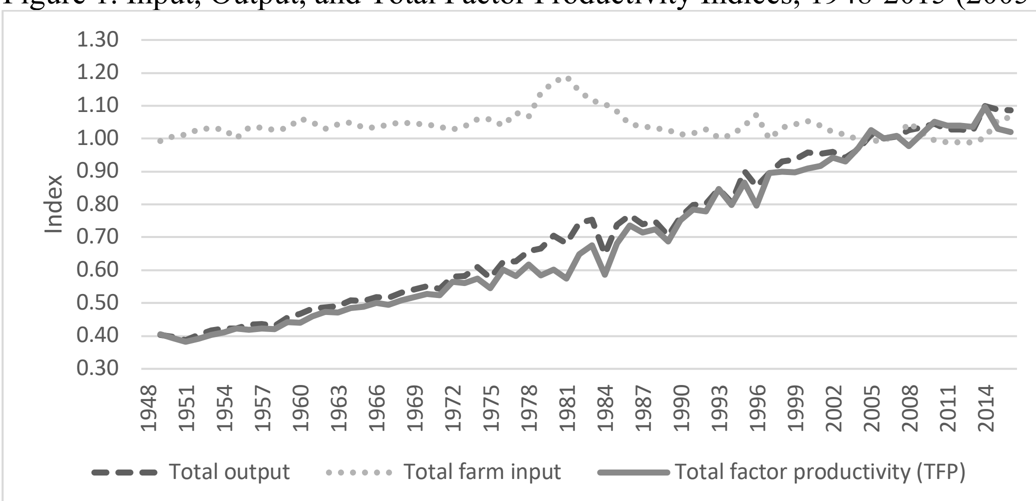
The USDA Economic Research Service has developed an index measuring TFP in US agriculture (ERS, 2017). In this data series, there are indices of inputs and outputs. Components of inputs include labor, capital, and intermediate goods. Breaking it down further, capital consists of durable equipment, service buildings, land, and inventories, while intermediate goods includes feed and seed, energy, fertilizer and lime, pesticides, purchased services, and "other intermediate." The output index is a combined total of all agricultural outputs, divided into categories of livestock and products, and crops. In this index, TFP is measured as the total output index divided by the total input index.

All factors that affect output that are not measurable inputs are represented by TFP. These may include human capital, weather, technology, knowledge, management, and land or soil productivity. Fuglie, Macdonald, and Ball (2007) noted that "Analysts have attributed growth in TFP to factors such as innovation (new technology), but TFP is also affected by economies of scale, measurement error, the educational attainment of the labor force, the regulatory environment, and managerial ability." In the same paper, they assert that "In the long run, growth in TFP is the primary source of new wealth creation in the economy."

1.2. PRODUCTIVITY GROWTH IN AMERICAN AGRICULTURE

For much of the history of the United States, the majority of Americans worked as farmers. In the colonial era, 90 percent of the population were farmers. By 1870, this proportion had fallen to 53 percent, and today it rests at 2 percent. In the same period, the population of the US has increased from 3.9 million to 308.7 million in 2010 (Spielmaker, 2018). In response to market demand, agricultural output has increased rapidly in spite of a declining share of farmers. Much of this increase in output can be attributed to increases in productivity (Wang et al. 2015). Looking at recent data, we see that between 1948 and 2011 output more than doubled, increasing at an average annual rate of 1.49 percent. In that same time, aggregate input use increased by only 0.07 percent annually. Of the major input categories, capital and intermediate goods have increased, while land and labor input decreased. Due to overall stability in input levels, productivity growth has likely been the main driver of output growth.

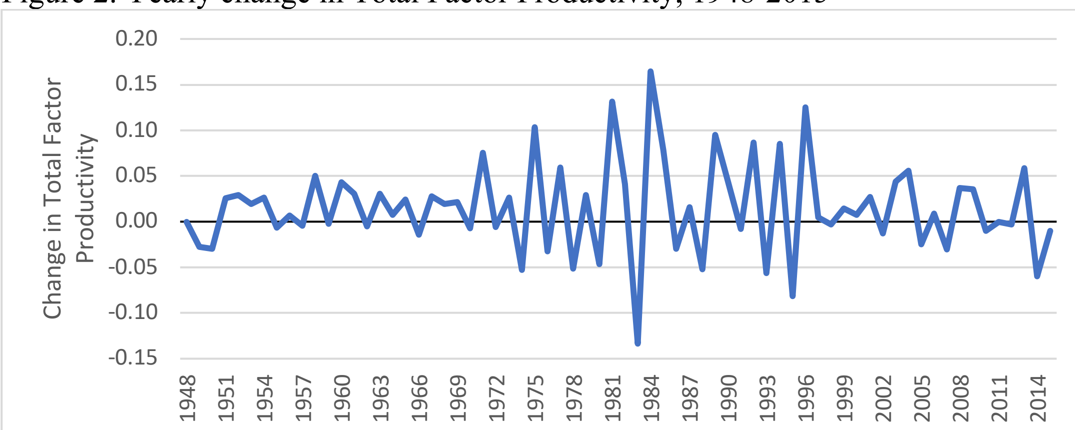
Figure 1. Input, Output, and Total Factor Productivity Indices, 1948-2015 (2005=1)



Source: ERS 2017. Indices of farm output, input, and total factor productivity for the United States, 1948-2015

US productivity growth may be slowing. Between 1948 and 1999, productivity on average grew at a yearly rate of 1.71%, whereas since 2000 it has grown at an average rate of 0.77% (ERS, 2017). Fuglie (2012 and 2018) shows that fears of slowing productivity growth overall internationally are unfounded, but that there is evidence that agricultural output and productivity growth has slowed in industrialized countries. However, Wang et al. (2015) caution that comparing growth averages between decades may be misleading due to year-to-year changes in the frequency of shocks from policy changes and weather events. For example, in 1983, drought and the Federal Payment-In-Kind (PIK) program caused a significant drop in output. The expensive PIK program offered farmers surplus grain and cotton out of government stockpiles in exchange for planting less of the same commodities. This took 82 million acres out of production (Sinclair, 1984). High temperatures in 1988, 1993, and 1995 also caused drops in output (Wang et al., 2015)(figure 2).

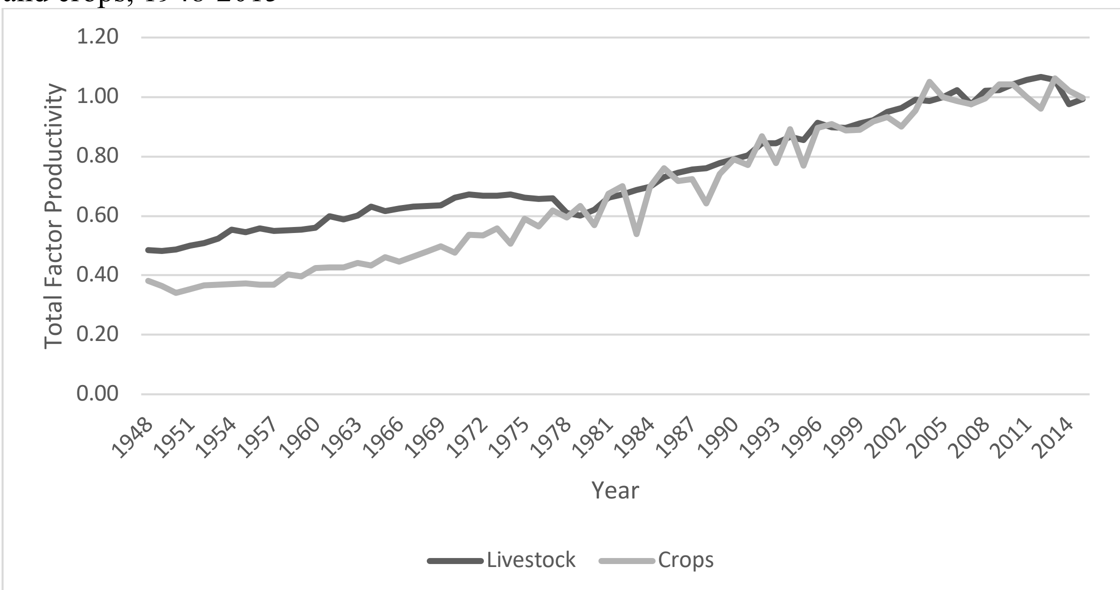
Figure 2. Yearly change in Total Factor Productivity, 1948-2015



Source: ERS 2017. Indices of farm output, input, and total factor productivity for the United States, 1948-2015

Growth is more variable in crop productivity than in animal productivity (figure 3). This is likely because crop output is more variable year to year; the standard deviation in annual crop output growth from 1948-2015 was 7.7 percent, while the standard deviation of annual livestock output growth was 1.8 percent over the same period (table 1). By analyzing animal and crop output indices separately, approximating their respective productivity by dividing both measures by total inputs, it can be seen that on average crop productivity grew more quickly during both periods, but have grown more slowly since the beginning of the twenty-first century.

Figure 3. Approximation of Total Factor Productivity split between livestock products and crops, 1948-2015



Source: ERS 2017. Indices of farm output, input, and total factor productivity for the United States, 1948-2015

Table 1: Average annual growth rates in productivity

	1948-1999	2000-2015
Total Factor Productivity	1.71%,	0.77%
Animal Productivity	1.28%	0.58%
Crop Productivity	2.21%	0.82%

Source: ERS 2017. Indices of farm output, input, and total factor productivity for the United States, 1948-2015

Slowing rates of productivity growth are likely caused in part by low growth in domestic demand for food (Fuglie, 2018). Alston, Beddow, and Pardey (2009) attribute this decline to reduced growth investment for agricultural R&D.

1.3. FUTURE THREATS TO PRODUCTIVITY MAINTENANCE AND GROWTH

As a society, we will be challenged to not only prevent decreases in agriculture productivity, but also to continue increasing productivity levels. As the global population increases to a projected 9.7 billion people by 2050 and 11.2 billion by 2100, (UN DESA, 2015), it is imperative that we find solutions to produce more food, both to battle current global food insecurity and to prevent future food insecurity while sustainably maintaining our natural resource supports and ecosystem. Factors that may have contributed to a slowing in agricultural productivity growth, and that are likely to affect future growth include changes in climate, land degradation, shifts of the location of production, farmer responses to resource scarcity or higher prices of inputs, and evolving pests and diseases (Alston, Beddow, and Pardey, 2009).

As weather patterns shift, areas will be impacted differently. In some cases, farmers will benefit. One study suggests that US corn farmers have seen greater yields as a result of lengthening growing seasons and cooling of the hottest temperatures (Butler, Mueller, Huybers, 2018). However, US agriculture as a whole is expected to be negatively impacted by climate change, as increases in temperature coupled with more variable precipitation will reduce productivity of crops (Walthall et al., 2013). Liang et al. (2017) found that projected climate changes could cause TFP to decrease by 2.84 to 4.34 percent per year, causing TFP to fall to pre-1980 levels by 2050 even when accounting for present rates of innovation.

Land degradation and loss to urbanization are also factors that will lead to reduced agricultural output. Unsustainable farming practices and climate change will reduce soil organic carbon and negatively impact soil health (van Gestel, 2018). Since 2010 we have seen a steady decline in total US farm acreage (NASS, 2018), and between 1992 and 2012 almost 31 million acres of farmland was converted for development, much of which was highly productive (Sorensen et al., 2018).

In the face of these problems, it is vital that agricultural productivity continues to increase sustainably and that our natural resources are preserved. Many of the threats to productivity come as a result of ecologically unsustainable practices. As noted environmentalist Lester Brown (2011) points out, “No civilization has survived the ongoing destruction of its natural support system. Nor will ours.” Research may be an important tool in increasing productivity while mitigating impacts from environmental changes and preventing future ecological damage.

1.4. US AGRICULTURE RESEARCH FUNDING

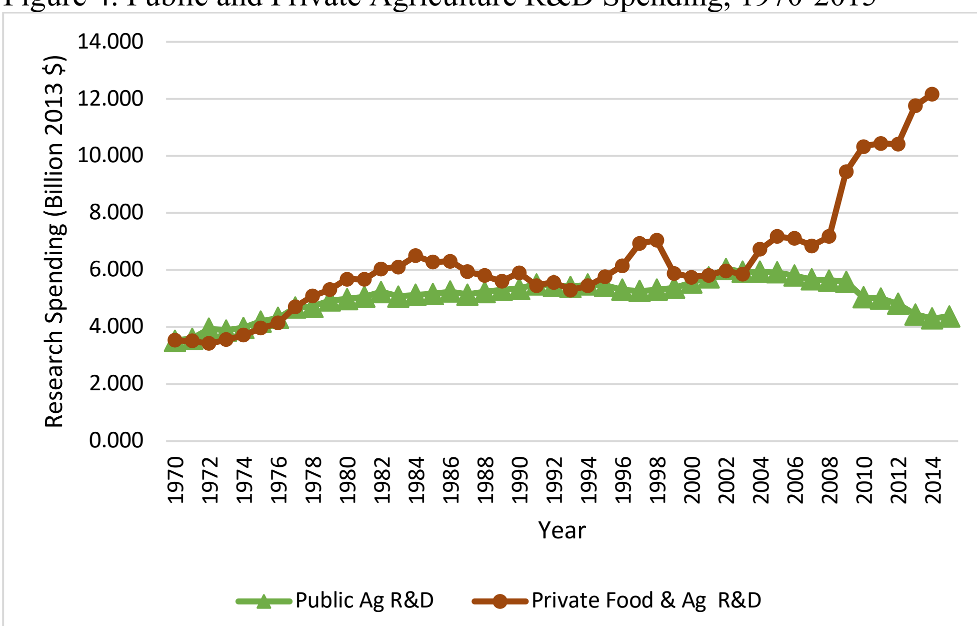
The United States has one of the most robust agricultural research systems in the world, and many attribute investments in agriculture R&D to our significant gains in farm productivity.

Agricultural research and extension were not uniquely American ideas. They were first practiced in the ancient world in Chinese and Mesopotamian cultures. Our modern idea of extension dates back to the European Middle Ages and the Renaissance, with the earliest Renaissance text on agriculture being written in 1304. Through the 1700s and into the 1800s, predominately aristocratic European agricultural societies worked through experiments, demonstrations, and information dissemination to make agricultural improvements. By 1800, some of these agricultural societies had been founded in the United States and eastern Canada. The first modern extension services were put in place in Europe in the 1840s and 50s. In this time, North American Delegations visited Europe and reported back on the progress in agricultural research and education. In 1862, passage of the Morrill Act amidst the civil war created the land grant colleges, which were to teach “agricultural and mechanical arts.” Land grant colleges were called such, as their establishment was funded by land granted to states from the federal government. In most cases, the granted land was sold, and the resulting proceeds were used to establish the colleges. The farmers institute movement also began in this era, in which farmers organized meetings between farmers and with speakers, who were largely professors at the state colleges of agriculture (Jones and Garforth, 1997).

In 1887, the Hatch Act established funding for experiment stations, usually run by the land grant colleges. These stations were meant to provide for more localized research and information. In 1890, a second Morrill Act passed. Aimed at former Confederate states, it required each state either to show that race was not a factor in admissions, or to designate a separate land grant institution for persons of color (1890 Universities, 2015). In 1914, the Smith-Lever Act established the cooperative extension services, a cooperation between federal, state, and county governments, which meant to “aid in diffusing among the people of the United States useful and practical information on subjects relating to agriculture and home economics, and to encourage the application of the same.” (Jones and Garforth, 1997). Between the land-grant colleges, Hatch Act experiment stations, and Smith-Lever extension services, the US possessed a robust system of agricultural research, education, and extension by the early 20th century that continues operating today.

As agriculture as an industry begins to make up a lower portion of the US economy as a whole, some question the value of maintaining such an extensive system focused primarily on agriculture. In addition to USDA funding for research and extension, agricultural research funding also comes from the National Science Foundation and other federal entities. At federal and state levels, some legislators have not made agricultural research spending a priority, as is reflected in the fact that from 2000-2015, total federal and state spending on agricultural research decreased by 23 percent. Meanwhile, in the same time period, private R&D spending has more than doubled (ERS, 2018) (figure 4). With the agriculture sector shrinking as a part of the US economy as a whole, and with private entities providing more research funding than ever before, is public agricultural research a valuable use of taxpayer dollars?

Figure 4. Public and Private Agriculture R&D Spending, 1970-2015



Source: USDA Economic Research Service. 2018. "Agricultural Research Funding in the Public and Private Sectors, 1970-2015".

Several studies support the idea that agricultural research is a valuable public investment, and that it is undersupplied at current levels. Pardey and Alston (2011) note that surveys of hundreds of studies quantifying the returns from agricultural research suggest rates of return in the range of 40-60 percent per year. Fuglie and Heisey (2007) reviewed 35 studies published over 1965-2005 and found that the median estimate of the social rate of return to agricultural research was 45 percent per year. Per their findings, "As a rough approximation, this implies that each dollar spent on agricultural research returned about $10 worth of benefits to the economy."

Alston, Beddow, and Pardey (2009) attribute slowed productivity growth to reduced growth rates in agricultural R&D spending and a changing balance in public and private research funding. They point out that funds have been directed away from farm productivity and toward other concerns, including environmental effects of agriculture, food safety, and alternative uses of agricultural commodities. They also note that another impact of research spending is the spillover of knowledge and technology to other countries, and therefore reduced levels of spending are likely to impact productivity in both developed and developing countries.

There is little research focused on understanding the impact of the changing public and private structure in agricultural research, and there is a possibility that growing private research spending could make up for stagnating public research spending. Fuglie and Heisey (2007) found that there do appear to be significant social returns to private agricultural research. There is also the chance that public R&D crowds out private R&D. Alfranca and Huffman (2001) found that this was the case in Europe, implying that public entities may be discouraging private investment through focusing too much on applied research rather than basic sciences. At the same time, Wang et al. (2015) write that "public R&D has an irreplaceable role in developing fundamental science that does not have short-term reward and hence receives less attention from the private sector, but provides much of the foundation for long run progress." It can be argued that this public research is a public good that is undersupplied by the free market.

The structure of agricultural R&D has changed in part because federal science policy changes have encouraged greater public-private partnerships, but mostly because private research as a whole has accelerated. One cause of this is the application of biotechnology to crops[2], as before 1980 private research focused on providing improved machinery and chemical inputs to farmers. Seven studies have found evidence supporting complementarity between public and private agricultural research, while two other studies have found evidence of crowding out between public and private agricultural R&D. This body of evidence is too small and varied to draw credible conclusions (Fuglie and Toole, 2014). Fuglie and Toole further assert that "To date, changes in the institutional structure of public and private agricultural research have outpaced systematic investigation, and new theoretical and empirical research is needed to help guide policy and address key societal challenges, such as climate change, clean energy, water scarcity, food safety, and health."

[2] Biotechnology research allowed private entities an avenue to produce a highly excludable product, as the efficacy of most biotech crops depends on annual private production of hybrid seed, as compared to traditional non-hybrid seed. Non-hybrid seed is self-pollinated and can be saved by farmers after harvest in order to plant subsequent crops without significant losses in productivity.

2. ECONOMETRIC ANALYSIS

To evaluate the economic impact of agricultural research, economists have traditionally used either econometric analysis or economic surplus methods. This study uses the former method in order to assess the impact of public spending on agricultural R&D, as well as the impact of R&D spending from both public and private sources. Econometric models are able to account for a variety of changes and to analyze data at the aggregate level. Econometric models are also able to isolate the effect of research from other influences. (Heisey et al., 2010).

In this study, five econometric models were developed (see table 4). Using Ordinary Least Squares (OLS) as an estimator, TFP was regressed on a variety of explanatory variables outlined in table 2 and section 2.1.

OLS works to minimize the differences between collected observations in a dataset and its approximated responses. This principle says that to fit a line to the data values, the sum of the squares of the vertical distances from each point to the line should be as small as possible. In the simple regression model, OLS can be represented as:

$$y = \beta_1 + \beta_2 x + e.$$

β_1 and β_2 represent the intercept and slope of the regression function, respectively, while y and x represent the dependent and explanatory variables. e is the error term and is measured by the sum of deviations within the regression line. It represents all factors affecting y that are not accounted for by x.

OLS is considered to be a Best Linear Unbiased Estimator (BLUE), meaning that it satisfies the conditions of the Gauss-Markov Theorem. An estimator is unbiased if its expected value is equal to its actual value. For the multiple regression model, the conditions of the Gauss-Markov Theorem are as follows, with β representing coefficients, x representing explanatory variables, and e representing the error term:

MR1. There is linear causality. The value of y, depends on the values of the explanatory variables and the unknown parameters: $y_i = \beta_1 + \beta_2 x_{i2} + \cdots + \beta_K x_{iK} + e_i, i = 1, \ldots, N$

MR2. There are no bias intercept problems. Each random error has a probability distribution with zero mean. Some errors will be positive, some will be negative; over a large number of observations, they will average out to zero:

$$E(y_i) = \beta_1 + \beta_2 x_{i2} + \cdots + \beta_K x_{iK} \Leftrightarrow E(e_i) = 0$$

MR3. Homoskedasticity is present. The variance of the probability distribution of y does not change with each observation. Some observations on y are not more likely to be further from the regression function than others: $var(y_i) = var(e_i) = \sigma^2$

MR4. Serial correlations are not present. Any two observations on the dependent variable are uncorrelated. For example, if one observation is above E(y), a subsequent observation is not more or less likely to be above E(y): $cov(y_i, y_j) = cov(e_i, e_j) = 0 \ (i \neq j)$

MR5. There is no presence of multicollinearity. The variables of each x_{iK} are not random and are not exact linear functions of the other explanatory variables.

MR6. We sometimes will assume that the values of y are normally distributed about their mean: $y_i \sim N[(\beta_1 + \beta_2 x_{i2} + \cdots + \beta_K x_{iK}), \sigma^2] \Leftrightarrow e_i \sim N(0, \sigma^2)$

These assumptions require that explanatory variables are exogenous, or determined outside of the system. When these assumptions are violated, bias can be introduced to the model, making it no longer BLUE, or the significance of the model can be decreased.

2.1. DATA DESCRIPTION

The econometric model consists of data from variables listed in table 2. Summary statistics for the variables are listed in table 3.

Table 2: Variable Description

Abbreviation	Description	Source
TFP	Total Factor Productivity index	USDA Economic Research Service. 2017. "Productivity in the United States data product"
RD	Total research spending, real billion 2013 dollars.	USDA Economic Research Service. 2018. "Agricultural Research Funding in the Public and Private Sectors, 1970-2015".
RDRAT	Public Research Ratio: public research spending divided by total research spending for a given year.	
FARMCRIS	Farm Crisis year (1982-1983) (Dummy variable)	Calomiris et al., "The Farm Debt Crisis and Public Policy"
RECESS	Recession year, by quarter (i.e. recession for one quarter in a year is equal to 0.25, two quarters as 0.5, etc.).	Federal Reserve Economic Data. 2018. "Dates of U.S. recessions as inferred by GDP-based recession indicator, +1 or 0, Quarterly, Not Seasonally Adjusted".
INC	Returns to Farm Operators, real billion 2018 dollars.	USDA Economic Research Service. 2018. "U.S. and State-Level Farm Income and Wealth Statistics".
CRP	CRP Acreage, millions of acres	USDA Farm Service Agency. 2018. "CRP Enrollment by Fiscal Year".
EDUC	Share of US Adults over 25 having completed four or more years of college.	U.S. Census Bureau, Education and Social Stratification Branch. 2017. "Years of School Completed by People 25 Years and Over, by Age and Sex: Selected Years 1940 to 2017".
PDSI	Palmer Drought Severity Index	NOAA, National Climatic Data Center. 2018. "US Climate Data, 1948-2015".
TMIN	National Average yearly Minimum Temperature	
TMAX	National Average yearly Maximum Temperature	

The focus of this study is to understand how overall research spending affects TFP, as well as to understand how public research spending specifically impacts TFP. In each model, TFP is the dependent variable, as I am measuring how productivity is impacted by each variable. TFP was regressed on a variety of variables in order to create a total of fifteen models.

It is well established that both public and private research spending impact productivity (Fuglie and Heisey, 2007) and therefore total spending is included in almost every model. This variable is expected to carry a positive coefficient.

I encountered multicollinearity when using both variables in multiple regression. In order to isolate effects on TFP from public research in the model, the variable RDRAT (R&D Ratio) was created by dividing yearly public research spending by total research spending. This gives us an approximation of how the mix of public and private spending will affect TFP. It was unclear if this variable would be positive or negative, as it is still unclear how the structure of research spending affects TFP, or if it would have any impact.

There is mixed evidence on the effects of recessions on aggregate productivity. This relationship is difficult to model, as there are several complex and conflicting influences that the business cycle has on productivity. However, one theory that is reasonably well supported is that recessions have "cleansing effects" on economies, as they lead to more efficient job allocation of workers, and lead firms to engage in productivity-enhancing activities because of temporarily low opportunity costs in foregone profits (Aghion and Saint-Paul, 1991). Recessions also may hasten the exit of less productive firms from the market, leaving more resources available for more profitable firms (Caballero and Hammour, 1994). There is little available literature in this area, but Van den Bosch and Vanormelingen (2017) did find that recessions did have a cleansing effect on the small, open, developed economy of Belgium. The variables RECESS, representing US recession years, and FARMCRIS, representing years of the 1980s farm crisis, were included in models in order to incorporate this theory. In multiple regression, it is common to use indicator variables, also called dummy variables. These variables indicate the present or absence of a characteristic or indicate whether a condition is true or false. Both RECESS and FARMCRIS are dummy variables.

Following the theory outlined in the previous paragraph, in general, years with less overall farm income should also lead to a “cleansing” affect, in which the least efficient producers leave the market, and average productivity increases. To reflect this, the variable INC, representing yearly returns to farm operators, was included in some models. It is expected to have a negative coefficient.

Weather is an important consideration in understanding farm productivity. The local nature of weather favors low spatial studies (Powell & Reinhard, 2016). However, Liang et al. (2017) successfully studied the impact of regionally aggregated climate data on TFP. They found that temperature and precipitation in distinct agricultural regions and seasons explained around 70 percent of variations in TFP growth during 1981–2010. This data is likely to be less significant when aggregated at the national level, but at a low level, widespread events should be reflected in nationally aggregated weather data. For this reason, variables PDSI, TMIN, and TMAX are included.

Producers decide which land to put into production based off of its marginal productivity. One of the goals of the Conservation Reserve Program (CRP), in which farmers are paid to retire land from agriculture, is the long-term improvement of the country's agricultural productivity as a result of CRP treatments (Jacobson, 2010). CRP introduced an incentive for farmers to take their least productive land out of production, which should theoretically increase average land productivity, leading to increased productivity for grain and feed crops, which make up a significant portion of TFP. Boisvert and Chang (2005) found that levels of CRP participation are higher in areas where land quality is relatively low. As a result of this, I expect that mostly unproductive land is enrolled in CRP, leaving behind more fertile land and increasing average productivity. Therefore, this variable should have a positive coefficient. Note that data from this set is organized by fiscal year.

EDU is used as an approximation for the human capital of farm producers. While there is little existing research showing the impact of post-secondary research levels on agricultural productivity, there is significant evidence showing that higher shares of persons with post-secondary degrees increase overall economic productivity (Moretti, 2002). Although rural education rates tend to be only 60-65 percent as high as all US adults, rural education has increased proportionally with the increase of national education shares (ERS, 2018 and US Census Bureau, 2017). Because of this, and because of limited available data on rural or farmer post-secondary education rates, national post-secondary educational attainment shares are used as an approximation. It should be noted that this variable is likely to be monotonic, as is TFP, and they are highly correlated.

Table 3: Summary Statistics 1970-2014

Variable	Mean	Std. Dev.	Min	Max
Total Factor Productivity	0.80	0.18	0.52	1.10
Total Research Spending (Billion 2013 Dollars)	11.38	2.3	7.06	16.47
Public Research Spending (Billion 2013 Dollars)	5.08	0.63	3.53	6.04
Ratio of Public Research Spending to Total Research Spending	0.46	0.06	0.26	0.54
Private Research Spending (Billion 2013 Dollars)	6.30	2.06	3.42	12.18
Palmer Drought Severity Index	0.82	2.32	-4.44	5.01
CRP Land Enrollment (Million Acres)	19.78	15.89	0.00	36.77
National Average Yearly Maximum Temperature	64.46	1.09	62.68	67.69
National Average Yearly Minimum Temperature	40.74	0.93	38.87	42.88
Returns to Farm Operators (Billion 2018 Dollars)	71.27	22.52	18.02	143.76
Share of US Adults over 25 with a 4-year secondary degree	0.22	0.06	0.11	0.32

2.2. ECONOMETRIC MODEL

Five econometric models were developed, each containing RD and RDRAT variables.[3] Each was then regressed with three time offsets to RD and RDRAT, leading to a total of 15 models. Each model was regressed using Stata v. 14.2. Models were developed to use a variety of variables, but each with a different emphasis. For example, model II focuses on weather data. In order to avoid multicollinearity within the models, a correlation table was used to find right side data variables with correlation coefficients higher than 0.6 or lower than -0.6. Highly correlated explanatory variables were not included in the same model. Each model is listed in table 4.

In this study, the null hypothesis, H_0 is that TFP is not correlated with RD nor with RDRAT, meaning that increases in research spending or in the relative amount of public research spending will have no impact on productivity. The alternative hypothesis, H_a is that RD is positively correlated with TFP, and that RDRAT is either positively or negatively correlated with TFP.

Time offsets were included, as benefits from research are unlikely to be realized within the same year that spending for it has been allocated. This commonly recognized to be special problem in this area of research and is difficult to estimate. Kuehne et al. (2017) evaluated adoption of several different specific technologies and practices among Australian farmers and found that time until peak adoption ranged from 6-22 years. Alston, Norton, and Pardey (1995) and Fuglie and Heisey (2007) estimate that on average, new technology will be developed and farmers will begin to adopt it about 7 years after the original investment by a public or private institution.

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[3] Except for model V, which excludes the variable RD, as it is is highly correlated with EDUC.

From that point, the technology takes about an additional 8 years to be fully adopted and benefits maximized. This implies that maximum benefits are not realized until about 15 years after the original research investment. Eventually, technology goes out of use because something better replaces it or because it loses its effectiveness.

In models developed for this study, in order to test the significance of greater time lags, each regression was repeated with time offsets in RD and RDRAT of 0 years, 5 years, and 10 years. Greater time lags were not applied due to limitations in historical data availability. The equation for each model can be found in table 4.

Table 4: Econometric Models

I	$TFP_t = \beta_0 + \beta_1 RD_{t,t-5,t-10} + \beta_2 RDRAT_{t,t-5,t-10} + \beta_3 FARMCRIS_t + \beta_4 RECESS_t + \beta_5 PDSI_t + e_t$
II	$TFP_t = \beta_0 + \beta_1 RD_{t,t-5,t-10} + \beta_2 RDRAT_{t,t-5,t-10} + \beta_3 PDSI_t + \beta_4 TMIN_t + \beta_3 TMAX_t + e_t$
III	$TFP_t = \beta_0 + \beta_1 RD_{t,t-5,t-10} + \beta_2 RDRAT_{t,t-5,t-10} + \beta_3 INC_t + \beta_4 TMIN_t + \beta_4 TMAX_t + e_t$
IV	$TFP_t = \beta_0 + \beta_1 RD_{t,t-5,t-10} + \beta_2 RDRAT_{t,t-5,t-10} + \beta_3 INC_t + \beta_4 CRP_t + e_t$
V	$TFP_t = \beta_0 + \beta_1 RDRAT_{t,t-5,t-10} + \beta_2 INC_t + \beta_3 EDU_t + e_t$

3. RESULTS

The results from the different estimation procedures and expected coefficients are shown in tables 5, 6, and 7. Most variables were shown to be statistically significant at the one percent level, with the notable exceptions of RECESS, PDSI, TMIN, and TMAX. This means that for significant variables, we can reject the null hypothesis that they are not correlated with TFP.

Across the fifteen models, the average coefficient on RD was approximately 0.1. This indicates that for every increase in RD of one billion dollars, the TFP index increases by 0.1. The average coefficient for RDRAT was 2.17, which means that a one percentage point increase in the ratio of public research spending to total spending would lead to a 0.02 increase in the TFP index.

Overall, RD and RDRAT were found to be positive and statistically significant, and in almost every instance coefficients for each variable increased as the timeframe of RD and RDRAT was shifted back, which aligns with previous research, and shows that R&D spending happening at an earlier time is more significantly correlated with productivity. This consistency suggests that the results are robust to alternative specifications (table 8).

Collectively, the models are shown to explain a high proportion of the variance in the dependent variable, TFP, with an overall average r-squared of 0.885, and an adjusted r-squared of 0.876. Each model is also collectively significant, with each having F-values of less than 0.001 (table 9).

Table 5. Regression Results, no time offset (1980-2014).

Variable	Expected Sign	I	II	III	IV	V
R-squared		0.847	0.834	0.898	0.935	0.965
Adj. R-squared		0.828	0.813	0.884	0.928	0.963
Total Research Spending	+	0.10***	0.09***	0.10***	0.06***	--
(t)		(0.00)	(0.00)	(0.00)	(0.00)	
Public Research Ratio	±	1.40***	1.22***	1.75***	0.49	0.31***
(t)		(0.00)	(0.00)	(0.00)	(0.19)	(0.01)
Farm Crisis Year	+	-0.15**	--	--	--	--
		(0.01)				
Recession Year	+	-0.01	--	--	--	--
		(0.79)				
Returns to Farm Operators	±	--	--	0.002***	0.001***	0.001***
				(0.00)	(0.00)	(0.00)
CRP Acreage	+	--	--	--	0.004***	--
					(0.00)	
4-year degree share	+	--	--	--	--	3.03***
						(0.00)
Drought Severity Index	+	0.00	0.00	--	--	--
		(0.89)	(0.78)			
Minimum Temperature	+	--	0.00	0.00	--	--
			(0.88)	(0.84)		
Maximum Temperature	-	--	0.03	0.02	--	--
			(0.41)	(0.31)		

Notes: All variables deflated. *p*-value is in parentheses. The asterisks ***,**, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6. Regression Results, 5-year time offset (1980-2014).

Variable	Expected Sign	I	II	III	IV	V
R-squared		0.840	0.830	0.894	0.895	0.959
Adj. R-squared		0.817	0.805	0.878	0.883	0.955
Total Research Spending	+	0.11***	0.11***	0.10***	0.09***	--
(t-5)		(0.00)	(0.00)	(0.00)	(0.00)	
Public Research Ratio	±	2.70***	2.62***	2.50***	2.37***	0.44**
(t-5)		(0.00)	(0.00)	(0.00)	(0.00)	(0.04)
Farm Crisis Year	±	-0.09	--	--	--	--
		(0.13)				
Recession Year	+	-0.01	--	--	--	--
		(0.86)				
Returns to Farm Operators	±	--	--	0.002***	0.002***	0.001***
				(0.00)	(0.00)	(0.00)
CRP Acreage	+	--	--	--	0.002	--
					(0.12)	
4-year degree share	+	--	--	--		2.98***
						(0.00)
Drought Severity Index	+	0.00	-0.01	--	--	--
		(0.54)	(0.53)			
Minimum Temperature	+	--	0.01	0.01	--	--
			(0.74)	(0.47)		
Maximum Temperature	-	--	0.00	0.00	--	--
			(0.94)	(0.82)		

Notes: All variables deflated. *p*-value is in parentheses. The asterisks ***,**, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7. Regression Results, 10 year offset (1980-2014).

Variable	Expected Sign	I	II	III	IV	V
R-squared		0.869	0.861	0.862	0.862	0.943
Adj. R-squared		0.846	0.837	0.838	0.843	0.938
Total Research Spending	+	0.11***	0.11***	0.11***	0.12***	--
(t-10)		(0.00)	(0.00)	(0.00)	(0.00)	
Public Research Ratio	±	3.09***	2.69***	2.57***	2.64***	-0.36
(t-10)		(0.00)	(0.00)	(0.00)	(0.00)	(0.16)
Farm Crisis Year	+	-0.05	--	--	--	--
		(0.37)				
Recession Year	+	0.04	--	--	--	--
		(0.23)				
Returns to Farm Operators	±	--	--	0.000	0.000	0.001**
				(0.64)	(0.80)	(0.01)
CRP Acreage	+	--	--	--	-0.001	--
					(0.52)	
4-year degree share	+	--	--	--	--	2.73***
						(0.00)
Drought Severity Index	+	0.00	0.00	--	--	--
		(0.47)	(0.77)			
Minimum Temperature	+	--	0.02	0.01	--	--
			(0.55)	(0.54)		
Maximum Temperature	-	--	-0.02	-0.01	--	--
			(0.62)	(0.61)		

Notes: All variables deflated. *p*-value is in parentheses. The asterisks ***,**, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8. Summary of Total Research Spending and Public Research Ratio Variables across time offsets

Variable	Time Offset	I	II	III	IV	V	Average (I-IV)
Total Research Spending	t	0.10	0.09	0.10	0.06	--	0.08
	t-5	0.11	0.11	0.10	0.09	--	0.10
	t-10	0.11	0.11	0.11	0.12	--	0.11
Public Research Ratio	t	1.40	1.22	1.75	0.49	0.31	1.22
	t-5	2.70	2.62	2.50	2.37	0.44†	2.55
	t-10	3.09	2.69	2.57	2.64	-0.36†	2.75

Notes: All variables deflated. All coefficients are statistically significant at the 1% level except those marked with crosses.

Table 9. Summary of explanatory power of the models

	Avg. R-squared	Avg. Adjusted R-squared	Avg. Prob(f) statistic
t	0.896	0.883	<0.001
t-5	0.884	0.868	<0.001
t-10	0.879	0.860	<0.001

5. CONCLUSIONS

In this thesis I econometrically estimated impacts from R&D spending (RD) and the ratio of public R&D spending to total spending (RDRAT). Results showed that both of these measures are significantly correlated with Total Factor Productivity (TFP).

From this analysis, there is evidence that higher proportions of public research spending in overall spending have an effect on farm productivity. This result contradicts earlier research findings that higher public research spending leads to crowding out of private research spending (Fuglie and Toole, 2014). If this were the case, RDRAT should not be significantly positive. One possible implication of this result is that public research boosts the return to private investment, and that private research is more impactful when paired with higher levels of public spending.

Other variables with consistent significant correlations to TFP in each time division include returns to operators (INC) and 4-year degree share of US adults over 25 (EDU). Though these measures are significantly correlated with TFP, we should be wary of drawing conclusions from these variables. INC as a righthand side variable may be partially endogenous to the model, as productivity gains or losses are likely to impact farm income. EDU is highly correlated with TFP, but it may not be a significant explanatory variable independently, as both it and TFP consistently increase over time, making it difficult to prove a causal relationship between these variables. Aside from these cautions, INC and EDU are valuable additions to the models, as help to account for more variation in TFP.

Variables that were not significant throughout the three time offsets include farm crisis year (FARMCRIS), recession year (RECESS), CRP acreage (CRP), Palmer Drought Severity Index (PDSI), Maximum Temperature (TMAX), and Minimum

Temperature (TMIN). Although these variables individually are not significant, literature implies that they each may have an impact. They each add to overall significance of the model.

This study has several limitations. Because public spending data is only available since 1970, in order to allow for time offsets in the model, only data occurring since 1980 could be analyzed. Some explanatory variables, INC and CRP, have limited evidence in prior research implying that they should significantly impact productivity. There is slightly more evidence supporting that FARMCRIS and RECESS might be significant, but it is still relatively inconclusive. FARMCRIS is also weakened as an explanatory variable by the fact that in one of the years of the farm crisis, 1983, policy changes and a major drought that were not accounted for in the model likely had a significant impact on TFP. Weather data is very significantly impactful at local levels, but it is questionable that nationally aggregated weather data should have an impact on TFP. Finally, some variables on the right-hand side of the regression were assumed to be exogenous but could be endogenous.

In future research, these limitations should be accounted for. Climate data should be adjusted to reflect more local weather conditions, with modeling based off of previous studies, including a 2017 study done by Liang et al. in which the impact of weather on national productivity was analyzed at regional levels. More variables reflecting the imposition of government policies, such as the 1983 PIK program, should be added to the models in order to account for their impact on productivity. A better variable than INC measuring farm financial stress should be found that is unlikely to be endogenous to the model. Lastly, human capital should be accounted for in a measure more directly related to agricultural producers and workers than the measure used. In spite of these limitations, this thesis adds to the evidence that overall R&D spending impacts farm productivity. Furthermore, it adds to the body of knowledge regarding the impact of the changing mix of public and private research spending.

As the structure of the agricultural research system changes, it is necessary to understand the differing impacts between public and private agricultural research. This will allow for better policy decisions and will help us understand how to allocate resources in order to most efficiently work towards maintaining and increasing agricultural productivity. This study's results have implications for legislators and other stakeholders as we work towards sustainably maintaining and increasing agricultural production in the wake of a rising global population and environmental changes.

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