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L’impact des nouvelles technologies de l’information et de la communication sur la productivité du travail.

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CHAPTER 1 - INTRODUCTION

This dissertation analyzes the role of information technology in the economy of the United States, through its effects on regional labor productivity. The concept of information technology refers here to the convergence of computing power and communication technology that began in the late 1970s. Information technology (hereafter IT) can be embodied in a certain type of capital stock or in employment inputs or in both.

This study was motivated by the debate over the so-called “productivity paradox,” the oft-cited finding that investment in information technology appears to have had no visible effect on aggregate productivity. Indeed, until the mid-1990s, productivity gains remained sluggish while information technology was booming. Today, even after the recent jump in productivity, the strength of the “new economy” is once again called into question with the “deceleration” of growth and the apparent failure of the “e-economy.” During this last decade, many authors proposed explanations for the productivity paradox:

First, Ives(1994), Brynjolfsson and Hitt (1998) questioned the quality of measurement of national figures. Moving from a “hard” to a “soft” economy, with knowledge and information becoming primary resources, the productivity of difficult-to-measure intangibles has become more difficult to estimate. Second, David (1990) argued that long learning lags are associated with the diffusion of a new technology. The parallel was drawn from previous technological revolutions such as electricity or steam power, which had no significant impact on aggregate productivity figures until several decades after their discoveries. Roach (1998), Powell (2000), Chapman (1996) and Pentland (1989) proposed the “mismanagement” hypothesis, which stated that investors in information technology have underestimated its true cost (hidden costs include maintenance and training). A fourth hypothesis stated that unless IT investment is accompanied by work reorganization, productivity improvement will not occur [Brynjolfsson and Hitt (1995), Bowen (1986)]. Another explanation for the productivity paradox was the "redistribution" hypothesis, which proposed that IT is beneficial for individual firms, but not necessarily for the nation as a whole, as shown by Brynjolfsson and Hitt (1993), Jorgenson and Stiroh (1999, 2000).Finally, Oliner and Sichel (1994, 2000) argued that the income share of information technology capital is too small to have had visible macroeconomic effects, even if it does exhibit excess returns at the microeconomic level. Each hypothesis is a possibly valid explanation for the productivity paradox. However, today there seems to be a consensus around the idea that information technology finally started to increase productivity in the mid-1990s, as more and more firms completed the long reorganization of work process needed to accompany IT investment.

This study re-examines the historical data (1977-1997) in light of the redistribution hypothesis, which may deserve further investigation at the regional level. If information technology has a redistribution effect, then it "redistributes the shares of the pie without making it bigger," as stated by Brynjolfsson and Hitt (1993), who showed that IT capital does increase an individual firm's productivity. Thus, the slow diffusion of information technology across firms as well as across space may partly explain the productivity paradox.

The purpose of this dissertation is to further investigate the impact of the spatial diffusion of IT on the validity of the productivity paradox, by analyzing the productivity of IT at the regional level. Because information technology activity tends to be very localized (eight states own more than half of the entire national IT capital stock), there is reason to hypothesize regional redistribution effects regarding the impact of information technology. If this hypothesis is confirmed, then the productivity paradox is shown to have been a problem only at the aggregate level.

This dissertation is composed of three essays, each dealing with a particular feature of the regional relationship between information technology and productivity. First, though, chapter 2 offers a deeper presentation and statement of the problem. Then, the first essay, articulated in chapters 3, 4 and 5, analyzes information technology embodied in the stock of capital. A panel dataset is constructed for the 50 states plus the District of Columbia, covering 52 industry categories from 1977 through 1997. The data come from the U.S. Bureau of Economic Analysis. This dataset is separately analyzed for both industries and states. Using production function regressions and growth accounting techniques, the productive capacity and growth contribution of the IT capital stock is estimated at the state level. The results indicate a positive contribution to state productivity growth that amounts to 10% of the observed growth. Furthermore, decreasing returns to capital accumulation are found to apply to information technology capital, since its growth contribution is lower in states that own the highest shares of IT capital.

The second essay, in chapters 6, 7 and 8, analyzes IT and productivity at the state and county levels for the year 1990. Its purpose is to identify the productivity effects of the location patterns of IT employment across counties. The dataset built in the first essay is used to estimate output and capital stock at the county level. Data on employment by industry at the county level come from the U.S. Bureau of Census. Twenty-one of the 2-digit SIC industries, among those used in the first essay, are identified as IT industries. The concentration, localization and density of IT employment are found to have significant positive effects on labor productivity. Indeed, the agglomeration effects associated with the spatial distribution of IT employment are found to be greater than those associated with traditional employment. Between 5% and 10% of productivity differences can be explained by the spatial distribution of IT employment.

In the third essay, in chapters 9, 10 and 11, the impact of information technology on income inequality across states is estimated for the year 1990. The motivation for this analysis is the simultaneous increase in information technology and income inequality that took place in the 1980s (Greenwood 1999). To investigate empirically this relationship, Gini coefficients and variances of logarithms of median incomes are used alternatively as dependent variables, regressed on various factors explaining income inequality at the state level. According to Lervernier, Rickman and Patridge (1995), these factors include economic, demographic and human capital variables. IT intensity variables are then added to the model and are found to significantly increase income inequality. This result may be explained by the substitution/complement effects of information technology, as described by Krueger (1993), Levy and Murnane (1996) and Autor, Katz and Krueger (1998). Finally, chapter 12 summarizes findings, discusses outcomes and concludes the dissertation

CHAPTER 2 - STATEMENT OF THE PROBLEM

This chapter starts by defining two crucial terms at the core of this dissertation: information technology and productivity. Looking at their respective trends will lead to the identification of the productivity paradox, which challenges economic researchers. I will also provide some stylized facts about information technology and productivity across industries and states. This will bring out various research questions and will clearly state the purpose of this study.

2.1Definitions and Trends

“Information technology” and “productivity” are two terms widely, but not so wisely, used in many disciplines today. Since there does not appear to be one unique definition for these terms, it is important to cite the different approaches that have been adopted in the past. After discussing the definitions, I will briefly explain why it is important to study information technology and productivity in economics. Finally, I will describe their respective trends over the last thirty years.

2.1.1 Information Technology

2.1.1.1What is Information Technology?

In ordinary discourse, information technology (IT) refers to everything that uses high technology for informational purposes, such as computers, the Internet, mobile phones, satellite dishes and other wireless communication tools. In economics, Machlup (1962) first assessed the existence of some "information machines" and "information services" used in the production and distribution of knowledge. The following is a more formal definition adapted from the Macmillan Dictionary of Information Technology (1985):

The acquisition, processing, storage and dissemination of information in all its forms (auditory, pictorial, textual and numerical) through a combination of computers, telecommunication, networks and electronic devices.

More specifically, Freeman (1987) referred to information technology as:

A generic term for the widening array of electronic-based products and services generated out of the convergence in computer and telecommunications innovations.

Clearly, defining information technology is not easy. While the concept is readily grasped, giving precision to the definition is difficult. IT can be understood as all means by which we collect, process, store, manipulate, analyze and communicate information. The means include the hardware devices (such as computers, computer networks, satellite dishes, fiber optic cables and microwave transmitters), the software which operates with the hardware devices, and the people with various levels of education, training and experience who are involved in the IT sector.

The Organization for Economic Cooperation and Development (OECD 1997) divided IT capital into three categories: (1) *hardware* (multi-user system, data communication equipment, PCs and workstations), (2) *packaged software* (system software and utilities, application tools, application solutions) and (3) *services* (professional services, support services).

In his voluminous dissertation, Porat (1977) elaborated on the "service side" of IT. He attempted to write a detailed description of what he called the "information economy." Doing so, he identified "information producers," "information processors," "information distributors" and "information infrastructure occupations." His classification was later used by the Organization for Economic Co-operation and Development in its listing of information occupations. "Information producers" are people creating knowledge including scientists or professional researchers. "Information processors," including professors, use this raw knowledge to process it into more readable concepts. The "distributors," including the media, contribute to the diffusion of this knowledge, which will be used by all workers in "information infrastructure occupations." Similarly, the Bureau of Census (1997) defines the IT sector as encompassing three types of establishments: (1) those producing and distributing information and cultural products, (2) those providing the means to transmit or distribute these products as well as data or communications, (3) those processing data. In academic journals, authors often consider IT capital as a subset of nonresidential equipment. The Bureau of Economic Analysis (BEA 1998) lists different types of nonresidential producers' durable equipment as seen in Figure 2.1. Based on this classification, researchers have distinguishably considered three measures of IT. The most restrictive definition is "Computers and peripheral equipment." While "Office computing and accounting machinery" (OCAM) might be the most common measure of IT, "information processing equipment" (IPE) offers a broader measure of IT, and is the one I will use in this study.

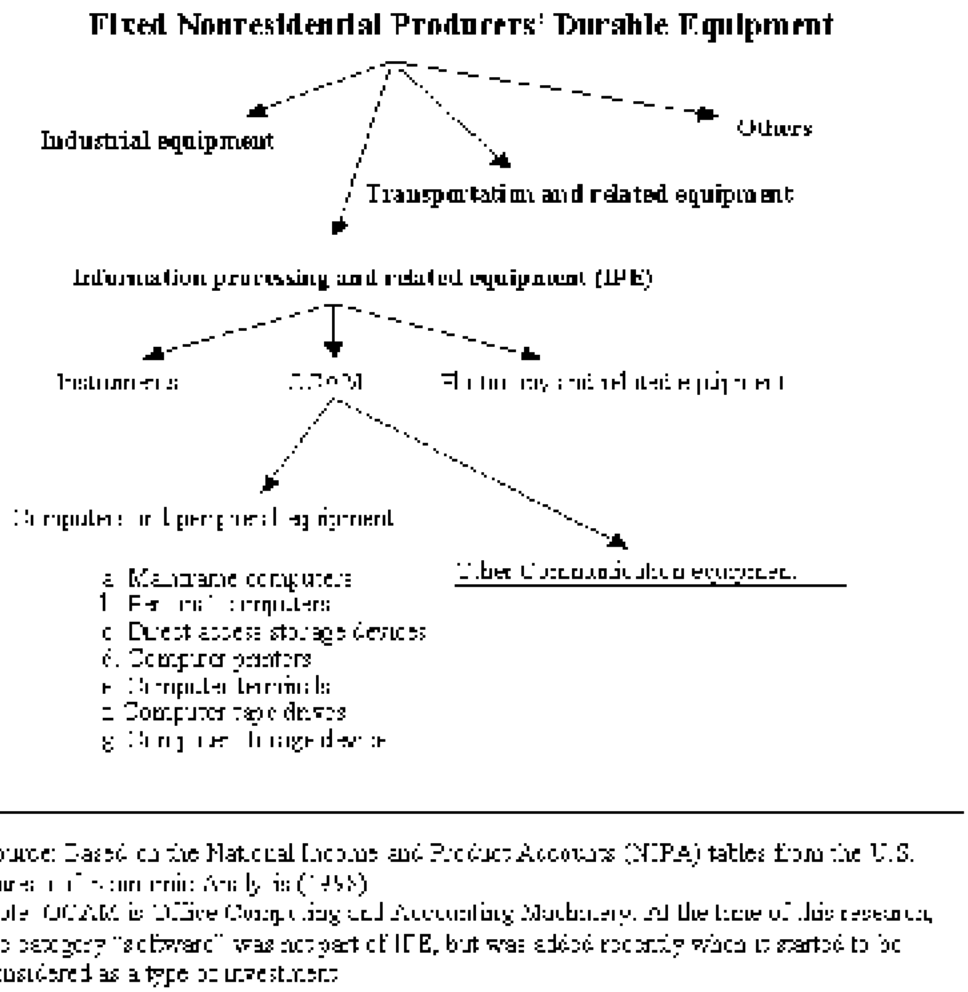


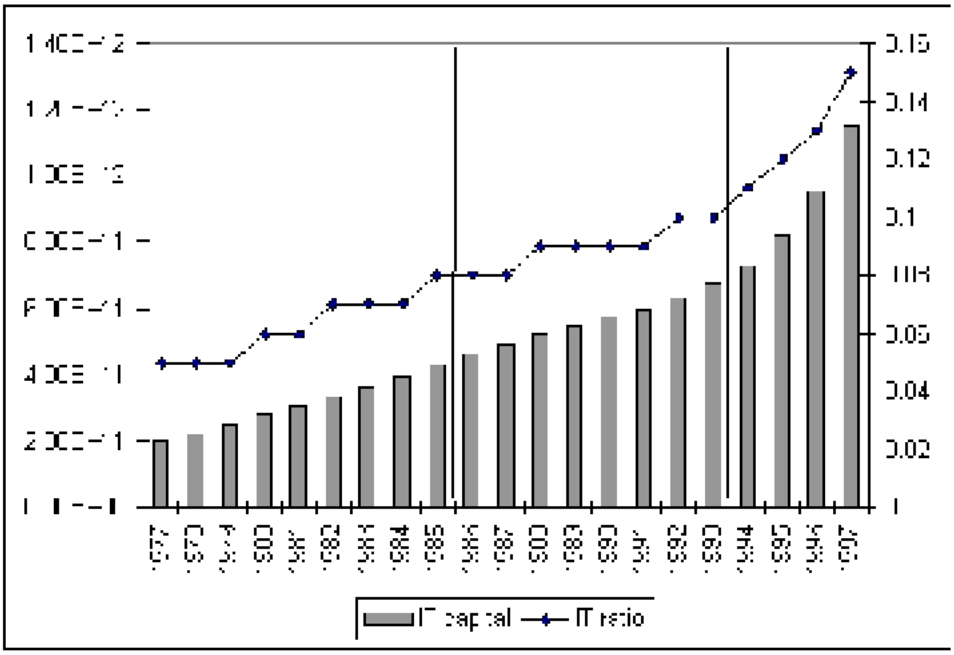
Figure 2.1Distribution of Producers' Durable Equipment

Thus, the concept of information technology is not well defined even though it is widely used today. It refers not only to physical high-tech devices but also to the people who use them for informational purposes. While it is often reduced to computer hardware, this study will use a wider definition for IT as information processing and related equipment.

2.1.1.2Trends in Information Technology Capital Since 1977

The evolution of IT has been well-documented for the last thirty years. Since the 1960s, the density of transistor circuits has increased at a rate of 10% per year. In 1964, Gordon Moore, co-founder of Intel, observed that the density of transistors in semiconductor chips doubled every 18 months. This became known as "Moore's law."

According to a report on information technology from the OECD (1997), between 1987 and 1995 the size of the IT market more than doubled in the United States, increasing from $105 billion to $213 billion in real terms (1995 dollars). Spending on PCs and workstations alone increased from less than $50 billion to more than $130 billion per year between those years. Since the mid-1980s, the number of connections to a network has doubled every year. As a result, the total stock of IT capital in the U.S. economy has more than doubled between 1977 and 1987, and is six times greater in 1997 than in 1977, as shown in Figure 2.2. In comparison, the non-IT capital stock did not even double during the same period. Figure 2.2 also shows the evolution of the IT proportion of total capital (IT ratio), defined as the ratio of IT capital stock to total capital stock. The relative growth of the IT ratio followed the same trend as the absolute level of capital stock trend, confirming a much lower growth in non-IT capital stock.



Source: Based on data from the Bureau of Economic Analysis (BEA). IT capital stock is measured as the net stock of Information Processing Equipment (IPE) in the private nonfarm sector, in real 1992 dollars. IT ratio is the ratio of IT capital stock (IPE) to total capital stock (total fixed nonresidential equipment).

Figure 2.2Trends in Information Technology Capital Stock, Absolute and Relative Levels 1977-1997

Looking at Figure 2.2 there seem to be three distinct sub-periods characterizing the evolution of the IT ratio between 1977 and 1997. The first period runs from 1977 to 1986, with an average annual growth rate of the IT ratio of 6.6%. There seems to be a plateau during the second period 1987-1993, with an average annual growth rate of only 3.3%. The growth in the first two periods seems to follow a linear trend, whereas the third period seems to be characterized by an exponential growth in the share of IT in total capital. The average annual growth rate for this period is 10.5%. A recent article from The Economist (2000) confirms this trend, reporting that spending in IT equipment and software now accounts for about half of all investment by American firms.

In this section, using the BEA's definition of IT capital as information processing equipment, I reported the tremendous growth in this form of capital over the last thirty years. This significant growth is reported in absolute as well as in relative terms (IT ratio). The following section focuses on productivity.

2.1.2Productivity

2.1.2.1What is Productivity?

The concept of productivity is generally well-understood, but there is no unique way to define and measure it. In general, it refers to the ratio of output to input(s) used in the production function of any good or service. Historically, as noted by Norsworthy and Jang (1992), productivity was expressed such as bushels of wheat per acre in agriculture. In Europe, as craftsmen became more numerous, output per worker, per day or per week became common measures of productivity. In the United States, because natural resources were relatively abundant, labor productivity or the marginal product of labor was considered more important.

Unfortunately, there is no single definition of productivity because it involves a complex set of issues. The Bureau of Labor Statistics, the reference source for productivity measures in the United States, defines two distinct measures of productivity: labor productivity and total factor productivity (TFP).

Labor productivity relates output to the labor time used to generate that output. In other words, it is the ratio of output to labor input (hours worked). It is the most commonly used measure of productivity because labor is the dominant cost of production in the economy, and it is also the major part of value added in most industries.

Total factor productivity, which is also called multifactor productivity, refers to the relationship between output and the combined inputs of labor, capital and intermediate purchases. It is a broader measure of productivity because it includes all purchased inputs. It does not measure the efficiency of labor only but of all of the inputs that enter the production process. When output is measured as *value-added*, only capital and labor inputs are considered, and all intermediate inputs are netted out. When output is measured as gross output, then the associated inputs are the factors of production (labor, capital...) and purchased intermediate products (materials, supplies, energy, and other services consumed in the production process). Multifactor productivity has been called "the residual" because it is the change in output that could not be explained by the change in inputs with constant productivity. Because firms are interested in the least-cost combination of inputs, total factor productivity is the concept of most interest for establishments, companies and industries.

2.1.2.2Why Study Productivity?

Productivity is considered as a fundamental economic measure. It is used as an indicator of the wealth of a country because most economists believe it is a critical determinant of the standard of living. It is obvious that producing more output with the same or fewer inputs is a significant source of increasing national product. Over time, developed countries have grown because they were able to produce more, not necessarily by working more, but most importantly by being more productive. Furthermore, labor productivity is a significant determinant of the standard of living because, theoretically, wages are equal to the marginal product of labor, which is closely related to productivity. Output per worker and wages are two measures of productivity, at the average and marginal level, respectively. Holding constant the percentage of the working population as well as hours of labor per worker, it follows that movements in per capita income must follow those in average output per worker. In other words, productivity is a long-term determinant of wages. Firms are willing to pay a wage that is commensurate with labor productivity and as it rises, so does the earning capacity of labor, increasing consumer buying power and, therefore, standard of living. Hence, increasing productivity will increase the standard of living. Conversely, a decrease in the relative growth rate of productivity will eventually lower the standard of living. This could be illustrated by what happened to the United Kingdom at the end of the nineteenth century. This country suffered lower per capita incomes during the extended period when output per worker decreased from 1870 to 1914.

Productivity is also viewed as an inflation indicator since it has an inverse relationship with unit labor cost. If unit labor cost increases for some reason, productivity decreases and inflation occurs through a higher price level. There is also a long-run productivity concept in neoclassical theory, associated with Alfred Marshall’s notions of increasing, constant and diminishing returns in various industries and more recently in various geographical areas.

Even though an increase in productivity growth generally contributes to reducing poverty in a nation, it will not reduce inequalities, because the market mechanism by which gains in productivity are distributed favors those who contributed the most to the increase. Productivity growth is also a necessary condition for a society to provide for its elderly because, without it, the nation would have to cut into the real incomes of the working-age population to prevent a decline in the living standard of the elderly. Moreover, if growth comes from higher productivity in terms of use of inputs, it can contribute to a better environment by producing more output without using more resources. Finally, gains in productivity at the national level are a necessary condition to remain an active player in today’s global competitive environment.

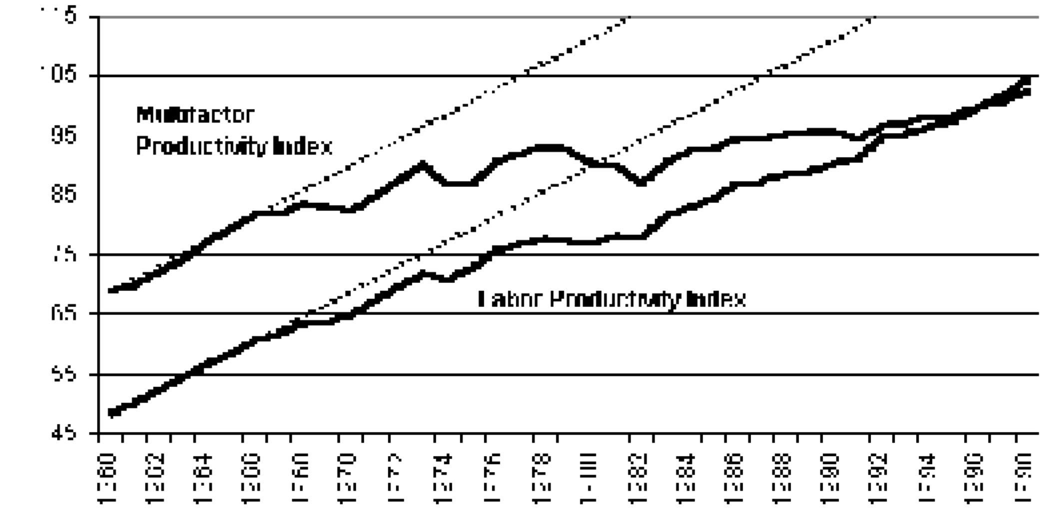
2.1.2.3Productivity Trends Since 1977

Figure 2.3 shows the average annual growth rates of labor productivity for different periods between 1960 and 1998. In the United States, productivity increased at a very high rate during the period between the end of the Second World War and the middle of the 1960s. From 1960 to 1973, the average annual growth rate of labor productivity was around 3%. Since 1973, then, there has been a productivity slowdown. Between 1973 and 1985, this growth rate was around 1.3%. It was around 1.5% on average between 1986 and 1995. Finally, between 1995 and 1998, average labor productivity growth increased to 2.3%. Thus, since 1995 a productivity recovery has appeared. As a matter of fact, productivity growth today has reached its 1960s level of more than 2.5% annually, compared to a mere 1% during the 1980s.

The slowdown in productivity can also be seen in Figure 2.4, which reports the trend in labor and multifactor productivity over the last thirty years. The two doted lines represent the hypothetical trends that these indexes would have followed if they had evolved steadily as they did between 1960 and 1966. The areas between these doted lines and the actual respective trends are visual representations of the productivity slowdown, which seems more important for multifactor productivity.

Source: Based on data from the Bureau of Labor Statistics, Private nonfarm business sector productivity

Figure 2.3Trend in Annual Growth Rates of Labor Productivity, 1960-1998



Source: Based on data from the Bureau of Labor Statistics (Indexes are 1996 based)

Figure 2.4Trends in Labor Productivity and Multifactor Productivity Indexes, 1960-1998

This section has shown that productivity is seen as a major concept in economics because it relates how much was produced with a given quantity of inputs. It is often used as an indicator of the wealth of a nation. Since the late 1960s there has been a significant productivity slowdown, which seems to have been even more dramatic for multifactor productivity compared to labor productivity. These facts will help identify the problem tackled in this study. This is the object of the next section.

2.2Problem Identification

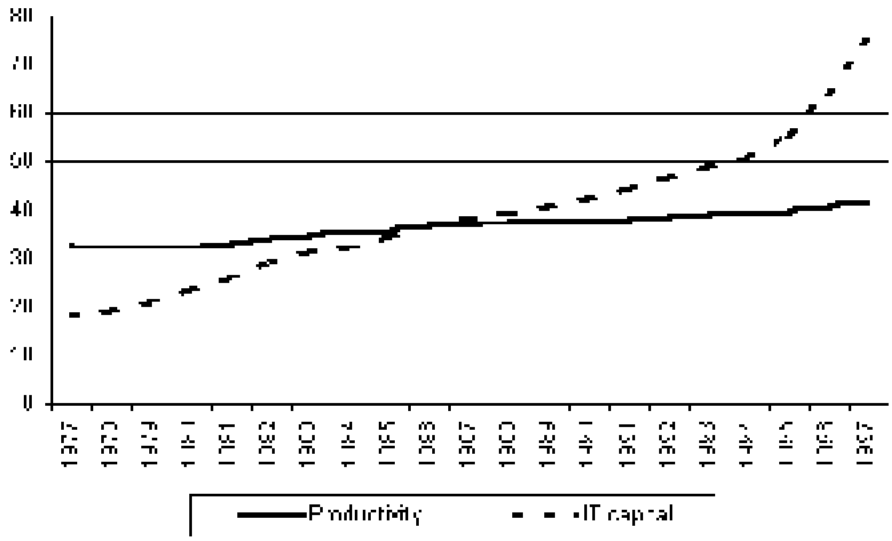
Combining the trends in IT and productivity will bring out a contradictory relationship known as the “productivity paradox.” Also, looking at the unequal distribution of IT across industries and states will raise further concerns. Finally, the parallel growth in IT and income inequality will question their relationships. These stylized facts will help to identify the problem studied in this dissertation.

2.2.1The Productivity Paradox

At the origin of the productivity paradox is a long-standing expectation that computerization will enhance productivity. As Powell (2000) argued:

Personal computers were supposed to make our lives easier by allowing us to complete certain clerical tasks more easily and accurately, and maybe even save a little paper in the process by generating, distributing, and storing documents electronically

Based on this premise, the heavy computerization that has occurred since the mid 1970s should have been accompanied by consequent productivity improvements. During the 1970s and the 1980s, skyrocketing investment in information technology figures were opposed to sluggish labor productivity growth. Hence, some researchers started to believe that computerization might not enhance productivity. Solow (1987) quipped “we can see computers everywhere but in the productivity figures.” This argument was then referred to as the “productivity paradox.” Indeed, Figure 2.5 shows that representing together IT capital and productivity trends exhibits a paradoxical relationship.



Source: Based on data from the Bureau of Economic Analysis (for IT) and the Bureau of Labor Statistics (for productivity). Productivity is measured as the ratio of value added to labor hours (labor productivity). IT capital is measured by the stock of information processing equipment (tens of real 1992 billions of dollars).

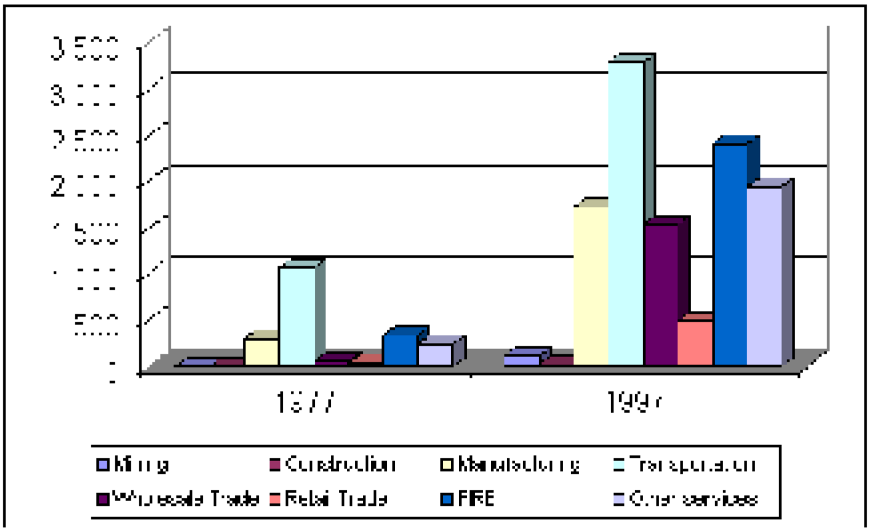
Figure 2.5The productivity paradox: Trends in Labor Productivity and IT Capital Stock, 1977-1997

As seen in Figure 2.5, the stock of IT capital increased tremendously over the period from 1977 to 1997, with an average annual growth rate of 9.25%. Meanwhile, labor productivity was relatively stagnant, with an average annual growth rate of 1.1%. This counter-intuitive fact is the core of the productivity paradox, which raised some important questions about the role of IT in economics. Many authors have attempted to explain the productivity paradox. The next chapter will report their main findings. Nevertheless, this presentation of the productivity paradox hides some important facts: the increase in IT capital was very unequal across industries. States also differ greatly in their stock of IT capital because of different industry mixes. Finally, beyond industrial and spatial differences in IT capital stock, IT growth seems to have paralleled the growth in income inequality. Understanding these issues is the object of the following section.

2.2.2Information Technology and Inequalities

2.2.2.1Inequality across Industries

Figure 2.6 pictures the important increase in the level of IT capital stock in most industry sectors between 1977 and 1997. Between these two years, total private nonfarm IT capital stock grew from less than $2 billion in 1977 to more than $12 billion in 1997. Table 2.1 reports absolute and relative levels of IT across industries, as well as IT ratios, in 1977, 1987 and 1997. The transportation sector alone owned more than half of the total IT capital stock in 1977 (53%), but only 29% in 1997.This relative decrease was due to the tremendous growth of IT capital stock in the wholesale trade sector, going from a $53 million to a $1.5 billion dollars stock and owning 13% of the total IT capital stock in the country in 1997 (only 3% in 1977).



Source: Based on data from the Bureau of Economic Analysis. IT capital stock is net stock of information processing equipment (IPE), in millions of real 1992 dollars.

Figure 2.6Distribution of IT Capital Stock Across Industries in 1977 and 1997

Table 2.1Absolute Levels, Shares and Ratios of IT Capital Stock by industry

Industry	Level of IT			Share of IT			Ratio of IT		
	1977	1987	1997	1977	1987	1997	1977	1987	1997
Mining	1.09	97	107	0	2	1	0	2	3
Construction	2.57	6.7	11.1	0	0	0	0	1	1
Manufacturing	277	757	1720	14	15	15	3	6	12
Transportation	1060	2200	3290	53	45	29	7	12	16
Wholesale Trade	52.7	421	1520	3	9	13	4	16	34
Retail Trade	39.4	118	479	2	2	4	2	3	9
F.I.R.E.	322	811	2400	16	17	21	4	6	13
Services	228	506	1930	12	10	17	7	11	25

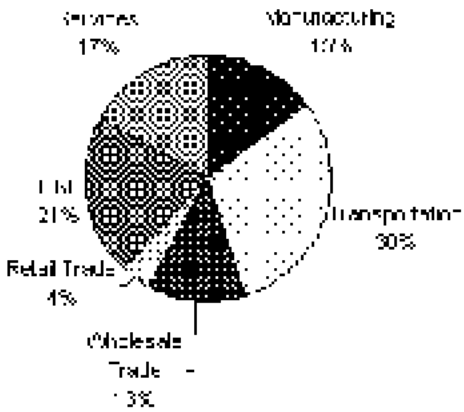
Note: "Levels" represent the absolute value of IT capital stock in 1992 constant million dollars. "Shares" are the industry percent of the aggregate stock of IT, and "ratios" express IT capital stock as a percentage of total capital stock. F.I.R.E. represents Finance, Insurance and Real Estate sector.

Between 1977 and 1997, the service industry[1] held a little more than 80% of total IT equipment in the United States. Most of the remaining share of IT capital stock was in the manufacturing sector. Relative shares of IT capital stock by industries are reported in Figure 2.7. The manufacturing and service shares of IT capital stock remained relatively stable over time (around ¼ and ¾, respectively).

On the other hand, the intensity of IT capital has been very unequal across industries. As stated in section 2.1, the IT ratio is usually low (in 1997, around 15% on average). However, Figure 2.8 shows that this ratio varies greatly across industries. In 1977, transportation was the most IT intensive sector (IT capital was 7% of total capital), followed by service, FIRE, wholesale trade, manufacturing and retail trade, respectively. This ranking changed in 1997, with the transportation sector becoming the third most IT intensive industry. The most impressive growth of IT intensity was observed in the wholesale trade sector, growing from an IT ratio of 4% in 1977 to 34% in 1997.

Thus, industries vary greatly regarding their IT capital stock in absolute level, in shares, and in IT capital intensity. These differences have remained between 1977 and 1997. It appears that sectors that own the highest share of IT capital are also the most IT intensive, with highest IT ratios. Furthermore, because of different industry mixes, U.S. states differ also greatly in their absolute and relative levels of IT capital and IT intensity. This fact is presented in the following section.

[1] The service industry here groups five sectors: transportation, wholesale and retail trade, F.I.R.E. and other services.



Note: Mining and Construction industries omitted because their shares are negligible

Figure 2.7Shares of IT Capital Stock by Industry in 1997

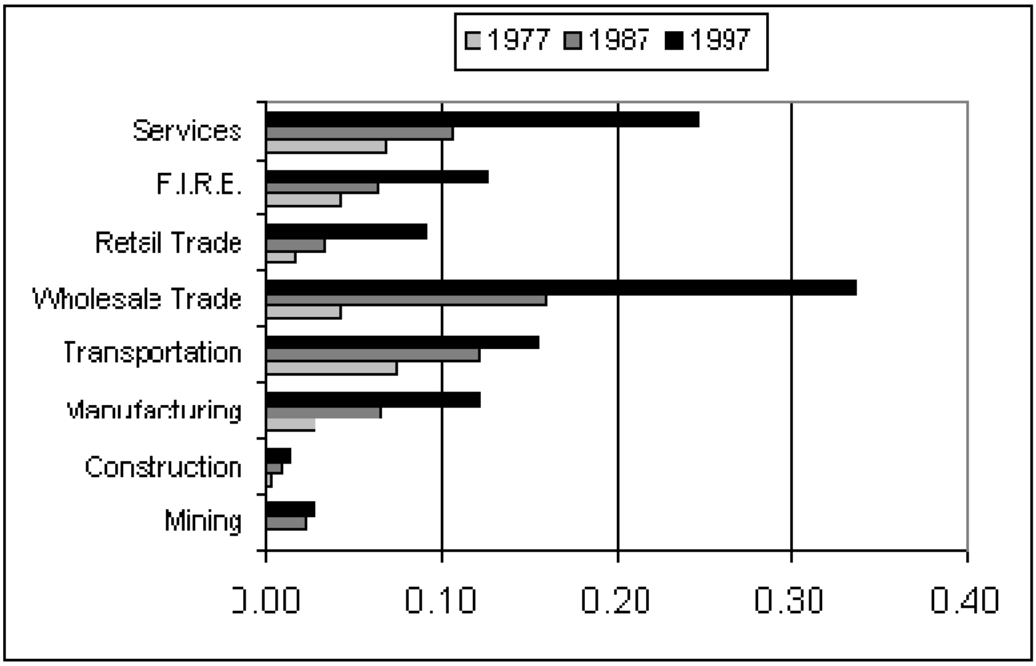


Figure 2.8Ratios of IT Capital to Total Capital (IT Ratios) by Industry in 1977, 1987 and 1997

2.2.2.2Inequality Across States

States differ in their levels of output, capital and labor inputs. By the same token, they differ in their levels, shares and ratios of information technology. More than half of the total IT capital stock is located in only eight states: California, New York, Texas, Illinois, Florida, Pennsylvania, New Jersey and Ohio (Figure 2.9). California has the highest ranking by far, owning 13% of total IT capital stock of the United States in 1997, followed by New York with 9% and Texas with 8%. However, it is only the eighth most IT intensive state with an IT ratio of 9%, behind Washington D.C. (13%) and New York (11%). IT ratios vary between less than 4% and more than 13% as shown in Figure 2.10, but the dispersion is less important than the dispersion of their absolute and relative levels of IT capital.

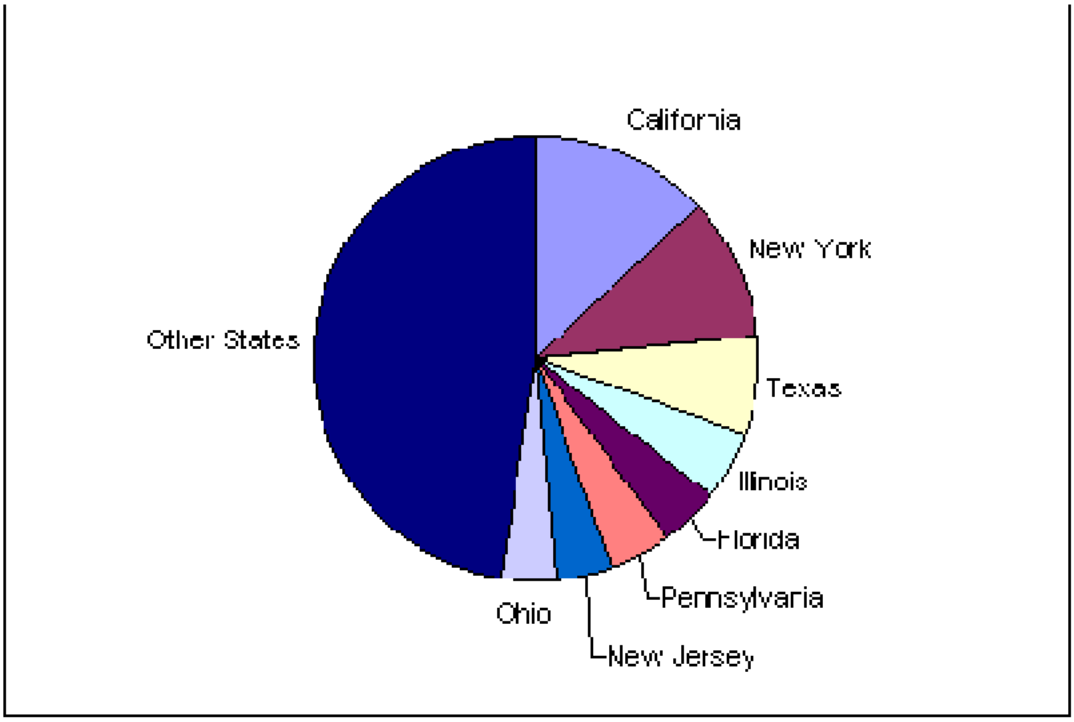


Figure 2.9Distribution of IT Capital Stock Across States in 1987

Figure 2.10Ratios of IT Capital Stock to Total Capital (IT Ratios) by State in 1987

2.2.2.3IT and Income Inequality

Some authors (Krueger (1993), Autor, Katz and Krueger (1998)) have noticed that along with the tremendous increase in information technology in the United States there took place an alarming increase of income inequality. Indeed, as shown in Figure 2.11, IT accumulation, since the mid 1970s, has paralleled income inequality growth as measured by the Gini coefficient. This fact made researchers wonder about the relationships between high information technology and income inequality. Is it possible that the “new economy” generates higher inequality in income? Figure 2.12, which scatter plots Gini coefficients and IT capital stock at the national level, tends to support this view. Thus, a higher level of IT capital in the United States appears to have been compensated by a higher level of income inequality. However, Figure 2.13 shows that this relationship is less obvious at the state level. Note that a state with a high level of IT capital does not necessarily exhibit higher income inequality. Still, this relationship deserves to be further analyzed.

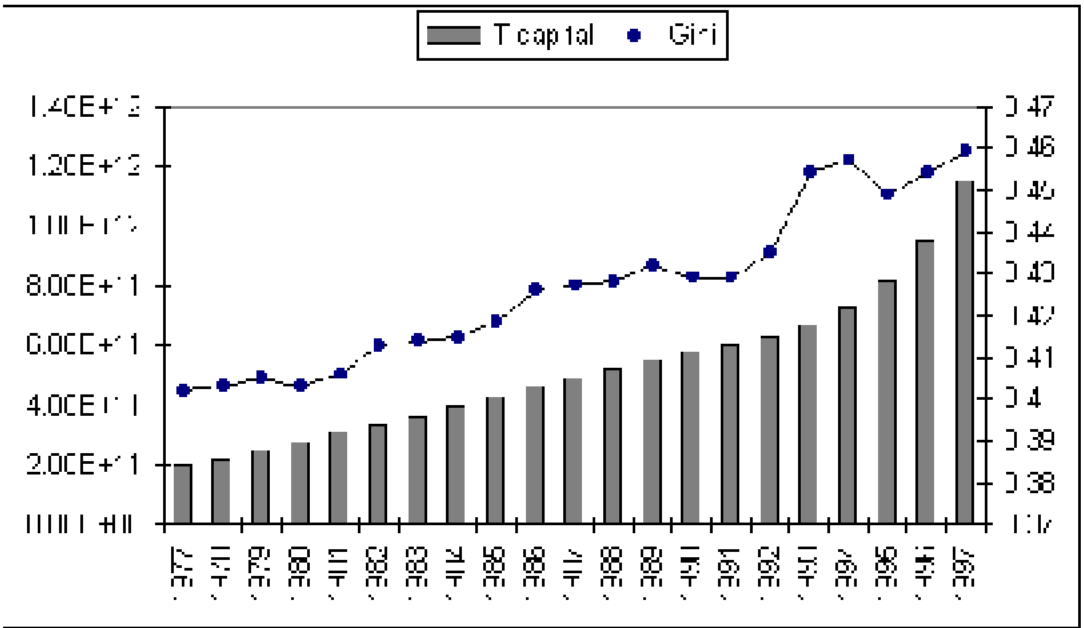
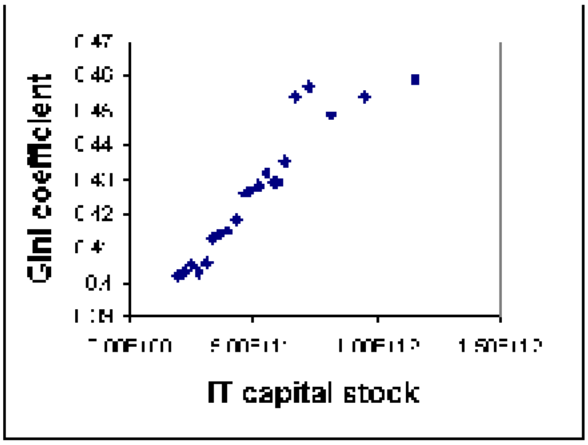
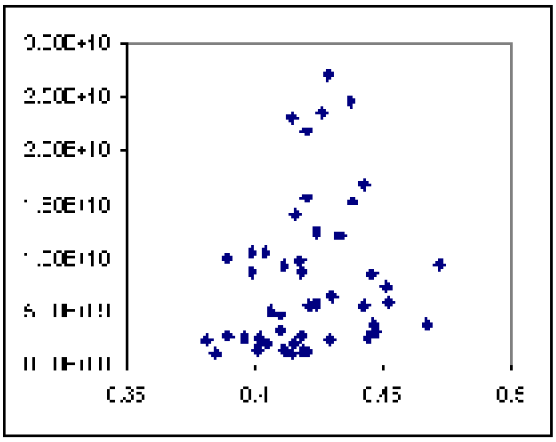


Figure 2.11Trends in Gini Coefficients and IT Capital Stock, 1977-1997



Source: Based on data on Gini coefficients from the U.S. Bureau of Census, IT capital stock from the Bureau of Economic Analysis.

Figure 2.12Scatter Plot of National Gini Coefficients and IT Capital Stock, 1977-1997



Source: states' Gini coefficients are taken from Laura Langer (1999) based on data from the U.S. Bureau of Census.

Figure 2.13Scatter Plot of States' Gini Coefficients and IT Capital Stocks in 1990

After reporting some stylized facts about information technology in the United States, some questions arise about the relationships between IT and productivity, as well as various sorts of inequality. The next section summarizes these issues and states the purpose of this dissertation.

2.3Purpose of the Study

The previous sections revealed several issues related to the role of information technology in the United States. They can be grouped into three distinct issues: the productivity paradox, the spatial dimension of IT and the relationship between IT and income inequality. Here are some interesting questions related to the issues: How can we explain the productivity paradox? Do computers and other IT equipment really enhance productivity? If so, then how do they do it, *i.e.* what is the mechanism by which IT affects productivity? Are the returns to IT capital higher than the returns to “traditional” capital? What is the contribution of IT capital growth to output and productivity growth? Is the productivity paradox only a concern at the aggregated national level? Are the relationships between IT and productivity also paradoxical at the industry level? In particular, are there differences in the returns to IT capital among industries that could partially explain the national paradox? At the state level, are there differences in the returns to IT capital across states that could also explain the national paradox? These are the questions being addressed in the first part of this dissertation (chapters 3, 4 and 5). Its purpose is to shed some light on the productivity paradox debate. In order to do so, I will build a dataset disaggregated at the detailed industries level by state, and analyze econometrically the relationships between IT capital stock and productivity. I will base my analysis on the framework constructed by Lehr and Lichtenberg (1999). I expect to find a positive and significant contribution of IT capital to productivity growth across industries and states. I intend to show why the aggregation at the national level has led to a paradox.

The second part is aimed at answering questions about the spatial aspect of information technology in the United States. For instance, why do the returns to IT capital differ across states? How to evaluate the externality effects associated with employment location? Are the agglomeration or congestion effects important? What is the role of the density of IT (namely the number of IT employees by county)? Does the location of IT activity affect productvitity? I intend to answer these questions based on my dataset at the county level in the United States. My work is inspired by the study of Hall and Ciccone (1996) who analyzed the effects of the density of economic activity on productivity.

Finally, I will focus on the ambiguous relationships between information technology and income inequality. Have computers and other information technology increased inequality? If so, by which mechanism has this occurred? What are the variables affecting income inequality? Is there a positive and significant relationship between the information technology intensity in a given state and its level of income inequality? To answer these questions, I will use an original framework based on the regressions of states Gini coefficients on different independent variables representing the importance of IT in that state (such as the level and intensity of IT capital stock).

Each of these three essays presents the same structure composed of three levels. A first chapter (3, 6 and 9) discusses the literature relevant to the subject and previous findings. A second chapter (4, 7 and 10) describes the methodology adopted to tackle the problem: which model(s) will be used? What variables? How the dataset is constructed? Then, a final chapter (5, 8 and 11) presents the results and discusses the outcomes. Finally, chapter 12 will summarize and interpret the main findings of this study, indicate fruitful directions for future research and conclude the dissertation.

CHAPTER 3 - LITERATURE SURVEY: INFORMATION TECHNOLOGY AND PRODUCTIVITY

This chapter surveys the literature on the relationship between information technology and productivity. The first section starts with a description of the conceptual grounding used to analyze the productive effects of information technology capital. This framework is mostly due to Sichel (1997). Section 3.2 summarizes the different theoretical explanations of the productivity paradox. Finally, section 3.3 describes some of the main empirical studies attempting to quantify the effects of IT capital on output and productivity growth.

3.1Conceptual Grounding

Following Sichel (1997), a supply and demand analysis framework is used to quantify the relationships between IT capital and productivity. The goal of this analysis is to measure the output and productivity growth contribution of IT. Then, a production function empirical framework is presented. It allows the measurement of the productive capacity of IT using basic econometric techniques.

3.1.1A Supply and Demand Analysis of IT and Productivity

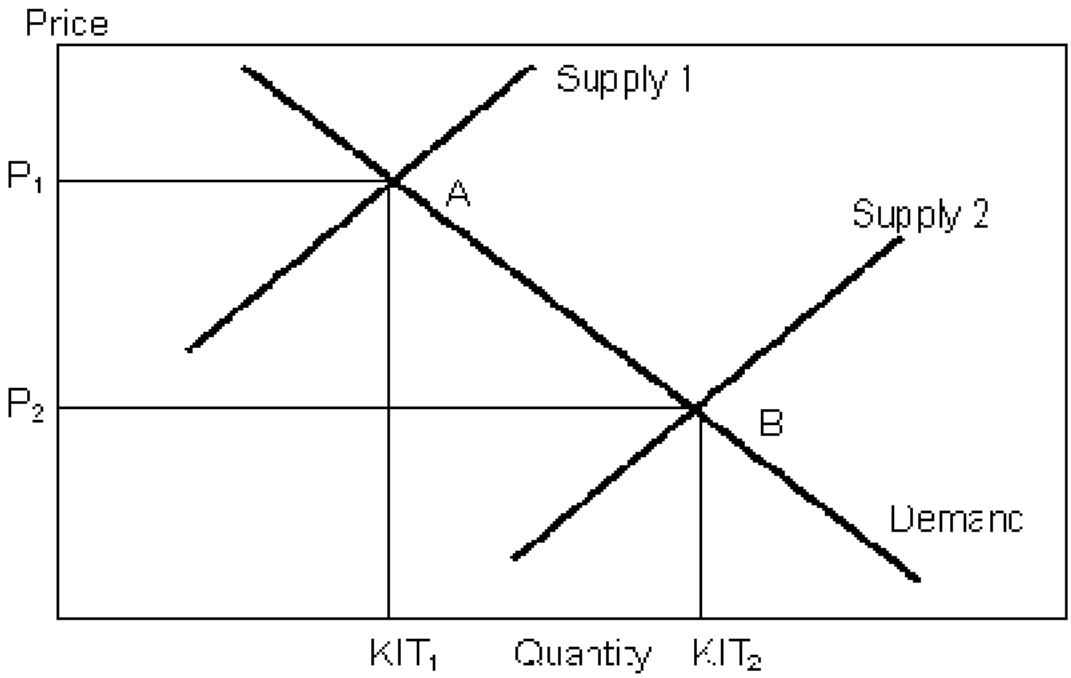
At the core of the infamous productivity paradox is the assumption that computers and information technologies in general must have visible effects on productivity. Berndt and Malone (1995) described this common belief:

From the simple observation that computers can do certain kinds of things much faster and less expensively than individual people can, it is a natural leap to assume that replacing selected employees of a business with computers will greatly increase the speed and reduce the costs of certain business activities.

Thus, in the early 1980s people were buying computers expecting important productivity gains. Berndt and Malone believed these gains were visible until the late 1980s when the productivity paradox was revealed. How is it possible for information technology equipment to affect productivity?

Using a neoclassical supply and demand analysis approach, Denison (1985, 1989) pioneered an original framework for assessing the role of information technology in economic growth. Sichel (1997) developed this analytical framework, which helps understand why productivity growth has remained sluggish while information technologies were booming. Note that in Sichel's analysis, "computer hardware" only is considered when measuring IT capital, whereas this study considers the broader category information processing equipment. Hence, I will alternatively use the word "computers" for "information technology." Sichel also distinguished two sectors in the economy: the computer-producing sector and the computer-using sector. He argued that the large increase in computer spending over the last twenty years was mainly driven by a considerable price decline that resulted from important productivity gains in the computer-producing sector. These gains were the results of dramatic technological progress, mainly in the manufacture of computer components. The supply-driven price drop caused real investment in computers to increase every year, as illustrated in the simple supply and demand framework in Figure 3.1.

In a neoclassical world, economic agents always make optimal investment decisions and all types of capital earn the same marginal return. After comparing returns on investment and costs of capital, firms stop buying computers at point A where the economy is in equilibrium. Now suppose technological progress in the computer producing sector shifts the supply curve from S_1 to S_2. The price of computers drops from P_1 to P_2. Then, the cost of computer capital is less than its return and firms invest. Hence, the quantity of computers increases from KIT_1 to KIT_2. As a result, the equilibrium point shifts from A to B. The question is how and by how much this increase in computers will affect output growth?



Source: Sichel (1997)

Figure 3.1Supply and Demand Framework for Computers

In the neoclassical framework, suppose computers earn a competitive return r_{COMP}. Let ΔKIT represent the change in the capital stock of computers from one year to the next ($KIT_2 - KIT_1$). The neoclassical boost to the level of output from computers only is the product of the change in the stock of computers and the competitive return to computers. If Y_1 and Y_2 denote output levels at time *t-1* and *t*, respectively, then

$Y_2 - Y_1 = r_{COMP}\, \Delta KIT$(3.1)

If output *Y* and capital input *K* are measured in real quantities and depreciation affects the return to computers then

$Y_2 - Y_1 = [(r_{COMP} + d)\, (P_{KIT} / P_Y)]\, \Delta KIT$(3.2)

Where *d* is the rate of depreciation, P_{KIT} and P_Y express the respective price index of IT capital and output. This is an expression of the increase in real output due to an increase in IT capital input. Sichel then divided both sides by Y_1 and multiplied the right-hand side by KIT_1 / KIT_1, which led to

$(Y_2 - Y_1)\, /Y_1 = [(r_{COMP} + d)\, (P_{KIT} / P_Y)\, (KIT_1 / Y_1)]\, (\Delta KIT / KIT_1)$

 gr $(Y_1) = [(r_{COMP} + d)\, (P_{KIT}\, KIT) / (P_Y\, Y)]$ gr(KIT) (3.3)

where gr(.) represents the growth rate of the variable in parenthesis and $P_{KIT}\, KIT$ is the nominal stock of IT capital, which earns a return of $r_{COMP} + d$. The product of these terms yields the total income flow generated by IT capital. Dividing this term by total income gives the share of income generated by IT capital, s_{IT} such as

$gr(Y_1) = s_{IT}\, gr(KIT)$(3.4)

where s_{IT} is (in nominal terms)

$s_{IT} = [(r_{COMP} + d)\, KIT] / Y$(3.5)

A decline in computer price leads to higher computer investment, which induces growth in output as seen in equation 3.4. Another way to measure the impact of the growth in IT capital on output growth is discussed next.

3.1.2A General Empirical Framework for Measuring the Returns to IT capital

As stated by Brynjolfsson and Hitt (1995), most of the empirical literature on IT and productivity has used a production function framework to econometrically estimate the effects of IT capital on output and productivity. In general, the theory of production states that firms transform inputs (*Z*) into output (*Y*) via a production function (F), with embodied technical progress

$Y = A\, F(Z)$(3.6)

where *A* represents the Solow residual, which captures the effects on output not explained by the explicit use of inputs (e.g., capital and labor). To estimate the specific effects of IT capital input on output, many authors have separated total capital into IT capital (*KIT*) and traditional or "non-IT capital" (*KNIT*). If *L* denotes labor input[2], then

$Y = F(KIT, KNIT, L)$(3.7)

A conventional form of the production function is Cobb-Douglas. Brynjolfsson and Hitt (1995) have shown that the use of a less restrictive translog production function does not significantly change estimates of IT elasticity and marginal product. Thus, the following Cobb-Douglas production function is frequently used in the literature

$Y = A.KNIT^{\alpha 0}\, KIT^{\alpha 1}\, L^{\beta}$(3.8)

where α_0, α_1 and β represent the output elasticities of traditional and IT capital and labor hours, respectively. Hence, α_1 is also the marginal product of IT capital, which represents the percent change in output due to a 1% change in IT capital input. Taking logarithms and adding an error term (ε), the econometric form of (3.8) is

$\ln(Y) = \ln(A) + \alpha_0 \ln(KNIT) + \alpha_1 \ln(KIT) + \beta \ln(L) + \varepsilon$(3.9)

Using national, industry or firm specific datasets, authors have been able to empirically estimate the parameters of this equation (α_0, α_1 and β). To determine the effect of IT capital on productivity, both sides of equation 3.8 are divided by *L*, assuming constant returns to scale ($\alpha_0 + \alpha_1 + \beta = 1$):

$\ln(Y/L)$ □ $TFP + \alpha_0 \ln(KNIT/L) + \alpha_1 \ln(KIT/L)$(3.10)

where TFP stands for Total Factor Productivity. Thus, information technology capital

[2] Labor input (*L*) can also be separated into IT labor (*LIT*) and traditional labor (*LNIT*) as done by Lichtenberg (1995) and discussed later.

can boost labor productivity in three ways: (1) accumulating IT capital, which increases capital deepening (K/L,) (2) increasing TFP in the computer-producing sector, (3) increasing TFP in the computer-using sector. Later in this chapter I will describe some empirical studies that have adopted this way of measuring the return to IT capital.

This framework is very simple for the sake of clarity. Various authors have considered different extensions. For instance, computers might earn a "supernatural" rate of return, which will increase the contribution of computers to output growth even if the share of computers is small. Furthermore, the social return to computers might be greater than the private return because of externalities associated with investment in information technology such as knowledge spillovers. Assuming these spillovers are greater when IT activity is denser, I will investigate this hypothesis in the second part of this dissertation (chapters 6,7 and 8). I will then measure the impact of the density of information technology on labor productivity at the county and state levels. In the next section I discuss the different theoretical explanations of the productivity paradox.

3.2Theoretical Answers to the Productivity Paradox

Since Solow's famous quip questioning the productive capacity of computers, authors have expended considerable efforts scrutinizing the relationships between information technologies in general and different measures of productivity. Basically, the productivity paradox debate divides the advocates and the opponents of the "new economy," which is driven by a technological revolution born from the fusion of computing and communication technologies. From the literature originating over this debate, six main hypotheses have been isolated as potential explanations for the productivity paradox: (1) mismeasurement, (2) long learning lags, (3) mismanagement, (4) complementarity, (5) redistribution and (6) small income share. Table 3.1 classifies the literature according to authors' sensitivity to these hypotheses. This section briefly describes each of these arguments.

3.2.1Mismeasurement

The mismeasurement hypothesis can be interpreted as the idea that gains in productivity were not visible because not measured properly by national agencies. Indeed, as stated in section 2.1.2, productivity is a major concept in economics, but is also a very difficult one to measure. This is particularly true in the "information economy" where inputs and outputs are more intangible than in the "industrial economy." Brynjolfsson and Hitt (1998) interestingly noted that

While we have more raw data today on all sorts of inputs and outputs than ever before, productivity in the information economy has proven harder to measure than it ever was in the industrial economy.

Table 3.1Classification of Theoretical Literature on the Productivity paradox by Hypothesized Explanation

Hypothesis	Authors
Mismeasurement	Griliches (1994)- Baily and Gordon (1988) - Ives (1994) - Brynjolfsson and Hitt (1993) - Brynjolfsson, Hitt (1998)
Long learning lags	David (1990) - Greenwood (1999) - Powell (2000) – Brynjolfsson and Hitt (1993) - Roach (1998)
Mismanagement	Chapman (1996) - Powell (2000) - Pentland (1989) – Roach (1998)
Complementarity	Bowen (1986) - Brynjolfsson & Hitt (1995) - Chapman (1996)
Redistribution	Jorgenson, Stiroh (1999) - Brynjolfsson and Hitt (1993) – Gordon (1999)
Small share	Oliner, Sichel (1994, 2000)

Ives (1994) reports the weaknesses of the economy-wide productivity data produced by the Bureau of Labor Statistics. Supporters of the paradox often relied upon these data. However, according to Ives (1994), U.S. government productivity data are not available for 58% of service industries, and are suspect in others. As a matter of fact, in education, health care, government and financial services productivity is often arbitrarily set to one (output to input) because of measurement difficulties.

Apart from the quality of the *process* measuring productivity is the questioning of the *nature* of productivity and its appropriateness to reflect gains from IT capital. Information technology deals with intangible materials such as knowledge and communication of knowledge. Thus, it might be difficult to measure the productivity benefits of intangible capital with tools made for older tangible inputs. In other words, the gains from IT might be represented as greater quality, convenience, reliability, timeliness, safety, flexibility, and variety, which is hard to measure. To illustrate this point, Ives noticed that a supplier's order entry system is able to automatically replenish a retailer's depleting shelves based on scanner data, but this quality improvement is not necessarily reported in productivity figures.

In the same fashion, Brynjolfsson and Hitt (1998) argued that productivity is becoming difficult to measure in the information economy, because of the change in the very nature of output and inputs. On one hand, output is becoming hard to measure because value depends today more and more on product quality, timeliness, customization, convenience, variety and other intangibles. On the other hand, as stated by Brynjolfsson and Hitt (1998), to measure properly inputs one should include

(...) not only labor hours, but also the quantity and quality of capital equipment used, materials and other resources consumed, worker training and education, even the amount of organizational capital, such as supplier relationships cultivated and investments in new business processes

Finally, new products such as software or ATMs have appeared with the booming of information technology. Until recently, these were not accounted for by national statistics agencies in their measurement of output, underestimating productivity growth. For instance, BEA started counting software as an output only in 1998, after considering it as an intermediate product for a long time. Another argument reinforcing the mismeasurement hypothesis is that roughly 80% of IT capital is located in service industries, where output is most difficult to measure because of its intangible aspect. Thus, new techniques for measuring productivity should be adopted, as stated by Brynjolfsson and Hitt (1993)

Just as some managers look beyond "productivity" for some of the benefits of IT, some researchers must be prepared to look beyond conventional productivity measurement techniques.

Therefore, if benefits from IT capital are not measured properly, the return to IT capital would be understated, explaining in part the productivity paradox. Another argument deals with the long learning lags associated with the introduction of new technologies.

3.2.2Long Learning Lags

This argument is mainly due to David (1990). It states that it takes time for technological revolutions to produce significant effects as reported by traditional macroeconomic indicators. For instance, David showed that productivity growth did not accelerate until forty years after the introduction of electric power in the early 1880s. Part of the reason is that it took until 1920 for at least half of American industrial machinery to be powered by electricity. This was also the time needed to re-organize businesses around electric power. David argued a technology starts to have significant effects only when it has reached 50% penetration rate. The Economist (2000) suggested that this level of diffusion was reached only recently for IT capital in the United States. In fact, labor productivity has increased to an annual average 2.9% since 1996, from 1.4% on average between 1975 and 1995. In the second quarter of the year 2000 this rate was estimated at 5.2%. These facts tend to support this long learning lags hypothesis. Thus, because it takes time for new technologies to produce visible aggregate effects, comparing current costs with current benefits might not show high returns to IT investment. Brynjolfsson and Hitt (1993) gave a numerical example, starting by assuming it would take thirty years for IT capital stock to represent 100% of the current level of gross national product (GNP). Then, if returns to investment in IT are 20%, then GNP should increase by 20% over thirty years, which means only 0.06% a year.

Furthermore, rapid technical progress in the computer-producing industry makes information technologies change rapidly. IT-users have to upgrade constantly not only their equipment but also their skills at the same time. Not only computers do things faster they also do it in different ways that are constantly evolving. It takes time to learn new techniques. Indeed, a commercial for a famous computer brand states that the average user exploits only 30% of computers' capabilities. One reason for this "under utilization" may be the difficulties for users to understand the language and communicate with their computers, and the time needed to receive benefits from the use of information technologies fully.

On the other hand, using computers is becoming easier. For instance, the Windows-type operating system certainly facilitated the use of computers compared to the previous DOS-type system. Similarly, Internet editing software avoids the use of the complicated HTML language. Hence, over time, it becomes easier to exploit new technologies. However, computers might remain relatively complicated to use for a large part of the labor force. Long learning lags are then necessary for improvements made by computers and information technology to appear in national productivity statistics. Depicting a brighter picture for the future, Powell (2000) argued:

Today's college students were born at the same time as PCs, and they'll enter the workforce having grown up with them as part of their landscape. For them, there's no transition to computer technology. It's always been there and they've always used it. In the hands of a generation for whom computer technology is less of a novelty and more of a given, and who have no outdated work habits to break, the promise of computerized productivity can finally be realized.

Economists have observed that the adoption of new technologies is usually slow. According to Greenwood (1999) it is regulated by two interrelated factors that form a feedback loop: the speed of learning and the speed of diffusion. On one hand, the harder it is for users to learn about a new technology, the slower its diffusion. On the other hand, the faster its diffusion, the easier it may be to learn about it. This may be a reason for some of today's new marketing techniques. A few years ago, to prevent espionage, manufactures would keep an innovation secret until the date it was first publicly sold. New technologies are now introduced to the public with commercials and samples before they even are officially sold (DVD copiers for instance). Apart from marketing strategies, manufactures may want to test the market and get early feedback from potential consumers in order to refine the new product, which will then be able to diffuse more rapidly, and therefore produce benefits faster.

Price decline is also the engine of diffusion. At the beginning, a new technology needs enormous investments before it can be sold to the public. Its price is therefore very high. But, over time, manufactures learn how to produce more efficiently and begin to achieve economies of scale. In addition, new competitors start entering the market. All these factors drive the price of the new technology down, accelerating its diffusion at the same time. Still, Roach (1998), a productivity paradox advocate, emphasized the differences between previous revolutions and the breakthrough in IT capital. Previous innovations were made for tangible goods whereas computers are dealing with intangible output. The comparison with past technological revolutions should therefore be made cautiously.

Thus, the long learning lags hypothesis seems to be a valid explanation for the productivity paradox, supported by the fact that most authors now seem to agree that IT capital has proven its productive capacity since the late 1990s. Still, another argument explaining the productivity paradox refers to the mismanagement of information technologies.

3.2.3Mismanagement

This hypothesis suggests that the true cost of information technology capital is higher than the market price (P_1 in Figure 3.1). For instance, there are hidden costs associated with the purchase of a computer. When managers make investment decisions, they may not account for these costs. Hence, the true marginal cost of a computer is actually higher than the expected return to investment, making the return to computer investment lower than the competitive rate. This partly explains why computers may appear “unproductive.”

These hidden costs are numerous. For instance, Chapman (1996) cited a study from Software Business Technology Accounting Systems of San Rafael California. It showed that workers spend on average 5.1 hours per week “futzing” with their computer. The term “futzing” refers to trivial actions such as loading or changing software, organizing the hard disk, tweaking the interface or trying out new features of the computer. This study estimated the actual price of hardware and software equipment to represent only 21% of the true cost, which is evaluated at $13,000. Hidden costs are mostly due to administration, technical support, and “futzing.”

Powell (2000) also mentioned the importance of “futzing.” He noticed that frequent computer crashes often forced employees to do the work twice. Powell (2000) also considered that computers were often used for trivial and unnecessary tasks:

It’s been said of the guillotine that once such an efficient method of execution was devised, it seemed to demand victims. There seems to be a similar implied imperative in the office that computers be used as much as possible to justify their expense. Instead of using computers to do the same amount of work in less time, we use them to do more work in the same amount of time. [...] Rather than simply using computers to generate, store, access, and manipulate the data we actually need, we use them to generate more data than we can possibly digest, simply because we can.

It is important to mention other typical wastes of time due to information technologies, such as is playing games on computers (originally made for getting familiar with using the mouse), checking e-mail or surfing the Internet. This activity has been well-reported through different computer use surveys from the Bureau of Census, although it remains difficult to measure.

A study from Pentland (1989) surveyed the effects of recent use of laptops by 1,000 U.S. Internal Revenue Agents. Pentland found that the time spent to complete a tax audit actually increased, even if agents’ self esteem improved because they felt more professional using a laptop. Roach (1998) sustained that information technology indeed made employees working longer, and productivity gains come not from working longer but delivering more value-added per hour of work. In fact, longer hours of work are typical in the service sector. Then, if it is true that output is underestimated by measurement techniques (mismeasurement hypothesis), labor hours input is also underestimated and therefore the ratio of those two variables, which defines productivity, should not be underestimated. Therefore Roach, sustaining the productivity paradox, estimated that two hypotheses attempting to explain the productivity paradox (mismeasurment and mismanagement) actually cancel one another out. The next section describes the hypothesis of complementarity, which underscores the necessity of efficient work organization internal to the firm using IT.

3.2.4Complementarity of IT Capital and Work Reorganization

In the 1980s, Bowen (1986) proposed that, ideally, firms should invest in new IT equipment only after they have reorganized their work practices. He believed payoffs from IT would not come from doing old tasks more efficiently, but from changing the way things are done by reorganizing the work process around IT equipment. If, indeed, information technology helps doing things faster, it could also do the wrong thing faster.

Along these lines, Brynjolfsson and Hitt (1995) argued: "cutting-edge computer shops can provide ingredients needed to increase productivity," but only if "they are aligned properly with the company's strategy and organizational structure." To illustrate this matter, the authors noticed that before 1995, *InformationWeek* used to report the big spenders in IT, the ones that were using the latest technology. After 1995, the rankings considered their performance as well, and the top companies were the ones that combined computers with new strategies and structures to generate more wealth than their competitors. Using a small sample of top and bottom companies, Brynjolfsson and Hitt found that firms that were investing in IT for customer-oriented reasons did better than the ones worried about savings and management controls. For instance, Wal-Mart and K-Mart both used high-technology systems to get information by satellite about their sales in each of their stores nationwide. However, K-Mart centralized this information and gave it to their decision makers, whereas Wal-Mart left the decision making power to local store managers so that they could match local competitors. Even if a company is customer-oriented, decentralized and reorganized to take advantage of IT, it might still do badly "if it does not have an ear for customers' desires and a nose for technology's capabilities that can't be reduced to a financial statement or a checklist," as stated by Brynjolfsson and Hitt.

Chapman (1996) called this hypothesis the "complementarity condition," meaning investment in IT "needs to be accompanied by a rethinking of the job process, employees' role, and organizational hierarchy." Indeed managers had to reorganize working methods to use IT capabilities more efficiently, instead of simply computerizing traditional methods.

3.2.5Redistribution

This hypothesis proposes that information technology capital is vulnerable to rent dissipation, as stated by Brynjolfsson and Hitt (1993) who argued "information technology capital rearranges the shares of the pie without making it bigger." In other words, if IT capital is indeed beneficial to individual firms, it may not be so for the whole industry or economy. Because competition is fierce in the chase for information technologies, there are no winners without losers. Since IT might only redistribute wealth, the effects of information technology on output growth would be negligible because they cancel out.

Jorgenson and Stiroh (1999) gave an original explanation to the productivity paradox. According to them, computers should not have had any impact on TFP growth (technical change), but only a substitution effect.

Under standard assumptions of diminishing marginal products and decreasing marginal utility, a fall in the price of an input or a consumption good will lead to substitution toward the relatively cheap input or consumption good.

According to BEA and as widely accepted, the constant quality price decline in computers has been dramatic. Consequently, businesses and households have massively substituted toward IT equipment, but no substantial growth in TFP has been reported in the 1990s (a decline was even reported).

Even if indeed information technologies have made a significant contribution to growth over the last two decades, external factors such as fierce global competition may have forced productivity gains to remain sluggish. Without the massive investment in information technology, national productivity figures would have been even more dramatic. This argument is also called the offsetting factors hypothesis.

3.2.6 Small Share of Computer Capital

Oliner and Sichel (1994) have shown that the small share of IT capital to total capital (IT ratio) was a reason why effects from IT on productivity have been so negligible. The authors estimated the contribution of computer equipment capital to output growth, using the neoclassical framework previously described in section 3.1.1. As stated in equation 3.4, the contribution of any input to output growth is measured as the product of this input's nominal income share and the growth rate of its nominal net stock.

First, computer income share is estimated using equation 3.5. Sichel (1997) considered the following values for 1992:

- r_{COMP}, the competitive rate of return to all nonresidential equipment and structures, is 12% as calculated by the Bureau of Labor Statistics
- *d*, the rate of depreciation for computers is estimated at 25%, based on data from the Bureau of Economic Analysis.
- *KIT*, the nominal stock of computers and peripheral equipment was $95.9 billion in 1992.
- *Y*, total nominal income in 1992 was $4,494.4 billion.

Hence, computers had a very small income share of 0.8 % in 1992. Finally, price decline in computer equipment may have lower marginal returns to IT investment, thus reducing the income share of IT capital. As a matter of fact, the drop in computer price was spectacular over the last three decades, as noted by Brynjolfsson and Yang (1996):

The price of computing has dropped by half every 2-3 years. If progress in the rest of the economy had matched progress in the computer sector, a Cadillac would cost $4.98, while ten minutes of labor would buy a year's worth of

groceries.

As the price of computers falls, firms will buy them and use them for tasks with lower payoffs that were not profitable with the higher price. In other words, firms will invest in computers until the marginal product from an additional computer just equals its marginal cost. If the price of computers drops, companies can then invest in additional computers that have a lower marginal product. Pioneer computers of the 1960s cost millions of dollars, but they were used for high-level applications such as space programs, whereas today's computers are used for more trivial tasks such as scheduling meetings, surfing the Internet or typing reports. Therefore Sichel (1997) argued:

Thus, when one considers how much more computing power a dollar buys today than some years ago, one must remember that today's marginal computer dollar may be going to a lower payoff activity and to a machine that is less heavily utilized.

After reviewing the different theoretical explanations of the productivity paradox, the literature survey continues with the description of some of the main empirical studies measuring the effects of IT capital on productivity.

3.3Empirical Studies

This section reports the main findings of several empirical studies measuring the impact of information technology on productivity. First, I focus on the literature questioning the productive capacity of IT and the possibility of excess returns to IT capital investment. Then, I report the results from various studies measuring the contribution of IT to output and productivity growth.

3.3.1Returns to Information Technology

In the basic framework described in section 3.1, authors often measured the return to IT with r_{COMP}. It can be interpreted as the output elasticity or marginal product of IT capital. If this return is significantly greater than zero, then IT is a productive resource. Findings in the previous literature vary from – 20% to +68%.

Morrison and Berndt (1991) reported a surprising negative value for the return to IT. They studied twenty two U.S. 2-digit manufacturing industries over the 1952-1986 period. Their data on information technology capital consist of the Information Processing Equipment (IPE) section of nonresidential types of equipment from the Bureau of Economic Analysis (BEA). A generalized Leontief variable cost function with non-constant returns to scale is estimated by three-stage least squares. The variable of interest is the shadow value of IT capital, revealing its marginal efficiency. This return varies across industries but is estimated on average at - 0.20%. Hence, the marginal costs of investment in this type of equipment are greater than the marginal benefits, and $1 invested in IT capital returned on average $0.80. At a disaggregated level, a study from Brynjolfsson and Hitt (1993) showed more optimistic results. Their study is based on data from Compustat and *InformationWeek* at the firm level for 367 business units. Using a production function framework, they estimated econometrically the output elasticity of IT capital between 54% and 68%.

Apart from estimating the value of the return to IT investment, some authors have tested whether this return was greater than that of investment in traditional equipment. Berndt and Morrison (1995) studied twenty manufacturing industries with data on investment and capital stock from BEA. They found that the returns from computer investment are not significantly different from that of other types of capital. On the other hand, a firm level analysis of Lichtenberg (1995) found that IT capital earns positive and significant returns also significantly greater than the return to traditional capital. However, the author argued that using capital stock instead of capital services overestimates returns. Moreover, the production function framework used in this study distinguishes IT and non-IT workers. Lichtenberg found that one IT worker is six times as productive as a non-IT worker. Hence, there is some evidence of excess returns to IT employment too.

Lehr and Lichtenberg (1999) built an original framework for measuring excess return to IT capital. They used firm-level computer asset and financial data for non-agricultural firms during the period 1977-1993. Their model is based on a Cobb-Douglas production function where total capital (K) is divided into computer capital (KIT) and non-computer capital ($KNIT$). Technical progress is embodied as follows:

$$Y = A\,[KNIT + (1-\theta)\,KIT]^{\alpha}.\,L^{(1-\alpha)} \quad (3.11)$$

where α measures the elasticity of output with respect to the effective capital stock, and θ is a parameter that measures the “excess productivity” of computer capital relative to non-computer capital. Re-arranging and taking logarithms leads to (details in section 4.1.1)

$$\ln(Y) = \ln(A) + \alpha \ln(K) + \alpha\theta\, IT\% + (1-\alpha)\ln(L) \quad (3.12)$$

where *IT%* represents the IT ratio defined as the ratio of IT capital to total capital.

Estimating 3.12, the authors found that not only did computers contribute to productivity growth but they also yielded excess returns relative to other types of capital.

Gera, Gu and Lee (1999) performed regression analysis on a pooled cross-section time-series data set consisting of 27 industries in the United States and in Canada during five sub-periods between 1971 and 1993. They regressed the annual average labor productivity growth rate of a given industry on its IT and non-IT investment rates and other variables. Their results indicate IT investments are an important source of labor productivity growth across industries. Brynjolfsson and Hitt (1995) showed that the size of the productivity impacts is similar for manufacturing and service firms.

Quinn and Baily (1994) noted that national accounts data are extremely misleading and contain major gaps. Thus, they shifted the focus away from quantifying productivity benefits of IT capital toward measuring qualitative strategic performance improvements. The authors interviewed over 100 executives in top management, finance, information, and operating positions in the service industry. Their results indicate 80% of the companies surveyed had achieved adequate to high returns on their IT investments. Because of the difficulty of measuring output in the service sector, these gains were mainly qualitative such as greater flexibility and adaptability, improved responsiveness to new product lines, enhanced quality of work life and increased predictability of operations. More specifically, David, Grabski and Kasavana (1996) estimated the gains from to the use of IT in the hotel industry. They surveyed 100 large hotel companies, and measured qualitative gains related to IT investments. They argued "the productivity paradox may be less a paradox than a conscious strategy to select improvements in guest service over increase in productivity." Finally, Reardon, Hasty and Coe (1996) surveyed 871 retailers and found IT capital has a positive effect on the output of retail institutions. According to the authors, retailers gained relatively more output per dollar's worth of IT input than the marginal return on other types of capital.

3.3.2Output and Labor Productivity Growth Contributions of Information Technology Capital

Since the productivity paradox was first identified, several empirical studies have attempted to quantify the contribution of IT capital (*KIT*) to output growth or labor productivity growth (Table 3.2). Even if productivity growth was sluggish during the 1970s, IT capital may still have contributed to its increase. The BLS framework is usually used to evaluate the contribution to growth of various inputs. This framework is derived from the general growth accounting techniques previously described. The equation used to calculate output growth contributions is:

$$gr(Y) = \alpha_{KIT}\, gr(KIT) + \alpha_{KNIT}\, gr(KNIT) + \alpha_{L}\, gr(L+q) + gr(TFP) \quad (3.13)$$

where gr(.) represents growth rate, *Y* represents output, *KIT* is information technology capital, *KNIT* is other types of capital, *L* measures labor hours, *q* controls for labor quality and *TFP* is total factor productivity. The alpha coefficients (α) represent the income shares of the inputs, which under neoclassical assumptions are equal to output elasticities and sum up to one when constant returns to scale are assumed. Growth rates are expressed by gr. Thus, the output growth contribution of IT capital is measured by the product of its income share (α_{KIT}) and the growth rate of its stock (grKIT).

The value of the income share is a crucial variable needed to evaluate the growth contribution of any input. Authors have either calculated it following the method used by BLS [Oliner and Sichel (1994, 2000), Jorgenson and Stiroh (1998, 2000)], or estimated it using regression techniques [(Brynjolfsson and Hitt (1993), Lichtenberg (1995), Lehr and Lichtenberg (1999), Gera,Gu and Lee (1999)].

Oliner and Sichel (1994) published one of the first well-recognized studies of the contribution of computer capital to output growth. Their measure of IT capital (*KIT*) is based on data on "Computer and Peripheral Equipment" (CPE) from the Bureau of Economic Analysis (BEA). CPE belongs to the broader category IPE (Figure 1.1). Over the period 1970-1992, the average yearly growth rate of computer equipment was estimated at 27.6%. To calculate the computer income share (α_{KIT}), Oliner and Sichel followed the BLS formulation

$$\alpha_{KIT} = (r_{COMP} + d - \pi_{KIT})\,(P_{KIT}\, KIT)) \,/\, (P_{Y}\, Y) \quad (3.14)$$

where r_{COMP} is the nominal rate of return common to all capital, d is the depreciation rate, π_{KIT} is the rate of nominal computer capital loss, $P_Y Y$ is nominal output and $P_{KIT} KIT$ represents nominal net stock of computer capital. Using data from BEA and BLS, Oliner and Sichel found an income share for computer equipment of 0.6 percent on average over the 1970-1992 period. Therefore, the growth contribution from computing equipment is estimated around 0.16 (= 0.6*0.276) percentage points per year during the period 1970-1992, compared to a total growth rate of output of 2.77 percentage points. According to the authors, the small contribution to output growth may be due to the small income share of computer capital (0.6). Indeed, even if investment in computers has skyrocketed during the last two decades, this form of equipment still represents a relatively small share of total capital input. To answer Solow's famous quip, Oliner and Sichel attempt to solve the productivity paradox arguing that computers are actually not seen "everywhere."

Oliner and Sichel (1994) then considered three extensions of their study in order to explain the low contribution to growth from computers. First, computers may earn greater than competitive returns to investment for two reasons. On one hand, they might generate positive externalities as stated by Romer (1986, 1987) and De Long and Summers (1991,1992). Indeed, the "computer knowledge" that workers gain using this new technology might spread to other workers, generating positive externalities for the economy as a whole. On the other hand, computers might simply have higher private returns (even if there are no externality effects), as suggested by Brynjolfsson and Hitt (1993) and Lichtenberg (1993). Still, even when higher returns are assumed (values for r_{COMP} up to 56%), the growth contribution of computer equipment remains small (increases from 0.16 up to 0.35 percentage points) according to Oliner and Sichel's calculations.

Second, Oliner and Sichel (1994) measured the growth contribution of computers correcting for mismeasurement errors. In order to do so, they assumed that one dollar of measured output from computer capital corresponds to one other dollar of unmeasured intangible output. This is equivalent to assuming a return of 50% to computer capital, and as seen earlier, this would not change significantly the growth contribution of computer equipment.

Finally, the authors explored the effects of considering not only computer equipment, but also other communication devices. They found that information processing equipment (IPE) contributed 0.31 percentage point annually to output growth over the period 1970-1992. Thus, even if computers represent a small share of the stock of information processing equipment (1/6), they still account for most of its growth contribution (about 50%).

Using essentially the same framework, Oliner and Sichel (2000) found a greater contribution of computers to output growth for several reasons. First of all, the stock of computer equipment boomed during the 1990s and is now relatively much more important than a decade ago. Furthermore, Oliner and Sichel have enlarged their definition of computer capital, which now includes software and communication equipment. The return to computer capital is also suspected of having increased this last decade. Thus, the income share of the computer capital equipment was 5.3% and 6.3% respectively for the periods 1991-1995 and 1996-1999. For those periods, the contributions to output growth of information technology capital are respectively 0.54 and 1.08 percentage points. The growth contribution of information processing equipment doubled between the 1996-1999 and 1974-1995 periods. The contribution of different inputs to growth in labor productivity is calculated simply by subtracting the growth rate of total hours from both sides of equation (3.13), yielding:

$$gr(Y/L) = \alpha_{KIT}\, gr(KIT/L) + \alpha_{KNIT}\, gr(KNIT/L) + \alpha_L\, gr(q) + gr(TFP) \quad (3.15)$$

In this framework, the growth in labor productivity is decomposed into capital deepening, gr(K/L), change in labor quality, gr(q) and change in TFP, gr(TFP).

Oliner and Sichel reported a substantial increase of 1.05 percentage point in labor productivity between the first and second half of the 1990s. This increase was mostly due to due growth in TFP (+0.68) and capital deepening (+0.50), with a negative contribution of labor quality (-0.13). The authors also compared the growth contribution from the *use* and from the *production* of information technology, which is embedded in the growth of TFP. They divided the nonfarm business sector into three sectors: a sector s produces semiconductors for the computer manufacturing sector (sector *c*) and all other industries (sector *o*). Using a framework based on the work of Hulten and Schwab (1984), Triplett (1999), Stiroh (1998) and Whelan (1999), they showed that MFP growth could be decomposed according to the following equation:

$$gr(MFP) = \mu_c\, gr(MFP)_c + \mu_o\, gr(MFP)_o + \mu_s\, gr(MFP)_s \quad (3.16)$$

where parameters μ_c and μ_o represent the shares of output for each of these sectors, and μ_s is the value of semiconductors used by others. The output of the computer sector is estimated using the sum of computer spending by U.S. business, households and all level of government, plus net exports of computers, published by BEA. The semiconductor output is estimated using data from the Federal Reserve Board.

Finally, sectoral MFP growth rates are estimated using the "dual" method from Triplett (1999) and Whelan (1999). Oliner and Sichel's results indicate that the 1.05 percentage point gain in labor productivity between the first and second half of the 1990s is decomposed into: (1) 0.46 point from the growth in information technology capital per hour – capital deepening, (2) 0.04 from other capital deepening, (3) – 0.13 point from labor quality decline, (4) 0.26 from MFP growth in the computer-producing sector, (5) 0.11 from MFP growth in semiconductor producing sector and (6) 0.32 point MFP growth in all other industries. Jorgenson and Stiroh (1999) used a framework based on the work of Christensen and Jorgenson (1973). They attempted to quantify the output contribution of IT equipment as both an input used by firms to produce as well as a consumption good for households. They started with a production function of the form:

$$g(I,C,S) = f(K,D,L,T) \quad (3.17)$$

where *I* represents investment goods, *C* consumption goods and services, *S* flow of services from consumers' durable goods, *K* inputs of capital services, *D* consumers' durable services, *L* labor input and *T* technology. Then, the distinction is made between computer (*c*) and non-computer (*n*) portions of those inputs and outputs:

$$g(I_c, I_n, C_c, C_n, S_c, S_n) = f(K_c, K_n, D_c, D_n, L, T) \quad (3.18)$$

Measuring the growth contribution shows that computer investment goods (I_c) made the largest contribution with 0.26 percentage points during the 1990-1996 period. Computer equipment and services (C*c*) made a contribution of 0.13 percentage points. Taken together, computer inputs contributed 0.16 percentage points to output growth of 2.4% per year for the period 1990-1996, and are directly due to substitution toward IT equipment. Jorgenson and Stiroh (1999) concluded:

The resolution of the Solow paradox is that computer-related gains, large returns to the production and use of computers, and network effects are fundamentally changing the U.S. economy. However, they are not ushering in a period of faster growth of output and total factor productivity. Rather, returns to investment in IT equipment have been successfully internalized by computer producers and computer users.

Using a similar approach, Jorgenson and Stiroh (2000) found results slightly different than Oliner and Sichel (2000). Using recent data from BEA (1999), they considered information technology as investment in computers, software and communication equipment, as well as consumption of computers and software as outputs. IT is again considered as both an input and an output. Assuming constant returns to scale and competitive product and factor markets, the model starts from a Hicks neutral production function of the form:

$Y(I, C) = A f(K, L)$(3.19)

where *I* and *C* represent investment and consumption goods respectively, and will be decomposed into sub-components. *K* and *L* stand for capital services and labor inputs respectively, also decomposed into sub-components. The share-weighted growth of outputs is then expressed as

$w_I \Delta\ln(I) + w_C \Delta\ln(C) = v_K \Delta\ln(K) + v_l \Delta\ln(L) + \Delta\ln(A)$(3.20)

where w and v represent the shares of nominal output and income respectively. Therefore, it is possible to estimate the growth contributions of different inputs as well as outputs (computers, software and communication equipment distinctively).

Considering average labor productivity (ALP) as the ratio of output (Y) to hours worked (H), and the ratio of capital services to hours (k), labor input (L), the growth in average labor productivity is then expressed as:

$\Delta\ln(ALP) = v_k \Delta\ln(k) + v_l \Delta\ln(L) - \Delta\ln(H) + \Delta\ln(A)$(3.21)

Hence, average labor productivity growth is a function of capital deepening (k), labor quality (L-H), and TFP (A).

Jorgenson and Stiroh (2000) then considered the computer-producing and computer-using sectors separately. They argued that on one hand rapid technical progress in the computer-producing sector will increase TFP and therefore labor productivity at the aggregate level. On the other hand, computer equipment accumulation in the computer-using sector will only increase aggregate labor productivity through capital deepening according to equation 3.21. It will not affect aggregate TFP. The usefulness of this framework also lies in the consideration of substitution between outputs and between inputs. First, the distinction is made between capital services and capital stock. Capital stocks are measured using the perpetual inventory method on investment series from

BEA, and aggregated using rental prices as weights. Jorgenson and Stiroh also identify rental prices with marginal products of different types of capital. Those prices incorporate differences in asset prices, service lives and depreciation rates, and the tax treatment of capital incomes. The difference between growth of capital services and capital stocks reflects the growth in capital quality, which represents the substitution towards assets with higher marginal products. Using this methodology, the authors found that information technology equipment had an output growth contribution of 0.17 and 0.36 percentage points for the periods 1973-1990 and 1996-1998 respectively.

Jorgenson and Stiroh (2000) also used an original framework to evaluate the contribution of individual industries to aggregate TFP growth. They argued that

Aggregate TFP gains – the ability to produce more output from the same inputs - reflects the evolution of the production structure at the plant or firm level in response to technological changes, managerial choices, and economic shocks. These firm- and industry- level changes then cumulate to determine aggregate TFP growth.

Output is considered as "gross output" and therefore inputs include capital (K), labor (L), energy (E) and materials (M) such as:

$Q_i = A_i . X_i (K_i, L_i, E_i, M_i)$(3.22)

The growth accounting equation becomes:

$\Delta\ln(Q_i) = \Delta\ln(A_i) + w_k \Delta\ln(K_i) + w_l \Delta\ln(L_i) + w_e \Delta\ln(E_i) + w_m \Delta\ln(M_i)$(3.23)

where *w* represents the average share of the subscripted input in the i^{th} industry, and $\Delta\ln(A_i)$ represents industry productivity based on "gross output" measures. This productivity is often referred to as multifactor productivity (MFP) and is analogous to TFP, which is based on a value-added concept.

Following Domar (1961), Jorgenson and Stiroh (2000) then decomposed aggregate TFP as a weighted average of industry productivity:

$\Delta\ln(A) = \Sigma_{i=1...37} w_i . \Delta\ln(A_i)$ (3.24)

where P_iQ_i is current dollar gross output in sector i, P_yY is current dollar aggregate value-added and wi is the "Domar weight." Data come from BLS and BEA, for 37 industries. The Domar weight can be expressed as:

$w_i = ½ * [(P_{it}Q_{it} / P_{y,t}Y_t) + (P_{it-1}Q_{it-1} / P_{y,t-1}Y_{t-1})]$ (3.25)

Jorgenson and Stiroh (2000) found that productivity (TFP) has increased in both sectors, but it seems that this increase was not due to investment in IT for the IT-using sector. Indeed, more investment is correlated with lower TFP growth.

Whelan (1999) used a slightly different approach for measuring the output growth contribution of IT capital. Instead of using the Solow vintage model to construct capital stocks, Whelan stressed the importance of using "productive" instead of "wealth" stocks. The productive stock accounts for "technical obsolescence," which occurs when computers are retired while they still retain productive capacity. Whelan found output growth contribution of IT capital of 0.39, 0.33 and 0.82 percentage points during the 1980-89, 1990-1995 and 1996-1998 periods respectively. Following Oliner and Sichel

(2000) and Jorgenson and Stiroh (2000), the productivity growth contribution of IT capital is decomposed between the computer-producing and computer-using sector. According to Whelan, TFP growth in the computer-producing sector and capital deepening in the computer-using sector account for almost all of the recent increase in labor productivity during the 1996-1998 period (valued at 2.2% per year).

Kiley (1999) augmented the traditional growth accounting framework by including a common specification of investment adjustment costs. Earlier, Morrison and Berndt (1992) also included these costs in their analysis. Investment adjustment costs require that increases in investment lower the productive capacity of the firm and the economy. Typically, in a steady state framework, investments are small relative to the capital stock and do not influence the firm's productive capacity. However, according to Kiley, the recent massive increase in IT capital investment has made investment adjustment costs more important and the Solow growth accounting framework becomes inappropriate when studying the productivity effects of IT capital. Using this augmented framework and data on computer capital stock from BLS, Kiley estimates that the investment adjustment costs lower MFP growth by 0.50 percentage points since 1974. These adjustment costs include "costs of reorganizing plant layouts to incorporate new machinery, managerial costs stemming from alterations to production plans consistent with the installation of new capital, and other costs associated with the interruption of normal work activity to install (or disinstall) capital." Thus, he found a negative output growth contribution of computer capital of –0.34 and –0.27 annual percentage points during the 1974-84 and 1985-1998 periods respectively.

Adopting a firm-level analysis, Brynjolfsson and Hitt (1993) found a more optimistic contribution of computers to growth. With data on 367 business units for five years (1988-1992), the authors estimated a yearly output growth contribution of 1% for IT capital. Lau and Tokusu (1992) found an even greater contribution of 1.5%. On the other hand, studying 60 business units, Loveman (1994) found the output growth contribution of IT capital to be not significantly different from zero. His results were robust to numerous variations in the formulation of the basic framework. Gordon (1999) has a different view about the productivity paradox, when he argued:

There has been no productivity growth acceleration in the 99 percent of the economy located outside the sector which manufactures computer hardware, beyond that which can be explained by price remeasurement and by a normal (and modest) procyclical response.

Thus, the problem of the productivity paradox remains because authors have not unanimously dismissed it yet. Even after the increase in productivity observed in the last 4 years, researchers still need to understand the reasons for the productivity paradox for information technology capital in prior years. This is what I intend to do in this dissertation, using a model that I describe in the next chapter.

Table 3.2Summary of Some Empirical Literature on Information Technology and Productivity

Authors	Unit of Analysis	Data Source	Findings
Franke (1987)	Insurance and Banking Industries		- Capital and labor productivity decrease

Authors	Unit of Analysis	Data Source	Findings
			after major technical innovations (ATMs or PCs) are introduced
Roach (1991)	Service industry,1975-86		- Productivity of production workers (LNIT) increased by 16.9% between 1975 and 1986 - Productivity of information workers (LIT) decrease by 6.6% between 1975 and 1986
Morrison & Berndt (1991)	22 manufacturing 2-digit industries, 1952-86	Office Computing AccountingMachinery(OCAM), from BEA	$1 invested in IT capital returns $0.80 (varies across industries)(Used a generalized Leontief variable cost function)(3-stage Least Squares estimation)
Lau &Tokutsu (1992)	Aggregate level		Output growth contribution of computer capital is 1.5% (which represents 50% of total output growth)
Berndt, Morrison& Rosenblum (1992)	Industry		Increase in IT capital stock is positively and significantly correlated with increase in hours of non-production workers (which has accounted for most of the decrease in labor productivity)
Lee& Barua (1993)	Firm level,60 business units,1978-84	IT capital stockProfit Impact of Market Strategy Database	- Positive and significant relationship between IT capital and productivity- IT capital stock is more productive than traditional capital- IT capital and IT labor are complements while IT

Authors	Unit of Analysis	Data Source	Findings
			and non-IT capital are substitutes
Oliner & Sichel (1994)	Aggregate1970-1992	Computers Peripheral Equipment (CPE), BEA	Contribution of computers to output growth is 0.16% a year (up to 0.32% when less restrictive conditions are used)
Brynjolfsson & Hitt (1994)	Firm-level,367 large firms,1988-1992	Information-week,Compustat	- Returns to IT investment between 54% and 68%- Yearly output growth contribution is around 1%
Loveman (1994)	Firm-level60 business units1978-83	Profit Impact of Market Strategy Database	The output growth contribution of IT capital is not significantly different from 0, and this result is robust to numerous variations in the formulation of the basic framework
Knon and Stoneman (1995)	Firm-level,6 case studies in the U.K.	Investment in new technology	The use of computer has increased output and productivity significantly
Authors	Unit of Analysis	Data	Findings
Berndt & Morrison (1995)	20 manufacturing industries (2-digit SIC)	Investment and capital stockBEA	- Broad correlation between IT investment and productivity- Returns from computer investment are not significantly different from that of other types of capital- Investment in IT capital is positively and significantly correlated with increasing demand for skilled labor
Brynjolfsson & Hitt	Firm-level	Stock of OCAM and IS budget from	- The use of a translog instead of

Authors	Unit of Analysis	Data Source	Findings
(1995)		InformationWeek and Compustat	Cobb-Douglas production function gives similar results- The size of the productivity impacts is similar for manufacturing and service firms. Also same impact between firms with "measurable" and "unmeasurable" output- Firm effects account for half of the productivity gains. Large returns to IT capital not only reflect gains from computerization but also other exogenous facts such as management techniques
Lichtenberg (1995)	Firm-level,1988-1991	Information-weekComputer-world	- IT capital earns positive and significant return, which is also significantly greater than the return to traditional capital- Using capital stock instead of capital services overestimates returns- IT labor is six times more productive than traditional labor
Jorgenson & Stiroh (1995)	1972-1992		- Average output growth contribution of computers is 0.45% a year (0.52% between 1979 and 1985, 0.38% between 1985 and 1992) - Other types of capital contribute for 0.72% a year

Authors	Unit of Analysis	Data Source	Findings
Reardon, Hasty & Coe (1996)	871 Retailers	Survey	- IT has a positive effect on the output of retail institutions- Marginal investments in IT are not equal to the value of its marginal product. - Retailers are gaining relatively more output per dollar's worth of input than they should at the margin
David, Grabski & Kasavana (1996)	Hotel industry	Survey	The productivity paradox may be less a paradox than a conscious strategy to select improvements in guest service over increase in productivity

Authors	Unit of Analysis	Data	Findings
Brynjolfsson & Yang (1997)	1000 firms	Information System (IS)spending from Computer Intelligence Infocorp	- The financial market puts a very high value on installed computer capital (valuation at least 4 times greater than conventional assets)- An increase of $1 in the quantity of computers leads to an increase of $10 in the

Authors	Unit of Analysis	Data Source	Findings
			financial market valuation of the firm
Stiroh (1998)	Industry level,1947-1991		Computers have a different impact across sectors: increase multifactor productivity in computer producing sectors, not so much in computer using sectors.
Wehland (1999)	Aggregate		- Should use productive stocks instead of wealth stocks- Contribution is 0.82% with obsolescence model- Total Factor Productivity (TFP) growth in computer producing sector and productive capital

Authors	Unit of Analysis	Data Source	Findings
			deepening in computer using sector account for almost all of the recent increase in productivity during 1996-1998 (+2.2%)
LichtMoch (1999)	Aggregate and firm-level,474 service firms,317 manufacturing firms	Survey on computer capital	- Plausible correlation between qualitative output indicators and capital investment, R&D and Human Capital. IT seems to affect quality only- The type of IT capital is more important than the quantity
LehrLichtenberg(1999)	Firm Level	Census BureauComputer IntelligenceInfocorpCompustat	- Excess return to computer capital compared to traditional capital-Firm

Authors	Unit of Analysis	Data Source	Findings
			specific effects increase productivity- Computers allow firms to be more decentralized and alter employment composition- Computer do increase productivity
Jorgenson, Stiroh (1999)	35 types of durable goods producers	Capital stock	- Drop in computer prices => ; Substitution effects, no technical change - Returns to investment in IT have been internalized by computer producers and users
Kiley (1999)	Aggregate		- Augmented traditional growth accounting framework by including a common specification of investment adjustment costs- Contribution of computers to economic growth has been held down (by 0.50 % point) by the large adjustment costs required to incorporate

Authors	Unit of Analysis	Data Source	Findings
			a new investment good

CHAPTER 4 - A METHODOLOGY FOR MEASURING THE PRODUCTIVE CAPACITY OF INFORMATION TECHNOLOGY CAPITAL

This chapter first describes the model used in this dissertation to measure the role of IT in growth. The growth accounting framework presented earlier (section 3.1.2) is further developed to measure the returns to IT capital stock and its contribution to output and labor productivity growth. The second section defines the variables used in this analysis and the way these were constructed from different data sources. Finally, the last section describes the data trends at the national, industry and state levels.

4.1The Model

This section describes the empirical model used to estimate the returns to IT capital stock and to evaluate the possibility of excess returns. It also discusses the procedure used to estimate the output and productivity growth contributions of IT capital.

4.1.1 Estimation of the Returns to IT Capital Stock

The data presented in chapter 2 showed that U.S. businesses have invested heavily in IT equipment during the last two decades. At the origin of this massive investment was there certainly the premise that computer and information technology equipment in general could eventually increase firms' productivity, simply because this type of equipment was assumed to be more productive than traditional capital. This premise was empirically tested and authors reached different conclusions. On one hand, Berndt and Morrison (1995) argued that aggregate returns from IT investment were not significantly different from that of other types of capital. On the other hand, at the firm level, Brynjolfsson and Hitt (1993) estimated returns to IT investment between 50% and 60%. I intend to use a model derived from the work of Lehr and Lichtenberg (1999) to test whether returns from IT equipment are greater than that of traditional capital. This section describes this model.

To start with, assume that at time *t*, within state *s*, industry *i* transforms capital (*K*) and Labor (*L*) into output (*Y*) according to a constant returns to scale Cobb-Douglas production function and embodied technical progress:

$$Y_{its} = A\, K_{its}^{\alpha}\, L_{its}^{1-\alpha} \quad (4.1)$$

The parameter α represents the elasticity of output with respect to capital. Next, decompose total capital into information technologyy capital (*KIT*) and other types of capital aggregated into "traditional" or "non-IT" capital (*KNIT*). Thus

$$K_{its} = KNIT_{its} + KIT_{its} \quad (4.2)$$

Equation 4.1, given equation 4.2, now becomes

$$Y_{its} = A\, (KNIT_{its} + KIT_{its})^{\alpha}\, L_{its}^{1-\alpha} \quad (4.3)$$

The neoclassical theory postulates that all types of capital earn the same marginal returns. This argument constitutes the null hypothesis that will be tested using this model. Under the alternative hypothesis, the return to IT capital differs from the return to traditional capital and is most likely greater. Let parameter θ capture the "excess productivity" from IT capital. Thus equation (4.3) becomes

$$Y_{its} = A.[KNIT_{its} + (1+\theta).\, KIT_{its}]^{\alpha}.L_{its}^{1-\alpha} \quad (4.4)$$

I will test the "excess returns" from IT capital hypothesis H_1, which is derived next.

Replacing KNIT by K – KIT in equation 4.4 and dropping the subscripts for the sake of simplicity leads to

$$Y = A\, [K - KIT + (1+\theta)\, KIT]^{\alpha}\, L^{1-\alpha}$$

$$Y = A\, [K + \theta KIT]^{\alpha}\, L^{1-\alpha}$$

$$Y = A\, [K (1+ \theta KIT/K)]^{\alpha}\, L^{1-\alpha} \quad (4.5)$$

Taking logarithms, we can write

$$\ln(Y) = \ln(A) + \alpha \ln [K (1+ \theta KIT/K)] + (1-\alpha) L \quad (4.6)$$

Finally, letting IT% represent the ratio of IT capital to total capital (KIT/K)

$\ln(Y) = \ln(A) + \alpha\ln(K) + \alpha\ln[1+ \theta.IT\%] + (1-\alpha)\ln(L)$(4.7)

The null hypothesis states that all types of capital earn the same returns, net of depreciation and other costs associated with each type of capital asset. The first order condition for profit maximization requires that the ratio of the marginal products of IT capital to traditional capital be equal to the ratio of the user costs of these types of capital. This hypothesis refers to the equilibrium point A in figure 3.1. If the ratio of returns were not equal to the ratio of user costs, then firms would be better off investing in the type of capital that had higher returns, and less on capital equipment with lower returns. Thus,

$MP_{KIT} / MP_{KNIT} = R_{KIT}/ R_{KNIT}$

$1+\theta = [(r + \delta_{KIT} - \pi_{KIT}) p_{KIT}] / [(r + \delta_{KNIT} - \pi_{KNIT}) p_{KNIT}]$(4.8)

where *MP* is the marginal product, *R* is the user cost of capital, *r* measures the discount rate common to all types of capital, δ is the depreciation rate, π is the expected rate of capital gain (or loss in the case of IT capital), and *p* is the purchase price per unit of capital. Various authors have reported different estimates of user costs, mainly because they considered different values for *r*, *δ* and π. The ratio p_{KIT}/p_{KNIT} is set to unity because the two types of capital are measured in dollar values so that their prices are both $1. Table 4.1 reports various estimates of the elements of the user costs according to different authors' calculations. Averaging these estimates and replacing them in equation 4.8 leads to a value for the ratio of user costs of capital between 3 and 6, which is also equal to 1+θ. Lehr and Lichtenberg chose 5 as an upper bound estimate of θ. The null hypothesis of no excess returns then becomes a test of θ=5. If θ is significantly greater than 5, then the null hypothesis is rejected and the alternative hypothesis of excess returns to IT capital cannot be rejected.

Interestingly, Lehr and Lichtenberg argued that as long as IT% is small (in the order of 2%), it is possible to substitute αθ (IT%) for α ln(1 + θIT%).[3] Consequently, equation 4.7 becomes:

$\ln(Y) = \ln(A) + \alpha \ln(K) + \alpha\theta IT\% + (1-\alpha) \ln(L)$(4.9)

From equation 4.1, the growth in productivity not explained by inputs or total factor productivity (TFP) is

$TFP = A = Y/ (K^{\alpha} L^{1- \alpha})$(4.10)

Taking logarithms and replacing TFP in equation 4.9 leads to

$\ln(TFP) = \ln(A) + \alpha\theta IT\%$(4.11)

Also, dividing both sides of equation 4.5 by L and taking logarithms

$\ln(Y/L) = \ln(A) + \alpha \ln(K/L) + \alpha\theta IT\%$(4.12)

Table 4.1Values of Discount Rate, Depreciation and Price Appreciation Estimated from Various Sources

[3] The validity of this substitution was tested using a set of values between 1% and 15% for IT% (values found in the dataset between 1977 and 1997), and between 4 and 10 for θ. A linear regression of [α ln (1+θIT%)] on [αθIT%], with no constant, produces a coefficient for [αθIT%] not statistically different from 1 at the 0.01 level.

Variable	Source	Estimates	Mean
Risk-adjusted discount rate r	Lau & Tokutsu (1992) Oliner & Sichel (1994)	0.07 0.12	0.10
IT capital Depreciation rate δ_{KIT}	Kiley (1999) Lau & Tokutsu (1992) Whelan (1999) Oliner & Sichel (2000)	0.12 0.20 0.22 0.30	0.21
Non-IT capital Depreciation rate δKNIT	Whelan (1999) Lau & Tokutsu (1992)	0.13 0.05	0.09
Rate of price depreciation for IT capital π_{KIT}	Lau & Tokutsu (1992) Kiley (1999) Oliner & Sichel (2000)	-0.15 -0.24 -0.34	-0.24
Rate of price appreciation for non-IT capital π_{KNIT}	Lau & Tokutsu (1992)	0.05	0.05

Under the null hypothesis of no excess returns to IT capital, the share of IT capital (IT% or IT ratio) will not increase TFP and labor productivity according to equations 4.11 and 4.12, respectively ($\alpha\theta = 0$). However, if the null hypothesis is rejected, then TFP and labor productivity might increase with the share of IT capital ($\alpha\theta > 0$).

In this study, I use a pooled cross-section dataset on industry variables at the state level between 1977 and 1997. Econometric analysis of pooled data requires the introduction of fixed effects or dummy variables for years, industries and states. These fixed effects will control for exogenous differences among years (γ_t), industries (λ_i), and states (v_s). The first Cobb-Douglas production function that will be estimated at the national, industry and state levels is

$$Y_{its} = A\ KNIT_{its}^{\alpha 0}\ KIT_{its}^{\alpha 1}\ L_{its}^{\beta} \quad (4.13)$$

Taking logarithms and introducing dummy variables to control for fixed effects, the least squares dummy variables (LSDV) functional form is:

$$\ln(Y_{its}) = \Sigma\gamma_{t-1} + \Sigma\lambda_{i-1} + \Sigma v_{s-1} + \alpha_0 \ln(KNIT_{its}) + \alpha_1 \ln(KIT_{its}) + \beta.\ln(L_{its}) + \varepsilon_{its} \quad (4.14)$$

A simple test of whether IT capital is productive is to test the null hypothesis H_0: $\alpha_1 > 0$. Then, equation 4.9 needs to be estimated. Its econometric form is:

$$\ln(Y_{its}) = \gamma_{t-1} + \lambda_i + v_s + \alpha.\ln(K_{its}) + \alpha.\theta.(IT\%)_{its} + (1-\alpha)\ln(L_{its}) + \varepsilon_{its} \quad (4.15)$$

where α_0 and α_1 measure the output elasticities of traditional and IT capital respectively. If θ is significantly greater than 5 then the hypothesis H_0 of similar returns for IT and traditional capital would be rejected.

4.1.2 Contribution to Output and Productivity Growth

After testing for the sign and significance of the output elasticity of IT capital, I will measure the contribution of this type of capital to output and productivity growth.

Considering equation 4.14 in growth rates leads to

$$gr(Y_{its}) = \gamma_{t-1}+\lambda_i+v_s+ s_{KNIT}\, gr(KNIT_{its}) + s_{KIT}\, gr(KIT_{its}) + s_L\, gr(L_{its}) + \mu_{its} \quad (4.16)$$

The contribution to output growth from IT capital is measured by $s_{KIT} gr(KIT_{its})$ where gr stands for "growth rate" measured as the ratio of the difference between variables at time *t* and *t-1*, divided by the value at time *t-1*. Many authors use first log differences to measure growth rates, but I believe the previous formula is more accurate.[4] Variable *s* represents the income share of inputs (previously defined by equation 3.5), and in equilibrium it is equal to the input's marginal product times its share of output. Finally, μ represents the error term.

Following Oliner and Sichel (2000), equation 4.16 is divided on both sides by L_{its} to estimate the labor productivity growth contribution of a given input. The authors also control for labor quality by adding variable gr(q), where *q* could represent years of experience or education:

$$gr(Y_{its}/L_{its}) = \gamma_{t-1}+\lambda_i+v_s+ \alpha_0\, gr(KNIT_{its}/L_{its})+ \alpha_1\, gr(KIT_{its}/L_{its}) + \alpha_L\, gr(q) + \mu_{its} \quad (4.17)$$

Thus, growth in labor productivity depends on growth in TFP (which is captured by various fixed effects ($\gamma_{t-1} + \lambda_i + v_s$), capital deepening (growth in KNIT/L and KIT/L) and change in labor quality gr(*q*).

4.2 Variables and Data

The main variables of the model previously described are output (Y), traditional and IT capital (KNIT and KIT respectively) and labor (L). Different levels of study (national, industries and states) make the construction of the dataset complex.

In this study, I consider pooled cross-section data for 52 industries, for 50 contiguous U.S. states and the District of Columbia, for the 21 years between 1977 and 1997 inclusive. The industries account for all of the nonagricultural nongovernmental production in the U.S. economy. Next, I describe the various levels of study considered in this dissertation before discussing the construction and data source for each variable.

4.2.1 Industries

The 52 industries studied are reported in Table 4.2. The choice of these industries originates from the need to match two different sources of data from the Bureau of Economic Analysis (BEA 1999a, 1999b): "Fixed Reproducible Tangible wealth in the United States, 1925-1997" and "Gross Product Originating 1947-1997." The first contains data on capital stocks by industry at the aggregate level, the latter gives the gross state product by industry. The industry classifications used in these two sources are not exactly the same, and I had to aggregate some of the 62 original industries to obtain a set of 52

[4] I use $(Z_t - Z_{t-1}) / Z_{t-1}$. Note that $\ln [(Z_t - Z_{t-1}) / Z_{t-1}] = \ln (Z_t - Z_{t-1}) - \ln (Z_{t-1})$, which is different from $\ln (Z_t) - \ln (Z_{t-1})$

industries common to all sources of data. The BEA (1999b) methodology is for industries based on the 1987 Standard Industry Classification (SIC) where

Industry data are presented on an ’establishment’ basis; establishments, as defined for the purposes of the SIC, are economic units, generally at a single physical location, where business is conducted or where services or industrial operations are performed.

Table 4.2List of the 52 Industries Used in this Study

1-digit industry	Code	2-digit Industry
Mining	31	Metal mining
Mining	32	Coal mining
Mining	33	Oil & gas
Mining	34	Nonmetalic minerals
Construction	4	Construction
Manufacturing	521	Lumber & wood
Manufacturing	522	Furniture and fixtures
Manufacturing	523	Stone, clay, glass
Manufacturing	524	Primary metals
Manufacturing	525	Fabricated metals
Manufacturing	526	Industrial machinery
Manufacturing	527	Electronic, instrument and related equipment
Manufacturing	528	Motor vehicles
Manufacturing	529	Other transport. equip.
Manufacturing	5210	Misc. manufacturing
Manufacturing	531	Food & kindred products
Manufacturing	532	Tobacco products
Manufacturing	533	Textile mill products
Manufacturing	534	Apparel & textile
Manufacturing	535	Paper products
Manufacturing	536	Printing & publishing
Manufacturing	537	Chemicals
Manufacturing	538	Petroleum products
Manufacturing	539	Rubber & plastics
Manufacturing	5310	Leather products
Transportation	611	Railroad transportation
Transportation	612	Local & interurban
Transportation	613	Trucking and warehousing
Transportation	614	Water transportation
Transportation	615	Transportation by air
Transportation	616	Pipelines, ex. nat. gas
Transportation	617	Transportation services
Transportation	62	Communications
Transportation	63	Electric, gas, & sanitary
Wholesale trade	7	Wholesale trade
Retail trade	8	Retail trade
F.I.R.E.	91	Banking
F.I.R.E.	92	Security brokers
F.I.R.E.	93	Insurance carriers
F.I.R.E.	94	Insurance agents
F.I.R.E.	95	Real estate
F.I.R.E.	96	Holding and investment

1-digit industry	Code	2-digit Industry
Services	101	Hotels & lodging
Services	102	Personal services
Services	103	Business and Other Services
Services	104	Auto repair & parking
Services	105	Misc. repair services
Services	106	Motion pictures
Services	107	Amusement and recreation
Services	108	Health services
Services	109	Legal services
Services	1010	Educational services

Note: industry 37 (Banking) includes "Federal Reserve Banks, Other depository institutions and Nondepository institutions. Variable *1-digit industry* corresponds to 1-digit SIC industry name. Variable *code* is an arbitrary number closely related to the 2-digit SIC, of which name is reported by variable *2-digit industry*.

4.2.2Output

Variable Y_{its} expresses output originating from industry *i*, in state *s*, during the year *t*. It is defined as the total real 1992 dollar value of the final goods and services produced in industry *i* within state *s*. It is similar to value added, which is gross output less intermediate inputs. Gross output measures the sales or receipts and other operating income, commodity taxes, and inventory change. Intermediate inputs define the consumption of goods and services purchased from other US industries or imported. Thus, Y_{its} is the state/industry counterpart of the nation's Gross Domestic Product (GDP) or a state's Gross State Product (GSP). At the state level, Y_{st} is the sum of outputs originating in all industries in state *s* during year *t*. Similarly, for industry *i* at the national level, output Y_{it} is the sum of all outputs from that specific industry *i* originating from all states. Finally, Y_t is national output for year *t* and is measured as the sum of all outputs originating from all industries and all states. The following equation summarizes these relationships between outputs at various levels:

$$Y_t = \Sigma_i Y_{it} = \Sigma_s Y_{st} = \Sigma_i \Sigma_s Y_{its} \quad (4.18)$$

Note that Y_t is not exactly equal to the nation's GDP, because it does not include output from government and the foreign sector. Indeed, previous studies have also considered "private nonfarm" data.

The source of data for Y_{it} is the Bureau of Economic Analysis (1999b). Values in real 1992 dollars are available from 1982 to 1997, and are available in current dollars for the years 1977 to 1981. I computed the real 1992 values for the years 1977 to 1981. In order to do so, I obtained values for the quantity index for these years and industries, and multiplied them by the current dollar value, based on the following relationship:

Real 1992 dollar value = Current value * Quantity index (base 1992) /100(4.19)

Thus, data for Y are available by state and 2-digit industry for the period 1977-1997, in real 1992 dollars.

4.2.3 Capital

Authors studying the productivity effects of IT have considered distinct definitions of total and IT capital. Total capital is here represented by fixed private nonresidential capital, equipment and structures. Capital can be measured as a *stock* or a flow of *services* (also called capital *input*) concept. Ideally, capital *services* are used in productivity studies involving production functions with capital and labor inputs. Jorgenson and Stiroh (1995) noticed that capital *stock* underestimates the growth of capital input because it ignores quality adjustments. However, data on capital *services* are not directly available at the state and industry level. Still, as noted by Norsworthy and Jang (1992), neoclassical theory assumes that “the quantity of capital services that each asset type contributes to capital input is proportional to the stock of that asset.” Thus, I will use data on capital *stocks* as a measure of capital input. Furthermore, Oliner and Sichel (2000) considered *productive* stocks instead of *wealth* stocks, arguing it is more appropriate to consider “how much computers and other assets produce each period” and not “tracking their market value.” Still, I have to consider *wealth* stocks because of data availability reasons.

Real 1992 values of capital stocks are available for the 52 industries nationally from the Bureau of Economic Analysis (1999a). BEA considers “net stock,” which means the perpetual inventory method and Tornqvist aggregations were applied to gross stocks of capital [detailed explanation in Norsworthy and Jang (1992)]. Capital stocks data are decomposed into 57 types of assets. This detailed description of assets allows the decomposition of total capital (K) into IT capital (KIT) and non-IT capital ($KNIT$). Table 4.4, a different version of Figure 2.1, shows the distribution of nonresidential equipment and structures. Variable KIT measures the stock of Information Processing Equipment (IPE), which is constituted of assets #1 to #11: mainframe computers, personal computers, direct access storage devices, computer printers, computer terminals, computer tape drives, computer storage devices, other office equipment, communication equipment, instruments and photocopy and related equipment. Note that BEA recently added the stock of software to this category, but it was not available when I constructed my dataset. Thus, the variable KIT might be underestimated. The variable $KNIT$ is constituted of all other nonresidential equipments and structures containing assets #12 to #57 (Table 4.3).

Thus, data on aggregate *industry* variables K_{it}, KIT_{it} and $KNIT_{it}$ were obtained from BEA for all 52 industries (at the national level), for the years between 1977 and 1997 (in real 1992 dollars). Data for aggregate *national* variables K_t ,KIT_t and $KNIT_t$ were obtained by simple aggregation across industries for each year, according to the following definitions

$$K_t \equiv \Sigma_i K_{it} \,;\; KIT_t \equiv \Sigma_i KIT_{it} \,;\; KNIT_t \equiv \Sigma_i KNIT_{it} \quad (4.20)$$

Data for the remaining *state* and *state industries* capital variables (K_{st}, KIT_{st}, $KNIT_{st}$, K_{its}, KIT_{its} and $KNIT_{its}$) are not directly available and had to be estimated. Next I describe the procedure used to estimate these variables.

Marcus (1964) discussed the capital to output and capital to labor ratios in 2-digit industries by states. For each 2-digit industry, he assumes: (1) all states use the same production function which is homogeneous of degree one and is well-behaved, that is, has convex isoquants; (2) labor, measured in manhours, is homogeneous; (3) similarly, capital (measured in net stock of fixed private nonresidential equipment and structure) represents homogenous physical inputs, and (4) value-added represents homogenous physical output. Then, productivity differences across states are mainly due to differences in states' industry mixes. Based on these assumptions, Marcus noticed that the state 2-digit industry capital to output ratio (K_{its} / Y_{its}) differs from the national 2-digit ratio (K_{it} / Y_{it}) only through 3-digit weights. Assuming these weights are negligible (this hypothesis is tested next), I can then calculate the state industry variables using aggregate industry variables.

Table 4.3Types of Assets in Nonresidential Equipment and Structures

Category	Type of Equipment or Structures
A	Information Processing Equipment
1	Mainframe computers
2	Personal computers
3	Direct access storage devices
4	Computer printers
5	Computer terminals
6	Computer tape drives
7	Computer storage devices
8	Other office equipment
9	Communication equipment
10	Instruments
11	Photocopy and related equipment
B	Industrial Equipment
C	Transportation Equipment
D	Other Equipment
Source: The Bureau of Economic Analysis (1999a)	

Thus, I need to test if the following hypothesis is true

$K_{it} / Y_{it} = K_{its} / Y_{its}$ (4.21)

This equation means that the capital to output ratios are equal across states within the same 2-digit industry and for the same year. For instance, if the capital to output ratio in the Food & kindred products industry is 2 at the aggregate *national* level in 1990, then this ratio is also 2 in the Food & kindred products industry at the aggregate *state* level in 1990, for any of the 51 states. To empirically test hypothesis 4.21, I had to find a proxy for K_{its} since it was the only variable in equation 4.21 for which I did not have data. I obtained capital stock data for the manufacturing industry (1-digit level) for the year 1992 from the U.S. Bureau of the Census (1994). Indeed, the *Annual Census of Manufactures* reports annually the "gross book value of depreciable assets, capital expenditures, retirements, depreciation, and rental payments by state: 1992" for the manufacturing sector only, by state[5]. Hence, these data concern variable K_{its} at the level of aggregate manufacturing data (industries *ind1* = 5 according to Table 4.2) for 1992, for each of the 51 states. Calling this variable *KCENS*

$KCENC \approx \Sigma_i K_{its}$ (4.22)

Where $i = 521,...,5310$, t=1992, s =1,...,51. Thus, equation 4.19 is equivalent to

$KCENC / Y_{its} \approx K_{it} / Y_{it'}$, (4.23)

Where $i = 521,...,5310$, t=1992 and s = 1,...,51. Creating the variable *KYSTATE*, which represents the capital-to-output ratio at the state level in a given industry (left-hand side of equation 4.23), and *KYNAT*, which represents this ratio at the national level for that industry (right-hand side of equation 4.23), the relationship to be tested becomes

$KYSTATE \approx KYNAT$(4.24)

Using the data available, I calculated the variable *KYNAT* and found a value of 1.11, which represents the value of the capital to output ratio for the manufacturing 1-digit sector nationally in 1992. Then, I performed a t-test on variable *KYSTATE* to check if it was significantly different from 1.11. The results appear in Table 4.4. The hypothesis of equality between *state industry* and *national industry* capital to output ratio (equation 4.24) can be rejected at the 15% level, but cannot be rejected at the 10% level. Note that this test was established at the 1-digit industry level (aggregate manufacturing), and it can safely be assumed that the t-statistic would have been greater if the test had been realized at the more detailed 2-digit industry level. Indeed, if the test of capital to output ratio defined in equation 4.21 is "almost" true for 1-digit industries, it is more likely to be true at the more detailed 2-digit industry level where the amplitude of errors is limited. Since no capital stock data for 2-digit industry are available by state, the test, unfortunately, cannot be done at this level.

Table 4.4Significance of the Capital-to-Output Ratio Hypothesis

	KYSTATE	KYNAT
Mean	1.24	1.11
Standard Error	0.62	-
N	51	-
Mean of Differences	0.1349	
95% Confidence Interval of the Differences Lower Upper	-0.04 0.30	
t-test for the differences = 0	1.546	
Probability value (2-tailed)	0.129	

Based on this evidence and the work of Marcus, I cannot reject the null hypothesis stated in equation 4.21, and I assume this relationship is valid. This equation can also be written as

[5] The tangible wealth stock variable from BEA previously described is somewhat different than the gross book value of depreciable assets from Census. However, for the purpose of the test, only the proportion of capital is needed. Thus, it does not matter much if the definition of capital is not exactly the same.

$K_{its} / K_{it} \square Y_{its} / Y_{it}$(4.25)

A state's proportion of a given industry's capital is equal to this state's proportion of that industry's output. In other words, I assume the total aggregate capital used in industry *i* can be distributed among states proportionally to states' shares of output from that industry. This crucial hypothesis allows me to estimate the capital stocks at the detailed industries level by state, for each year, according to the following equation:

$K_{its} \square K_{it} Y_{its} / Y_{it}$(4.26)

Following the same procedure, I can compute the states' industries' IT capital (KIT_{its}) and non-IT capital stocks ($KNIT_{its}$) according to the following relationships:

$KIT_{its} \square KIT_{it} .Y_{its} / Y_{it}$(4.27)

$KNIT_{its} \square KNIT_{it} .Y_{its} / Y_{it}$(4.28)

4.2.4Hours Worked

Labor input (L) is represented by hours worked. It is the product of the number of full time equivalent employees (*N*) times the yearly sum of average weekly hours (*H*). Thus

$L_{its} = N_{its} + H_{its}$; $L_{it} = N_{it} + H_{it}$; $L_{ts} = N_{ts} + H_{ts}$ and $L_t = N_t + H_t$(4.29)

The Bureau of Labor Statistics (BLS 1999) provides data on the number of full time equivalent employees by 2-digit industries for the years 1977 to 1997 ($\mathbf{N}_{it}$). The corresponding number of average weekly hours was also obtained from BLS, but by 1-digit industry only. I assume that 1-digit industry average weekly hours can be used as a proxy for the more detailed 2-digit average weekly hours. Considering a year is constituted of 52 weeks, the yearly number of hours is equal to the weekly average hours times 52. This is the procedure I used to obtain data for variable H_{it}. Finally, multiplying the number of employees (N_{it}) by the number of hours (H_{it}) gives data for annual aggregate industry labor input (L_{it}). The corresponding national variable is obtained according to the following relation:

$L_t = \Sigma_i L$it.(4.30)

Problems arise once again when data for the *state industry* level (L_{its}) are constructed. BLS provides data on variable N_{its} for only 45% of my dataset (25,061 cases over 55,692), and on H_{its} for 20% only. Thus, I need to find a procedure to estimate L_{its}.

In order to do so, I use an approach similar to the one used to estimate K_{its}, which is described in the previous section. I introduce the following hypothesis to be tested:

$L_{it} / Y_{it} \square L_{its} / Y_{its}$ (4.31)

$\square L_{its} / L_{it} \square Y_{its} / Y_{its}$ (4.32)

I create variables *PROPL* and *PROPY* equal to the left hand side and right hand side of equation 4.32, respectively. Thus, I want to test whether these two variables are equal. To test this hypothesis, I use the 20% of data that are available for L_{its} and I run a paired sample t-test on variables *PROPL – PROPY*. Results appear in Table 4.5. They indicate that I can reject the hypothesis that these two variables have similar values at the 1% level (t-statistic is 23.32). Hence, the differences are significant but, on average, of moderate size. Thus, the assumption of equality might be a workable way forward, and the proportion of hours worked in industry *i* in state *s* (L_{its} / L_{it}), is assumed to be equal to the proportion of output for that same industry in that same state (Y_{its} / Y_{it}). I can then compute data for variable L_{its} according to equation 4.32 since it is the only unknown variable in that equation. Finally, I obtain data on *state* labor variable (L_{ts}) by simple aggregation of *state industry* labor variable such as:

$$L_{ts} = \Sigma_i L_{its} \quad (4.33)$$

Table 4.5Significance of the Labor-to-Output Ratio Hypothesis

	PROPL	PROPY
Mean	0.0373	0.0317
Standard Error	0.00043	0.00038
N	11,138	11,138

Mean of Differences	0.0055
95% Confidence Interval of the Differences LowerUpper	0.0050.006
t-test for the differences = 0	23.32
Probability value (2-tailed)	0.000

4.3Descriptive Statistics

This section presents some descriptive statistics for the main variables constituting my dataset. I describe data trends at three levels: (1) the aggregate national level (for t = 1...21), (2) aggregate industry levels (for t = 1...21 and i = 1...52), (3) aggregate state levels (for t = 1...21 and s = 1...51).

4.3.1Variables at the National Level

The main variables are output, total capital, IT capital, non-IT capital, labor hours and the ratio of IT capital to total capital (IT ratio). Table 4.6 shows the values of these aggregate national variables for each year between 1977 and 1997. The percentage change from the previous year is also given for the output and IT capital variables.

Table 4.6Description of Variables at the National Level

Year	Output	Total Capital	ITCapital	Non-ITCa	Labor Hours	IT ratio(%)	% Change in Output	% Change in IT Capital
1977	3.55	4.26	0.20	4.06	1.1	4.65	-	-
1978	3.73	4.42	0.22	4.20	1.2	5.02	5.1	12.1
1979	3.85	4.60	0.25	4.35	1.2	5.41	3.2	12.2
1980	3.84	4.76	0.28	4.48	1.2	5.83	-0.3	11.6
1981	3.92	4.93	0.31	4.62	1.2	6.23	2.1	10.4
1982	3.85	5.07	0.33	4.73	1.1	6.57	-1.8	8.5
1983	4.00	5.18	0.36	4.82	1.2	6.95	3.9	8.1
1984	4.32	5.36	0.40	4.97	1.2	7.37	8.0	9.7
1985	4.48	5.57	0.43	5.14	1.3	7.74	3.7	9.1
1986	4.57	5.73	0.47	5.27	1.3	8.11	2.0	7.9
1987	4.74	5.88	0.49	5.39	1.3	8.37	3.7	5.8
1988	5.00	6.03	0.52	5.51	1.3	8.64	5.5	5.9
1989	5.11	6.18	0.55	5.63	1.4	8.93	2.2	6.0
1990	5.13	6.33	0.58	5.75	1.4	9.13	0.4	4.5
1991	5.09	6.42	0.60	5.82	1.3	9.31	-0.8	3.5
1992	5.21	6.51	0.63	5.88	1.4	9.66	2.4	5.4
1993	5.37	6.63	0.67	5.96	1.4	10.13	3.1	6.8
1994	5.66	6.79	0.73	6.06	1.4	10.73	5.4	8.3
1995	5.85	7.00	0.82	6.18	1.5	11.67	3.4	12.2
1996	6.09	7.28	0.95	6.32	1.5	13.09	4.1	16.6
1997	6.39	7.63	1.15	6.48	1.6	15.04	4.9	20.7

Source: Based on BEA. Values for output and capital are in real 1992 trillion of dollars. Hours are in hundreds of billions (rounded to the first decimal). "IT ratio" is IT capital divided by total capital, in percent.

National output rose from 3,550 trillion 1992 dollars in 1977 to 6,390 trillion in 1997, with an average yearly growth rate of 2.8%. In 1980, 1982 and 1991, national output declined in real terms, corresponding to recession periods. On the other hand, the growth rate of IT capital (% change in IT capital) is much more important, averaging a yearly 8.8% growth. However, this rate of growth decreased in the late 1970s, seesawed in the 1980s, was at a bottom value of 3.5% in 1991, and started to increase thereafter. The growth rate of IT capital reached its 1979 value of 12.2% in 1995, and boomed to more than 20% in 1997. The ratio of IT capital to total capital (IT ratio) increased from less that 5% in 1977, to more than 15% in 1997. This is a direct consequence of booming investment in IT since the 1970s, and stresses the growing importance of this type of capital in the economy.

4.3.2Variables at the Industry Level

This section describes data on output, capital and hours at the aggregate industry level. Table 4.7 describes the average values for each variable between 1977 and 1997. Not surprisingly, the top 10 most IT intensive industries (highest IT ratio) belong to the service sector, except for the “Electronic, instruments and related equipment” manufacturing industry. In these 10 industries, the IT capital stock represents more than 15% of the total capital stock. This ratio is highest for the “Communications” industry, where almost half of the total capital stock is IT capital.

4.4.3 Variables at the State level

This section describes the main variables (output, capital and labor hours) at the state level. Table 4.8 shows averages values of these variables during the period 1977-1997. States are ranked in descending order of IT intensity (IT ratio). The average IT ratio across states varies between less than 4% to almost 13.5%. The District of Columbia is, not surprisingly, the most IT intensive state, followed by New York, New Jersey. Among the top 10 most IT intensive states, 4 states (California, New York, Florida and New Jersey) are some of the 8 states that own more than half of the national stock of IT capital (see Figure 2.9). Furthermore, the District of Columbia, Delaware and Rhode Island own a very small share of the national stock of IT capital, but they are in the top 10 most IT intensive states.

This chapter has described the methodology used in this study to measure the productive capacity of information technology capital. A model measuring the returns to IT capital and its contribution to output and productivity growth was constructed. The variables and data needed for estimation are defined and described in Table 4.9. The next chapter will present the main results of this research

Table 4.7Description of Variables at the Industry Level

Rank	Code	Industry	Output	Totalcapit	ITcapital	Labor hours	IT ratio(%)
1	62	Communications	1.37	3.96	1.62	1.22	41.02
2	106	Motion pictures	0.18	0.15	0.04	0.42	25.25
3	103	Business and Other Services	3.88	1.44	0.33	8.09	19.61
4	7	Wholesale trade	3.36	2.56	0.46	9.29	17.49
5	108	Health services	3.29	0.88	0.15	10.60	15.65
6	109	Legal services	0.80	0.15	0.03	1.24	15.19
7	93	Insurance carriers	0.76	0.83	0.14	2.51	14.53
8	92	Security brokers	0.44	0.08	0.01	0.72	14.04
9	527	Electronic, instrument...	1.44	1.23	0.19	2.78	13.35
10	91	Banking	2.23	2.86	0.40	2.14	11.49
11	96	Holding and investment	0.10	0.25	0.03	0.34	11.35
12	537	Chemicals	1.05	1.55	0.18	2.22	11.21
13	536	Printing & publishing	0.78	0.46	0.05	2.79	11.12
14	94	Insurance agents	0.36	0.06	0.01	1.08	10.34
15	617	Transportation services	0.17	0.27	0.03	0.57	9.34
16	529	Other transport. equipment	0.58	0.45	0.04	2.16	9.24
17	102	Personal services	0.40	0.21	0.02	1.62	8.88
18	526	Industrial machinery	0.99	1.04	0.10	4.48	8.65
19	615	Transportation by air	0.35	0.79	0.05	1.20	5.60
20	612	Local & interurban	0.11	0.19	0.01	0.62	5.47
21	107	Amusement and recreation	0.36	0.35	0.02	1.39	5.24

Rank	Code	Industry	Output	Totalcapit	ITcapital	Labor hours	IT ratio(%)
22	531	Food & kindred products	0.95	1.16	0.06	3.38	4.95
23	523	Stone, clay, glass	0.25	0.41	0.02	1.21	4.77
24	532	Tobacco products	0.34	0.08	0.00	0.12	4.45
25	63	Electric, gas, & sanitary	1.57	7.84	0.36	1.77	4.44
26	538	Petroleum products	0.28	0.77	0.03	0.36	4.35
27	535	Paper products	0.42	0.76	0.03	1.43	3.99
28	105	Misc. repair services	0.18	0.09	0.00	0.51	3.98
29	5210	Misc. manufacturing	0.19	0.12	0.00	0.82	3.96
30	8	Retail trade	5.05	3.57	0.15	24.90	3.78
31	104	Auto repair & parking	0.49	0.70	0.03	1.34	3.70
32	95	Real estate	6.45	8.67	0.35	2.06	3.58
33	534	Apparel & textile	0.25	0.11	0.00	2.23	3.48
34	1010	Educational services	0.41	0.10	0.00	2.35	3.44
35	524	Primary metals	0.44	1.26	0.04	1.79	3.41

Table 4.7(Continued)

Rank	Code	Industry	Output	Totalcapit	ITcapital	Labor hours	IT ratio(%)
36	522	Furniture and fixtures	0.16	0.10	0.00	1.01	2.72
37	613	Trucking and warehousing	0.80	0.73	0.02	2.88	2.62
38	539	Rubber & plastics	0.31	0.37	0.01	1.73	2.48
39	525	Fabricated metals	0.71	0.67	0.02	3.04	2.38
40	33	Oil & gas	0.69	3.12	0.07	1.01	2.38
41	533	Textile mill products	0.22	0.35	0.01	1.52	2.27
42	5310	Leather products	0.05	0.03	0.00	0.34	2.21
43	521	Lumber & wood	0.32	0.27	0.01	1.50	2.11
44	528	Motor vehicles	0.67	0.65	0.01	1.82	2.00
45	614	Water transportation	0.11	0.40	0.01	0.36	1.81
46	101	Hotels & lodging	0.46	0.91	0.01	2.09	1.31
47	611	Railroad transportation	0.19	3.33	0.04	0.67	1.21
48	616	Pipelines, ex. nat. gas	0.06	0.42	0.00	0.04	1.12
49	34	Nonmetalic minerals	0.08	0.18	0.00	0.25	0.89
50	4	Construction	2.30	0.81	0.01	9.16	0.82
51	31	Metal mining	0.04	0.31	0.00	0.15	0.48
52	32	Coal mining	0.11	0.33	0.00	0.38	0.25
Note: Values are averages over 1977-1997. Industries are sorted by descending order of IT intensity (IT ratio)							

Table 4.8Description of Variables at the State Level

Rank	State	Output	Total Capital	IT capital	Labor Hours	IT Ratio
1	Dist. of Col.	24.30	23.60	3.31	0.56	13.54
2	New York	430.00	454.00	50.30	10.70	10.73
3	New Jersey	178.00	206.00	21.80	4.64	10.03
4	Colorado	65.10	81.50	8.51	1.74	9.78
5	Massachusetts	136.00	137.00	14.00	3.72	9.68
6	Delaware	17.30	22.60	2.40	0.40	9.63
7	Florida	204.00	230.00	23.50	5.40	9.61
8	Connecticut	81.70	85.90	8.73	2.22	9.56
9	Rhode Island	17.60	17.80	1.77	0.51	9.49
10	California	614.00	672.00	66.30	15.80	9.38
11	Georgia	116.00	143.00	14.60	3.36	9.38
12	Maryland	85.00	94.30	9.29	2.21	9.32
13	Washington	89.80	99.60	9.88	2.50	9.30
14	Virginia	113.00	129.00	12.70	2.87	9.20
15	Missouri	92.80	113.00	10.80	2.70	9.16
16	Vermont	9.10	10.40	0.97	0.26	8.90
17	Hawaii	21.70	25.80	2.38	0.57	8.84
18	Tennessee	82.20	90.30	8.31	2.58	8.73
19	New Hampshire	20.40	22.60	2.11	0.58	8.72
20	South Dakota	10.20	12.70	1.17	0.28	8.63
21	Illinois	246.00	298.00	26.60	6.80	8.61
22	Oregon	50.10	57.50	5.15	1.41	8.47
23	Iowa	46.70	56.60	4.91	1.39	8.39
24	North Carolina	124.00	131.00	11.70	3.49	8.32
25	Alabama	57.90	78.20	6.74	1.79	8.26
26	Arizona	57.80	72.10	6.38	1.56	8.20
27	Minnesota	84.40	102.00	8.69	2.43	8.10
28	Pennsylvania	218.00	273.00	22.60	6.32	8.03
29	Wisconsin	87.20	100.00	8.39	2.62	8.03
30	South Carolina	50.00	63.10	5.34	1.60	8.01
31	Maine	18.00	20.80	1.74	0.55	7.98
32	Ohio	204.00	255.00	20.80	6.02	7.95
33	Michigan	175.00	200.00	15.80	5.01	7.66
34	Kansas	42.60	64.10	5.03	1.21	7.58
35	Indiana	98.30	126.00	9.83	2.95	7.57
36	Arkansas	32.60	45.20	3.52	0.99	7.43
37	Nebraska	25.80	39.90	3.06	0.74	7.33

Rank	State	Output	Total Capital	IT capital	Labor Hours	IT Ratio
38	Idaho	14.70	19.50	1.50	0.42	7.30

Table 4.8(Continued)

Rank	State	Output	Total Capital	IT capital	Labor Hours	IT Ratio
39	Texas	334.00	525.00	40.00	8.66	7.22
40	Mississippi	32.80	48.80	3.62	1.01	7.17
41	Utah	26.20	38.00	2.86	0.74	7.11
42	Oklahoma	48.50	76.30	5.41	1.33	7.00
43	Kentucky	60.00	76.20	5.47	1.70	6.92
44	North Dakota	9.22	14.60	1.02	0.25	6.88
45	West Virginia	25.50	45.30	2.83	0.72	6.16
46	New Mexico	23.30	40.00	2.56	0.57	6.14
47	Nevada	26.20	39.30	2.51	0.79	5.95
48	Montana	11.30	20.70	1.22	0.32	5.82
49	Louisiana	82.40	156.00	9.02	2.04	5.69
50	Alaska	17.20	50.00	1.92	0.37	3.85
51	Wyoming	11.40	33.00	1.23	0.27	3.62

Table 4.9Variable Definitions and Sources

Variable	Name	Definition	Data
T	Time	Year indices	t = 1...21 for years = 1977-1997
I	Industry	Industry indices	i = 1...52 for 2-digit SIC = 31-5310
S	State	State indices	s = 1...51 for fips = 01-56
Y	Output	Aggregate Value-added	"Gross Product Originating" BEA
K	Total Capital	Capital Stock, measured as the net wealth stock of nonresidential equipment and structure	"Fixed Reproducible Tangible Wealth" BEA
KIT	Information technology capital	IT capital stock, measured as the stock of Information Processing Equipment	"Fixed Reproducible Tangible Wealth" BEA
KNIT	Traditional or non-IT capital	Capital stock other than Information Processing Equipment	KNIT = K – KIT
IT%	IT ratio	Share of IT capital in total capital	ITP = KIT/K
E	Employment	Number of full-time equivalent employees	GPO from BEA
H	Hours	Average yearly hours (52* average weekly hours)	Bureau of Labor Statistics
L	Labor hours	Total number of hours worked	L = E * H

CHAPTER 5 - EMPIRICAL RESULTS

This chapter describes the empirical results from the analysis presented in chapter 4. The sections 5.1 and 5.2 report evidence on the returns to IT capital stock and the “excess” return hypothesis, respectively. Then, in section 5.3, the contribution to output growth of IT capital is estimated for each state between 1977 and 1997. Section 5.4 describes the results regarding the labor productivity growth contribution of IT capital, by state. Finally, section 5.5 summarizes findings and draws the comparison with other studies.

5.1Is IT Capital a Productive Input?

In this section, I present the empirical results related to the measurement of the productive capacity of IT capital. Derived from equations 4.14 and 4.13, the two following equations are estimated:

$\ln(Y)_{its} = \ln(A) + \alpha_1 \ln(KIT)_{its} + \alpha_2 \ln(KNIT)_{its} + \beta \ln(L)_{its}$ (5.1)

Using fixed effects for industries, states and years

$\ln(Y)_{its} = \ln(A) + \Sigma_{i-1} Di + \Sigma_{s-1} Ds + \Sigma_{t-1} Dt + \alpha_1 \ln(KIT)_{its} + \alpha_2 \ln(KNIT)_{its} + \beta \ln(L)_{its}$ (5.2)

Coefficients α_1, α_2, and β represent the output elasticities to various inputs, which are also the percent change in output for a 1% change in the quantity of input. An input is a productive resource if its output elasticity is significantly positive. These parameters can also be considered as the marginal products of each input, which represent the amount of additional output provided for an additional dollar invested in the input. Table 5.1 reports estimates of elasticities for equation 5.1. Results indicate a positive and significant elasticity (or marginal product) of IT capital input at all levels of study (with a value between 0.115 and 0.211), except for the estimation of equation 5.2 at the level of detailed industries nationally.

First, equations 5.1 and 5.2 were estimated at the detailed industries level, by state and year, representing 55,692 observations (one observation for each industry, in each state, for each year). Without the use of fixed effects (equation 5.1), results indicate output elasticities of 0.196 for IT capital, 0.162 for traditional capital, and 0.638 for hours worked. These coefficients are close to their expected values in the presence of constant returns to scale (0.66 for labor and 0.33 for total capital). The R-squared and Durbin Watson (0.95 and 1.83, respectively) indicate a high degree of explanatory power of the model and the absence of serial correlation in the error term. However, the elasticity of IT capital drops from 0.196 to 0.021 when industry, state and time fixed effects are accounted for (equation 5.2). This result indicates that roughly 90% of the elasticity of IT capital may be attributable to industry, state and time effects. Thus, there are industry and state differences, across years, regarding the productive capacity of IT capital, and these differences may increase the estimates of the marginal product of IT capital by 90%. Still, this elasticity is significantly positive, and IT capital can be considered as a productive input.

Table 5.1Estimates of Elasticities for Equations 5.1 and 5.2 for Detailed Industries by State, for Aggregated Industries by State and for Detailed Industries at the National Level

Equation Estimated	(5.1)	(5.2)	(5.1)	(5.2)	(5.1)	(5.2)
Level of study	Detailed Industries by State	Detailed Industries by State	Aggregated Industries by state	Aggregated Industries by state	Detailed Industries at the National level	Detailed Industries at the National level
Fixed Effects	No	Yes: D_i, D_s, D_t	No	Yes: D_t, D_s	No	Yes: D_i, D_t
Constant	2.936	1.470	2.684	3.414	4.298	14.591
IT capital	0.196	0.021	0.211	0.092	0.210	(-0.007)
Non-IT capital	0.162	0.337	0.125	0.216	0.130	(-0.000)
Labor	0.638	0.632	0.671	0.650	0.597	0.386
R^2	0.95	-	0.99	-	0.95	0.98
Durbin Watson	1.83	-	1.56	-	-	-
Time periods	21	21	21	21	21	21
Industries	52	52	-	-	52	52
States	51	51	51	51	-	-
N	55,692	55,692	1,071	1,071	1,092	1,092
Note: All coefficients are significant at the 0.01 level, except those in parentheses.						

Equation 5.1 is also estimated at the state level (aggregated industries, by state and by year). Results are similar, but vary when fixed state and time effects are introduced (equation 5.2). The estimated elasticity drops from 0.211 to 0.092 because of state and time effects. Equation 5.1 is finally estimated at the detailed industries national level. Results show that the output elasticities are similar to the ones at the detailed industries level by state. However, regression using fixed effects (equation 5.2) produces estimates of output elasticities of capital not significantly different from zero.

To understand better how input elasticity estimates vary at the different levels of analysis, I estimated equations 5.1 (or 5.2 when fixed effects were needed) by selected industry sector, by year and by state. Results appear in Tables 5.2, 5.3 and 5.4, respectively.

Results of regression 5.2 vary across industry sectors as reported in Table 5.2. The output elasticity of IT capital is positive and significant for all sectors except Finance, Insurance and Real Estate (F.I.R.E.). This is probably due to mismeasurement errors resulting from the difficulty of measuring inputs and outputs in this sector.

Table 5.2Estimates of Elasticities from Equation 5.2 for Selected Industry Sectors across States

[6] Except mining and construction sectors, for which the estimated coefficients are insignificant

Sector	Constant	IT capital	Non-IT capital	Labor
All[6]	3.719	0.247	0.126	0.600
Manufacturing:	4.209	0.191	0.247	0.470
Durable goods	3.149	0.113	0.194	0.664
Nondurable Goods	5.333	0.317	0.124	0.435
Service Sector:	3.301	0.219	0.127	0.657
Transportation	3.120	0.213	0.250	0.500
Trade[7]	1.944	0.016	0.920	(-0.01)
F.I.R.E.[8]	5.069	-0.556	0.970	0.335
Service Industry	4.210	0.171	-0.030	0.835
Note: Separate regressions for each sector, with time and state dummies. All coefficients are significant at the 0.01 level, except those in parentheses. The number of observation for each regression is 1,071 (1 observation for each state, each year: 51*21 = 1,071)				

For all sectors aggregated, the output elasticity of IT capital is 0.247, and it is greater than the output elasticity of traditional capital (0.126). The sum of output elasticities is not significantly different from one for all regressions, which support the constant returns to scale hypothesis. The service sector has a greater output elasticity of IT capital than the manufacturing sector (0.219 and 0.191 respectively), but the difference is small. The nondurable goods manufacturing sector has the highest elasticity of IT capital (0.317). IT capital has a greater output elasticity than traditional capital in the service sector, while the reverse is true in the manufacturing sector. The coefficients for Finance, Insurance and Real Estate (F.I.R.E.) sector is negative for IT capital. Once again, this may be due to the difficulty of measuring output in that industry (mismeasurement hypothesis).

The output elasticities of inputs vary also across time during the last two decades. Table 5.3 reports estimates of equation 5.1 for each year between 1977 and 1997. These output elasticities are all positive and significant. The aggregate output elasticity of IT capital ranges from 0.13 in 1977 to more than 0.27 in 1982. Figure 5.1 clearly shows the gap between output elasticities of IT capital and traditional capital. The difference between the output elasticities of the two types of capital was highest during the 1980s.

Table 5.4 presents elasticities estimates from equation 5.2 for each of the 51 states at two levels: (1) at the detailed industries level (controlling for industry fixed effects) and (2) at the aggregated industry level. At the detailed industries level, all coefficients are significant and the output elasticity of IT capital (α_1) averages 8.48% across states, with a standard deviation of 1.22.

Table 5.3Estimates of Equation 5.1 Over Time

[6] Except mining and construction sectors, for which the estimated coefficients are insignificant

[7] Wholesale and Retail trade

[8] Finance, Insurance and Real Estate sector, Except “holding and investment” industry because of data concerns

YEAR	Constant	IT capital	Non-IT capital	Labor
1977	3.13	0.13	0.21	0.65
1978	3.26	0.17	0.15	0.67
1979	3.36	0.21	0.12	0.65
1980	3.28	0.24	0.07	0.68
1981	3.25	0.26	0.07	0.67
1982	3.28	0.27	0.05	0.67
1983	3.17	0.27	0.07	0.66
1984	3.06	0.25	0.09	0.66
1985	3.06	0.25	0.10	0.65
1986	3.02	0.23	0.12	0.64
1987	3.08	0.24	0.13	0.62
1988	3.00	0.23	0.15	0.62
1989	3.06	0.24	0.13	0.63
1990	2.97	0.23	0.13	0.63
1991	2.79	0.22	0.17	0.62
1992	2.73	0.21	0.17	0.62
1993	2.78	0.22	0.17	0.61
1994	2.78	0.22	0.18	0.60
1995	2.83	0.23	0.18	0.59
1996	2.77	0.24	0.19	0.56
1997	2.83	0.25	0.19	0.55
Note: No fixed effects included. All coefficients significant at the 0.01 level				

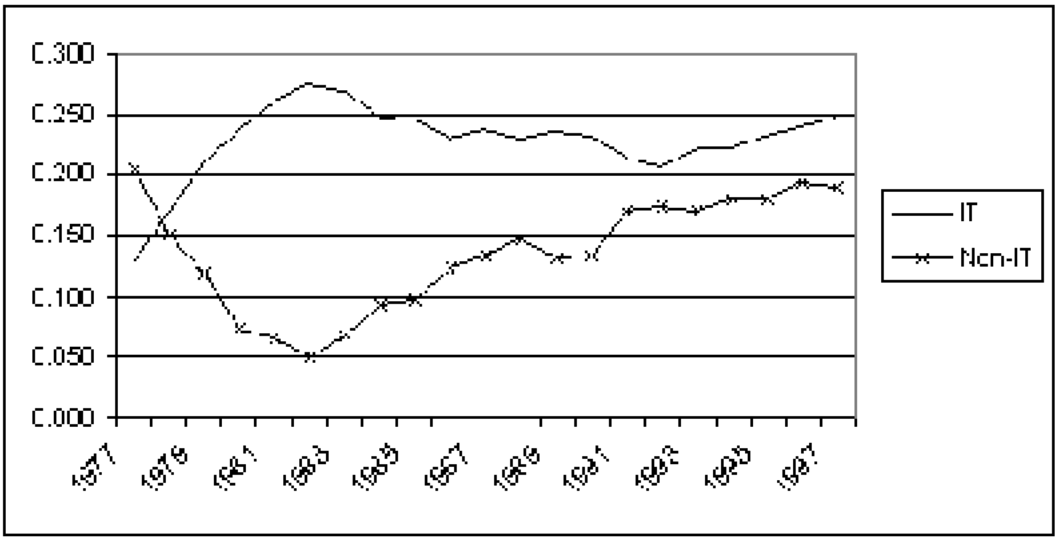


Figure 5.1Trends in Aggregate Output Elasticities of IT and Traditional Capital, 1977-1997

Table 5.4Estimates of Elasticities from Equation 5.1 for Detailed and Aggregated Industries by State

Level of Analysis	**Detailed Industries**				**Aggregate Industries**			
State	Constant	IT capital	Non-IT capital	Labor	Constant	IT capital	Non-IT capital	Labor
Alabama	2.61	9.2	27.6	55.2	(-3.96)	(11)	(21)	98
Alaska	0.68	7.9	36.0	60.0	9.88	17	14	33
Arizona	3.06	11.0	33.6	45.6	2.31	21	(9)	72
Arkansas	4.95	10.2	23.6	42.4	(-0.27)	11	20	81
California	2.17	8.6	28.0	60.2	(-0.71)	13	30	68
Colorado	3.86	10.5	30.7	43.7	6.44	20	(-5)	70
Connecticut	4.02	8.7	15.4	61.6	(-0.77)	13	31	69
Delaware	2.11	7.8	28.3	61.3	-7.90	(-6)	77	73
Dist. Of Col.	2.18	6.3	29.9	59.6	1.62	8	19	78
Florida	3.02	8.9	22.8	60.7	1.58	9	24	70
Georgia	3.13	8.6	21.7	57.0	-5.40	(2)	44	82
Hawaii	3.08	6.5	21.3	71.6	1.86	7	15	82
Idaho	2.09	9.1	30.9	56.2	3.42	21	(-199)	88
Illinois	4.69	8.3	19.0	51.7	-6.06	14	57	60
Indiana	3.10	7.6	27.9	59.9	-7.69	8	57	75
Iowa	5.16	8.1	29.5	47.5	(-0.14)	15	34	61
Kansas	4.05	8.2	32.5	48.3	13.90	19	(-11)	42
Kentucky	4.23	8.3	24.0	58.4	9.76	18	-57	1.19
Louisiana	1.61	8.0	33.6	57.2	11.62	16	(-6)	52
Maine	4.23	9.9	20.9	49.4	-7.62	(5)	53	87
Maryland	3.04	8.9	30.5	50.7	-1.84	9	46	61
Massachusetts	2.65	7.9	25.3	57.7	-1.55	13	42	60
Michigan	3.78	8.9	25.8	52.7	-8.31	7	66	68
Minnesota	4.72	9.6	24.7	48.5	(2.27)	18	(-5)	92
Mississippi	3.93	7.4	26.2	58.2	(-0.45)	15	20	79
Missouri	4.54	9.2	27.7	44.0	-8.50	(2)	71	69
Montana	1.86	9.2	37.2	49.1	10.34	20	-26	76
Nebraska	2.32	6.9	30.5	58.7	(-0.31)	10	29	73
Nevada	2.59	9.7	31.7	51.9	(0.28)	(-1)	15	97
New Hampshire	2.64	7.3	28.7	63.3	(0.21)	20	18	73
New Jersey	3.05	7.5	20.6	62.9	-4.01	10	18	66
New Mexico	1.91	9.7	37.6	47.8	7.55	20	-45	1.13
New York	6.74	6.6	10.3	52.5	(0.85)	20	16	71

Table 5.4(Continued)

Level of Analysis	Detailed Industrie				Aggregat Industrie			
State	Constant	IT capital	Non-IT capital	Labor	Constant	IT capital	Non-IT capital	Labor
North Carolina	2.36	6.7	21.9	71.0	6.91	20	-61	1.34
North Dakota	2.62	7.8	36.1	52.4	6.88	13	-4	37
Ohio	3.78	8.2	23.5	48.1	(-0.70)	20	(12)	82
Oklahoma	4.12	9.1	28.0	41.9	11.70	16	-10	55
Oregon	2.36	9.3	33.0	49.5	1.68)	19	(1)	87
Pennsylvania	2.94	7.4	23.5	58.5	(-0.47)	18	40	51
Rhode Island	4.49	7.2	17.8	66.5	-7.38	6	47	92
South Carolina	1.49	5.7	26.6	72.2	-3.95	15	27	86
South Dakota	1.67	8.2	31.7	58.7	4.76	14	21	53
Tennessee	5.21	11.4	16.6	51.6	-4.04	7	41	79
Texas	1.74	8.7	32.1	57.1	16.45	37	-44	56
Utah	1.96	9.7	37.4	47.9	11.27	33	-43	79
Vermont	4.92	8.9	20.9	58.9	(0.44)	14	26	69
Virginia	3.09	9.7	27.5	50.7	5.34	14	(-2)	79
Washington	2.07	10.1	37.0	46.7	2.09	11	42	45
West Virginia	4.22	6.9	21.1	55.0	12.93	41	-55	76
Wisconsin	3.09	8.8	27.6	52.4	(2.82)	20	(-8)	91
Wyoming	2.33	8.5	38.9	43.9	21.35	44	-79	60

Note: Elasticities are expressed in percentage. All coefficients are significant at the 0.01 level except those in parentheses. For detailed industries regressions (using industry dummy variables), there are 52 industries * 21 years = 1,092 observations for each state. For aggregated industry there are 21 observations for each state.

Tennessee and Arizona present the highest returns to IT capital stock (greater than 11%), and South Carolina and Hawaii the lowest. This means that some states seem to use IT capital more efficiently than others, even though the differences do not seem to be very important. Eight of the “most IT” states (Figure 2.9) present an output elasticity of IT capital less than or equal to the overall states’ average of 8.48%. Hence, the returns to IT capital do not seem to be the greatest for states that own the highest share of IT capital. At the aggregated industry level by state, many coefficients are not significant, and regression results vary significantly from the results at the detailed industries level. This is certainly due to the fact that, at the aggregated industry level, only 21 observations are available for each state (one for each year), as opposed to 1,092 observations per state at the detailed industries level (one for each industry each year). The average output elasticity of IT capital at the aggregated industries level is higher than at the detailed industries level (14.82% and 8.48%, respectively), and the standard deviation is 10 times greater. Furthermore, at this aggregated industries level, output elasticities of IT capital for the most IT states are greater than or equal to average elasticity, except for California, which owns the highest share of the nation's IT capital stock.

Hence, several conclusions can be drawn from the estimates of equations 5.1 and 5.2. First of all, IT capital is a productive input, that has an output elasticity estimated at roughly 0.20 at the detailed industry level by state, but industry and state fixed effects may account for most of this value. At the sectoral level, there are no major differences between manufacturing and the service sector regarding output elasticities of IT capital (also estimated at around 0.20), but there are some differences at a more disaggregated level. Indeed, the elasticity IT capital is highest for the nondurable goods sector (0.32) and lowest for the trade sector (0.02), not including the negative elasticity for the F.I.R.E. sector, which may be due to measurement difficulties in that sector. The returns to IT capital are relatively stable at the national level over time (between 0.15 and 0.25), with an increase until 1983, a plateau for the rest of the 1980s, and a slight increase since the early 1990s. Finally, the average returns to IT capital across states is around 0.08 at the detailed industries level across states, and is around 0.14 at the aggregated industries level across states. However, results from the aggregated industries level must be interpreted carefully since only 21 observations were available for each state. From the detailed industries regression results, the returns to IT capital appear lower than average in states that own the highest share of the nation's IT capital stock.

Hence, based on all these findings, IT capital stock seems to be a productive input with an output elasticity that varies between 10% and 20%, and between 2% and 10% when fixed effects are introduced. In order to further investigate the productive capacity of IT capital, the next section discusses the "excess" returns hypothesis.

5.2Excess returns from IT capital

In this section I present some evidence on the "excess" return hypothesis, which states that returns to IT capital are greater than those to traditional capital. In order to test this hypothesis, I estimated the following equation (based on equation 4.9 and 4.15, respectively):

$$\ln(Y)_{its} = \ln(A) + \alpha.\ln(K)_{its} + \alpha\theta(IT\%)_{its} + (1\text{-}\alpha)\ln(L)_{its} + \varepsilon_{its} \quad (5.3)$$

Introducing fixed effects and taking logarithms:

$$\ln(Y)_{its} = \ln(A) + \Sigma\gamma_{t-1} + \Sigma\lambda_i + \Sigma v_s + \alpha\ln(K)_{its} + \alpha\theta(IT\%)_{its} + (1\text{-}\alpha)\ln(L)_{its} + \varepsilon_{its} \quad (5.4)$$

Table 5.5 reports estimates of equations 5.3 and 5.4. The coefficients for capital and labor reach their expected constant return to scale values of 1/3 and 2/3 respectively. When no fixed effects are accounted for, θ has a value significantly greater than 5 (7.54), which leads to the conclusion that IT capital exhibits excess returns over traditional capital. Regressions with fixed industry effects show a value of θ =9, also significantly higher than 5, which means that IT capital has a return higher than that of traditional equipment. Finally, regression results at the state level also indicate excess returns to IT capital (θ =7.91), but not when state and time effects are introduced. Thus, the excess returns of IT capital may be partly due to differences across states and time.

Table 5.5Estimates of Elasticities for Equations 5.3 and 5.4 for Detailed Industries by State, for Aggregated Industries by State and for Detailed Industries at the National Level

Regression	(5.3)	(5.4)	(5.3)	(5.4)	(5.3)	(5.4)
Level of study	Detailed Industries by State	Detailed Industries by State	Aggregated Industries by state	Aggregated Industries by state	Detailed Industries at the National level	Detailed Industries at the National level
Fixed Effects	No	Yes: D_i, D_s, D_t	No	Yes: D_t, D_s	No	Yes: D_i
Constant	2.126	1.350	2.004	3.614	3.010	11.44
Capital	0.336	0.345	0.314	0.270	0.321	0.219
IT Ratio	2.533	-1.129	2.483	(0.131)	2.634	1.974
Labor	0.663	0.645	0.694	0.671	0.639	0.276
R^2	0.945	-	-	-	0.803	0.976
θ	7.54	-3.27	7.91	(0.48)	8.20	9.01
Time periods	21	21	21	21	21	21
Industries	52	52	-	-	52	52
States	51	51	51	51	-	-
N	55,692	55,692	1,071	1,071	1,092	1,092

Equation 5.3 is then estimated for selected sectors, years and states. Results appear in Tables 5.6, 5.7 and 5.8, respectively. Table 5.6 shows that, except for F.I.R.E. and transportation industries, the value of θ is significantly greater than 5, which confirms the hypothesis of excess returns to IT capital. The highest value was found in the service industry (θ = 22.2). Equation 5.3 is also estimated for each year between 1977 and 1997. Results appear in Table 5.7. First, the coefficients for capital increased over time (from 0.271 to 0.433), and the coefficient for labor decreased (from 0.693 to 0.535), but these coefficients remained close to their expected values of 0.33 and 0.66, respectively.

Table 5.6Estimates of Elasticities from Equation 5.4 for Selected Industry Sectors across States

[9] Except mining and construction sectors, which yield insignificant estimates.

Sector	Constant	Capital	IT Ratio	Labor	θ
All[9]	2.461	0.347	2.517	0.633	7.3
Manufacturing:	3.269	0.446	3.908	0.457	8.8
Durable goods	2.867	0.282	3.810	0.673	13.5
Nondurable Goods	3.494	0.479	4.557	0.405	9.5
Service Sector:	2.325	0.306	1.933	0.701	6.3
Transportation	1.993	0.414	1.866	0.553	4.5
Trade[10]	3.167	0.611	0.584	0.297	1.0
F.I.R.E.[11]	1.187	0.306	-6.331	0.826	-20.7
Service Industry	3.468	0.105	2.329	0.871	22.2

The increase in the coefficient for capital is probably mostly due to the increase in the returns to IT capital over time. Between 1980 and 1993, the estimated value of θ is significantly greater than 5, indicating excess returns to IT capital for these years.

Figure 5.2 represents the evolution of θ over the period 1977-1997. The first and last three years of the period do not seem to exhibit excess returns to IT capital because of a low value of θ. This is explainable by the heavy fixed costs associated with the introduction of IT capital in the economy in the late 1970s, preventing excess returns. Finally, in the early 1990s the excess returns capacity of IT capital may have been exhausted after its important price (and marginal return) declined.

Equations 5.3 and 5.4 are finally estimated for each state at the detailed and aggregated industries levels, by state. However, the elasticities estimates do not indicate excess returns to IT capital for any of the states, with a value for θ not significantly different or even lower than 5. Therefore, IT capital does seem to exhibit excess returns at the national aggregated level and at the sectoral level, but not at the state level.

[9] Except mining and construction sectors, which yield insignificant estimates.

[10] Wholesale and Retail trade

[11] Finance, Insurance and Real Estate, except "holding and investment" industry

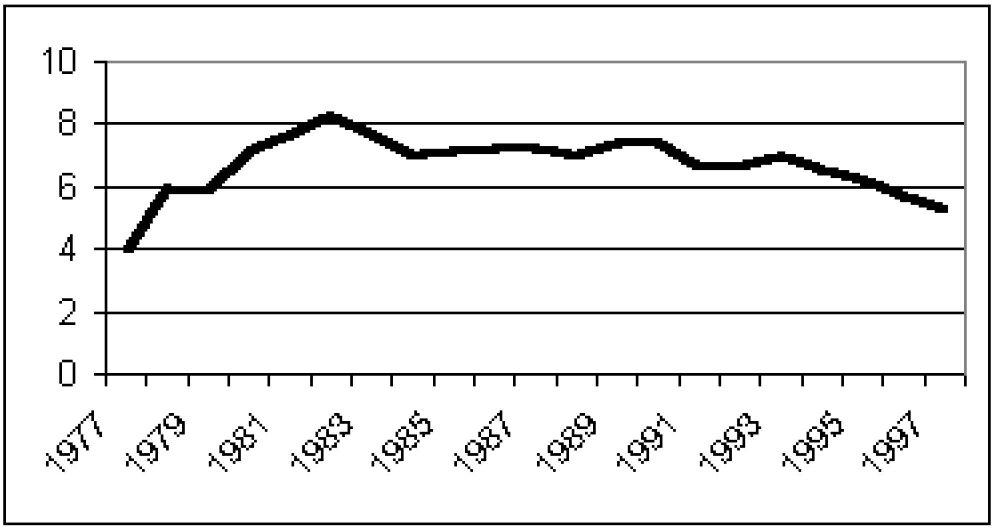


Figure 5.2Trend in Parameter θ, 1977-1997

Table 5.7Estimates of Elasticities from Equation 5.4 Over Time

YEAR	Constant	Capital	IT Ratio	Labor Hours	θ
1977	2.550	0.271	1.079	0.693	4.0
1978	2.516	0.253	1.505	0.720	6.0
1979	2.354	0.274	1.616	0.693	5.9
1980	2.211	0.263	1.891	0.717	7.2
1981	2.079	0.281	2.172	0.698	7.7
1982	2.107	0.281	2.331	0.694	8.3
1983	1.980	0.299	2.304	0.682	7.7
1984	2.027	0.307	2.164	0.678	7.0
1985	2.087	0.315	2.257	0.667	7.2
1986	2.300	0.317	2.297	0.663	7.3
1987	2.295	0.341	2.476	0.632	7.3
1988	2.246	0.351	2.454	0.629	7.0
1989	2.291	0.344	2.546	0.632	7.4
1990	2.231	0.340	2.523	0.641	7.4
1991	2.168	0.360	2.395	0.628	6.7
1992	2.149	0.358	2.380	0.636	6.7
1993	2.205	0.369	2.589	0.620	7.0
1994	2.230	0.383	2.507	0.603	6.6
1995	2.263	0.399	2.475	0.580	6.2
1996	2.249	0.424	2.444	0.549	5.8
1997	2.315	0.433	2.307	0.535	5.3

5.3Output Growth Contribution of IT Capital, by State

This analysis is concerned with the *relative* contributions of IT to output growth among states, and not their *absolute* levels. IT capital might have a low *absolute* contribution, and still a high contribution *relative* to a state's share of national IT stock. The idea is that many states have seen positive effects of IT on productivity but these states account for a small share of the national IT capital stock. Only 10% of the states own more than 50% of the total U.S. stock of IT capital. Hence, aggregating the states' contributions may show a small overall contribution of IT to productivity in the United States. Indeed, as stated in chapter 2, more than 50% of the U.S. total IT capital stock is located in 8 states: California, New York, Texas, Illinois, Florida, Pennsylvania, New Jersey and Ohio. More than 80% of this stock is located mainly in the service sector (and more specifically in transportation, F.I.R.E, services and retail trade, respectively) and manufacturing accounts for 15%. Thus, the question of IT and productivity should be analyzed with a closer look at what happened in these eight states and specifically in their transportation, F.I.R.E, services, manufacturing and wholesale trade industries.

Following the method of Oliner and Sichel (1994), I assume the output growth contribution of IT capital (OGC_{KIT}) can be computed as the product of IT capital's income share and its growth rate. The income share is defined as the product of the return to IT capital (*r*) times the ratio of its stock with total output (KIT/Y):

$$OGC_{KIT,\, t} = [r * (KIT/Y)_{t-1}] * gr(KIT)_t \quad (5.5)$$

where *t* denotes the year and *r* is the return to IT capital net of depreciation. I computed the average yearly output growth contribution for each state. Results appear in Table 5.8. States are sorted in descending order by their respective growth contribution. This contribution is also expressed as a percentage of a state's output growth rate. The average growth rates of output and IT capital stock are also given for each state. The average share of a state IT capital stock over the total national stock and the state IT ratio also appear in Table 5.8. According to these results, the contribution of IT capital to output growth ranges from less than 5 to more than 14 average yearly percentage points.

Table 5.8Contribution of IT Capital to Output Growth, by State, 1977-1997

Rank	State	Output growth contrib of IT	Percen of output growth due to IT	Output growth	Growth of IT capital	Share of national IT capital stock	IT ratio
1	Colorado	14.16	3.38	4.19	10.91	1.59	10.02
2	Arizona	13.06	2.28	5.72	11.41	1.18	8.38
3	Georgia	11.76	2.42	4.85	11.68	2.66	9.61
4	Delaware	11.20	2.71	4.13	11.41	0.43	9.83
5	New Mexico	11.20	2.71	4.13	10.58	0.49	6.31
6	Washington	11.18	3.01	3.72	10.43	1.86	9.51
7	Utah	11.07	2.41	4.60	10.73	0.54	7.27
8	Virginia	10.92	3.29	3.32	10.57	2.37	9.41
9	Texas	10.69	2.89	3.70	10.74	7.63	7.41
10	Tennessee	10.38	2.83	3.66	9.14	1.59	8.90
11	Florida	10.09	2.19	4.61	10.01	4.45	9.79
12	Nevada	9.94	1.68	5.91	10.94	0.47	6.04
13	Arkansas	9.75	3.22	3.03	9.01	0.68	7.60
14	Minnesota	9.58	2.82	3.39	10.07	1.65	8.31
15	Oregon	9.55	2.47	3.87	10.26	0.97	8.67
16	Missouri	9.53	3.96	2.41	9.11	2.09	9.39
17	Kansas	9.30	4.26	2.18	9.84	0.97	7.78
18	Connecticut	9.18	2.66	3.46	10.06	1.65	9.77
19	South Dakota	9.17	2.74	3.35	10.29	0.22	8.82
20	Oklahoma	9.00	4.92	1.83	8.86	1.09	7.19
21	Alabama	8.86	3.01	2.94	8.69	1.31	8.45
22	Maryland	8.69	2.68	3.24	9.30	1.76	9.52
23	Wyoming	8.66	4.00	2.16	9.32	0.25	3.72
24	Vermont	8.60	2.35	3.66	9.34	0.19	9.08
25	Idaho	8.52	2.36	3.62	9.42	0.29	7.45
26	California	8.48	2.41	3.52	9.46	12.71	9.57
27	Maine	8.32	2.87	2.90	8.87	0.33	8.16
28	New Jersey	7.88	2.42	3.26	9.04	4.16	10.23
29	New Hampshire	7.81	1.42	5.52	10.98	0.39	8.87
30	Alaska	7.75	3.72	2.09	8.71	0.39	3.84
31	Wisconsin	7.74	2.84	2.73	9.21	1.61	8.23
32	Illinois	7.66	3.36	2.28	8.73	5.14	8.82
33	Montana	7.47	5.02	1.49	7.41	0.25	5.95
34	Nebraska	7.41	2.84	2.61	9.32	0.59	7.50

Rank	State	Output growth contrib of IT	Percent of output growth due to IT	Output growth	Growth of IT capital	Share of national IT capital stock	IT ratio
35	Iowa	7.19	3.46	2.08	8.61	0.96	8.59
36	Massachusetts	7.19	2.10	3.42	9.07	2.68	9.86
37	Louisiana	7.14	4.53	1.57	8.15	1.83	5.83
38	North Dakota	7.09	3.93	1.80	8.14	0.20	7.02
39	Mississippi	7.05	2.64	2.66	8.77	0.70	7.33
40	North Carolina	6.83	2.14	3.19	11.02	2.18	8.52
41	Ohio	6.80	3.29	2.07	8.07	4.09	8.14
42	Kentucky	6.64	3.17	2.09	8.55	1.07	7.08
43	Michigan	6.49	3.90	1.67	8.06	3.07	7.84
44	Pennsylvania	6.34	3.04	2.09	8.46	4.38	8.23
45	Dist. of Col.	6.34	3.56	1.78	7.41	0.65	13.81
46	Rhode Island	6.28	2.58	2.44	8.83	0.34	9.68
47	Indiana	6.05	2.54	2.38	7.93	1.93	7.74
48	Hawaii	5.90	1.92	3.07	8.30	0.46	9.01
49	New York	5.90	2.68	2.20	7.80	9.92	10.96
50	South Carolina	5.59	1.33	4.19	9.44	1.02	8.17
51	West Virginia	4.81	3.63	1.32	6.17	0.57	6.28

Source: based on data from BEA. The output growth contribution of IT capital is expressed in average yearly percentage points, all others are percentages.

Oliner and Sichel (1994) found a comparable average contribution of 16 percentage points for the period 1970-1992 at the national level. However, this absolute value depends on the methodology adopted, which varies greatly among authors. Here, the focus is on the relative contribution by state. The main result is that there are some important variations in the output growth contribution of IT capital among states. Furthermore, according to the theory of convergence, as capital accumulates, the speed of convergence is reduced. In other words, it is possible that the output growth contribution of IT capital is lower in states that own a larger share of the national IT capital stock. As stated earlier, eight states own more than half of the IT capital stock of the United States. If output growth contributions are lower in these states, the overall national aggregated contribution of IT capital to output growth would also be lower. This would also partly explain the productivity paradox. Looking at Table 5.8, it seems that these eight states do not indeed present the highest growth contribution of IT capital: California, New York, Texas, Illinois, Florida, Pennsylvania, New Jersey and Ohio are ranked 26th, 49th, 9th, 32nd, 11th, 44th, 28th and 41st, respectively. The average ranking for those eight states is 30th. Although not significant, the correlation between the contribution to growth and the share of national IT capital stock is estimated at -0.07. Hence, IT capital may make an important contribution to growth for many states and a less important one in the few states that account for most of the national IT capital stock. Thus, the productivity paradox may be true at the national level, not at the level of individual states.

5.4Labor Productivity Growth Contribution of IT Capital, by State

This section focuses on the contribution of IT capital stock to growth in labor productivity by sate. The equation estimated is:

$$gr(Y_s/L_s)= \alpha_0\, gr(KNIT_s/L_s)+ \alpha_1\, gr(KIT_s/L_s) + TFP \quad (5.6)$$

Labor productivity growth depends on IT and traditional capital deepening (KIT/L and KNIT/L), and total factor productivity (TFP), which includes labor quality in this study. First, output, capital and hours worked are aggregated across industries for each state each year between 1977 and 1997. In order to compute income shares for each state and years, the lagged ratio of input to output must be multiplied by the input's marginal return. Average output elasticities, or marginal returns of IT and traditional capital, are estimated from equation 5.2 for each state at the detailed industry level (Table 5.4). Income shares are computed for each state each year. Growth rates of IT and traditional capital per hour worked (capital deepening) are computed for each state each year. All these values are averaged over the period 1977-1997. Then, the labor productivity growth contribution of IT and traditional capital deepening are computed by state, as the product of average income shares and average growth rates. Table 5.9 shows: the productivity growth contribution and percentage of average growth in state productivity for IT and traditional capital; the average growth rate of state productivity; IT and traditional capital deepening; and TFP, respectively. Across states, 6% of the average labor productivity growth was due to IT capital deepening, 18% was due to other non-residential capital deepening, and the remaining 76% was due to residential capital deepening, labor quality improvement and total factor productivity. However, these results vary by state. The contribution of IT capital deepening varies from 2.25% to 11.07% across states. Furthermore, some of the lowest contributions of IT capital deepening are observed in the states that own more than half of the country's IT capital stock. Indeed, California, New York, Texas, Illinois, Florida, Pennsylvania, New Jersey and Ohio are ranked 34th, 44th, 17th, 37th, 7th, 42nd, 43rd and 38th (average ranking is 33rd). The correlation between a state's share of national IT capital stock and the contribution of this stock to productivity growth is negative although not significant (-0.133). The productivity paradox may again be explained with the convergence theory: IT capital highly contributes to growth in productivity when states start to accumulate IT capital. The magnitude of this contribution is then reduced as states converge to their ideal level of IT capital stock. However, when IT capital stock is considered nationally, its contribution to productivity growth seems lower because it is actually lower in states that own the highest share of this capital stock. Thus, long learning lags are needed to allow benefits from IT capital, bur rent dissipation make the returns to IT capital diminish over time as capital accumulates.

Table 5.9Average Labor Productivity Growth Contribution of IT and Traditional Capital by State

Rank	State	Productivity growth contribution of IT	% of productivity growth due to IT	Productivity growth contribution of non-IT capital	% of productivity growth due to non-IT capital	Growth rate of productivity	IT capital deepening	Non-IT capital deepening	TFP
1	Colorado	9.78	9.82	12.15	12.19	4.19	7.54	0.35	77.99
2	Delaware	8.84	4.65	71.29	37.51	4.13	9.01	2.16	57.84
3	Georgia	8.33	5.14	22.86	14.10	4.85	8.27	0.94	80.76
4	Washington	8.21	7.55	30.62	28.17	3.72	7.66	0.82	64.28
5	New Mexico	8.12	5.86	-40.94	-29.54	4.13	7.68	-0.64	123.68
6	Virginia	8.08	11.07	24.06	32.98	3.32	7.82	0.86	55.95
7	Missouri	8.05	7.87	13.62	13.32	2.41	7.70	0.44	78.81
8	Texas	7.95	6.96	18.44	16.15	3.70	7.99	0.39	76.89
9	Kansas	7.87	10.16	1.75	2.26	2.18	8.33	0.04	87.58
10	Oklahoma	7.86	9.66	3.01	3.70	1.83	7.73	0.07	86.64
11	Arizona	7.80	5.89	-3.70	-2.80	5.72	6.81	-0.09	96.91
12	Tennessee	7.68	5.71	11.89	8.84	3.66	6.77	0.71	85.45
13	Arkansas	7.60	7.02	21.80	20.13	3.03	7.03	0.72	72.85
14	Connecticut	7.45	4.51	22.66	13.73	3.46	8.16	1.56	81.76
15	Oregon	7.44	4.45	13.61	8.14	3.87	8.00	0.38	87.41
16	Minnesota	7.43	5.99	1.16	0.94	3.39	7.81	0.04	93.07
17	Utah	7.10	7.30	-5.04	-5.19	4.60	6.88	-0.10	97.89
18	Alabama	7.08	5.70	24.51	19.72	2.94	6.95	0.71	74.58
19	Illinois	7.00	4.53	13.19	8.53	2.28	7.98	0.62	86.94
20	South Dakota	6.97	7.12	38.70	39.55	3.35	7.82	1.08	53.33
21	Montana	6.92	7.52	32.19	34.95	1.49	6.86	0.50	57.53
22	Maine	6.75	5.33	16.37	12.93	2.90	7.20	0.73	81.74
23	Maryland	6.65	5.88	20.07	17.73	3.24	7.12	0.65	76.39
24	Iowa	6.56	4.97	25.32	19.19	2.08	7.85	0.77	75.84
25	Wisconsin	6.55	4.96	18.18	13.79	2.73	7.79	0.62	81.25
26	California	6.39	4.91	24.17	18.56	3.52	7.13	0.87	76.53
27	Idaho	6.39	4.87	17.81	13.57	3.62	7.06	0.46	81.56
28	Louisiana	6.36	8.34	43.44	56.96	1.57	7.26	0.72	34.70
29	New Jersey	6.35	4.08	23.57	15.15	3.26	7.29	1.10	80.77
30	Ohio	6.25	4.53	12.96	9.39	2.07	7.41	0.47	86.08
31	Vermont	6.20	5.34	14.18	12.21	3.66	6.73	0.65	82.45
32	Nebraska	6.19	5.42	56.01	49.01	2.61	7.78	1.28	45.57
33	North Dakota	6.10	8.26	51.09	69.21	1.80	7.00	0.96	22.53
34	Florida	5.97	8.50	6.90	9.82	4.61	5.92	0.30	81.68

Ra	State	Produ growt contri of IT	% of productiv growth due to IT	Productiv growth contribut of non-IT capital	% of productiv growth due to non-IT capital	Growth rate of productiv	IT capital deepenin	Non-IT capital deepenin	TFP
35	Michigan	5.93	6.49	14.36	15.70	1.67	7.37	0.52	77.81
36	Pennsylvania	5.85	4.11	8.67	6.10	2.09	7.8	0.32	89.79
37	Rhode Island	5.73	3.44	35.05	21.08	2.44	8.05	2.17	75.48
38	Mississippi	5.72	5.43	9.84	9.34	2.66	7.12	0.27	85.23
39	Massachusetts	5.64	3.62	25.53	16.38	3.42	7.12	1.11	80.00
40	Kentucky	5.53	8.34	12.75	19.26	2.09	7.12	0.45	72.40
41	New York	5.31	3.68	7.53	5.21	2.20	7.02	0.77	91.11
42	West Virginia	5.31	2.80	48.47	25.53	1.32	6.81	1.36	71.67
43	Dist. of Col.	5.27	9.94	4.46	8.41	1.78	6.17	0.18	81.65
44	North Carolina	5.26	6.93	25.00	32.99	3.19	8.48	1.19	60.08
45	Indiana	5.16	4.42	12.65	10.84	2.38	6.76	0.38	84.74
46	New Hampshire	5.13	2.69	56.12	29.46	5.52	7.2	1.95	67.85
47	Nevada	4.78	10.32	14.29	30.85	5.91	5.27	0.32	58.83
48	South Carolina	4.18	2.25	38.06	20.46	4.19	7.07	1.22	77.29
49	Hawaii	4.17	6.20	18.01	26.75	3.07	5.86	0.79	67.05

Note: Values are sorted in descending order by the percentage contribution of IT capital. All values are percentages, except the productivity growth contribution of IT and non-IT capital, expressed in average yearly percentage points. The states of Alaska and Wyoming were not included.

5.5 Summary of Findings and Comparison with Other Studies

This chapter has presented the results from estimation techniques aimed at measuring the productive capacity of IT capital and its effect on output growth and labor productivity growth. These techniques were applied at various levels of analysis: national, sector, state detailed and aggregated industry levels.

The first equation (5.1) measured an output elasticity of IT capital valued at up to 21% (Table 5.1). Lehr and Lichtenberg (1999), using a similar model, found an elasticity of IT capital between 4% and 17%. They also showed that IT capital exhibited excess returns to investment, and my results are similar, although these excess returns may be mostly due to state and time effects.

Information technology capital is also found to have contributed to output growth between approximately 0.05 and 0.15 percentage points across states (Table 5.8). Various authors have found values ranging from –0.34 to +1.50, as reported in Table 5.10. Hence, my results fall into this range, but are specific to the methodology and data I have used. Oliner and Sichel (1994) have found that IT capital contributed 0.16 percentage points per year to output growth during the period 1970-1992, which is close to my results. Finally, the contribution of IT capital to labor productivity growth is estimated between 0.04 and 0.10 percentage points per year. The percentage of output and labor productivity growth due to IT capital varies across states from 1% to 11%. Hence, IT capital has proven to be a productive input, even if its small share of total capital prevented it from having had higher effects on growth.

An interesting finding that helps understand the national productivity paradox is that the productivity effects of IT capital seem to be lower for states that own the highest share of national IT capital stock (such as California and New York). This confirms the hypothesis of redistributions of gains of IT capital among states. Therefore, the productivity paradox may have been only a problem at the national level.

The next chapter reviews the literature on state productivity differences and the role of externalities. It precedes a presentation of a model measuring the effects of the localization patterns of IT on state and county labor productivity.

Table 5.10Values of Output Growth Contribution of IT Capital from Various Empirical Studies

Authors	**Period Studied**	**Output growth contribution of IT capital**
Oliner & Sichel (1994)	1970-1992	0.16
Oliner & Sichel (2000)	1974-1995 1996-1999	0.27 0.62
Brynjolfsson & Hitt (1993)	1987-1991	0.35
Jorgenson & Stiroh (1995)	1979-1985 1985-1992	0.52 0.38
Jorgenson & Stiroh (1999)	1973-1990 1990-1996	0.12 0.16
Jorgenson and Stiroh (2000)	1973-1995 1996-1998	0.17 0.36
Wehlan (1999)	1980-1995 1996-1998	0.37 0.82
Kiley (1999)	1974-1984 1085-1998	-0.34 -0.27
Lau & Tokutsu (1992)	1973-1990	1.50
Note: Measured in percentage points per year		

CHAPTER 6 - LITERATURE SURVEY: REGIONAL PRODUCTIVITY DIFFERENCES AND THE ROLE OF EXTERNALITIES

The purpose of this study, composed of chapters 6, 7 and 8, is to evaluate the productivity effects of externalities associated with the location of IT vs. non-IT employment. This chapter is an attempt to describe the state of knowledge in the field of agglomeration economies and spatial productivity differentials. Its purpose is to understand better different externality measurement techniques used in regional economics, before applying them to study IT and non-IT externalities specifically in chapters 7 and 8. Chapter 7 will describe the methodology used for such analysis and chapter 8 will present and comment on the results obtained.

The first section of this chapter starts by defining agglomeration economies and various economies of scale. It also reports some findings regarding the role of localization and urbanization economies. The second section describes the different techniques used to assess the role played by externalities in explaining spatial productivity variation, such as shift-share analysis, some empirical studies and the sources of growth framework. The third section focuses on a study that is more closely related to the method used in chapter 7, since it is a county-based analysis. This study was conducted by Ciccone and Hall

(1996), who showed that the density of economic activity at the county level can explain half of the variance in output per worker across states. Finally, some studies have attempted to analyze the localization patterns of information technology activity and their effects on productivity. The last section will discuss some of these studies.

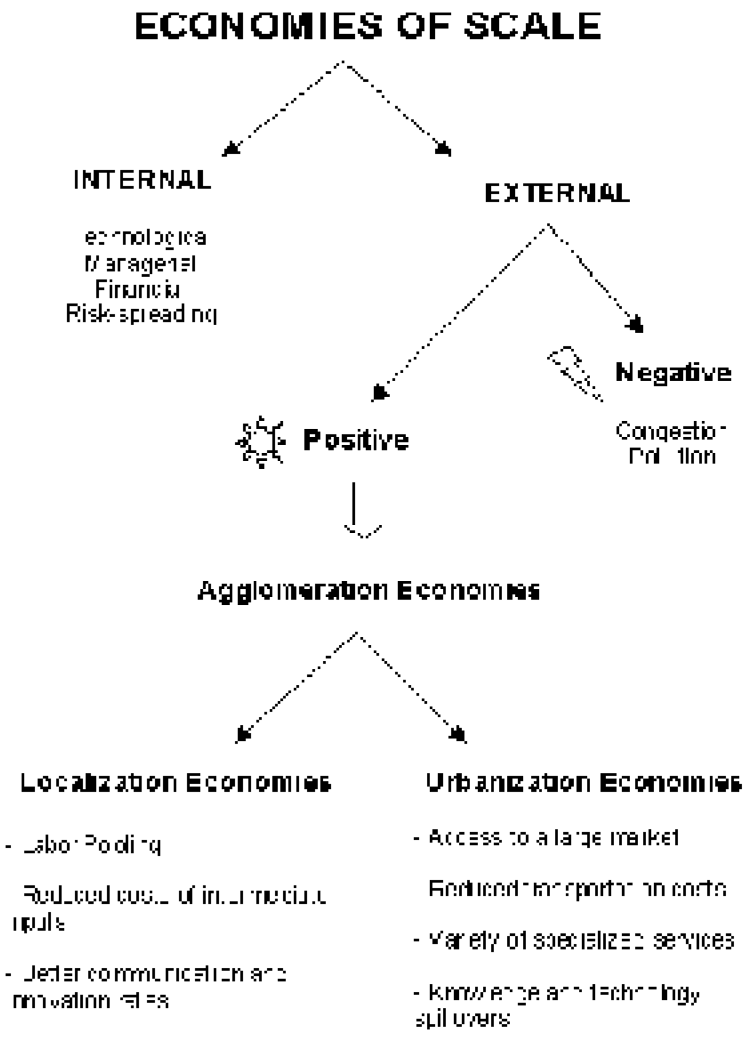
6.1Agglomeration Economies

According to neoclassical theory, there are decreasing returns to all inputs, such as capital and labor. Therefore, the marginal product of labor at any location should decrease as the density of workers increases, where density is defined as the number of workers per acre. Because wages are determined by the value of the marginal product, a worker located in a denser area with lower marginal product would have an incentive to move to a less dense area where his/her marginal product and wage would be higher. In equilibrium, all workers would be evenly distributed across all locations in a given county, state or country.

In reality however, population tends to be concentrated at nodes of different sizes, both within countries and around the world. Looking at a map representing the distribution of the population around the world, Krugman (1991) noticed that the neoclassical theory of decreasing returns to density seemed to be in contradiction with reality. Many authors have attempted to justify the existence of cities and other population clusters by noting the existence of externalities and increasing returns to scale to population density (Sveikauskas (1975), Henderson (1986) and Krugman (1995)). Their arguments that the externalities identified as agglomeration, localization and urbanization economies should arise with employment concentration, are persuasive.

6.1.1Definition of Agglomeration Economies

Agglomeration economies are one of the main determinants of spatial productivity variation. They are related to economies of scale, which play an essential role in productivity growth. Agglomeration economies reduce average costs of a product in the long run, resulting from an expansion of some activity. There are different kinds of scale economies, and the literature has not always been clear on how to label them. Bogart (1998) presents a well-defined approach to the problem. Figure 6.1 helps inform the following discussion. There are two kinds of economies of scale: *internal*, which result from an expansion wholly within a given economic unit (a firm, an industry, a city, a state, a region), and *external* economies of scale, which result from an expansion in the size of a group of economic units (firms in an industry, industries in a region, and so on). Internal economies arise from the expansion of, say, a single firm and may be attributed to declines in costs from technological, managerial, financial or risk-spreading sources. External economies of scale or *externalities*, arise from the expansion in the size of the industry, even if the firm's size remains constant, and could be positive or negative. For instance, spatial proximity of firms to each other could result in positive externalities, referred to as *agglomeration economies*, or negative externalities or *agglomeration diseconomies*, which could result from congestion, pollution and other sources. Finally, agglomeration economies are of two types*: localization economies* and *urbanization economies*. Localization economies arise when a firm benefits from being near other related firms in the same industry. There are three sources of localization economies. The first is the benefit from labor pooling, *i.e.* the reduction in labor search costs from both the availability of a high-skilled labor force for the demand side of the labor market, and a variety of employment opportunities for the supply side of the labor market.



Source: Based on Bogart (1998)

Figure 6.1Description of Various Types of Economies of Scale

The second source of localization economies is reduced costs of intermediate inputs for a given product when economies of scale are realized in the intermediate input industries. Finally, proximity contributing to better communication and faster spreading of innovation are the last sources of localization economies. On the other hand, urbanization economies arise when firms are located in a large city, even if these firms do not belong to the same industry. These urbanization economies come from three sources: access to a large market, access to a variety of specialized services available only in large cities, and potential for cross-industry spillovers of knowledge and technology.

6.1.2Urbanization Economies vs. Localization Economies

A question that has generated many empirical studies is whether localization economies or urbanization economies have the stronger effects. Sveikauskas (1975), Segal (1976) and Moomaw (1981) have attempted to show that gains in productivity increase with city size, which illustrates urbanization economies. Shefer (1973) examined the effects of local industry size on productivity (localization economies) but ignored the effects of population (urbanization economies). He found that localization economies have unstable effects on productivity over time. Carlino (1978) rejected this result in favor of urbanization economies, arguing that "population is a worthless surrogate for business agglomeration economies." Population reflects urban diseconomies, such as congestion, which offset business agglomeration economies. Finally, in order to clarify the debate, Moomaw (1983) suggested a refinement of the estimates measuring urbanization and localization economies. He asked whether urban agglomeration economies or diseconomies dominate.

The methodology employed by Moomaw consisted of regressing the logarithm of value added per worker on population and other variables. His data covered 2-digit manufacturing industries for the year 1977. He found a positive and significant coefficient for population for most industries, which refutes Carlino's proposition, and shows that population does matter in agglomeration economies. These studies have led to additional work on measuring the contribution of agglomeration economies to labor productivity, in a static and dynamic fashion.

Henderson (1986) studied urbanization and localization economies in U.S. and Brazilian cities, further developing Moomaw's work. Instead of a specific production function, he used a flexible functional form. He found that two-stage least squares estimation had the effect of strengthening estimates of localization economies and weakening estimates of urbanization economies. Unlike Moomaw's results, Henderson's results showed stronger effects of urbanization economies.

Sveikauskas, Gowdy, and Funk (1988) studied urbanization and localization economies in the food processing industry. Focusing on one industry only allowed the authors to get better data. They used a translog production function, allowing for increasing returns to industry size in order to measure localization economies. Their results indicate that, when the extent of nearby agricultural production is included in the production function, the economies of scale coefficient is not significantly different from 1. The coefficient for SMSA population is positive and significant. These results contrast with the ones that would have been obtained using Henderson's method. Thus, productivity estimates seem to be very sensitive to the production function specification, measurement of industry scale effects, and the particular data used.

Garnick and Renshaw (1980) and Hawley and Fogarty (1981) argued that the productivity advantages of urban areas have declined relative to these enjoyed by other locations. Carlino (1985) explained this phenomenon by the changes in production method made in communication and in transportation. He used a CES production function, assuming the labor market is in equilibrium and estimated the following equation:

$$\ln W_{it} + \ln L_{it} = \ln A + \alpha_1 N_{it} + \alpha_2 N^2_{it} + \beta \ln Q_{it} + h_o(1-\beta) \ln L_{it} + h_1(1-\beta) \ln L^2_{it} \quad (6.1)$$

where N is population, Q total manufacturing value added per establishment, W is total manufacturing payroll per employee, L is manufacturing employment per establishment, h= $h_0 + h_1 t$ is the returns to scale parameter, β is the elasticity of the wage with respect to changes in output. Data are for 80 SMSA, for the 1957-1977 period. His results indicate that h= 1.13 + 0.002t, which means that scale economies were present but increased slowly.

Moomaw (1985) then extended Carlino's work by regressing value added in manufacturing per productive and nonproductive worker hour on SMSA population, value added minus payroll, and dummies for regions. The 1967 and 1977 data come from 18 2-digit manufacturing sectors. Moomaw used a fixed-effects model (dummy for 1977) and found little evidence of change in Hicks-neutral productivity advantages of large relative to small SMSAs.

Henderson (1997) estimated dynamic externalities in a panel analysis framework, which allows separation of externalities from fixed effects and identification of a lag structure. He found strong evidence of localization economies. Urbanization economies effects are smaller, but their effects persist to the end of the time horizon, whereas localization economies' effects usually disappear after six years.

The next section describes in further detail the different techniques used to measure spatial differences in productivity and the role of externalities.

6.2Some Techniques for Explaining Spatial Productivity Differences

Explaining economic growth is an important task for economists. Traditionally, studies have focused on understanding the process at the level of the aggregate economy. The Solow-Swan model helped to explain output growth in many countries. It has also been used in cross-country analysis, where it left most of the disparities unexplained, contained in the "Solow residual" term. More recently, with the ongoing globalization phenomenon and the fluidity of national boundaries, it has become more relevant to use smaller units of analysis: the region, the state or the city. For instance, productivity levels vary tremendously between these units, and many authors have tried to explain these variations. Moomaw (1983) summarized the earlier work on this subject. Pioneer authors found that the main sources of spatial variations of productivity were: the capital-labor ratio, the age of the capital stock, the rate of technology adoption and diffusion, the quality of the labor force and agglomeration economies. This section presents a survey of the earlier work on spatial growth variation through shift-share analysis, various empirical techniques, and the sources of growth framework. This description is largely inspired by the work of Gerking (1994). Finally, different techniques used to study agglomeration economies (*i.e.* the use of particular production functions) are presented. Following Abdel-Rahman (1988) and Rivera-Batiz (1988) I will show how product differentiation and monopolistic competition relate to agglomeration economies.

6.2.1Shift-Share Analysis

It was only in the late 1950s that economists started to study the differences in economic performance between U.S. regions. Edgard Dunn (1960) introduced a new technique called *shift-share analysis*, which distinguishes between growth factors operating uniformly at a national level, and specific growth factors. The first step of the technique is to compute the expected employment level in each region in a target year, say 1990, based on the percentage increase in total employment in the nation between a base year, say 1980 and the target year. The gap between the expected and the actual target year total employment level in each region is called the *net shift*, and is expressed as a percentage of the base year total employment. Dunn then divides the net shift into *differential* and *proportional* components. The differential shift is the sum of the shifts by industry sectors for the region, where each industry's share is defined as the difference between regional and national growth in the industry. The proportional shift is merely the difference between the total and differential shifts. While Stilwell (1970) and others noted that the technique of shift-share analysis has little basis in the theory of regional growth, the technique remains a useful descriptive tool as when studying historical data on population or employment for instance**.**

Norcliffe (1977) built an interesting model for disaggregating regional productivity performance into *average, mix, scale* and *residual* effects. This model is similar in form to shift-share analysis but with the addition of two structural effects. The structural effects are incorporated in the productivity component associated with the particular mix of industries in a region on one hand, and the size distribution of establishments within each industry, on the other hand. Thus, in Norcliffe's model, regional productivities differ from each other in four ways: averages (the difference with global productivity), mix and scale effects (the structural effects), and residuals.

6.2.2Empirical Evidence on Productivity Measurement Across Space

Gerking (1994) provides a complete survey on later empirical evidence concerning measurement of productivity levels and patterns of changes in these levels over time. Most of the empirical studies use the same methodology. The model usually starts with a production function of the form:

$Q = g(Z)\, f(K,L)$ (6.2)

where *g()* represents Hicks-neutral productivity, *Z* is a vector of variables affecting productivity and *f()* is a Cobb-Douglas or CES production function. The variable *L* is easy to measure, it is merely the number of employees, sometimes weighted by average years of education to add some quality aspects to the labor force variable. *Z* contains variables that reflect agglomeration economies (population, size of the industry) as well as dummies for the geographical unit of analysis (region, state or city). However, there is usually no good measure of capital services at the level of these geographical units. Authors have adopted several options to conduct their studies: (1) avoid the use of *K*, (2) constructing their own measures of *K*, or (3) use some proxies:

1. Sveikauskas (1975) introduced the notion that productivity may be systematically higher in large urban areas. He was only concerned with the size of cities, measured by population. He separated estimates of *g()* and *f()*. His concern was to study the effect of *Z* on *Q* and therefore he omitted *K*, the capital variable. Using a CES production function and manufacturing data, his results indicate that Hicks-neutral productivity increases by about 6 % with a doubling of the population size. Segal (1976) considered a Cobb-Douglas production function and economy-wide data on a set of SMSAs and found that productivity is 8% higher in larger SMSAs (population is more than 2 million) compared to smaller SMSAs (with a population less than 250,000). Finally, Moomaw (1981) criticized these two studies, arguing that their results are both biased upward for different reasons. First, Sveikauskas omitted *K*, which is probably positively correlated with population size, explaining the overestimation. Then, the upward bias to Segal's productivity estimates might have been due to underestimation of the capital stock. Moomaw re-estimated these results introducing a theory of firm behavior that incorporates the firm's choice of city size. He found that a doubling in population size would increase productivity by only 2.5%.

2. The *Annual Survey of Manufacturers* from the U.S. Census Bureau (1990) reports book value of capital assets for 2-digit industries by state. However, this measure is not corrected for price level changes. An alternative is to estimate the level of capital stock by summing investment of different vintages after adjustment for depreciation rate, technical change and inflation. This is also called the perpetual inventory method as used by Hulten and Schwab (1984) at the regional level, and Segal (1976) at the city level, and discussed further below.

3. The last method of capital stock estimation assumes that non-labor costs, which are equal to the value of capital services, are simply the difference between value added and labor cost. Unfortunately, this method is not better than the perpetual inventory approach, because labor costs are themselves proxies.

6.2.3 The Sources of Growth Framework

The sources of growth framework was introduced by Hulten and Schwab (1984). It represents an alternative to econometric cross-sectional analyses, which measures productivity level differences. This method focuses on measuring factor accumulation and productivity growth rate over time. Hulten and Schwab (1984) were the first authors to apply this technique at the regional level. They looked at the regional productivity growth in U.S. manufacturing for the period 1951-1978. Using a Hicks-neutral production function, the growth rate of real product is partitioned into the share-weighted growth rates of inputs (capital, labor and intermediate input), and a residual representing total factor productivity.

$Q_t = F(A_t V(K_t, L_t), M_t)$(6.3)

where gross manufacturing output in period *t*, Q_t, is a function of capital K_t, labor L_t, intermediate input M_t, and technology A_t. Under profit maximization, the marginal product conditions imply:

$\delta Q_t / \delta M_t = p_t^M / p_t$; $\delta Q_t / \delta K_t = p_t^K / p_t$; $\delta Q_t / \delta L_t = p_t^L / p_t$ (6.4)

where p_t is the price of output at time t, and p_t^M, p_t^K, p_t^L the relevant factor prices. Combining these marginal products with the logarithmic differentiation of (6.2) leads to

$gr(v) = S^t_k\, gr(k) + S^t_L\, gr(l) + gr(A)$(6.5)

where gr(.) represents the growth rate of the variable in parenthesis. S^t_i represents factor shares in value added such that $S^t_k + S^t_L = 1$ (constant returns to scale) and

$S^t_k = p_t^K K_t / Q_t$ and $S^t_L = p_t^L L_t / Q_t$ (6.6)

Finally, gr(A) is the growth rate of technical progress, or total factor productivity (TFP). It represents here the growth rate in output not attributable to growth in inputs. It could include things such as better education quality and quantity, intensive training of the workforce, better health and safety measures, quality of equipment, communication and transportation. The main problem with this framework is that it leaves most of the national growth in productivity unexplained, under the form of total factor productivity.

Williams (1985) allowed technical progress to be factor augmenting instead of Hicks-neutral, which means that there is a factor augmenting parameter associated with each input instead of the production function F(.) itself. The production function becomes:

$V_{it} = F(\alpha_t K_{it}, \beta_t L_{it})$ (6.7)

where i stands for region, t for time, α_t and β_t are factor augmenting parameters that convert the quantity of capital and labor (K_{it} and L_{it}) into efficiency units, and V_{it} represents value added in manufacturing. Equation 6.6 expressed in relative rates of change over time becomes:

$gr(v) = S^t_k\, [gr(k) + gr(\alpha)] + S^t_L\, [gr(l) + gr(\beta)] + gr(A)$(6.8)

Setting equation 6.5 equals to equation 6.8, the share-weighted sum of factor-specific efficiency growth rates could then serve as an estimate of total factor productivity:

$gr(A) = S^t_k\, gr(\alpha) + S^t_L\, gr(\beta)$(6.9)

Assuming competitive factor markets, Williams was able to estimate gr(α) and gr(β) and therefore it was possible to estimate gr(A) directly instead of indirectly as a residual. This is known as Sato's method, which is an alternative to Hulten and Schwab's method using residuals only.

Beeson (1990) used data on 42 states and 45 large SMSAs so that sources of growth could be compared between, as well as within, regions. Total factor productivity was computed using the residual method and capital stock figures were estimated by the perpetual inventory method. The author found smaller growth rates in real manufacturing value added within SMSAs than outside large SMSAs.

Fogarty and Garofalo (1988) used the total factor productivity methodology to identify the contribution of agglomeration economies to productivity differentials. First, they estimated a variable elasticity of substitution (VES) production function, and used it to calculate the sources of total factor productivity growth. Value added was significantly related to agglomeration economy variables such as the density of the manufacturing sector. Their results indicate that total factor productivity was the dominant source of growth. Agglomeration economy variables were positively and significantly related to total factor productivity growth.

Williams and Moomaw (1989) used a translog production function to compare estimates of total factor productivity for 48 states. Their findings indicate higher growth rates of manufacturing value added in Southern and Western states. Overall, they found a greater interstate variation in total factor productivity than estimated by Hulten and Schwab. These results come from a single equation regression model, which explains 50% of interstate TFP variation. The most significant positive explanatory variables were: the rate of change in R&D spending, the rate of growth in manufacturing output, the rate of growth of the capital/labor ratio and the rate of growth of production workers as a percentage of all workers in manufacturing. The rate of unionization was found to be negatively correlated to growth in TFP.

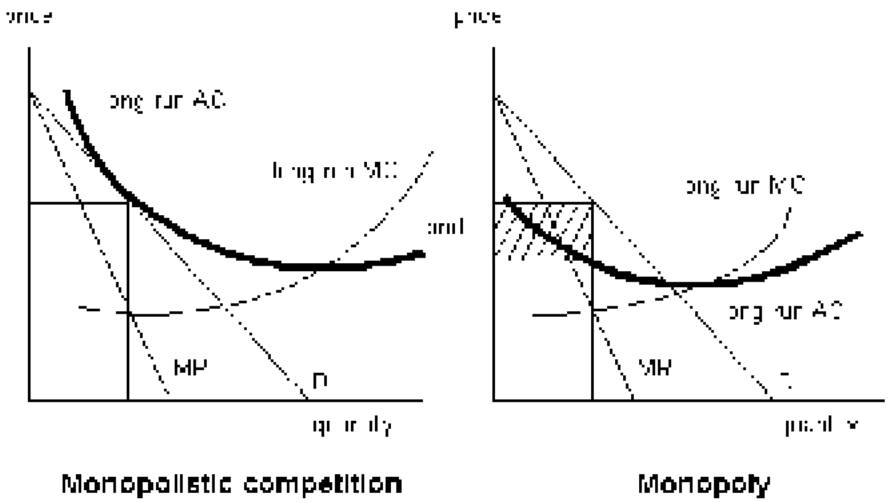
Whereas most of the previous literature focused on manufacturing productivity, Carlino and Voith (1992) were the first to study state variations in aggregate productivity using Gross State Product (GSP) data. Value added at the metropolitan, state or regional level has been available previously only for manufacturing industries. Then, the U.S. Commerce Department's Bureau of Economic Analysis (BEA) introduced annual gross state product in May of 1988. In their model, Carlino and Voith consider several determinants of state-to-state variations in productivity. They found that a state's industry mix, infrastructure, education level, and metropolitan structure all significantly affect productivity. Another important finding is that a ranking of states by productivity gains based on GSP data differs markedly from a ranking based solely on manufacturing data. This raises reservations regarding previous studies and their inferences regarding aggregate productivity at the regional level based on manufacturing data.

6.2.4Product Differentiation and Monopolistic Competition

Studying the economics of agglomeration and increasing returns supposes some knowledge of the theory of the firm and its market. Mills (1967) was an early contributor to the agglomeration literature. Assuming that all goods are produced by monopolists, he demonstrated that, in equilibrium, disamenities from agglomeration on the side of households may offset the productivity advantages on the side of the firm. Recent papers have used a monopolistically competitive market structure to study agglomeration with increasing internal returns to scale. Abdel-Rahman (1988) and Rivera-Batiz (1988) used a monopolistic competition framework to demonstrate that nontransportable intermediate inputs produced with increasing returns imply agglomeration.

Traditionally, urban agglomeration has been explained as either a production or a demand phenomenon. The production explanation relies on internal scale economies, localization economies, or urbanization economies while demand explanation involves the consumption of public goods. Depending on which force dominates, different types of cities will emerge. Abdel-Rahman's (1988) innovation was the integration of the demand and supply side explanations. On one hand, suppliers of differentiated services face higher demand, with an increase in the number of producers at low cost. On the other hand, households enjoy a higher utility from these numerous differentiated services because of their taste for product differentiation. Product differentiation and monopolistic competition becomes a more appropriate framework.

As seen in Figure 6.2, firms make no profit in the monopolistic competition framework because the long run average cost curve is tangent to the demand curve. This is due to free entry in the market. Therefore, firms produce at more than the minimum cost with excess capacity. The firm will choose its production level where its marginal revenue equals its marginal cost. At the equilibrium, the same quantity of all services is produced, and all firms have the same cost and face the same demand function. Firms will enter the market until there is zero profit. On the demand side, it is assumed that all households maximize an identical utility function with respect to a transport cost function. Rivera-Batiz (1988) used a similar approach to model agglomeration economies endogenously. The emphasis is on how product variety is determined and how it generates agglomeration economies. The key element is the local service sector. On the production side, local services include maintenance, repair, transportation and communication, engineering, advertising, banking, security. On the demand side, local services could be restaurants, theatres, taxicabs, barbershops and other personal services. The presence of this local service sector could generate agglomeration economies in two ways. First through localization economies, because an expansion of the market will lead to specialization, which will in turn lead to gain in productivity. Secondly, a large populated area generates a variety of consumer services valued positively by individuals.



Note: MR is marginal revenue, MC is marginal cost, AC is average cost D is Demand

Figure 6.2Monopolistic Competition and Monopoly

6.3Productivity and the Density of Economic Activity

This section provides a description of a study by Ciccone and Hall (1996) [CH hereafter], who evaluated the role of county density of economic activity in explaining the variation of average labor productivity across the U.S. states. Their most important finding is a positive elasticity of productivity with respect to density. Their estimates indicate that doubling average employment density at the county level can increase by 6% the average labor productivity at the state level. This goes again because of diminishing marginal product. Here CH found that workers are more pro st the neoclassical assumption that the marginal product of labor would be lower in denser areas ductive when moved to a denser area.

To explain the mechanism by which density affects productivity, they use two models. The first model is based on geographically localized externalities, comparing agglomeration and congestion effects of density. However, it does not reveal the source of agglomeration effects. The second model gives density an explicit role. It builds on earlier work by Abdel-Rahman (1988) and Rivera-Batiz (1988), and is based on the fact that denser areas exhibit a greater variety of intermediate products, which increases productivity. The last part of CH's analysis deals with capital and total factor productivity, in an attempt to determine the ways in which density affects productivity. First, assuming constant returns in technology and increasing transportation costs, output will rise with density because firms will avoid transportation costs by concentrating in space. Second, there might also be externalities emerging from the physical proximity of production. Finally, density might affect productivity through a higher degree of specialization.

CH made an important contribution to the literature with their empirical work on productivity based on actual measures of density. Previous studies had assumed agglomeration benefits implicitly only. Theoretically, the economics of agglomeration state that a greater variety of intermediate inputs will increase productivity. The purpose of CH is to consider density explicitly, at the county level, and measure its effect on average labor productivity at the state level.

CH's first model explains how density affects productivity and how to aggregate across productive units. Their model, which is based on externalities, considers labor and land only as factors of production. They first made the assumption that the externality depends multiplicatively on output per acre, which is the measure of density. The elasticity of output with respect to density is a constant, $(\lambda - 1) / \lambda$, and the elasticity of output with respect to employment is also a constant, α. Elasticity α measures the effect of congestion whereas λ measures the effect of agglomeration. If λ is less than one, the elasticity is negative and there are agglomeration diseconomies. A CES production function gives the output *q* produced in an acre of space by employing *n* workers:

$$f(n,q,a) = n^{\alpha} (q/a)^{(\lambda -1)/\lambda} \quad (6.10)$$

The county-wide production density function is then given by

$$q_c / a_c = (n_c / a_c)^{\gamma} \quad (6.11)$$

where γ is the product of the production elasticity, α, and the elasticity of the externality, λ. If $\alpha < 1$ and $\lambda > 1$ then $\gamma > 1$ and agglomeration effects exceed congestion. Empirical results show that the net effect favors agglomeration. The technique used to aggregate county production density to at the state level is to calculate average labor productivity in the state by summing the county production densities weighted by each county's area and dividing by total state employment, N_s

$$Q_s / N_s = [\Sigma n_c^{\gamma} a_c^{-(\gamma -1)}] / N_s \quad (6.12)$$

This magnitude is also defined as the factor density index $D_s(\gamma)$. CH then decomposed this density index into three components. The density effect becomes the product of a national effect, a state effect and a county effect. The neoclassical model assumes $\gamma < 1$ and leads to the hypothesis that productivity and density are negatively related if congestion effects are greater than agglomeration effects.

In their second model, CH hypothesized increasing returns in production of local intermediate goods, as suggested by Abdel-Rahman (1988) and Rivera-Batiz (1988). This model treats density endogenously, and shows its relationship to productivity. The production function now depends on the amount of labor *m*, used directly in the making of the final good, and *i*, the amount of intermediate service input, which cannot be transported outside the acre. The production function for the final good is:

$$f(m, i) = [m^{\beta} i^{(1 - \beta)}]^{\alpha} \quad (6.13)$$

where α and λ still represent respectively congestion and agglomeration effects.

The level of output of *i* at the zero-profit level is given by the following CES production function

$\int_0^z x(t)^{1/\mu} dt)^{\mu}$ (6.14)

where $x(t)$ denotes the individual differentiated services, indexed by type t, z is the number of different types of individual services produced, and μ is the markup of price (defined as a ratio of the marginal cost that the producer will set in order to maximize profit). If labor is paid at w, the profit function for an intermediate product maker will be π = (μ -1) wx – wv. Because of the monopolistic competitive market situation, competitors can enter freely and eventually profit will be driven to zero, where the level of output will then be x = v / (μ - 1). Substituting into the intermediate production function gives $i = z^{\mu} x$. The productivity of the *i*-making process will then be $z^{\mu -1}$ and because μ >1, productivity will rise with the available variety of intermediate goods. In a denser area there is more variety of intermediate goods and therefore there is a positive relationship between density and productivity. CH then elaborated an equation that is similar to the county production function found in the first model and concluded " both models provide a theoretical foundation for the same estimation procedure in state data." The production function describing output produced in an acre of space is then define as:

$A_s [(e_c n_c)^{\beta} k_c^{1-\beta}]^{\alpha} (q_c / a_c)^{(\lambda -1)/\lambda}$ (6.15)

where A_s is Hicks-neutral technology multiplier for state s, n_c is employment in county c and k_c is capital in county c. It is assumed that labor and capital employed in a county are distributed equally among the acres in the county. Finally, e_c is a measure of the efficiency of labor, which depends on the average years of education h_c, and is defined by $e_c = h_c^{\eta}$ (where η is the elasticity of education).

CH dealt with capital by first assuming a uniform rental price of capital *r*. Then, they substituted factor price for factor quantity in the factor demand function. Further, they defined the elasticity of labor, θ, by the ratio γβ / [1 - γ (1 - β)].

Assuming a log-normal distribution of state productivity around a nationwide level and allowing for mismeasurements in an error term, the final model of production is:

$\ln (Q_s / N_s) = \ln \varphi + \ln D_s (\theta, \eta) + u_s$ (6.16)

where φ is a constant that depends on the interest rate, and u_s is the measurement error, assuming that errors of different states are uncorrelated.

According to neoclassical assumptions, in equilibrium density should be equal everywhere and nobody would have the incentive to move. However, if θ >1, a worker would be more productive if moved to a denser area. The only equilibrium would then be for all workers to concentrate in one single county. In reality, states and counties have different densities, so how can they be in equilibrium? The answer given by CH is the same one used by urban theorists: some workers simply prefer to live in less dense areas, with lower wages, to avoid the disamenities from agglomeration (pollution and traffic for example).

Many studies have estimated the effects of agglomeration economies for manufacturing industries. The industries studied have been usually 2-digit SIC industries at the regional level. However, as we have seen, Ciccone and Hall built an ingenious model estimating net external economies of employment density for counties. Their output measure is almost the same as the one used by Carlino and Voith (1992): Gross State Product (GSP) minus agricultural and mining output. Their analysis goes beyond the manufacturing sector. Data on employment by county come from the U.S. Bureau of Economic Analysis for the year 1991. Data on education are gathered at the state and county level by the U.S. Bureau of Census. At the state level, it is the number of years of education times the number of hours worked. At the county level it is simply the average years of education.

Using nonlinear least squares, Ciccone and Hall first estimated the returns to scale parameter, θ, and the elasticity of average product with respect to education, η. To prevent their results from being biased by "reverse causation," they used nonlinear instrumental variables for the density index. The characteristics used as instruments refer to the historical and geographical situations of the states. The instrumental variables estimate for θ is 1.06, which means that doubling the employment density in a county increases labor productivity by 6%. They also found that the estimate of γ was close to 1.04, meaning that doubling employment density in a county would result in an increase of 4% in total factor productivity.

According to the density index D_s (γ), the District of Columbia is the densest area, followed closely by New York state, which also contains the densest county in the U.S., New York City county (with a factor density index of 1.94). Workers in New York city are 22% more productive than in New York state. Plotting productivity by state against education, they showed a significant role of education in determining productivity (positive slope of the regression line).

Finally, CH showed that the differences in productivity were not due to factors such as public capital, and the differences persisted even when controlling for education. The positive relationship between density and productivity was also not due to the size of the market.

6.4Localization of Information Technology Activity and Productivity

This section describes some literature on the relationships between the localization patterns of IT activity across space and regional productivity.

First, Malecki (1991) applied the method of Location Quotients at the county level in the state of Florida to study the effects of changes in employment profiles and demographic trends on regional economic growth between 1982 and 1987. He used a cross-sectional econometric model that relates the change in total employment to various demographic and occupational variables. He found that half of the counties studied had real economic growth between 1982-1987. These counties exhibited the highest concentration of their basic employment in the secondary sector. Their location quotients for manufacturing were either greater than one or were increasing during the period studied. This implies that even though Florida's economy is service-oriented and a small fraction of the labor force is employed in the secondary sector, manufacturing remains a catalyst for economic growth.

Malecki (1987) elaborated on the issue of geographic localization of high tech industry. He noticed the efforts from communities and all 50 states to reproduce the success of Silicon Valley and Route 128 as leading technological clusters. He emphasized the necessity of strong governmental support in order to do so. However, each state or community must also understand that its unique local conditions are important. Being part of a large urban region, having abundant air transportation and strong universities constitute great advantages that will attract high tech firms. Still, as Malecki argued, “encouraging and nurturing new companies bears more fruit than trying to lure firms from elsewhere. (...) the hope is that rapidly growing local high-tech firms might replace declining industries.’ Finally, Silicon Valley or Route 128 are a proof of the significant advantages to be acquired through investment in human capital.

Zucker et al. (1998) studied empirically localized knowledge spillovers, using data on California biotechnology. They argued that the output that results from R&D investment in this industry is not a public good because it is neither nonrivalrous nor partially excludable, which is contradictory with the traditional definition of knowledge spillovers as given by Romer (1990). Indeed, Zucker et al. (1998) found that the positive impact of university research on nearby firms comes from identifiable market exchanges between two parties that both benefit from:

For an average firm, five articles co-authored by academic stars and the firm’s scientists imply about five more products in development, 3.5 more products on the market, and 860 more employees. Stars collaborating with or employed by firms, or who patent, have significantly higher citation rates than pure academic stars.

Beardsell and Henderson (1999) examined the spatial evolution of the computer industry and its impact on productivity across 317 metropolitan areas in the USA from 1970 to 1992. First, they studied the evolution of employment to see if it concentrates in fewer locations or if patterns appear relatively fluid. They also emphasized the importance of locational characteristics (such as labor pooling, state taxes, intermediate product diversity) as determinants of the location behavior of computer firms. Finally, they found strong evidence of localization economies (own industry externalities) as determinants of productivity growth, and little evidence of urbanization economies. Pollard and Storper (1996) studied the growth in three growth-generating sectors: industries handling information and advanced management functions (“intellectual capital”), high technology industries (“innovation based”) and “variety-based” industries, which represents industries with high levels of product differentiation, relatively short production runs, and lower level of mechanization than mass-production industries. They focused on twelve metropolitan areas across the United States between 1977 and 1987. Their findings suggest that the determinants of regional employment growth of the 1980s might no longer be the ones of the 1990s. “Variety-based” industries are no longer a motor of growth, but intellectual capital and innovation-based industries exhibit high growth in all areas studied. Therefore, it could be possible that these industries have a low propensity to agglomerate, as asked by the authors. One reason could be the telecommunication revolution, which might have reduced the importance of localization economies.

This chapter presented findings in the field of regional economics, regarding the externality effects of location patterns of employment. Agglomeration effects explain in part why productivity differs across regional units (regions, states, counties). A study from Ciccone and Hall (1996) showed that the density of economic activity at the county level could increase labor productivity at the state level. This finding goes against principles of neoclassical theory, which stipulate that congestion effects dominate when employment density increase. The next chapter describes a methodology for measuring the externality effects of the location patterns of information technology employment.

CHAPTER 7 - A METHODOLOGY FOR MEASURING THE EXTERNALITY EFFECTS OF IT AND NON-IT LOCATIONAL PATTERNS

This chapter describes the methodology used to evaluate the role of IT and non-IT employment localization in explaining regional productivity differences. The first section presents the models used in this analysis, and the second section defines and describes the variables.

7.1Three Models to Evaluate the Externality Effects of the Spatial Distribution of IT Employment

Three models will be used to evaluate the externality effects of IT and non-IT concentration (model 1), localization (model 2), and density (model 3). This section describes these models.

7.1.1 Model 1: The Concentration of IT Activity and Labor Productivity

States have different profiles regarding the location of their IT activity. This model assumes that the differences in state labor productivity can be explained by differences in the localization patterns of IT activity across states. The concept of “employment concentration” is introduced, as well as the definition of the ratio used to measure it. This ratio is computed for IT and non-IT employment concentration. The purpose is to evaluate the effect of the concentration of IT activity relative to non-IT activity on state labor productivity.

States differ not only in their physical sizes and their total numbers of employees, they also differ in their spatial distributions of population and workers. Neoclassical theory argues that employees should be evenly distributed across all areas, including counties within states and across acres within counties). The concentration ratio represents the deviation of the distribution of employees across counties from the neoclassical distribution given by the state’s global employment density. In other words, it is the ratio of the sum of county employment densities, weighted by their share of state’s employment, and state overall density. For a given state, *s*, the concentration ratio (CON) is given by:

$$CON_s = \Sigma_c [(n_c/a_c).(nc/ns)] / (n_s / a_s) \quad (7.1)$$

where n_c is employment in county *c*, a_c is the number of acres in county *c*, n_s is total employment in state *s* and as is the total number of acres in state s. After rearranging,

$$CON_s = (\Sigma_c n_c^2 / a_c) / n_s^2 / a_s \quad (7.2)$$

A value of 1 for the concentration ratio will indicate an even distribution of employment across counties in state *s*. The higher the value, the more employment is concentrated into few counties. The maximum value depends on the physical sizes of the counties in state *s*. Although this measure is not perfect, it has the merit of expressing at the state level what is happening across counties within each state. It is similar to the location quotient, which may be computed at the county level and does not take into account the area of counties (only their shares of employment in a given industry compared to the state’s share).

According to neoclassical theory, with decreasing returns to labor, the higher the concentration ratio is in a given state, the lower should be its labor productivity. Based on the work of Graham (2000), using a simple Cobb-Douglas production function, I intend to test the validity of this neoclassical premise by estimating the following equation:

$$\ln p_s = \ln A + \alpha \ln kn_s + \beta \ln CON_s \quad (7.3)$$

where p_s is a measure of labor productivity in state *s*, namely output per worker, which depends on total factor productivity as captured by the term lnA, the state’s capital to labor ratio represented by kn_s, and the measure of employment concentration in state s as defined previously by CON_s. The elasticity of capital deepening (kn_s) in state *s*, represented by the parameter α, is expected to be close to a third, which is the value for the share of capital usually observed nationally. Parameter β, the elasticity of productivity with respect to employment concentration, is expected to be negative under the neoclassical theory of decreasing returns to scale to labor density. If the sign of β is positive and significant, then it must be that there are some externalities associated with employment concentration, which increase labor productivity. According to previous findings in the field of regional economics, I expect to find a positive and significant sign for β.

However, my goal in this study is not to limit my analysis of employment location and productivity to total employment only, but to estimate the effect of IT employment localization relative to traditional employment. In order to do so, I first need to compute the concentration ratios for each type of employment in each state. Using the same definition of concentration as in equation 7.2:

$$CON_{s,e} = (\Sigma_c n_{c,e}^{2} / a_c) / n_{s,e}^{2} / a_s \quad (7.4)$$

where *e* indexes IT or non-IT employment (*e*=1 and *e*=2, respectively). However, since I am interested in the relative effect of IT vs. non-IT employment concentration on state productivity, I will consider the ratio of those two employment concentration measures as defined by $RCON = CON_{s,\ IT} / CON_{s,\ NIT}$. Using the same production function form as in equation 7.3, I will estimate the effect of RCON on productivity.

$$\ln p_s = \ln A + \alpha_s \ln kn_s + \delta \ln RCON_s \quad (7.5)$$

A positive sign for δ will indicate that the IT employment concentration has a greater effect on productivity relative to traditional employment concentration. This elasticity δ also indicates by how much state labor productivity will increase if the ratio, RCON, doubles.

7.1.2Model 2: The Productivity of IT Employment at the County Level

This model explores production functions for counties in order to relate county labor productivity to some measures of IT vs. non-IT location of activity. Whereas the previous model was at the state level, this one is at the county level. I intend to estimate the relative effect of the location of IT vs. non-IT activities on county productivity using the location quotient measure of county differences in industrial mixes. Although this measure is usually used when many different industries are considered, the technique is also applicable when only two types of industries are considered, namely the IT and non-IT types of industries. The location quotient for state *s* (LOC_s) is defined as:

$$LOC_{s,e} = (n_{c,e} / n_c) / (n_{s,e} / n_s) \quad (7.6)$$

Two location quotients will be computed for each county, for each type of employment, IT and non-IT. A high value of the location quotient for one type of industry in a given county indicates that activity in that industry is more intense in that county compared to the overall state intensity in that industry. This measure is conceptually related to the concentration ratio previously defined, but does not take the sizes of counties into account and is computed for each industry in each county.

My goal is to compare the relative effect of IT concentration compared to non-IT concentration on productivity. To do so, I will use the ratio of the two location quotients to evaluate the effect of one compared to the other. This ratio is expressed by

$$RLOC= LOC_{1,c} / LOC_{2,c} \quad (7.7)$$

If RLOC increases in a county, then it means that IT activity in the county is more concentrated, or that non-IT activity is less concentrated. I will introduce this measure of activity into an equation estimating county labor productivity, based on a Cobb-Douglas specification:

$\ln p_c = \ln A + \alpha_c \ln kn_c + \mu \ln RLOC_c + \Sigma D_{s-1}$ (7.8)

where D_{s-1} is a set of state dummy variables controlling for state fixed effects.

Finding a positive and significant estimate for parameter μ will indicate a positive effect of the ratio of location quotients on productivity. In other words, it would mean that if the location quotient of IT activity in a county increases relative to the location quotient of non-IT activity in that county, then labor productivity should increase in that county. If results go in the same direction as those found using model 1, then conclusions relative to the location of IT vs. non-IT activity and its effect on productivity will be more reliable. I will now turn to the third model, which is an attempt to link county activity location patterns to state productivity.

7.1.3Model 3: County Density of IT vs. Non-IT Activity and Labor Productivity

This model is an attempt to evaluate the relationships between county density of employment and state labor productivity. It is largely inspired by the study of Ciccone and Hall (1996), who built an ingenious model that leads them to conclude that when average employment density doubles in the counties of a state, gains in labor productivity at the state level amount to 6%. My first goal is to approximately replicate their results, using my datasets at the state level and county level. The nonlinear equation estimated by the authors is:

$\ln p_s = \ln A + \varepsilon \ln edu_s + \ln D_s(\theta)$ (7.9)

where edu_s is a measure of education level for state *s* and is given by the weighted average years of education. D_s (θ) is a measure of the density of activity at the county level, nonlinear in parameter θ, and is defined as:

$D_s(\theta) = [\Sigma_c (n_c^{\theta} . a_c^{1-\theta})] / n_s$ (7.10)

where the density index (D_s) depends on employment in county *c* (n_c), the area of county *c* (a_c), and state employment (n_s). Parameter θ is the elasticity of state labor productivity with respect to employment density at the county level. Ciccone and Hall estimated this parameter at a value of 1.052, and 1.06 when the same equation is estimated using instrumental variables to control for the direction of causality. Since CH have already demonstrated that controlling for causality direction does not significantly alter the results, I will simply estimate equation 7.9, without adding instrumental variables. I expect to find a value for parameter θ to lie between 1.05 and 1.06. If I do, then this will indicate the dataset produced in part I, and the county data set built in this part of the dissertation are of quality that is as good as the data used by CH. Based on this fact, will then be able to use my state-county dataset with confidence.

Finally, my goal is to estimate urbanization economies associated with IT and non-IT employment. In order to do so, I need to construct a variable that will allow me to evaluate these economies of scale. Urbanization economies arise when the number of establishments in all industries taken together increases in a county. These agglomeration economies are therefore internal to the urban area. In the literature, Carlino (1985) argues that a good variable capable of gauging the magnitude of urbanization economies is the total number of establishments in a given SMSA divided by the distance from close-by SMSAs. However, this measure, involving the calculation of physical distances between SMSAs, is very difficult to construct, and would be even more difficult at the county level. Instead, I will construct a measure of the density of employment in a given industry as a variable capable of measuring urbanization economies.

The variable reflecting urbanization economies is very similar to the location quotient, except that it relates to the density instead of the intensity of employment. It will be called the density quotient (DQ) and is computed for each industry *e* in each county *c* such as:

$$DQ_{e,c} = (n_{e,c} / a_c) / (n_{e,s} / a_s) \quad (7.11)$$

It is also similar to the concentration ratio, but the density quotient is computed at the county level, not the state level. The higher the value of $DQ_{e,c}$, the higher the density of employment of type *e* in county *c* with respect to state density.

This variable will be related to labor productivity as:

$$\ln p_{e,c} = \ln A + \alpha_c \ln kn_{e,c} + \pi \ln DQ_{e,c} + \Sigma D_{s-1} \quad (7.12)$$

Again, since we are interested in the differences between IT and non-IT effects, I will also use the ratio of the IT density quotient to the non-IT density quotient (RDQ), and estimate its effect on labor productivity using the following relationship:

$$\ln p_c = \ln A + \alpha_c \ln kn_c + \varphi \ln RDQ_c \quad (7.13)$$

If φ is positive and significant, then the increase in the density of IT employment relative to the density of non-IT employment will increase labor productivity.

7.2 Variables, Data and Descriptive Statistics

The variables needed for this analysis were obtained at the state and county level. I considered the 50 U.S. states and the District of Columbia (containing 3141 county equivalents) for the year 1990. Four counties had to be dropped from the analysis because of missing corresponding values between various data sources. These counties are Kalawao county, HI, Aleutians and Lake counties, AK and Yellowstone county, MT. The primary variables needed are output, capital, employment and land area. Secondary variables are education, population and the number of establishments. The variables are aggregated for two types of employment, IT and non-IT. The way these two types are defined is discussed next. Table 7.1 presents the variables needed for this study.

Just as there are different ways to define IT capital (see chapter 2), there are also various ways of defining information technology employment vs. non-IT employment. My measure is based on four sources: Porat (1977), Hepworth (1990), Hudson and Leung

(1988) and Drennan (1989).

Table 7.1Definitions of Variables

Variable	Definition	Link to other variables
$n_{e,c}$	Number of employees in industry type e in county c	
$n_{e,s}$	Total number of employees in industry type e in state s	$n_s = \Sigma_c n_c$
$y_{e,c}$	Output of industry type e in county c	
$y_{e,s}$	Output of industry type e in state s	$y_s = \Sigma_c y_c$
$k_{e,c}$	Capital stock of industry type e in county c	
$k_{e,s}$	Capital stock of industry type e in state s	$k_s = \Sigma_c k_c$
$p_{e,c}$	Labor productivity of industry type e in county c	$p_{e,c} = y_{e,c} / n_{e,c}$
$p_{e,s}$	Labor productivity of industry type e in state s	$p_{e,c} = y_{e,c} / n_{e,c}$
$kn_{e,c}$	Capital to labor ratio of industry type e in county s	$kn_{e,c} = k_{e,c} / n_{e,c}$
$kn_{e,c}$	Capital to labor ratio of industry type e in county s	$kn_{e,c} = k_{e,c} / n_{e,c}$
a_c	Land area of county c	
a_s	Total land area of state s	$A_s = \Sigma_c a_c$
pop_c	Population of county c	
ed_s	Average years of education in state s	

Porat is considered as a pioneer regarding the definition of the information economy. In his voluminous dissertation, he identified four “layers” of information occupations based on the general SIC industry codes. He defined IT occupations as employees who produce, disseminate, analyze and distribute information. His definition served also as a reference to the Organization for Economic Cooperation and Development [O.E.C.D. (1997)] for identifying IT activities. Hepworth, Dreenan, Hudson and Leung have all studied various effects of information technology in light of Porat’s definition, but with some restrictions and/or enlargements. The industries considered as IT industries are usually industries dealing with information as their main resource, and where the ratio of IT capital stock to total capital stock is usually high. Note that this definition differs from the common understanding of IT occupations as mainly limited to computer and network engineers. The data at the county level are available by SIC codes. At the state level, I will use my dataset built in chapter 4, which contains information on production function variables for 52 2-digit SIC industries (Table 4.2). Based on all these considerations, I define IT employment as the number of employees working in industries that are more involved with information and knowledge than traditional industries, and that correspond roughly to the classification in the previously cited references. Tables 7.2 and 7.3 list the IT and non-IT industries, and how they relate to the 52 industries in Table 4.2.

Note that some adjustments had to be made in order to match the two sources of data coming from BEA for the state level data and the U.S. Bureau of Census for county data. In doing so, I could use 50 industries, which resulted from the match of data sources. Among these, 21 are IT industries and 29 are non-IT industries. Following Drennan, another “industry” was added to the IT classification, the one that corresponds to administrative and auxiliary employment in all the industries, and which is reported for each 1-digit industry by the Bureau of Census. Indeed, administrative and auxiliary workers are managing information as their main occupation. As described here, then, data on employment, IT and non-IT, were assembled for the year 1990 at the county level from the County Business Patterns of the U.S. Bureau of Census.

Table 7.2IT Industry Classifications

SIC code	CODE	IT INDUSTRIES
50--	7	Wholesale trade
4800	62	Communications
6000 + 6100	91	Banking
6200	92	Security brokers
6300	93	Insurance carriers
6400	94	Insurance agents
6700	96	Holding and investment
7200	102	Personal services
7300 + 8300 + 8600 + 8700	103	Business and Other Services
7800	106	Motion pictures
8000	108	Health services
8100	109	Legal services
3500	526	Industrial machinery
3600 + 3800	527	Electronic, instrument and related equipment
3700	528 + 529	Transportation equipment
2700	536	Printing & publishing
2800	537	Chemicals
4100	612	Local & interurban passenger transit
4500	615	Transportation by air
4700	617	Transportation services
8200	1010	Educational services
/-1999	+	Administrative and Auxiliary of all industries
Note: Code refers to the code defined in Table 4. 2		

Table 7.3Non-IT Industry Classifications

SIC code	CODE	Non-IT or "traditional" INDUSTRIES
15--	4	Construction
52--	8	Retail trade
1000	31	Metal mining
1200	32	Coal mining
1300	33	Oil & gas
1400	34	Nonmetalic minerals
4900	63	Electric, gas, & sanitary
6500	95	Real estate
7000	101	Hotels & lodging
7500	104	Auto repair & parking
7600	105	Misc. repair services
7900	107	Amusement and recreation
2400	521	Lumber & wood
2500	522	Furniture and fixtures
3200	523	Stone, clay, glass
3300	524	Primary metals
3400	525	Fabricated metals
2000	531	Food & kindred products
2100	532	Tobacco products
2200	533	Textile mill products
2300	534	Apparel & textile
2600	535	Paper products
2900	538	Petroleum products
3000	539	Rubber & plastics
3100	5310	Leather products
4200	613	Trucking and warehousing
3900	5210	Misc. manufacturing
4400	614	Water transportation
4600	616	Pipelines, ex. nat. gas
Note: Code refers to the code defined in chapter 2		

Regarding output and capital stock, getting data at the county level is more complicated. There are simply no such data available. Therefore, I had to estimate output and capital stock series for the 3141 U.S. counties for the year 1990. In order to do so, I based my procedures on the methodology of Hicks and Nivin (2000), who implemented regional industry productivity measures based on national figures. This method is based on the premise that labor productivity within each industrial sector is uniform across regions. I considered a similar premise in chapter 4, when I estimated state capital stock series based on national industry figures, holding the capital to output ratio within an industry across states constant. Here I have to hold labor productivity (output divided by employment) constant within each of the 50 industries considered in this analysis, and across counties. Such an assumption may seem unrealistic at first, but it is possible to justify with the need to narrow sector-specific labor quality across regions that has taken place in the 1980s and that was due to increasing competitiveness. As Hicks and Nivin (2000) argued:

We suggest that the transformation of metro-regional economies during the 1980s was such that individual industries surviving and emerging within them were increasing likely to reflect ever- rising competitiveness pressures. As more and more goods producers and services providers faced the need to retain or regain competitiveness in expending nation-scale (and often global) markets, it is likely the the net effects was to narrow intra-industry labour quality differentials, especially within the nation's largest metro regions. It follows that to be competitive in geographically- expanding markets, then the skill-sets and productivity of workers (...) – whether in Boston or Boise – would of necessity tend to converge over time. Moreover, as new enterprise is incubated, new entrants would be increasingly likely to meet the rising competitiveness requirements for survival. Taken together, such forces likely had the effect of substantially narrowing the range of sector specific labour quality differentials across regions.

I also assume that, just as labor productivity is held constant within industries across counties, the capital per worker ratio also remains constant at the same level. Of course, taken together, these hypotheses amount to saying that a given industry faces the same production function across counties within a given state, considering only capital and labor inputs. Although this is a somewhat strong assumption, the need to justify it becomes less crucial when the regional *aggregated* output is considered. Indeed, the need to estimate industry inputs and output levels across counties is only motivated by the goal of obtaining county *aggregate* output and capital stock levels. Thus, I obtained county output level data based on the following assumption:

$y_c / n_c = y_s / n_s$ (7.14)

And county specific levels of capital stock are obtained using

$k_c / n_c = k_s / n_s$ (7.15)

Finally, other county information such as area (in square miles), population, education levels, were obtained from the decennial census of population from the U.S. Bureau of the census. An education level variable, *edc*, is defined at the county level and represents the percentage of the population that has graduated from high school, but not from college. At the state level, the education variable *eds* represents the average years of education and. The data were taken from Ciccone and Hall (1996). Following this presentation of the three models and the variables used in this analysis, the next chapter describes and discusses the estimation results.

CHAPTER 8 - EMPIRICAL RESULTS OF IT AND NON-IT EXTERNALITY EFFECTS MEASUREMENTS

This chapter presents the results obtained from estimating the models described in chapter 7. Three levels of analysis are implemented: (1) state-level dependent variables with state-level regressors, (2) county-level dependent variables with county-level regressors, and (3) state-level dependent variables with county-level regressors. As explained in chapter 7, this analysis is aimed at capturing the external effects of IT vs. non-IT employment location on labor productivity. These external effects can be further decomposed, following Carlino (1978), into internal economies of scale, localization economies and urbanization economies.

In the first section the results of Ciccone and Hall are approximately replicated using my county and state dataset in order to assess the reasonableness of the data generation procedure described in Chapter 7. The second section describes the results of concentration ratio regressions at the state level and their effects on state labor productivity. The third and fourth consider location and density quotients respectively, and their effects on county labor productivity. The last section summarizes these results and attempts to decompose external effects of each type of employment across counties.

8.1 The Density of Employment and Productivity

First, I intend to approximately replicate Ciccone and Hall's results regarding the effect of county employment density on state labor productivity, as proposed in section 7.3. The equation to be estimated is:

$$\ln p_s = \ln A + \varepsilon \ln edu_s + \ln D_s(\theta) \quad (8.1)$$

It can by estimated by nonlinear least squares. The parameter θ to be estimated reflects the product of a congestion and an agglomeration effect due to increasing employment density. Estimates appear in Table 8.1. In order to test my capital stock data, I also added the capital per employee variable to the labor productivity regression as:

$$\ln p_s = \ln A + \alpha . \ln kn_s + \varepsilon . \ln ed_s + \ln D_s(\theta) \quad (8.2)$$

where $D_s(\theta)$ is defined as:

$$D_s(\theta) = [\ \Sigma_c\ (n_c^{\ \theta} . a_c^{\ 1-\theta})] / n_s \quad (8.3)$$

The estimated value for parameter θ is similar to the one obtained by Ciccone and Hall, with a 95% confidence interval ranging from1.0492 to 1.0592. CH's value of 1.051 falls into this confidence interval. Furthermore, they found a value of 0.51 for the elasticity of the education variable, which is not far from 0.30 considering that the capital-to-labor ratio may have captured some effects attributed to education by CH.

Table 8.1 Estimates of Elasticities from Equation 8.2

	Constant	Capital/labor	Education	θ (own)	θ (CH)
Coefficient	3.563	0.523	0.298	1.054	1.051
Standard Deviation	0.384	0.025	0.071	0.005	0.008

Thus, using my own datasets at the state and county level, I am able to confirm that doubling employment in a county will increase state labor productivity by almost 6%. This brings more confidence to the results presented in the next sections.

8.2 State Level Analysis: IT and Non-IT Concentration Ratios (Model 1)

This section focuses on the spatial concentration aspect of IT employment and non-IT employment at the state level, and their effects on labor productivity. Table 8.2 shows the estimates of equations based on:

$$\ln p_s = \ln A + \alpha_s \ln kn_s + \delta \ln CON_{e,s} \quad (8.4)$$

where state labor productivity (p_s) is regressed on state capital-to-labor ratio (kn_s), state level of education (ed_s) [regression (8.1)] and the state concentration ratios of IT and non-IT employment [regressions (8.2) and (8.3), respectively], as well as their ratio [regression (8.4)] and the two concentration variables together [regression (8.5)].

The first noticeable result is that all coefficients are statistically significant at the 0.01 level, and the explanatory power of all the models is satisfactory, with adjusted R-square values between 0.66 and 0.71. The control regression (8.1) and all the others indicate that labor productivity varies across states with the capital to labor ratio (elasticity between 0.440 and 0.471) and the level of educational attainment (0.112 to 0.246).

Table 8.2Estimates of Elasticities from Equations of Model 1: State Concentration of Employment and Productivity

Regression #	(8.1)	(8.2)	(8.3)	(8.4)	(8.5)
Constant	5.046 (59.00)	5.361 (64.95)	5.489 (63.27)	4.538 (53.48)	4.916 (52.73)
Capital-to-labor	0.457 (77.58)	0.440 (77.98)	0.437 (75.21)	0.471 (83.96)	0.456 (78.80)
Education	0.177 (13.79)	0.129 (10.42)	0.112 (8.61)	0.246 (19.46)	0.192 (13.90)
IT concentration		0.028 (19.23)			0.085 (14.27)
Non-IT concentration			0.028 (16.02)		-0.067 (-199.78)
Ratio of concentrations				0.107 (19.53)	
R^2- adjusted	0.66	0.70	0.69	0.70	0.71
F-statistic	3087	2424	2311	2435	1896
Note: all coefficients are statistically significant at the 0.01 level. T-stat values are in parentheses					

When the concentration ratios of IT and non-IT employment variables are introduced separately [regressions (8.1) and (8.2)], they have the same elasticity value of 0.028. This result means that if in a given state the concentration of IT *or* non-IT employment doubles, gains in state labor productivity amount to 2.8%. So concentration in general increases productivity. However, when these variables are considered together in the regression (8.5), the employment elasticity of state labor productivity is positive (0.085) with respect to the concentration of IT employment, and negative (-0.067) with respect to non-IT employment concentration. Thus, the concentration of IT employment in a state would have positive external effects on labor productivity maybe through agglomeration economies. On the other hand, the concentration of non-IT employment must be subject to congestion effects greater than agglomeration effects, which would explain its negative contribution to labor productivity once the IT concentration has been accounted for. However, estimates of regression (8.5) have to be considered carefully since multicollinearity between the IT and non-IT employment concentration ratio may arise. Indeed, the correlation coefficient between these two variables is estimated at 0.965. The F-statistic computed for this regression is also lower than the other ones. Hence, this model may not be used to compare the contribution of IT relative to non-IT employment concentration on labor productivity differences. Another model was then introduced, using the ratio of these two variables, which prevents multicollinearity from influencing the results. Indeed, the level of correlation between this ratio and other independent variables is less than 0.11. Results appear in regression (8.4) and indicate a stronger coefficient for this ratio compared to individual concentration variables. Indeed, the elasticity of 0.107 means that the ratio of the concentration of IT relative to non-IT employment concentration may explain 10% of the variation in state labor productivity. These findings suggest that states should favor the concentration of IT employment *relative* to the concentration of traditional employment in order to increase their level of labor productivity.

The next two sections report results of county level analyses. The location and density quotient are computed for each county, and their effects on county labor productivity is evaluated.

8.3IT vs. Non-IT Location Quotients and Labor Productivity (Model 2)

This section presents the results of the analysis, at the county level, of the localization economies or diseconomies arising from IT and non-IT employment. Equations estimates are based on the model described in equation 8.4, with location or density quotients in place of concentration rate. Estimates appear in Table 8.3.

Looking at Table 8.3, it appears that all coefficients are significant at the 0.01 level, except for regression (8.9), where multicollinearity between $\ln loc_{1,c}$ and $\ln loc_{2,c}$ may corrupt the results. This is confirmed by a strong positive coefficient of correlation of –0.86 between these two variables. Therefore, independent regressions for each of those have to be considered. Regression (8.7) indicates a positive coefficient of 0.071 for the IT location quotient variable. On the other hand, the coefficient for the non-IT location quotient is negative in regression (8.8), with a value of –0.107. This means that if the county percentage of IT employee doubles, holding the state percentage constant, county labor productivity should increase by 7.1%. In other words, if a county "imports" an extra 100% of IT employees from other counties in the same state, labor productivity in that county should increase by 7.1%. On the other hand, if a county does the same regarding its non-IT employment level, its labor productivity may decrease by more than 10%. These results can be interpreted once again as reflecting externality effects, reaching conclusions similar to those in the previous section about employment concentration. Indeed, IT employment may be subject to agglomeration effects stronger than congestion effects, and the reverse should be true regarding traditional employment.

Finally, the ratio of the two location quotients is used as an explanatory variable in regression (8.10). The resulting coefficient is positive and strongly significant, with a value of 0.046. This ratio could be simplified as shown in the following equation:

$$rloc = loc_{1,c} / loc_{2,c} = \{[(n_{1,c}/n_c)/(n_{1,s}/n_s)] / [(n_{2,c}/n_c)] / (n_{2,s}/n_s)]\}$$

$$\Rightarrow rloc = n_{1,c} \cdot n_c^{-1} \cdot n_{1,s}^{-1} \cdot n_s \cdot n_{2,c}^{-1} \cdot n_c \cdot n_{2,s} \cdot n_s^{-1}$$

rloc = $(n_{1,c} / n_{1,s}) / (n_{2,c} / n_{2,s})$(8.5)

Table 8.3Estimates of Elasticities from Equations of Models 2 and 3: Location and Density Quotients and Productivity

Regression #	(8.6)	(8.7)	(8.8)	(8.9)	(8.10)	(8.11)	(8.12)
Constant	6.034 (72.27)	6.142 (75.30)	6.141 (75.83)	6.142 (75.79)	6.143 (75.64)	6.163 (71.21)	6.047 (69.75)
Capital-to-output ratio	0.370 (82.14)	0.381 (84.57)	0.382 (85.72)	0.382 (85.38)	0.382 (85.31)	0.372 (81.68)	0.369 (81.59)
Education	0.152 (9.45)	0.102 (6.33)	0.097 (6.10)	0.097 (6.07)	0.097 (6.05)	0.114 (6.39)	0.150 (8.53)
IT location quotient		0.071 (11.88)		0.002 (0.23)			
Non-IT location quotient			-0.107 (-13.58)	-0.104 (-6.60)			
IT density quotient						0.005 (4.26)	
Non-IT density quotient							-0.000 (-0.01)
Ratio of location quotients					0.046 (13.01)		
R^2-adjusted	0.79	0.80	0.80	0.80	0.80	0.79	0.79
F-stat	231	240	245	240	244	229	228
Note: All variables are significant at the 0.01 level except for the coefficient on IT location quotient in regression (8.9). All regressions include (1-s) state dummy variables, which are almost all significant at the 0.01 level							

Thus the ratio of location coefficients may be interpreted as the percentage of IT employment in a county relative to the state percentage, divided by the same percentage measure for non-IT employment. Then, the value of the coefficient for the ratio of location quotients expresses the percentage of change in county labor productivity due to an increase in the county percentage of state employment in IT relative to the county percentage of state employment in traditional industry. Hence, given the value of 0.046, it must be that if IT employment doubles in a county, holding traditional employment constant, 4.6% gains in labor productivity would be observed in this county as a result.

8.4County Density Quotients and Labor Productivity

(Model 3)

This section discusses the results of density quotient regressions, as defined in section 7.3. The unit of observation is still the county, and I want to analyze the effects of the density of employment in the two types of industry on county labor productivity. Elasticities estimation results appear in Table 8.3 [regressions (8.11) and (8.12)], which consider the density quotients independently. Indeed, strong multicollinearity rendered the simultaneous use of these two measures meaningless. Furthermore, after a mathematical simplification similar to the one used in deriving equation 8.2, the ratio of the density quotients ends up being equal to the ratio of the location quotients. Thus, the estimates of regressions using either ratio should be the same.

The coefficient for the IT employment density quotient is small but significantly positive at the 0.01 level as shown in regression (8.11). The coefficient for this measure of density is however not significant regarding non-IT employment, as indicated in regression (8.12). These results mean that, at the county level, the density of IT employment significantly affects labor productivity in a positive way, whereas the density of traditional employment does not seem to play any role regarding labor productivity differences. It follows from regression (8.11) that if the number of IT employees *per acre* doubles in a given county, labor productivity may increase by half a percentage point in this county.

8.5Summary of Findings and Discussion of Outcomes

The main findings of this chapter are summarized in Table 8.4. By using regression analyses at the state and county levels, I was able to estimate some externality effects associated with the location patterns of IT and non-IT employment.

Table 8.4Summary of Findings: Elasticities with Respect to Location Variables

Measure of employment location and level of study	Concentration (state)	Intensity (county)	Density (county)
Variable used:	Concentration Ratio	Location Quotient	Density Quotient
IT employment	+ 2.8%	+ 7.1%	+ 0.5%
Traditional employment	+ 2.8%	- 10.7%	0.0
Ratio of IT over non-IT	+ 10.7%	+ 4.6%	+ 4.6%

Overall, it seems that the location of IT employment does have a positive effect on labor productivity. Surprisingly, results indicate localization *diseconomies* for traditional, non-IT, employment, and the coefficient corresponding is strongly significantly negative. Even though the data quality has been verified, results should still be interpreted carefully because of the detailed level of data that had to be estimated first and then aggregated. The results show that strong localization economies are associated with IT employment location quotient. This result is also confirmed by the positive effect of the ratio of the location quotients. This means that, with traditional employment remaining constant, if a county doubles its labor force in IT industries by attracting IT employees from other counties in the same state, then labor productivity could increase by 4.6% in that county. In the same fashion, if a county simply doubles its number of IT employees, allowing traditional employment to vary also, gains in productivity amount to 0.5%. Finally, looking at a state map, if the concentration of IT *or* non-IT employment doubles, then this state will increase its productivity level by 2.8%. Relatively, if the concentration of IT employment doubles, holding the concentration of traditional employment constant, state labor productivity should increase by almost 11%, which seems to be the strongest effect on productivity among all the measures of location patterns.

CHAPTER 9 - SIGNIFICANT FEATURES IN THE LITERATURE ON INCOME INEQUALITY AND THE ROLE PLAYED BY INFORMATION TECHNOLOGY

This chapter surveys some of the literature on income inequality in the U.S. and the role played by the boom in information technology. Its purpose is to understand recent changes in income inequality, and how these were explained in the literature. Following this chapter, the methodology used for evaluating the impact of information technology on income inequality will be presented in chapter 10. Finally, chapter 11 will report and discuss the results of this analysis.

The first section of this chapter presents some facts about trends in income inequality in the United States since the 1970s, and reports the different theories explaining this trend. The second section focuses on the demand-side explanation of income inequality, describing the effects of the tremendous increase in information technology on labor demand and wage differentials. Finally, before analyzing income inequality across states in chapters 10 and 11, the third section of this chapter discusses regional income inequality across space (e.g., states and counties) in the United States.

Income, earnings and wages inequality are alternatively discussed in this chapter. Income is composed of earnings and transfers. Earnings include wages and non-wage income. Since wages usually account for the most part of income, inequality in income, earnings and wages should follow roughly the same trend and that is what is assumed in this study.

9.1Some Facts About Income Inequality in the United States

Katz and Autor (1999), Levy and Murnane (1992) offered thoughtful descriptions of the trends in the U.S. earnings levels and inequalities. Overall, income inequality was stable in the 1970s, increased sharply in the 1980s, and increased moderately in the 1990s, as shown in Table 9.1. A first sub-section (9.1.1) will describe trends in more details. One striking fact of the 1980s is that not only was there an increase in inequality between groups, but also inequality within groups increased. The groups considered here are usually workers of the same sex, age, educational level, or level of experience. In subsections 9.1.2 and 9.1.3, Levy and Murnane discuss *between* and *within* inequalities .

Fortin and Lemieux (1997), Topel (1997), Johnson (1997), Katz and Murphy (1992), Borjas and Ramey (1994) have all searched for explanations for the observed changes in inequality. Candidates include education, age, experience, industry of employment, supply and demand shifts, and institutional changes. Sub-sections 9.1.4 will discuss Fortin and Lemieux's study on the effects of three institutional changes: "deunionization," weak minimum wage, and deregulation. Regarding the supply-side explanation, it states that the arrival of numerous well-educated baby boomers increased the supply of labor tremendously and affected income inequality. This will be discussed in the last sub-section. The demand-side explanation, arguing that fierce competition and booming information technology implied an increase in the demand for highly skilled labor and increased income inequality, is left to be discussed in the section following this one (9.2).

9.1.1Inequality in the 1970s, 1980s and 1990s

Changes in income inequality differ by decades. Features of trends in income inequality during the 1970s, 1980s and 1990s appear in Table 9.1. The overall situation regarding income inequality has deteriorated since the 1970s. The only improvement comes from the diminution of the gender gap since the 1980s.

Table 9.1Features of Trends in Income Inequality for the 1970s, 1980s and 1990s

	1970s	1980s	1990s
Overall inequality	Stable	Sharp increase	Increase
- Between groups	Decrease	Sharp increase	Increase
- Within groups	Increase	Increase	Increase
Real wages	Decrease	Decrease	Decrease
Gender gap	Stable	Decrease	Decrease
Return to education	Sharp decrease	Sharp increase	Increase

Levy and Murnane distinguished three periods in earnings inequalities that correspond roughly to the past three decades.

1. 1970-1982 was characterized by stable inequality, well-educated baby boomers increasing the overall wage and the return to age and experience. However, a substantial decline in the education premium was observed. Therefore, between groups inequality decreased while within group inequality increased, explaining the stable trend in overall inequality during the 1970s.

2. 1983 to 1987 was a period of vanishing middle class jobs. According to the authors, the “Economic Recovery and Taxation Act in 1982” was a mistake. Following the advice of supply-side growth theorists, this act had reduced taxes, especially in the top brackets of the income scale. Its aim was to increase saving and investment. However, the result was an increase of 9.7% in the unemployment rate. The rich were getting richer and the poor poorer. Apart from this supply-side explanation, the decline in middle class jobs was also attributed to demand-side factors such as de-industrialization. Indeed, during the decline in industrialization “production workers and craftsmen [became] hamburger flippers” according to Levy and Murnane (p1347). Furthermore, the number of female workers increased moderately in middle class jobs. Still, the demand-side was not a sufficient explanation of increasing inequalities because these appeared *within* sector too.

3. During the last period, from 1988 to 1991 the education premium increased because of technological change and the dramatic decrease in low-skilled wages due to numerous young high school dropouts. Murphy and Welch (1992) carefully studied supply and demand effects and showed that the “decline in earnings of less-educated men in the 1980s reflected an inward demand shift arising from the increased import competition in U.S. markets.” Thus, over the three periods, *between* groups inequalities were stable in the 1970s and grew rapidly in the 1980s, whereas *within* group inequalities were steadily growing over the same period. Levy and Murnane analyzed these two types of group inequalities.

How income inequality occurred at the first place is an interesting question that has generated a lot of academic research. According to Levy and Murnane (1992), in the “postwar golden age” real wages doubled because of increasing productivity. Since 1973 average real wages have increased much more slowly, causing an end to rapid real earnings growth and the start of slower growth nearing stagnation. The trend in earnings growth is different from the trend in inequality: if both increase, then poor people get richer but rich people get richer faster, and if there is only an increase in inequality with stagnant earnings, then the rich get richer and the poor poorer. In 1979, there was a sharp acceleration in the growth of inequality, especially among men, and the increase was at both ends of the wage distribution scale. This phenomenon is called "polarization," where the increase in inequality is observed for the young as well as the older workers. Inequalities *between* and *within* groups by age or education have increased. However, the female/male gap in earnings has narrowed. Regarding earnings of women, there has been an increase in the hourly wage and annual hours worked.

9.1.2Between Groups Inequality

The increase in the premium associated with labor market experience for males contributed to an increase in *between* groups earnings inequality in the 1980s, which offset the general decreasing trend in this type of inequality in the 1970s. Inequality also grew sharply in the 1980s because of a sharp increase in the education premium for all groups, and an increase in the age-related premium for high school educated workers. However, there was also the first sustained decline in the male/female wage differential, with the female median earnings increasing from 58% of the men median earnings in 1979 to 67% in 1987. This closing of the gender gap may be due to the fact that women's educational achievement increased relative to men's. Katz and Murphy (1992) concluded

Fluctuations over time both in education and age premiums can be explained by changes in the rates of growth of different labor force groups (supply shift), coupled with a stable rate of growth in the relative demand for college educated workers (demand shift)

Immigration also contributed to the supply-side explanation because immigrants were usually less educated and worked in low paid jobs. On the demand-side, one factor is the post-1982 increased value of the dollar, which increased the price of exports and thus reduced the demand for U.S. manufacturing goods. The gender gap was also reduced because of the diminishing demand for relatively high paying jobs in manufacturing that were held primarily by high school educated males. Finally, two macroeconomic factors reinforced the effects of supply and demand changes in inequalities. According to Levy and Murnane "inflation of the 1970s helped to camouflage production inefficiencies." During this decade, firms could survive international competition by giving nominal wage increases just below the inflation rate. This was no longer possible in the 1980s when inflation decreased, leading to an increase in inequality and unemployment. Labor markets became very tight and for this reason the wage differential associated with education was less likely to increase.

9.1.3Within Group Inequality

Within group inequality is explained by factors based on covariates other than age and education. As a matter of fact, this type of inequality increased steadily after 1970 for groups defined by education, age/experience and gender (they were 30% greater in 1987 than in 1970). Several factors can explain this increase. One factor is increasing returns to skill. Indeed, according to Levy and Murnane,

A change in the desired skill mix of workers within industry, brought about by non-neutral technological change, has increased the value of skilled vs. less skilled workers.

Still, evidence on this hypothesis is limited and increasing returns to skill do not seem to be the only reason for *within* group variation. Another factor explaining the increase in within group inequality is the increasing industry specific wage differentials *within* industry. Indeed, Levy and Murnane found that in the 1970s, 25% of *within* group earnings inequalities were due to differences in wages paid to equally able workers across industries. Finally, changing wage setting institutions and the decline in unionization in the 1980s may have increased *within* group inequality, as discussed next.

Before moving on to the next section, Figure 9.1 reports the main explanations that have been given for the trends in income inequality since the 1970s. The following sub-sections concentrate on two of those determinants: institutional changes and supply-side explanations.

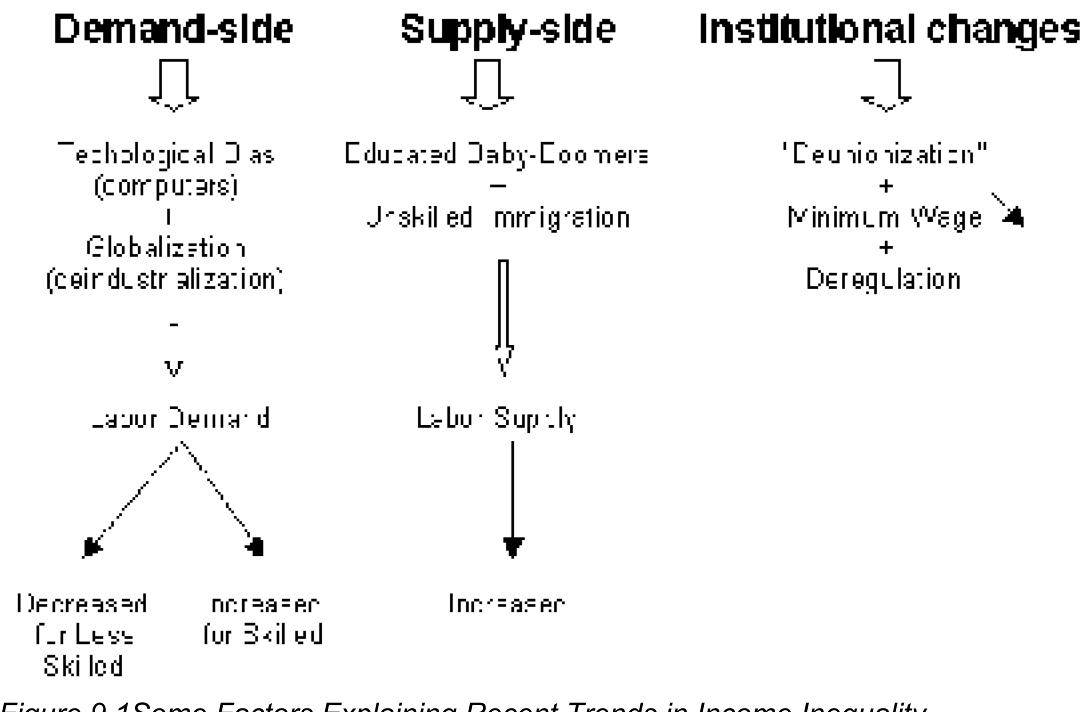


Figure 9.1Some Factors Explaining Recent Trends in Income Inequality

9.1.4Institutional Changes: “Deunionization,” Minimum Wage and Deregulation

Fortin and Lemieux (1997) studied the impact of institutional changes on wage inequalities. Their analysis varies from explanations based on supply and demand effects. They acknowledge that *between* groups and *within* group inequalities have both increased in 1980s and their sources are still debated. They studied the impact of three institutional changes: (1) the decline in the real value of minimum wage, (2) the decline in unionization rate (3) economic deregulation. They argued that a third of the increase in male and female inequalities during the 1980s is due to these institutional changes. During this decade, the real minimum wage decreased from 45% to 31% of the average manufacturing wage. Unionization fell by 1% each year and this "deunionization" had significant effects on inequalities among men but not among women. For women, the decline in the real value of the minimum wage has contributed to the increase in earnings inequality. The impact of deregulation was small. Fortin and Lemieux's analysis differs from explanations based on supply and demand effects. They argued that demand explanations cannot really account for certain empirical puzzles. For instance, France and Germany were exposed to similar technological and trade shocks but reported almost no changes in the distribution of wages in the 1980s. These countries have institutions setting wages collectively. In the United States market forces have a greater impact on wages because it is a more market-based economy. Thus, institutional structure cannot explain, by itself, the growth in wage inequality, but can be a source of rising inequality. Therefore, institutional forces simply cannot be overlooked in any serious attempt to understand the recent rise in wages inequality in the U.S. labor market.

9.1.5Supply Determinants of Inequality

Topel (1997) focused on the supply-side determinants of wage inequality. First, he noticed that inequality seems more important in the United States than in any other country. For instance, in 1990 U.S. households at the highest decile of the wage distribution had disposable income 6.0 times higher than those at the lower decile. The comparable multiples were 4 and 3.8 in Canada and in the United Kingdom, respectively. These differences in the levels of inequality between countries were not as important in the 1960s. In the United States, the increase in inequality is partly due to a fall of 20% in the real wages of men at the bottom decile since1970. According to Topel, increasing inequality has also been driven by a steady increase in demand for skilled labor, which has outrun the increasing supply of such labor. Topel considers that a "solution" to this problem may be to increase the supply of educated workers (human capital) in order to match up supply and demand for skilled labor.

Topel then evaluated the impact of changes in the supply of skills on wage differentials and inequality. The first aspect is that certain changes in labor supply, such as increasing immigration and female labor supply, are alleged to exacerbate earning inequalities. A second reason to study the impact of labor supply on relative wages is to evaluate the likelihood that human capital investment will mitigate rising inequality. Evidence shows that the main effects would be among relatively high-wage workers, and human capital will probably not raise low-skill wages. The answers depends mainly on how well different skill groups substitute to one another.

Topel concluded that rising wage inequality is one of the most important social changes in modern history. If this change is demand-driven, supply-side factors might have also raised inequality, although existing research is not conclusive. Furthermore, there is hope that investment in human capital will reduce inequality. As the author put it:

The increase in return to college education has encouraged more young people to go to college, but there is a myriad of skills demanded in the labor market (elementary education, on-the-job training). Still, college educated labor will have its main impact on the upper end of the wage distribution, when social pathologies of inequality are actually at the lower end.

9.2The Effect of Information Technology on Income Inequality

As discussed in the previous section, one demand-side explanation of increasing income inequality proposes that globalization and the extraordinary increase in high technology investment has shifted demand from low-skilled to high-skilled workers. For example, computers may be seen as a factor increasing income inequality, as reported by The Economist (1999):

Information technology replaces the unskilled; less demand means lower wages. At the same time, computers complement the skills of more sophisticated types – the "knowledge workers" who represent (...) the future of work. This complementarity raises individuals' productivity and thereby increases their earning power. The prosperous get more so, the unskilled get dumped.

Levy and Murnane (1996) studied the effects of computerization on the demand for skilled and unskilled labor. They found that the computer revolution seems to have been responsible for a large part of the decline in the demand for unskilled labor during the 1980's. Levy and Murnane (1996) studied the custodian unit of a bank intensively and noticed that computers generate two opposite effects:

By changing skill requirements, computerization increases the optimal ratio of skilled to unskilled labor per unit of output. By improving labor productivity, computerization nonetheless reduces the quantity of skilled labor per unit of output.

Computerization has, however, not eliminated the need for knowledge that underlies the routine work. That is why training must also be accompanied by hiring of new graduates. Levy and Murnane found that more than one out of four trained workers left the bank after the training period, generating extra costs for the bank. Those costs are associated with the computerization of the firm, and might constitute another reason for the failure to see the important productivity gains expected from IT. The trained workers who have left the bank are most likely to sell their new skills to another company, which will benefit indirectly from the bank's spending in training program. The negative effect on the bank and the positive effect on the new hiring firm should even out at the aggregate level, but are part of the reason why some firms might succeed better than others with IT. This fact might generate the need for government intervention, which will adjust the skills of the labor force to the needs of the new "computerized" firm. However, private markets might have ways of reducing turnover of trained workers. For instance, firms may avoid these extra costs by paying their workers a wage equal to their marginal revenue product while they are being trained (trainees get usually paid less than trained workers). Hence, trainees would have incentives to stay with the training firm.

As discussed in Chapter 3, David (1990) offered an explanation of the productivity paradox through historical consideration, pointing out the "diffusion lags" that have accompanied most of the great scientific discoveries of the twentieth century. The reason for this delay in productivity results comes in part from the labor force, which is not ready to use new technologies right away. Workers have to gain the necessary skills, and producers of new technologies have to improve their interface with humans.

Autor, Katz and Krueger (1998, hereafter AKK) studied the effects of computers on the labor market. They looked at the changes in the relative supplies and wages of workers by education from 1940 to 1996. They note that the literature relates the importance of technology to wages because of a skill-biasing effect and a demand shift to more educated workers. However, AKK argued that in order to evaluate the skill-biased technological change, it is necessary to (1) use a framework combining shifts in both the relative demand and relative supply of skills, (2) consider a longer time frame, (3) look at the relationships among observable technology indicators and skill upgrading over this long time period. They found that the utilization of more-skilled workers is greater in the most computer-intensive industries, but could not conclude whether a causal interpretation of this relationship is appropriate or not.

Krueger (1993) used data from the Current Population Surveys (CPS) to determine, on one hand, if workers using computers at work earn more than similar workers without computer skills, and, on the other hand, if the premium associated with computer skills can account for the increasing wage inequalities in the 1980s. According to Krueger (1993):

The new computer technology may be a complement or a substitute for skilled labor. In the former case the computer revolution is likely to lead to an expansion in earnings differentials based on skill, and in the latter case it is likely to lead to compression in skill-based differentials.

Krueger estimated wages equations by OLS, and found that the wage premium to workers using a computer at work was 10 to 15 percent between 1984 and 1989. Krueger also estimated a wage equation with and without a dummy variable controlling for computer use and found that "nearly 40% of the increase in the return to schooling can be attributed to the expansion in computer use." He concludes that these results suggest that the computer revolution has certainly contributed to changes in the wage structure of the 1980s.

However, Krueger's results must be taken with caution. A study from Dinardo and Pischke (1997) has stressed the importance of causality and cast some doubt on the interpretation of results concerning the wage differential associated with computer use. Indeed, the authors have measured a "large differential for on-the-job use of calculators, telephones, pens or pencils, or for those who work while sitting down." Obviously, these characteristics do not have a real effect on wages. Thus, this study was intended to be a warning for careful interpretation of results.

Artus and Lefeuvre (1998) argued that *between* groups inequality rose mainly in the 1980s, and remained relatively stable in this last decade, which was “the most computerized.” However, in the 1990s, there appeared a new type of inequality: *wealth* inequality. They reported that over the 1989-1998 period, the wealth of households who earn income greater than $100,000 increased by 18%, and by only 10% for others. Similarly, the wealth of college-educated workers has increased by 46% and 20% only for others between 1995 and 1998. Still, Artus and Lefeuvre noted that this type of inequality may not be attributable to the “new economy” only. Indeed, the wealth of the richest households may be simply due to the growth of the stock market, which constitutes an important part of this wealth. In the new economy, workers’ capacity to react, innovate and adapt to new challenges becomes more important than their education level. The next section looks at income inequality in a spatial dimension, through a survey of some literature on regional income inequality.

9.3Regional Income Inequality

Levernier, Rickman and Patridge (1995) studied income inequality across the 48 contiguous U.S. states in 1960, 1970, 1980 and 1990. They regressed states’ Gini coefficients on several economic, demographic, human capital and labor market variables, controlling for fixed regional effects. Their economic regressors include real per capita income and its square, the industrial composition of a state’s workforce and the growth rate of non-agricultural employment. Demographic and labor force variables include urbanization rate, labor force participation rate, racial composition, age characteristics, rate of female-headed households, unionization and the immigration level of the state, as well as the share of government transfer payments in income. Finally, human capital variables are represented by the proportion of the population that has graduated from high school and from college. The authors estimated an OLS regression on their pooled cross section time series data with states’ Gini coefficients as the dependent variable and the variables mentioned above as the regressors and dummies for region and years.

First, they found that dummies for years had an increasing value, meaning that inequality has increased over time between 1960 and 1990. Second, the variables having a negative and significant coefficient (reducing inequality) were: the unionization rate, the proportion of the labor force that has graduated from high school, the level of income, the labor force participation rate and the proportion of workforce in the mining, construction and manufacturing industries. However, the square of the income level and the urbanization level variables were insignificant when the regression is estimated for each year separately. Since the square of the income variable is not significant, the authors conclude that the level of economic development of a state does not appear to significantly affect inequalities, unlike the percentage of the labor force that is in the goods producing sector and that is educated at the high school level. However, the proportion of the workforce that is college educated is not significantly related to the level of income inequality. Hence, even if the greater premium associated with college education has increased U.S. wage inequality, it does not seem to have influenced *regional* differences in inequality. The racial composition of the state, measured as the percentage of the labor force that is black, surprisingly does not affect income inequality. Finally, the variables found to increase inequalities (having a positive and significant effect on the Gini coefficient) are: the percentage of the state's population that works on a farm and the share of female-headed households. Mixed effects were reported for the growth rate of the labor force, the level of immigration, the age characteristics, the unionisation rate and the rate of transfer payments of the state, although the latter were positively correlated to inequality for some years.

In discussing their results, Levernier Rickman and Patridge (1995) argued that the Gini coefficient is not a perfect measure of income inequality, and multicollinearity may influence the yearly estimates. Indeed, the Gini coefficient raises concern regarding its construction, as stated by Levernier Rickman and Patridge (1995)

The Gini coefficient suffers from the well-known problem that changes in the middle of the distribution have larger influence than changes in the tails of the distribution. If most of the changes in income inequalities are in the tails – i.e. among the lowest or highest income families – the Gini coefficient may be an inadequate measure of income inequality.

To prevent such difficulties, the authors reestimated their regressions using the variance of the log family income instead of the Gini coefficient, as suggested by Levy and Murnane (1992). Their results are similar to the original ones, and Levernier, Rickman and Patridge concluded that the results are robust to changes in the measurement of income inequality. This analysis also indicated that multicollinearity did not appear to have affected the results, since results using the variance of the log family income would have probably been different from the original ones. Furthermore, the pooled regression results are generally consistent with the yearly regressions.

Levernier, Rickman and Patridge also concluded that there is evidence of convergence in state income inequality over time. Indeed, this type of inequality used to be much more important in the southern states, and over time other states have reached the same level of inequality. Income inequality has increased in New York, California, Illinois and New Jersey and it has decreased in most of the mid Atlantic states including Delaware, Maryland and Virginia.

Langer (1999) also studied income inequality across states for the same years as well as for each year between 1976 and 1995. She measured income inequality with the Gini coefficient, which is computed from two sources: the Bureau of Census decennial census of population, and the Current Population Survey (CPS) for the yearly measure. However, the values she computed for the Gini coefficients are slightly different from the ones used by Levernier, Rickman and Patridge. This might explain some differences in their results. She observed three kinds of general patterns in income inequality over time. First, some states such as New York, California, Louisiana and Delaware exhibit a steady linear increase in their level of inequality since the 1970s. Second, states such as Nebraska have shown a cyclical pattern in inequality over time. Finally, other states such as Virginia have followed a decreasing trend in income inequality, at least until the mid-1980s. Still, Langer further admitted that “the variation in income inequality across states and over time begs theoretical explanation,” but proposed that “the American states are ideal settings to study the forces affecting income inequality.”

Finally, Greenwood (1999) studied the relationships between technology, productivity and income inequality. He first assumes that the development of new technologies such as information technology involves considerable learning costs, and these costs are lower for skilled workers. The demand for skilled workers will then increase, and so will their wages relative to unskilled workers’. Thus income inequality should rise with the development of new technologies. Furthermore, productivity may stall as investment in new technology equipment and knowledge increases. Greenwood (1999) argued that

Technological progress is associated with growth in productivity and wage inequality. In the short term, skilled employees earn more than unskilled ones; also, wealthy individuals take advantage of new profit opportunities. However, over time, the level of skill needed to master new technologies declines; also opportunities to make profits are reduced. Therefore, over a long period, everyone gains from technological innovations.

This chapter has presented a short survey of some of the literature on income inequality, which remained stable in the 1970s, increased sharply in the 1980s, and increased moderately in the 1990s. A new feature of income inequality appeared in the 1980s, with an increase both in *between* and *within* groups inequality. Several factors were held responsible for this trend. Candidates include: institutional changes, supply-side and demand-side determinants. Each of these determinants could explain about a third of income inequality. The role of computers and IT was also stressed, with a positive effect on the wage differential. Finally, regional income inequality was discussed, mainly through an empirical analysis of the U.S. states form Levernier, Rickman, and Patridge (1995). The next chapter describes the methodology applied to the analysis of the effects of IT characteristics on income inequality at the state level for the year 1990.

CHAPTER 10 - A METHODOLOGY FOR MEASURING THE IMPACT OF INFORMATION TECHNOLOGY ON INCOME INEQUALITY

The methodology adopted in this analysis is based on the work of Levernier, Rickman and Patridge (1995, hereafter LRP) who used a simple econometric model linking measures of income inequality to economic, demographic and human capital variables. The units of analysis of their model were the 48 contiguous U.S. states, for four different years: 1959, 1969, 1979 and 1989. Their model allowed them to identify some of the key variables affecting income inequality. My goal is first to replicate their results approximately for the year 1990, so that these important variables can be also identified using my dataset. Then, I will introduce variables measuring the level of states' IT development, such as the IT intensity or the density of IT activity at the county level. I will thus be able to evaluate the effects of IT on income inequality across states. The first section describes the model used by LRP to explain income inequality.

10.1Modeling Income Inequality

In the literature the general model evaluating the effects of different variables on income inequality, say at the state level, is defined as:

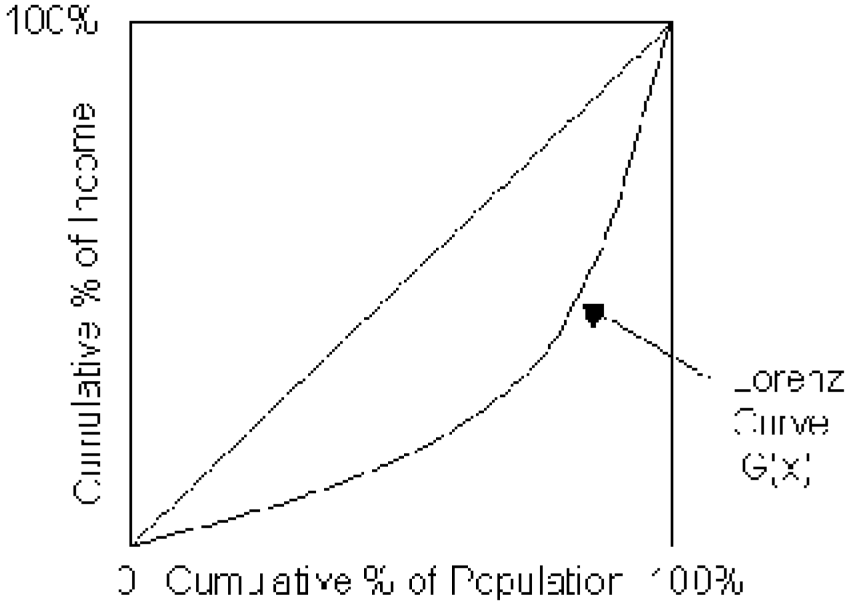
$Inequality_s = X_s\beta + e_s$ (9.1)

where *Inequality* represents a measure of income inequality in state s (usually the Gini coefficient or the variance of the log of income), X_s is a set of variables assumed to affect income inequality (such as demographic, economic and human capital factors), and e_s represents the error term. The sign and significance of the coefficients of vector β express the effect of a given independent variable on income inequality. A positive (negative) sign is associated with a variable that increases (decreases) income inequality.

The Gini coefficient is not a perfect measure of inequality,[12] but it is well known and has been computed at the state level for each decennial census of the U.S. population since 1950. This index represents the proportion of total income that must be redistributed in order to achieve perfect income equality among classes of income population. It varies between 0 and 1, from the lowest to the highest degree of inequality, respectively. Figure 10.1 shows a detailed description on the construction of the Gini coefficient. This study covers the 48 contiguous states in 1990. The values of states' Gini coefficients for the year 1989 are taken from LRP. As stated by the authors, the Gini coefficients for 1989 are matched with 1990 values of the explanatory variables "because the Bureau of Census obtains income information on families for the year *prior* to the year the census is conducted."

In order to replicate approximately their results, this analysis uses several of the independent variables that LRP considered as explanatory variables. First, the industrial mix of a state's workforce may influence the distribution of income. For several reasons such as a strong union power, less skilled workers may earn higher wages in mining, construction and manufacturing industries. Income inequality may then be lower in states that have a high share of their working population in these industries.

[12] As reported by Levy and Murnane (1992), the Gini coefficient cannot reflect some changes in inequality such as the "polarization" phenomenon due to vanishing middle class. Mathematically, according to the Lorenz curve, the Gini coefficient represents the area between the diagonal and the curve of income distribution, but is insensitive to changes in the shape of the curve, if the value of the area remains the same.



$$GINI = 1 - 2G(x)dx$$

Source: Smith (1998)

Figure 10.1The Lorenz Curve and the Gini Coefficient

Second, LRP cited Kuznets'(1955) theory, which stated that income inequality may be related to the level of economic development, and "income inequality will increase as income becomes concentrated in the hands of the owner/capitalist class." However, after some threshold, the level of inequality should decrease. In order to account for this possibility, variables measuring income and income squared are introduced.

Third, demographic factors such as the labor force participation rate or the racial composition of a state may influence income inequality. Indeed, because wages and salaries are the major component of money income, income should be more equally distributed where the labor force participation rate is higher. On the other hand, racial discrimination may increase income inequality. This effect can be captured with a variable representing the state percentage of non-white population. LRP used the percentage of the population that is black, but I think the percent of non-white is a better measure since segregation may exist for all non-whites, not only blacks.

Human capital is also an important factor influencing income inequality. LRP considered two measures of educational level for the states. First, the percent of the 25 year-old population that graduated from high school (but not from college), and the percent that graduated from college. The literature on income inequality has related the importance of human capital in reducing income inequality. Indeed, as the labor force gets more educated, workers get more skilled, which allows them to earn higher salaries. This will reduce the gap between low-paid and high-paid jobs, thus reducing income inequality. However, the effect of the percent of college graduates is less obvious. On one hand its increase can contribute to the reduction of income inequality, as it is the case for the percent of high school educated workers. On the other hand, its increase can aggravate income inequality simply because it increases the upper bound of the wage distribution, because highly educated people earn higher wages. Therefore the effect of an increase in the percent of college graduates on income inequality is ambiguous. All these variables are defined formally in Table 10.1, described in Table 10.2, and will be used to replicate approximately the results obtained by LRP. Then, the most significant variables will be retained, and some IT variables added to the model in order to analyze the effects of IT on income inequality.

As stated in chapter 2, the increase in IT activities over the last two decades has paralleled the increase in income inequality. Figure 2.11 reports similar trends in the Gini coefficient and the IT capital stock between 1977 and 1997. For various reasons, the demand-side explanation suggests that the increase in IT has somehow deteriorated the situation regarding income inequality. This is also suggested by Figure 2.12, which shows a scatter plot of the Gini coefficients and the stock of IT capital stock for the 1977-1997 period. The main reason may be the substitution and complementary effect of IT. Indeed, IT capital might substitute for unskilled workers, and be a complement for skilled employees. Still, the causality between IT and income inequality is not clear and must continue to be tested empirically.

In this analysis, I will focus on IT as a characteristic of the labor force, not the capital stock. First, I will consider IT employment and non-IT or "traditional" employment as the main variables for which I want to analyze the effect on income inequality. IT employment is defined as the number of employees in 16 types of 2-digit SIC industries that are considered as IT industries, as defined in chapter 7. Employees in these industries are believed to deal with information and knowledge more than any employees in the other industries. Furthermore, IT employment refers to jobs that are usually paid better than non-IT employment. The reason is that the economy moved from an "industry based" to "information based" paradigm. Today, the term "new economy" refers to an economic system where knowledge and information are the new "raw materials." Some authors relate this change as the passage from a "hard" to a "soft" economy. Hence, workers who are able to create, process, transmit and analyze information will have a higher marginal product than non-IT workers. As a consequence, salaries of IT employees are usually higher than those of non-IT employees. On the other hand, since the ability to deal with information technology has become the scarce skill in the job market, workers that do not possess such knowledge have a lower marginal product. Therefore, states with a high percentage of IT employees are most likely to exhibit higher income inequality, since the "IT knowledgeable" workers get richer and the "IT ignorant" workers poorer.

Finally, the density of IT employment may also affect income inequality. Indeed, information is subject to externalities that increase with density. A university for instance, is a place where people exchange ideas and benefits from knowledge spillovers due to interactions with one another. Other IT workers could benefit from being close by. These externalities should increase with the agglomeration of IT employees. Therefore, the marginal product of IT employees should increase with the density of this type of employment, aggravating income inequality even more.

After having defined the models measuring the impact of IT employment on income inequality, the next section will now describe the variables and data needed, as well as some descriptive statistics.

10.2Variables, Data and Descriptive Statistics

This section describes the variables and data as well as some descriptive statistics. Because of data availability concerns, not all the variables used by LRP are considered in this analysis. The purpose is to build a basic model of regional income inequality in order to introduce IT variables and study their effects.

The different variables used in the model presented above are defined in Table 10.1, and are described in Table 10.2. Data for the socio-demographic variables come from the decennial census of population for the year 1990 [U.S. Bureau of the Census (1994)]. Detailed explanations on the construction of the three IT variables appear in chapter 7. The data for the share of IT employment among total employment is obtained at the county level from the County Business Patterns survey of the Bureau of the Census (1990). These are aggregated at the state level. Finally, the densities of IT and traditional employment are calculated at the county level according to the model of Ciccone and Hall (1996). Data on county employment previously cited are used to compute these density indexes at the state level.

Table 10.1Definitions of Variables

Short name	Name	Definition
INC	Income	Per capital income
INC2	Income^2	Square of per capita income
NWHITE	Nonwhite	Percent of the population that is not white
HS	High school	Percent of the 25 years or older population that graduated from high school only
COL	College	Percent of the 25 years old population that graduated from college
LABPART	Participation rate	Percent of 16 years or older population that is in the labor force
PCGOODPW	Goods employment	Percent of nonfarm employment that is in manufacturing, mining and construction.
LITP	IT employment	Percent of private nonfarm employment that is IT employment (chapter 7)
ITDENS	IT density	Density index for the concentration of IT employment at the county level (chapter 7)
NITDENS	Non-IT density	Density index for the concentration of non-IT employment at the county level (chapter 7)
REG2	Midwest	Regional dummy variable for Midwest
REG3	South	Regional dummy variable for South
REG4	West	Regional dummy variable for West

Table 10.2Description of the Variables

Short name	Name	Mean	SD	Minimum	Maximum
GINI	Gini	0.3943	0.0226	0.3527	0.4518
INC	Income	13760	2436	9648	20189
PCNWHITE	Nonwhite	0.1716	0.1394	0.0145	0.7039
PCHSPLUS	High school	0.5001	0.0424	0.3677	0.5735
PCCOLGRA	College	0.2621	0.0471	0.1613	0.3638
LABPART	Participation rate	0.6575	0.0379	0.5300	0.7470
PCGOODPW	Goods employment	0.2448	0.0546	0.0857	0.3485
LITP	IT employment	0.3005	0.0528	0.2000	0.4300
ITDENS	IT density	1.2599	0.1141	0.9700	1.5800
NITDENS	Non-IT density	1.2737	0.0969	1.0200	1.4700

The average Gini coefficient is 0.3943 with a standard deviation of 0.0226. Hence, income inequality differs across states, but not in high proportions. The share of employment that is of IT type is 30% on average, ranging from 20% to 43% across states. The density of traditional employment is, on average, higher than that of IT employment. However, the standard deviation of IT employment is higher than that of traditional employment. This fact supports the idea that the localization of IT employment varies across states more than the localization of traditional employment.

Finally, Table 10.3 reports values of the Gini coefficients, IT intensities and densities by state, as well as rankings. The table shows that New York is the most IT intensive and IT dense state and has the third greatest level of inequality. However, Massachusetts is the second state regarding IT variables, but ranks only 27th regarding its level of inequality. Thus it is hard to draw conclusions about the effects of IT on income inequality just from the gross data so a regression analysis is used.

Table 10.3Descriptive Statistics by State

State	Gini	Share of IT employment (LITP)	Density index of IT employment (ITDENS)	Ranking by Gini coefficients	Ranking by LITP	Ranking by ITDENS
Louisiana	0.4518	0.32	1.28	1	18	23
Mississippi	0.4401	0.22	1.16	2	47	41
New York	0.4373	0.43	1.58	3	1	1
Texas	0.4373	0.35	1.32	3	9	17
Kentucky	0.4272	0.25	1.27	4	38	26
New Mexico	0.4272	0.30	1.17	4	27	40
Florida	0.4260	0.34	1.30	5	11	19
California	0.4235	0.36	1.36	6	8	8
Georgia	0.4204	0.31	1.34	7	23	15
Alabama	0.4200	0.25	1.22	8	39	32
Tennessee	0.4185	0.27	1.28	9	34	22
Oklahoma	0.4175	0.30	1.25	10	25	29
West Virginia	0.4158	0.25	1.18	11	42	38
Arizona	0.4155	0.33	1.18	12	14	36
Arkansas	0.4145	0.23	1.18	13	43	37
Illinois	0.4094	0.36	1.41	14	7	3
Missouri	0.4035	0.33	1.35	15	13	10
Connecticut	0.4033	0.37	1.36	16	5	9
Virginia	0.4006	0.31	1.40	17	22	5
Pennsylvania	0.3999	0.35	1.36	18	10	7
New Jersey	0.3997	0.36	1.41	19	6	4
Michigan	0.3993	0.31	1.33	20	19	16
North Carolina	0.3971	0.23	1.26	21	45	27
South Carolina	0.3967	0.23	1.21	22	44	34
Colorado	0.3945	0.33	1.30	23	12	18
Ohio	0.3939	0.32	1.35	24	17	11
Nevada	0.3936	0.20	1.12	25	48	44
Oregon	0.3915	0.29	1.24	26	29	30
Massachusetts	0.3900	0.42	1.43	27	2	2
Kansas	0.3894	0.29	1.22	28	31	31
Montana	0.3887	0.26	1.03	29	37	48
Idaho	0.3886	0.23	1.13	30	46	43
Maryland	0.3854	0.37	1.38	31	4	6

Table 10.3(continued)

State	Gini	Share of IT employment (LITP)	Density index of IT employment (ITDENS)	Ranking by Gini coefficients	Ranking by LITP	Ranking by ITDENS
South Dakota	0.3842	0.26	1.11	32	36	45
Washington	0.3827	0.31	1.26	33	21	28
Minnesota	0.3804	0.32	1.34	34	15	14
Rhode Island	0.3778	0.32	1.35	35	16	12
Nebraska	0.3774	0.31	1.28	36	20	25
Indiana	0.3767	0.25	1.28	37	40	21
Delaware	0.3766	0.39	1.34	38	3	13
Maine	0.3766	0.28	1.17	38	32	39
North Dakota	0.3756	0.30	1.07	39	26	47
Iowa	0.3728	0.28	1.19	40	33	35
Wyoming	0.3721	0.20	0.97	41	49	49
Utah	0.3686	0.30	1.28	42	28	24
Wisconsin	0.3675	0.29	1.29	43	30	20
Vermont	0.3654	0.25	1.15	44	41	42
New Hampshire	0.3527	0.27	1.21	45	35	33

CHAPTER 11 - EMPIRICAL RESULTS FOR THE MEASUREMENT OF THE EFFECTS OF INFORMATION TECHNOLOGY ON INCOME INEQUALITY

This chapter presents results of estimating the model described in the preceding chapter. After reporting the main findings, I will interpret them and comment further. Finally, I will test the robustness of the results using a different measure of income inequality.

11.1Presentation and Interpretation of the Results

Several OLS specifications based on the model presented in the preceding chapter are reported in Table 11.1. Regression (11.1) shows the results from Levernier, Rickman, and Patridge (1995). Regression 11.2 presents the results from the approximate replication of 11.1, using my own dataset. In regression 11.3, a variable measuring the intensity of IT employment (LITP) is introduced, and several independent variables are dropped from the analysis to avoid multicollinearity. Finally, two variables measuring the density of IT and traditional employment are added to this model in regression (11.4). Because there are exogenous factors that account for differences in states' Gini coefficients, regional dummy variables must be used to control for fixed regional effects. The omitted dummy is the Census' North region.

First, the results of regression (11.2) are similar to the ones obtained by LRP as reported in regression (11.1). Indeed, the income variables are insignificant in both cases. This tends to contradict Kuznets' hypothesis according to which income inequality rises with income until a certain threshold is reached where society becomes more generous towards the poor and inequality starts to decrease. The percent of non-whites (NWHITE) has a positive and significant coefficient in all regressions. Therefore, it seems that income inequality increases for states that have a high proportion of non-white population, perhaps because of segregation or other racial issues. On the other hand, high school (HS), labor participation (LABPART) and goods production employees (PCGOODW) have negative and significant coefficients, which means that an increase in these variables must decrease income inequality. Thus, states with a higher proportion of high school graduates have lower income inequality. Still, the coefficient for the college graduate (COL) is not significant, and the effect of higher education on income inequality is ambiguous, as stated previously. Similarly, states with a high rate of labor force participation or a high percentage of workers in good producing industries have lower income inequality.

Before introducing the IT employment intensity variable (LITP), I had to drop some variables from the model of regression 11.2. There are only 45 states, and adding variables would decrease the degrees of freedom, and eventually increase the risk of multicollinearity. Thus, I dropped the variables that were not significant in regression 11.2 (INC, INC2, COL) except the regional dummies to keep controlling for regional fixed effects. I also dropped the variables high school (HS) and goods employees (PCGOODPW) in order to prevent multicollinearity with the IT employee variable LITP.

Table 11.1OLS Regressions for Gini Coefficients in 1990

VARIABLE	(11.1)	(11.2)	(11.3)	(11.4)
Constant	-	0.678*** (10.70)	0.587*** (17.85)	0.590*** (16.08)
Income (INC)	1.67E-03 (0.17)	5.204E-03 (0.73)	-	-
$Income^2$ (INC2)	-4.45E-08 (0.16)	-1.282E-07 (0.52)	-	-
Non-whites (NWHITE)	-	0.116*** (4.28)	0.137*** (6.11)	0.132*** (5.84)
High school (HS)	-1.26E-3* (1.48)	-0.168* (1.95)	-	-
College graduates (COL)	-5.19E-4 (0.63)	-0.131 (1.57)	-	-
Participation rate (LABPART)	-5.32E-3*** (5.13)	-0.304*** (4.10)	-0.346*** (7.30)	-0.340*** (7.24)
Good production workers (PCGOODPW)	-8.24E-4** (1.72)	-0.108** (2.61)	-	-
IT employees (LITP)	-	-	0.068** (1.97)	-
IT density (ITDENS)	-	-	-	0.139** (2.25)
Non-IT density (NITDENS)	-	-	-	-0.128* (1.70)
Midwest (REG1)	7.61E-3 (1.03)	-4.35E-03 (0.07)	-2.61E-3 (0.53)	-4.92E-3 (1.01)
South (REG2)	7.69E-3 (1.02)	-1.32E-03 (0.20)	-1.31E-3 (0.22)	-2.57E-5 (0.01)
West (REG3)	5.49E-3 (0.81)	-5.89E-03 (0.83)	-3.94E-3 (0.74)	-3.44E-3 (0.61)
R^2	0.90	0.83	0.80	0.82
Durbin Watson	-	1.55	1.79	1.96

Note: *** Significant at the 0.01 level ** Significant at the 0.05 level * Significant at the 0.10 level. The absolute value of the t-statistic is shown in parentheses under each coefficient. Regression 11.1 refers to Levernier, Rickman, and Patridge (1995). Income and income squared are in thousands of dollars

Regression (11.3) shows the results of the regression of the Gini coefficient on high school, labor force participation and IT employee variables (NWHITE, LABPART, LITP) and regional dummies. Results still indicate a strong significance of NWHITE and LABPART. The coefficient for LITP is positive and significant at the 0.05 level. Therefore, states with a higher share of their employees working in occupations that are IT intensive have greater income inequality. This result might come from the fact that IT employees usually have greater income than “traditional” employees. The aggregate income gap between these two categories must increase with the share of IT workers (LITP).

Finally, regression (11.4) estimates the effect of the density of employment on income inequality. The effect is different whether the density of IT employment or traditional employment is considered. Although their sizes are similar, these coefficients have a different sign. The density of IT employment has a positive impact on income inequality, which means that as IT workers concentrate in one location, income inequality at the state level is rising. The coefficient for the density of IT employees (ITDENS) is estimated at

0.139 and is significant at the 0.05 level. This means that if the density of IT employees doubles in a county, the level of labor productivity in that county may increase by 13.9%. On the other hand, the coefficient for non-IT employment density is negative and significant at the 0.10 level. Hence, as traditional workers concentrate in one location, the level of income inequality at the state level decreases.

This last result may come from the fact that these two types of employment (IT and traditional) may have different agglomeration and congestion effects. As stated in the second part of this dissertation (chapters 6 through 8), state productivity may increase with the density of IT employment at the county level, and increase less or even decrease with the county density of non-IT employment. Indeed, the literature on regional economics states that the externality effect (or spillover) associated with density is the product of two opposite effects: agglomeration and congestion. First, agglomeration economies arise when workers benefit from being concentrated in space. For instance, workers in research and development departments benefit from physical encounters with co-workers, which allows ideas to spread all over the local area. Since IT workers are dealing with knowledge and information as their main resource, strong agglomeration effects must result from higher employment density in this type of employment. The effect should not be as strong for traditional workers for whom information is not the main resource. In the non-IT density case, the congestion effect might be greater than the one associated with the density of IT employment. This effect might even be greater than the agglomeration effect, resulting in a negative effect of density on productivity. In this case, if productivity is lowered by density then wages and income should also be lowered, reducing income inequality by the same token. Whereas for IT employment density, agglomeration effects should offset congestion effects, resulting in higher productivity, wages and income inequality. This may explain the positive and negative signs obtained for the coefficient of IT and non-IT density (ITDENS, NITDENS) in regression (11.4).

11.2Robustness of Results

According LRP, the methodology used in this analysis raises concern about the robustness of the data, due to mainly two factors. On one hand, as mentioned previously, the Gini coefficient presents some limitations in reporting income inequality, due to its construction procedure. First, it is necessary to assume that income for each family or household equals the midpoint of its income class. Second, for the highest income class, the mean of family income is estimated by subtracting the sum of the income of the other classes from total income. These approximations may result in approximate measures of income inequality. On the other hand, the small number of observations (45 states) compared to the number of variables raises concern about multicollinearity issues. Following LRP, the way to deal with these two problems is to consider a different measure of income inequality, and see if results differ significantly from the ones obtained using the Gini coefficient. Table 11.2 shows the results.

Estimates of regressions with Gini and with the log of variance as a measure of inequality are similar. At least, they are similar regarding the sign and significance of the coefficients for IT employment and density variables (LITP, ITDENS) and non-IT density variable (NITDENS). They are also similar for the non-white variable (NWHITE), but are not significant for the constant and labor force participation variable (LABPART), which leads to suspicion about the true effect of the rate of labor force participation on income inequality. Furthermore, the R-squared is lower when using variance of logarithms, which adds some suspicion to the robustness of the model. Nevertheless, results using each type of measure of inequality tend to be fairly similar, especially regarding the IT variables, which are of most interest in this study.

Table 11.2Comparison of Regressions Using Gini and Variance of Log of Income as Measures of Income Inequality

Regression	**(11.3)**	**(11.4)**	**(11.5)**	**(11.6)**
Dependent variable	GINI	GINI	Variance of log of median family income	Variance of log of median family income
Constant	0.587*** (17.85)	0.590*** (16.08)	-3.249E-02 (0.82)	1.981E-02 (0.40)
Non-whites (NWHITE)	0.137*** (6.11)	0.132*** (5.84)	5.270E-02* (1.874)	5.520E-02** (2.02)
Participation rate (LABPART)	-0.346*** (7.30)	-0.340*** (7.24)	1.947E-02 (0.34)	3.540E-02 (0.65)
IT employees (LITP)	0.068** (1.97)	-	0.108** (2.435)	-
IT density (ITDENS)	-	0.139** (2.25)	-	0.253*** (3.35)
Non-IT density (NITDENS)	-	-0.128* (1.70)	-	-0.271*** (3.00)
Midwest (REG1)	-2.61E-3 (0.53)	-4.92E-3 (1.01)	1.261E-02** (2.03)	6.440E-03 (1.06)
South (REG2)	-1.31E-3 (0.22)	-2.57E-5 (0.01)	1.924E-02** (2.518)	1.420E-02** (2.02)
West (REG3)	-3.94E-3 (0.74)	-3.44E-3 (0.61)	1.769E-02** (2.634)	1.160E-02 (1.64)
R^2	0.80	0.82	0.42	0.48
Durbin Watson	1.79	1.96	2.19	2.07
*** Significant at the 0.01 level ** Significant at the 0.05 level * Significant at the 0.10 level				

CHAPTER 12 - CONCLUSION

This dissertation supports the view that the productivity paradox was only a problem at the national aggregate level. Evidence presented in the preceding chapters shows that redistribution certainly played a role in producing the paradox. Analysis of the redistribution hypothesis in the regional dimension shows that there were redistribution effects across states.

Using a panel dataset covering the U.S. states and a comprehensive set of industries during the period 1977-1997, production function regressions show that the elasticity of output with respect to IT capital was positive and significant throughout the period, although it was sensitive to industry fixed effects. This elasticity was the highest during the early 1980s, and varies across states. Information technology was also found to have exhibited excess returns across industries. Because of a small income share (around 10%), the output growth contribution of IT capital goes up to 15 percent per year from 1977 to 1997. This value is very close to the 16 percent estimated by Oliner and Sichel (1994). However, my estimates vary between 5 and 15 percent across states, supporting the regional redistribution hypothesis. Furthermore, the contribution to labor productivity growth from information technology capital varies from 5 to 10 percent across states. The surprising fact is that states that own the largest shares of the national stock of IT capital also exhibit some of the smallest contributions of this type of capital to productivity growth. The highest contributions were found for Colorado, Delaware, Georgia, Washington and New Mexico, while the bottom-ranked states included New York, Washington D.C., North Carolina and Indiana. Hence, the paradox at the aggregate level can be attributed to the fact that the states that accounted for the largest volume in the aggregation process also had the smallest contributions. This fact can be explained by convergence theory, which states that as capital accumulates, the speed of convergence is reduced.

Considering information technology as a special type of employment, this study shows that there are agglomeration externalities associated with the spatial distribution of IT employment. These externalities of IT employment are usually higher than those associated with traditional non-IT employment. Indeed, in a given state the concentration of IT employment can explain up to 10% of the differences in state labor productivity, holding the concentration of traditional non-IT employment constant. Similarly, at the county level, 5% of labor productivity differences can be explained by the location and density of IT employment relative to traditional non-IT employment. The strongest agglomeration effects of IT employment come from localization economies. Therefore, since information technology employment tends to be very localized across states, the effect of agglomeration economies varies across space, further supporting the regional redistribution hypothesis.

Finally, evaluating the effects of information technology on income inequality across space indicates a state Gini coefficient elasticity of 7% with respect to the percentage of IT employment. The density of IT employment is also found to increase state income inequality, whereas the density of traditional non-IT employment decreases it.

Therefore, on one hand I found that the stock of IT capital and IT employment have positive and significant effects on productivity across states. On the other hand, the intensity of information technology in a given state is associated with higher income inequality, showing that there is indeed a "digital divide" regionally.

Consequently, policy recommendations at the state level would be (1) to facilitate investment in information technology capital, (2) to favor the concentration and the density of employment in IT intensive industries as opposed to traditional non-IT industries, and (3) to control the negative effects on income inequality with various training and social programs.

Future research should be oriented towards further investigations at various disaggregated levels such as the firm, industry or city level, using panel data analysis. For data availability reasons, this dissertation addresses a period running only through 1997, but extended research over more recent periods should be undertaken. Indeed, productivity has picked up only since 1996, starting an astonishing period of growth similar to the 1960s. Following Oliner and Sichel (2000) as well as Jorgenson and Stiroh (2000), more investigations on the contribution to growth from information technology during these last five years must take place. Furthermore, the role that the stock market (especially the NASDAQ) has played in influencing the availability of IT capital during this period of growth should be evaluated. Finally, the recent "deceleration" of growth observed in the last six months (since the last quarter of 2000), combined with the semi-collapse of the "dot com economy," constitutes a challenge for the most enthusiastic IT researchers.

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