CONTRIBUTION OF PUBLIC INVESTMENTS AND INNOVATIONS TO TOTAL FACTOR PRODUCTIVITY

A Thesis
Submitted to the Graduate Faculty
of the
North Dakota State University
of Agriculture and Applied Science

By

Anna Glazyrina

In Partial Fulfillment of the Requirements
for the Degree of
MASTER OF SCIENCE

Major Department:
Agribusiness and Applied Economics

March 2011

Fargo, North Dakota

North Dakota State University
Graduate School

Title

CONTRIBUTION OF PUBLIC INVESTMENTS AND INNOVATIONS

TO TOTAL FACTOR PRODUCTIVITY

By

ANNA GLAZYRINA

The Supervisory Committee certifies that this ***disquisition*** complies with North Dakota State University's regulations and meets the accepted standards for the degree of

MASTER OF SCIENCE

ABSTRACT

Glazyrina, Anna, M.S., Department of Agribusiness and Applied Economics, College of Agriculture, Food Systems and Natural Resources, North Dakota State University, March 2011. Contribution of Public Investments and Innovations to Total Factor Productivity. Major Professor: Dr. Saleem Shaik.

This study examines the importance of public research and development (R&D) expenditures and innovations (prices) to U.S. agricultural productivity employing panel vector error correction econometric technique. Specifically, time-series and panel unit root tests, panel cointegration procedures, panel causality tests, and vector error correction model are used in the analysis. Empirical application to U.S. state-level data for 1960-2004 suggests positive and statistically significant influence of both supply-side drivers, in the form of public R&D expenditures, and demand-side drivers, in the form of innovations (prices), on total factor productivity growth.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Figure | Page

LIST OF APPENDIX TABLES

LIST OF APPENDIX FIGURES

CHAPTER 1.

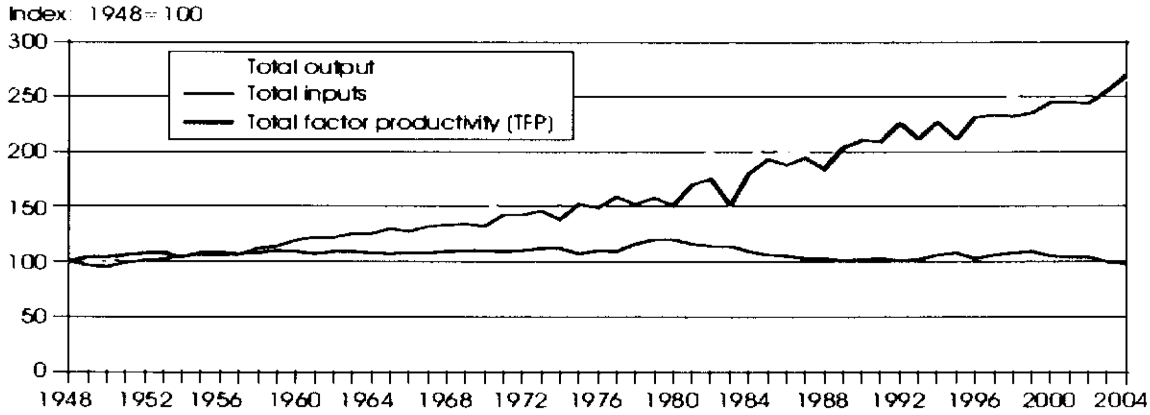
INTRODUCTION

> What is productivity? It seems to be like love in that everyone knows they want it, but few have a good definition of it.
>
> Diewert and Nakamura (2005)

Total factor productivity (TFP) or productivity, defined as the ratio of aggregate output over aggregate input quantity indexes, is one of the concepts of neoclassical economics which has been the subject of intense research over the last half of the century. At the macro-level, the focus has been on linking productivity growth with the economic growth of a country and on explaining cross-country differences in economic development by productivity differences (Solow, 1956; Hall and Jones, 1999). At the micro-level, economists use productivity to evaluate the performance of manufacturing firms and industries. Overall, the contributions of neoclassical economists have led to the development of theory and new empirical methods to examine productivity and its causes. According to neoclassical theory, exogenous technical progress drives long-run output and productivity growth. In contrast, new growth theory explains log-run growth endogenously. Common to both views is that investment in both tangible and intangible assets is a fundamental part of the growth process. Endogenous growth theory reflects that policy measures, such as subsidies on education or research and development (R&D), provide a motivation to innovate and, thus, can have an impact on a long-run growth rate. Therefore, measures of R&D expenditures are typically included in productivity analyses. But is R&D the only driver of productivity growth?

1.1. Rationale and significance

The issue of output and productivity growth in agriculture becomes especially important since the world population has been growing. Analyzing trends in U.S. agriculture, one will inevitably notice that, in contrast to other production sectors of the American economy, increase in inputs (capital, land, labor) has not been a dominant source of output growth. According to USDA journal *Amber Waves* (2005), agricultural output in 2002 was 2.6 times as high as it was in 1948, but input use actually declined over the past half century. From Figure 1.1.1 it is observable that US agricultural productivity trended upward over time. The causes and sources of this positive trend have caught the attention of policy makers.



Source: USDA/ERS; Fuglie, McDonald, Ball, 2007

Figure 1.1.1. Changes in U.S. agricultural output, inputs, and total factor productivity since 1948

Studies conducted since 1950s significantly enhanced knowledge about the sources of productivity growth and methods to estimate TFP (Solow, 1957; Jorgenson and Griliches, 1967; Denison, 1972; Diewert, 1974, 1976). However, these studies focused on the supply driven changes with very little attention given to the demand driven changes and to the simultaneous changes in supply and demand as to the sources of a productivity change (see Shaik, 1999).

According to the existing literature, the major sources or contributors to agricultural productivity growth are supply driven. The supply driven factors include investment in research and development (public and private R&D), extension, education, and infrastructure, with the most attention given to research and development. In this study we set aside private R&D expenditures since our main interest is to evaluate the importance of publicly funded R&D.

The value of publicly funded research in agriculture is indeed demonstrated by numerous analyses. To evaluate the importance of R&D investments, the "social rate of return" on the investment is often estimated or computed. This social rate of return reflects the total value of all benefits associated with an investment to the members of the society. Many economic studies find high social returns to investments in agricultural research. For 35 studies published over 1965-2005 that were reviewed by Huffman and Evenson, the median estimate of the social rate of return was 45% per year (see Table 1.1.1).

Table 1.1.1. Summary estimates of the rate of return to U.S. agricultural research

ITEM	STUDIES, 1965-2005	MEAN ESTIMATE	MEDIAN ESTIMATE
Social rate of returns to public agricultural research	35	53	45
Social rate of returns to private agricultural research	4	45	45

Source: Fuglie, Heisey (USDA, ERS, 2007) using data from Huffman and Evenson, 2006, and Fuglie et al., 1996

Thereby, research investments accompanied by new knowledge make a vital contribution to the economic development leading to increased productivity due to rightward shift in the supply. Traditionally, these supply driven changes in productivity, attributed to R&D expenditures, are treated as the principal source of productivity changes at all levels of economic activity (Alston et al, 1995; Baumol and Wolff, 1983), while less or no attention is given to demand driven changes.

Prices and productivity are not yet clearly linked, although some work has been conducted in this direction. For example, induced innovation theory (Fellner, 1961; Kennedy, 1964; Ahmad, 1966; Schmookler, 1966; Binswanger, 1978; Scherer, 1982; Dosi, 1988; Ruttan, 2002) considers endogenous demand driven price changes as the other causal factor affecting productivity conditional or unconditional on supply changes. This study attempts to enlarge induced-innovation framework by including output prices in the analysis. By introducing the price ratio, input price over output price, we investigate demand-side driver of a productivity shift. Hereby, the influence of both supply and demand factors on TFP is taken into account in this thesis using panel vector autoregressive (VAR) or vector error correction (VEC) modeling. Investigating the supply and demand driven effects in a dynamic panel framework is the primary objective of this study. This extends earlier research that estimates the unconditional and conditional linear dependence between R&D, prices and TFP based on the econometric methods using time-series data.

1.2. Research contribution

This study contributes to the existing literature by examining the importance of public investments via the shift in supply and innovations via the demand shift affecting the U.S. agricultural TFP. Specifically, this study employs dynamic adjustment through VAR / VEC mechanism in a panel framework. Second, this study covers a longer time span compared to other current studies. The final contribution is the construction of the data set on public research expenditures for the period 1889-2009.

This research is organized as follows: the second chapter summarizes the literature on the analysis of R&D investments and prices, as factors driving TFP change, and the estimation methods planned to be employed in the current study. Data utilized in the estimation and the sources are discussed in the third chapter. The fourth chapter explains theoretical model and estimation procedure. Empirical results are given in the fifth chapter, which is followed by the conclusions in the final chapter.

CHAPTER 2.

LITERATURE REVIEW

2.1. R&D investments as a factor driving TFP

2.1.1. Literature on R&D and TFP analysis

The question of how limited resources should be allocated to sustain and enhance agricultural productivity growth has been a vital and urgent issue for policy makers. It generated vigorous discussions on determining the factors having the largest influence on TFP. Over half of a century ago, in 1953, Schultz explained **all** the productivity growth in agriculture by public investments in agricultural research. However, he offered no sufficient quantitative evidence to support his view. Later, with the development of econometric techniques, the situation has changed. Currently, hundreds of studies quantifying effects of R&D investments on productivity patterns in agriculture, and the resulting social payoffs, have been conducted and published (e.g., Evenson, 1967; Evenson, 1980; Huffman and Evenson, 1992; Alston, Craig, and Pardey, 1998; Griliches, 1998; Huffman, 2009). Many of these studies were reviewed by Echeverria (1990), Huffman and Evenson (1993), Alston and Pardey (1996), Alston et al. (1997). An important outcome of these analyses is providing evidence that stock and new knowledge are major sources of productivity growth in the long run.

USDA's own research supports this conclusion confirming the importance of R&D investments for TFP growth and economic well-being as a whole. For example, the USDA Agriculture Information Bulletin *Agricultural Productivity in the United States* emphasizes high rates of return to agricultural research which result in "higher yielding crop varieties, better livestock breeding practices, more effective fertilizers and pesticides, and better farm management practices" and which is required "not only to increase agricultural productivity, but to keep productivity from falling" (AIB-740, 1998, p.10). Analysis presented in the USDA Agricultural Economic Report *U.S. Agricultural Growth and Productivity: An Economy-Wide Perspective* revealed that public agricultural R&D accounted for approximately 50 percent of the growth in agricultural productivity (TFP) between 1949 and 1991 (AER-758, 1998). The 2000 National Academy of Sciences report *The National Research Initiative: A Vital Competitive Grants Program in Food, Fiber, and Natural Resources Research* found that "20th century research in food, fiber, and natural resources has contributed substantially - in both quantitative and qualitative terms - to the stability and prosperity of the US economy and to the broader world economy" (NRI, 2000, p. 22).

Thus, much effort was taken to investigate the benefits from research through research-induced supply shifts. Such models consider research-based technological change which reduces supplier costs, hence, consumer prices, and increases the volume of transactions. If to represent it graphically, then the commodity supply curve moves downward against the stationary demand curve (e.g., Alston, Norton, and Pardey, 1995).

While there is a plethora of works devoted to the analysis of R&D outlays as to a TFP driver, not much attention in the literature is given to such raw material as data needed for these analyses to be conducted. Meanwhile, it requires much effort to develop historical dataset of agricultural research investments. If data on other variables can usually be accessed online or through other readily available sources, data on R&D expenditures is not easy to access prior to 1970. Recently, Alston, Andersen, et al. (2010) published a US-level data on agricultural research investments since 1890. Earlier, Huffman and Evenson (1993) published US-level dataset since 1888 which is still widely utilized by researchers. They also documented state-level R&D expenditures. Another group of researchers, Alston & Pardey (1996), constructed state-level dataset as well. However, neither of these datasets is available for general public. As Alston et al. (2009) note: "To derive the relevant measures of public research spending requires delving through various government documents and sorting out those elements from particular spending lines that are truly research and truly applied to agriculture; it requires going across places and backwards through time, dealing with changing definitions, changing reporting procedures, and inevitable omissions"[1]. Thus, constructing state-level dataset of R&D expenditures is one of the important outcomes of this study.

2.1.2. Public research investments: historical perspective

Since research investments are proven to drive productivity, it may be helpful to provide a brief history of public agricultural research in the United States to set the scene.

Agricultural research in the U.S. is conducted primarily by the state agricultural experiment stations, SAES, at the state level and USDA agencies at the federal level implying that these two institutions are the main recipients of public funding. As Huffman (1993) notes, establishment of SAES through the passing of the Hatch Act was one of the most important steps to develop public agricultural research in the U.S. Therefore, we will

[1] Alston J.M., Pardey P.G., James, J. S., Andersen, M.A. The Economics of Agricultural R&D. *Annual Review of Resource Economics*. 2009, p. 549. Retrieved 12/01/2011, from 10.1146/annurev.resource.050708.144137.

further discuss a history of major federal legislation affecting research in agriculture through financing of the SAES at the federal level.

"Agricultural experiment stations are institutions engaged in systematic research that seeks to enlarge the existing body of scientific knowledge as this applies to agriculture and scientific fields".[2] Creation of the state agricultural experiment stations in most states was initiated by passing the **Hatch Act** of 1887. Each qualifying state, i.e. each of 48 continental states, was to receive $15,000 annually to maintain the station. Since then, the federal support grew gradually. The **Adams Act** of 1906 enabled states to receive additional $15, 000 for conducting original research and experiments: according to this act, in 1906 each state was entitled to an increase of $5,000; this sum was increased by $2,000 each year, until it reached $15,000 in 1911. The payments under this Act continued till 1955. The **Purnell Act** of 1925 further expanded the scope of agricultural research and provided funds for the investigation of the social and economic problems associated with agriculture: in 1926 each authorized state received additional $20,000; this amount was increased by $10,000 annually from 1927 to 1930, and from 1930 to 1955 the support under the Purnell Act equaled $60,000.

The **Bankhead-Jones Act** of 1935 appropriated a total from $600,000 in 1936 to $ 2,863,708 in 1955 to the states, territories and Puerto-Rico. Funds were to be distributed to the states based on the proportion of the population in each state to the US population. Unlike the previous acts, this act also required that each state and territory would have available funds from other than federal sources, equal in amount to those received under the Bankhead-Jones Act for each fiscal year.

[2] USDA. (1962). Funds for Research at State Agricultural Experiment Stations. Washington, D.C.: Government Printing service, p. 3.

The passage of the **Research and Marketing Act** of 1946 authorized state and federal cooperation in research on problems of regional and national importance as well as in research on marketing of agricultural products and other related fields. The funds were allotted to the cooperating states for the solution of problems concerning the agriculture of more than one state. The funds were appropriated to the states since 1948 till 1955 (title I, section 9) and till 1964 (title II, section 204 (b)).

In 1955 the original Hatch Act and subsequent authorizing legislation, namely: Adams Act, Purnell Act, Bankhead-Jones Act and Title I of Research and Marketing Act, - were combined in a single **Amended Hatch Act**. Similar to the original Hatch Act, Amended Hatch Act declared promotion of the efficient production, marketing, distribution, and utilization of farm products.

In 1964-1967 SAES received grants for conducting a basic scientific research under the Public Law 85-934 (Grants for Basic Scientific Research Authorized Under the Act of September 6, 1958). **McIntire Stennis Act** of 1962 (P.L. 98-788) provided funding for forestry research since 1964. **Research Facilities Act** of 1963 (P.L. 88-74) appropriated funds to SAES which were earmarked for pesticides facilities in 1965. Funds appropriated in subsequent years (1966-1968) did not carry this restriction. Since 1966 SAES also were assigned grants for conducting applied and basic research authorized under the Act of 1965, **P.L. 89-106**.

Consolidated Farm and Rural Development Act of 1972, which represents the amendment of Consolidated Farmers Home Administration Act of 1961, made it possible for SAES to receive funds for rural development and small farm research. **National Agricultural Research, Extension, and Teaching Policy Act** of 1977, enacted as Title

XIV of the Food and Agriculture Act of 1977 (P.L. 95-113), established a new program of grants for high-priority agricultural research to be awarded on the basis of competition among research workers and all colleges and universities. It also established a mechanism for improved coordination and planning of agricultural research. Title XIV of the **Food Security Act** of 1985 (also cited as National Agricultural Research, Extension, and Teaching Policy Act Amendments of 1985) amended the Competitive Grants Program having included emphasis on biotechnology research (a total of $70 million per fiscal year was appropriated for this program). Title XII of the **Food, Agriculture, Conservation, and Trade Act** of 1990 (Forest Stewardship Act of 1990) reaffirmed the importance of McIntire-Stennis Cooperative Forestry Act (P.L. 87-788) and established a competitive forestry, natural resources, and environmental grant program to award grants for the conduct of research in related fields. Title XVI of the same act increased appropriations and extended the length of the existing programs: Agricultural Research Facilities Grants established by Research Facilities Act ($50 million was appropriated per year since 1991) and programs established in the National Agricultural Research, Extension, and Teaching Act of 1977 including Agricultural Research Programs, Animal Health and Disease Research, Critical Agricultural Materials Research.

The **Federal Agriculture Improvement and Reform Act** of 1996 appropriated $10 million for pilot research programs to combine medical and agricultural research and also extended programs of National Agricultural Research, Extension, and Teaching Act of 1977 in animal health and disease research, policy research, etc. The **Farm Security and Rural Investment Act** of 2002 further extended existing programs established by National Agricultural Research, Extension, and Teaching Act of 1977 and Food, Agriculture, Conservation, and Trade Act of 1990 including aquaculture research, National Genetics Resources Program, Nutrient Management Research, as well as continued Integrated Research, Education, and Extension Competitive Grants Program and other competitive grant programs. The Act also established a biosecurity planning and response program, and grant programs for biotechnology risk assessment research and biotechnology research on crops important for developing countries. It reauthorizes and broadens the energy program and establishes new programs and grants for procurement of biobased products to support development of biorefineries. The **Food, Conservation, and Energy Act** of 2008 authorized research initiatives for specialty and organic crops, bioenergy, nutrition, and pollinators, and revised high-priority research areas. It also increased role of competitive funding for most programs.

Thus, the development of agricultural science was rigorously stimulated on a public level since 1988, when the Hatch Act first provided a large increase in funds for state agricultural experiment stations. From year to year research activities at SAES were becoming more diverse via increased federal support including competitive grant programs what promoted rapid agricultural development in the US.

2.2. Prices as a factor driving TFP

While supply-side TFP drivers, such as R&D investments, were analyzed with alacrity by many researchers, demand-side drivers, such as prices, were not approached with the same intensity, although some work has been done in this direction (see Shaik, 1999).

The hypothesis stating that change in relative prices of factors drives technical change affecting productivity growth, or induced innovation hypothesis, was introduced by Hicks (1932) in his work "The Theory of Wages". According to Hicks, one of the forces driving inventions is seen in changes in relative prices and factor substitution: "change in the relative prices of the factors of production is itself a spur to invention, and to invention of a particular kind - directed to economizing the use of a factor which has become relatively expensive"[3]. Thus, "production isoquants change in response to the changes in relative factor prices"[4]. The hypothesis has been analyzed in a number of works (e.g., Felner, 1961; David and Klundert, 1965; Hayami and Ruttan, 1970; Binswanger, 1974; Antle, 1984; Kawagoe *et al.*, 1986; Huffman and Evenson, 1989; Olmstead and Rhode, 1993) for many countries and industries, with a majority of works devoted to the US agriculture.

Another stream of studies deals with the causality between output prices and productivity. Baumol and Wolff (1983) claim that productivity affects the price of output, and, hence, the cost of R&D relative to output price. In its turn, the investment in research is affected by prices and productivity. Shaik (1999), analyzing the bidirectional causality between R&D expenditures, output prices and TFP for Nebraska agricultural sector, found the evidence of influence of both R&D and prices on productivity with a greater influence of the former. Recent research has been done to find the relationship between TFP slowdown and rise in agricultural commodity prices (Fuglie, 2010).

---

[3] Hicks, J.R. (1932). *The Theory of Wages*, Macmillan, London, p. 124

[4] Hayami, Y. and Ruttan, V.W. (1970) Factor Prices and Technical Change in Agricultural Development: The United States and Japan, 1880-1960. *The Journal of Political Economy* 78, p. 1124

It is worth noting that along with R&D expenditures, other variables such as public extension, farmers' schooling, government commodity program variables, weather variables, general business cycle variables, and geoclimatic variables were analyzed in a number of studies (e.g. Huffman and Evenson, 1992). But, still, much less attention in the current literature was given to prices as to a driver of agricultural TFP change.

This study enlarges existing frameworks by incorporating changes in **the input prices relative to output prices** in the analysis. We propose that this price ratio represents a true demand-side factor driving productivity changes.

2.3. VAR / VEC techniques, unit roots and cointegration

In productivity analysis scholars typically made use of either time series estimation (e.g. Evenson (1967) utilized US-level data for 1938-1963; Alston, Craig, Pardey (1998) used US aggregate data for 1949-1991 data), or panel estimation (e.g. Evenson (1980) conducted analysis with the data for 1948-1971 for 48 states; Huffman (2009) used 1970-1999 state-level data for 48 states; Alston *et al.* (2010) made use of 1949-2002 data for 48 states). The advantages of panel data estimation are obvious: it gives ample degrees of freedom and allows accounting for both spatial and temporal variation. However, less work was made to incorporate dynamics in proposed panel models of U.S. agricultural TFP, though some researchers considered dynamic panels. For example, Liu, Shumway, Rosenman, Ball (1998) considered dynamic panel using 1927-1995 state-level data on R&D expenditures in their study for TFP convergence.

Thereby, this study attempts to fill this void in U.S. agricultural productivity literature by employing VAR/VEC model for panel data. Prior to explaining these models, a word should be said about unit root (nonstationarity) tests and cointegration techniques.

Stationarity is a characteristic of a series' mean and variance over time. The series is referred to as stationary if both mean and variance are constant over time. Otherwise, the series is said to be nonstationary, or to contain a unit root. The determination of the stationarity has important consequences, since the regression with nonstationary variables will lead to spurious results. The phenomenon of the spurious regression was first discovered by Yule (1926) and analyzed in detail by Granger and Newbold (1974). Since the first formal test for unit roots were developed by Dickey (1976) and Dickey and Fuller (1979), many alternative unit root tests have been proposed, among them are augmented Dickey-Fuller test, test by Phillips and Perron (1988), test by Kwiatkowski, Phillips, Schmidt, and Shin (1992) which are still widely used in time series analysis. Foundations for panel unit roots were established by Levin and Lin (1993). Modification of this test by Levin, Lin and Chu (2002) along with the ones suggested by Im, Pesaran and Shin (1997, 2003), Maddala and Wu (1999) are among of the most commonly used tests in practice.

The problem of nonstationarity can often be resolved by differencing. The order of differencing determines the order of integration of a variable, commonly denoted as $I(d)$. As already emphasized, a regression of one nonstationary time series to another nonstationary time series may produce spurious results. However, if two nonstationary variables are of the same order of integration, but their linear combination is stationary or has a lower order of integration, then the series are said to be cointegrated, and a traditional regression may be then applied to variables in levels. This idea comes from Granger

(1981). Among the most popular tests for cointegration are Engle-Granger test (1987) and Johansen procedure (1991), which permits for more than one cointegrating equation unlike the first test. There are generalizations and modifications of both these tests for panel data.

Vector autoregressive model, VAR, popularized by Sims (1980), represents a multiple time-series generalization of AR model and also serves as a starting point for cointegration analysis. An alternative to VAR is the error correction model (ECM), proposed by Sargan (1964) and popularized by Davidson *et al.* (1978) which encompasses a long-run equilibrium relationship, at the same time allowing for a short-run dynamics. The recent interest in VECM has been based on a demonstration by Granger and Weiss (1983) that if two I(1) variables are cointegrated, they can be modeled by a VEC. Panel VAR and VEC are relatively new econometric techniques. The next two chapters explain data used in the analysis and the hypothesized model generated as panel VAR/VEC.

CHAPTER 3.

DATA AND SOURCES

3.1. Data sources

The data on federal and nonfederal funds for agricultural research were collected for SAES, USDA and other cooperating institutions. The funding for forestry research (including support under the McIntire Stennis Act) was not accounted for in the analysis since forestry goes beyond the scope of this study.

State-level data on funds available to SAES were obtained from the following USDA public documents: *Organization of the Agricultural Experiment Stations in the United States* in Experiment Station Bulletin No. 1 for 1889 (data for 1889 is also available in the *Report of the Commissioner of Agriculture*), *Report of the Secretary of Agriculture* for 1890-1893, *Statistics of Agricultural Colleges and Experiment Stations* in OES Circular No. 27 for 1894, *Statistics of Land-Grant Colleges and Agricultural Experiment Stations* in OES Circular No. 35 for 1896, *Statistics of Land-Grant Colleges and Agricultural Experiment Stations in the United States* in OES Bulletin Nos. 51, 64, 78, 97 for 1897-1900, *Annual Report of the Office of Experiment Stations* for 1901-1912, *A Report on the Work and Expenditures of the Agricultural Experiment Stations* for 1913-1924, *Report on the Agricultural Experiment Stations* for 1925-1959, *Funds for Research at State Agricultural Experiment Stations* for 1960-1963, *Funds for Research at State Agricultural Experiment Stations and Other State Institutions* for 1964-1969, and *Inventory of Agricultural Research* for 1970-1992. For 1993-2009 the data come from USDA's webbased Current Research Information System (CRIS), http://cris.nifa.usda.gov/fsummaries.html. Data for 1895 were interpolated.

During the period of 1966-1974 USDA had been issuing two publications on funds for research: *Funds for Agricultural Research* and *Inventory of Agricultural Research.* However, total funds reported by SAES and published in *Funds for Agricultural Research* do not match exactly with CRIS data published in *Inventory of Agricultural Research.* It is especially true for the first years of transition to the Current Research Information System (1966-1968). Since 1970s data from two sources becomes more consistent. Thereby, in this study, data on SAES funds is extracted from *Funds for Agricultural Research* up to 1969, and from *Inventory of Agricultural Research* since 1971. Data for a year of 1970 is found as an average of values in two publications.

State-level data on funds for USDA research agencies, 1890 Universities and Tuskegee University are available from 1970, for other cooperating institutions - from 1972, for Colleges of Veterinary Medicine – from 1982 up to 1992 from Inventory of Agricultural Research, and from CRIS website, http://cris.nifa.usda.gov/fsummaries.html, the data for all listed institutions are available from 1993 to 2009. USDA federal funds at the US level were collected from Huffman (1993). The relative share of federal funding in total funding for each state was then computed based on average between the mean for all available years and the mean for 1970-1985 period, thereby giving more weight to earlier years. Based on these shares, the data on federal funds for USDA were extrapolated back to 1901.

Summary of funding sources for research institutions is schematically presented in Figure 3.1.1.

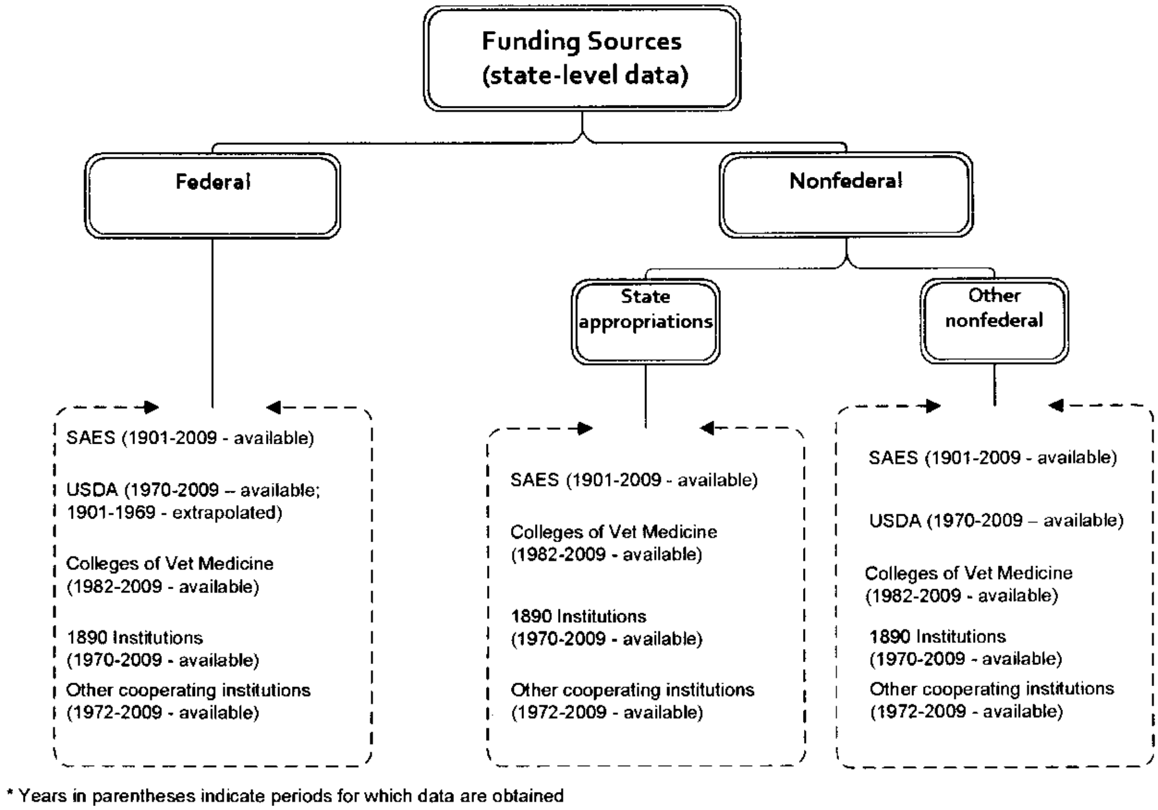


Figure 3.1.1. Funding sources for agricultural research institutions

US insular territories and Puerto Rico were not included in the analysis, nor were Hawaii and Alaska. The last two states officially became a part of the United States only in 1959; federal support for them also differed significantly from the support available to other states. Thereby, the analysis is conducted only for 48 continental states.

The data on output and input quantity and price indexes from 1960 to 2004 are from Eldon Ball, USDA (http://www.ers.usda.gov/Data/AgProductivity).

Data on two exogenous climate variables, average annual temperatures (measured in F^{o}) and precipitation (measured in inches), which were included to capture state-level variation, can be obtained from the Time Bias Corrected Divisional Dataset provided by the National Climatic Data Center (TD-9640, http://www7.ncdc.noaa.gov/CDO/CDODivisionalSelect.jsp).

Finally, the exogenous political party variable was obtained from Shaik (2009).

3.2. Summary statistics

Summary statistics is given for states and their respective regions. States included in each production region (according to ERS classification) are listed in Table 3.2.1. Summary statistics for series used in the analysis are presented in Tables 3.2.2 -3.2.3 and A1-A2 (Appendix). R&D funds were converted to real terms (adjusted for inflation) using the agricultural R&D deflator by Pardey et al. (2009).

Table 3.2.1. Farm production regions

Region	**States**
Appalachia	Kentucky, North Carolina, Tennessee, Virginia, West Virginia
Corn Belt	Illinois, Indiana, Iowa, Missouri, Ohio
Delta	Arkansas, Louisiana, Mississippi
Lake States	Michigan, Minnesota, Wisconsin
Mountain	Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming
Northeast	Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont
Northern Plains	Kansas, Nebraska, North Dakota, South Dakota
Pacific	California, Oregon, Washington
Southeast	Alabama, Florida, Georgia, South Carolina
Southern Plains	Oklahoma, Texas

Table 3.2.2 shows research expenditures averaged by period of time for each state. Regional averages are also presented in Table 3.2.2.

Table 3.2.2. Summary statistics for R&D funds (thousands of real dollars)

Region/State	1889-1900	1901-1910	1911-1920	1921-1930	1931-1940	1941-1950	1951-1960	1961-1970	1971-1980	1981-1990	1991-2000	2001-2009
Appalachia	*935*	*2,088*	*4,875*	*9,267*	*13,313*	*17,124*	*23,803*	*36,819*	*52,612*	*60,796*	*59,198*	*67,948*
Kentucky	1,072	3,172	9,456	12,267	17,060	18,851	22,572	37,305	43,906	42,023	44,148	51,247
North Carolina	1,104	2,757	5,063	12,744	17,947	24,495	36,507	58,221	98,129	124,735	115,125	127,020
Tennessee	779	1,515	3,367	7,217	11,708	15,818	21,532	33,659	50,327	44,411	45,336	49,005
Virginia	805	1,230	2,872	5,916	9,269	13,413	22,879	36,969	53,326	66,864	65,435	73,409
West Virginia	916	1,766	3,616	8,192	10,581	13,042	15,525	17,941	17,373	25,945	25,945	39,057
Corn Belt	*1,238*	*4,317*	*12,271*	*24,136*	*33,709*	*42,191*	*47,199*	*63,823*	*75,173*	*85,445*	*95,280*	*105,132*
Illinois	1,085	6,440	15,900	32,704	45,608	53,518	56,384	78,399	89,944	99,712	111,980	115,006
Indiana	894	2,906	12,587	20,933	31,333	38,720	45,021	49,288	68,913	80,250	81,102	98,040
Iowa	1,028	3,546	10,800	25,156	35,323	45,592	57,813	73,597	87,091	111,188	144,892	145,776
Missouri	974	3,083	7,106	14,128	21,179	25,997	31,738	53,373	63,335	67,420	75,437	92,992
Ohio	2,209	5,612	14,961	27,759	35,103	47,125	45,040	64,458	66,583	68,656	62,991	73,848
Delta	*1,345*	*3,564*	*8,213*	*22,498*	*33,711*	*41,207*	*44,827*	*68,821*	*85,597*	*85,939*	*87,305*	*107,397*
Arkansas	658	1,550	2,477	4,137	6,506	10,185	19,247	32,474	40,913	48,619	63,146	84,794
Louisiana	2,333	5,505	13,465	38,895	58,328	66,398	67,735	107,918	129,666	106,263	96,401	104,472
Mississippi	1,043	3,635	8,696	24,460	36,299	47,039	47,498	66,072	86,210	102,934	102,367	132,925
Lake States	*1,152*	*2,662*	*7,338*	*16,086*	*22,725*	*28,519*	*42,342*	*56,442*	*74,211*	*89,413*	*107,512*	*152,475*
Michigan	919	2,077	4,436	13,958	19,453	21,877	37,521	52,367	71,028	76,568	86,368	108,636
Minnesota	1,304	3,717	11,809	19,130	25,921	31,141	43,071	58,162	75,836	95,074	121,905	222,437
Wisconsin	1,232	2,194	5,770	15,171	22,802	32,540	46,434	58,797	75,768	96,597	114,263	126,352
Mountain	*755*	*1,741*	*4,076*	*9,843*	*14,746*	*16,878*	*19,019*	*27,137*	*34,204*	*39,692*	*40,595*	*46,908*
Arizona	814	2,131	5,743	14,004	20,696	22,297	23,214	42,244	54,716	64,217	77,168	80,088
Colorado	1,192	2,842	7,080	19,352	27,706	31,104	31,661	43,868	64,060	90,960	86,843	112,008
Idaho	583	1,554	3,662	9,451	14,553	16,741	21,216	29,937	33,909	39,798	41,116	46,959
Montana	619	2,110	5,367	11,417	16,017	20,783	26,048	33,158	37,854	35,757	33,772	43,438
Nevada	740	1,145	2,213	4,657	7,560	7,715	7,427	12,477	16,939	14,885	14,675	19,496
New Mexico	686	1,216	2,867	5,648	9,191	10,819	12,063	16,530	19,894	22,342	22,477	20,761
Utah	798	1,727	3,426	8,197	11,903	14,069	17,535	21,919	27,845	31,738	33,437	37,115
Wyoming	605	1,203	2,252	6,021	10,343	11,494	12,985	16,963	18,417	17,834	15,272	15,400
Northeast	*1,293*	*2,222*	*4,510*	*10,524*	*17,383*	*19,080*	*21,987*	*30,327*	*34,411*	*48,870*	*52,422*	*55,565*
Connecticut	1,352	2,092	3,045	6,330	10,171	10,223	15,586	18,177	17,852	16,069	19,111	26,873
Delaware	671	992	2,187	4,232	6,647	8,219	9,395	12,103	13,415	15,332	13,343	11,012
Maine	774	1,356	2,627	4,349	6,702	8,928	9,292	12,405	17,625	18,931	17,825	18,553

(Continued)

Table 3.2.2 - (Concluded)

Region/State	1889-1900	1901-1910	1911-1920	1921-1930	1931-1940	1941-1950	1951-1960	1961-1970	1971-1980	1981-1990	1991-2000	2001-2009
Maryland	850	2,225	5,155	13,175	19,782	22,311	23,545	33,332	34,078	128,382	176,227	163,801
Massachusetts	1,338	2,138	4,245	9,100	13,663	12,652	13,587	17,801	13,983	40,861	39,364	44,923
New Hampshire	687	831	1,608	2,030	3,860	3,164	4,304	6,406	6,608	6,836	6,766	5,707
New Jersey	1,200	2,096	5,090	8,982	17,322	17,058	22,463	31,817	37,736	29,395	35,105	29,084
New York	4,211	6,834	13,217	37,015	63,815	69,810	82,335	114,773	133,612	170,629	152,748	187,720
Pennsylvania	1,557	3,831	9,588	25,987	41,451	49,262	50,539	71,986	84,797	97,378	104,315	111,947
Rhode Island	756	1,025	1,587	2,760	4,424	4,929	6,291	8,271	11,204	6,258	4,345	4,843
Vermont	832	1,026	1,256	1,804	3,379	3,326	4,515	6,526	7,608	7,500	7,494	6,746
Northern Plains	*823*	*2,266*	*6,479*	*14,230*	*19,307*	*22,450*	*28,276*	*44,665*	*54,893*	*63,784*	*67,173*	*72,358*
Kansas	779	2,360	5,904	11,421	16,409	20,959	30,945	46,263	59,380	69,945	71,757	76,667
Nebraska	838	2,624	7,934	15,175	21,546	24,800	32,875	55,232	73,060	89,743	103,902	113,431
North Dakota	944	2,838	9,221	24,669	30,856	33,689	34,823	53,005	60,568	74,481	70,435	73,118
South Dakota	729	1,241	2,858	5,653	8,419	10,350	14,460	24,159	26,563	20,965	22,598	26,215
Pacific	*1,205*	*3,824*	*10,660*	*28,039*	*43,593*	*54,316*	*73,520*	*111,532*	*131,946*	*154,269*	*165,703*	*192,734*
California	1,765	6,374	15,502	41,354	67,504	85,935	128,447	198,096	242,282	312,913	330,251	396,759
Oregon	812	1,799	6,499	15,162	23,211	27,832	36,846	54,891	63,325	69,912	78,270	82,727
Washington	1,038	3,299	9,979	27,602	40,065	49,180	55,267	81,608	90,232	79,983	88,590	98,716
Southeast	*1,117*	*2,533*	*6,411*	*19,337*	*31,751*	*41,266*	*47,467*	*67,594*	*89,437*	*107,577*	*105,410*	*95,279*
Alabama	1,257	1,704	3,443	7,692	16,202	24,878	32,669	44,262	54,577	60,663	61,156	41,941
Florida	1,024	2,871	7,679	26,328	43,539	61,079	70,478	97,830	135,816	174,997	174,795	177,380
Georgia	1,357	3,983	10,929	32,558	50,422	55,965	64,507	96,060	124,449	146,435	137,808	125,205
South Carolina	831	1,575	3,594	10,770	16,842	23,141	22,213	32,224	42,906	48,215	47,881	36,588
Southern Plains	*949*	*2,854*	*9,034*	*24,767*	*39,901*	*52,267*	*59,717*	*75,772*	*93,321*	*124,739*	*141,453*	*153,713*
Oklahoma	664	1,858	4,244	10,859	20,832	28,319	32,883	43,023	48,134	55,476	60,751	68,052
Texas	1,234	3,849	13,824	38,675	58,969	76,215	86,551	108,522	138,507	194,002	222,154	239,375
Average Chain Growth Rates, %												
Appalachia	-	223.29	233.49	190.11	143.65	128.63	139.00	154.68	142.89	355.03	97.37	114.78
Corn Belt	-	348.70	284.21	196.69	139.66	125.16	111.87	135.22	117.78	202.52	111.51	110.34
Delta	-	265.04	230.47	273.93	149.84	122.24	108.78	153.53	124.37	208.55	101.59	123.01
Lake States	-	231.16	275.63	219.21	141.27	125.49	148.47	133.30	131.48	313.52	120.24	141.82
Mountain	-	230.73	234.13	241.48	149.81	114.46	112.69	142.69	126.04	235.17	102.28	115.55
Northeast	-	171.82	202.91	233.37	165.18	109.76	115.23	137.93	113.47	256.13	107.27	105.99
Northern Plains	-	275.39	285.99	219.61	135.68	116.27	125.95	157.96	122.90	284.12	105.31	107.72
Pacific	-	317.35	278.76	263.04	155.47	124.60	135.36	151.70	118.30	284.02	107.41	116.31
Southeast	-	226.71	253.09	301.62	164.20	129.97	115.03	142.40	132.31	260.70	97.99	90.39
Southern Plains	-	300.64	316.60	274.14	161.11	130.99	114.25	126.89	123.16	238.66	113.40	108.67

From Table 3.2.2, it is easy to see the differences in average distribution of investments between the states and regions in absolute values. For the last nine decades, the Pacific region had been getting the largest financing, for the most part due to the share of California in total R&D budget of a region. The second place based on average size of funding belongs to the Southern Plains region due to ample financing of Texas's agricultural research. For the last six decades Mountain and Northeast regions have been getting the least funding. On the whole, it the spread is quite significant, especially in the last decade: from 4,843 in Rhode Island (Northeast region) to 396,759 thousand dollars in California (Pacific region).

Average chain growth rates of R&D funding are given in the second part of Table 3.2.2 by region and in Table A1 (Appendix) by state.

Average TFP as well as input and output (quantity indices) annual percentage changes by region can be found in Table A2 (Appendix). In general, input grows at a lower rate than output, and even tends to decline over time, while output exhibits stable increase, providing a positive rate of productivity growth.

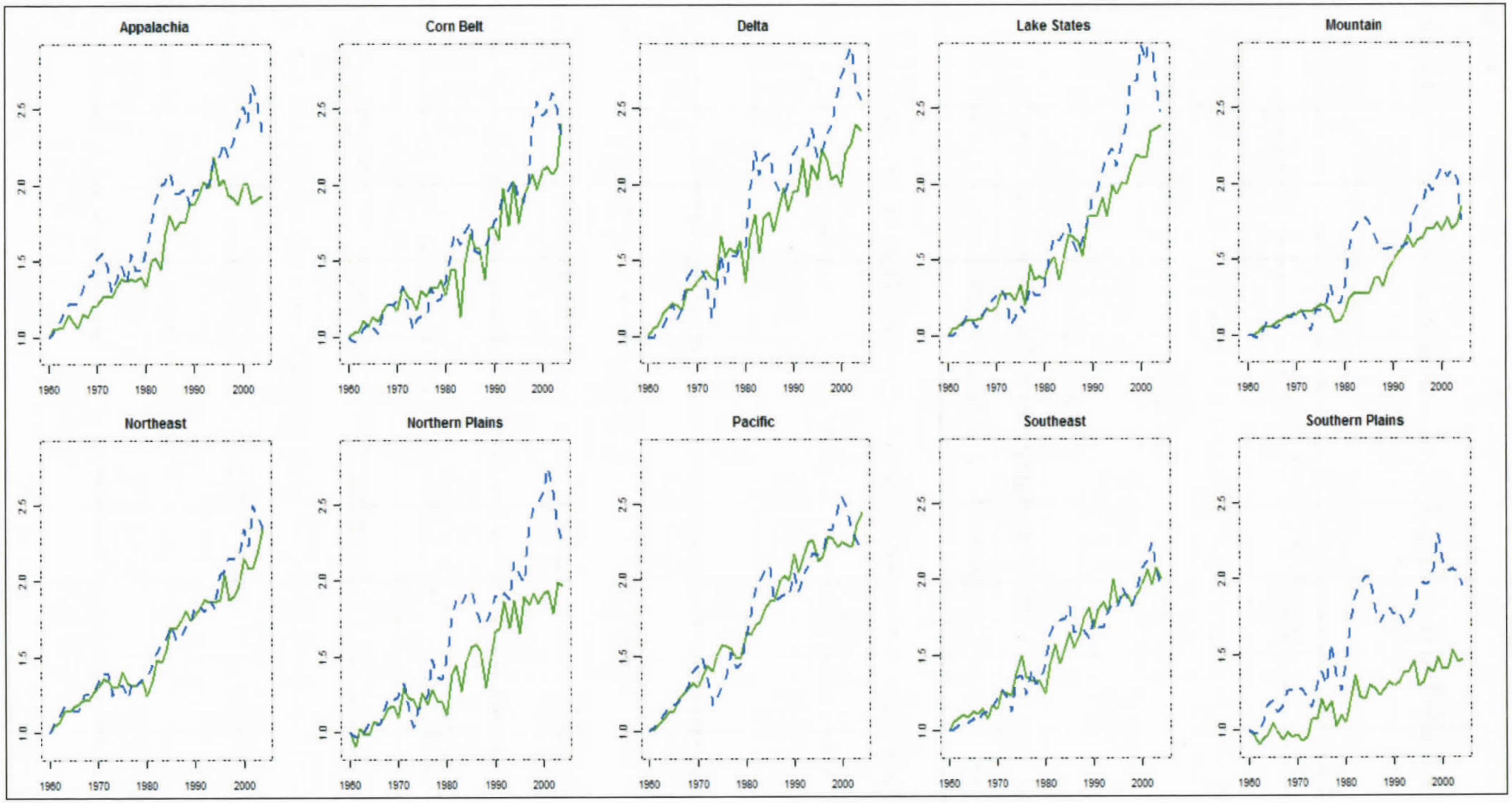
Average values of TFP and price ratio (input/output) are given in Table 3.2.3. From Table 3.2.3 it can be noted that, for every region and state, TFP and price ratio share similar (increasing) trends. It is difficult to make any other observations based on the tabled values. Figures 3.2.1 and A1-A2 (Appendix), however, allow a better visualizing of the dynamics of productivity and prices by region and state, respectively. It now can be observed that two lines do not wander too far from each other in most cases. Thus, this graphical evidence supports our hypothesis of possible causality between the two.

Table 3.2.3. Average values of TFP and price ratio

Region	TFP				Price ratio			
	1960-1970	1971-1980	1981-1990	1991-2004	1960-1970	1971-1980	1981-1990	1991-2004
Appalachia	*1.11*	*1.34*	*1.69*	*1.97*	*1.24*	*1.46*	*1.95*	*2.28*
Kentucky	1.16	1.41	1.84	2.09	1.23	1.49	2.02	2.48
North Carolina	1.13	1.51	1.83	2.33	1.26	1.48	1.87	2.17
Tennessee	1.09	1.29	1.57	1.71	1.20	1.43	1.94	2.28
Virginia	1.09	1.29	1.69	1.96	1.18	1.40	1.87	2.22
West Virginia	1.07	1.18	1.53	1.78	1.31	1.49	2.02	2.26
Corn Belt	*1.11*	*1.29*	*1.52*	*1.99*	*1.09*	*1.22*	*1.64*	*2.20*
Illinois	1.11	1.25	1.46	1.91	1.12	1.27	1.76	2.26
Indiana	1.15	1.35	1.63	2.22	1.12	1.27	1.73	2.36
Iowa	1.09	1.20	1.36	1.84	1.07	1.17	1.52	2.00
Missouri	1.07	1.22	1.42	1.75	1.06	1.18	1.63	2.22
Ohio	1.14	1.42	1.71	2.23	1.09	1.20	1.56	2.19
Delta	*1.18*	*1.49*	*1.79*	*2.14*	*1.18*	*1.43*	*2.08*	*2.46*
Arkansas	1.13	1.36	1.66	2.09	1.07	1.26	1.88	2.22
Louisiana	1.23	1.57	1.91	2.16	1.24	1.52	2.33	2.82
Mississippi	1.20	1.53	1.79	2.16	1.25	1.52	2.02	2.34
Lake States	*1.10*	*1.32*	*1.59*	*2.08*	*1.11*	*1.23*	*1.67*	*2.47*
Michigan	1.17	1.58	2.00	2.56	1.26	1.41	1.90	2.62
Minnesota	1.05	1.22	1.46	1.92	1.03	1.20	1.72	2.44
Wisconsin	1.09	1.15	1.32	1.76	1.04	1.08	1.39	2.35
Mountain	*1.07*	*1.15*	*1.33*	*1.68*	*1.06*	*1.19*	*1.65*	*1.88*
Arizona	1.03	1.06	1.22	1.59	1.02	1.19	1.66	1.86
Colorado	0.99	1.11	1.26	1.56	1.00	1.10	1.39	1.68
Idaho	1.13	1.30	1.57	2.13	1.12	1.21	1.60	2.02
Montana	1.14	1.24	1.36	1.65	1.10	1.34	1.93	2.24
Nevada	1.07	1.10	1.32	1.59	1.04	1.07	1.51	1.61
New Mexico	1.04	1.09	1.32	1.76	1.08	1.19	1.91	2.14
Utah	1.11	1.24	1.46	1.81	1.09	1.24	1.59	1.83
Wyoming	1.06	1.10	1.16	1.37	1.05	1.18	1.60	1.69

(Continued)

Region	TFP				Price ratio			
	1960-1970	1971-1980	1981-1990	1991-2004	1960-1970	1971-1980	1981-1990	1991-2004
Northeast	*1.16*	*1.33*	*1.63*	*2.00*	*1.18*	*1.33*	*1.64*	*2.12*
Connecticut	1.16	1.26	1.63	2.20	1.15	1.20	1.40	1.98
Delaware	1.17	1.50	1.66	1.96	1.24	1.48	1.73	2.02
Maine	1.17	1.34	1.56	2.05	1.35	1.51	1.91	2.48
Maryland	1.12	1.33	1.57	1.89	1.13	1.33	1.70	2.08
Massachusetts	1.20	1.38	1.71	2.23	1.24	1.43	1.67	2.34
New Hampshire	1.19	1.45	1.64	1.96	1.12	1.29	1.63	2.10
New Jersey	1.08	1.10	1.43	1.82	1.10	1.28	1.70	2.25
New York	1.12	1.15	1.37	1.70	1.10	1.21	1.43	1.85
Pennsylvania	1.15	1.29	1.66	2.00	1.13	1.25	1.59	2.03
Rhode Island	1.27	1.42	2.19	2.30	1.18	1.30	1.79	2.33
Vermont	1.15	1.35	1.49	1.86	1.20	1.28	1.49	1.88
Northern Plains	*1.05*	*1.21*	*1.47*	*1.84*	*1.09*	*1.28*	*1.82*	*2.26*
Kansas	0.99	1.14	1.27	1.54	1.05	1.22	1.58	1.90
Nebraska	1.08	1.25	1.53	1.85	1.14	1.30	1.61	1.95
North Dakota	1.12	1.36	1.71	2.21	1.15	1.45	2.33	3.06
South Dakota	1.02	1.11	1.36	1.78	1.00	1.16	1.77	2.15
Pacific	*1.16*	*1.50*	*1.88*	*2.23*	*1.19*	*1.39*	*1.95*	*2.25*
California	1.09	1.31	1.68	1.87	1.10	1.29	1.82	1.94
Oregon	1.18	1.60	1.95	2.48	1.26	1.52	2.07	2.61
Washington	1.21	1.59	2.01	2.34	1.22	1.38	1.95	2.20
Southeast	*1.10*	*1.32*	*1.60*	*1.92*	*1.08*	*1.30*	*1.70*	*1.92*
Alabama	1.00	1.16	1.39	1.60	1.04	1.24	1.64	1.77
Florida	1.10	1.35	1.55	1.86	1.12	1.44	1.91	2.22
Georgia	1.17	1.44	1.82	2.25	1.12	1.34	1.63	1.84
South Carolina	1.13	1.33	1.66	1.97	1.05	1.20	1.60	1.84
Southern Plains	*0.97*	*1.07*	*1.27*	*1.41*	*1.13*	*1.33*	*1.84*	*1.96*
Oklahoma	0.93	1.01	1.21	1.24	1.20	1.40	1.89	1.92
Texas	1.01	1.13	1.33	1.57	1.07	1.26	1.79	2.00



Note: Green solid line denotes TFP, blue dotted line – price ratio.

Figure 3.2.1. TFP and price ratio dynamics by region

3.3. Variables

Description of variables used in the analysis is presented in Table 3.3.1.

Table 3.3.1. Description of variables

Variable	Description
TFP	Total factor productivity
Trap_Stock	R&D stock (with assumed trapezoidal lag structure)
Inv_V_Stock	R&D stock (with assumed inverted-V lag structure)
PR	Price ratio
Temp	Average annual temperature (F^o)
Precip	Average annual amount of precipitation (inches)
Party	Political party dummy variable: 1 – Democratic Party, 0 – Republican Party

TFP is computed as aggregate output quantity index over aggregate input quantity index. Price ratio (*PR*) represents the ratio of aggregate input price index over aggregate output price index.

R&D stock variables were to be constructed because investments in research do not affect production immediately: a presence of the lag between expenditures in R&D and their impact on TFP is commonly accepted in the literature. However, the structure and length of this lag have been an issue for researchers for over half of the century. Most of them agree on the fact that there is an initial "gestation" lag – a time before research has any impact; an adoption lag, during which the weights increase until reaching the maximum; and disadoption lag with declining weights, when the impact of the research starts diminishing at some point. In practice, specific weights have been estimated or, more often, imposed based on the assumptions made. This study involves consideration of the most commonly used lag structures to construct stock of knowledge: trapezoidal and inverted-V.

Trapezoidal lag was introduced by Huffman and Evenson (1989) and adopted by many others later. This lag structure assumes a gestation period of two years during which the impacts are negligible, a seven-year period when the impacts are positive and the weights tend to increase, a six-year period of maturity during which weights are high and constant, and then twenty-year span when weights decline gradually to zero (see, for example, Huffman and Evenson, 2003).

The use of a finite *inverted-V lag* was introduced by F. de Leeuw (1962) and required considerable computation. Evenson (1967) developed a weighting procedure such that a lag still could be represented in the form of inverted-V:

(3.3.1) $$w_i = \frac{i}{s + 2\sum_{j=1}^{s-1} j} \text{ for } i = 1, \ldots, s$$

and

(3.3.2) $$w_i = \frac{n-i}{s + 2\sum_{j=1}^{s-1} j} \text{ for } i = s+1, \ldots, n,$$

where w_i is a weight for period i;

n is a total number of lags;

s is a mean lag: $s = n/2$.

We attempt to compare the outcomes from using two different lag structures. For purposes of comparison the total lag length for the inverted-V structure was assumed the same as for the trapezoidal structure, that is, 35 years. The structures are compared in Figure 3.3.1.

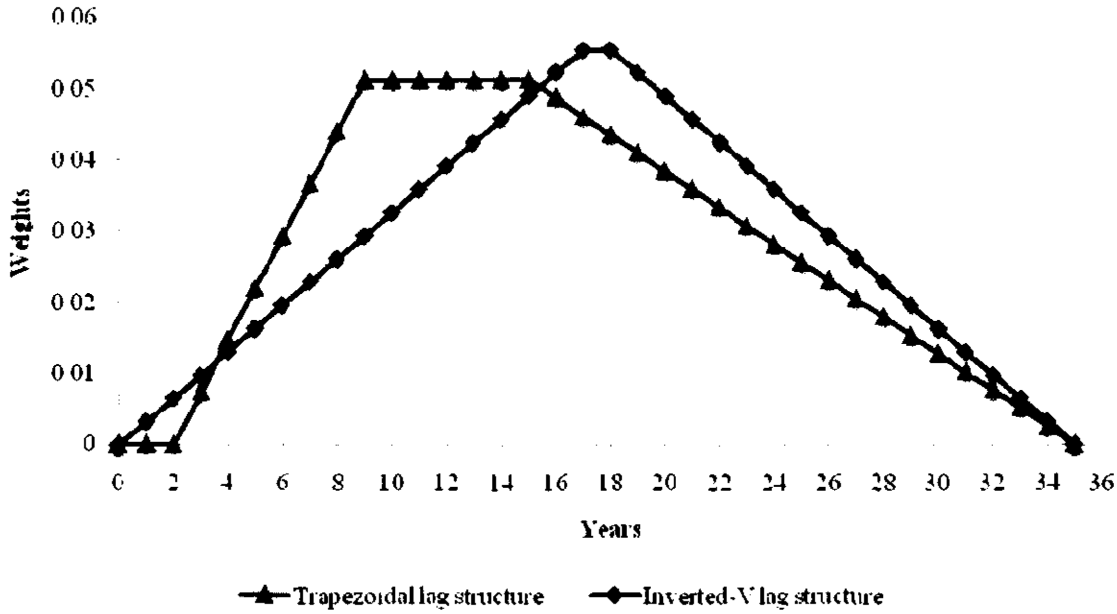


Figure 3.3.1. Trapezoidal and inverted-V lag structures

R&D expenditures were deflated prior to constructing knowledge stocks.[1]

The research conducted in a given state is not solely defined by the amount of public appropriations for this state, but is also influenced by the spillovers, primarily from the neighboring states. Thus, the effects of the interstate spillovers have to be taken into account. Measures of spillover potential are defined based on ERS farm production regions: the spillovers of agricultural research in a particular state are computed by subtracting this state's R&D stock from the sum of the R&D stocks for all the states associated with its respective region[2]. The R&D stock (*Trap_Stock* or *Inv_V_Stock*) for a particular state is then defined as a sum of its own stock and respective spillovers.

The description of the theoretical model and estimation methods is given in the next chapter.

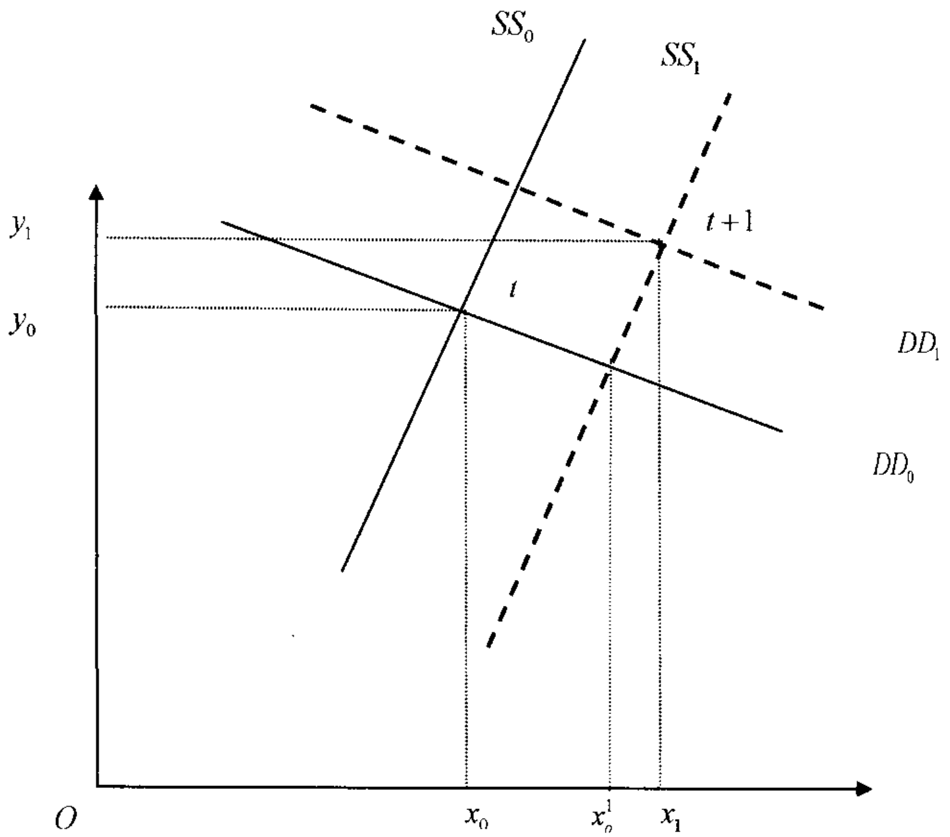
[1]Agricultural R&D deflator is from Pardey (2009).
[2] Liu et al. (2008) use an analogous approach in computing public R&D spillovers.

CHAPTER 4.

THEORETICAL MODEL AND METHODS

4.1. Conceptual framework

As it has already been noted, this study attempts to determine the effects of research-induced supply shift together with a price-induced demand shift on total factor productivity. The Figure 4.1.1, developed by Shaik (1999), illustrates the possibility of such influence on productivity change from time period t to $t+1$ under the assumption of technical efficiency.



DD_0 and DD_1 – demand curves at time periods 0 and 1, respectively; SS_0 and SS_1 – supply curves at time periods 0 and 1, respectively.
Source: Shaik, S. (1999).

Figure 4.1.1. Supply and demand sources of productivity

As a rule, the change in productivity from period t to period $t+1$ is viewed as a result of a shift in the supply curve (SS_0 to SS_1) while a demand curve is assumed to be stationary. However, the simultaneous movements in demand and supply are more likely to take place in reality. Assuming flexibility of the demand curve, the productivity change can then be explained by the two sources: by the movement along the DD_0 till it reaches SS_1 due to change in R&D expenditures and the movement along the SS_1 till it reaches DD_1 due to change in the price ratio.

This study's objective is to empirically examine graphically demonstrated influence of supply and demand sides on productivity utilizing the panel data set for 48 U.S. states. At the same time the linear feedback relationship from productivity to the magnitude of R&D investments does not seem impossible (Baumol, Wolff, 1983), as well as the linear feedback from productivity to prices (Shaik, 1999). In this study, following Shaik (1999), it is hypothesized, there may be a causality running not only from public R&D outlays and price ratio to TFP, but a two-way causality between TFP and R&D activity, between TFP and price ratio, and between R&D activity and price ratio (Figure 4.1.2).

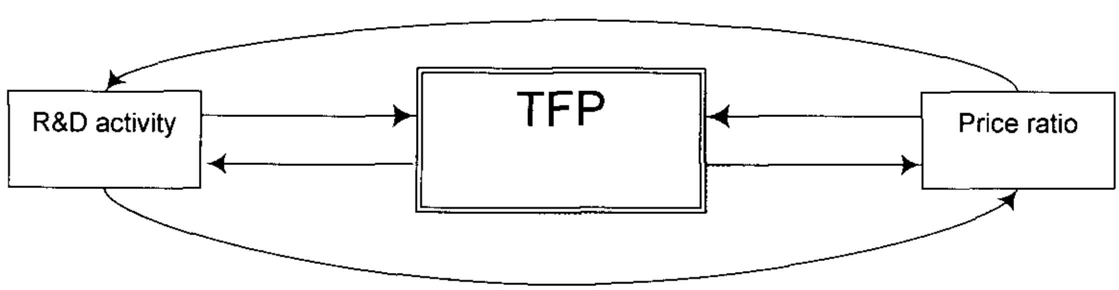


Figure 4.1.2. Causal relationship between TFP, R&D activity and price ratio

To capture various causal informational relationships, VAR / VEC model is proposed, where the three main variables of interest are thought to be endogenous (see

Section 4.2 for details). To capture a state-level variation, three exogenous variables – two climate variables (temperature and precipitation) and a political party dummy variable - are introduced to explain the remaining state level variation not explained by the endogenous variables.

4.2. Hypothesized model and estimation method

The relationships between the variables of interest are not straightforward. To account for a possible causality between all the variables in the analysis (see *Chapter 3, Section 3.3* for description of the variables), the following model, where each variable is explained by its own lags as well as by the lags of all other variables is proposed:

$$
(4.2.1)\qquad \begin{cases} TFP_{it} = \alpha_1 + \sum_{j=1}^{n} \beta_{1j} TFP_{i,t-j} + \sum_{j=1}^{n} \gamma_{1j} Stock_{i,t-j} + \sum_{j=1}^{n} \lambda_{1j} PR_{i,t-j} + \varepsilon_{1t}, \\ Stock_{it} = \alpha_2 + \sum_{j=1}^{n} \beta_{2j} TFP_{i,t-j} + \sum_{j=1}^{n} \gamma_{2j} Stock_{i,t-j} + \sum_{j=1}^{n} \lambda_{2j} PR_{i,t-j} + \varepsilon_{2t}, \\ PR_{it} = \alpha_3 + \sum_{j=1}^{n} \beta_{3j} TFP_{i,t-j} + \sum_{j=1}^{n} \gamma_{3j} Stock_{i,t-j} + \sum_{j=1}^{n} \lambda_{3j} PR_{i,t-j} + \varepsilon_{3t}, \end{cases}
$$

where ε_t are unobservable zero-mean white noise processes; $\varepsilon_{1t,}$ $\varepsilon_{2t,}$ ε_{3t} are uncorrelated.

System of equations (4.2.1) is a mathematical representation of a vector autoregressive model (VAR). Prior to estimating this model, unit root tests (tests for nonstationarity) and cointegration tests have to be performed. If the variables are found to be stationary, a VAR may be then safely estimated with variables in levels. But if the underlying series are nonstationary and nonstationarity will not be accounted for, the regression of one such variable against another can lead to spurious results (Gauss-Markov theorem will not hold, as random walk does not have finite variance, hence, OLS would not yield a consistent parameter estimator). Moreover, the answer to the question of whether series are stationary or nonstationary has implications for our understanding of the economy and the forecasting (Pindyck, 1998). If a variable follows a random walk, the effects of the temporary shocks will not dissipate after several periods, but instead will have permanent effects. However, if nonstationary variables are cointegrated, that is, there exists a long-term equilibrium relationship between them, the regression will not yield spurious results. The presence of a long-run (cointegrating) relationship can be controlled by a vector error correction model (VEC) which is a generalization of a VAR.

Summing it up, testing the dynamic relationships between the variables of the system under study requires three steps:

1) testing for unit roots;

2) testing for cointegration and endogeneity (causality);

3) estimation of VAR or VEC depending on the results of the procedures in the first two steps.

4.2.1. Unit roots

Karlsson and Löthgren (2000) suggest that the individual and panel unit root test results should be jointly analyzed for a better evaluation of the stationarity properties of the panel. Their rationale is that for large T there is a risk to conclude that the whole panel is stationary even if only a small proportion of the series in the panel is indeed stationary. For small T, one runs potential risk to conclude that the whole panel is nonstationary even if a large proportion of the series is stationary. Therefore, both types of the tests are conducted in this study.

Three following individual time-series unit root tests are applied for each cross-section:

- Augmented Dickey-Fuller (1981) — Testing the null of unit root
- Phillips-Perron (1988) — Testing the null of unit root
- Kwiatowski, Phillips, Schmidt, and Shin (1992) — Testing the null of stationarity

Brief description of the tests is given further.

Augmented Dickey-Fuller (ADF) unit root test is based on estimating the regression:

$$(4.2.1.1) \quad Y_t - Y_{t-1} = \alpha + \beta \cdot t + (\rho - 1)Y_{t-1} + \sum_{j=1}^{p} \lambda_j \Delta Y_{t-j} + \varepsilon_t,$$

where ε_t are assumed to be white noise.

It further requires computing ADF statistics which is equal to $\widehat{(\rho-1)}/se\widehat{(\rho-1)}$ and comparing it with the DF (1979) or more recent MacKinnon (1996) critical values[7]. Adding a lagged dependent variable ΔY_t controls for serial correlation in the residuals. The null hypothesis is that of unit root ($H_0 : \rho - 1 = 0$); the alternative – there is no unit root ($H_a : \rho - 1 < 0$).

Phillips-Perron (PP) test for the null of unit root uses nonparametric statistical methods to account of serial correlation in the error terms without adding lagged ΔY_t.

[7] The more recent MacKinnon critical value calculations are used by EViews.

Kwiatowski, Phillips, Schmidt, and Shin (KPSS) test in contrast to two other tests has (trend-) stationarity as the null hypothesis. Kwiatowski, Phillips, Schmidt, and Shin start with the model[8]:

(4.2.1.2) $y_t = \delta t + \varsigma_t + \varepsilon_t$,

where ε_t is a stationary process and ς_t is a random walk given by

(4.2.1.3) $\varsigma_t = \varsigma_{t-1} + u_t$, $\quad u_t \sim \text{iid}\ (0,\ \sigma_u^2)$.

The formulation of the null hypothesis is:

(4.2.1.4) $H_0: \sigma_u^2 = 0$ or ς_t is constant.

The LM test statistic for this hypothesis is defined as

(4.2.1.5) $$LM = \frac{\sum_{t=1}^{T} S_t^2}{\hat{\sigma}_e^2},$$

where e_t are the residuals from regression of y_t on constant, or on constant and a time trend, $\hat{\sigma}_e^2$ is the residual variance from this regression (residual sum of squares divided by T), S_t is a partial sum of e_t:

(4.2.1.6) $$S_t = \sum_{t=1}^{T} e_t,\ t = 1, 2, \ldots, T.$$

Critical values for LM statistic were derived by Nabeya and Tanaka.

Along with time series unit root tests, the following panel-based unit root tests will be conducted:

[8] Maddala, G.S. and In-Moo Kim. *Unit Roots, Cointegration, and Structural Change*. Cambridge University Press. 1998, p. 120.

- Im, Pesaran and Shin (2003)
- ADF - Fisher Chi-Square (1999)
- PP – Fisher Chi-Square (2001)
- Levin, Lin and Chu (2002)
- Breitung (2000)

Tests of unit root under the null

- Hadri (2000)

Test of stationarity under the null

Summary of the listed tests is given below.

Consider AR(1) process for panel data defined as follows:

(4.2.1.7) $y_{it} = \rho_i y_{it-1} + X_{it}\delta_i + \varepsilon_{it}$ [9],

where X_{it} represent exogenous variables in the model (e.g., any fixed effects or individual trends), ε_{it} are mutually independent idiosyncratic disturbance terms. If autoregressive coefficients $|\rho_i|$ are less than unity, y_i is said to be weakly (trend-) stationary; and if $|\rho_i|$ is equal to unity, then y_i has a unit root.

The conducted panel unit root tests can be divided into two groups based on the assumption about ρ_i : tests with common unit root process and tests with individual unit root process. Both groups of the tests are briefly discussed below.

I. Tests with *common unit root process*, so that $\rho_i = \rho$ for all i. They include Levin, Lin and Chu (LLC), Breitung, and Hadri tests.

LLC and Breitung consider the ADF formulation:

(4.2.1.8) $\Delta y_{it} = \alpha y_{it-1} + \sum_{j=1}^{p_i} \beta_{ij}\Delta y_{it-j} + X'_{it}\delta + \varepsilon_{it}$, [10]

[9] EViews 6. User Guide II, p. 104.
[10] EViews 6. User Guide II, p. 105.

where $\alpha = \alpha_i = \rho - 1$ is common for all cross-sections, but the lag p_i may vary for different *i*.

Both tests, LLC and Breitung, has unit root under the null and stationarity (for all the cross-sections) under the alternative, i.e.: $H_0 : \alpha = 0$ and $H_a : \alpha < 0$. Again, the restriction here is that α_i is the same for all the cross-sectional units under the alternative. Inclusion of the lagged first differences of y_{it} allows controlling serial correlation of error terms.

Levin, Lin and Chu define $\Delta\bar{y}_{it}$ by taking Δy_{it} and eliminating the autocorrelations and deterministic components:

(4.2.1.9) $\Delta\bar{y}_{it} = \Delta y_{it} - \sum_{j=1}^{p_i} \hat{\beta}_{ij} \Delta y_{it-j} + X_{it}' \hat{\delta}$.

Similarly, they define $\bar{y}_{it-1}$ as

(4.2.1.10) $\bar{y}_{it-1} = y_{it-1} - \sum_{j=1}^{p_i} \hat{\hat{\beta}}_{ij} \Delta y_{it-j} + X_{it}' \hat{\hat{\delta}}$.

$\hat{\beta}_{ij}$, $\hat{\delta}$, and $\hat{\hat{\beta}}_{ij}$, $\hat{\hat{\delta}}$ represent estimated coefficients from the regression of Δy_{it} and y_{it-1}, respectively, on lagged terms Δy_{it-j} and exogenous variables X_{it}.

Then, $\Delta\bar{y}_{it}$ and $\bar{y}_{it-1}$ are divided by standard errors of each ADF regression defined by Equation (4.2.1.8) to obtain proxies:

(4.2.1.11) $\Delta\tilde{y}_{it} = \Delta\bar{y}_{it} / s_i$,

(4.2.1.12) $\tilde{y}_{it-1} = \bar{y}_{it-1} / s_i$.

Finally, the estimate of α is obtained from pooled proxy equation:

(4.2.1.12) $\Delta\tilde{y}_{it} = \alpha\tilde{y}_{it-1} + \eta_{it}$

Levin, Lin and Chu show that modified t-statistic for $\hat{\alpha}$ converges to normal distribution asymptotically:

$$(4.2.1.13)\quad t^*_\alpha = \frac{t_\alpha - (N\widetilde{T})S_N\hat{\sigma}^{-2}se(\hat{\alpha})\mu^*_{m\widetilde{T}}}{\sigma^*_{m\widetilde{T}}} \rightarrow N(0,1).$$

where N – number of cross sections,

t_α – standard t-statistic for $\hat{\alpha}$ =0,

$\hat{\sigma}^2$ – estimated variance of the error term η,

$\widetilde{T}$ – average number of observations per cross-section in the panel,

$$(4.2.1.14)\qquad \widetilde{T} = T - \frac{\sum_{i=1}^{N} p_i}{N} - 1,\ T \text{ – number of time periods,}$$

S_N – average standard deviation ratio (the mean of the ratios of the long-run standard deviation to the innovation standard deviation for each individual),

$\mu^*_{m\widetilde{T}}$ – adjustment term for the mean,

$\sigma^*_{m\widetilde{T}}$ – adjustment term for the standard deviation.

In *Breitung* test, in contrast to LLC, only autoregressive part is eliminated for constructing the standardized proxies, $\Delta\widetilde{y}_{it}$ and $\widetilde{y}_{it-1}$, i.e.:

$$(4.2.1.15)\quad \Delta\overline{y}_{it} = \Delta y_{it} - \sum_{j=1}^{p_i} \hat{\beta}_{ij}\Delta y_{it-j} \ ,$$

$$(4.2.1.16)\quad \overline{y}_{it-1} = y_{it-1} - \sum_{j=1}^{p_i} \hat{\hat{\beta}}_{ij}\Delta y_{it-j},$$

$$(4.2.1.17)\quad \Delta\widetilde{y}_{it} = \Delta\overline{y}_{it}/s_i,$$

$$(4.2.1.18)\quad \widetilde{y}_{it-1} = \overline{y}_{it-1}/s_i.$$

The proxies are then transformed and detrended:

$$(4.2.1.19)\quad \Delta y_{it}^{*} = \sqrt{\frac{T-t}{T-T+1}}(\Delta\widetilde{y}_{it} - \frac{\Delta\widetilde{y}_{it+1} + \ldots + \Delta\widetilde{y}_{iT}}{T-t}),$$

$$(4.2.1.20)\quad y_{it}^{*} = \widetilde{y}_{it} - \widetilde{y}_{i1} - \frac{t-1}{T-1}(\widetilde{y}_{iT} - \widetilde{y}_{i1}).$$

The estimate of α is then obtained from pooled proxy equation:

$$(4.2.1.21)\quad \Delta y_{it}^{*} = \alpha y_{it-1}^{*} + v_{it}.$$

Estimator α^{*} is asymptotically distributed as a standard normal under the null hypothesis.

Hadri test is a generalization of the time-series KPSS unit root test for the panel data. It differs from LLC and Breitung in that it has stationarity for all the series under the null. Hadri allows the error term to be homoskedastic or heteroskedastic across cross-sectional units. The test is based on OLS residuals from regression of y_{it} on a constant, or a constant and a trend:

$$(4.2.1.22)\quad y_{it} = \varsigma_{it} + \varepsilon_{it}$$

or

$$(4.2.1.23)\quad y_{it} = \delta_i t + \varsigma_{it} + \varepsilon_{it},$$

where ς_{it} is a random walk:

$$(4.2.1.24)\quad \varsigma_{it} = \varsigma_{it-1} + u_{it},$$

$\varepsilon_{it} \sim$ IIN (0, σ_{ε}^{2}) and $u_{it} \sim$ IIN (0, σ_{u}^{2}).

The formulation of the null hypothesis is given as

$$(4.2.1.25)\quad H_{0}: \sigma_{u}^{2} = 0.$$

Lagrange multiplier (LM) statistic is:

$$(4.2.1.26)\quad LM_1 = \frac{1}{N}\left(\sum_{i=1}^{N}\frac{\sum_{t=1}^{T} S_{it}^2}{T^2}\right)/\hat{\sigma}_{\varepsilon}^2,$$

where S_{it} are partial sums of the OLS residuals:

$$(4.2.1.27)\quad S_{it} = \sum_{s=1}^{t}\hat{\varepsilon}_{is}.$$

LM test accounting for heteroskedasticity across cross-sections is given by:

$$(4.2.1.28)\quad LM_2 = \frac{1}{N}\left(\sum_{i=1}^{N}\left(\frac{\sum_{t=1}^{T} S_{it}^2}{T^2}/\hat{\sigma}_{\varepsilon i}^2\right)\right).$$

The test statistic of Hadri is

$$(4.2.1.29)\quad Z = \frac{\sqrt{N}(LM - \xi)}{\zeta} \rightarrow N(0,1),$$

where ξ=1/6 and ζ =1/45 if the model includes only constant; ξ=1/15 and ζ =11/6300, otherwise.

II. Tests with *individual unit root process* when ρ_i can vary across cross-sections. This assumption is employed by Im, Pesaran and Shin (IPS), Maddala and Wu (Fisher-ADF) and Choi (Fisher-PP). Instead of pooling the data, these tests use separate unit root tests for N cross-sections.

Im, Pesaran and Shin (IPS) unit root test is a balanced-panel-based equivalent of ADF test with the null of a unit root in all cross-sectional units. The alternative allows for heterogeneity. In other words, rejection of the null may imply that there may be a unit root present in some of the cross-sections while other cross-sectional units may be stationary. The test statistic is the average of the t-statistics for α_i from Equation (4.1.2.8):

$$(4.2.1.30)\quad \bar{t}_{NT} = (\sum_{i=1}^{N} t_{iT_i}(p_i))/N,$$

which converges to a standard normal distribution in large samples when properly standardized:

$$(4.2.1.31)\quad W_{\bar{t}_{NT}} = \frac{\sqrt{N}(\bar{t}_{NT} - N^{-1}\sum_{i=1}^{N} E(\bar{t}_{iT}(p_i)))}{\sqrt{N^{-1}\sum_{i=1}^{N} Var(\bar{t}_{iT}(p_i))}} \rightarrow N(0,1).$$

Fisher-ADF and *Fisher-PP* tests, proposed by Maddala and Wu (1999) and by Choi (2001), utilize the Fisher's results and are based on p-values of individual unit root tests. The null hypothesis is that all series are non-stationary against the alternative that at least one of the series is stationary. The test statistic is

$$(4.2.1.32)\quad -2\sum_{i=1}^{N} \ln(\pi_i) \rightarrow \chi^2_{2N},$$

where π_i is p-value from any individual unit root test for a cross section i.

Choi (2001) shows that

$$(4.2.1.33)\quad Z = \frac{1}{\sqrt{N}}\sum_{i=1}^{N} \mathbf{\Phi}^{-1}(\pi_i) \rightarrow N(0,1),$$

where $\mathbf{\Phi}^{-1}$ is a cumulative standard normal distribution function.

Fisher-type tests differ from IPS in that they do not require a balanced panel, so T can differ across cross-sections.

In case the series under analysis are found to be nonstationary, based on the results of the unit root tests, cointegration tests will need to be employed. In either case, whether variables contain unit root or not, testing for causality will be performed to ensure endogeneity of the analyzed series.

4.2.2. Cointegration and causality

Given that the variables are found to be nonstationary, there is a possibility that a linear combination of them will cancel out stochastic trends in the series, i.e. the variables can be cointegrated. In an economic sense, it will imply that the variables have a long-term, or equilibrium, relationship among them. In this study Johansen testing procedures for panel data is employed for the reason that it allows several cointegrating vectors in the system. Many other tests, such as Pedroni (1995, 1999, 2004), Kao (1999) which are based on Engle-Granger framework, assume that there is only one cointegrating vector.

The starting point for *Johansen cointegration test* is VAR model of order p, VAR(p):

(4.2.2.1) $y_t = A_1 y_{t-1} + \ldots + A_p y_{t-p} + Bx_t + \varepsilon_t$,

where y_t is k x 1 vector of variables integrated of order one, I(1);

x_t is d x 1 vector of deterministic variables;

ε_t is k x 1 vector of innovations.

An error-correction model for the VAR(p) process y_t is:

(4.2.2.2) $\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + Bx_t + \varepsilon_t$, (4.2.2.3) where $\Pi = \sum_{i=1}^{p} A_i - I$ and $\mathbf{\Gamma}_i = -\sum_{j=i+1}^{p} A_j$.

Three cases are possible in considering the VECM in Equation (4.2.2.2);

1) Rank(Π) =0. This implies that there are no cointegrating relationships;

2) Rank(Π) =k. This implies that none of the series has a unit root and stationary VAR may be specified in terms of the levels of the series;

3) 0 < Rank(Π) = r < k. In this case one can write Π as

(4.2.2.4) $\Pi = \boldsymbol{\alpha\beta}'$,

where α and β are k x r matrices with Rank(α)=Rank(β) =r, and $\boldsymbol{\beta}'\mathbf{y}_t$ is stationary. r is the number of cointegrating relations (cointegrating rank), each column of β is a cointegrating vector, elements of α are adjustment parameters for the VEC model.

If there is only one cointegrating equation, then a single linear combination of I(1) endogenous variables, $\boldsymbol{\beta}'\mathbf{y}_{t-1}$, should be added to each equation in VAR. When multiplied by a coefficient for an equation, the resulting term, $\boldsymbol{\alpha\beta}'\mathbf{y}_{t-1}$, is referred to as an error correction term. If there are more than one cointegrating equations, each will contribute an additional error correction term involving a different linear combination of I(1) series.

Thus, to test for cointegration, Johansen (1988) suggests examining the rank of Π (for a specified deterministic term) by applying two statistics: trace statistics and maximum eigenvalue statistics. The trace statistics tests the null hypothesis that there are r or fewer cointegrating vectors against a general alternative that there are more than r vectors:

(4.2.2.5) $LR_{tr}(r \mid k) = -T \sum_{i=r+1}^{k} \log(1 - \lambda_i)$, where λ_i is the i-th largest eigenvalue of the Π matrix in Equation (4.2.2.3).

The maximum eigenvalue test evaluates the null hypothesis of r cointegrating relations against the alternative of $r+1$ cointegrating relations and is computed as:

(4.2.2.6) $LR_{tr}(r \mid r+1) = -T\log(1-\lambda_{r+1}) = LR_{tr}(r \mid k) - LR_{tr}(r+1 \mid k)$

for $r=0,1,\ldots k-1$.

It should be noted, that the number of cointegrating equations (CE) is determined conditional on the assumption made about the trend. Altogether, five possible combinations of deterministic components are contained in the Johansen procedure:

Model (1) The level data y_t have no deterministic trends and CE do not have intercepts:

(4.2.2.7) $\Pi y_{t-1} + Bx_t = \alpha\beta' y_{t-1}$.

Model (2) The level data y_t have no deterministic trends and CE have intercepts:

(4.2.2.8) $\Pi y_{t-1} + Bx_t = \alpha(\beta' y_{t-1} + \rho_0)$.

Model (3) The level data y_t have linear trends and CE have intercepts:

(4.2.2.9) $\Pi y_{t-1} + Bx_t = \alpha(\beta' y_{t-1} + \rho_0) + \alpha_{\perp}\gamma_0$.

Model (4) The level data y_t and CE have linear trends:

(4.2.2.10) $\Pi y_{t-1} + Bx_t = \alpha(\beta' y_{t-1} + \rho_0 + \rho_1 t) + \alpha_{\perp}\gamma_0$.

Model (5) The level data y_t have quadratic trends and CE have linear trends:

(4.2.2.11) $\Pi y_{t-1} + Bx_t = \alpha(\beta' y_{t-1} + \rho_0 + \rho_1 t) + \alpha_{\perp}(\gamma_0 + \gamma_1 t)$.

The terms related to $\alpha_{\perp}$ are deterministic terms "outside" the CE.

As can be noted that the most restrictive model, Model (1), contains no deterministic components and the least restrictive model, Model (5), contains unrestricted quadratic trends in level data. The five models are nested within one another, so that Model

(1) is contained in Model (2) and so on. Johansen (1992, 1995) suggests a method for simultaneously determining rank and deterministic components, which is also known as *Pantula* principle. This principle is applied in this study to ascertain deterministic assumption and can be described as follows: first, a test of the null of no cointegrating vector for Model (1) is performed. If this hypothesis is rejected, one proceeds with the test using Model (2) and so on. If the null of zero rank is rejected for all five models, the procedure is repeated for the null of at most rank one. The process stops when one fails to reject the null for the first time, and the corresponding model is then chosen.

Maddala and Wu (1999) extend Johansen's approach to panel data based on Fisher's results. They obtain test statistic for a whole panel by combining tests from individual cross-sections:

(4.2.2.12) $-2\sum_{i=1}^{N}\log(\pi_i) \rightarrow \chi^2_{2N}$,

where π_i's are the p-values from an individual cointegration tests.

After the test for cointegration is performed, we proceed with a test for the causal relationship among the four variables and check whether all the variables belong to the system using conventional bivariate Granger causality tests.

In pairwise Granger causality tests the following equations are estimated for each possible pair *(x, y):*

(4.2.2.13) $y_{it} = \alpha_0 + \alpha_1 y_{t-1} + \dots + \alpha_l y_{t-l} + \beta_1 x_{t-1} + \dots + \beta_l x_{t-l} + u_{it}$,

(4.2.2.14) $x_{it} = \alpha_0 + \alpha_1 x_{t-1} + \dots + \alpha_l x_{t-l} + \beta_1 y_{t-1} + \dots + \beta_l y_{t-l} + \varepsilon_{it}$.

The null hypothesis, H_0: $\beta_1 = \beta_2 = \dots = \beta_l = 0$, is tested based on the F-statistic for each equation. The null hypothesis is that *x* does not Granger-cause *y* in the first regression

(4.2.2.13) and that y does not Granger-cause x in the second regression. The test is performed in the following way: first y is regressed on lagged values of y until the t-statistic for a given lag of y is significant. Then the regression is augmented by adding lagged x values, and the F-test that jointly these lagged x add explanatory power to the regression is conducted. If the variables are found to be nonstationary, then the test is performed with differenced series rather than levels.

Besides uncovering the feedback mechanism between the variables, these tests allow making conclusions about possible exogeneity of some variables with respect to others. Exogenous variable is a variable that is not caused by any other variable in the model.

Alternatively, the VAR/VEC multivariate block exogeneity test is applied. For each equation in the VAR, χ^2 statistics for the joint significance of each of the other lagged endogenous variables in each equation and also for the joint significance of all the other lagged endogenous variables is computed. In a VEC case, the lagged variables that are tested for exclusion are only those that are first differenced, that is, short-run causality is tested. The null hypothesis is that the lags of one set of variables do not enter the equations for the remaining variables.

4.2.3. Vector autoregression / vector error correction specifications

In case the series are stationary and all the variables are endogenous, panel VAR model, given in a system of equations (4.1.1), is a relevant econometric approach. In this model each variable is written as a linear function of its own lagged values and lagged values of all other variables in the system. Estimation can be undertaken using the method of ordinary least squares by running a separate regression for each variable, regressing it on lags of itself and of all other variables.

If nonstationarity is evidenced, panel VAR can be estimated for differenced variables. However, if the series are cointegrated, then the long-run information may be lost by running VAR. According to "Granger Representation Theorem", if the variables are cointegrated, then there must exist an associated error-correction model. Therefore, if evidence of cointegration is found, we will proceed with a development of a VEC model. A VEC is a generalization of a VAR in which multiple error correction term (cointegration term) appears. VEC model captures both short-run dynamics and long-run relationships among the variables.

The procedure involves regressing the differenced dependent variable on the lagged values of itself all other endogenous differenced variables as well as on the lagged residuals from the cointegrating vector (long-run equilibrium regression).

CHAPTER 5.

ESTIMATION PROCEDURE AND EMPIRICAL RESULTS

This chapter describes the results of the previously proposed procedures. The chapter organized as follows: first, we test for stationarity of the variables; second, cointegration and causality tests are performed; and, finally, VAR/VEC model is estimated[11].

5.1. Testing for stationarity

Prior to starting investigating the time-series properties of the data, the natural logarithms were taken. The rationale for it lies in the fact that many unit root tests (e.g., ADF, KPSS) are based on the linear regression, and log-transformation can convert an exponential trend, possibly present in the data, into a linear trend. Therefore, it is common to take logs of the data before conducting unit root tests (Wang, 2006).

Even though a number of tests for unit roots are readily available to help answer the question at issue regarding stationarity of the series, it is convenient to start with a simple graphical analysis of the data under study before conducting any formal tests. From Figures A3-A6 (Appendix), it can be observed that all of the series have been increasing over time; these trends may be suggesting that the means have been changing, implying possible nonstationarity.

At the next step it may be helpful to investigate the plots of the autocorrelation function, or correlogram, which also can provide us with the initial idea of

---

[11] EViews software was used for estimation.

stationarity / nonstationarity of the data and show how much interdependency there is between neighboring data points. It is expected that autocorrelation function will drop rather quickly as the lag length increases if the series is stationary.

The sample autocorrelation function at lag k is defined as:

$$(5.1.1.)\quad \hat{\rho}_k = \frac{\sum_{t=k+1}^{T}(y_t - \bar{y})(y_{t-k} - \bar{y})}{\sum_{t=1}^{T}(y_t - \bar{y})^2},$$

which is the ratio of sample covariance to sample variance.

The number of lags k is basically an empirical question. A rule of thumb is to compute autocorrelation function (ACF) up to one third to one-quarter the length of the time series[12]. Here ACF is computed up to one third of the series length.

Autocorrelation coefficients (AC), Q-statistics with p-values, and correlograms for variables in levels are presented in Table 5.1.1 and Figure 5.1.1. Individual insignificant autocorrelation coefficients are marked with asterix in Table 5.1.1. Another statistics given is Ljung-Box Q-statistics which allows testing the joint hypothesis that all AC coefficients up to lag k are simultaneously equal to zero, that is, there is no autocorrelation up to lag k:

$$(5.1.2)\quad Q_{LB} = T(T+2)\sum_{k=1}^{m}\frac{\hat{\rho}_k^2}{T-k} \sim \chi_m^2.$$

The pattern seen in Table 5.1.1 and Figure 5.1.1 shows that autocorrelation coefficients for all series start at very high values (0.849 and higher) at lag 1 and decline quite slowly. Thus, it is possible that all series are nonstationary. The p-values of Q-statistics reinforce this supposition.

[12] Gujarati, D.N. (2003). *Basic Econometrics*. 4th ed. McGraw-Hill, p. 812.

Table 5.1.1. Sample autocorrelation function

Lag	Log(TFP)			Log(PR)			Log(Trap_Stock)			Log(Inv_V_Stock)		
	AC	Q-stat	p-value	AC	Q-stat	p-value	AC	Q-stat	p-value	AC	Q-stat	p-value
1	0.849	1558.0	0.000	0.882	1683.7	0.000	0.906	3190.5	0.000	0.904	3182.6	0.000
2	0.753	2784.6	0.000	0.752	2907.3	0.000	0.814	5766.4	0.000	0.812	5748.6	0.000
3	0.669	3754.3	0.000	0.631	3768.5	0.000	0.724	7808.6	0.000	0.723	7782.9	0.000
4	0.588	4504.2	0.000	0.529	4375.2	0.000	0.638	9393.9	0.000	0.637	9364.6	0.000
5	0.510	5067.0	0.000	0.451	4815.1	0.000	0.555	10595	0.000	0.555	10566	0.000
6	0.436	5479.7	0.000	0.382	5132.1	0.000	0.476	11478	0.000	0.477	11455	0.000
7	0.368	5773.8	0.000	0.323	5358.1	0.000	0.401	12104	0.000	0.403	12089	0.000
8	0.306	5977.4	0.000	0.270	5516.6	0.000	0.330	12529	0.000	0.334	12523	0.000
9	0.253	6116.5	0.000	0.231	5632.3	0.000	0.264	12800	0.000	0.268	12803	0.000
10	0.209	6211.4	0.000	0.193	5713.6	0.000	0.202	12960	0.000	0.207	12970	0.000
11	0.171	6275.3	0.000	0.156	5766.8	0.000	0.146	13043	0.000	0.150	13057	0.000
12	0.145	6320.9	0.000	0.129	5803.0	0.000	0.094	13077	0.000	0.097	13094	0.000
13	0.136	6361.2	0.000	0.116	5832.1	0.000	0.047	13086	0.000	0.049	13104	0.000
14	0.118	6391.7	0.000	0.082	5846.6	0.000	0.004*	13086	0.000	0.005*	13104	0.000
15	0.093	6410.7	0.000	0.060	5854.5	0.000	-0.034	13090	0.000	-0.035	13109	0.000
16							-0.069	13109	0.000	-0.072	13129	0.000
17							-0.099	13147	0.000	-0.104	13171	0.000
18							-0.126	13209	0.000	-0.133	13240	0.000
19							-0.149	13296	0.000	-0.158	13337	0.000
20							-0.169	13408	0.000	-0.180	13463	0.000
21							-0.187	13544	0.000	-0.199	13618	0.000
22							-0.201	13703	0.000	-0.215	13799	0.000
23							-0.214	13882	0.000	-0.229	14004	0.000
24							-0.224	14079	0.000	-0.240	14230	0.000
25							-0.233	14292	0.000	-0.250	14473	0.000
26							-0.240	14518	0.000	-0.257	14731	0.000
27							-0.246	14755	0.000	-0.262	14999	0.000

Note: * - insignificant at 5% significance level

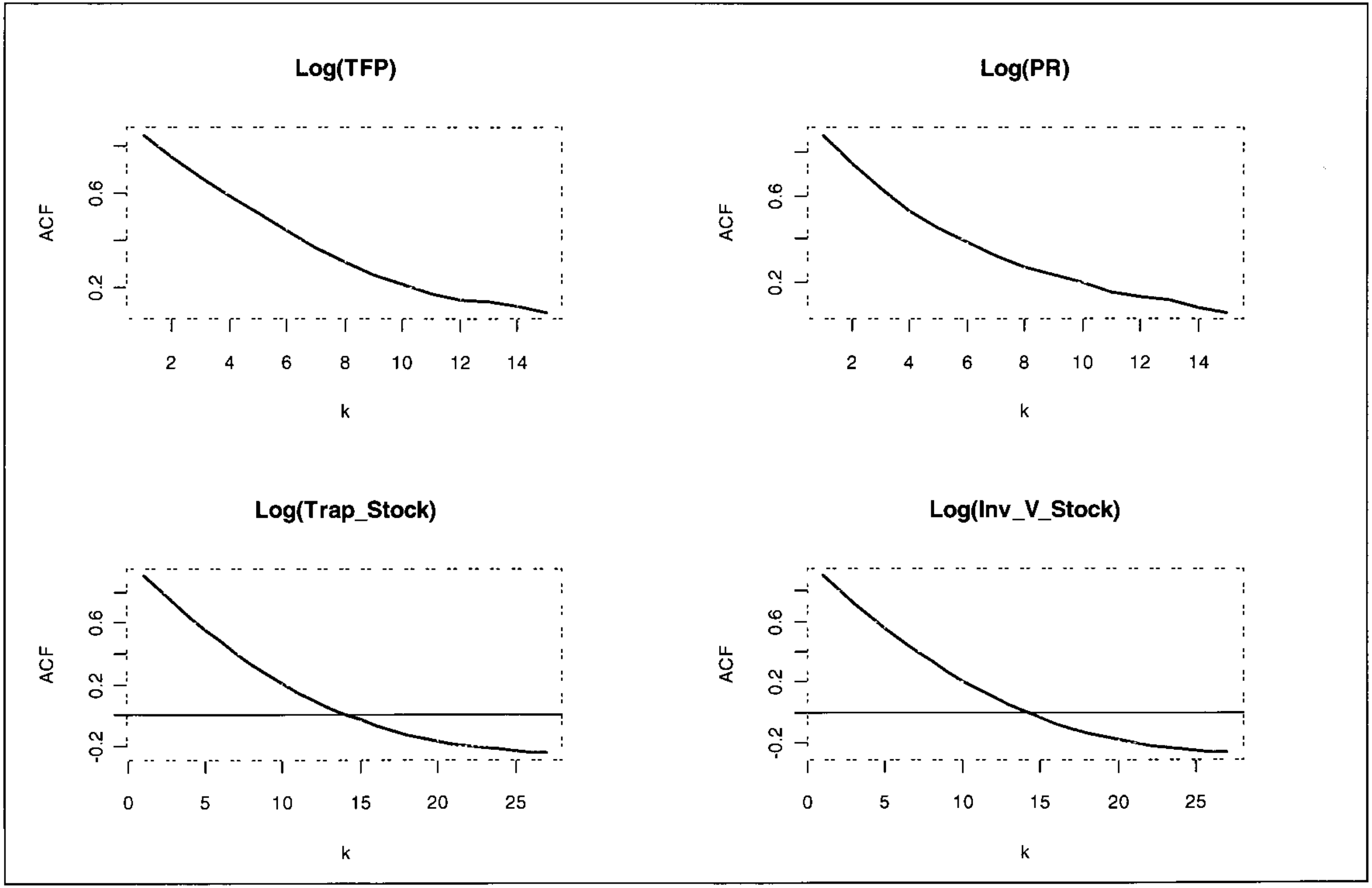


Figure 5.1.1. Correlograms

Thus, the next step involves conducting a formal test for unit roots. A well known weakness (initially noted by Perron, 1989) of most such tests is that they are affected by structural change: the null of a unit root tends to be underrejected, that is, the unit root tests may fail to reject unit root hypothesis in case of structural break(s) due to interpreting the break as an evidence of nonstationarity. Therefore, prior to testing for unit roots, state-specific tests for stability of the parameters (under the null hypothesis) were conducted using CUSUM procedure which is based on the cumulative sum of the recursive residuals (proposed by Brown, Durbin, and Evans, 1975) and is designed for the detection of abrupt changes. This test builds the plot of the quantity:

(5.1.3) $W_m = \frac{1}{s}\sum_{t=k+1}^{m} w_t,$

where $m=k+1 \ldots T$, w_t – *recursive* residual, s – standard error of the regression fitted to all T sample points.

Six linear models of the following type were considered:

(5.1.4) $y_t = c + \beta'\mathbf{x}_t + \varepsilon_t,$

where y_t is a dependent variable: *log(TFP), log(Trap_Stock), log(Inv_V_Stock), or log(PR)*, $\mathbf{x}_t$ is a vector of independent variables which includes two variables, other than a dependent variable, for each model. If β vector remains constant from period to period, $E(W_m)=0$, but if it changes, W_m will tend to diverge from the zero mean line. The null is rejected if W_m crosses the probabilistic boundary for the path of W_m. At 5% significance level no structural change was observed for most states. At different periods the borders were slightly crossed for several states in each of the models. However, analysis of recursive coefficient estimates did not reveal any indication of instability for these particular states.

Though, according to National Institute of Standards and Technology (1999), the use of residual charts, such as CUSUM or EWMA[13], has the advantage that they can be applied to any autocorrelated data even if the data comes from the nonstationary processes, the same analysis was repeated for variables in first and second differences, as well as for the mixture: second differences for TFP, and R&D stock variable and first difference of PR, to ensure that the data under analysis is stationary (the reasons to test models with mixed orders of differences will be revealed further). When checking models with the differenced variables, the cumulative sums in all cases were located within two standard deviation band indicating parameters' stability. Therefore, no evidence of possible structural break was found.

Next, the formal tests for unit roots disregarding possible structural change, defined in *Chapter 4* (Section 4.2.1), are applied. There are two important practical issues with implementing described unit root tests that need to be mentioned:

1) Choosing the lag length. Various information criteria are usually used for making this decision. Stock (1994), however, argued in favor of the use of BIC (for ADF unit root test). Thus, decision regarding lag length, where appropriate, was based on minimizing Bayesian (Schwarz) information criterion; in addition, this is a consistent estimator of a true lag length.

2) Specification of exogenous variables: constant and/or trend. This decision was based on graphical analysis of the data. A constant and a trend were included when testing variables in levels, and only constant was accounted for when testing differenced variables.

The following notations were used for constructing Tables 5.1.2 - 5.1.4: x_1 – *log(TFP)*, x_2 – *log(Trap_Stock)*, x_3 – *log(Inv_V_Stock)*, x_4 – *log(PR)*. Table 5.1.2 shows the results of three state-specific unit root tests for variables in levels.

[13] Exponentially weighted moving average

Table 5.1.2. Individual unit root tests (levels)

		AL	**AZ**	**AR**	**CA**	**CO**	**CT**	**DE**	**FL**	**GA**	**ID**	**IL**	**IN**
x_1	ADF	0.0077	0.9969*	0.0000	0.4648*	0.0233	0.1277*	0.0528*	0.0372	0.0011	0.2921*	0.0000	0.0000
	PP	0.0087	0.2787*	0.0000	0.0246*	0.0233	0.1541*	0.0520*	0.0324	0.0013	0.2921*	0.0000	0.0000
	KPSS	0.0651	0.2238*	0.0950	0.1515*	0.1461*	0.1491*	0.0979	0.0741	0.0862	0.1109	0.1949*	0.1631*
		IA	**KS**	**KY**	**LA**	**ME**	**MD**	**MA**	**MI**	**MN**	**MS**	**MO**	**MT**
	ADF	0.0016	0.2728*	0.0308	0.0105	0.0165	0.0040	0.4545*	0.0003	0.0000	0.0001	0.0000	0.0014
	PP	0.0007	0.0042	0.0273	0.0126	0.0152	0.0033	0.3793*	0.0002	0.0000	0.0001	0.0000	0.0014
	KPSS	0.2311*	0.0661	0.1909*	0.1927*	0.1407	0.0606	0.1053	0.2070*	0.2827*	0.1617*	0.1564*	0.0691
		NE	**NV**	**NH**	**NJ**	**NM**	**NY**	**NC**	**ND**	**OH**	**OK**	**OR**	**PA**
	ADF	0.0004	0.0740*	0.0075	0.3031*	0.3553*	0.4979*	0.7663*	0.0000	0.0000	0.0071	0.0704*	0.0267
	PP	0.0003	0.0665*	0.0072	0.4192*	0.3553*	0.5768*	0.6772*	0.0000	0.0000	0.0076	0.0704*	0.0242
	KPSS	0.0831	0.1572*	0.0696	0.1421	0.1841*	0.1621*	0.1026	0.1013	0.0823	0.1024	0.1217*	0.0829
		RI	**SC**	**SD**	**TN**	**TX**	**UT**	**VT**	**VA**	**WA**	**WV**	**WI**	**WY**
	ADF	0.3099*	0.0000	0.0027	0.0270	0.0029	0.4077*	0.0968*	0.3041*	0.9447*	0.5190*	0.9785*	0.0209
	PP	0.2278*	0.0000	0.0026	0.0161	0.0027	0.3915*	0.0968*	0.2972*	0.9765*	0.4936*	0.4274*	0.0255
	KPSS	0.0633	0.0924	0.1509*	0.1429	0.0841	0.0089	0.0614	0.1112	0.1985*	0.1149	0.2127*	0.1154
		AL	**AZ**	**AR**	**CA**	**CO**	**CT**	**DE**	**FL**	**GA**	**ID**	**IL**	**IN**
x_2	ADF	0.9935*	0.9996*	0.0047	0.4382*	0.9996*	0.0000	0.0000	0.9935*	0.9935*	0.9996*	0.9997*	0.9997*
	PP	1.0000*	0.9993*	0.9999*	0.9998*	0.9993*	0.3286*	0.3286*	1.0000*	1.0000*	0.9993*	0.9999*	0.9999*
	KPSS	0.1791*	0.1623*	0.2103*	0.2246*	0.1623*	0.0979	0.0979	0.1791*	0.1791*	0.1623*	0.2012*	0.2012*
		IA	**KS**	**KY**	**LA**	**ME**	**MD**	**MA**	**MI**	**MN**	**MS**	**MO**	**MT**
	ADF	0.9997*	0.9990*	0.9987*	0.0047	0.0000	0.0000	0.0000	0.9928*	0.9928*	0.0047	0.9997*	0.9996*
	PP	0.9999*	1.0000*	1.0000*	0.9999*	0.3286*	0.3286*	0.3286*	0.9762*	0.9762*	0.9999*	0.9999*	0.9993*
	KPSS	0.2012*	0.2136*	0.2073*	0.2103*	0.0979	0.0979	0.0979	0.2229*	0.2229*	0.2103*	0.2012*	0.1623*
		NE	**NV**	**NH**	**NJ**	**NM**	**NY**	**NC**	**ND**	**OH**	**OK**	**OR**	**PA**
	ADF	0.9990*	0.9996*	0.0000	0.0000	0.9996*	0.0000	0.9987*	0.9990*	0.9997*	0.2184*	0.4382*	0.0000
	PP	1.0000*	0.9993*	0.3286*	0.3286*	0.9993*	0.3286*	1.0000*	1.0000*	0.9999*	0.7399*	0.9998*	0.3286*
	KPSS	0.2136*	0.1623*	0.0979	0.0979	0.1623*	0.0979	0.2073*	0.2136*	0.2012*	0.1439	0.2246*	0.0979
		RI	**SC**	**SD**	**TN**	**TX**	**UT**	**VT**	**VA**	**WA**	**WV**	**WI**	**WY**
	ADF	0.0000	0.9935*	0.9990*	0.9987*	0.2184*	0.9996*	0.0000	0.9987*	0.4382*	0.9987*	0.9928*	0.9996*
	PP	0.3286*	1.0000*	1.0000*	1.0000*	0.7399*	0.9993*	0.3286*	1.0000*	0.9998*	1.0000*	0.9762*	0.9993*
	KPSS	0.0979	0.1791*	0.2136*	0.2073*	0.1439	0.1623*	0.0979	0.2073*	0.2246*	0.2073*	0.2229*	0.1623*

(Continued)

		AL	AZ	AR	CA	CO	CT	DE	FL	GA	ID	IL	IN
x_3	ADF	0.7220*	0.7015*	0.7245*	0.7287*	0.7015*	0.6929*	0.6929*	0.7220*	0.7220*	0.7015*	0.7094*	0.7094*
	PP	0.7086*	0.6874*	0.7112*	0.7155*	0.6874*	0.6786*	0.6786*	0.7086*	0.7086*	0.6874*	0.6952*	0.6952*
	KPSS	0.1569*	0.1426	0.1929*	0.2226*	0.1426	0.1503*	0.1503*	0.1569*	0.1569*	0.1426	0.1923*	0.1923*
		IA	**KS**	**KY**	**LA**	**ME**	**MD**	**MA**	**MI**	**MN**	**MS**	**MO**	**MT**
	ADF	0.7094*	0.7003*	0.6998*	0.7245*	0.6929*	0.6929*	0.6929*	0.7094*	0.7094*	0.7245*	0.7094*	0.7015*
	PP	0.6952*	0.6859*	0.6847*	0.7112*	0.6786*	0.6786*	0.6786*	0.6948*	0.6948*	0.7112*	0.6952*	0.6874*
	KPSS	0.1923*	0.2019*	0.2018*	0.1929*	0.1503*	0.1503*	0.1503*	0.2253*	0.2253*	0.1929*	0.1923*	0.1426
		NE	**NV**	**NH**	**NJ**	**NM**	**NY**	**NC**	**ND**	**OH**	**OK**	**OR**	**PA**
	ADF	0.7003*	0.7015*	0.6929*	0.6929*	0.7015*	0.6929*	0.6998*	0.7003*	0.7094*	0.7178*	0.7287*	0.6929*
	PP	0.6859*	0.6874*	0.6786*	0.6786*	0.6874*	0.6786*	0.6847*	0.6859*	0.6952*	0.7044*	0.7155*	0.6786*
	KPSS	0.2019*	0.1426	0.1503*	0.1503*	0.1426	0.1503*	0.2018*	0.2019*	0.1923*	0.1965*	0.2226*	0.1503*
		RI	**SC**	**SD**	**TN**	**TX**	**UT**	**VT**	**VA**	**WA**	**WV**	**WI**	**WY**
	ADF	0.6929*	0.7220*	0.7003*	0.6998*	0.7178*	0.7015*	0.6929*	0.6998*	0.7287*	0.6998*	0.7094*	0.7015*
	PP	0.6786*	0.7086*	0.6859*	0.6847*	0.7044*	0.6874*	0.6786*	0.6847*	0.7155*	0.6847*	0.6948*	0.6874*
	KPSS	0.1503*	0.1569*	0.2019*	0.2018*	0.1965*	0.1426	0.1503*	0.2018*	0.2226*	0.2018*	0.2253*	0.1426
		AL	**AZ**	**AR**	**CA**	**CO**	**CT**	**DE**	**FL**	**GA**	**ID**	**IL**	**IN**
x_4	ADF	0.0711*	0.0316	0.1368*	0.6538*	0.0425	0.9473*	0.0055	0.1408*	0.0028	0.0747*	0.1620*	0.0744*
	PP	0.0666*	0.0169	0.1224*	0.5893*	0.3523*	0.8147*	0.0056	0.1287*	0.0033	0.0600*	0.1620*	0.0569*
	KPSS	0.1429	0.0984	0.0804	0.1522*	0.0698	0.1899*	0.1017	0.1595*	0.1019	0.0902	0.0595	0.0959
		IA	**KS**	**KY**	**LA**	**ME**	**MD**	**MA**	**MI**	**MN**	**MS**	**MO**	**MT**
	ADF	0.1184*	0.0304	0.1936*	0.1255*	0.0033	0.0048	0.7154*	0.2127*	0.1017*	0.1149*	0.1197*	0.2771*
	PP	0.0922*	0.0304	0.1939*	0.1255*	0.0025	0.0048	0.6074*	0.2127*	0.1311*	0.1291*	0.0847*	0.2771*
	KPSS	0.1129	0.0476	0.0706	0.0927	0.0898	0.0473	0.1477*	0.0858	0.1288	0.1407	0.1089	0.0812
		NE	**NV**	**NH**	**NJ**	**NM**	**NY**	**NC**	**ND**	**OH**	**OK**	**OR**	**PA**
	ADF	0.0945*	0.5057*	0.1223*	0.0430	0.8186*	0.0508*	0.0647*	0.3240*	0.2110*	0.2363*	0.3276*	0.1021*
	PP	0.0945*	0.3796*	0.1087*	0.0451	0.7228*	0.0466	0.0647*	0.2500*	0.1794*	0.2491*	0.2422*	0.0738*
	KPSS	0.0528	0.0620	0.1392	0.1185	0.0929	0.1692*	0.0998	0.0622	0.1592*	0.1444	0.0515	0.1058
		RI	**SC**	**SD**	**TN**	**TX**	**UT**	**VT**	**VA**	**WA**	**WV**	**WI**	**WY**
	ADF	0.2683*	0.0192	0.1435*	0.0426	0.4024*	0.1655*	0.2143*	0.2411*	0.6094*	0.0462	0.5593*	0.0783*
	PP	0.1980*	0.0153	0.1456*	0.0426	0.3263*	0.1576*	0.1679*	0.1890*	0.4926*	0.0467	0.5266*	0.3146*
	KPSS	0.1390	0.0710	0.0875	0.0651	0.1042	0.0462	0.1371	0.0567	0.0797	0.0587	0.1989*	0.0747

Note: For ADF and PP tests one-sided MacKinnon p-values are given, for KPSS – LM test statistic.
KPSS critical values: 1% level – 0.216; 5% level – 0.146; 10% level – 0.119.
* indicates UR at 5 % level.

To facilitate reading the previous table, Table 5.1.2, the number of cross-sections with the identified unit root at 5% level for each test and each variable is given in Table 5.1.3.

Table 5.1.3. Number of nonstationary series in panels (5% level)

Variable	ADF	PP	KPSS
x_1 - *log(TFP)*	20	19	20
x_2 – *log(Trap_Stock)*	34	48	35
x_3 - *log(Inv_V_Stock)*	38	48	40
x_4 – *log(PR)*	37	37	7

In most cases the test results are not uniform, but they all indicate that a large proportion of time series in each of the panels is nonstationary. The only exclusion is that KPSS test results diverge from ADF and PP results when testing a price ratio. At the same time, KPSS test is usually used for the purposes of confirmatory analysis: to confirm the results of ADF and/or PP tests. However, Maddala and Wu (1998) do not recommend making use of such confirmations claiming that proportion of correct confirmations is low. Burke (1994) conducted a detailed Monte Carlo study to determine usefulness of the confirmatory analysis with KPSS test and concluded that using 10% significance level gives better results than using 5% significance level. In this case, by using 10% level for testing stationarity of *log(PR)*, we arrive at a conclusion that 14 series in a panel are not stationary. Thus, the results of individual unit root tests indicate that all the variables are nonstationary in levels. Table 5.1.4 shows results of panel-based unit root tests.

Table 5.1.4. Panel unit root tests

Variable	IPS	Fisher-ADF		Fisher-PP		LLC	Breitung	Hadri (hetero)
		Choi	MW	Choi	MW			
	Null – Unit Root							Null – Stationarity
x_1	-15.2023	-13.0205	464.409	-14.6580	500.833	-14.2251	2.08218	10.5353
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.9813)	(0.0000)
x_2	11.4439	11.8313	49.6845	15.4634	26.1361	18.1776	14.6389	17.7334
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(0.0000)
x_3	-2.7709	-3.0549	106.550	-1.7584	88.0193	-6.4448	-1.2123	14.9544
	(0.0028)	(0.0011)	(0.2168)	(0.0393)	(0.7069)	(0.0000)	(0.1127)	(0.0000)
x_4	-7.34328	-7.2486	212.805	-7.6033	216.181	-1.7878	-2.9775	5.7767
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0369)	(0.0015)	(0.0000)
Δx_1	-51.0247	-36.7684	1622.04	-35.7998	1579.18	-46.1923	-	1.9168
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.0276)
Δx_2	-6.5125	-5.7728	260.591	3.6194	53.5002	0.4664	-	9.6481
	(0.0000)	(0.0000)	(0.0000)	(0.9999)	(0.9999)	(0.6795)		(0.0000)
Δx_3	-44.1088	-36.4634	1506.00	-35.4634	1506.00	-54.2235	-	3.7799
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.0001)
Δx_4	-43.4257	-33.7879	1402.55	-34.4939	1458.27	-40.8735	-	-2.5517
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.9946)
$\Delta^2 x_1$	-46.6119	-34.8277	1483.18	-26.6429	942.00	-7.4131	-	1.4314
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.0762)
$\Delta^2 x_2$	-8.9717	-9.1826	246.739	-7.0255	181.977	-3.3862	-	0.9795
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.1637)
$\Delta^2 x_3$	-53.8940	-40.1545	1871.96	-25.7661	884.193	-60.0594	-	15.4919
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.0000)

Note: P-values in parentheses. MW – Maddala and Wu statistic; Choi – Choi Z-statistics. "Hetero" stands for "heteroskedasticity consistent".
Here and further " Δ " stands for first difference, "Δ^2"- for second difference.

IPS, Fisher-ADF and Fisher-PP tests assume non-zero percent of stationary series under the alternative, therefore rejection of the null of a unit root often does not mean that the whole panel is stationary - there may be just a small proportion of stationary series in a panel. Results of LLC and Breitung tests diverge for some variables in levels. Moon *et al.* (1995) show that Breitung test is more powerful than LLC, therefore it should be given more weight while analyzing the outcomes. Hadri tests reject the null of stationarity for all the variables in levels at 5% significance level. In this study the conclusions will be based primarily on Hadri test[14]. It provides us with the evidence of a unit root in all the variables. This conclusion is consistent with earlier discussed results. Therefore, all the variables were differenced.

IPS, Fisher-ADF, Fisher-PP and LLC panel-based tests applied to the first differences reject the null of nonstationarity for x_1, x_3 and x_4. As was mentioned before, since IPS and Fisher-type tests allow for hererogeneity under the alternative, the rejection of the null does not necessarily imply that the whole panel is stationary. In its turn, LLC test indicates stationarity of the whole panel for Δx_1, Δx_3 and Δx_4. However, Baltagi (2000) shows that Fisher-type tests have better size performances than the group mean type tests. Thus, more attention should be given to IPS, Fisher-ADF, and Fisher-PP rather than to LLC. The only panel test with the null of stationarity, Hadri, allows us to conclude that Δx_4 is stationary (as supported by all other tests), but Δx_1, Δx_2 and Δx_3 are not and should be differenced one more time.

If for Δx_2 Fisher-PP and LLC tests support the hypothesis of nonstationarity, i.e. support results of Hadri, then for Δx_1 and Δx_3 there is no such support, and the conclusion of testing second differences of these variables can be grounded solely on Hadri test results. Consequently, there is a possibility of overdifferencing for Δx_1 and Δx_3. However, choosing between underdifferencing and overdifferencing, one should give preference to the latter. As shown by Sánchez and Peña (1998), for forecasting purposes it is better to overdifference than to underdifference. Therefore, x_1, x_2 and x_3 were differenced twice.

The hypothesis of stationarity cannot be rejected for $\Delta^2 x_1$ and $\Delta^2 x_2$. The null of a unit root is rejected by all the tests. Thus, uniform outcomes support the conclusion about

[14] Liu et al. (2008) base their conclusions regarding stationarity solely on Hadri test.

stationarity properties of the variables $\Delta^2 x_1$ and $\Delta^2 x_2$, while there is no confidence in stationarity of $\Delta^2 x_3$.

Summing it up, x_4, *log(PR)*, is found to be I(1), x_1, *log(TFP)*, and x_2, *log(Trap_Stock)* – I(2). Variable x_3, *log(Inv_V_Stock)*, probably needs to be differenced three times to become stationary, but the interpretation of third-differenced variables may be very confounding. By this reason, the variable associated with the own-state knowledge stock and spillovers for inverted-V structure is excluded from further analysis. We proceed exclusively with a trapezoidal lag structure.

As Juselius (2007) notes, unit roots, though primarily applied to economic data, are not restricted to it and may be also found in other fields, for example in climate data. Therefore, exogenous climate variables for temperature and precipitation also passed panel-based tests and were found to be integrated of order one, I(1).

5.2. Testing for cointegration and causality

Given the evidence that all the series contain unit root, we proceed by determining whether the series are cointegrated, and if they are, by identifying the cointegrating (long-run equilibrium) relationships.

Johansen procedure, which permits more than one cointegrating relationship, requires all variables to be integrated of order one. Since *log(PR)* was found to be I(1) while *log(TFP)* and *log(Trap_Stock)* were found to be I(2), then Δ *log(TFP)*, Δ *log(Trap_Stock)*, *log(PR)* will be I(1).

To determine the lag length for Johansen cointegration test, single-state VARs were estimated with first differences for Δ *log(TFP)*, Δ *log(Trap_Stock)*, *log(PR)*, that is, with

Δ^2 *log(TFP)*, Δ^2 *log(trap_stock)*, Δ *log(PR)*. For 40 states one lag was selected, according to Schwarz Information Criterion; it gave us the confidence that one period lag is appropriate for differenced endogenous variables in the Johansen cointegration test equation (and in VEC if cointegration is evidenced).

The optimal model for the deterministic components in the system (see *Chapter 4*, Section 4.2.2), selected based on Pantula principle, is Model (1) – a model with no intercept or trend in cointegrating equation (CE) or VAR. Results of trace and maximum eigenvalue statistics are reported in Table 5.2.1.

Table 5.2.1. Results of Johansen cointegration test

Trace test				**Maximum eigenvalue test**			
H_o	**H_a**	**Trace statistic**	**0.05 critical values**	**H_o**	**H_a**	**Maximum eigenvalue statistic**	**0.05 critical values**
*r=0**	*r>0*	1872.032	24.27596	*r=0**	*r=1*	1603.491	17.79730
*r≤1**	*r>1*	268.5409	12.32090	*r=1**	*r=2*	265.5599	11.22480
r≤2	*r>2*	2.9812	4.129906	*r=2*	*r=3*	2.9812	4.129906

Note: *r* – number of cointegrating equations;
* denotes rejection of the hypothesis at 5% level.

The results reported in Table 5.2.1 indicate the existence of two cointegrating relations and therefore the presence of long-run linear relationships between three variables cannot be rejected. The conclusion of two cointegrating vectors is supported by both trace and maximum eigenvalue statistics.

The natural question arises whether it is a desirable or undesirable to have many cointegrating relations. Since cointegrating vectors represent constraints that an economic system imposes on the movements of the variables in the long run, then it seems that the more such vectors are present, the more "stable" the system is. As Dickey *et al.* (1991) notes, the fewer the number of cointegrating vectors, the less constrained is the long-run relationship, and therefore, all other things the same, it is desirable for an economic system to have many cointegrating equations in order to be stationary in as many directions as possible. Thus, despite unrevealing of the cointegrating relationships among three variables and an estimation of their respective error correction processes may not be an easy task in an economic sense, observing several such cointegrating vectors is an indication of a "stability" of a system in the long run.

Having found the evidence of cointegration, Granger-causality tests were performed in order to test whether some variables can be treated as exogenous and to verify the informational relationships between them (Table 5.2.2).

Table 5.2.2. Granger causality tests

Null hypothesis	Lags	F-statistic	P-value
$\Delta \log(PR)$ does not Granger cause $\Delta^2 \log(TFP)$	10	6.3019	0.0000
$\Delta^2 \log(TFP)$ does not Granger cause $\Delta \log(PR)$	2	6.9567	0.00098
$\Delta^2 \log(Trap\_Stock)$ does not Granger cause $\Delta^2 \log(TFP)$	10	4.9165	0.0000
$\Delta^2 \log(TFP)$ does not Granger cause $\Delta^2 \log(Trap\_Stock)$	4	3.5710	0.0067
$\Delta^2 \log(Trap\_Stock)$ does not Granger cause $\Delta \log(PR)$	2	15.9855	0.0000
$\Delta \log(PR)$ does not Granger cause $\Delta^2 \log(Trap\_Stock)$	4	17.6879	0.0000

The results of Granger causality tests are summarized in Table 5.2.3.

Table 5.2.3. Summary of results of Granger causality tests

Variable	$\Delta^2 \log(TFP)$	$\Delta \log(PR)$	$\Delta^2 \log(Trap\_Stock)$
$\Delta^2 \log(TFP)$	-	Yes	Yes
$\Delta \log(PR)$	Yes	-	Yes
$\Delta^2 \log(Trap\_Stock)$	Yes	Yes	-

Note: "Yes" indicates a statistically significant causation running from a row variable to a column variable at 5% significance level.

According to pairwise Granger causality tests (Table 5.2.2- 5.2.3), all the variables may be treated as endogenous. For all the pairs of variables there is an evidence of Granger causality in both directions. Further, Granger causality tests for multivariate VEC framework are performed (Table 5.2.4). Number of lags is based on SIC (1 lag).

Table 5.2.4. VEC Granger causality / Block exogeneity Wald tests

Dependent variable: $\Delta^2 \log(TFP)$		**Dependent variable:** $\Delta^2 \log(Trap\_Stock)$		**Dependent variable:** $\Delta \log(PR)$	
Variable excluded	P-value	Variable excluded	P-value	Variable excluded	P-value
Without exogenous climate variables					
$\Delta^2 \log(Trap\_Stock)$	0.0035	$\Delta^2 \log(TFP)$	0.9070	$\Delta^2 \log(TFP)$	0.0000
$\Delta \log(PR)$	0.0000	$\Delta \log(PR)$	0.0000	$\Delta^2 \log(Trap\_Stock)$	0.2168
All	0.0000	All	0.0000	All	0.0000
With exogenous climate variables					
$\Delta^2 \log(Trap\_Stock)$	0.0033	$\Delta^2 \log(TFP)$	0.9317	$\Delta^2 \log(TFP)$	0.0000
$\Delta \log(PR)$	0.0003	$\Delta \log(PR)$	0.0000	$\Delta^2 \log(Trap\_Stock)$	0.2517
All	0.0000	All	0.0000	All	0.0000

This group of tests justifies previous conclusion regarding endogeneity of the variables. Also, according to block exogeneity test results, $\Delta^2 \log(TFP)$ is not useful for predicting $\Delta^2 \log(Trap\_Stock)$, and $\Delta^2 \log(Trap\_Stock)$ does not help in predicting $\Delta \log(PR)$. The most important observation here is that both $\Delta^2 \log(Trap\_Stock)$ and

$\Delta \log(PR)$ are helpful in predicting $\Delta^2 \log(TFP)$. The inference is not changed when exogenous variables are added to the model.

The findings regarding directions of the causality are consistent with Shaik (1999). Utilizing time series data for Nebraska agricultural sector, Shaik (1999) found the evidence of bidirectional causality between TFP and prices conditional (and unconditional) on supply, and unidirectional causality from R&D investments to productivity (conditional on demand). Consequently, current panel data analysis does not contradict previous results, and the conclusion that TFP is affected by both supply-side R&D investments and demand-side price ratio is supported.

5.3. Estimation of vector error correction model

The presence of cointegrating relations forms the basis of the VEC specification, which requires the variables to be integrated of the same order and to have a long-run relationship. Based on conducted tests, we proceed with a VEC model which includes three endogenous variables and two cointegrating vectors.

In a system of equations (5.3.1) a linear combination

$(\Delta \log(TFP)_{i,t-1} - \beta_{j1} \Delta \log(Trap\_Stock)_{i,t-1} - \beta_{j2} \log(PR)_{i,t-1})$ represents error correction term, further denoted as ECT, which is stationary. Differenced variables are also stationary. Coefficients of the ECT, α_{ij}, are referred to as adjustment parameters showing how quickly the equilibrium is restored if the systems is exposed to shocks. They should take on absolute values between 0 and 1; the closer the adjustment parameter to 1, the prompter the system returns to equilibrium. Estimation results are presented in Table 5.3.1. Number of lags is selected based on SIC.

$$
(5.3.1)\quad
\begin{cases}
\begin{aligned}
\Delta^2 \log(TFP)_{it} = {} & \alpha_{11}(\Delta \log(TFP)_{i,t-1} - \beta_{11}\Delta \log(Trap\_Stock)_{i,t-1} - \beta_{12} \log(PR)_{i,t-1}) + \\
& + \alpha_{12}(\Delta \log(TFP)_{i,t-1} - \beta_{21}\Delta \log(Trap\_Stock)_{i,t-1} - \beta_{22} \log(PR)_{i,t-1})) + \\
& + z_{11}\Delta^2 \log(TFP)_{i,t-1} + z_{12}\Delta^2 \log(Trap\_Stock)_{i,t-1} + z_{13}\Delta \log(PR)_{i,t-1} + \\
& + \omega_{11}\Delta Temp_{it} + \omega_{12}\Delta Precip_{it} + \omega_{13}\Delta Temp_{it} \cdot \Delta Precip_{it} + \varepsilon_{1it} \\[2ex]
\Delta^2 \log(Trap\_Stock)_{it} = {} & \alpha_{21}(\Delta \log(TFP)_{i,t-1} - \beta_{11}\Delta \log(Trap\_Stock)_{i,t-1} - \beta_{12} \log(PR)_{i,t-1}) + \\
& + \alpha_{22}(\Delta \log(TFP)_{i,t-1} - \beta_{21}\Delta \log(Trap\_Stock)_{i,t-1} - \beta_{22} \log(PR)_{i,t-1})) + \\
& + z_{21}\Delta^2 \log(TFP)_{i,t-1} + z_{22}\Delta^2 \log(Trap\_Stock)_{i,t-1} + z_{23}\Delta \log(PR)_{i,t-1} + \\
& + \omega_{21}\Delta Temp_{it} + \omega_{22}\Delta Precip_{it} + \omega_{23}\Delta Temp_{it} \cdot \Delta Precip_{it} + \varepsilon_{2it} \\[2ex]
\Delta \log(PR)_{it} = {} & \alpha_{31}(\Delta \log(TFP)_{i,t-1} - \beta_{11}\Delta \log(Trap\_Stock)_{i,t-1} - \beta_{12} \log(PR)_{i,t-1}) + \\
& + \alpha_{32}(\Delta \log(TFP)_{i,t-1} - \beta_{21}\Delta \log(Trap\_Stock)_{i,t-1} - \beta_{22} \log(PR)_{i,t-1})) + \\
& + z_{31}\Delta^2 \log(TFP)_{i,t-1} + z_{32}\Delta^2 \log(Trap\_Stock)_{i,t-1} + z_{33}\Delta \log(PR)_{i,t-1} + \\
& + \omega_{31}\Delta Temp_{it} + \omega_{32}\Delta Precip_{it} + \omega_{33}\Delta Temp_{it} \cdot \Delta Precip_{it} + \varepsilon_{3it}
\end{aligned}
\end{cases}
$$

Table 5.3.1. Estimation results

Explanatory variables	Dependent variables					
	$\Delta^2 \log(TFP)$	$\Delta^2 \log(Trap\_Stock)$	$\Delta \log(PR)$	$\Delta^2 \log(TFP)$	$\Delta^2 \log(Trap\_Stock)$	$\Delta \log(PR)$
$ECT1_{i,t-1}$	0.0266* (0.0000)	-0.000009** (0.0836)	0.0041* (0.0000)	0.0296* (0.0000)	-0.000006 (0.2650)	0.0040* (0.0000)
$ECT2_{i,t-1}$	0.7914* (0.0000)	-0.0079* (0.0000)	0.9591* (0.0000)	0.9344* (0.0000)	-0.0101* (0.0000)	0.5044* (0.0000)
$\Delta^2 \log(TFP)_{i,t-1}$	0.2583* (0.0000)	-0.00002 (0.9317)	0.1197* (0.0000)	0.2644* (0.0000)	-0.00001 (0.6295)	0.1090* (0.0000)
$\Delta^2 \log(Trap\_Stock)_{i,t-1}$	3.1277* (0.0033)	0.8531* (0.0000)	1.3009 (0.2517)	3.5954* (0.0033)	0.8515* (0.0000)	2.2161* (0.0486)
$\Delta \log(PR)_{i,t-1}$	0.0809* (0.0003)	0.0014* (0.0000)	-0.0398** (0.0946)	0.0875* (0.0000)	0.0013* (0.0000)	-0.0652* (0.006)
$\Delta Temp_{it}$	-0.0005 (0.6275)	0.000004 (0.7156)	0.0046* (0.0000)	-0.0004 (0.7485)	0.000001 (0.8890)	0.0042* (0.0003)
$\Delta Precip_{it}$	0.0165* (0.0000)	-0.00002 (0.3472)	0.0032 (0.2403)	0.0161* (0.0000)	-0.00002 (0.4330)	0.0037 (0.1762)
$\Delta Temp_{it} \cdot \Delta Precip_{it}$	0.0025 (0.2012)	-0.00002 (0.1715)	0.0010 (0.4911)	0.0024 (0.2045)	-0.00002 (0.1887)	0.0014 (0.4854)
R^2	0.7294	0.7828	0.0378	0.7331	0.7877	0.0630
Adjusted R^2	0.7284	0.7820	0.0344	0.7320	0.7869	0.0593

Note: P-values in parentheses. * indicate significance at 5% level, ** - significance at 10% level.

Estimation results indicate the significant and positive influence of both supply and demand sides on productivity growth. The effects are difficult to interpret in absolute values due to different orders of differencing. However, it can be noted that the effect of a supply-side driver, R&D expenditures, is the largest in magnitude, as was expected. The most important observation here is that a demand-side driver, input price over output price, is also highly statistically significant. The increase in a price ratio, that is a decrease in output price relative to input price, drives productivity growth along with R&D public investments. The R-squared is rather high for this equation, implying that almost 73% of variation in TFP changes may be explained by the variables under analysis. Its value is very close to a value of adjusted R-squared indicating a good fit of a model.

Other two equations, with $\Delta^2 \log(Trap\_Stock)$ and $\Delta \log(PR)$ as dependent variables, respectively, show that $\Delta^2 \log(TFP)_{i,t-1}$ does not have explanatory power for explaining changes in public research investments, at least in the short run, and $\Delta^2 \log(Trap\_Stock)_{i,t-1}$ is not useful for explaining changes in price ratio. These results coincide with the conclusions made on the basis of block exogeneity tests. At the same time, changes in price ratio help to explain changes in the amounts invested in research. R-squared is 0.78 for the second equation, meaning that about 78% of variation in R&D outlays growth may be explained by its own lagged values and prices. For the third equation less than 4% of price ratio variation may be explained by given variables.

Adjustment parameters represent short-term responses to disequilibrium. At 10% significance level, all the parameters on error correction terms are significant indicating that an adjustment occurs to restore the long-run equilibrium between the three variables.

When a political party dummy was included in the analysis, all adjusted R-squareds slightly raised meaning that some variability in the variables of interest can be explained by this variable, which is individually highly statistically significant. For two first equations the inference on the three variables did not change while in the third equation all the endogenous variables became significant at 5% level. Therefore, probably, movements in prices can be explained by their own past values and by the shifts in R&D expenditures.

The most important observation which can be made from these results is that public R&D investments and price ratio affect TFP. This finding gives support to the previous numerous analyses providing the statistical evidence of significant R&D influence on TFP growth. A new observation is that TFP growth is also driven by the price ratio. These results imply that there are simultaneous effects of both supply and demand-side factors on productivity.

CHAPTER 6.

CONCLUSIONS

The relationship between R&D investments and TFP has been a popular subject of research among production economists for over half of the century. This study extended a traditional TFP analysis by including a demand-side driver of the productivity growth, along with the supply-side R&D expenditures. Specifically, the purpose was to examine TFP-price ratio (input price over output price) nexus. To test the hypothesis of the relationship between the price ratio and TFP, this study applied individual and panel unit root tests, panel cointegration and causality procedures and employed panel vector error correction model.

The use of panel unit root tests along with standard time-series tests was necessary since the latter group of tests may have quite low power given the sample sizes of individual series. According to these tests, all the variables of interest: TFP, R&D stock, and price ratio, exhibited nonstationarity which served a necessary condition for a cointegration analysis. The long-run relationship between TFP, price ratio, and R&D expenditures was tested and the results showed that in the long run the three variables tend to regain equilibrium. A possible policy implication from this finding is that measures, that seek to increase agricultural TFP growth by increasing expenditures for research, should also be based on the analysis of prices in agriculture.

The presence of cointegrating relationship suggests that an appropriate dynamic structure can be obtained through a vector error correction mechanism by imposing long-run behaviour on a short-run behavior of a system, and, hence, allowing assessing both long-term and short-term dynamics. Most error correction terms are significant at 5% significance level indicating that variables do adjust to shocks to restore the equilibrium relationship. Short term coefficients, which may be interpreted as elasticities, are also highly statistically significant implying a significant impact of changes in R&D activity and price ratio on TFP change.

Another interesting finding is the importance of climate variables and political party variable to explain the remaining state-level TFP variation.

A major finding of this study is the evidence of contribution of both supply- and demand-side factors, public R&D expenditures and prices, respectively, to TFP growth. The results of the study are consistent with previous analyses in supporting the hypothesis that public investment in R&D is an important factor in TFP growth. A new finding is that price ratio, which allows accounting for input substitution over time, is also useful in explaining the changes in productivity.

The overall policy implication of these results is that the agricultural TFP growth can be managed both in short- and long-run, that further investments in R&D are required to sustain and increase TFP, and that prices have to be taken into account when elaborating policy aimed at enhancing the productivity growth. Although the influence of prices has been proven important by this study, more precise conclusions are hindered by the aggregate nature of the data employed in the analysis. Further work with the use of disaggregated data is needed for a fuller assessment of the relationships between the factors of interest.

REFERENCES

Ahearn, M., Yee, J., Ball, E., & Nehring, R. (1998). Agricultural Productivity in the United States. In *Agriculture Information Bulletin* (Vols. AIB-740). Washington, D.C.: U.S. Department of Agriculture, Economic Research Service.

Ahmad, S. (1966). On the Theory of Induced Innovation. *Economic Journal* (76), 344-57.

Alston, J. M., & Pardey, P. G. (1996). *Making Science Pay: Economics of Agricultural R&D Policy.* Washington D.C.: American Enterprise Institute for Public Policy.

Alston, J. M., Andersen, M. A., James, J. S., & Pardey, P.G. (2010). *Persistence Pays: U.S. Agricultural Productivity Growth and the Benefits from Public R&D spending.* Springer.

Alston, J. M., Andersen, M. A., James, J. S., & Pardey, P. G. (2010). Revisiting the Returns to U.S. Public Agricultural Research: New Measures, Models, Results, and Interpretation. *Staff Paper P10-8. InSTePP Paper 10-04.* St. Paul, MN: University of Minnesota.

Alston, J. M., Craig, B. J., & Pardey, P. G. (1998). Dynamics in the Creation and Depreciation of Knowledge, and Returns to Research, EPTD Discussion Paper 35. Washington D.C.: International Food Policy Research Institute.

Alston, J. M., Marra, M. C., Pardey, P. G., & Wyatt, T. J. (1997). *Research Returns Redux: A Meta-Analysis of Agricultural R&D Evaluations.* Washington D.C.: International Food Policy Research Institute (draft).

Alston, J. M., Norton, G. W., & Pardey, P. G. (1995). *Science Under Scarcity: Principles and Practice for Agricultural Research Evaluation and Priority Setting.* Ithaca, NY: Cornell University Press.

Alston, J. M., Pardey, P. G., & Ruttan, V. W. (2008). Research Lags Revisited: Concepts and Evidence from U.S. Agriculture. *Staff Paper P08-14. InSTePP Paper 08-02.* St. Paul, MN: University of Minnesota.

Alston, J. M., Pardey, P. G., James, J. S., & Andersen, M. A. (2009). *The Economics of Agricultural R&D.* Retrieved December 01, 2010, from resource.annualreviews.org: 10.1146/annurev.resource.050708.144137

Ball, E. (2005, June). Ag Productivity Drives Output Growth. *Amber Waves.* Retrieved September 2009, from http://www.ers.usda.gov/AmberWaves/June05/pdf/FullIssueJune2005.pdf.

Ball, E. (2010, May 5). *Agricultural Productivity in the United States.* Retrieved January 11, 2010, from http://www.ers.usda.gov/Data/AgProductivity/

Baltagi, B. (2005). *Econometric Analysis of Panel Data* (3d ed.). John Wiley and Sons, Ltd.

Baltagi, B. (2000). *Nonstationary Panels, Panel Cointegration, and Dynamic Panels* (Vol. 15). New York, NY, USA: Elsevier Science.

Baumol, W., & Wolff, E. (1983). Feedback from Productivity Growth to R & D. *Scandinavian Journal of Economics* (85), 147-157.

Binswanger, H. P. (1978). Induced Technical Change: Evolution of Thought. In H. P. Binswanger, & V. Ruttan (Eds.), *Induced Innovation: Technology, Institutions and Development.* Baltimore: The John Hopkins University Press.

Bowditch, E., & McConnel, J. (2001). *County Voting Patterns in US Presidential Elections, 1976-2000. A GIS Analysis.* Retrieved March 01, 2011, from http://www.poppyware.com/bowditch/maps/elections/elect_top.html

Brown, R., Durbin, J., & Evans, J. (1975). Techniques for Testing the Constancy of Regression Relationships over Time. *Journal of the Royal Statistical Society* (Series B, 37), 149-192.

Burke, S. (1994). Confirmatory Data Analysis: The Joint Application of Stationarity and Unit Root Tests. *Discussion paper No.20.* University of Reading, UK.

Committee on an Evaluation of the US Department of Agriculture National Research Initiative Competitive Grants Program, Board on Agriculture and National Resources. (2000). *The National Research Initiative: A Vital Competitive Grants Program in Food, Fiber, and Natural Resources Research, National Research Council.* Washington, D.C.: National Academy Press.

Copeland, M. A., & Martin, E. M. (1938). The Correction of Wealth and Income Estimates for Price Changes. In *Studies in Income and Wealth* (Vol. 2, 85-135). New York: National Bureau of Economic Research,.

Copeland, M. (1937). Concepts of National Income. In *Studies in Income and Wealth* (Vol. 1, 3-63). New York: National Bureau of Economic Research.

David, P., & Van de Klundert, Th. (1965). Biased Efficiency Growth and Capital-Labor Substitution in the U.S., 1899-1960. *A.E.R.* (55), 357-94.

Davidson, J. E. H., Hendri, D. F., Srba, F., & Yeo, S. (1978). Econometric Modeling of the Agreggate Time-Series Relationship Between Consumer's Expenditure and Income in the United States. *Economic Journal*, *88*, 661-692.

Davis, J. (1979). A Comparison of Alternative Procedures for Calculating the Rate of Return to Agricultural Research Using the Production Function Approach. *Staff Paper P79-19.* St. Paul, Minnesota: University of Minnesota. Institute of Agriculture, Forestry and Home Economics.

Denison, E. (1972). Some Major Issues in Productitivy Analysis: An Examination of the Estimates by Jorgenson and Griliches. *Survey of Current Business*, *5* (2), 1–27.

Dickey, D. A. (1976). Estimation and Hypothesis Testing for Nonstationary Time Series. *Ph.D. Dissertation. Iowa State University*.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the Estimators for Autoregressive Time Series with a Unit Root. *Journal of the American Statistical Association*, *74*, 427-431.

Dickey, D. A., Jansen, D. W., & Thornton, D. L. (1991, March). A Primer on Cointegration with an Application to Money and Income. *Review*, 58-78.

Diewert, W. E. (1976). Exact and Superlative Index Numbers. *Journal of Econometrics*, *4* (2), 115-46.

Diewert, W. E. (1974). *Homogeneous Weak Separability and Exact Index Numbers.* Stanford, California: Institute for Mathematical Studies in the Social Sciences.

Diewert, W. E., & Nakamura A.O. (2005). Concepts and Measures of Productivity: An Introduction. In Lipsey and Nakamura (Eds.), *Services Industries and the Knowledge Based Economy* (Chapter 2), University of Calgary Press,

Dosi, G. (1988). Sources, Procedures and Microeconomic Effects of Innovation. *Journal of Economic Literature* (26), 1120-1171.

Echeverria, R. (1990). Assessing the impact of Agricultural Research. In R. Echeverria (Ed.), *Methods for Diagnosing Research System Constraints and Assessing the Impact of Agricultural Research* (Vol. II). The Hague: ISNAR.

Evenson, R. (1980). A Century of Agricultural Research and Productivity Change Research, Invention, Extension and Productivity Change in U.S. Agriculture: A Historical Decomposition Analysis. In A. Araji (Ed.), *Research and Extension in Agriculture* (146-228). Moscow, ID: Department of Agricultural Economics, University of Idaho.

Evenson, R. (1967). The Contribution of Agricultural Research to Production. *Journal of Farm Economics*, *49*, 1415-1425.

EViews 6 User's Guide I, II. (2007). Quantitative Micro Software.

Fellner, W. (1961). Two Propositions in the Theory of Induced Innovations. *Economic Journal* (71), 305-8.

Fuglie, K. (2008). Is a Slowdown in Agricultural Productivity Growth Contributing to the Rise in Commodity Prices. *Agricultural Economics* (39), 431-441.

Fuglie, K., & Heisey, P. (2007). *Economic Returns to Public Agricultural Research.* USDA, ERS.

Fuglie, K., MacDonald, J., & Ball, E. (2007). *Productivity Growth in U.S. Agriclture.* US Department of Agriculture, ERS.

Gonzalo, J. (n.d.). Retrieved February 20, 2011, from http://www.eco.uc3m.es/~jgonzalo/teaching/timeseriesMA/eviewsvar.pdf

Granger, C. W. (1981). Some Properties of Time Series Data and Their Use in Econometric Model Specification. *Journal of Econometrics* , *16*, 121-130.

Granger, C. W., & Newbold, P. (1974). Spurious Regressions in Econometrics. *Journal of Econometrics* , *2*, 111-120.

Griliches, Z. (1998). R&D and Prodictivity: The Econometric Evidence. Chicago, IL: The University of Chicago Press.

Griliches, Z. (1996). The Discovery of the Residual: A Historical Note. *Journal of Economic Litarture* (34), 1324–30.

Gujarati, D. (2003). *Basic Econometrics* (4th ed.). McGraw-Hill.

Hall, R., & Jones, C. (1999). Why Do Some Countries Produce So Much More Output per Worker than Others? *Quarterly Journal of Economics* , *114*, 83-116.

Hall, R., & Sutch, R. (1968, February). A Flexible Infinite Distributed Lag. *Working Paper No. 124* . Berkeley, CA: Institute of Business and Economic Research. Center for Research in Management Science. Univercity of California.

Hayami, Y., & Ruttan, V. (1970). Factor Prices and Technical Change in Agricultural Development: The United States and Japan, 1880-1960. *The Journal of Political Economy* (78), 1115-1141.

Hicks, J. R. The Theory of Wages. (1932). London: Macmillan.

Hjelm, G., & Johannson, M. W. (2002, February 5). *A Monte Carlo Study on the Pitfalls in Determining Deterministic Components in Cointegrating Models.* Retrieved February 01, 2011, from http://www.nek.lu.se/publications/workpap/Papers/WP02_3.pdf

Huffman, W. E.; Evenson, R. E. (1993). *Science for Agriculture: a Long Term Perspective.* Ames: Iowa State University Press.

Huffman, W. (2009, November). Measuring Public Research Capital and Its Contribution to State Agricultural Productivity. *(Working Paper 09022)* . Ames: Iowa State University.

Huffman, W., & Evenson, R. (1992). Contributions of Public and Private Science and Technology to U.S. Agricultural Productivity. *American Journal of Agricultural Economics* (74), 751-56.

Huffman, W., & Evenson, R. (2003). New Econometric Evidence on Agricultural Total FactorProductivity Determinants: Impact of Funding Sources. *Working Paper # 03029.* Ames, Iowa: Iowa State University. Department of Economics.

Huffman, W., & Evenson, R. (1989). Supply and Demand Functions for Multiproduct U.S. Cash Grain Farms: Biases Caused by Research and other Policies. *American Journal of Agricultural Economics* (71), 761-773.

Jaffe, A. (1988). Demand and Supply Influences in R&D Intensity and Productivity Growth. *Review of Economics and Statistics* (70), 431-437.

Johansen, S. (1992). Determination of Cointegration Rank in the Presense of Linear Trend. *Oxford Bulletin of Economics and Statistics , 54* (3), 383-97.

Johansen, S. (1988). Statistical Analysis of Cointegration Vectors. *Journal of Economic Dynamics and Control* (12), 231-254.

Johansen, S. (1994). The Role of the Constant and Linear Terms in Cointegration Analysis. *Econometric Reviews , 13*, 205-229.

Juselius, K. (2007). *Cointegration Analysis of Climate Change: An Exposition.* Retrieved March 01, 2011, from http://www.math.ku.dk/~susanne/Klimamode/Juselius.pdf

Karlsson, S., & Löthgren, M. (2000). On the Power and Interpretation of the Panel Unit Root Tests. *Economic Letters* (66), 249-255.

Kennedy, C. (1964). Induced Bias in Innovation and Theory of Distribution. *Economic Journal* (74), 541-7.

Leeuw, F. d. (1962). The Demand for Capital Goods by Manufacturers: A Study of Quarterly Time Series. *Econometrica* (30).

Liu, Y., Shumway, C. R., Rosenman, R., & Ball, V. E. (2008). Productivity Growth and Convergence in U.S.: New Cointegration Panel Data Results. *WP 2008-4.* Washington State University.

Maddala, G., & Kim, I.-M. (1998). *Unit Roots, Cointegration, and Structural Change.* Cambridge University Press.

Moon, H., Perron, B., & Phillips, P. (2005). *Incidental Trends and the Power of Panel Unit Root Tests.* Retrieved February 20, 2011, from http://mapageweb.umontreal.ca/perrob/power.pdf

National Climatic Data Center. (2011). *Time Bias Corrected Divisional Dataset.* Retrieved March 01, 2011, from http://www7.ncdc.noaa.gov/CDO/CDODivisionalSelect.jsp

National Institute of Standards and Technology. (1999). *Statistical Engineering Division Annual Report.* Retrieved February 01, 2011, from http://www.itl.nist.gov/div898/pubs/ar/ar1999/node1.html

Olmstead, A., & Rhode, P. (1993). Induced Innovation in American Agriculture: A Reconsideration. *Journal of Political Economy* (101), 100-118.

Pardey, P. G., Andersen, M. A., & Alston, J. M. (2009, forthcoming). A Long-Run Price Index and the Real Cost of U.S. Agricultural Research. *Staff Paper.* St. Paul, MN: University of Minnesota. Department of Applied Economics.

Pardey, P. G., & Craig, B. (1989). Causal Relationships between Public Sector Agricultural Research Expenditures and Output. *American Journal of Agricultural Economics.* (71), 9-19.

Pardey, P., Craig, B., & Hallaway, M. (1987, August). U.S. Agricultural Research Deflators: 1890:1985. *Staff Papers Series P87-25* . St. Paul, MN: University of Minnesota. Department of Agricultural and Applied Economics.

Perron, P. (1989). The Great Crash, the Oil Price Shock, and the Unit Root Hypothesis. *Econometrica* (57), 1361-1401.

Pub. L. No. 101-624, 104 Stat. 3359. (1990, Nov. 28). Food, Agriculture, Conservation, and Trade Act of 1990.

Pub. L. No. 104–127. (1996, Apr. 4). Federal Agriculture Improvement and Reform Act of 1996.

Pub. L. No. 107–171. (2002, May 13). Farm Security and Rural Investment Act of 2002.

Pub. L. No. 79-733. (1946, Aug. 14). Agricultural Marketing Act of 1946.

Pub. L. No. 92-419. (1972). Consolidated Farm and Rural Development Act of 1972.

Pub. L. No. 95-113, 91 Stat. 913. (1977, Sep. 29). Food and Agriculture Act of 1977.

Pub. L. No. 99-198, 99 Stat. 1354. (1985, Dec. 23). Food Security Act of 1985.

Pub. L. No.110–246. (2008, June 18). Food, Conservation, and Energy Act of 2008.

Ruttan, V. W. (2002). Sources of Technical Change: Induced Innovation, Evolutionary Theory and Path Dependence. In W. Nordhaus, N. Nakicenovic, & A. Grubler (Eds.), *Induced Technical Change*. Washington, DC: Resources for the Future.

Sánchez, I., & Peña, D. (2001). Properties of Predictors in Overdifferenced nearly Nonstationary Autoregression. *Journal of Time Series Analysis* , *22* (1), 45-66.

Sargan, J. D. (1964). Wages and Prices in the United Kingdom: A Study in Econometric Metholology. In D. F. Hendri, & K. F. Wallis (Eds.), *Econometrics and Quantitative Economics*. New York: Basil Blackwell, 1984.

Scherer, F. M. (1982). Demand-Pull and Technological Invention: Schmookler Revisited. *Journal of Industrial Economics* (30), 225-37.

Schmookler, J. (1966). *Invention and Economic Growth*. Cambridge, MA: Harward University Press.

Schultz, T. (1953). The Economic Organization of Agriculture. New York, NY: MCGraw-Hill Book Co. Inc.

Shaik, S. (1999). Causality between TFP, R&D and Prices: Unconditional and Conditional Linear Feedback. Nashville, TN: American Agricultural Economics Association Meeting.

Shaik, S. (1999). Linear Dependence of Supply and Demand on Productivity. Unpublished paper.

Shaik, S. (2009). Do Technology/Economies of Size, Institutional or Political force affect Input Demand Functions? Unpublished paper.

Shane, M., Roe, T., & Gopinath, M. (1998). *U.S. Agricultural Growth and Productivity: An Economy-Wide Perspective.* Market and Trade Economics. USDA, ERS.

Sims, C. (1980). Macroeconomics and Reality. *Econometrica*, *48*, 1-48.

Solow, R. (1956). A Contribution to the Theory of Economics Growth. *Quarterly Journal of Economics*, *70* (1), 65-94.

Solow, R. (1957). Technical Change and the Aggregate Production Function. *Review of Economics and Statistics*, *39* (3), 312-20.

Stiroh, K. (2001, March). What Drives productivity Growth? *FRBNY Economic Policy Review*, 37-59.

Stock, J. (1990). A Class of Tests for Integration and Cointegration. *Manuscript*. Harvard University.

Tsay, R. S. (2005). *Analysis of Financial Time Series.* Hoboken, NJ: John Wiley & Sons.

U.S. Department of Agriculture. (2010). Retrieved January 5, 2011, from http://www.ers.usda.gov/Data/AgResearchFunding

U.S. Department of Agriculture. (1902-1913). *Annual Report of the Office of Experiment Stations.* Washington, D.C.: Govertment Printing Office.

U.S. Department of Agriculture. (1889). *Report of the Commissioner in Agriculture. 1888.* Washington, D.C.: Government Printing Office.

U.S. Department of Agriculture. (1891-1894). *Report of the Secretary of Agriculture. 1890-1893.* Washignton: Government Printing Office.

U.S. Department of Agriculture. (1895). Statistics of Agricultural Colleges and Experiment Stations, 1894. *Office of Experiment Stations Circular No.27* . Washington, D.C.: U.S. Government Printing Office.

U.S. Department of Agriculture. (1898-1901). Statistics of Land-Grant Colleges and Agricultural Experiment Stations in the United States. *Office of Experiment Stations Bulletin Nos. 51, 64, 78, 97* . Washington, D.C.: U.S. Government Printing Office.

U.S. Department of Agriculture. (1897). Statistics of Land-Grant Colleges and Agricultural Experiment Stations, 1896. *Office of Experiment Stations Circular No. 35* . Washington, D.C.: U.S. Government Printing Office.

U.S. Department of Agriculture. Agricultural Research Administration. Office of Experiment Stations. (1943-1954). *Report on the Agricultural Experiment Stations.* Washington, D.C.: Government Printing Office.

U.S. Department of Agriculture. Agricultural Research Service. (1961). *Funds for Research at State Agricultural Experiment Stations.* Washington, D.C.: Government Printing Office.

U.S. Department of Agriculture. Agricultural Research Service. (1955-1960). *Report on the Agricultural Experiment Stations.* Washington, D.C.: Government Printing Office.

U.S. Department of Agriculture. Cooperative State Experiment Station Service. (1962-1963). *Funds for Research at State Agricultural Experiment Stations.* Washington, D.C.: Government Printing Office.

U.S. Department of Agriculture. Cooperative State Research Service. (1964). *Funds for Research at State Agricultural Experiment Stations.* Washington, D.C.: Government Printing Office.

U.S. Department of Agriculture. Cooperative State Research Service. (1965-1971). *Funds for Research at State Agricultural Experiment Stations and Other State Institutions.* Wahington, D.C.: Government Printing Office.

U.S. Department of Agriculture. Cooperative State Research Service. (1971-1993). *Inventory of Agricultural Research.* Washington, D.C.: U.S. Department of Agriculture.

U.S. Department of Agriculture. Office of Experiment Stations. (1914-1926). *A Report on the Work and Expenditures of the Agricultural Experiment Stations.* Washington, D.C.: Government Printing Office.

U.S. Department of Agriculture. Office of Experiment Stations. (1889). Organization of Agricultural Experiment Stations in the United States. *Experiment Station Bulletin No. 1.*

U.S. Department of Agriculture. Office of Experiment Stations. (1925-1942). *Report on the Agricultural Experiment Stations.* Washington, D.C.: Government Printing Office.

Wang, W. (2006). *Stochasticity, Nonlinearity and Forecasting of Streamflow Processes.* Delft University Press.

www.usda.gov. (2010). *Farm Bill Resources.* Retrieved October 5, 2010, from http://www.ers.usda.gov/FarmBill

Yule, G. U. (1926). Why Do We Sometimes get Nonsense Correlations Between Time Series? A Study in Sampling and the Natura of Time Series. *Journal of the Royal Statistical Society* , *89*, 1-64.

Table A1. Average chain growth rates of R&D funding (%)

Region/State	1889-1900	1901-1910	1911-1920	1921-1930	1931-1940	1941-1950	1951-1960	1961-1970	1971-1980	1981-1990	1991-2000	2001-2009
Appalachia	-	*223.29*	*233.49*	*190.11*	*143.65*	*128.63*	*139.00*	*154.68*	*142.89*	*355.03*	*97.37*	*114.78*
Kentucky	-	295.99	298.11	129.73	139.07	110.50	119.74	165.27	117.69	95.71	105.06	116.08
North Carolina	-	249.81	183.64	251.74	140.82	136.49	149.04	159.48	168.54	127.11	92.30	110.33
Tennessee	-	194.42	222.34	214.32	162.22	135.11	136.12	156.32	149.52	88.25	102.08	108.09
Virginia	-	152.74	233.58	206.01	156.66	144.71	170.57	161.59	144.25	125.39	97.86	112.19
West Virginia	-	192.81	204.76	226.56	129.16	123.27	119.03	115.56	96.83	149.35	100.00	150.54
Corn Belt	-	*348.70*	*284.21*	*196.69*	*139.66*	*125.16*	*111.87*	*135.22*	*117.78*	*202.52*	*111.51*	*110.34*
Illinois	-	593.72	246.88	205.68	139.46	117.34	105.36	139.04	114.73	110.86	112.30	102.70
Indiana	-	324.93	433.10	166.31	149.68	123.58	116.27	109.48	139.82	116.45	101.06	120.88
Iowa	-	344.88	304.60	232.93	140.41	129.07	126.80	127.30	118.33	127.67	130.31	100.61
Missouri	-	316.50	230.45	198.82	149.91	122.75	122.08	168.17	118.66	106.45	111.89	123.27
Ohio	-	253.99	266.61	185.54	126.46	134.25	95.58	143.11	103.30	103.11	91.75	117.24
Delta	-	*265.04*	*230.47*	*273.93*	*149.84*	*122.24*	*108.78*	*153.53*	*124.37*	*208.55*	*101.59*	*123.01*
Arkansas	-	235.76	159.79	167.00	157.27	156.54	188.98	168.72	125.99	118.83	129.88	134.28
Louisiana	-	235.97	244.59	288.87	149.96	113.84	102.01	159.32	120.15	81.95	90.72	108.37
Mississippi	-	348.54	239.22	281.27	148.40	129.59	100.98	139.10	130.48	119.40	99.45	129.85
Lake States	-	*231.16*	*275.63*	*219.21*	*141.27*	*125.49*	*148.47*	*133.30*	*131.48*	*313.52*	*120.24*	*141.82*
Michigan	-	225.87	213.60	314.67	139.37	112.46	171.51	139.56	135.64	107.80	112.80	225.87
Minnesota	-	285.05	317.74	162.00	135.50	120.14	138.31	135.04	130.39	125.37	128.22	285.05
Wisconsin	-	178.06	263.02	262.93	150.30	142.71	142.70	126.63	128.86	127.49	118.29	178.06
Mountain	-	*230.73*	*234.13*	*241.48*	*149.81*	*114.46*	*112.69*	*142.69*	*126.04*	*235.17*	*102.28*	*115.55*
Arizona	-	261.71	269.48	243.84	147.79	107.73	104.11	181.98	129.53	117.36	120.17	103.78
Colorado	-	238.38	249.17	273.32	143.16	112.27	101.79	138.56	146.03	141.99	95.47	128.98
Idaho	-	266.53	235.72	258.08	153.98	115.03	126.74	141.10	113.27	117.37	103.31	114.21
Montana	-	340.85	254.32	212.72	140.29	129.76	125.33	127.29	114.16	94.46	94.45	128.62
Nevada	-	154.81	193.32	210.44	162.33	102.04	96.27	167.98	135.76	87.88	98.59	132.85
New Mexico	-	177.33	235.65	197.03	162.74	117.71	111.50	137.03	120.35	112.30	100.60	92.37
Utah	-	216.52	198.36	239.24	145.21	118.20	124.63	125.00	127.03	113.98	105.35	111.00
Wyoming	-	198.90	187.16	267.41	171.79	111.13	112.97	130.63	108.57	96.83	85.63	100.84

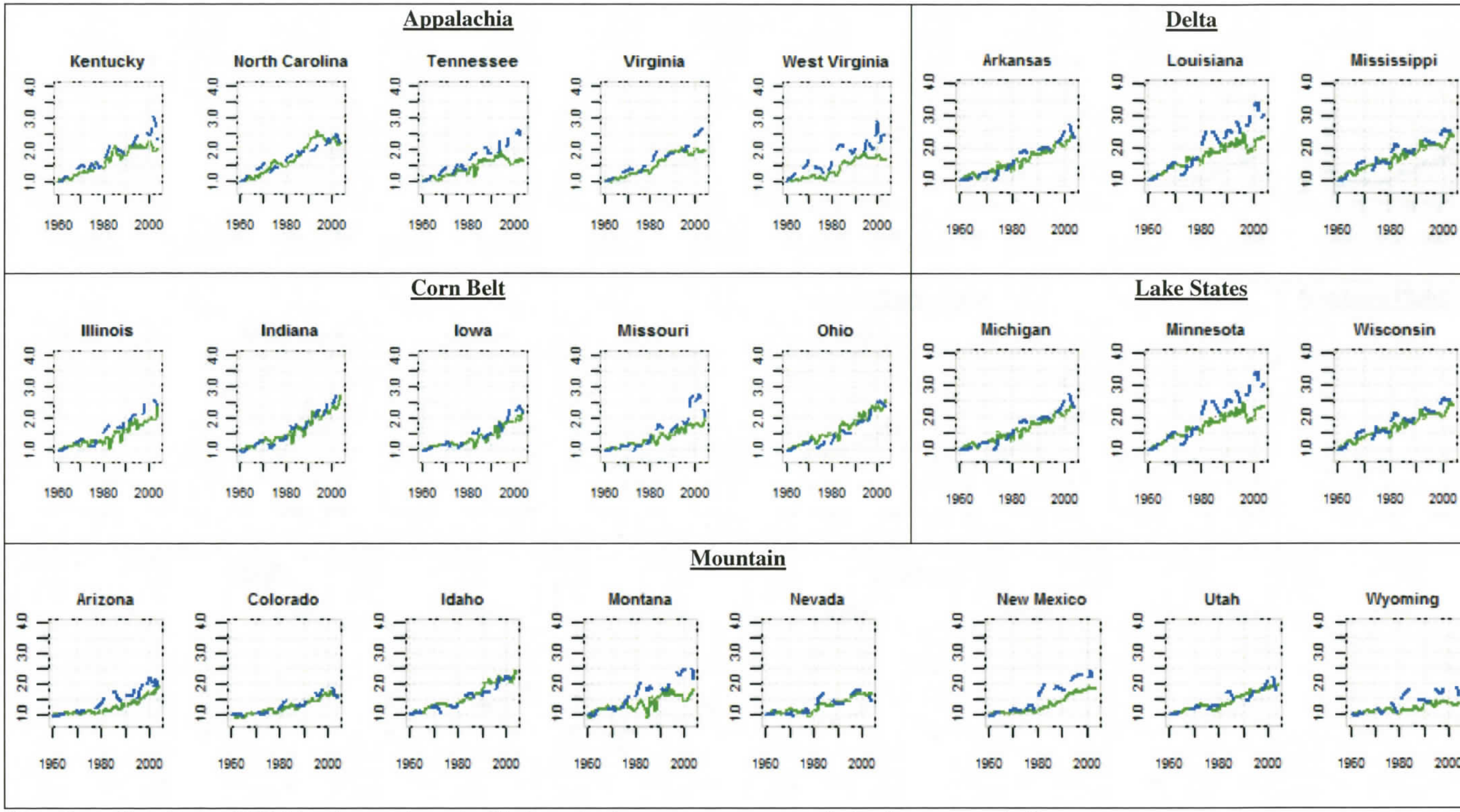
(Continued)

Table A1 - (Concluded)

Region/State	1889-1900	1901-1910	1911-1920	1921-1930	1931-1940	1941-1950	1951-1960	1961-1970	1971-1980	1981-1990	1991-2000	2001-2009
Northeast	-	*171.82*	*202.91*	*233.37*	*165.18*	*109.76*	*115.23*	*137.93*	*113.47*	*256.13*	*107.27*	*105.99*
Connecticut	-	154.71	145.55	207.85	160.69	100.52	152.45	116.63	98.21	90.02	118.93	140.62
Delaware	-	147.68	220.52	193.55	157.05	123.66	114.30	128.82	110.85	114.29	87.03	82.53
Maine	-	175.35	193.68	165.54	154.13	133.21	104.08	133.49	142.09	107.41	94.16	104.09
Maryland	-	261.86	231.67	255.55	150.15	112.78	105.53	141.57	102.24	376.73	137.27	92.95
Massachusetts	-	159.83	198.55	214.37	150.14	92.60	107.39	131.01	78.55	292.21	96.34	114.12
New Hampshire	-	120.93	193.52	126.24	190.21	81.96	136.03	148.83	103.16	103.45	98.98	84.35
New Jersey	-	174.68	242.86	176.49	192.84	98.48	131.68	141.64	118.60	77.90	119.42	82.85
New York	-	162.29	193.40	280.06	172.40	109.39	117.94	139.40	116.41	127.70	89.52	122.90
Pennsylvania	-	246.01	250.28	271.05	159.51	118.84	102.59	142.43	117.80	114.84	107.12	107.32
Rhode Island	-	135.63	154.82	173.88	160.30	111.41	127.62	131.48	135.45	55.85	69.43	111.47
Vermont	-	123.33	122.40	143.58	187.37	98.42	135.75	144.55	116.58	98.57	99.93	90.02
Northern Plains	-	*275.39*	*285.99*	*219.61*	*135.68*	*116.27*	*125.95*	*157.96*	*122.90*	*284.12*	*105.31*	*107.72*
Kansas	-	302.86	250.20	193.45	143.67	127.73	147.65	149.50	128.35	117.79	102.59	106.84
Nebraska	-	313.12	302.34	191.25	141.98	115.10	132.56	168.00	132.28	122.83	115.78	109.17
North Dakota	-	300.60	324.93	267.54	125.08	109.18	103.37	152.21	114.27	122.97	94.57	103.81
South Dakota	-	170.07	230.39	197.76	148.94	122.93	139.71	167.08	109.95	78.92	107.79	116.01
Pacific	-	*317.35*	*278.76*	*263.04*	*155.47*	*124.60*	*135.36*	*151.70*	*118.30*	*284.02*	*107.41*	*116.31*
California	-	361.16	243.20	266.77	163.24	127.30	149.47	154.22	122.31	129.15	105.54	120.14
Oregon	-	221.65	361.23	233.32	153.08	119.91	132.38	148.97	115.36	110.40	111.96	105.70
Washington	-	317.72	302.50	276.60	145.15	122.75	112.38	147.66	110.57	88.64	110.76	111.43
Southeast	-	*226.71*	*253.09*	*301.62*	*164.20*	*129.97*	*115.03*	*142.40*	*132.31*	*260.70*	*97.99*	*90.39*
Alabama	-	135.47	202.09	223.44	210.63	153.55	131.32	135.49	123.30	111.15	100.81	68.58
Florida	-	280.43	267.45	342.87	165.37	140.29	115.39	138.81	138.83	128.85	99.88	101.48
Georgia	-	293.51	274.42	297.91	154.87	110.99	115.26	148.92	129.55	117.67	94.11	90.86
South Carolina	-	189.52	228.13	299.66	156.37	137.40	95.99	145.07	133.15	112.37	99.31	76.41
Southern Plains	-	*300.64*	*316.60*	*274.14*	*161.11*	*130.99*	*114.25*	*126.89*	*123.16*	*238.66*	*113.40*	*108.67*
Oklahoma	-	279.76	228.42	255.84	191.84	135.94	116.12	130.84	111.88	115.25	109.51	112.02
Texas	-	311.88	359.17	279.76	152.48	129.24	113.56	125.38	127.63	140.07	114.51	107.75

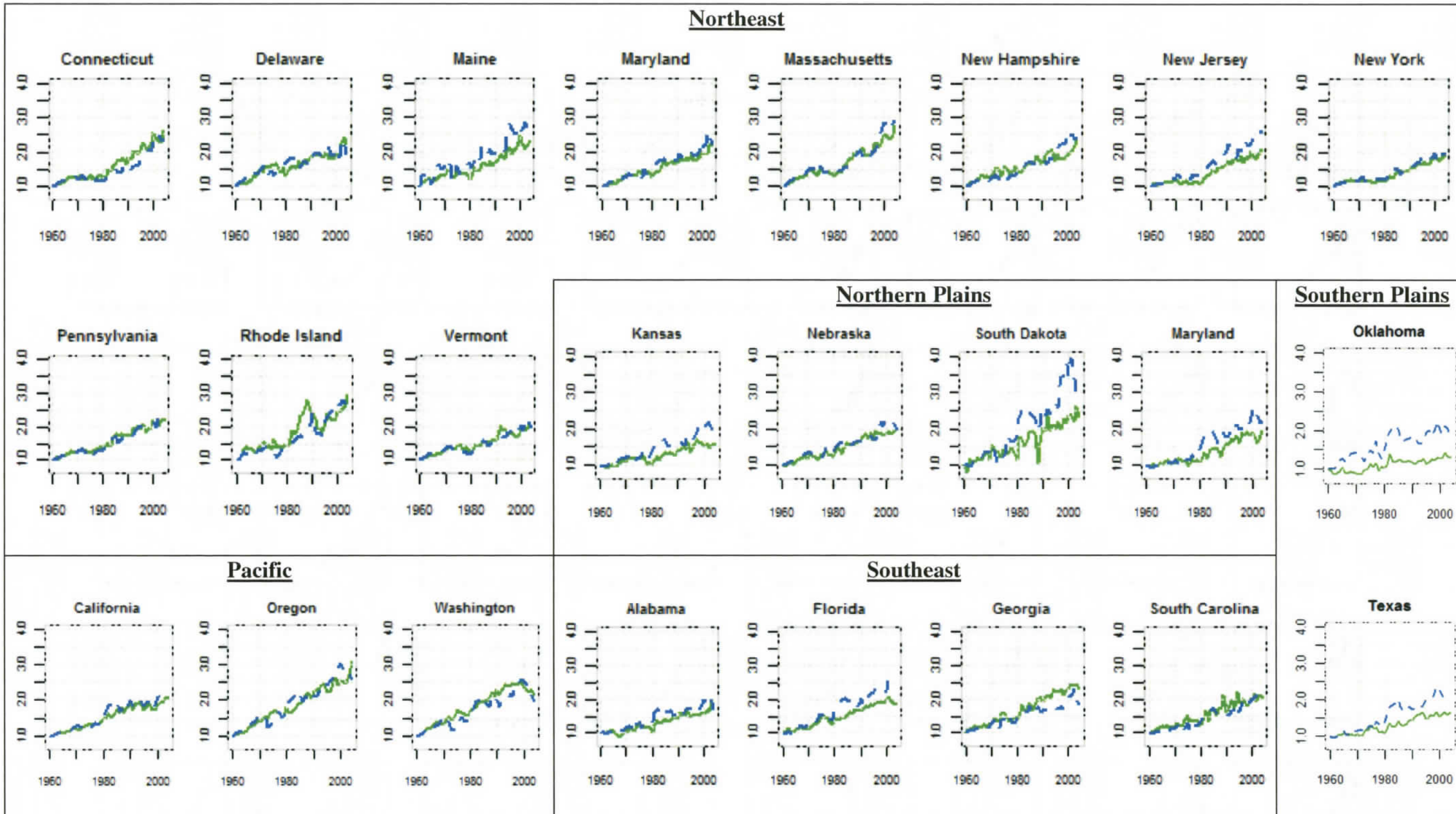
Table A2. Average annual changes of input and output quantity indices, and TFP (%)

Region	1960-1970	1970-1980	1980-1990	1990-2004
	Input Quantity Index			
Appalachia	-1.69	0.29	-1.67	0.05
Corn Belt	-0.98	1.18	-2.28	1.28
Delta	0.43	0.88	-0.51	-0.63
Lake States	-1.23	1.63	-1.70	0.10
Mountain	1.37	1.48	-1.49	-1.23
Northeast	-3.01	1.17	-2.05	0.21
Northern Plains	0.72	2.08	-1.17	-0.83
Pacific	-0.71	1.22	-0.10	0.25
Southeast	0.74	1.22	-1.80	1.00
Southern Plains	0.89	1.06	-0.50	0.75
	Output Quantity Index			
Appalachia	0.30	1.23	1.98	0.05
Corn Belt	0.58	2.26	1.62	1.57
Delta	3.57	0.88	3.55	2.15
Lake States	0.46	3.03	1.31	1.74
Mountain	2.69	1.45	1.15	1.04
Northeast	-0.44	0.71	1.35	1.76
Northern Plains	1.78	2.53	3.28	0.98
Pacific	1.81	3.72	2.64	1.69
Southeast	2.11	2.21	1.16	1.59
Southern Plains	0.62	2.19	1.71	2.10
	TFP			
Appalachia	1.99	1.03	3.68	0.05
Corn Belt	1.66	1.05	4.17	0.34
Delta	3.22	0.36	4.25	2.89
Lake States	1.76	1.83	2.94	1.60
Mountain	1.36	0.05	2.77	2.19
Northeast	2.68	-0.32	3.67	1.60
Northern Plains	1.13	0.48	4.80	2.11
Pacific	2.63	2.62	2.76	1.50
Southeast	1.41	1.13	3.25	0.94
Southern Plains	-0.22	1.15	2.37	1.45



Note: Green line denotes TFP, blue line – price ratio. Horizontal axis represents years, vertical axis represents indices.

Figure A1. TFP and price ratio dynamics by state (Appalachia, Corn Belt, Mountain, Delta and Lake States regions)



Note: Green line denotes TFP, blue line – price ratio. Horizontal axis represents years, vertical axis represents indices.

Figure A2. TFP and price ratio dynamics by state (Northeast, Northern Plains, Pacific, Southeast and Southern Plains regions)

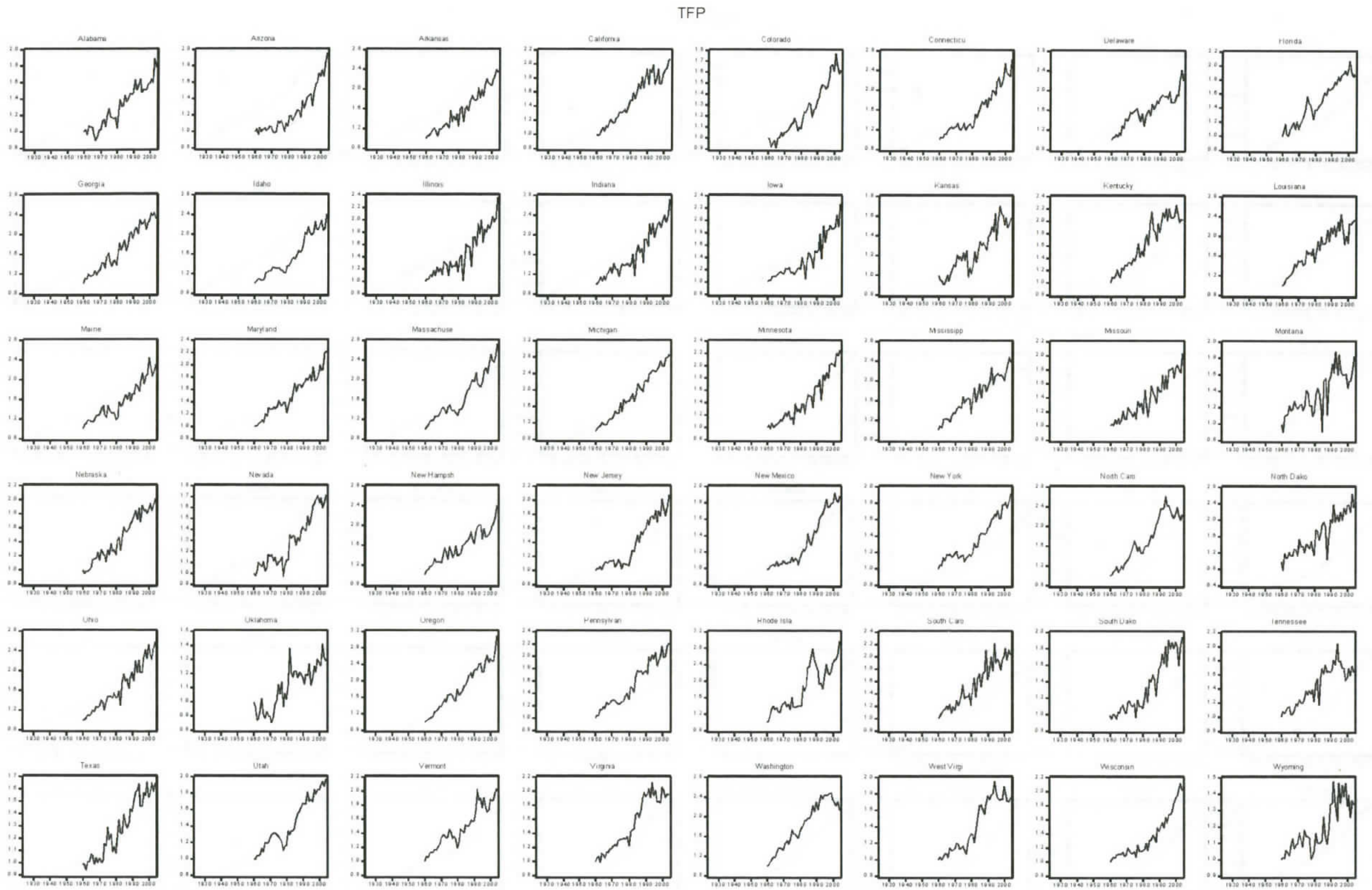


Figure A3. Trends in TFP by state (1960-2004)

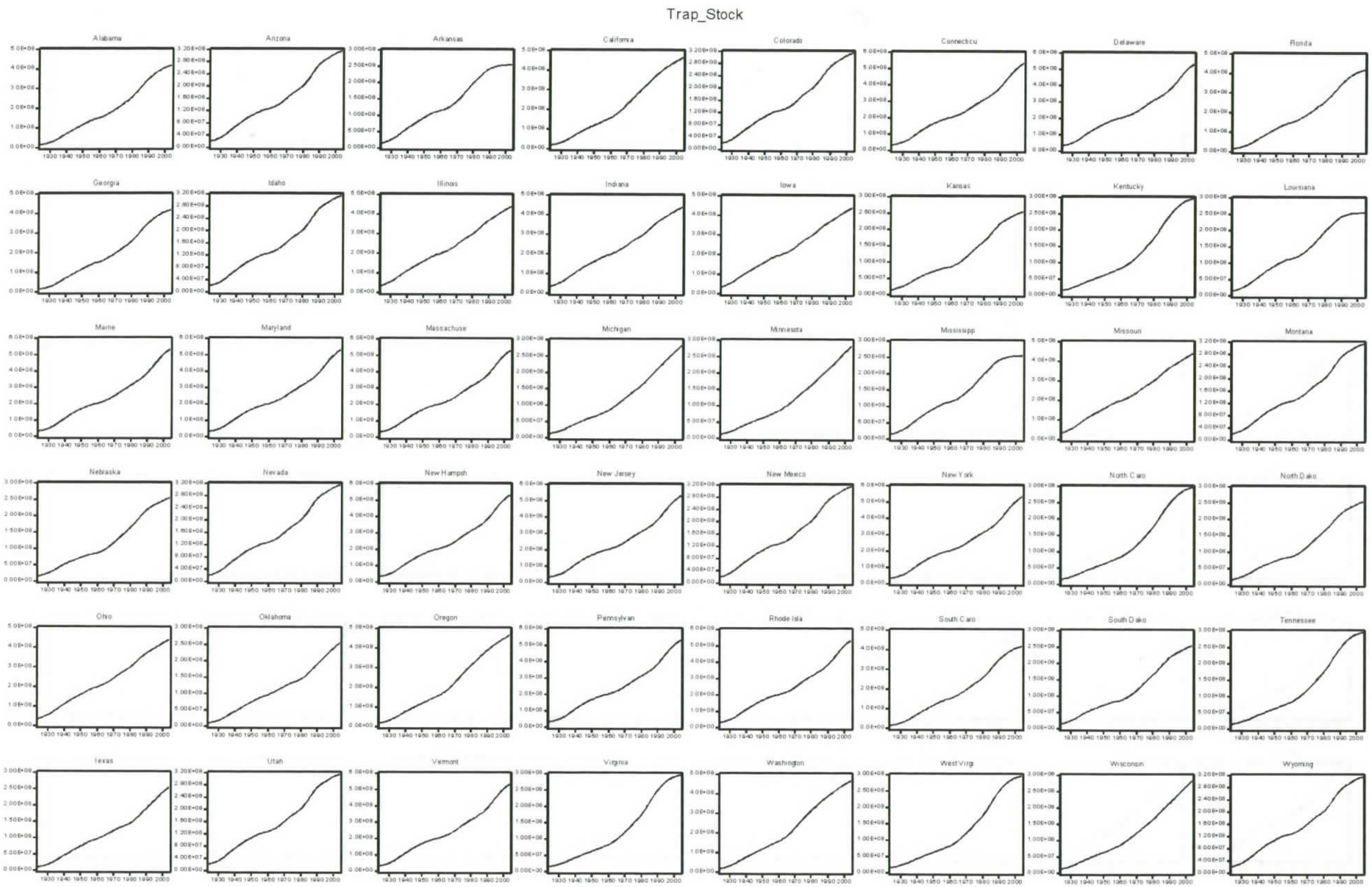


Figure A4. Trends in R&D stock by state (trapezoidal lag structure, 1924-2004)

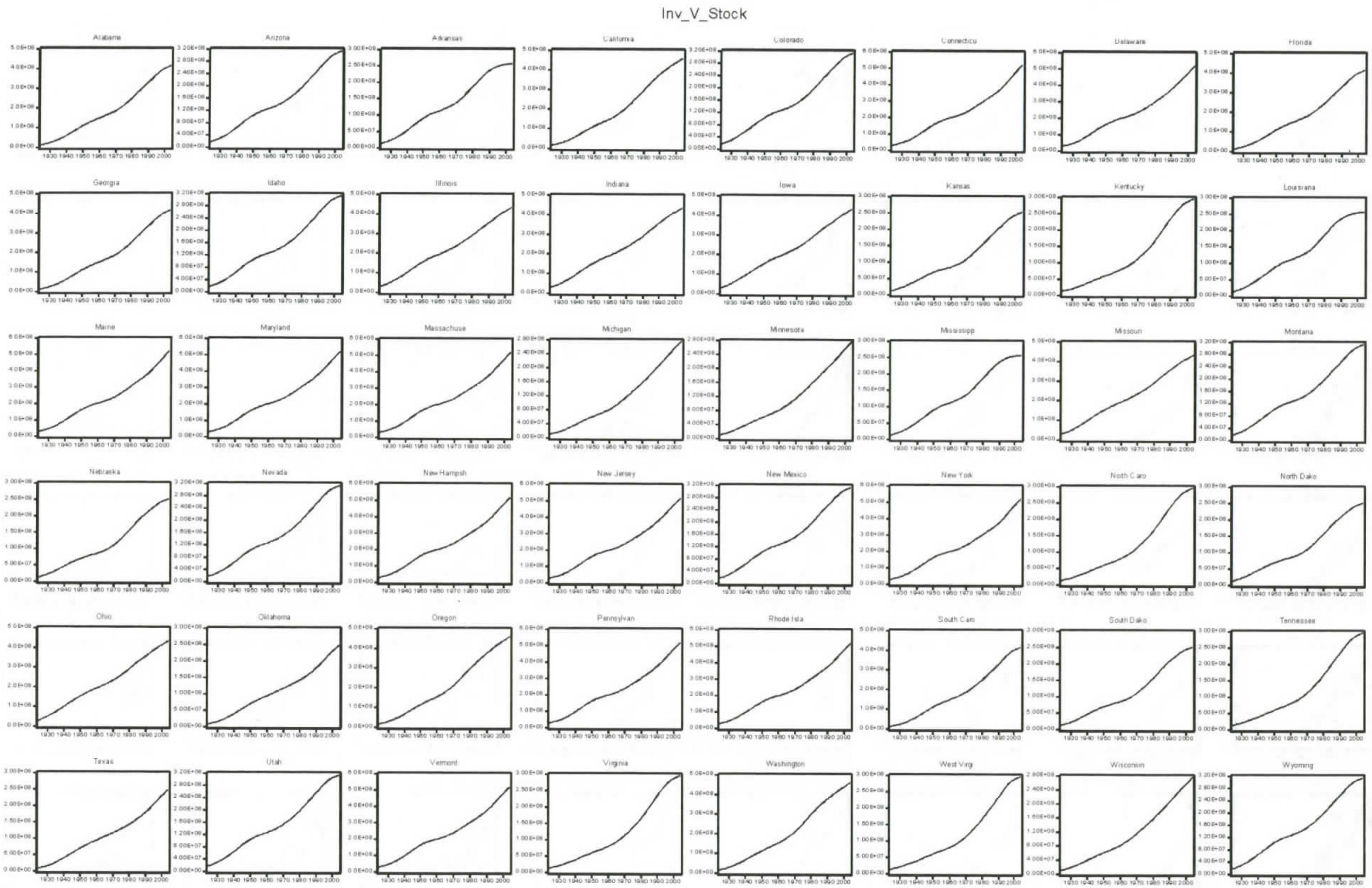


Figure A5. Trends in R&D stock by state (inverted-V lag structure, 1924-2004)

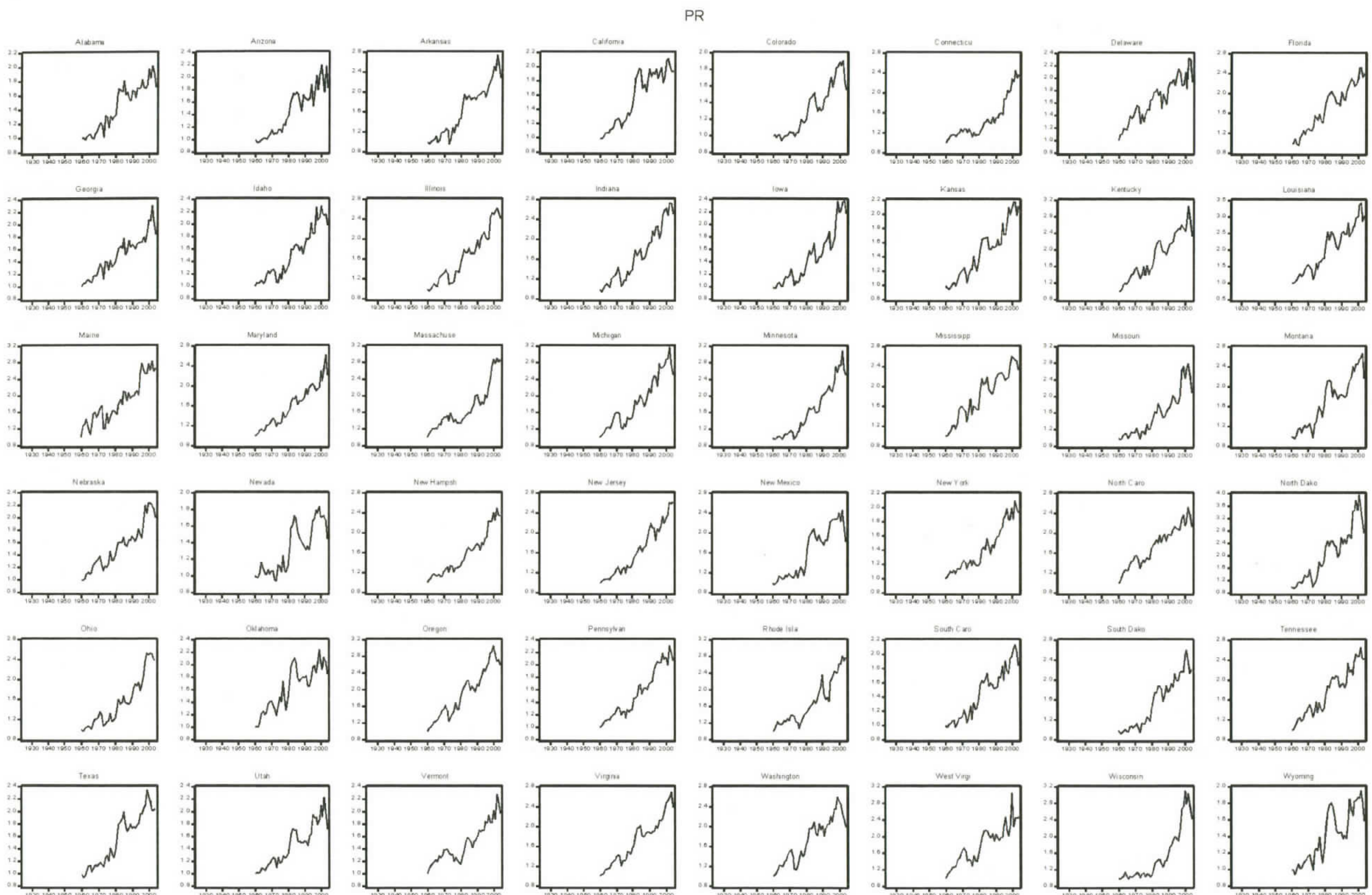


Figure A6. Trends in price ratio by state (1960-2004)