Economic Growth, Productivity and Technological Change

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Abstract

The objectives of this thesis are: (1) to examine whether and how indicators of financial intermediary development influences economic growth in order to explore possible nonlinearities; (2) to investigate the relationship between information technology (IT) and economic performance in the presence of adjustment costs; and (3) to determine whether IT causes skill-biased technical change (SBTC).

Three different dynamic approaches are used for the examination of the three topics under investigation, as well as the appropriate data sets. Nonparametric estimation techniques will be used for answering the questions concerning the two sources of growth mentioned above, while a system of factor demand equations derived from a general cost function will be estimated along with some price expectation processes in order to evaluate the relationship between IT and SBTC.

The estimation results show that in contrast to recent research, the finance-growth relationship is linear when the previously documented nonlinearity between initial per capital income and human capital, on the one hand, and economic growth, on the other, is taken into account. When these nonlinearities are ignored, the finance-growth relationship appears nonlinear. Additionally, the results indicate that IT has a positive effect on productivity growth that varies among industries and time. Moreover, adjustment costs are important when identifying this effect since their omission tends to understate the effect of IT-capital on economic performance. Furthermore, the relationship between IT-capital and productivity appears to be nonlinear especially when adjustment

costs are included in the model. Finally, the results suggest that IT does cause SBTC. The dramatic decline in the price of IT equipment that has appeared in the US economy the last decade causes the demand for skilled workers to rise and the demand for unskilled one to decline.

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Finally, I want to dedicate this thesis to the memory my father, Spyros Kettenis.

Table of Contents

Chapter 1

Introduction

Why have some countries grown rich, while others remain poor? Temple (1999) states that it is hard to think of a more fundamental question for economists to answer. According to Temple, in the definition used by the World Bank's 1996 World Development Report, over 4.5 billion of the world's 5.6 billion people live in developing countries and so a better understanding of what generates economic growth could make a huge contribution to human welfare.

In discovering the sources of economic growth, a question exists in the literature on whether financial development exerts a positive influence on economic growth. Recent empirical evidence suggests a positive first-order relationship between financial development and economic growth. Evidence also suggests that there is a statistically significant and economically large empirical relationship between financial development and future rates of economic growth and productivity improvements.

Recently, nonlinearities became an issue in the relationship of financial development and economic growth. Recent studies find that the effect of financial development on growth may vary in different groups of countries or may vary according to the level of financial development of the country. These papers seem to suggest that the relationship between financial development and economic growth is nonlinear.

Concerning the sources of growth, attention in the literature has turned to another issue: the slowdown in productivity that started some time in the late

1960s or early 1970s. This issue has never been resolved satisfactorily, despite a significant research effort. This, in turn, has been supplanted by yet another mystery: why has the widely touted information revolution not reversed the productivity slowdown?

This view has become a rising issue in economics and has created a debate among economists. The debate was based on two views. The one suggests that the development of information technology (IT) is one of a series of positive temporary shocks and has no effect on economic productivity and growth. The other indicates that IT has produced a fundamental change in the economy under examination leading to a permanent improvement in growth prospects.

Most of the early evidence, that was based on aggregate data, suggests that information technology and especially computers have no effect on either productivity or growth. In recent years, the results from different analyses indicate that IT is indeed playing a major role in the productivity of an economy. Most of these studies have deviated from the use of aggregate data for their estimation procedures and have instead used industry or sectoral data. They claim that these data sets result in a superior method of estimation. Based on their methodology, the firms and industries that produce IT assets have experienced considerable technological progress that enabled them to improve the performance of IT goods as measured by a rapid total factor productivity (TFP) growth.

Another issue arising in the literature on IT, has been the substitution of information technology for other forms of capital and labor inputs. A number of papers in the literature have investigated the relationship between IT and labor demand. They indicate that IT causes the relative demand for more highly educated and experienced workers, as well as the relative demand for highly skilled workers, to rise. IT-based production processes also cause substitution for low skill human work. This is referred in the literature as skill-biased technical change (SBTC).

Following the above literature, this thesis deals with three topics. The first issue is whether and how indicators of financial intermediary development influence economic growth. Here we study the relationship between financial development and economic growth to explore possible nonlinearities. We use the same data as previous researchers but employ nonparametric estimation techniques. We find that, in contrast to recent research, the finance-growth relationship is linear when the previously documented nonlinearity between initial per capita income and human capital, on the one hand, and economic growth, on the other, are taken into account. When these nonlinearities are ignored, the finance-growth relationship appears to be nonlinear. The second investigation concerns the relationship between IT capital and economic performance and examines whether IT capital promotes productivity growth. Similar data sets as previous researches are used, but nonparametric estimation techniques are employed in order to explore possible nonlinearities and directly estimate the output elasticities of IT for each industry in the US economy. The results indicate that IT has a positive effect on productivity that varies among industries and time. Moreover, adjustment costs are important when identifying this effect since their omission tends to understate the effect of IT-capital on productivity. Finally, the relationship between IT-capital and productivity appears to be nonlinear, especially when adjustment costs are implicitly included in the model. The last topic of this thesis examines whether IT causes SBTC, that is, whether IT causes the relative demand for skilled workers to rise and substitute for low-skill human work. A framework is used for estimation, which allows efficiency gains in production to arise when new inputs generate an improvement in technical efficiency that is not fully offset by costs of adjustment. Specifically, a system of factor demands derived from a general cost function is estimated, along with some price generation processes in order to avoid some pitfalls in the use of IT equipment price indexes which appear problematic. Data from various sources are combined to create a database for 42 US industries over the period 1984-2001. The results indicate that IT-capital has large efficiency gains, the largest among all other inputs used. Furthermore, IT does cause SBTC. The dramatic decline in the price of IT equipment that has appeared in the US economy over the last decade causes the demand for skilled workers to rise and the demand for unskilled ones to decrease.

The rest of the thesis is organized as follows. Chapter 2 examines the relationship between financial intermediary development and economic growth. Chapter 3 investigates the impact of IT capital on productivity in the presence of adjustment costs, while chapter 4 examines whether IT causes SBTC. The last chapter concludes.

Chapter 2

Financial Development and Economic Growth: Is the Finance-Growth Relationship nonlinear?

2.1 Introduction

Does financial development exert a positive influence on economic growth? Is the finance-growth relationship linear? Empirical evidence provides an affirmative answer to the first question: it suggests a positive first-order relationship between financial development and economic growth. Evidence also suggests that the level of financial development is a good predictor of future rates of economic growth, capital accumulation and technological change. More recently, several papers have questioned the linearity assumption and have argued that the answer to the second question is negative. Studies have uncover evidence to show that the impact of financial development on economic growth may vary in different groups of countries or may vary according to the level of financial development of the country.

This chapter examines whether and how indicators of financial intermediary development (as measured by a number of indicators of financial intermediary development) influence economic growth. Methodologically it uses both parametric and nonparametric econometric techniques to establish whether financial development is a significant determinant of economic growth and whether this relationship is linear or nonlinear. We apply both techniques to investigate whether the Levine, Loayza and Beck (2000) results establishing a significant positive and linear relationship between financial development and growth are consistent under different frameworks as well as to investigate whether nonlinearities exist in the growth-finance relationship. Recent research has questioned the validity of the linearity of the finance-growth relationship. Both Levine, Loayza and Beck and their critics treat other determinants of economic growth, namely the initial level of per capita income and human capital, linearly: Levine, Loayza and Beck additionally treat financial development linearly while the critics consider it nonlinearly. Previous research has established the nonlinear impact of human capital and per capita income. This chapter uses a general framework that allows all three determinants of economic growth to be treated nonlinearly and provides specification tests for choosing amongst the alternative models.

The parametric technique used is the generalized method of moments (GMM) dynamic panel estimators [Arellano and Bond (1991) and Arellano and Bover (1995)]. Semi-parametric estimation as well as marginal integration is used to establish whether nonlinearities exist. A nonparametric framework is one in which the regression function is estimated without any assumptions about specific functional form as is the case of GMM estimation. The methodology of both frameworks is discussed in the following sections. We use an unbalanced panel data set from 74 countries during the 1960-1995 period. The data are averaged over non-overlapping five year periods, so that there exist maximum seven observations per country. The dependent variable is the growth rate of real per capita GDP. The level of financial development is measured using three indicators: liquid liabilities, commercial versus central bank credit and private credit.

Both GMM and semiparametric methodologies provide consistent results that predict that better functioning financial intermediaries accelerate economic growth. In both frameworks, all three financial development indicators have a positive and significant effect on economic growth. The marginal integration approach indicates that only when we account for the nonlinearity between initial income and schooling, on the one hand, and economic growth on the other, the financial intermediary index has a positive, significant and *linear* effect on growth. On the contrary, if the nonlinearity of initial income and human capital is not taken into account then the finance-growth relationship appears to be nonlinear. Using specification tests for the validity of different models, the semiparametric model with initial income and secondary schooling appearing nonlinearly and financial development linearly is supported in *lieu* of a model where either all three variables appear linearly or one where all three appear nonlinearly.

The rest of the chapter is organized as follows. Section 2 presents evidence from the literature. Section 3 discusses the data and section 4 the methodology and the results of the GMM dynamic panel estimator. Section 5 presents the methodology and the results from the nonparametric framework as well as the tests for the validity of alternative models. The last section concludes.

2.2 Financial Development and Economic Growth

The cost of acquiring information, enforcing contracts and making transactions creates incentives for the emergence of financial markets and institutions. Financial markets and institutions may arise to deal with problems created by information and transaction frictions. In doing that financial systems serve one primary function, they facilitate the allocation of resources across space and time in an uncertain environment.

Specifically, financial systems facilitate the trading, hedging, diversifying and pooling of risk with implications for resource allocation and growth. There are two types of risk: liquidity and idiosyncratic risk. Liquidity risk usually arises due to uncertainties associated with converting assets into a medium of exchange, information asymmetries and transaction costs. These frictions create incentives for the emergence of financial markets and institutions that augment liquidity.

The link between liquidity and economic growth arises because some high return projects require long-run commitment of capital, but savers do not like to invest their savings in projects that require long periods of implementation before yielding returns. Thus, if the financial system does not augment the liquidity of long-term investments, less investment is likely to occur in high-return projects. With liquid capital markets, savers can hold assets (like equity, bonds or demand deposits) that they can see quickly and easily if they seek access to their savings. Then, capital markets transform these liquid financial instruments into long-term capital investments in illiquid production processes.

Economists have recently modeled the emergence of financial markets in response to liquidity risk and examined how these financial markets affect economic growth. Some of the results mentioned in the literature state that with liquid stock markets, equity holders can readily sell their shares, while firms have permanent access to the capital invested by the initial shareholders [Levine (1991)]. Others have supported that liquidity affects production decisions, [Bencivenga, Smith and Starr(1995)] and they have concluded that greater liquidity will include a shift to longer-gestation, higher-return technologies. In Bencivenga, Smith and Starr(1995), high-return, long-gestation technologies require that ownership be transferred throughout the life of the production process in secondary markets. If exchanging ownership claims is costly, then longer-run technologies will be less attractive. Thus liquidity affects production decisions and as a result greater liquidity will induce a shift to longer-gestation, higher-return technologies. As discussed in Diamond and Dybvig (1983), financial intermediaries and especially banks, can also enhance liquidity and reduce liquidity risk. By eliminating liquidity risk, banks can increase investments in the high-return, illiquid assets and accelerate growth.

Besides reducing liquidity risk, financial systems also mitigate the risks associated with individual projects, firms, industries, regions and so on. The ability of the financial system to provide risk diversification services can affect long-run economic growth by altering the resource allocation and the savings rates and it tends to induce a portfolio shift towards projects with higher expected returns. Additionally, risk diversification can affect technological change. Innovation is risky. The ability to hold a diversified portfolio of innovative projects helps reduce the risk involved, thus promoting investment in growth- enhancing innovative activities.

Financial systems also acquire information about investment opportunities and allocate resources towards the most profitable firms and keep capital flowing to its highest value use. It is difficult and costly to evaluate firms, managers and market conditions [Carosso (1970)]. Individual savers will be reluctant to invest in activities where they have little reliable information. Thus high information costs keep capital from flowing to its highest value use. Information acquisition costs create incentives for financial intermediaries to emerge [Diamond (1984), Boyd and Prescott (1986)]. Economizing on information acquisition costs facilitates the acquisition of information about investment opportunities and thereby improves resource allocation.

The ability to acquire and process information may have important growth implications. Because many firms and entrepreneurs solicit capital and capital is scarce, financial intermediaries that produce better information on firms will thereby fund more promising firms and managers and induce a more efficient allocation of capital and faster growth [Greenwood and Jovanovic (1990), Bagehot (1873)]. The Greenwood and Jovanovic (1990) paper models the dynamic interactions between finance and growth to obtain the above result. Growth, according to the authors, means that more individuals can afford to join financial intermediaries, a fact that improves the ability of the financial intermediaries to produce better information. Besides identifying the best production technologies, financial intermediaries may also boost the rate of technological innovation by identifying those entrepreneurs with the best chances of successfully initiating new goods and production processes [King and Levine (1993c)].

Besides reducing costs of acquiring information, financial markets and intermediaries may arise to mitigate the information acquisition and enforcement costs of monitoring firm managers and exerting corporate control after financing the activity. For example, firm owners will create financial arrangements that compel firm managers to manage the firm according to the interest of the owners. Also outside creditors that do not manage firms will create financial arrangements to compel owners and managers to run firms in accordance with the interests of outside creditors [Levine (1997)]. The absence of these arrangements that enhance corporate control, can keep capital from flowing to profitable investments. This way intermediaries economize on aggregate monitoring costs because a borrower is monitored only by the intermediary and not by all, individual savers. Savers, however, can easily verify that the intermediary‘s portfolio is well diversified. Furthermore, as financial intermediaries and firms develop long-run relationships, this can further lower information acquisition costs.

In terms of long-run growth, financial arrangements that improve corporate control tend to promote faster capital accumulation and growth by improving the allocation of capital. In terms of economic growth, Bencivenga and Smith (1993) show that financial intermediaries that improve corporate governance by economizing on monitoring costs will reduce credit rationing and thereby boost productivity, capital accumulation and growth. Sussman (1993) and Harisson, Sussman and Zeira (1999) develop models where financial intermediaries facilitate the flow of resources from savers to investors in the presence of information asymmetries with positive growth effects. Focusing on innovative activity, De la Fuente and Marin (1996), develop a model in which intermediaries arise to undertake the costly process of monitoring innovative activities. This leads to an improvement in credit allocation among competitive technology producers with positive effects on economic growth.

Mobilization involves the agglomeration of capital from disparate savers for investments. Furthermore, mobilization involves the creation of small denomination instruments. These instruments provide opportunities for households to hold diversified portfolios, to invest in efficient scale firms and to increase asset liquidity. Mobilization improves resource allocation [Levine (1997)].

Mobilizing savings is costly. It involves overcoming the transaction costs associated with collecting savings from different individuals and the information asymmetries associated with making savers feel comfortable in relinguishing control of their savings. In light of the information costs, numerous financial arrangements may arise to overcome these frictions. Financial systems that are more effective at pooling the savings of individuals can profoundly affect economic growth.

Besides technological innovation and growth financial arrangements that lower transaction costs can also promote specialization. Modern theories have attempted to explain the ties between exchange, specialization and innovation [Greenwood and Smith (1997)]. The authors have modeled the connections between exchange, specialization and innovation. More specialization requires more transactions. Because each transaction is costly, financial arrangements that lower transaction costs will facilitate greater specialization. In this way, markets that promote exchange, encourage productivity gains. There may also be feedback from these productivity gains to financial market development.

According to the literature, there exists two channels through which the above financial functions may affect economic growth: capital accumulation and technological innovation. In capital accumulation models, the functions performed by the financial system affect steady-state growth by influencing the rate of capital formation. The financial system affects capital accumulation either by altering the savings rate or by reallocating savings among different capital producing technologies. In the technological innovation models, the functions performed by the financial system affect steady-state growth by altering the rate of technological innovation.

2.2.1 Empirical Evidence on the Finance-Growth Relationship

Are differences in financial development structure associated significantly with differences in economic growth rates? To examine the relationship between financial systems and economic growth, two points should be mentioned. First, there does not exist a sufficiently rigorous understanding of the emergence, development and economic implications of different financial structures [Boyd and Smith (1996)]. Comprehensive theories of why different financial structures emerge or why financial structures change have not yet been developed. Second, the influence of the level and growth rate of the economy on the financial system must be considered. Economic growth provides the means for formation of growth-promoting financial intermediaries, while the formation of financial intermediaries accelerates growth by enhancing the allocation of capital. In this way financial and economic development are jointly determined [Greenwood and Jovanovic (1990)].

A substantial literature demonstrates a strong positive link between financial development and economic growth. There is even evidence that the level of financial development is a good predictor of future economic growth. Evidence on the relationship between financial structure, the functioning of the financial system and economic growth, however is inconclusive.

In studying the relationship between the level of financial development and economic growth, Goldsmith (1969), used data on 35 countries from 1860-1963. He finds that there are indications that periods of more rapid economic growth have been accompanied, with some exceptions, by an above-average rate of financial development. Ever since, researchers have taken steps to extend the work performed by Goldsmith.

King and Levine (1993a, 1993b, 1993c) study 80 countries over the period 1960-1989 and systematically control for other factors affecting long-run growth. To examine the capital accumulation and productivity growth channels they construct four measures of the level of financial development, and analyze whether the level of financial development predicts long-run economic growth, capital accumulation and productivity growth. Their results (1993a) indicate that there is a strong positive correlation between each of the four financial development indicators and economic growth. Not only are all the financial development coefficients statistically significant, the sizes of the coefficients imply an economically important relationship.

To examine whether finance follows growth, King and Levine (1993b) test whether the value of financial depth in 1960 predicts the rate of economic growth, capital accumulation and productivity improvements over the next 30 years. Their results indicate that financial depth in 1960 is significantly correlated with each of the growth indicators averaged over the period 1960-1989. They conclude that high levels of financial development in one decade are significantly correlated with economic growth, physical capital accumulation and economic efficiency improvements in the following decade.

King and Levine (1993c) also use a general equilibrium framework in which financial systems evaluate prospective entrepreneurs, mobilize savings to finance the most promising activities, diversify the risks associated with these activities and reveal the expected profits from engaging in innovation. They evaluate the effects of financial sector policies on economic growth and find that better functioning financial systems improve the probability of successful innovation and thereby accelerate economic growth. Similarly, financial sector distortions reduce the rate of economic growth by reducing the rate of innovation.

La Porta, DeSilanes and Shleifer, (2002) use an alternative indicator of financial development: the degree of public ownership of banks. To the extent that publicly-owned banks are less effective at acquiring information about firms, exerting corporate governance, mobilizing savings, managing risks and facilitating transactions, this measure provides direct evidence on the connection between economic growth and the services provided by financial intermediaries. The authors conclude that higher degrees of public ownership are associated with lower levels of bank development and high levels of public ownership of banks are associated with slower economic growth.

These studies conclude that the relationship between the initial level of financial development and growth is significant and finance does not merely follow economic activity. The strong link between the level of financial development and the rate of economic growth does not simply reflect contemporaneous shocks that affect both financial development and economic performance [Levine (1997)]. There is a statistically significant (and economically large) empirical relationship between the initial level of financial development and future rates of economic growth, capital accumulation and productivity improvements.

Following King and Levine (1993a, 1993b), Levine, Loayza and Beck, (2000) examine whether the exogenous component of financial intermediary development influences growth. They present evidence concerning the legal, regulatory and policy determinants of financial development and new data and econometric techniques that directly confront the potential biases induced by simultaneity, omitted variables and unobserved country effects. They use a GMM dynamic panel estimator as well as a cross sectional instrumental-variable estimator. Both estimation techniques produce consistent findings: the exogenous component of financial intermediary development is positively and robustly linked with economic growth. Their findings support the view that legal and regulatory changes that strengthen creditors rights, contract enforcement and accounting practices boost financial intermediary development with positive repercussions on economic growth.

Beck, Levine and Loayza, (2000) use the same dataset as Levine, Loayza and Beck (2000) and the same econometric techniques to evaluate the empirical relationship between the level of financial intermediary development and economic growth, total factor productivity growth, physical capital accumulation and private savings rates. They find that financial intermediaries exert a large, positive impact on total factor productivity growth. The long-run links between financial intermediary development and both physical capital growth and private savings rates are tenuous. They find a positive and significant relation between financial intermediary development and the growth rate of capital. The results, however, are not consistent across alternative measures of financial development in the cross-sectional regressions. They also find conflicting results for private savings.

Benhabib and Spiegel (2000) examine the relationship between an assortment of financial intermediary development indicators and economic growth, investment and total factor productivity growth. They use a panel estimator that allows for the endogeneity of the regressors. They find that financial development indicators are correlated with both total factor productivity growth and the accumulation of both physical and human capital. Working with a panel of cross-country and time series observations Loayza and Ranciere (2005) estimate a model encompassing both short and long run effects through the use of a Pooled Mean Group estimator. They conclude that a positive long-run relationship between financial intermediation and output growth coexists with a, mostly, negative short-run relationship.

Other authors, assume that financial markets in the United States are relatively frictionless and use it as benchmark [Rajan and Zingales (1996, 1998)]. Then, they examine industries across a large sample of countries and test whether the industries that are more dependent on external finance grow relatively faster in countries that begin the sample period with better developed financial systems. They find that industries that rely heavily on external funding grow comparatively faster in countries with well developed intermediaries and stock markets than they do in countries that start with relatively weak financial systems.

Wurgler (2000), also employs industry-level data to examine the relationship between financial development and economic growth. Using data for 65 countries for period 1963-1995, and standard measures of financial development, he shows that countries with higher levels of financial development both increase investment more in growing industries and decrease investment more in declining industries than financial underdeveloped economies. To do that he computes an investment elasticity that gauges the extent to which a country increases investment in growing industries and decreases investment in declining ones. Demirguc-Kunt and Maksimoric (1998), examine whether financial development influences the degree to which firms are constrained from investing in profitable growth opportunities. They focus on the use of long-term dept and external equity in funding firm growth and estimate the external funding needs of each individual firm in the sample. They use a firm-level data set that consists of accounting data for the largest publicly traded manufacturing firms in 26 countries and calculate the proportion of firms whose growth rates exceed the estimate of the maximum growth rate that can be financed by relying only on internal and short-term financing. They find that both banking system development and stock market liquidity are positively associated with the excess growth of firms. Love (2000), using firm-level data from 40 countries, concludes that financial development will reduce the degree to which firm expansion is constrained by the availability of internally generated funds and that financial development will have a particularly large impact on the ability of small firms to expand.

Demetriades and Hussein (1996) conduct causality tests between financial development and real GDP growth using both VAR and the ECM representation. They also use cointegration tests to examine evidence of a stable long-run linear relationship between economic growth and financial development. Their results provide little support for finance as a leading sector in the process of economic development. They find though some evidence of reverse causality and considerable evidence of bi-directionality. They state that their findings clearly demonstrate that causality patterns vary across countries. Xu (2000) uses a multivariate vector-autoregressive approach to examine the effects of financial development on domestic investment and output in 41 countries between 1960 and 1993. The results reject the hypothesis that financial development simply follows economic growth. Financial development is an important determinant of GDP growth and domestic investment is an important channel through which financial development affects economic growth. Xu finds a negative/positive effect of permanent financial development on economic growth depending on the income country group under investigation. Christopoulos and Tsionas (2004) use panel unit root tests and panel cointegration analysis to examine the relationship between financial development and economic growth in ten developing countries.

They find strong evidence in favor of the hypothesis that long-run causality runs from financial development to growth and there is no evidence of bi-directional causality. Furthermore, they find a unique cointegrating vector between growth and financial development and emphasize the long-run nature of the relationship between finance and growth.

In sum, these papers suggest that it is important to account for the endogenous determination between financial development and economic growth. In our analysis we take this into account by including the exogenous component of financial development as a determinant of the rate of economic growth.

A complement to the above studies is the literature on country case studies. These country case studies do not use formal statistical analysis. Instead, the researchers carefully examine the legal, economic and financial linkages between banks and industry during industrialization. Typically, the case studies start by describing the political system, economic conditions and financial structure of the period of analysis in a specific country. Then, they provide a detailed description of the financial system during a period of rapid economic development. Finally, they document critical interactions among financial intermediaries, financial markets, government policies and the financing of industrialization. They fail though to control for other characteristics determining economic development. Nonetheless, the body of country case studies suggests that, while financial system responds to demand from the nonfinancial sector, well functioning financial systems have in some cases during some periods, greatly spurred economic growth.

Guiso, Sapienza and Zingales (2002b) examine the individual regions of Italy. Using a data set on households and financial services across Italy, they examine the effects of differences in local financial development on economic activity across different regions. They find that local financial development enhances the probability that an individual starts a business, increases industrial competition and promote the growth of firms. Haber (1991, 1997) compared the industrial and capital market development in Brasil, Mexico and the United States between 1830 and 1930. Using firm-level data, Haber finds that capital market development affected industrial composition and national economic performance. Additionally, Haber (1997) concludes that international differences in financial development impacted the rate of industrial expansion and under-developed financial systems that restrict access to institutional sources of capital non-negligible obstacles to industrial expansion in the ninetieth century.

Recent research has questioned the linearity assumption of the finance growth relationship.

Rioja and Valev (2003, 2004) examine whether there exist nonlinearities in the financial development-growth relationship. They (2004) study the effects of financial development on the sources of growth in three different groups of countries: low- medium- and high-income, classified according to the relative per capita income ranking in the middle of the sample period. They use panel data from 74 countries and GMM dynamic panel techniques (same data and methodology as Levine, Loayza and Beck); their results indicate that the effects of finance on growth may vary between different groups of countries. Furthermore, they find that finance has a strong positive influence on productivity growth primarily in more developed economies. Conversely, in less developed economies, the effect of finance on output growth occurs primarily through capital accumulation and not productivity. To verify their analysis they conduct robustness checks. First they group countries according to income levels earlier and later in the sample period and, second, they use only two group of countries: high and low income. Their results are robust.

Using the same data set and the GMM dynamic panel techniques, the same authors (2003) propose that the relationship between financial development and growth may not be uniform but it varies according to the level of financial development of the country. In particular, they argue that there exist three distinct regions of financial development: financial development exerts a strong positive effect on economic growth only once it has reached a certain threshold, that is the 'middle' region. The thresholds are not known *a priori*, so they estimate the model repeatedly varying the location of thresholds using the percentiles of the distribution of each financial development measure (same indices as Levine, Loayza and Beck). They estimate 64 regressions and report results where strong evidence is observed. In the "low" region (below the threshold), the effect is uncertain as different empirical measures of bank-based financial development suggest a zero or a positive effect. At the other end, in the "high" region, the growth effect of financial development declines once it reaches very high levels: in the "high" region additional financial improvements have a positive, but smaller, effect on growth when compared to the "middle" region effect.

Deidda and Fattouh (2002) present a simple two-period overlapping generations model with risk averse agents and costly financial transactions which establishes a non-linear and possibly non-monotonic relationship between financial development and economic growth. Applying a threshold regression model to King and Levine's data set, they find that in low income countries there is no significant relationship between financial development and growth whereas in high income countries this relationship is positive and strongly significant.

2.3 Data Description

The data set used, as well as the three indicators of financial intermediary development, is by Levine, Loayza and Beck (2000); it is also the data used by other researchers to ensure direct comparability of our results. The three indicators of financial development are: (i) *Liquid Liabilities:* liquid liabilities of the financial system (currency plus demand and interest-bearing liabilities of banks and non bank financial intermediaries) divided by GDP. This is a measure of financial depth and thus of the overall size of the financial intermediary sector. This commonly used measure has shortcomings, since it may not accurately account for the effectiveness of the financial sector in ameliorating information asymmetries and easing transaction costs. Additionally, liquid liabilities include deposits by one financial intermediary in another and may involve double counting. (ii) *Commercial-Central Bank:* the ratio of commercial bank assets divided by commercial plus central bank assets. This ratio measures the degree to which commercial banks (versus the central bank) allocate society's savings. It is not a direct measure of the quality and quantity of financial services provided by financial intermediaries; rather, the intuition provided by King and Levine (1993a, 1993b) is that commercial banks are more likely than central bank to identify profitable investments, monitor managers, facilitate risk management and mobilize savings. (iii) *Private credit:* the value of credits by financial intermediaries to the private sector divided by GDP. This ratio isolates credits issued to the private sector as opposed to credit issued to governments, government agencies and public enterprises. Furthermore, it excludes credits issues by the central bank. While private credit does not directly measure the amelioration of information and transaction costs, the authors interpret higher levels of private credit as indicating higher levels of financial services and therefore greater financial intermediary development.

The panel data set consists of 74 countries and the data are averaged over 5-year intervals, so that there are maximum seven observations per country (1961-1965, 1966-1970, etc.). The dependent variable is the growth rate of real per capita gross domestic product (GDP). The regressors include the level of financial intermediary development along with a broad set of exogenous variables: the logarithm of initial income per capita (real per capita GDP), government size (government expenditures as share of GDP), openness to trade (sum of real exports and imports as share of GDP), inflation (log difference of consumer price index), human capital (average years of secondary schooling in the population aged over 15) and black market premium (the ratio of black market exchange rate to the official exchange rate minus one). The data are from Levine, Loayza and Beck (2000);[1] summary statistics are in Table 3.1.

Table 3.1: DESCRIPTIVE STATISTICS

	Mean	Maximum	Minimum	Std. dev.	Obs.
GDP growth	1.56	9.85	-10.02	2.75	363
Initial Income	4682	20135	188	5216	363
Schooling.	1.30	5.15	0.03	0.95	363
Private Credit	42.63	205.95	1.56	35.11	363
Commercial-Central	77.01	99.98	14.02	20.71	363
Liquid Liabilities	45.14	191.44	6.72	26.96	363
Trade Openness	54.35	180.09	9.29	27.48	363
Government Size	14.85	38.02	4.89	5.36	363
Inflation Rate	17.77	344.4	-3.06	32.90	363
Black Market	74.54	10990	-4.11	606.26	363

2.4 GMM METHODOLOGY

In this section we replicate previous linear results. We use the generalized method of moments (GMM) estimators developed for dynamic models of panel data introduced by Holtz-Eakin, Newey and Rosen (1990), Arellano and Bond (1991) and

[1]Our data set differs slightly from Levine, Loayza and Beck.: they include 359 observations and our data set includes 363.

Arellano and Bover (1995). Our data are averaged over five-year periods and the subscript t designates each of these averages. Consider the following regression equation:

$$Y_{it} - Y_{it-1} = (\alpha - 1)Y_{it-1} + \beta' X_{it} + n_i + \epsilon_{it} \tag{2.1}$$

where Y_{it} is the logarithm of real per capita GDP, $Y_{it} - Y_{it-1}$ is the rate of per capita income growth, Y_{it-1} is the initial level of per capita income, X_{it} represents a vector of explanatory variables, n_i is an unobserved country-specific effect, ϵ_i is the error term and the subscripts i and t represent country and time period respectively. Rewriting (2.1), we obtain:

$$Y_{it} = \alpha Y_{it-1} + \beta' X_{it} + n_i + \epsilon_{it} \tag{2.2}$$

To eliminate country-specific effects, we take first differences of (2.2):

$$Y_{it} - Y_{it-1} = a(Y_{it-1} - Y_{it-2}) + \beta'(X_{it} - X_{it-1}) + \epsilon_{it} - \epsilon_{it-1} \tag{2.3}$$

Levine, Loayza and Beck (2000) suggest the use of instruments for two reasons: to deal with the likely endogeneity of the financial development and economic growth and because by construction the new error term $(\epsilon_{it} - \epsilon_{it-1})$ in (2.3) is correlated with the lagged dependent variable, $(Y_{it-1} - Y_{it-2})$.The GMM panel estimator uses the following moment conditions:

$$\begin{aligned} E[Y_{it-s}(\epsilon_{it} - \epsilon_{it-1})] &= 0 \quad \text{for} \quad s \geq 2; t = 3, ..., T \\ E[X_{it-s}(\epsilon_{it} - \epsilon_{it-1})] &= 0 \quad \text{for} \quad s \geq 2; t = 3, ..., T \end{aligned}$$

under the assumptions that the error term, ϵ, is not serially correlated and that the explanatory variables, X, are weakly exogenous. The authors refer to this as the difference estimator.

There are, though, statistical shortcomings with this estimator. Alonso-Borrego and Arellano (1996) and Blundell and Bond (1997) show that when the explanatory variables are persistent over time, lagged levels of these variables are weak instruments for the regression equation in differences. To reduce the potential biases associated with the difference estimator, the authors use a new estimator that combines in a system the regression in differences with the regression in levels The authors use a GMM estimator that uses lagged differences of Y_{it} as instruments for the equation in levels in addition to lagged levels of Y_{it} as instruments for equations in first differences. Blundell and Bond (1997) suggest that Monte Carlo simulations and asymptotic variance calculations show that this extended GMM estimator offers efficiency gains where the first-difference GMM estimator performs poorly. The instruments mentioned are appropriate under the following assumption: although there may be correlation between the levels of the right hand side variables and the country specific effect in the level equation, there is no correlation between the differences of these variables and the country specific effect. The additional moment conditions for the second part of the system which is the regression in levels are:

$$\begin{aligned} E[(y_{it-s} - y_{it-s-1})(n_i + \epsilon_{it})] &= 0 \quad \text{for} \quad s = 1 \\ E[(X_{it-s} - X_{it-s-1})(n_i + \epsilon_{it})] &= 0 \quad \text{for} \quad s = 1 \end{aligned}$$

Given that the lagged levels are used as instruments in the differences specification, only the most recent difference is used as instrument in the levels specification. Using other lagged differences will result in redundant moment conditions [see Arellano and Bover (1995)]. The authors use the moment conditions above and employ a GMM procedure to generate consistent and efficient parameter estimates.

2.4.1 GMM Dynamic Panel Results

Levine, Loayza and Beck (2000) find that the exogenous component of financial intermediary development is positively correlated and robustly linked with economic growth. The exogenous component is used in order to confront the potential biases induced by simultaneity, omitted variables and unobserved country-specific effects that according to the authors had plagued previous empirical work on the finance-growth link. As instruments they use lagged values of the explanatory variables. They find that the three financial intermediary development indicators are significant at the five percent significance level. Their regression estimates are also economically large: exogenous changes in financial intermediary development imply large changes in economic growth. Their results pass diagnostic and sensitivity tests: they are robust to modifications in the information set and to alternative sample periods. Additionally, outliers are not responsible for the results and different specification tests support the appropriateness of the instruments used in their analysis.

Using the same estimation technique the financial intermediary indexes do indeed have a positive and significant effect on the economic growth . The results are placed in the tables A1, A2, A3 in Appendix A. Each table refers to a different financial development index[2].

The specification tests computed are the Sargan test where the null hypothesis is that the instrumental variables are uncorrelated with the residuals and the serial correlation test where the null hypothesis is that the errors in the differenced equation exhibits no second order serial correlation. The test results show no evidence of second order serial correlation and the instrumental variables are indeed uncorrelated with the residuals. In sum the GMM results confirm a

[2] All variables are in logarithms form except schooling. Also Inflation and Black market premium are defined as $\ln(1 + variable)$

strong significant positive relationship between financial development and economic growth. Next, we examine the nature of the finance-growth relationship using nonparametric techniques that allow for more flexible functional forms.

2.5 Nonparametric Techniques

In this section we consider nonparametric techniques in order to investigate the possible nonlinearity between economic growth and financial development. The papers in the literature seem to suggest that the relationship between financial development and economic growth is nonlinear. They, however, suffer from two major deficiencies. First, they employ rather rudimentary econometric tests of nonlinearity. They examine the existence of a threshold in the finance-growth relationship by imposing a threshold exogenously in an *ad hoc* fashion (Rioja and Valev (2003, 2004)). Deidda and Fattouh (2002) use an endogenous threshold technique but one, nonetheless, that imposes a specific (linear) functional form for the relationship above and below the threshold. Second, they ignore previous research that has showed a nonlinear relationship exists between economic growth and two determinants: initial income and human capital (measured by mean years of schooling)[3]. In subsequent sections we describe a methodology for evaluating the financial development-growth relationship that takes into account these two important drawbacks. The methodology is general enough to allow us to estimate a regression model that imposes the least amount of structure on the estimates of the finance-growth relationship.

Nonparametric regression assumes little about the shape of the regression function beyond some degree of smoothness. The added value of nonparametric tech-

[3]See for instance Durlauf and Johnson (1995), Quah (1996), Kalaitzidakis et al (2001), Liu and Stengos (1999), Mamuneas, Savvides, Stengos (2004) and Kourtelos (2003).

niques consists in their ability to deliver estimators and inference procedures that are less dependent on functional form assumptions [Yatchew (1998)]. Nonparametric techniques estimate the value of the regression function at a given point using neighboring observations. Nonparametric regressions typically involves either local averaging or some form of least squares estimation. Unfortunately, nonparametric methods also have critical elements that are not present in the parametric analysis. The two more important elements are, the "curse of dimensionality" and the need to select a smoothing parameter.

Perhaps the major complication in a purely nonparametric approach is the "curse of dimensionality". Every estimation method has some costs associated with it and, in the case of nonparametrics, it is the need for very large samples if an accurate measurement of the function is to be made. Moreover, the size of the sample required increases rapidly with the number of variables involved in any relation. Such features lead to the proposition that one might prefer to restrict some variables to have a linear impact while allowing a much smaller number to have a nonlinear one. Some models allow the nonlinearity to be located either in the conditional mean or the conditional variance. Effectively estimation involves a combination of parametric and nonparametric methods, leading to the estimators being described as semi-parametric.

In order to provide tractability and to overcome the so-called "curse of dimensionality", nonparametric techniques typically impose some structure on the functional form to be estimated.

The objective is to estimate the regression function:

$$y = \theta(z) + \epsilon \tag{2.4}$$

given data for y and z and errors that are iid. There are several ways by which one can approximate the regression function $\theta(z)$. One approach is the "local" histogram approach, the other is based on the use and selection of Kernel estimators and the nonparametric least squares.

Here we will use a Kernel estimator in order to approximate the regression function. This is also called the local averaging estimator. Local averaging estimators are extensions of conventional estimators of location to a nonparametric framework. That is, one can compute means (or medians) as approximations to the regression function. The local linear approximation involves nothing more than joining the observed points with a straight line. It is the same methodology as local means, but instead of local means we have local ordinary least squares estimation (that is local OLS or GLS because of the weights used). If a function is smooth, its value at a given point can be approximated reasonably well by evaluations of the function at neighboring points.

A general formulation of local averaging estimators is as follows:

$$\hat{\theta}(z_0) = \sum \omega_t(z_0) y_t \tag{2.5}$$

The estimate of the regression function at z_0 is a weighted sum of y_t where the weights $\omega_t(z_0)$ depend on z_0. One would expect that observations close to z_0 would have conditional means similar to $\theta(z_0)$, so it is natural to assign higher weights to these observations and lower weights to those that are further away. One estimates the function for each observation by GLS and connects the estimates for each observation to get the estimated function.

Kernel Estimators: One way to construct the local averaging weights mentioned above is to use a unimodal function centered at zero, which declines in either direction at a rate controlled by a scale parameter. Natural candidates for such functions, which are known as Kernels, are probability density functions. Let K be a bounded function which integrates to one and is symmetric around zero. Define the weights to be:

$$\omega_t = \frac{\frac{1}{\lambda T} K(\frac{z_t - z_0}{\lambda})}{\frac{1}{\lambda T} \sum K(\frac{z_t - z_0}{\lambda})} \tag{2.6}$$

The shape of the weights (by construction they sum to one) is determined by K while their magnitude is controlled by λ which is known as the bandwidth (smoothing parameter). A large value of λ results in greater weight being put on observations that are far from z_0. A variety of different Kernels is available (and we use the standard normal that is $K(\dfrac{z_t - z_0}{\lambda}) = \frac{1}{\sqrt{2\pi}} \exp[-(\dfrac{z_t - z_0}{\lambda})^2)$. Generally, the selection of the Kernel is less important than selection of the bandwidth over which observations are averaged.

In the more general case, in which we are conditioning upon two or more explanatory variables (that is $z = (z_1, z_2)$) the procedure followed is the same as with one explanatory variable. Analytically, the model becomes:

$$y = \theta(z_1, z_2) + \epsilon$$

In this case, when constructing the weights from which we approximate the regression functions, instead of using one kernel estimator we have a product of two. Thus, K is a product of two kernels K_1 and K_2 from the standard normal distribution ($K = [K_1(\frac{z_{1t} - z_{10}}{\lambda_1})K_2(\frac{z_{2t} - z_{20}}{\lambda_2})]$) and we have to select two smoothing parameters λ_1 and λ_2.

The choice of the smoothing parameter is essential. Several criteria and different methods are discussed in the literature for the selection of the optimal smoothing parameter.

There are two conditions that should be imposed on λ. The first is that $\lambda \to 0$ which ensures that averaging takes place over a shrinking bandwidth, thus eventually eliminating bias. The second is that $\lambda T \to \infty$ (where T denotes the sample size) which ensures that the number of observations being averaged grows, which allows the variance of the estimate to decline to zero.

One can choose $\lambda = cst.dev(z)T^{-\frac{1}{4+p}}$, where c is a constant and $st.dev(z)$ is the standard deviation of the conditioned variable and p is the number of variables included in z. Based on the above, we choose $\lambda = cst.dev(z)T^{-\frac{1}{5}}$ in the case where we have one explanatory variable , and $\lambda_i = c_i st.dev(z_i)T^{-\frac{1}{6}}$ for the bivariate case ($i = 1, 2$). This selection of λ is based on a "rule" of thump proposed in the literature by Silverman (1986). Another way to select the smoothing parameter is by choosing it to minimize the mean integrated squared error (cross validation method). We used cross validation to select the value of c in the range of 0.8 to 2.

It is also worth mentioning that, there are three essential results for a simple Kernel estimator: (i) it is consistent; (ii) averaging over a neighborhood which shrinks at an appropriate rate results in a rate of convergence that balances bias against variance; (iii) and it is asymptotically normal.

Below we consider the semi-parametric regression model.

2.5.1 The Semi-Parametric Regression Model

In this case part of the model is linear and part is represented by an unknown non-linear functional form. Consider the following model (where time and country subscripts have been omitted for clarity of presentation):

$$y = x\beta + \theta(z) + \epsilon \tag{2.7}$$

where y is the rate of economic growth, x and z are a vector and a scalar that determine the rate of economic growth, respectively, and β and θ are a parameter and an unknown functional form, respectively, to be estimated and $E(\epsilon/x, z) = 0$. In addition, $E(y/z, x) = x\beta + \theta(z)$ and $\sigma_\epsilon^2 = Var(y/z, x)$.

Rewriting (2.7), conditional on z, we have:

$$y - E(y/z) = y - E(x/z)\beta - \theta(z) = [x - E(x/z)]\beta + \epsilon \tag{2.8}$$

The parameter of interest is β so the issue is how to estimate it in the presence of an unknown function. If $E(y/z)$ and $E(x/z)$ are known then least squares can be applied to (2.8); this yields an estimate of β which is asymptotically normal with variance $\dfrac{\sigma_e^2}{T\sigma_u^2}$ where σ_u^2 is the variance of x conditional on z.

The regression functions $E(y/z)$ and $E(x/z)$ are generally not known to have a particular parametric form but they can be approximated by Kernel estimators that converge sufficiently quickly so that their substitution in the least squares estimator does not affect its asymptotic distribution. Therefore, the estimate of β is given by:

$$\widehat{\beta} = \left[\sum(x - \widehat{m}_{xz})(x - \widehat{m}_{xz})'\right]^{-1} \left[\sum(x - \widehat{m}_{xz})(y - \widehat{m}_{yz})\right]$$

where $\widehat{m}_{xz} = E(x/z)$ and $\widehat{m}_{yz} = E(y/z)$ are Kernel-based estimators [see Robinson (1988)].

That is, the kernel based estimators of $E(y/z)$ and $E(x/z)$ at z_0 are given by $\sum \omega_t(z_0)y_t$ and $\sum \omega_t(z_0)x_t$ respectively, and the weights are approximated through kernel functions as described in the previous section.

We consider the determinants of economic growth that belong to the linear component, x, and those to the unknown nonlinear component, $\theta(z)$. In the semi-parametric model we assume that financial development enters linearly i.e. is included in x in order to verify whether a positive relationship still exists under a different framework. As for the nonlinear component, $\theta(z)$, in the first instance we assume that it includes initial income per capita. Second, we consider both per capita income and human capital as components of unknown part of the model, $\theta(z_1, z_2)$, that needs be estimated. The variables included in the nonlinear component were chosen on the basis of the literature on nonlinearities in economic growth that has shown these two to affect economic growth nonlinearly [see Kalaitzidakis *et al* (2001) and Liu and Stengos (1999)]. In both cases all the other explanatory variables, including the indicators of financial development, are included in the linear part of the model.

After approximating the regression functions concerned via Kernel estimators, we use them to obtain an estimate of β from least squares estimation of :

$y - E(y/z_j) = [x_i - E(x_i/z_j)]\beta + \epsilon$, where $i =$ all linear regressors and $j =$ nonlinear

The estimate of β allows testing the significance of financial intermediary development. In order to be consistent with previous research and to account for endogeneity we have included the exogenous component of financial development in the model: the instruments used are lags of the explanatory variables, lag differences of the explanatory variables and year dummies.

The results from the semiparametric model using all three indices respectively are in Tables A4 ,A5 ,A6 in Appendix A. All three indices have positive and significant effect on economic growth. The other exogenous variables have the expected signs but not all of them appear significantly. Semiparametric estimation shows that financial intermediary indices have a significant positive effect on economic growth when we allow for possible nonlinear effects of initial income and schooling on economic growth.

We have also estimated the semiparametric model conditioned only on the logarithm of initial income. The results are the same as when conditioning on both initial income and secondary schooling. The only difference is that when secondary schooling enters linearly in the regression and (see Tables A7 ,A8 ,A9 in Appendix A) it has a positive significant effect on economic growth.

So far, we have used two different methodological frameworks, one parametric and one nonparametric, and we have discovered a positive relationship between all financial development indices and economic growth. In the next section we are interested in investigating possible nonlinearities in the specific relationship. Based on the results of recent evidence in the literature, we proceed to examine whether the relationship is nonlinear.

2.5.2 Marginal Integration and the Partially Additive Linear (PLR) Model

Semiparametric estimation of the model presented in equation (2.7) is useful if one is interested primarily in estimating the parameter β.Once we obtain the estimate of β, then the redefined variables $y - x\widehat{\beta}$ can be regressed on z nonparametrically using kernel techniques to obtain an estimate of the unknown function $\theta(.)$. If one wants to uncover the shapes of the individual components of z (in order to investigate whether nonlinearities exist) it is necessary to impose more structure on the equation to be estimated assuming an additive structure on the unknown components. Yatchew (1998) notes that an additive structure tackles the curse of dimensionality problem and it is more efficient than a general nonparametric structure. For the growth regression model in (2.7) we allow several variables ($z's$) to enter nonlinearly including the variable of interest - financial development - as well as initial income and average years of schooling (a measure of human capital) to enter nonlinearly. In general, the PLR model can be written as:

$$y = x_i\beta+\theta(z_{1,}z_{2,\ldots}z_p)+\varepsilon = x_i\beta+\theta_1(z_{1i})+\theta_2(z_{2i})+\ldots+\theta_p(z_{pi})+\varepsilon \qquad i = 1\ldots n \quad (2.9)$$

Linton and Nielsen (1995), Fan, Hardle and Mammen (1996) and Fan and Li (1996) use marginal integration to estimate the components of the additive semi-parametric partially linear regression (PLR) model in (2.9).

Applying marginal integration to the additive PLR model, leads to the result that the asymptotic distribution of $(\widehat{\theta}_s(z) - \theta_s(z),\ s = 1...p)$ is the same as if the other components $\theta_l(.)$ for $l \neq s$ and β were known. In other words $\widehat{\theta}_s(z)$ behaves the same way as if it were a one-dimensional local nonparametric estimator. This is one of the strongest arguments in favor of this method (it amounts to a model with only one nonlinear explanatory variable) against the more traditional non-parametric estimation methods such as nonparametric least squares. Additionally, the additive semiparametric PLR allows for separate treatment of the individual $\theta_s(z)$ components, for their graphical representation and their respective pointwise 95 percent confidence intervals as diagnostic tool to establish any non-linearities in these components.[4] The linear benchmark can be compared to the additive semiparametric PLR and in the case where the linear benchmark lies outside the confidence bounds there is direct evidence of a nonlinear structure not captured by the linear benchmark model.

The idea behind marginal integration can best be illustrated in the context of a model with only two regressors. The model has the following additive structure:

$$y_i = a + g_1(z_{1i}) + g_2(z_{2i}) + u_i \tag{2.10}$$

where $\{y_i, z_{1i}, z_{2i}\}, i = 1...n$ are independently and identically distributed (iid) random variables, $E(u_i/z_{1i}, z_{2i}) = 0$, a is an unknown parameter, $g_1(.)$ and $g_2(.)$

[4] For estimation purposes we use the Gaussian Kernel. The choice of the bandwidth is $c \cdot \sigma_{zs} \cdot T^{-\frac{1}{4+p}}$,where σ_{zs} is the standard deviation of z_s, c is a constant and T is the number of observation. Selection of c was based on cross validation: we tried values between 0.8 and 2 and we have concluded that c=2 gives us smoother graphs.

are unknown univariate functions that obey the identifiability condition that $E(g_1(z_1)) = 0$ and $E(g_2(z_2)) = 0$.

Marginal integration in the context of the above equation can be described as follows. Let $E(y/Z_1 = z_1, Z_2 = z_2) = a(z_1, z_2)$. One can estimate $a(z_1, z_2)$ by a nonparametric local smoother, say $\hat{a}(z_1, z_2)$ and then obtain an estimator of $\{g_1(z_1) + a\}$ by integrating $\hat{a}(z_1, z_2)$ over z_2, i.e. $\tilde{m}_1(z_1) = n^{-1} \sum_{j=1}^{n} \hat{a}(z_1, Z_{2j})$. Since $E(g_1(z_1)) = 0$ we can obtain the estimator of $g_1(z_1)$ by substracting the sample mean of $\tilde{m}_1(.)$ from $\tilde{m}_1(z_1)$, i.e. $\tilde{g}_1(z_1) = \tilde{m}_1(z_1) - n^{-1} \sum_{i=1}^{n} \tilde{m}_1(Z_{1i})$. Similarly, we can obtain an estimator for $g_2(z_2)$.

Marginal integration is used to recover the form of any nonlinear relationship using graphical representations. We begin our analysis using the additive semiparametric PLR model of equation (2.9) that allows three variables as nonlinear determinants of economic growth: initial per capita income (z_1), human capital (z_2) and, the focus of our study, the financial intermediary index (z_3). Following Levine, Loayza and Beck (2000), we use instrumental variables to compute the exogenous component of the financial development index to counter the possible endogeneity between financial development and growth. The instruments are the same as in Levine, Loayza and Beck. The other explanatory variables are included in the linear part of the model ($x_i\beta$). All the explanatory variables in the linear part of the model are in logarithmic form and we introduce time dummies for each of the periods 1971-75, 1976-80, 1981-85, 1986-90, 1991-95. The model under consideration can deal effectively with an unbalanced dataset because the estimation is taking place for each observation using Kernels. For estimation purposes we have used the Gaussian kernel. The choice of bandwidth is given by $c \times s_{Z_i} \times n^{-1/5}$, where s_{Z_i} $(i = 1, 2, 3)$ is the standard deviation of z_i, c is a constant, and n is the number of observations. We used cross-validation to select the value of c in the range 0.8 to 2.0.

We have calculated 95% confidence intervals and the linear benchmark to enable us evaluate nonlinearities in the relationship between financial development and economic growth. In situations where the linear benchmark lies outside the confidence bounds there is evidence of a nonlinear structure not capture by the model.

We have conducted our analysis using all three financial intermediary indices in order to enable a comparison with our previous results as well as with papers that claim to find nonlinearities in the finance- growth relationship. As before, we include the exogenous component of financial development to account for endogeneity, and for consistency.

We begin our analysis with private credit as the financial intermediary index.

Figure 2.1 shows the shapes of the relationship between economic growth and initial income (z_1), human capital (z_2) and private credit (z_3). The first graph shows that, in accordance with previous studies, the logarithm of initial income has a nonlinear effect on economic growth (and can be described with a fourth degree polynomial). In addition the relationship between growth and average years of secondary schooling is nonlinear (second graph). Noting the linear benchmark and the confidence bands we can see that nonlinearities in the relationship do appear in countries with relative high levels of secondary schooling (high levels of human capital).

The third graph shows that private credit has a positive effect on economic growth. This graph shows that, the relationship between economic growth and private credit appears to be linear because the linear benchmark falls entirely within the 95% confidence bands. The linearity/nonlinearity between financial

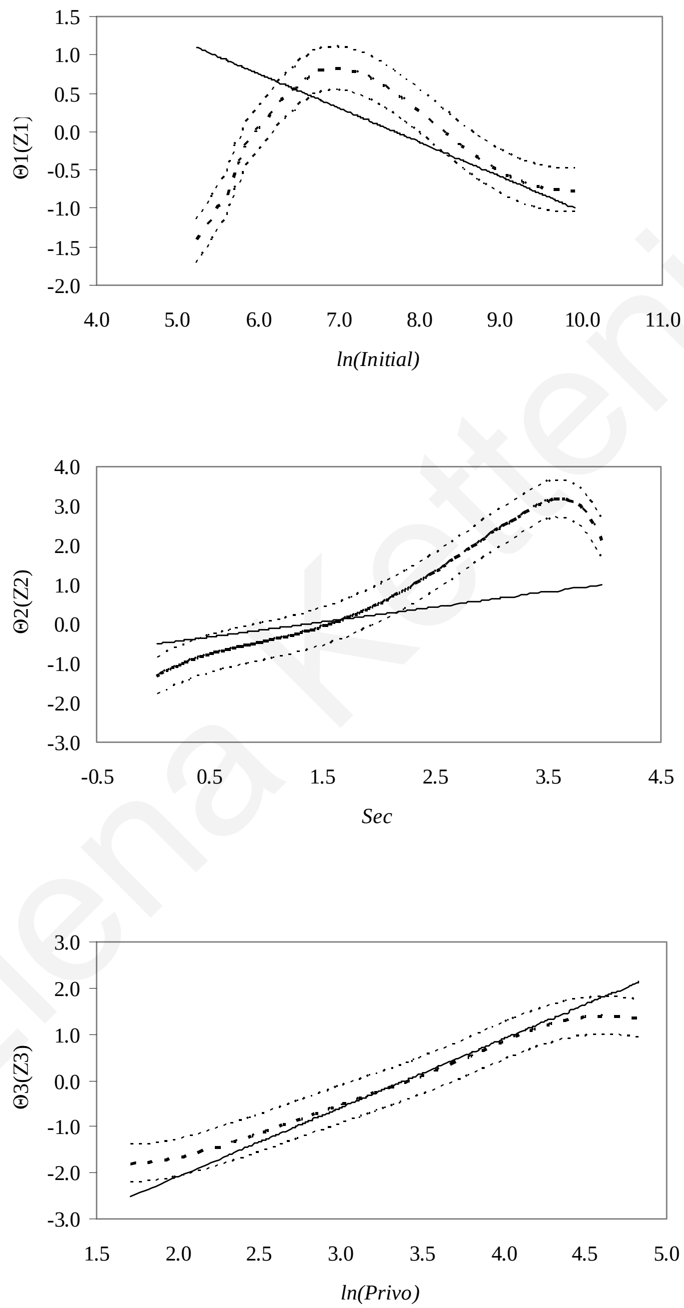

Figure 2.1: Semiparametric PLR model conditioned on initial income, human capital and private credit

development and growth forms an integral part of this paper and we explore this in detail below.

Based on our graphical analysis we conclude that the appropriate specification of the growth model should be one where initial income and human capital have a nonlinear effect on economic growth, while the financial index has a linear (and positive) effect on growth. Previous studies have also established a nonlinear effect of initial income per capita and human capital [see, for instance, Kalaitzidakis, Mamuneas, Savvides and Stengos (2001)] and claim that the nonlinear relationship between initial income and growth can be modelled as a fourth degree polynomial and the nonlinear relationship between human capital and growth as a third degree polynomial. We verify this assertion when we reestimate the model to include only initial income (z_1) and human capital (z_2) in the nonlinear part of equation 2.9). The estimated coefficients (along with t-statistics) of the linear part of this semiparametric PLR model are shown in the first two columns of Table 2.2 in a later section. The graphs of the nonlinear component (initial income and human capital) are in Figure 2.2.

Semiparametric estimation shows that the financial index has a significant, positive, and linear effect on economic growth when we allow for possible nonlinear effects of initial income and human capital on economic growth.

Previous research that claims to have found nonlinearities between financial development and growth [e.g Rioja and Valev (2003, 2004), Deidda and Fattouh (2002)] has ignored nonlinearities between initial income/human capital and growth.

To investigate further this point, we purposely misspecify the model to include in the nonlinear part of equation (2.9) only one variable, the financial index, considering the other two variables (initial income and human capital) as components of the linear part of the model. This amounts to the method used by previous

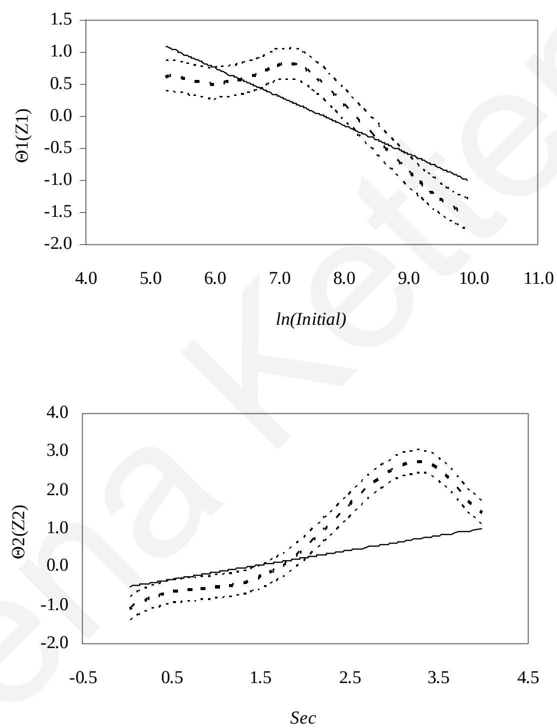

Figure 2.2: Semiparametric PLR model conditioned on initial income and human capital.

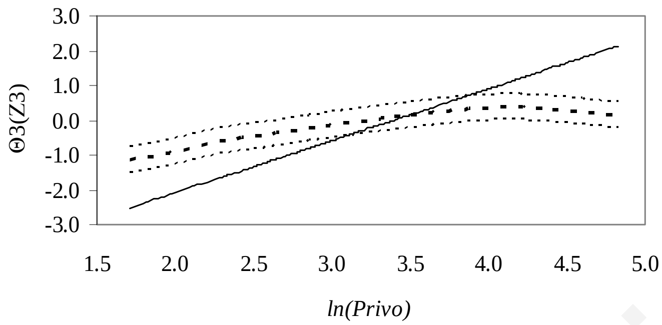

Figure 2.3: Semiparametric PLR model conditioned on private credit.

work on nonlinearities in financial development-economic growth. This result is in Figure 2.3.

In this case the relationship between finance and growth appears to be nonlinear: except for a small range of observations in the middle of the distribution, the linear benchmark lies almost entirely outside the confidence intervals. The nonlinearities occur in countries with high and low levels of financial development. The positive effect of financial development on growth in the middle-region countries (based on level of financial development) is in accordance with the findings of Rioja and Valev (2004a).

For comparison purposes we have used marginal integration, conditioning on only two variables: one is the financial intermediary index and the other is either the logarithm of initial income or human capital, respectively. Results are presented in Appendix A.

To begin with we include initial income and private credit in the nonlinear component and consider average years of secondary schooling as linear. The nonlinear relationship between initial income and economic growth continues to hold. Private credit seems to have a positive relationship with growth, as before, but the relationship becomes negative in countries with high levels of private credit, that is countries with better developed financial systems. When compared to the linear benchmark, the relationship appears again to be linear in most of the countries in the sample.

Second, we exclude the logarithm of initial income from the nonlinear variables and include human capital. The results are also in Appendix A. Again we observe a nonlinear relationship between secondary schooling and economic growth. Additionally, private credit appears to have a positive relationship with economic growth but, as before, at high levels of private credit the effect becomes negative and can be considered as a nonlinear relationship. It cannot be concluded, though, that in countries with better functioning financial systems the effect of private credit on economic growth is nonlinear because we have excluded initial income from the nonlinear component of the model. As we have observed the relationship between initial income and growth is highly nonlinear. So the nonlinearity in this case might be due to the absence of the initial income from the nonlinear component of the model.

The financial index appears to have a positive effect on growth and the relationship becomes nonlinear in countries with very high levels of private credit. It can not be concluded though that the effect of private credit on growth is nonlinear because, in either case, one highly nonlinear variable is excluded from the nonlinear component.

In conclusion, when we do not take into account nonlinearities between growth and initial income/average years of secondary schooling, the relationship between private credit and economic growth appears nonlinear. This might be because private credit absorbs the nonlinearities of income per capita/secondary schooling in the incorrectly specified model. When these two variables are introduced as nonlinear into the growth specification, the relationship between private credit and growth is linear. Moreover, private credit has a positive and significant effect on economic growth.

The same analysis was conducted for the other two financial intermediary indices, commercial versus central bank and liquid liabilities. The results appear to be consistent with the ones with private credit as the financial index. The graphs from the semiparametric additive model conditioned on initial income, secondary schooling and the financial index are placed in the appendix A.

Using the marginal integration approach for all three indices, we can conclude that the relationship between financial development and economic growth is positive, significant and linear when account is taken of the nonlinear relationship between initial income, human capital and economic growth.

In the next section we conduct several specification tests to assist us in determining the appropriate specification for the financial development-growth relationship. These tests support our preferred specification: a linear effect of financial development on growth when initial per capita income and human capital are specified as nonlinear determinants of economic growth.

2.5.3 Specification Tests

In order to verify the appropriate specification of the financial development-growth relationship we perform, first, a specification test proposed by Li and Wang (1998). It tests the null hypothesis of a linear regression model against a PLR alternative formulation, as in Robinson (1988). The data are given by $\{y_i, x_i, z_i\}_{i=1\ldots n}$ which is distributed as an *iid* process. The dimensions of x_i, z_i

are q and p respectively. The null hypothesis is given by:

$$H_0 : y_i = x_i\beta + z_i\gamma + u_i \tag{2.11}$$

and the alternative by

$$H_1 : y_i = x_i\beta + \theta(z_i) + u_i$$

where x_i contains all the determinants of economic growth except per capita income, secondary schooling and private credit and z_i contains these three variables.

Let $E(\widehat{y_i/z_i})$ and $E(\widehat{x_i/z_i})$ be the non-parametric Kernel estimates of $E(y_i/z_i)$ and $E(x_i/z_i)$ respectively. Under the null hypothesis, $E(u_i/x_i, z_i) = 0$ for $i = 1...n$. Therefore, a consistent test statistic can be constructed based on $E\{u_i E(u_i/z_i)\}$ since $E\{u_i E(u_i/z_i)\} = E\{E(u_i/z_i)^2\} \geq 0$ and the equality holds if and only if H_0 is true.

To obtain a feasible test statistic, we replace u_i by $\widehat{u}_i$ the least squares residuals from the linear regression given by the null hypothesis in (2.11). In that case $E(\widehat{u}_i/z_i)$ can be consistently estimated using non-parametric Kernel techniques. The test statistic is given by:

$$J_n = n\lambda^{\frac{p}{2}} I_n / \sqrt{\widehat{\Omega}} \tag{2.12}$$

where $I_n = \frac{1}{n(n-1)\lambda^p} \sum\limits_i \sum\limits_{i=j} \widehat{u}_i \widehat{u}_j K_{ij}$, and $K_{ij} = K(\frac{Z_i - Z_j}{\lambda})$ is the Kernel function, λ is the smoothing (bandwidth) parameter and $\widehat{\Omega} = \frac{2}{n(n-1)\lambda^p} \sum\limits_i \sum\limits_{i=j} \widehat{u}_i^2 \widehat{u}_j^2 K_{ij}^2$. The test statistic is shown by Li and Wang (1998) to have an asymptotic standard normal distribution under H_0 or $J_n \underset{a}{\sim} N(0,1)$

The value of the Li and Wang statistic is 1.98 (in the case where private credit is used as the financial development index) and therefore the null of a parametric specification is rejected. This implies that some nonlinearities do exist in the model and should be taken into account. The test statistic results for the other indices also support the rejection of the linear specification. The value when the liquid liabilities index is used is 2.18 and when the commercial versus central bank assets index is used is 1.91 (rejected at 10%).

Following Fan and Li (1996), we proceed to test for a partially linear specification (conditioned only on two variables, initial income and secondary schooling and where financial development enters linearly) against a general nonparametric alternative. This test is used in order to establish whether this model is appropriate when compared to the more general one that conditions upon three explanatory variables i.e one that includes nonlinearly the financial intermediary index as well as initial income and secondary schooling.

Based on Fan and Li (1996) the null hypothesis for a partially linear model is:

$$H_0 : y_i = x_i\beta + \theta_1(z_1) + \theta_2(z_2) + u_i \tag{2.13}$$

and the alternative is

$$H_1 : y_i = x_i\beta + \theta_1(z_1) + \theta_2(z_2) + \theta_3(z_3) + u_i$$

where, under the null, x_i includes all the determinants of the growth rate (including financial development, z_3) except per capita income z_1 and secondary schooling z_2. In this case, the null is the model suggested by our graphical analysis. The alternative hypothesis refers to the partially additive linear model which includes initial income (z_1), secondary schooling (z_2) and the financial index (z_3) in the nonlinear component of the model.

Fan and Li (1996) argue that if $u_i = y_i - x_i\beta - \theta(z_i)$, then $E(u_i/x_i, z_i)$ equals zero if and only if the null hypothesis is true. Let $W_i = (x_i', z_i')$, where x_i and z_i are of dimension q and p respectively. It is also true that $E[u_i E(u_i/W_i)] = E\left\{[E(u_i/W_i)]^2\right\} \geq 0$ and the equality holds iff H_0 holds. Fan and Li (1996) propose a test statistic for the null based on an estimator of

$n^{-1}\sum_{i}[u_i f_{zi}]E[u_i f_{zi}/W_i]f(W_i)$, where $f_{zi} = f_z(z_i)$, $f_z(.)$ is the probability density function of z_i and $f(.)$ is the pdf of W_i.

The estimator of $u_i\widehat{f}_{zi}$ is obtained by a two-step procedure as in Robinson (1988) and Fan, Li and Stengos (1995). In the first step, we estimate β as $\widehat{\beta}$ by semiparametric estimation. In addition we estimate u_i as $\widehat{u}_i = (y_i - \widehat{y}_i) - (x_i - \widehat{x}_i)'\widehat{\beta}$ the residuals after the semiparametric estimation where:

$$\widehat{y}_i = \frac{[(n-1)\lambda^p]^{-1}\sum_{j\neq i} y_j K_{ij}^z}{\widehat{f}_{zi}}$$

and

$$\widehat{x}_i = \frac{[(n-1)\lambda^p]^{-1}\sum_{j\neq i} x_j K_{ij}^z}{\widehat{f}_{zi}}$$

in which $\widehat{f}_{zi}$ is the corresponding kernel estimator of f_{zi} given by $\widehat{f}_{zi} = \frac{1}{(n-1)\alpha^p}\sum_{j\neq i} K_{ij}^z$, where $K_{ij}^z = K^z[(z_i - z_j)/\alpha]$ with $K^z(.)$ being a product Kernel and α a smoothing parameter.

The term $E[\widehat{u}_i\widehat{f}_{zi}/W_i]f(W_i)$ is estimated by $[(n-1)\lambda^{p+q}]^{-1}\sum_{j\neq i}[\widehat{u}_i\widehat{f}_{zi}]K_{ij}$, where $K_{ij} = K(W_i - W_j/h) = K(\frac{x_i - x_j}{h}, \frac{z_i - z_j}{h})$, K is a product Kernel and λ is a smoothing parameter. Fan and Li denote their test statistic as

$$I_n = \frac{1}{n(n-1)\lambda^{p+q}}\sum_{i}\sum_{j\neq i}[\widehat{u}_i\widehat{f}_{zi}][\widehat{u}_i\widehat{f}_{zj}]K_{ij} \tag{2.14}$$

Define $T = \frac{n\lambda^{\frac{p+q}{2}} I_n}{\sqrt{2}\widehat{\sigma}}$, where $\widehat{\sigma}^2 = \frac{1}{n(n-1)\lambda^{p+q}}\sum_{i}\sum_{j\neq i}[\widehat{u}_i\widehat{f}_{zi}]^2[\widehat{u}_i\widehat{f}_{zj}]^2 K_{ij}^2$. Using the above Fan and Li (1996) conclude that $T \underset{a}{\sim} N(0,1)$ under the null hypothesis. This forms the basis for the following one-sided asymptotic test for H_0: reject the null at significance level α_0 if $T \succ Z_{a_0}$ where Z_{a_0} is the upper a_0-percentile of the standard normal distribution.

The result from the Fan and Li statistic is 0.78 for the private credit index, 0.76 for liquid liabilities and 0.96 for the commercial versus central bank index. Therefore, the null hypothesis of a partially linear specification (semiparametric model conditioned on initial income and human capital) cannot be rejected against the alternative. We conclude that the semiparametric model conditioned on initial income and secondary schooling is the most appropriate specification compared to a specification where all three variables (initial per capita income, human capital and financial development) appear linearly or one where all three appear nonlinearly.

To verify the robustness of our results we use the GMM dynamic panel estimation procedure, when allowing for interaction terms and nonlinear components in the model. Based on Kourtellos (2003), interaction terms between the variables under investigation might play an important role in explaining economic growth, and should then be included in the nonparametric framework. Also nonlinear components of the financial index might affect growth, when the interaction terms are taken into account.

Interaction terms between variables under investigation may play an important role in explaining economic growth and should be included in the nonparametric framework. We have included a product term between z_i and z_j as a regressor in the linear part of equation (2.9) to test for possible interactions among the z variables. The interaction term was insignificant in every case. The GMM dynamic panel estimator results can be found in Tables A10 and A11 in Appendix A.

First we begin by estimating the model, adding in the explanatory variables interaction terms between the financial index (private credit-privo) and the two other variables under investigation, i.e. initial income and schooling respectively.

The results from the GMM procedure (Table A10), yields that the interaction term of initial income with private credit has a negative and significant effect as well as the interaction term between initial income and schooling.

In order to establish whether the interaction term should be included in the nonparametric procedures used in the paper, we reestimate the model including the nonlinear components of initial income and schooling variables, based on the marginal integration results. If the interaction term is still significant, then it should be included in the nonparametric models (Table A11).

When reestimating the model using the additional information we see that the interaction term variables are no longer significant, and should not be included in the nonparametric procedures.

The results from these specification tests are consistent with the graphical analysis: the appropriate specification for the financial development-economic growth relationship is one that considers human capital and initial income as the variables that affect economic growth in a nonlinear manner, while financial development enters linearly. Having established the appropriate specification of the model, we proceed to estimate the effects of financial development on economic growth using parametric techniques.

Based on the above results, we conclude that the effect of finance on growth is linear. This also verifies the results of the marginal integration procedure when all the variables are considered to enter the relationship nonlinearly.

One justification for the linearity could be that the financial development index enters the growth equation to substitute for investment. Levine (1997) stated that the emergence of financial intermediaries increases investment in high-return projects. Investment in the Solow model have a linear effect. Also we showed previously that when one of the two determinants, i.e. initial income or human capital, is excluded from the nonlinear part of the model, the finance-growth relationship appears nonlinear. Based on that, we can assume that there might be a relationship between initial income/human capital with the financial development index. So when these two are included in the model as nonlinear determinants, they capture also some of the effect from finance to growth and therefore the rest that remains is linear (constant and positive for all countries). But when the other determinants are excluded, the nonlinear relationship appears.

2.5.4 Parametric Results

We use the graphical representations of the two nonparametric components in Figure 2.2 as a guide to a more satisfactory parametric specification of the growth regression. Following Kalaitzidakis, Mamuneas, Savvides and Stengos (2001) we have augmented the linear parametric growth equation in Levine, Loayza and Beck (2000) with a fourth degree polynomial in initial income and a cubic polynomial in mean years of schooling. The results are in Tables 2.2-2.3-2.4 for each financial intermediary index.

For comparison purposes, in the Tables we present results from two parametric models: the linear model of Levine *et al.* (2000) (columns 3 and 4) and the nonlinear model (columns 5 and 6).

Table 2.2: Estimation Results

(Dependent variable: GDP growth; t-statistics in parenthesis)

	Semiparametric		*Parametric (GMM)*			
			Linear		Non-Linear	
Constant	1.111	(5.85)	4.723	(4.92)	412.17	(3.50)
Gov	-0.211	(-0.50)	-1.373	(-5.63)	-0.078	(-0.84)
Trade	0.042	(0.18)	0.212	(1.98)	0.854	(4.88)
Pi	-2.548	(-3.27)	-1.274	(-4.21)	-2.462	(-4.97)
Bmp	-1.046	(-3.20)	-0.741	(-8.54)	-0.460	(-3.10)
$D71-75$	-0.495	(-1.32)	-1.012	(-12.38)	-0.734	(-7.07)
$D76-80$	-0.670	(-1.63)	-1.152	(-7.83)	-0.785	(-4.27)
$D81-85$	-2.397	(-6.61)	-3.039	(-18.49)	-2.926	(-11.73)
$D86-90$	-1.430	(-4.07)	-2.182	(-15.90)	-1.889	(-8.15)
$D91-95$	-1.894	(-5.08)	-2.791	(-17.42)	-2.445	(-8.89)
Privo	0.811	(3.62)	1.608	(14.76)	1.493	(8.87)
Sec			0.127	(1.62)	1.383	(2.96)
$(Sec)^2$					-1.249	(-2.72)
$(Sec)^3$					0.261	(2.93)
Initial			-0.363	(-2.92)	-216.0	(-3.93)
$(Initial)^2$					40.63	(3.85)
$(Initial)^3$					-4.316	(-3.72)
$(Initial)^4$					0.134	(3.53)
Tests (p-value)						
Sargan				0.537		0.336
Serial Correlation				0.520		0.741
Wald test (z_1, z_2 *nonlinear VS linear*)						0.000
Wald test (z_1, z_2, z_3 *nonlinear VS* z_1, z_2 *nonlinear*)						0.531
Wald test (z_1, z_2 *nonlinear VS* z_3 *nonlinear*)						0.000

All variables are in logarithms except *Sec*. Also *Pi* and *Bmp* are defined as

Both models are estimated using the GMM dynamic panel estimator of Arellano and Bond (1991) and Arellano and Bover (1995). For both models the Sargan test for instrument adequacy and a serial correlation test are computed ($p-$values of all the tests are reported in Table 2.2). The tests show no evidence of second order serial correlation and also show that the instruments used are appropriate.

The nonlinear model shows that all the nonlinear coefficients for initial income and secondary schooling are significant and jointly significant as well. A Wald test (z_1, z_2 nonlinear vs linear) rejects the linear model in favor of the nonlinear one. Therefore, estimation results, both from parametric and nonparametric estimation, confirm a strong, significant, positive and linear relationship between financial development and economic growth; on the other hand, the relationship between growth and initial income and human capital is nonlinear. As a final check on our results we have tested the preferred nonlinear parametric specification against first a parametric model where initial income, human capital and the financial index enter nonlinearly (z_1, z_2, z_3 nonlinear vs z_1, z_2 nonlinear) and second a parametric model where only the financial index enters nonlinearly (z_1, z_2 nonlinear vs z_3 nonlinear). The p-values of the two Wald tests are reported in the last two rows of the Tables: clearly our preferred specification cannot be rejected against the alternatives[5].

Similar results are obtained for all the financial indices.

[5] In the tables privo is referred to private credit, lly to liquid liabilities and btot to commercial versus central bank. These are the three financial indices used in our analysis.

Table 2.3: Estimation Results

(Dependent variable: GDP growth; t-statistics in parenthesis)

	Semiparametric		*Parametric (GMM)*			
			Linear		Non-Linear	
Constant	0.662	(2.52)	-7.440	(-9.78)	40.94	(0.69)
Gov	-0.134	(-0.31)	-0.695	(-2.92)	-0.357	(-1.11)
Trade	-0.010	(-0.04)	0.322	(1.38)	0.625	(2.69)
Pi	-3.554	(-4.31)	-2.470	(-8.33)	-4.126	(-10.29)
Bmp	-1.128	(-3.27)	-0.779	(-9.16)	-0.388	(-2.68)
$D71-75$	-0.311	(-0.83)	-0.953	(-9.82)	-0.745	(-10.61)
$D76-80$	-0.378	(-0.92)	-0.792	(-7.20)	-0.626	(-5.47)
$D81-85$	-2.034	(-5.53)	-2.585	(-18.23)	-2.756	(-13.68)
$D86-90$	-1.086	(-2.95)	-1.778	(-12.71)	-1.758	(-8.27)
$D91-95$	-1.535	(-4.00)	-2.491	(-14.43)	-2.532	(-9.11)
Btot	0.210	(3.05)	2.793	(10.78)	3.146	(12.42)
Sec			0.396	(2.98)	2.806	(1.78)
$(Sec)^2$					-1.451	(-1.52)
$(Sec)^3$					0.276	(1.72)
Initial			-0.115	(-1.03)	-24.57	(-3.00)
$(Initial)^2$					3.42	(3.21)
$(Initial)^3$					-0.123	(-3.08)
$(Initial)^4$					-0.004	(-0.76)
Tests (p-value)						
Sargan				0.416		0.379
Serial Correlation				0.726		0.883
Wald test (z_1, z_2 nonlinear VS linear)						0.000
Wald test (z_1, z_2, z_3 nonlinear VS z_1, z_2 nonlinear)						0.111
Wald test (z_1, z_2 nonlinear VS z_3 nonlinear)						0.000

All variables are in logarithms except *Sec*. Also *Pi* and *Bmp* are defined as

Table 2.4: Estimation Results

(Dependent variable: GDP growth; t-statistics in parenthesis)

	Semiparametric		*Parametric (GMM)*			
			Linear		Non-Linear	
Constant	0.791	(4.37)	-0.253	(-0.30)	823.51	(4.70)
Gov	-0.229	(-0.54)	-0.756	(-2.09)	-0.674	(-1.62)
Trade	-0.021	(-0.09)	0.096	(0.39)	0.676	(2.85)
Pi	-2.481	(-3.92)	-0.073	(0.15)	-1.921	(-2.52)
Bmp	-1.353	(-3.88)	-1.787	(-14.13)	-1.460	(-10.82)
$D71-75$	-0.421	(-1.14)	-0.938	(-15.66)	-0.511	(-5.07)
$D76-80$	-0.566	(-1.39)	-0.964	(-8.87)	-0.878	(-5.16)
$D81-85$	-2.268	(-6.21)	-2.939	(-16.18)	-3.200	(-15.99)
$D86-90$	-1.319	(-3.65)	-2.221	(-12.27)	-2.139	(-10.53)
$D91-95$	-1.765	(-4.71)	-2.909	(-18.24)	-3.079	(-10.54)
Lly	0.887	(3.88)	2.641	(12.27)	2.166	(6.57)
Sec			0.319	(2.19)	3.432	(3.29)
$(Sec)^2$					-2.050	(-3.06)
$(Sec)^3$					0.377	(3.18)
Initial			-0.573	(-3.41)	-452.0	(-4.72)
$(Initial)^2$					90.48	(4.65)
$(Initial)^3$					-7.883	(-4.56)
$(Initial)^4$					0.252	(4.42)
Tests (p-value)						
Sargan				0.620		0.612
Serial Correlation				0.404		0.619
Wald test (z_1, z_2 nonlinear VS linear)						0.000
Wald test (z_1, z_2, z_3 nonlinear VS z_1, z_2 nonlinear)						0.228
Wald test (z_1, z_2 nonlinear VS z_3 nonlinear)						0.000

All variables are in logarithms except *Sec*. Also *Pi* and *Bmp* are defined as

2.6 Conclusion

This chapter examines the nature of the financial intermediary development-growth relationship. Empirical evidence suggests a positive relationship between finance and growth. We use the same data set as previous researcher and employ two different econometric approaches to establish whether such a relationship does exist and whether it is linear. The first, GMM dynamic panel estimators [Arellano and Bond (1991) and Arellano and Bover (1995)] verifies the existence of a positive and *linear* relationship between financial development and economic growth and also a linear relation between growth and initial income/human capital. The second, a nonparametric approach (semiparametric estimation) was used to verify the consistency of the results from the GMM method, under a different framework. The nonparametric techniques (PLR) are also used in order to investigate whether nonlinearities exist in the finance-growth relationship.

The nonparametric method used to uncover the individual shape of the financial index/growth relationship and to provide evidence on whether nonlinearities exist is marginal integration. This method was introduced conditioning on three variables: initial income, secondary schooling and the financial index. The results indicate that the first two do indeed have a nonlinear relationship with economic growth. The financial index appears to have a positive linear relationship with growth, a result that gives additional verification to the GMM methodology.

The same method was then used to condition on only two variables: one is the index and the other either initial income or human capital. This analysis again shows that the financial index has a positive effect on economic growth, and the effect can be considered linear for most of the countries in the sample. The other variable has a nonlinear effect.

Finally, the above method was used conditioned only on the financial intermediary index. In this case we observe a nonlinear relationship between the financial intermediary index and growth. We cannot conclude though, that in general the finance-growth relationship is nonlinear. The above result can be due to the fact that the other two variables are not included in the nonlinear component and, as a result, nonlinearities from them are subsumed in the private credit variable.

Based on the above we conclude that by applying marginal integration to the additive *PLR* model, we find that, in contrast to recent research, the finance-growth relationship is linear when the previously documented nonlinearity between economic growth and two of its determinants (initial per capita income and human capital) is taken into account. When these nonlinearities are ignored, the finance-growth relationship appears nonlinear.

Specification tests provide evidence on the appropriate functional form of the relationship under investigation. The first specification test rejects the parametric model (all variables enter linearly) against a nonparametric alternative. The second one, verifies the validity of the semiparametric model conditioned on initial income and secondary schooling because it cannot be rejected against the alternative which includes the financial intermediary index as well the other two variables nonlinearly. The third one, deals with the robustness of the results and it gives support to the other two tests as well as the results from the marginal integration approach that only when the nonlinearities of the other two variables are not included in the model the effect of the financial index on growth is nonlinear.

These tests provide evidence in favor of the semiparametric partially linear additive model with human capital and initial income as the only variables that affect growth in a nonlinear matter. In addition, we use the graphical representations of the nonparametric components to specify a parametric model which is then estimated through GMM techniques. This specification includes initial income and human capital in the nonlinear part of the model and financial intermediary index in the linear. The estimation results, from both parametric and semiparametric methods, indicate that the financial intermediary index has a positive and significant effect on growth.

We conclude that policies which target financial development will accelerate economic growth as well. Levine, Loayza and Beck (2000), argue that policies that promote the smooth functioning of financial intermediaries (e.g laws that give high priority to secured creditors getting the full present value of their claims against firms, legal systems that rigorously enforce contracts, including government contracts, and accounting standards that produce high-quality, comprehensive and comparable corporate financial statements) will result in higher economic growth. More importantly we conclude that, and contrary to recent research, the impact of financial development on economic growth is linear, when account is taken of the nonlinearity between growth and initial income/human capital. It appears that the alleged nonlinearity between finance and growth uncovered by recent research is the product of ignoring other established nonlinearities in the economic growth literature.

Chapter 3

Information Technology and Economic Performance: A smooth coefficient semiparametric approach

3.1 Introduction

In recent years, economists have observed a rapid diffusion of IT, which includes software, communication technology and hardware throughout the world. Some economists suggest that this fact is a direct consequence of the dramatic decline in the price of computers, which has led to a substitution of IT equipment for other forms of capital and labor. It has been suggested, that this substitution generates substantial returns for agents who undertake IT investment and also has had a very significant impact on economic growth. This view has become an important issue in economics and has given rise to a vigorous debate among economists. On the one hand, it is argued that the development of IT is one of a series of positive temporary shocks and IT has no effect on productivity and growth. On the other hand, there is the claim that IT has produced a fundamental change in the economy leading to a permanent improvement in growth prospects.

This debate, also, arises as a result of the Solow "Computer Productivity Paradox". Solow (1957) suggested that “You can see the computer age everywhere but in the productivity statistics”. A number of different views were put forward in order to offer a solution to the above paradox. Most of the early evidence based on aggregate data, suggests that IT and especially computers have had no effect on either productivity or growth. These studies are based on an aggregate production function, assume constant returns to scale and competitive markets, while factor shares are often used as a proxy for output elasticities. Clearly, under the above assumptions, these models will have likely missed important variation in the data among different industries [see Berndt and Morrison (1995), Morrison (1997), Jorgenson and Stiroh (1999)].

More recent studies relying primarily on the use of industry or sectoral data indicate that IT is indeed playing a major role in the productivity of an economy. They claim that firms and industries that produce IT assets have experienced considerable growth and benefited from the extraordinary technological progress. This in turn has enabled them to improve the performance of IT goods, measured as total factor productivity (TFP) growth in the IT - producing industries [see Stiroh (1998,2002), Oliner and Sichel (2000), Bayoumi and Haacker (2002)].

On the whole, microeconomic studies provide support to the positive relationship between IT investment and productivity growth. However in the recent literature a most important issue currently regarding the relationship between IT investment and growth is the role played by adjustment costs in the adoption of new technologies [see Ahn (1999), Bessen (2002), Mun (2002)]. In this context, IT investment depends on adjustment costs and it takes time for productivity gains to be realized.

In this chapter we investigate the impact of IT capital on the process of productivity growth by allowing the contribution of various inputs as well as that of IT capital to vary across industries and time. We accomplish the above task firstly, by constructing an index of TFP based on non-IT capital, labor and intermediate inputs and, secondly, by using this index to evaluate the impact of IT capital on TFP growth using semiparametric methods. The smooth coefficient semiparametric model used, allows us to directly estimate the elasticity of IT capital for each industry and each time period. In addition, this model offers a good solution in the case in which nonlinearities exist in the relationship between IT and productivity. This issue has not, yet, been investigated in the literature and a procedure such as this will provide a first step in that direction. Furthermore, we implicitly allow for adjustment costs in the productivity analysis, to establish their importance in evaluating this relationship.

In order to examine this relationship we use data for 42 U.S. private industries over the period 1984-2001, obtained from a variety of sources. Several tests were conducted and they suggest that adjustment costs are important and should be included in the analysis since it seems to affect the size of the output elasticity of IT-capital. This elasticity of IT-capital is positive and it is not constant across industries and time but varies considerably and it is positive. The graphical analysis suggests that the relationship between IT-capital and productivity is nonlinear, especially when adjustment costs are included in the model. An important result from the analysis, confirming earlier findings by Bessen (2002), Mun (2002), is that the omission of adjustment costs understates the effect of IT-capital on productivity. In addition, we establish that IT-capital growth is an important contributor to each industrys output growth.

The rest of the chapter is organized as follows. Section 2 presents a literature review. Section 3 presents the data used in our analysis. Section 4 gives the estimation analysis and methodology used. The estimation results are presented in section 5 and section 6 concludes.

3.2 Information Technology and Economic Growth

3.2.1 Studies Based on Aggregate (Macro) Data

Berndt and Morrison (1995),and Morrison (1997) examine the extent to which investment in high - tech office and IT capital has reduced costs and has facilitated productivity growth. Berndt and Morrison (1995) use manufacturing industries data, from 1968 to 1986. They examine the cost and profitability effects of the diffusion of high tech capital into these industries by using Ordinary Least Squares and multiple regression analysis. They find no significant relationship between profitability and high - tech capital. Also they find that increases in the share of high tech capital are negatively correlated with multifactor productivity and tend to be labor-using. Additionally, they conclude that industries with a higher proportion of high-tech capital have higher measures of economic performance, although within industries increasing the share does not appear to improve economic performance. Morrison (1997) extents their sample to cover the period from 1952 to 1986. She specifies a Generalized Leontief variable cost function and estimates various elasticities to examine the relationship between changes in the stock of IT equipment and technical progress. The results obtained indicate that there is little evidence that increases in office and IT - equipment have a substantial impact on technical progress.

Jorgenson and Stiroh (1999), provide evidence on whether the massive substitution of IT equipment for other types of inputs has been accompanied by technical change in the economic sense. They use a TFP (Total Factor Productivity) growth approach to quantify the importance of IT equipment as both an input in the production by firms and as a form of consumption by households. Employing aggregate U.S. data from 1990 to 1996, they conclude that rapid substitution existed but has not been accompanied by technical change. They suggest that returns to investment in IT equipment have been successfully internalized by computer producers and computer users. Jorgenson (2001), instead of an aggregate production function framework, uses a production possibility frontier to analyze the impact of IT. He uses this method because, as he states in his paper, it captures the substitution among outputs and inputs in response to the rapid deployment of IT and to the 1995 acceleration in the IT price decline. He concludes that this decline will continue for sometime, so will the substitution of IT for other production inputs but this cannot continue indefinitely. He also indicates that the contribution of information technology has increased, but more than 70 percent of the increased output can be attributed to non - IT products.

Gordon (2000) explores some of the intrinsic limitations of computers in general and the internet in particular for affecting productivity and quality of life when evaluated in comparison to the great inventions of the past. Gordon states that the acceleration in the price decline of computers since 1995 has been accompanied by a revival of productivity growth in the aggregate economy. Yet, when examined closely, it turns out that a major fraction of the revival in multifactor productivity growth has occurred within the part of the economy which is not related to information technology and computers. Moreover, the period from 1995 to 1999 is quite short, and during at least part of that time, it seemed clear even to many of the new economy optimists that output growth was running at a faster pace than the sustainable long term growth trend. Gordon (2000) concludes that computer investment has had a near zero rate of return outside of durable manufacturing and seventy five percent of all computer investment has been in industries with no trend increase in productivity.

On the whole, aggregate studies indicate no significant relationship between productivity growth and high-tech capital. However, there are certain important limitations with the above approach. Most of these studies are based on an aggregate production function, they assume constant returns to scale, competitive markets and factor shares are often used as a proxy for output elasticities. As a result, research has moved to the use of more detailed industry or sectoral data that allow for the adoption of a more flexible empirical framework .

3.2.2 Studies Using Industry / Sectoral Data

Siegel (1997), using detailed industry data estimates a multiple - indicators, multiple causes model that allows for the estimation of the relationship between computer usage and product (or labor) quality, while controlling for measurement errors. It is argued that previous studies, that obtain conflicting results for the relationship between computers and productivity, suffer from an inability to account for errors in measurement that may be induced by investment in computers. If the price or quantity of computers is measured with error then the estimates of the marginal productivity of computers may also be mismeasured. Siegel (1997) finds a positive and statistically significant relationship between productivity growth and investment in computers and concludes that the productivity paradox, or the absence of a positive correlation between computers and productivity growth at least in the manufacturing sector, could be a statistical illusion that can be attributed to measurement error.

Barua and Lee (1997), revisit the IT productivity paradox to highlight some potential limitations of earlier research. They apply a theoretical framework involving explicit modelling of a strategic business unit's (SBU) input choices to a secondary data set in the manufacturing sector and reveal a significant positive impact of IT investment on SBU output. The authors conclude, that output measurement is slightly less problematic in manufacturing and we should expect substantial productivity gains from IT investments in manufacturing and production management.

Stiroh (1998, 2002) offers a simple solution to the computer productivity paradox by making careful distinction between computers as an output from one sector and an input to other sectors. He (1998), uses sectoral data for 35 sectors and a gross output approach. His results indicate that computer - productive sectors show a rapid acceleration in multifactor productivity growth. This is not the case, though, for the other sectors, which experienced a multifactor productivity, MFP, slowdown. It is suggested that although MFP growth in the computer sector was extraordinary, the small size of the sector keeps this contribution small. Stiroh (2002), tries to find the link between IT and the post - 1995 U.S. productivity revival using industry level data and two different approaches. The first identifies one industry as IT - intensive and compares the relative productivity gains of IT - intensive industries to other industries. The second captures potentially important heterogeneity in IT - intensity. Both suggest that the impact of IT - related industries on aggregate U.S. productivity growth is quantitatively large and economically important.

Hendel (1999), uses a multiple discrete choice model for the analysis of the demand of differentiated products, which is estimated using micro - level data on the demand for personal computers. The estimated demand model is then used to compute the welfare effects from computerization and technological innovation in peripherals. The model assesses a surplus of about $1.16 billion in the banking industry in 1998 due to computerization, while the estimated return on investment in personal computers is 92%. Feldstein (2003), also finds that productivity in the US has been growing faster in the past seven years than it did in the previous quarter century. Furthermore, US productivity growth accelerated while in Europe declined. This difference is due to, the strong incentives for managers in the US at all levels to make changes that can raise productivity even if they involve risk and the information technology developments that took place in the US economy.

Brynjolfosson and Hitt (2000) examine how do computers contribute to business performance and economic growth using a model that looks at the economic role of computers in the same way as one would think about organizations and markets as information processors. IT investment are complements to organizational investments and cause productivity to increase by reducing costs and by enabling firms to increase output quality. Greenwood, Hercowitz and Krussel (2000) use a general equilibrium framework, along with simulation and calibration methods and they suggest that investment - specific technology accounts for the major part of growth.

Jorgenson, Stiroh and Ho (2002), estimate the economy wide sources of growth for the period 1958 to 1999 and various subperiods using industry level data through a production possibility frontier approach for IT - producing and non -IT producing industries. Their results indicate a rising contribution of IT - producing industries to U.S. economic growth. Oliner and Sichel (2000) estimate MFP growth using data on prices of outputs and inputs for three sectors of the Non -Farm U.S. business economy, namely semiconductors, manufactures of computers and all other industries. Their estimation results indicate that MFP contributions from computer and semiconductor producers increased sharply in the period between 1996 to 1999. They also find an estimate of the MFP contribution from the computer sector, which includes MFP from computer production plus sixty percent of the MFP contribution of semiconductor production, that accounted for roughly 2/5 of the growth in non - farm business MFP.

Bayoumi and Haacker (2002), analyze the welfare benefits from falling relative prices of IT goods across a wide range of countries. They use two different methodologies, one similar to earlier studies but expanded to look at both real GDP and real domestic demand and one in which they estimate by OLS the social savings associated with falling prices of IT goods. Two different data sets are used. They find that welfare benefits mainly accrue to users of IT, not their producers, because of falling relative prices. Their first approach indicates that while IT sectors have provided substantial output benefits to those countries with large production sectors, most of the demand-side benefits have been transferred to importing countries through changes in the terms of trade. Based on their second methodology, the gains in social savings are substantial.

Biscourp, Crepon, Heckel and Riedinger, (2002), estimate a translog production function, to investigate how the decrease in the cost of computers has affected the marginal cost of firms, their aggregate labor demand and their skill structure. Using a panel of 5000 French firms between 1994 and 1997, they find a strong but heterogeneous effect across firms. For the median firm, they find the elasticity of the marginal cost to price of computers to be 0.05, the elasticity of aggregate labor to the same price to be 0.07 and the elasticity of the ratio of unskilled to skilled labor to be 0.26.

On the whole, microeconomic studies provide support to the positive and significant relationship between investment in IT and productivity growth. Further issues in the literature, have arisen to give support to the significant relationship between IT investment and growth. These are, the existence of adjustment costs when adopting new technologies.

3.2.3 Studies Based on Adjustment Costs

Ahn (1999), offers an explanation for the productivity puzzle based on learning costs. Using firm level as well as industry level data, he finds that in adopting a new technology one may encounter a temporary decrease in productivity, as resources are spent acquiring the necessary skills and know-how to be able to fully utilize the new technology and realize its maximum potential gains. However, the long-run productivity gains outweigh the short-run costs. Amato and Amato (2000) estimate the impact of high tech production techniques on productivity and profitability, using a data set consisting of 122 selected US manufacturing industries for 1988-1992. They find that when industry dummies are excluded from the profitability model, the relationship between high technology adoption and profitability is negative. However, the coefficient becomes insignificant once industry dummies are added in the model. For MFP, there is a positive impact from high technology regardless of whether the specification includes industry effects.

Bessen (2002), suggests that new technologies may incur large adoption costs because they involve learning new skills, implementing new forms of organization and developing complementary investments. Using two panels of U.S. manufacturing industries, he estimates capital adjustment costs from 1961 to 1996 and revised productivity growth rates. He finds that capital adjustment costs rose sharply during the period 1974 to 1983, at the same time as investment sharply shifted towards IT. Adjustment costs are assumed to increase with the rate of embodied technical change, so they are considered to be costs of adopting new technologies. Applying these adjustment cost estimates, he obtains estimates of productivity growth from 1974 to 1983 of 0,91% compared to an official estimate of 0,52%. These growth rates compared favorably to the official growth measures, suggesting that any productivity slowdown was brief at most. The author concludes that omission of adoption costs tend to understate the effect of IT on productivity growth during the 1970s.

Mun (2002) in his paper adds a new parameter in the IT models discussed so far in that the costs of adopting new technology are different from the costs of expanding the capital stock. IT investment depends on adjustment costs associated with the installation of new IT equipment. There also exist internal adjustment costs arising from implementing new capital goods into the production process. He estimates a dynamic factor demand model in which adjustment costs of computer investment are allowed to depend on both technology adoption and quantity expansion for two digit U.S. manufacturing industries from 1983 to 1998. His results indicate that all industries except two exhibit positive productivity growth. Also the unmeasured TFP growth due to both quantity expansion and technology adoption is about 4.2% of the measured TFP growth. One can conclude from these results that the adjustment costs of investment in both computer and non - computer capital introduce a modest bias in the measured TFP growth for manufacturing industries.

To summarize, studies that examine the role of adjustment costs claim that new technologies may introduce large adjustment costs, since they involve the adoption of new skills, the implementation of new forms of organization and the development of complementary investments. IT investment also depends on adjustment costs associated with the installation of new IT equipment. Omission of adoption costs tend to understate the effect of IT on productivity growth, and that the adjustment costs in both computer and non-computer capital make a modest bias in the measured TFP growth for manufacturing industries.

Adjustment costs were initially introduced by Lucas (1967), who made a distinction between short and long-run behavior by introducing "fixity" of capital that arises from internal costs of investment in the form of output foregone into the production function.

Based on Lucas the investment rate is assumed to enter the production function with a negative and decreasing marginal productivity. The inclusion of the gross investment rate in the production function was motivated by Lucas through the following example. The introduction of new capital goods introduces new production methods and new capital becomes fully effective only after a learning period such as replacing a new computer with a newer model. From the first order conditions of the firm's maximization problem, the marginal product of capital equals the marginal cost of accumulating capital . The latter now includes an extra term based on the adjustment cost measuring the value of output foregone with each unit of investment.

Nadiri and Prucha (1989,1999), decomposed the traditional TFP measure, while allowing for the existence of adjustment costs. Their analysis includes the end of the period stock of quasi fixed inputs, and models internal adjustment costs in terms of foregone output due to changes in the quasi-fixed factors[1]. Like Lucas they assume that this effect on the production function will be negative. Their findings suggest that adjustment costs reduce output growth, but by a small percentage. A similar analysis was conducted by Morrison (1992), with the only difference that she didn't use the end of the period stocks of quasi-fixed inputs. The above studies suggest that the case where adjustment costs are not included in the analysis, results in a biased measure of TFP growth.

3.3 Data Description

This study covers 42 U.S. private industries over the period 1984-2001 and, for comparative purposes, the data are the same as those used in Mun (2002) and Nadiri and Mun (2002). The nominal values and chain-type price indexes of gross output and intermediate inputs are obtained from the Gross Product Originating (GPO) published by the BEA. The number of full time equivalent employees is used as the quantity of labor. The wage index is constructed by dividing compensation of employees by the number of full time equivalent employees. For capital stock, we use data for 61 types of assets from the Fixed Reproducible Tangible Wealth (FRTW) provided by the BEA. Using geometric depreciation

[1]Studies, in this literature, consider adjustment costs entering the production function in the form of gross investment rate or in the form of first difference of the capital stock.

rates for each asset from Fraumeni (1997), capital stocks are constructed using the perpetual inventory method.

Rental prices for each asset are estimated by:

$$w_{k,t} = \frac{(1 - itc_{k.t} - z_{k,t}u_t)}{1 - u_t}(r_t + \delta_k - \pi_{k,t})p_{k,t},$$

where it$c_{k.t}$ is the investment tax credit for asset k at time period t, u is the corporate tax rate, z is the present value of the capital consumption allowance, r is the nominal rate of return, δ_k is the depreciation rate, π_k is the asset specific capital gain, and $p_{k,t}$ is the investment deflator. All tax related variables were found from the Bureau of Labor Statistics (BLS). As in Mun and Nadiri (2002), we also use Moody's Aaa corporate bond yield for the nominal rate of return and set capital gains to zero.

Using the Tornqvist index method, we aggregate the 61 types of assets for each industry into two types of capital, IT and non-IT capital stocks. IT capital stock includes mainframe computers, personal computers, direct access storage devices, computer printers, computer terminals, computer tape drives, computer storage devices, integrated systems, software which consists of prepackaged software, custom software and own-account software and communication and other office and accounting equipment (hardware, software and communication technology). Non-IT capital stock consists of other non-IT equipment and structures.

3.4 Estimation Analysis

Here we investigate the impact of IT capital on the process of economic growth by allowing the contribution of traditional inputs (non IT capital, intermediate inputs and labor) as well as that of IT capital to vary both across industries and time. We will accomplish the above by constructing an index of TFP [see

Mamuneas, Savvides, Stengos (2005)] growth for traditional inputs. Next, we will use this index to evaluate the impact of IT capital on TFP via semiparametric methods that allow the effect of IT capital on productivity growth to be nonlinear.

The fundamental questions are the extent to which investment in IT capital contributes to raising productivity and the role of adjustment costs. The results from the literature appear to indicate that the impact of IT capital may differ across industries or countries.

To capture this variation we use the smooth coefficient semiparametric model which imposes no assumptions on the functional form of the coefficients which in turn are allowed to vary as smooth functions of other variables. This is the first study that deals with possible nonlinearities in the relationship between IT and productivity.

3.4.1 Econometric Model

We will assume that a general production function describes the technology of industry i at time t as follows:

$$Y = F(K, L, M, IT, t) \tag{3.1}$$

where Y, K, L and M represent the amounts of total output (gross output), physical capital (non-IT capital), labor and intermediate inputs respectively, IT is the information technology capital stock and t is a technology index measured by time trend.[2]

Total differentiation of (3.1) with respect to time and division by Y yields:

$$\hat{Y} = \hat{A} + \varepsilon_K \hat{K} + \varepsilon_L \hat{L} + \varepsilon_M \hat{M} + \varepsilon_{IT} \hat{IT}$$

[2]Including all inputs in the production function will provide more accurate results.

where $(\hat{\ })$ denotes a growth rate, $\hat{A} = \frac{(\partial F/\partial t)}{Y}$ is the exogenous rate of technological change and $\varepsilon_Q = \frac{\partial \ln Y}{\partial \ln Q}, (Q = K, L, M, IT)$ denotes output elasticity.

Assuming perfect competitiveness the output elasticities of labor, physical capital and intermediate inputs should be equal to the observed income shares of labor, s_{YL}, capital, s_{YK}, and intermediate inputs, s_{YM}. With data available for the above variables we can directly estimate the elasticities using panel data or cross-section analysis.

However, this is not the case for the output elasticity with respect to IT capital. Since we want to examine this effect directly while allowing it to take a nonlinear form we follow an alternative specification.

Firstly, we construct the TFP index (biased TFP index) based only on labor, non-IT capital and intermediate inputs. This index allows the contribution of each input to differ and to be dictated by the data. We define the Tornqvist index of TFP growth for industry i in year t as follows:

$$T\hat{F}P_{it} = \hat{Y}_{it} - w_{Lit}\hat{L}_{it} - w_{Kit}\hat{K}_{it} - w_{Mit}\hat{M}_{it} \tag{3.2}$$

where $w_{Qit} = 0.5(s_{Qit} + s_{Qit-1}), (Q = L, K, M)$ are weighted average cost shares of labor, non-IT capital and intermediate inputs and $\hat{Q}_{it} = \ln Q_{it} - \ln Q_{it-1}, (Q = Y, L, K, M)$.

This measure of TFP contains the components of output growth that can not be explained by the growth of the inputs (K, L, M) in equation (3.2) . Diewert (1976), suggested that this index is an exact index of technological change for a general translog production function, under certain conditions.

In the second step we will use a nonparametric methodology to estimate the effect of IT-capital on the TFP growth. That is, we will model the contribution of IT capital to aggregate production as a general unknown function $\theta(.)I\hat{T}_{it}$.

Hence we have:

$$T\hat{F}P_{it} = \hat{Y}_{it} - \hat{Q}_{it} = \hat{T}_{it} + \theta(.)I\hat{T}_{it} \tag{3.3}$$

where $\hat{Q}_{it} = w_{Kit}\hat{K}_{it} + w_{Lit}\hat{L}_{it} + w_{Mit}\hat{M}_{it}$[3].

Semiparametric estimation of the above equation allows IT-capital accumulation to influence TFP growth in a nonlinear fashion. The nonlinear aspects of IT capital growth will be investigated via semiparametric estimation techniques.

In equation (3.3) above, $\hat{T}_{it}$ (exogenous technical change) can be considered as a function of industry and year specific dummy variables. Industry specific dummies, D_i, capture idiosyncratic exogenous technological change and time specific dummies, D_t, capture procyclical behavior of TFP growth.

The equation of interest now becomes:

$$T\hat{F}P_{it} = \hat{Y}_{it} - \hat{Q}_{it} = \alpha_0 + \sum_{i=1}^{N-1} \alpha_i D_i + \sum_{t=1}^{T-1} \alpha_t D_t + \theta(.)I\hat{T}_{it} + u_{it} \tag{3.4}$$

$$= \hat{T}_{it} + \theta(.)I\hat{T}_{it} + u_{it}$$

where $E(u_{it}|X_{it}, IT_{it}, I\hat{T}_{it}) = 0$.

In order to obtain correct estimates of the effect of IT on productivity and evaluate the importance of adjustment costs we modify the production function to be:

$$Y = F(K, L, M, IT, II, t)$$

where II denotes gross IT investment. Following the literature on adjustment costs, [see Lucas (1967)], we assume that the production function can be written as a sum of the ordinary production function and an adjustment cost function.

[3] See Appendix B for the decomposition of TFP

This way we allow for no interactions between adjustment costs and the various inputs used, as well as the marginal adjustment cost to be zero (in the long run).

The equation for estimation purposes now becomes:

$$T\hat{F}P_{it} = \hat{Y}_{it} - \hat{Q}_{it} = \hat{T}_{it} + \theta(.)I\hat{T}_{it} + \delta I\hat{I}_{it} + u_{it} \tag{3.5}$$

where $I\hat{I}_{it}$ is the growth rate of gross investment in IT.

A more general version of the model would be:

$$T\hat{F}P_{it} = \hat{Y}_{it} - \hat{Q}_{it} = \hat{T}_{it} + \theta(V_{it})I\hat{T}_{it} + \delta I\hat{I}_{it} + u_{it} \tag{3.6}$$

where $V_{it} = \{IT_{it}, \Omega_{it}\}$ where Ω_{it} can be any other variable included in the smooth coefficient function. With regard to the unknown function $\theta(.)$ we assume that it depends on the level of IT capital. Checking for robustness we also use an alternative specification in which $\theta(.)$ depends on all inputs under consideration i.e., $\theta\left(IT_{it}, K_{it}, L_{it}, M_{it}\right)$

In estimating the $\theta(.)$ function we will adopt the smooth coefficient semiparametric approach [see Fan (1992), Fan and Zhang (1999) and Li, Huang, Li and Fu (2001)] in order to establish the effect of IT capital on productivity across industries and time.

3.4.2 Smooth Coefficient Semiparametric Approach

A smooth coefficient semiparametric model is considered to be a useful and flexible specification for studying a general regression relationship with varying coefficients. It is a generalization of varying coefficient models and it is based on polynomial regression [see Fan (1992), Fan and Zhang (1999), Kourtellos (2003)].

A semiparametric varying coefficient model imposes no assumption on the functional form of the coefficients, and the coefficients are allowed to vary as smooth functions of other variables. Specifically, varying coefficient models are linear in the regressors but their coefficients are allowed to change smoothly with the value of other variables. One way of estimating the coefficient functions is by using a local least squares method with a kernel weight function. Recent applications of the above model include Mamuneas, Savvides and Stengos (2005) and Stengos and Zacharias (2005). A semiparametric smooth coefficient model is given by:

$$y_i = \alpha(z_i) + x_i'\beta(z_i) + u_i$$

where $\alpha(z_i)$ and $\beta(z_i)$ are unspecified smooth functions of z_i.

Based on Li, Huang, Li and Fu (2002), the above semiparametric model has the advantage that it allows more flexibility in functional form than a parametric linear model or a semiparametric partially linear specification. Furthermore, the sample size required to obtain a reliable semiparametric estimation is not as large as that required for estimating a fully nonparametric model. It should be noted that when the dimension of z_i is greater than one, this model also suffers from the "curse of dimensionality", although to a lesser extent than a purely nonparametric model, where both z_i and x_i enter nonparametrically.

Li, Huang, Li and Fu (2002), proposed that the above model can be expressed more compactly as

$$y_i = \alpha(z_i) + x_i'\beta(z_i) + u_i = (1, x_i')\begin{pmatrix}\alpha(z_i)\\ \beta(z_i)\end{pmatrix} + u_i \equiv X_i'\delta(z_i) + u_i$$

where $\delta(z_i) = (\alpha(z_i), (\beta(z_i))')'$ is a vector of smooth but unknown functions of z_i, x_i is a $p \times 1$ vector, and z_i is of dimension q and $i = 1...n$.

They propose the following local least squares method to estimate $\delta(z_i)$:

$$\begin{aligned}\hat{\delta}(z_i) &= [(nh^q)^{-1}\sum_{j=1}^{n} X_j X_j' K(\frac{z_j - z}{h})]^{-1} \times [(nh^q)^{-1}\sum_{j=1}^{n} X_j y_j K(\frac{z_j - z}{h})] \\ &\equiv [D_n(z)]^{-1} A_n(z)\end{aligned}$$

where $D_n(z) = (nh^q)^{-1}\sum_j X_j X_j' K(\frac{z_j-z}{h})$, $A_n(z) = (nh^q)^{-1}\sum_j X_j y_j K(\frac{z_j-z}{h})$, $K(\cdot)$ is a kernel function and h is a smoothing parameter.

Based on the authors, the intuition behind the local least squares is apparent. Let us assume that z is a scalar and K is the uniform kernel. In this case:

$$\hat{\delta}(z) = [\sum_{|z_j - z| \preceq h} X_j X_j']^{-1} \sum_{|z_j - z| \preceq h} X_j y_j$$

Here $\hat{\delta}(z)$ is simply a least squares estimator obtained by regressing y_j on X_j where the corresponding z_j is close to z ($\mid z_j - z \mid \leq h$). Because $\delta(z)$ is a smooth function of z, $\mid \delta(z_j) - \delta(z) \mid$ is small when $\mid z_j - z \mid$ is small.

The condition that nh is large ensures that we have sufficient observations within the interval $\mid z_j - z \mid \leq h$ when $\delta(z_j)$ is close to $\delta(z)$. This condition allows the variance of the estimate to decline to zero. The condition $h \to o$ ensures that averaging takes place over a shrinking bandwidth, thus eventually eliminating bias. Therefore, under the conditions $h \to o$ and $nh \to \infty$ one can show that the local least squares estimator provides a consistent estimator of $\delta(z)$.

That is:

$\sqrt{nh^q}(\hat{\delta}(z) - \delta(z)) \longrightarrow N(0, \Omega)$.

Fan and Zhang (1999), suggest that the appeal of the varying coefficient model is that by allowing coefficients to depend on other variables, the modelling bias can significantly be reduced and the curse of dimensionality can be avoided.

Fan and Zhang (1999) denote the varying coefficient model as:

$$y_i = \gamma(z_i)' X_i + u_i$$

where $\gamma(z_i) = (\gamma_1(z_i), ..., \gamma_{p+1}(z_i))'$ is a smooth function that allows the coefficients to depend on z_i.

The varying coefficient model is characterized by the assumptions:

$$E(y_i \mid X_i = x_i) = \gamma(z_i)' x_i$$

$$Var(y_i \mid X_i = x_i) = \sigma^2(z_i).$$

Fan and Zhang (1999) and Kourtellos (2003) adopt an estimation procedure based on a simple local regression. Suppose that we have a random sample $\{(z_i, X_{i1}, ..., X_{ip}, y_i)\}_{i=1}^n$ from the varying coefficient model presented above. The estimation procedure solves a simple local least squares problem . To be precise, for each given point z_0, the functions $\gamma_j(z)$, $j = 1...p$, are approximated by local linear polynomials (first or second degree polynomials).

$$\gamma_j(z) \approx c_{j0} + c_{j1}(z - z_0)$$

for z in a neighborhood of z_0. This leads to the following weighted local least squares problem:

$$\sum_{i=1}^{n} [y_i - \sum_{j=1}^{p} \{c_{j0} + c_{j1}(z - z_0)\} X_{ij}]^2 K_h(z_i - z_0)$$

for a given kernel function K and bandwidth h, where $K_h(\cdot) = K(\cdot/h)/h$.

While this method is useful, it is implicitly assumed that the functions $\gamma_j(z)$ possess about the same degrees of smoothness and hence they can be approximated equally well in the same interval. Fan and Zhang (1999) propose a two-stage estimation procedure that allows the functional coefficients to possess different degrees of smoothness. In this case we only deal with one coefficient function so the one- stage approach is appropriate.

The solution to the least square problem can easily be obtained.

Let $y = (y_1, ..., y_n)'$, $W = diag(K_h(z_1 - z_0), ..., K_h(z_n - z_0)$, and

$$X = \begin{pmatrix} X_{11} & (z_1 - z_0)X_{11} & ... & X_{1p} & (z_1 - z_0)X_{1p} \\ . & . & . & . & . \\ . & . & . & . & . \\ X_{n1} & (z_n - z_0)X_{n1} & ... & X_{np} & (z_n - z_0)X_{np} \end{pmatrix}$$

The solution of the problem is given by:

$$\hat{\gamma}_j(z) = e'_{2j-1,2p}(X'WX)^{-1}X'Wy$$

where $e_{k,m}$ denote the unit vector of length m with 1 at the k_{th} position.

The conditional variance is also estimated by a normalized weighted residual sum of squares

$$\hat{\sigma}^2(z) = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 K_h(z_i - z)}{tr\left\{W - WX(X'WX)^{-1}X'W\right\}}$$

where

$$\hat{y}_i = (\hat{y}_1, ..., \hat{y}_n) = X(X'WX)^{-1}X'Wy$$

Based on the above our model becomes[4]:

$$T\hat{F}P_{it} = \hat{T}_{it} + \theta\left(V_{it}\right)I\hat{T}_{it} + u_{it}$$

[4]This is the general case. The same holds when adjustment costs are implicitly introduced into the model.

Let $V_{it} = \{IT_{it}, \Omega_{it}\}$ where Ω_{it} can be any other variable included in the smooth coefficient function.

The regression function becomes:

$$E(T\hat{F}P|T = t, V = v, I\hat{T} = \mathrm{I}\hat{\mathrm{T}}) = t + \theta\,(v)\,\mathrm{I}\hat{\mathrm{T}}$$

In general $\theta\,(.)$ is an unknown function approximated by a second order Taylor series at any given point v_0 as:

$$\theta\,(v) \simeq \theta\,(v_0) + \theta'(v_0)^T(v - v_0) + \frac{1}{2}(v - v_0)^T\theta''(v_0)(v - v_0)$$

where $\theta'(v_0)$ and $\theta''(v_0)$ are first and second derivatives respectively evaluated at v_0.

Our problem becomes the minimization of the following local nonlinear least squares criterion function over the parameter space:

$$C_n(W, \gamma) = n^{-1}\sum_{i=1}^{n}\{Y_{it} - m(W_{it}, \gamma)\}\,K_A(W_{it} - w)$$

where $K_A(.) = \det(A)^{-1}K(A^{-1})$ is a real valued multivariate Kernel, A is the bandwidth and $m(W_{it}, \gamma)$ is equal to:

$$m(X_{it}, V_{it}, it_{it}, \gamma) = \hat{T}_{it} + (\delta_1 + \delta_2^T(V_{it} - v) + (V_{it} - v)^T\delta_3(V_{it} - v))I\hat{T}_{it}$$

where $\gamma = (\beta, \delta_1, \delta_2, \delta_3)$. The parameters $\delta_1, \delta_2, \delta_3$ will give us the estimates of $\theta\,(.)$, its first and second derivatives respectively.

Here we use a standard multivariate kernel density estimator with Gaussian kernel and the rule of thumb suggested by Silverman (1986) as the choice of bandwidth. The bandwidth is chosen as $s_{zi}n^{-\frac{1}{4+q}}$, where s_{zi} is the estimate of the standard deviation of z_i and q is the dimension of the kernel.

3.5 Estimation Results

3.5.1 Specification Tests

In order to gain confidence about the validity of our estimated specifications we have performed several specification tests via a test proposed by Fan and Li (1996)[5].

Firstly, we have tested the semiparametric formulation used in our analysis against a general nonparametric model. In this case the null hypothesis of a semiparametric specification cannot be rejected against the alternative. The value of the statistic is -0.652.

Secondly, we proceed by testing the parametric specification against all the models mentioned so far in the paper. The parametric specification is rejected in all cases (p-values are zero for all cases).

We then test whether the model should include adjustment costs. This could be important since as mentioned in the literature omission of adjustment costs tends to understate the effect of IT on productivity. All test results suggest that the correct specification of our analysis should contain adjustment costs in the model. The specifications without adjustment costs were rejected in all cases with zero p-values.

The next step was to test which among the specifications with adjustment costs is appropriate, the one with the IT-capital growth rate in the current period $(I\hat{T}_{it})$ or the one with the IT-capital in the beginning of the period $(I\hat{T}_{it-1})$[6]. The

[5] Same test statistic was used and explained in the previous chapter.

[6] In order to check for robustness, we have also estimated the model with the end of period stock of IT to account for possible endogeneity, i.e.

$$T\hat{F}P_{it} = \hat{Y}_{it} - \hat{Q}_{it} = \hat{T}_{it} + \theta(.)I\hat{T}_{it-1} + \delta I\hat{I}_{it} + u_{it} \tag{3.7}$$

This model was also estimated using IT_{t-1} inside the θ function. All models provide similar results.

tests took place for both smooth coefficient semiparametric functions. Based on the test results we can conclude that the model with IT capital stock growth rate in the current period can not be rejected. The statistic when using the simple smooth coefficient function is 0.446 and when using the general coefficient function -0.979. Therefore, we will continue our analysis based on the model with adjustment costs and $I\hat{T}_{it}$ even though the two specifications provide similar results.

Finally, we have performed a test for the appropriate smooth coefficient function specification in the model with adjustment costs and IT-capital stock growth rate in the current period.

This test suggests that the model with the general smooth coefficient function, which captures cross effects among the other inputs and IT, is more appropriate. A zero p-value indicated the rejection of the null, which is the model with the simple smooth coefficient function.

Therefore the preferred specification is:

$$T\hat{F}P_{it} = \hat{Y}_{it} - \hat{Q}_{it} = \hat{T}_{it} + \theta(IT_{it}, K_{it}, L_{it}, M_{it})I\hat{T}_{it} + \delta I\hat{I}_{it} + u_{it}$$

Below we present the estimation results from our preferred specification[7].

[7]The TFP approach was used since the shares for the other inputs are allowed to be different for each industry and for each year. When estimating the TFP growth here, we are assuming optimizing behavior. For robustness check we have also estimated a Cobb-Douglas production function allowing the shares to be estimated and take one single value while the effect of IT capital was modeled as an unknown function. The results from both estimation procedures are similar. To be exact the intermediate input output elasticity is 0.652, the labor output elasticity is 0.146, the non-IT capital output elasticity is 0.069 and the output elasticities of IT vary from 0.023 to 0.061. Also the relationship appears nonlinear.

3.5.2 Results from the Smooth Coefficient Model

In estimating the semiparametric model, we have used two different smooth coefficient functions in order to check for robustness of our results under different settings. For the version of the semiparametric model with adjustment costs we use both $\hat{IT}_{t-1}$ and $\hat{IT}_t$ for each smooth coefficient function (equations 3.5 and 3.6). In addition, we have estimated the model without adjustment costs in order to establish whether the coefficients (estimated elasticities) are different. It has been mentioned in the literature that the omission of adjustment costs tends to understate the effect of IT on productivity growth. Estimating both models will help us clarify empirically this issue.

In this section we present the estimation results from our preferred specification, as indicated by the tests, and relevant comparisons when needed. The results from the other specifications are placed in Appendix D[8].

The estimate of the nonparametric component of this model, function $\theta(.)$, is examined using graphical tools. The preferred function $\theta\left(IT_{it}, K_{it}, L_{it}, M_{it}\right)$ is more general and it will capture any omissions made by $\theta\left(IT_{it}\right)$. The estimates of the function θ, in this case, cannot be examined using graphical tools unless we create a four dimensional graph. In order to obtain a graphical representation we could evaluate this relationship at the means of the three out of four variables. For example, we could take the value of $\theta(IT_{it}, \bar{K}, \bar{L}, \bar{M})$ and then use the new θ in a graph. In order to establish whether the effect differs among the two models (with and without adjustment costs) we plot the estimates of function θ from the smooth coefficient models mentioned above.

The importance of this work is the derivative of TFP growth with respect to IT-capital growth, or $\theta\left(.\right)$ without assuming that it can be proxied by the shares.

[8] Country and time specific dummies are included in all the models.

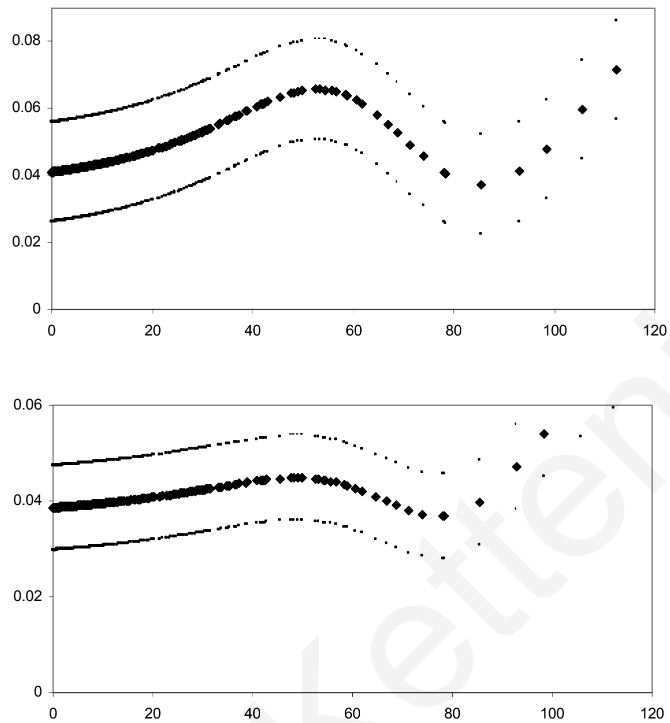

Figure 3.1: IT Output Elasticity with $\theta(IT_{it}, \bar{K}, \bar{L}, \bar{M})$

When estimating the nonparametric component of the smooth coefficient model we obtain the output elasticity of IT-capital i.e.,

$$\varepsilon_{YIT} = \frac{\partial F}{\partial IT_{it}} \frac{IT_{it}}{Y_{it}} = \theta\left(.\right)$$

Figure (3.1) plots the point-wise estimates of the output elasticity, $\theta\left(.\right)$, on the vertical axis and the level of IT-capital, IT_{it}, on the horizontal, revealing the effect of IT-capital (IT_t) obtained from the nonparametric component of the smooth coefficient model. The first graph was obtained from the model with adjustment costs and the second from the one without.

According to Figure (3.1), the effect of IT-capital is not constant across industries and time but varies considerably. Also we can state that the relationship between IT-capital and productivity appears to be nonlinear especially in the case where adjustment costs are included in the model[9]. The output elasticity appears to increase with the level of IT capital. Then at a certain level of IT it starts decreasing up to a point and it begins increasing again at very high levels of IT capital.

The two graphs give credence to the argument that the omission of adjustment costs understates the effect of IT-capital on productivity. We can see from Figure 3.1 that the output elasticities from the models with adjustment costs appear to be greater than the output elasticities from the model without adjustment costs. The vast majority of the output elasticity estimates from the model with adjustment costs lie in the range of 0.04-0.08, while for the model without from 0.04-0.06. However, the differences between the two are not large. This may be due to the fact that adjustment costs can not offset any gains from IT capital, even though they do exist.

From Figure 3.1 we observe that the output elasticities and therefore the effect of IT-capital on economic performance are understated when adjustment costs are not included in the model. The results are quite similar with the case in which the smooth coefficient function depends only on IT capital stock (presented in Appendix D).

Results are obtained for the average output elasticity per industry when $\theta(IT_{it}, K_{it}, L_{it}, M_{it})$ is used and are presented in Table 3.1 along with the average

[9]This gives further justification to the use of the smooth coefficient semiparametric model in our analysis.

IT-capital stock in order to examine in detail of what happens at the industry level [10]. Column 3 reports the elasticities from the model with adjustment costs and column 5 from the one without.

[10] Industry codes are presented in Appendix C.

Table 3.1: Output elasticities (Averages by Industry)

Code	*IT*	Elast.-Adj	Std. Error	Elast.-No Adj.	Std. Error
1	2.379	0.069	0.001	0.045	0.002
2	4.919	0.066	0.002	0.065	0.002
3	3.697	0.053	0.01	0.024	0.01
4	0.769	0.043	0.0003	0.042	0.0004
5	0.588	0.041	0.0004	0.043	0.0002
6	1.303	0.043	0.0003	0.042	0.0003
7	1.797	0.044	0.0005	0.039	0.0004
8	2.962	0.045	0.0006	0.039	0.0007
9	13.754	0.06	0.014	0.045	0.011
10	15.387	0.059	0.017	0.045	0.011
11	7.199	0.063	0.021	0.062	0.031
12	9.750	0.044	0.0007	0.04	0.0004
13	0.713	0.039	0.0002	0.043	0.0001
14	3.940	0.049	0.004	0.061	0.004
15	0.379	0.038	0.0003	0.043	0.0002
16	1.016	0.042	0.0002	0.042	0.0002
17	0.764	0.042	0.0004	0.042	0.0001
18	2.256	0.044	0.0003	0.039	0.0002
19	8.545	0.045	0.0004	0.039	0.0003
20	7.354	0.072	0.006	0.048	0.001
21	0.781	0.044	0.0003	0.039	0.0001
22	1.616	0.044	0.0002	0.04	0.0007

Table 3.1continue: Output elasticities

Code	*IT*	Elast-Adj.	Std. Error	Elast-No Adj.	Std. Error
23	0.098	0.036	0.0002	0.044	0.0001
24	34.920	0.08	0.011	0.044	0.013
25	67.078	0.085	0.019	0.05	0.009
26	26.977	0.053	0.006	0.026	0.006
27	58.537	0.084	0.005	0.052	0.006
28	26.787	0.088	0.003	0.055	0.003
29	73.499	0.093	0.004	0.056	0.005
30	20.843	0.061	0.007	0.04	0.002
31	30.977	0.074	0.013	0.046	0.016
32	2.086	0.044	0.0007	0.042	0.0006
33	1.035	0.042	0.0006	0.043	0.0004
34	55.098	0.091	0.019	0.046	0.009
35	1.857	0.043	0.001	0.042	0.0008
36	1.451	0.039	0.0006	0.044	0.0003
37	4.742	0.04	0.0012	0.043	0.0005
38	1.501	0.043	0.0015	0.042	0.001
39	6.541	0.066	0.012	0.034	0.013
40	4.385	0.046	0.0009	0.043	0.0005
41	0.785	0.045	0.0011	0.043	0.0006
42	17.285	0.064	0.005	0.033	0.004

The average elasticities from the model with adjustment costs lie within a range: 0.036 to 0.093. The average elasticities from the model without adjustment costs are lower. The elasticities from the model with adjustment costs, which is our preferred one, are larger for industries with high levels of IT- capital (IT-intensive industries), a result consistent with the literature. So the effect of IT on productivity is larger in industries with high levels of IT-capital. Also note that we observe larger elasticities particularly in the service sector. The same results hold in all the specifications used in this work and can be found in Appendix D[11].

The difference in the results between the two definitions of the smooth coefficient function, is that the output elasticities with $\theta\left(IT_{it}, K_{it}, L_{it}, M_{it}\right)$ appear to have shifted upwards for some industries, while for others have remained approximately the same. However, in both cases elasticity estimates are larger for the IT-intensive industries. The reason for that is that the change in the elasticities, is due to the fact that θ now depends on the other inputs, not just the IT capital and the cross effects among them affects the coefficient of IT. A technology can be intrinsically complementary with educated or skilled workers in the production process, who also have a role to play in the adoption of new technologies. If a new technology is embodied in a new machine, then it requires educated or skilled workers for successful adoption [see Helpam and Rangel (1999), Caselli (1999)]. If educated workers face smaller costs in the use of new machines than less educated workers, new machines will be assigned to educated workers. As a result IT causes the relative demand for less educated (unskilled labor) to decrease. Studies conclude that educated or skilled workers can facilitate the adoption of new technologies [see Bresnahan, Brynjolfsson, Hitt (2002), who conclude that IT capital is also a complement with human capital and organization structure]. The

[11] The same models were also estimated using Jorgensons KLEMS data for comparison purposes. The grpahs obtained are similar to the ones presented here, so the nonlinearity still exists. Also the average output elasticities, even though they are quite smaller than ours (0.032-0.058 with adjustment costs and 0.018-0.025 without), they are stll higher when adjustment costs are included in the model. Also IT intensive industries have higher output elasticities.

inclusion of these variables in the smooth coefficient function, since they affect IT in particular ways, leads to the shift of the output elasticities[12].

From the semiparametric smooth coefficient model analysis we can conclude that IT-capital has a positive effect on productivity and therefore economic growth. The effect appears to vary among industries and time and the output elasticities of IT are larger for IT-intensive industries[13]. Also, IT capital has a nonlinear effect on productivity, especially when adjustment costs are included in the model. In addition, we find that the omission of adjustment costs understate the effect of IT capital on productivity growth.

3.5.3 Sources of Output Growth

So far we have estimated the output elasticity of IT which was found to vary among industries and time. We have also found that IT capital growth has a positive but nonlinear effect on productivity growth. In this section we use the elasticities from the semiparametric smooth coefficient model in order to evaluate the sources of growth for each industry. We will present the results from the model that was tested to be the most appropriate for our analysis. When estimating the output elasticity of IT-capital, and assuming as before perfectly competitive markets that allow us to state that output elasticities equal observed income shares, we can recalculate a new total factor productivity growth rate variable as:

$$\hat{T}_{it} = \hat{Y}_{it} - w_{Lit}\hat{L}_{it} - w_{Kit}\hat{K}_{it} - w_{Mit}\hat{M}_{it} - w_{ITit}I\hat{T}_{it} + A\hat{D}J_{it}$$

[12]Further analysis is needed in order to investigate the relationship among the inputs included in the smooth function and IT capital. The cross effects should be obtained, (but a different methodology is needed) which is not an issue investigated in this chapter but it will follow in the next one.

[13]This is different from the results of Berndt and Morrison (1995) . The difference could be due to the fact that they have used different measures of IT capital. Their IT capital includes office, computing and accounting machinery, communication equipment, scientific and engineering instruments and photocopy and related equipment. The data, the sample period and the approach used differs as well.

where $w_{Xit} = 0.5(s_{Xit} + s_{Xit-1}), X = L, K, M$ denote weighted average shares of labor, non-IT capital and intermediate inputs and $w_{ITit} = 0.5(\varepsilon_{YITit} + \varepsilon_{YITit-1})$ under perfectly competitive theory and ADJ refers to the adjustment costs effect. Based on the above we can rewrite this equation in order to obtain the sources of growth:

$$\hat{Y}_{it} = w_{Lit}\hat{L}_{it} + w_{Kit}\hat{K}_{it} + w_{Mit}\hat{M}_{it} + w_{ITit}I\hat{T}_{it} + A\hat{D}J_{it} + \hat{T}_{it}$$

The growth rate of output is a weighted average of growth rates of inputs and $\hat{T}_{it}$ growth (includes scale effect, and technical change, also called efficiency effect). The contribution of each input is its weighted growth rate and the contribution of $\hat{T}_{it}$ is its growth rate. All contributions if added should give the output growth rate.

Table 3.2 presents results of growth decomposition for the period 1985-2001, using $\theta(IT_{it}, K_{it}, L_{it}, M_{it})$ as the smooth coefficient function of IT-capital growth rate, and results with $\theta(IT_{it})$ are also discussed for comparison purposes[14].

[14] The tables with $\theta(IT_{it})$ for the model with and without adjustment cost and for $\theta(IT_{it}, K_{it}, L_{it}, M_{it})$ but without adjustment costs, can be found in Appendix D.

Table 3.2: Sources of output growth, 1985-2001 (%)

Industry Code	Output Growth	Contrib. of capital	Contrib. of labor	Contrib. of interm. inputs	Contribution of IT capital	Contribution adjustment cost	Exogenous technical change
1	2.32	-0.006	0.36	1.26	0.65	0.07	-0.02
2	0.33	-0.08	-0.71	0.008	0.22	0.03	0.85
3	1.05	0.05	1.11	-0.13	0.55	-0.51	-0.007
4	1.15	-0.01	0.21	1.46	0.49	-0.26	-0.74
5	1.97	0.04	0.13	1.64	0.53	0.06	-0.43
6	0.97	0.07	-0.06	0.48	0.41	0.05	0.16
7	0.83	-0.08	-0.31	0.33	0.19	-0.19	0.89
8	1.45	0.03	-0.005	0.94	0.47	0.06	-0.05
9	5.88	0.03	-0.21	2.79	0.48	0.06	0.27
10	10.4	0.20	-0.27	4.62	0.42	0.08	5.34
11	1.84	0.05	-0.19	1.72	0.48	0.03	-0.25
12	1.93	0.06	-0.49	3.01	0.48	-0.26	-0.87
13	2.05	0.02	0.05	0.86	0.47	0.05	0.6
14	1.57	0.05	0.08	1.65	0.62	0.05	-0.87
15	-1.45	-0.02	-0.42	3.87	0.17	-0.002	-5.04
16	0.35	-0.04	-0.57	0.25	0.43	0.02	0.26
17	-0.17	0.003	-1.16	0.05	0.41	-0.12	0.67
18	0.97	0.09	-0.09	0.94	0.35	-0.27	-0.05
19	0.32	0.03	0.15	1.01	0.59	-0.41	-1.05
20	2.16	0.13	-0.04	1.16	0.54	0.03	0.33
21	0.59	-0.02	-0.14	0.67	0.24	-0.12	-0.04
22	4.23	0.14	0.36	2.66	0.59	0.06	0.42

Table 3.2continue: Sources of output growth

Industry Code	Output Growth	Contrib. of capital	Contrib. of labor	Contrb. of interm. inputs	Contribution of IT capital	Contribution adjustment cost	Exogenous technical change
23	-3.02	-0.05	-2.18	-1.69	0.48	-0.21	0.63
24	3.32	0.09	0.72	1.38	0.41	0.07	0.65
25	6.99	0.37	0.23	2.35	2.49	0.06	3.74
26	1.02	0.43	-0.06	-0.33	0.14	0.03	0.61
27	4.14	0.15	0.32	0.63	0.76	0.07	1.96
28	4.8	0.2	1.15	1.12	1.36	0.08	1.02
29	5.57	0.4	0.3	2.14	2.21	0.1	1.72
30	1.49	0.25	0.45	0.66	0.58	0.07	-0.52
31	2.9	0.44	0.1	2.51	0.49	0.08	-0.72
32	2.15	0.39	0.86	1.21	0.31	0.05	-0.66
33	2.59	0.05	0.59	2.6	0.64	0.08	-1.36
34	7.62	0.16	2.65	4.13	0.61	0.08	0.11
35	3.09	0.58	1.06	2.13	0.37	0.06	-1.11
36	2.39	0.05	0.31	3.36	0.77	-0.48	-1.62
37	4.9	0.25	1.9	3.37	0.76	-0.16	-1.24
38	5.11	0.26	1.96	3.49	0.18	0.06	-0.85
39	3.19	0.12	1.84	2.11	0.4	-0.46	-0.81
40	2.35	0.03	1.49	1.19	0.49	0.06	-0.91
41	3.06	0.05	1.74	1.68	0.56	-0.52	-0.44
42	4.78	0.08	1.93	2.77	0.45	0.08	-0.53

From Table 3.2, we can see that out of 42 industries, 39 experienced output growth during the period 1985-2001. A reduction in the growth rate of output occurred in tobacco products, apparel and other textile products and leather and leather products. These are manufacturing industries. Our results are similar to Mun (2002), who found that all manufacturing industries, except two exhibit positive productivity growth for the period 1983-1998. Leather and leather products experienced the larger reduction in growth (-3.02 percentage points). The reduction is mainly attributed to the negative contribution of non-IT capital, labor and intermediate input growth (-3.92). IT-capital growth contributed 0.06 percentage points in output growth and productivity 0.84. The reduction would have been larger by 0.9 percentage points in the absence of IT-capital growth and productivity. When adjustment costs are included in the model the contribution of IT capital increases to 0.48. The contribution of productivity reduces to 0.63, while adjustment costs have a negative contribution of -0.21 percentage points. In the electronics and other electrical equipment industry output grew 10.4% (the largest growth among all industries), as non-IT capital contributed 0.2, intermediate input 4.62 percentage points, IT-capital 0.37 and labor -0.27. TFP growth accounted for 5.46 percentage points. Based on that, input growth is the source of nearly 50 percent of growth in that industry. Note that the contribution would have been larger if labor contributed positively in output growth as well. IT-capital is the source of nearly 4 percent of output growth, while productivity accounted for 52.5 percent. Again, when adjustment costs are included the contribution of IT-capital increases to 0.42 and of productivity reduces to 5.34. Adjustment costs have a negligible effect which is close to zero and does not seem to affect output growth.

From Table 3.2 we obtain further verification to the fact that IT-capital contributes positively in an industry's output growth. Furthermore the contribution increases in most of the industries when adjustment costs are included in the model. One important finding from the decomposition of the sources of growth is that IT-capital growth contributed positively in raising income in all industries of our sample. As we can see this result holds even in industries who experienced a reduction in their output growth. Overall, the contribution of IT-capital growth was larger in communication, retail trade and bank and security, which are some of the IT-intensive industries[15].

We can conclude, based on the analysis above, that all industries (IT-intensive or not) benefited in terms of output growth from the existence of IT-capital. Therefore, we can claim that investment in IT-capital promotes output growth. Like in the case of output elasticities we can see that here too, omission of adjustment costs understates the effect of IT capital on productivity and therefore output growth. We can conclude that IT-capital growth is an important contributor to each industry's output growth, while most of the IT-intensive industries are those that experienced greater output growth.

[15]Looking at the results in Appendix D we can conclude that the positive contribution of IT holds also in the case in which the smooth coefficient function depends only on the level of IT capital.

3.6 Conclusion

In this chapter we investigate the impact of IT-capital to the process of productivity growth by allowing the contribution of various inputs to vary across industries and time. We construct a "biased" TFP index in order to evaluate the impact of IT on productivity growth. The use of the semiparametric smooth coefficient model allows us to estimate the output elasticities of IT-capital. Also, it allows us to examine possible nonlinearities in the relationship between IT capital and productivity. Furthermore, for consistency with the IT literature, adjustment costs are included in the model in order to establish their significance since IT capital is expected to incur adjustment costs.

Using data for 42 U.S. private industries over the period 1984-2001, consisting of gross output, intermediate inputs, labor, IT and non-IT capital we estimate a smooth coefficient semiparametric model to obtain the effect of IT-capital growth on productivity. We find this effect to be positive and to vary across industries and time. We find the output elasticity estimates to be larger for IT-intensive industries and the vast majority of output elasticities lie within a different range when comparing models with and without adjustment costs. Based on the elasticities, we can conclude that the omission of adjustment costs from the analysis understates the effect of IT capital on productivity. The graphical analysis, especially in the model with adjustment costs, indicates a nonlinear relationship between IT capital and productivity. Various specification tests provide support for the model with adjustment costs and a general smooth coefficient semiparametric function, giving further support to the results mentioned above and to the semiparametric model used. Based on that model, the sources of growth are recalculated. We find that IT is a positive contributor to output growth for all industries in the sample.

We leave the examination of the exact cross effects between IT capital and other inputs for the next chapter.

Chapter 4

Information Technology and Skill-Biased Technical Change

4.1 Introduction

A rising issue in the literature on IT has been the substitution of information technology equipment for other forms of capital and labor inputs. Some economists suggest that a direct consequence of the dramatic decline in the price of computer-related equipment has led to a substitution of IT equipment for other forms of capital and labor. Based on that, they suggest that this substitution generates substantial returns for agents who undertake IT investment.

A number of papers in the literature have investigated the relationship between IT and labor demand. They indicate that IT causes the relative demand for more highly educated and experienced workers, as well as the relative demand for highly skilled workers, to rise. IT-based production processes also causes substitution for low skill human work. This is referred to in the literature as skill-biased technical change (SBTC). Some economists argue that this SBTC has caused the wage inequality that has appeared in the US economy.

Overall wage inequality and the educational wage differentials have expanded substantially in the U.S over the past two decades. This widening of the wage structure has coincided with the rapid computerization of the work place. Thus, it is not surprising that many labor market analysts have tried to draw a causal connection between rising earnings inequality and increases in growth rate of the relative demand for more-skilled workers driven by technological and organizational changes associated with the computer revolution.

The rise in the U.S wage dispersion has involved both large increases in education wage differentials and a sharp growth in within-group wage inequality. One explanation that has been offered for the striking increase in wage inequality is the increase in the rate of growth of the relative demand for highly educated and more skilled workers arising from SBTC driven by the diffusion of computer-based technologies. Based on Katz (1999), it is clear that whatever is driving the rapid change of the relative demand growth for more-skilled workers over the past few decades is concentrated in the most computer-intensive sectors of the U.S economy. But these patterns do seem to have also contributed to recent movements in the US wage inequality and educational wage differentials.

The impact of technology on the demand for educated or skilled workers has been analyzed in two ways. A technology can be intrinsically complementary with educated or skilled workers in the production process. This complementarity predicts that the demand for educated workers will rise as long as the use of such technologies increases. There have been many empirical studies on the complementary relationship between the use of IT and skilled or educated workers. Most studies have used the IT capital stock or IT investment per worker as a measure of IT use and have found a positive relation between skilled labor and computer investment.

In contrast to the use of technologies, some studies emphasize the role of education or skill in the adoption of new technologies and they conclude that educated or skilled workers can facilitate the adoption of new technologies; that is, skilled workers convey a skill advantage in technology adoption. Helpman and Rangel (1999) and Caselli (1999) attempted to explain the interaction between technological change and labor markets. If educated workers face smaller costs in the use of new machines than less educated workers, new machines will more likely be assigned to educated workers, who in turn will increase their productivity and hence the demand for educated workers.

Chun (2003) suggests that the use and adoption effects have different implications for the future behavior of the employment structure by educational attainment. If educated workers are complementary with IT capital, then as long as the stock of IT rises, so will the demand for educated workers. This implies that there can be a long-run increase in the demand for educated or skilled workers. However, the increase in the demand for educated workers during the adoption process will disappear as technology implementation is completed.

An important drawback of the analysis on the impact of IT on various aspects of economic performance in the recent empirical literature is the non-existence of constant quality price indexes for various IT equipment. Constant quality price indexes are essential for identifying a change in price for a given level of performance. Accurate price indexes have not yet been developed or included in the statistics available for investments in important categories of IT equipment. Price indexes which do not hold performance constant present a distorted picture of the IT equipment price as well as their output and investment.

In this chapter we investigate whether IT causes SBTC. For our analysis, though, we use a framework general enough to be able to:

- capture the effect of IT prices on the demands of skilled and unskilled labor along with the same effect on the demands of non-IT capital and intermediate inputs
- capture the own and cross effects of all input prices and input demands (for all the inputs included in the analysis)
- avoid the use of IT equipment price indexes which appear problematic, and

- allow efficiency gains in production to arise when new inputs generate an improvement in technical efficiency that is not fully offset by costs of adjustment (adjustment costs are included explicitly in the model).

Based on the above, here we will be estimating a system of factor demand equations derived from a general cost function ("dynamic approach") along with some price expectation-generating processes from which we will be able to obtain the effect from IT capital on the demands of both skilled and unskilled labor. Data from various sources will be combined to create a database that divides workers into skilled and unskilled, includes IT and non-IT capital along with intermediate inputs and gross output for 42 US industries over the period 1983-2001. From the analysis we find that the efficiency gains from IT capital are the largest among all inputs included in the analysis. The efficiency gains can not be offset by costs of adjustment which are explicitly included in the model. Additionally the elasticities indicate that a decrease in the price of IT equipment causes the demand for skilled labor to rise and the demand for unskilled labor to decline. Therefore IT causes SBTC.

The rest of the chapter is organized as follows. Section 2 give evidence from the literature and section 3 describes the data used in this analysis. Section 4 presents the methodology for the theoretical model and section 5 the empirical model and the results. Section 6 presents the TFP analysis and last section concludes.

4.2 Information Technology and Skill-Biased Technical Change

Another issue arising in the literature based on Information Technology, has been the substitution of information technology equipment for other forms of capital and labor inputs. A number of papers in the literature have investigated the relationship between IT and labor demand. They indicate that IT causes the relative demand for more highly educated and experienced workers, as well as the relative demand for highly skilled workers to rise. IT - based production processes also causes substitution for low skill human work. This is referred in the literature as skill - biased technical change (SBTC). Some economists argue that this SBTC has caused the wage inequality that has appeared in the U.S. economy.

One line of research in this area has been concerned with the effect of information technology on the relative demand for workers with different education and skill levels.

Chun (2003), examines both the use and adoption effects of IT on the relative demand for educated workers. He uses data from 56 U.S industries for the period 1960-1996. His findings suggest that the demand for educated workers interacts with the use of IT as measured by the IT capital stock. Using the average age of IT capital as a proxy for IT adoption, the demand for educated workers increases as the age of IT capital declines. Specifically, he finds that the use of IT is complementary with educated workers, and that educated workers have a comparative advantage in the adoption of IT. The total IT effect accounts for almost 40 percent of the acceleration in the rate of relative demand growth for educated workers since 1970. Furthermore, the IT adoption effect contributed about one-third of the total IT effect on the acceleration in skill upgrading in the 1970s.

Bermand, Bound and Grilliches (1994), have investigated shifts in the demand away from unskilled and towards skilled labor in the U.S manufacturing over the 1980s. They decompose non-production labor into a term reflecting a reallocation between industries and another reflecting changes within industries. Their results suggest that this shift is due mostly to increased use of skilled workers within the industries rather than to a reallocation of employment between industries. Additionally, they indicate that increased use of non-production workers is strongly correlated with investment in computers and research and development (R&D). They also suggest that trade and defence demand are associated with only a small employment reallocation effect, so they don't serve as possible explanations for skill upgrading within the U.S manufacturing.

Autor, Katz and Krueger (1997) examine the effects of technological change and other factors on the relative demand for workers with different education levels and on the recent growth of U.S educational differentials. They use a supply-demand framework and data from 1940 to 1995. Their results indicate that the relative demand for college graduates grew more rapidly on average during 1970 to 1995 than during 1940 to 1995. The acceleration in demand for more skilled workers is entirely accounted for by an increase in within-industry changes in skill utilization rather than between industry employment shifts. They also suggest that the spread of computer technology may "explain" as much as 30 to 50 percent of the increase in the rate of growth of the relative demand for more skilled workers since 1970.

Bermand, Bound and Machin, (1998), find strong evidence for pervasive SBTC in developing countries. They state that industries increased the proportion of skilled workers despite generally rising or stable relative wages. Also they suggest an increased demand for skills in different countries. The authors conclude that SBTC was not only the major cause of decreased demand for less-skilled workers in the U.S, but also shifted demand from less-skilled to skilled workers throughout the developed world.

Falk and Stein (2001), use data for 1000 West German firms located in the service sector, and estimate a cencored least absolute deviations model as well as a Tobit model in order to examine the relationship between workers skill level and information technology. They find a significant relationship between firms skill structure and their IT investment output ratios. They suggest that IT serves as a substitute to unskilled labor and complement to both medium and high skills labor especially those who can efficiently use newly introduced IT structures. Based on the authors, there exists a complementarity between IT capital and the educational qualification structure of firms' workforce. Specifically, they indicate that the fall in demand for low skilled labor results from the systematic substitution of computers for human decision making. Note however that only a certain number of tasks can be replicated by IT so they are actually dealing with limited substitution.

Bresnahan, Brynjolfsson and Hitt (2002) examine how information technology could cause skill-biased technical change. They use for their estimation a panel data set of 400 U.S firms which covers the period between 1987 and 1994. They base their analysis on complementarities and they indicate that intensive use of IT, higher service level for customers and organizational change all go together, and together call for higher skilled labor. Based on their analysis, computerizing a firm requires that the firms work organization and the nature of its services and products must also be reinvented and as a result the types of workers employed and the skills of those workers are likely to change.

Based on the above studies we observe that IT causes the relative demand for more highly educated and experienced workers, as well as the relative demand for highly skilled workers to rise. And the relative demand for low-skilled workers to decrease.

There has been also a considerable amount of research on the impact of technological change on the wage structure. One line of research has focused on explaining interindustry wage differentials. These studies found a positive correlation between industry wages and technological change, using the capital to labor ratio or the research and development to sales ratio as proxies for technological change. A second line of research attempted to explain the dramatic increases in the earnings of more educated workers that took place during the 1980s. They showed that skill biased technical change was a major cause for the increase in the education premium. A third line of research utilized individual and plant - level data to study the wage impacts of technological change and find a positive relationship between workers's wage and their use of various new technologies.

Allen (1996) uses a cross section analysis to investigate how recent changes in technology are related to changes in wage differentials by schooling, experience and gender. He employs different measures of technological change and one of his main results is that returns to schooling and the wage gap between high school and college graduates increases much more in industries with rising employment share of scientists and engineers and industries that employ high-tech capital more intensively than in other industries. He also concludes that technology variables account for 30 percent of the increase in the wage gap between college and high school graduates.

Doms, Dunne and Troske, (1997), in their paper document how plant - level wages, occupation mix, workforce education and productivity vary with the adoption of new factory automation technologies. Based on the authors, dramatic changes in the types of technologies available to business have altered the production process in many workplaces , as well as the structure of employment. Specifically, it is argued that many of these new technologies increased the demand for skilled workers. The authors use two methods for approaching the question mentioned above. In their cross- section analysis, they show that plants that use new technologies employ more educated workers, employ relatively more managers and professionals and pay higher wages. In their time series analysis, they show little correlation between skill upgrading and the adoption of new technologies. Comparing the two models, they conclude that plants that adopt new technologies have more skilled force pre- and post adoption.

Autor, Katz and Krueger (1997) examine the effects of technological change and other factors on the relative demand for workers with different education levels and on the recent growth of U.S. educational differentials. They conclude that there are reasons to question whether an acceleration in the pace of skill - biased technological change is the primary reason for the recent sharp increase in U.S. wage inequality and educational wage differentials.

Bartel and Sicherman (1999), focus on the first two lines of research and they match a variety of industry level measures of technological change to a panel of young workers and examine the role played by observed and unobserved heterogeneity in explaining the positive relationship between technological change and wages. They use a sample of 12,686 individuals who were 14-21 and employed in manufacturing. They find that the wage premium associated with technological change is primarily due to the sorting of more able workers into those industries and this premium is uncorrelated to any sorting based on gender or age.

Caselli (1999), in his paper clarifies the mechanism by which on impact the information technology revolution generates absolute gains for those individuals with high cognitive ability and absolute losses for those with high costs of learning. The paper discusses the potential revolution of the wage structure. He concludes that ever - widening wage differentials, and potentially learning externalities will draw an increasing number of workers in the skilled pool, thereby reducing inequality. However, decreasing marginal returns to capital may lead the economy towards a steady state in which labor market remains split between skilled and unskilled workers. His main empirical finding is that the recent increase in wage inequality is associated with increased inequality in capital labor ratios.

Arabsheibani and Marin (1999) study the effect on wages of skill-biased technical technology (and especially the use of computers) using data from the UK collected based on questionnaires. They provide evidence that computers themselves raise wages. They conclude that although their impact on wages fall as other controls are included in the regression, it stills remains significant. Furthermore, improvements in computer use have an additional impact on earnings.

Black and Lynch (2000), use a unique nationally representative sample of US establishments in both 1993 and 1996 to examine the relationship between workplace innovation and establishment productivity and wages. To do so, they employ both cross-sectional and longitudinal data and they suggest that high performance workplace practices are associated with both higher productivity and higher wages.

Beaudry and Green (2001), try to answer the question "how population growth, through its interaction with recent technological and organizational developments can account for many of the cross - country differences in economic performance". Their analysis is based on a general equilibrium framework and their evidence are based on a comparative study of observed developments in the US, UK and Germany. They conclude that industrial countries with higher population growth rates will experience a more pronounced adoption of new technologies, a better performance in terms of increased employment rates, a poorer performance in terms of wage growth for less skilled workers, a large increase in the service sector and a large increase in the returns to education.

Jacobs and Nahuis (2002), use an endogenous growth model of wage inequality and technological change and indicate that a general purpose technology (GPT) explains the Solow productivity paradox. Based on their analysis, high - skilled workers spend more time learning in order to accumulate firm specific capital. The growth rate of output falls because time spent in production falls. So a GPT causes a slowdown in output growth. And wage inequality increases because skilled workers receive a premium as a result of higher productivity in learning in order to cope with the new technology. However over time output growth recovers as the stock of technology increases. As new technologies are implemented skilled - workers gradually reallocate their time and spend more time producing again. Wage inequality decreases as skilled workers cooperate with unskilled workers in production.

Card and DiNardo (2002), review the evidence for the skill - biased technical change hypothesis and conclude that it is not very helpful in understanding the myriad shifts in the structure of wages that have occurred over the past three decades. They mention that although the version of SBTC used is consistent with some of the changes that have occurred over the past three decades, both fall short in many key dimensions. A fundamental problem is that rises in overall wage inequality have not persisted in the 1990 despite the continuing advances in computer technology. They suspect that while some of the early rise in inequality may have been due to rapid technological change, the increase in the early 1980s is largely explained by other plausible factors. So as they suggest, it appears that the rise in wage inequality was an episodic event.

Existing studies, using various methodologies and data sets, have concluded that new technologies may induce wage differential among skilled and unskilled workers. Additionally, they have shown that the demand for skill workers have increased in a number of countries. However, the results in the literature remain somehow inconclusive.

Based on the IT literature [see Jorgenson (2004)], the rate of IT price decline is a key component of the cost of capital, required to assess the impacts of rapidly growing stocks of computers, communication equipment and software.

Constant quality price indexes are essential for identifying the change in price for a given level of performance. The challenge is to separate observed price changes in IT equipment performance and changes in price that hold performance constant. In order to do so, the "matched model" was introduced for semiconductor prices [Dulberger (1993)] which was based on the Fisher Ideal Index and combined price relatives for products with the same performance at different points of time. Grimm (1998), combined the "matched model" techniques with hedonic methods, based on an econometric model of semiconductors prices at different points of time. The hedonic model gives the price of a product as a function of the characteristics that determine performance.

However, semiconductors account for less than half of computers costs and computer prices have fallen much less rapidly than semiconductors prices. Accurately and timely computer prices have been part of the US National Income and Product Accounts since 1985. Unfortunately, important information gaps remain especially for trends in prices for closely related investments such as software and communication equipment.

Communication technology is crucial for the rapid development of the internet, perhaps one of the most striking manifestation of IT in the economy. Communication equipment is a major important market for semiconductors, but constant quality price indexes cover only a portion of this equipment. Grimm's (1997) constant quality price index for digital telephone switching equipment was incorporated into the national accounts in 1996. NIPA also incorporate a constant quality index for cellular phones. Doms (2004), has provided comprehensive price indexes for terminals, switching gear and transmission equipment, but are not yet included in the US NIPA.

Both software and hardware are essential for IT and this is reflected in the large volume of software expenditure. Software investment is growing rapidly and is now equally or even more important than investment in computer hardware. The Bureau of Economic Analysis (BEA) defines three types of software - prepackaged software, custom software and own-account software. However, only price indexes for prepackaged software hold performance constant (not prior 1998 though).

Price indexes which do not hold the performance constant, present a distorted picture of software and communication equipment prices as well as their output and investment. As a result the analysis of the impact of information technology on the US economy, which is based on the national accounts, can be considered incomplete.

4.3 Data Description

This study covers 42 U.S. private industries[1] over the period 1983-2001 and the data are the same with the data used in Mun (2002) and Nadiri and Mun (2002) for comparison purposes. The data used for the construction of IT capital are the same as the ones used in Chapter 3, except concerning the way prices are constructed.

Firstly, the nominal values and chain-type price indexes of gross output and intermediate inputs are obtained from the Gross Product Originating (GPO) published by the Bureau of Economic Analysis (BEA).

For the capital stock, we use data for 61 types of assets from the Fixed Reproducible Tangible Wealth (FRTW) provided by the BEA. Using geometric depreciation rates for each assets from Fraumeni (1997), capital stocks are constructed using a perpetual inventory method. We use the average (fixed) Moody's Aaa corporate bond yield for the nominal rate of return, the investment deflator and a fixed depreciation rate.

[1] See Appendix C for list of industries used.

Using the Tornqvist index method, we aggregate the 61 types of assets for each industry into two types of capital, IT and non-IT capital stocks.

IT capital stock includes mainframe computers, personal computers, direct access storage devices, computer printers, computer terminals, computer tape drives, computer storage devices, integrated systems, software which consists of prepackaged software, custom software and own-account software and communication and other office and accounting equipment (hardware, software and communication technology). The non-IT capital stock consists of other non-IT equipment and structures.

The number of full time equivalent employees (obtained from the GPO published by the BEA) is used as the total quantity of labor. The total wage index is constructed by dividing total compensation of employees by the number of full time equivalent employees.

To obtain data for skilled and unskilled labor we use the Panel Study of Income Dynamics (PSID) database. The PSID is a longitudinal study of a representative sample of US individuals and the family units in which they reside. It emphasizes the dynamic aspects of economic and demographic behavior but its content is broad including sociological and psychological measures. The PSID sample size includes nearly 8000 families and approximately 65,000 individuals.

Using the PSID, we collected data from 1983 to 2001 in order to match them with the range of our other variables range. For every year in our sample, we obtained for each individual data on his/hers education in order to be able to separate skilled and unskilled workers. We define skilled workers as the individuals with more that secondary education, the individuals, that is, with a college or a higher postgraduate degree. Additionally, we collected data for the individuals wages and the number of hours they spend working.

To match the two databases (BEA and PSID) we also obtained data on the kind of industry that specific individuals were involved in[2]. We kept the individuals who appear to work in the same 42 industries used in the BEA database.

Using the PSID, we obtained for each year the variables mentioned above for more than 15,000 individuals.

Next, we used the education variable to generate a dummy for skill. This dummy variable equals one if the individual has a college or higher degree and zero otherwise (which gives us information on the unskilled workers).

Using the dummy variable we found the percentage of skilled individuals in each industry, and therefore the percentage of unskilled ones. These percentages were then used to break the total number of employees (from the BEA) to skilled and unskilled (for each industry and each year).

So far we have obtained the total number of employees (N), the skilled (N_s) and unskilled (N_u) ones for each year and industry.

We know that :

$N = N_s + N_u$

Also:

$VL = P_L L = P_L NH = P_u L_u + P_s L_s = P_u N_u H_u + P_s N_s H_s = VL_u + VL_s$where VL is the total compensation of employees (value of labor) obtained from BEA, P_L is the price of labor (wage), L is the quantity of labor, N is the number of employees and H are the hours worked. Note that s defines the skilled and u the unskilled workers.

[2]The 3-digit industry codes used in the PSID are similar to those developed by the US Bureau of Census, with minor changes that dont matter in our case. The changes involve industries that are not included in the 42 we use.

To proceed, we use the wage variables from the PSID and the dummy created to break the wages into skilled and unskilled and calculate the share of each categories wage in total wage per industry.

Using the share we obtain (the compensation of each category):

$VL_s = VL * SW_s$

$VL_u = VL * SW_u$

We then proceed to use all the information from PSID to obtain the price of labor for both skilled and unskilled such that:

$P_s = VL_s/N_sH_s$

Similarly, we find P_u for each industry.

Summing up, for the estimation we have data for 42 industries from 1983-2001, for skilled and unskilled labor, their wages and their total compensation. Additionally from BEA we have variables for gross output, intermediate inputs, IT and non-IT capital. Our data set includes now all the information needed for the estimation procedure.

4.4 Methodology- Theoretical Model

The empirical analysis will be based on a more general production function following the methodology of Bernstein, Mamuneas and Pashardes (2004). Their paper introduces a parameterization of technical efficiency directly into the production function adding a dynamic dimension to the problem. Efficiency gains in production arise when new inputs generate an improvement in technical efficiency that is not fully offset by costs of adjustment.

Specifically, they consider a production function written as:

$$y_t = F[\upsilon_{1t-1} + h_1(\upsilon_{1t} - \upsilon_{1t-1}), ..., \upsilon_{nt-1} + h_n(\upsilon_{nt} - \upsilon_{nt-1}), t]$$

where y_t is the output quantity for period t, F is the production function, υ_{it} is the i^{th} input quantity in period t, and t is the exogenous disembodied technology index.

Factor accumulation is presented by:

$$\upsilon_{it} = x_{it} + (1 - \delta_i)\upsilon_{it-1}$$

where x_{it} is the addition to the i^{th} input quantity in period t, and $0 \leq \delta_i \leq 1$ is the i^{th} input depreciation rate.

Input demands are determined from minimizing the expected present value of acquisition and hiring costs. The expected value is given by the following:

$$\sum_{s=0}^{\infty} \sum_{i=1}^{n} a(t, t+s) q^e_{it+s} x_{it+s}$$

where q^e_{it+s} is the expectation in the current period t of the i^{th} factor acquisition or hiring price in period $t+s$ and $a(t, t+s)$ is the discount factor. The expected value is minimized subject to the production function and the factor accumulation equations.

This problem is equivalent to the following:

$$\min_{z_{it}} \sum_{i=1}^{n} \omega_{it} z_{it}$$

subject to the production function for periods $t = 0 ... \infty$. The $z_{it} = h_i(\upsilon_{it} - \mu_i \upsilon_{it-1})$ is the efficiency-adjusted i^{th} input quantity, $\mu_i = 1 - h_i^{-1}$and ω_{it} is the i^{th} user cost in period t.

By differentiating the cost function with respect to the user cost, it is possible to retrieve the efficiency-adjusted factor demands.

Based on the authors' estimation, the above method requires the specification of two elements: the cost function and the price expectation-generating process for the acquisition and hiring prices. When doing so a system can be estimated, by nonlinear SUR, which includes: the factor demand equations (derived from the cost function chosen) along with the specified price expectation-generating process (the authors suggested it to be an AR(1)).

Specifically, based on Bernstein, Mamuneas and Pashardes (2004), suppose a production function F in year t can be written as:

$$y_t = F(z_{1t}, z_{2t}, ..., z_{nt}, t)$$

where y_t is the quantity of output produced in year t, z_{it} is the efficiency adjusted quantity of input i used in year t and t captures exogenous disembodied technical change.

Net investment in input i involves two components. The first, x_{it}, represents the quantity of gross investment in the i^{th} input observed in year t, while the second, $\delta_i \upsilon_{it-1}$, represents the replacement investment, the amount needed to just replace the amount of old input that depreciates between the previous and the current year. The coefficient δ_i is the geometric decay rate for the input i, with $0 \preceq \delta_i \preceq 1$, and υ_{it-1} is the observed stock of input i in year $t-1$. When $\delta_i = 1$ input i is non-durable. Based on that, the observed stock of input i in year t is:

$$\upsilon_{it} = \upsilon_{it-1} + (x_{it} - \delta_i \upsilon_{it-1})$$

The approach to input efficiency allows for the possibility that the marginal product of new inputs may be higher or lower than old inputs. Any change in input levels involves an introduction of new inputs into the production process. While the technical efficiency of new inputs may exceed that of old ones, adjustment costs can offset positive efficiency effects.

Efficiency adjustment is defined as:

$$z_{it} = \upsilon_{it-1} + h_i(x_{it} - \delta_i \upsilon_{it-1})$$

where h_i is the efficiency adjustment parameter for input i. The authors suggest that the parameters h_i reflect the variations in net efficiency by capturing the gains from factor improvements and the losses associated with adjustment costs. Here following the results from chapter 3, since adjustments costs appear important they are explicitly introduced into the model. One attraction of this model is the parsimonious treatment of efficiency as a single parameter for each input. Moreover, in this model there is no fixed boundary between factors displaying efficiency gains (or losses) and factors for which efficiency growth is constrained a priori.

The value of h_i can lie in one of three possible ranges:

- $h_i > 1$. The marginal product of net additions of input i in current year exceeds that of existing units of the input. Specifically, the higher technical efficiency of net additions outweighs the adjustment costs of introducing these net additions into the production process.

- $0 < h_i < 1$. In this case, even if the technical efficiency of a net addition of the input is higher than that of existing units it is insufficient to offset costs of adjustment.

- $h_i = 1$. The increased technical efficiency of net additions is being just offset by costs of adjustment.

4.4.1 Cost Minimization

The optimal levels of efficiency adjusted inputs are determined by minimizing the expected present value of an infinite future stream of input requirements subject to three constraints:

$$\min_{\{x_{1t+\tau},\ldots,x_{Nt+\tau}\}_{\tau=0}^{\infty}} E_t \left\{ \sum\nolimits_{\tau=0}^{\infty} (1+\rho_{t+\tau})^{-\tau} \left(\sum\nolimits_{i=1}^{N} q_{it+\tau} x_{it+\tau} \right) \right\} , \tag{4.1}$$

$$\text{subject to: (i) } y_{t+\tau} = F(z_{1t+\tau}, z_{2t+\tau}, ..., z_{Nt+\tau}, t+\tau) \quad \forall t, \tau;$$

$$\text{(ii) } \upsilon_{it+\tau} = x_{it+\tau} + (1-\delta_i)\upsilon_{it+\tau-1} \ \ \forall t, \tau, \ i = 1, 2, ..., N \text{ ; and}$$

$$\text{(iii) } z_{it+\tau} = h_i(x_{it+\tau} - \delta_i \upsilon_{it+\tau-1}) + \upsilon_{it+\tau-1} \ \ \forall t, \tau; \ i = 1, 2, ..., N \ ,$$

where: E_t denotes an expectation based on information available in year t; $\rho_{t+\tau}$ is the discount rate in year $t+\tau$; and $q_{it+\tau}$ is the acquisition or hiring price for the i^{th} input for year $t+\tau$. Producers form expectations of the acquisition and hiring prices; assume, as is customary, that there are static expectations regarding the discount rate, i.e. assume that $E_t\left(\rho_{t+\tau}\right) = \rho_t \ \forall \tau$.

Rearranging the constraints to replace each z_i, the Lagrangian for the revised optimization problem which solves for the optimal levels of $\upsilon_{1t+\tau}, \ldots, \upsilon_{Nt+\tau} \nabla \tau$ is:

$$\begin{aligned} \mathcal{L} = \sum\nolimits_{\tau=0}^{\infty} (1+\rho_t)^{-\tau} \Big[\sum\nolimits_{i=1}^{N} & q^e_{it+\tau} \left(\upsilon_{it+\tau} - (1-\delta_i)\upsilon_{it+\tau-1} \right) \\ & + \lambda_{t+\tau} \left(y_{t+\tau} - F\left(\begin{matrix} \cdot \\ t+\tau \end{matrix} \right) \right) \Big] , \end{aligned} \tag{4.2}$$

where: $q^e_{it+\tau} = E_t(q_{it+\tau})$; $q^e_{it} = q_{it}$; $\lambda_{t+\tau}$ is the Lagrangian multiplier in year $t+\tau$; and $F\left(\begin{smallmatrix} \cdot \\ t+\tau \end{smallmatrix}\right)$ denotes:

$$F\Big(h_1(\upsilon_{1t+\tau} - \mu_1 \upsilon_{1t+\tau-1}), \ldots, h_N(\upsilon_{Nt+\tau} - \mu_N \upsilon_{Nt+\tau-1}), t+\tau \Big)$$

where $\mu_i = 1 - 1/h_i \ \forall i$.

The first-order condition for each input i in year $t+\tau$ is:

$$(1+\rho_t)^{-\tau} q^e_{it+\tau} - (1+\rho_t)^{-\tau} \lambda_{t+\tau} (\partial F \begin{pmatrix} \cdot \\ t+\tau \end{pmatrix} / \partial z_{it+\tau}) h_i \tag{4.3}$$

$$-(1+\rho_t)^{-(\tau+1)} q^e_{it+\tau+1} (1-\delta_i)$$

$$-(1+\rho_t)^{-(\tau+1)} \lambda_{t+\tau+1} (\partial F \begin{pmatrix} \cdot \\ t+\tau+1 \end{pmatrix} / \partial z_{it+\tau+1}) (-h_i \mu_i) = 0 \ ,$$

$$\tau = 1, 2 \ldots \ ; \ i = 1, 2 \ldots N.$$

Let

$$w^e_{it+\tau} = q^e_{it+\tau} - d_i a_t q^e_{it+\tau+1} \quad , \ \tau = 1, 2 \ldots \ ; \ i = 1, 2 \ldots N, \tag{4.4}$$

where: $d_i = (1-\delta_i)$ and $a_t = 1/(1+\rho_t)$. Multiply (4.3) by $(1+\rho_t)^\tau$, substitute (4.4) into the resulting expression and rearrange to get:

$$h_i \lambda_{t+\tau} \partial F \begin{pmatrix} \cdot \\ t+\tau \end{pmatrix} / \partial z_{it+\tau} = w^e_{it+\tau} \tag{4.5}$$

$$+ a_t \mu_i \left[h_i \lambda_{t+\tau+1} \partial F \begin{pmatrix} \cdot \\ t+\tau+1 \end{pmatrix} / \partial z_{it+\tau+1} \right] \ ,$$

$$\tau = 1, 2 \ldots \ ; \ i = 1, 2 \ldots N.$$

Successive substitutions on the right-hand side of (4.5) generate, for each year up to $T_M > t$:

$$h_i \lambda_{t+\tau} \partial F \begin{pmatrix} \cdot \\ t+\tau \end{pmatrix} / \partial z_{it+\tau} = w^e_{it+\tau} + \sum_{\upsilon=1}^{T_M-1} (a_t \mu_i)^\upsilon w^e_{it+\tau+\upsilon}$$

$$+ (a_t \mu_i)^{T_M} \left[h_i \lambda_{t+\tau+T_M} \partial F \begin{pmatrix} \cdot \\ t+\tau+T_M \end{pmatrix} / \partial z_{it+\tau+T_M} \right] \ , \tag{4.6}$$

$$\tau = 0, 1, 2, \ldots \ ; \ i = 1, 2, \ldots, N.$$

Provided that, for each τ and for each input i, the term

$$h_i \lambda_{t+\tau+T_M}\, \partial F \left(\underset{t+\tau+T_M}{\cdot} \right) / \partial z_{it+\tau+T_M}$$

is finite $\forall\, T_M$ – this is ensured by quasi-concavity of F – and, providing that $|a_t \mu_i|$ < 1,[3] the following limit condition (the tranversality condition) exists:

$$\lim_{T_M \to \infty} (a_t \mu_i)^{T_M} \left[h_i \lambda_{t+\tau+T_M} \partial F \left(\underset{t+\tau+T_M}{\cdot} \right) / \partial z_{it+\tau+T_M} \right] = 0.$$

Then, in the limit (4.6) reduces to:

$$\lambda_{t+\tau} \partial F \left(\underset{t+\tau}{\cdot} \right) / \partial z_{it+\tau} = (1/h_i) \left(w^e_{it+\tau} + \sum\nolimits_{\upsilon=1}^{\infty} (a_t \mu_i)^{\upsilon} w^e_{it+\tau+\upsilon} \right) \quad , \tag{4.7}$$

$$\tau = 0, 1, 2, ... \, ; \; i = 1, 2, ..., N.$$

This equation shows that the value of the marginal product at the cost-minimizing level of the efficiency-adjusted input i – the left-hand side of (4.7) – equals the discounted expected marginal cost of holding the input at that level in perpetuity – the right-hand side of (4.7).

[3] Note that to ensure that the marginal product is non-negative in all years, it must be that $h_i > 0 \; \forall i$. Also, since negative real rates of return are ruled out, $a_t > 0$. These preliminaries lead to a pair of cases for $|a_t \mu_i|$:

(a) When $\mu_i \geq 0$ ($h_i \geq 1$), the condition $a_t \mu_i < 1$ requires that

$$h_i > -1/\rho_t \, ,$$

which is always met since ρ_t is always > 0.

(b) When $\mu_i < 0$ ($0 < h_i < 1$)the condition $a_t \mu_i > -1$ requires that

$$h_i > 1/(2 + \rho_t) \; .$$

As a result, the only restriction on h_i is that it exceed $1/(2 + \rho_t)$. For a discount rate of 3%, this means that h_i must be greater than 0.49 $\forall i$.

The right-hand side of (4.7) is referred to as the user cost of efficiency-adjusted input i; in particular, this user cost in year $t+\tau$ is denoted by the variable:

$$\omega_{it+\tau} = (1/h_i)\left(w^e_{it+\tau} + \sum\nolimits_{\upsilon=1}^{\infty} (a_t\mu_i)^{\upsilon} w^e_{it+\tau+\upsilon}\right) \quad , \qquad (4.8)$$
$$\tau = 0, 1, 2, ... ; \; i = 1, 2, ..., N.$$

The derivations to this point are useful in the sense that they define the user cost of each input in terms of expected acquisition prices, the efficiency parameter and the decay rate for that input. These user costs affect factor requirements – a straightforward way to see this is with the cost function. To derive the cost function, consider the following minimization problem for processors in year t

$$\min_{z_{1t}, z_{2t}, \ldots, z_{Nt}} \left\{\sum\nolimits_{i=1}^{N} \omega_{it} z_{it} \;\; | y_t = F(z_{1t}, z_{2t}, ..., z_{Nt}, t)\right\}. \qquad (4.9)$$

The Lagrangian for (4.9) is

$$\mathcal{L}_z = \sum\nolimits_{i=1}^{N} \omega_{it} z_{it} - \lambda_{zt}\left[y_t - F(z_{1t}, z_{2t}, ..., z_{Nt}, t)\right]$$

with first-order conditions

$$\omega_{it} = \lambda_{zt} \partial F \binom{\cdot}{t} / \partial z_{it} \;\; , \;\; i = 1, 2, ..., N. \qquad (4.10)$$

Substitute for ω_{it} in (4.10) using (4.8) and rearrange to get:

$$\lambda_{zt} \partial F \binom{\cdot}{t} / \partial z_{it} = (1/h_i)\left(w^e_{it+\tau} + \sum\nolimits_{\upsilon=1}^{\infty} (a_t\mu_i)^{\upsilon} w^e_{it+\tau+\upsilon}\right) . \qquad (4.11)$$

Since $\lambda_{zt} = \lambda_t$ – compare (4.7) and (4.11) – the two problems give the same first-order conditions and therefore the same level of optimal demands for each efficiency-adjusted input. Since a cost function can be used to represent all relevant aspects of the production technology, the analysis that follows will use this function to derive all of the information needed.

A cost function is defined for all $\omega_{it+\tau}, y_{t+\tau}$ and $t+\tau$ as[4]

$$\begin{aligned} &C(\omega_{1t+\tau}, \omega_{2t+\tau}, ..., \omega_{Nt+\tau}, y_{t+\tau}, t+\tau) \equiv \\ &\min_{z_{1t+\tau}, z_{2t+\tau}, \ldots, z_{Nt+\tau}} \left\{ \sum\nolimits_{i=1}^{N} \omega_{it+\tau} z_{it+\tau} \mid \right. \\ &\qquad \left. F(z_{1t+\tau}, z_{2t+\tau}, ..., z_{Nt+\tau}, t+\tau) \geq y_{t+\tau} \right\} \quad , \ \tau = 0, 1, 2, \ldots \end{aligned} \tag{4.12}$$

Application of Shephard's Lemma to (4.12) gives the optimal efficiency-adjusted demand functions:

$$\begin{aligned} z^*_{it+\tau} &= Z_i(\omega_{1t+\tau}, ..., \omega_{Nt+\tau}, y_{t+\tau}, t+\tau) \\ &= \partial C(\omega_{1t+\tau}, \omega_{2t+\tau}, ..., \omega_{Nt+\tau}, y_{t+\tau}, t+\tau)/\partial \omega_{it+\tau} \\ &\qquad \tau = 0, 1, 2, \ldots; \ i = 1, 2, ..., N. \end{aligned} \tag{4.13}$$

Note that, while (4.13) allows a derivation of the optimal efficiency-adjusted input levels planned by producers in year t for years $t, t+1, t+2, t+3, \ldots$, as previously noted, the only levels of interest are those planned for year t. Thus, the only set of input demand functions relevant to this analysis is that where $\tau = 0$ in (4.13), i.e.

[4]Note that, given the properties of the production function F assumed earlier, the cost function $C : \Re_+^{N+L+M+2} \rightarrow \Re_+$ will fulfill several properties required for duality between F and C. The cost function can then be used to completely describe the production technology.

$$z_{it}^* = Z_i(\omega_{1t}, ..., \omega_{Nt}, y_t, t) \tag{4.14}$$
$$= \partial C(\omega_{1t}, \omega_{2t}, ..., \omega_{Nt}, y_t, t)/\partial \omega_{it} \ \ , \ i = 1, 2, ..., N.$$

Although z_{it}^* is unobservable, it is possible to relate this to v_{it}. Assuming that the efficiency-adjusted levels are cost-minimizing (i.e. $z_{it} = z_{it}^* \ \forall i, t$), combine constraints (ii) and (iii) and use (4.14) to obtain:

$$v_{it} = (1/h_i)\, Z_i \binom{\cdot}{t} + \mu_i v_{it-1} \ \ , \quad i = 1, 2, ..., N. \tag{4.15}$$

where: $Z_i \binom{\cdot}{t}$ is the demand function defined by (4.14). This expresses the current level of observed input i as a weighted average of the optimal level of efficiency-adjusted input – captured by the function $Z_i \binom{\cdot}{t}$ – and the observed input quantity from the previous year.

4.4.2 Price Expectations and User Costs for Efficiency-Adjusted Inputs

Price expectations play an important role in the optimization framework outlined above. This subsection provides details regarding the data generating process used to define the expected acquisition or hiring prices $q_{it+\tau}^e$ and the implications for user costs. Producers are assumed to know this data generating process and to use it when forming expectations about future acquisition or hiring prices of inputs.

Suppose that processors make expectations of the acquisition or hiring prices based on a first-order autoregressive process, which at time t ($\tau = 0$) is specified as:

$$q_{it+1}^e = \phi_i + \theta_i q_{it} \ , \ i = 1, 2 \ldots, N \, , \tag{4.16}$$

where: q_{it+1}^e denotes $E_t(q_{it+1})$, and ϕ_i, θ_i are parameters that are known to the processors, but are unknown to the analyst and therefore must be measured in the estimation stage. The expected realized error is zero;

$$E_t(e_{it+1}) = E_t(q_{it+1} - q_{it+1}^e) = 0 \, .$$

To determine the expected acquisition price in year $t + \tau$, note that

$$q_{it+2}^e = \phi_i + \theta_i q_{it+1}^e$$

where q_{it+2}^e denotes $E_t(q_{it+2})$, and substitute this into (4.16). Make substitutions in this manner successively for each year forward to obtain the following expression for the expected (in year t) acquisition or hiring price for year $t + \tau$:

$$q_{it+\tau}^e = \phi_i (1 - \theta_i^\tau)/(1 - \theta_i) + \theta_i^\tau q_{it} \tag{4.17}$$

$$\tau = 1, 2, \ldots \, ; \, i = 1, 2 \ldots, N \, ,$$

where $q_{it+\tau}^e$ denotes $E_t(q_{it+\tau})$ – as is clear from this expression, it is necessary that $\theta_i \neq 1$ for each input i; however, no other condition needs to be placed on either the sign or magnitude of ϕ_i or θ_i.[5]

[5] The successive substitutions lead to the following expression:

$$q_{it+\tau}^e = \phi_i \sum_{\upsilon=0}^{\tau-1} \theta_i^\upsilon + \theta_i^\tau q_{it} \, . \tag{i}$$

Since the sum $\sum_{\upsilon=0}^{\tau-1} \theta_i^\upsilon$ has the solution $(1 - \theta_i^\tau)/(1 - \theta_i)$ when $\theta_i \neq 1 \ \forall \ i$ (i) can be expressed as (4.17) in this case. Note that no restriction on θ_i at all is needed if $\phi_i = 0$ in the expectations process (4.16), since in this case, the process takes the simpler form

$$q_{it+1}^e = \theta_i q_{it} \ , \ i = 1, 2 \ldots, N \, . \tag{ii}$$

Use of (4.4) and (4.17) allows a substitution for $w^e_{it+\tau+\upsilon}$ in (4.8) to give:

$$\begin{aligned}\omega_{it+\tau} = (1/h_i)\Big\{&[\phi_i/(1-\theta_i)]\left[(1-\theta_i^\tau) - d_i a_t(1-\theta_i^{\tau+1})\right] \\ &+[\phi_i/(1-\theta_i)]\sum_{\upsilon=1}^{\infty}(a_t\mu_i)^\upsilon\left[(1-\theta_i^{\tau+\upsilon}) - d_i a_t(1-\theta_i^{\tau+\upsilon+1})\right] \\ &+\left[\theta_i^\tau - d_i a_t\theta_i^{\tau+1}\right]q_{it} + \sum_{\upsilon=1}^{\infty}(a_t\mu_i)^\upsilon\left[\theta_i^{\tau+\upsilon} - d_i a_t\theta_i^{\tau+\upsilon+1}\right]q_{it}\Big\} \quad , \\ &\tau = 0,1,2,\ldots\,;\ ,\ i = 1,2\ldots,N\,.\end{aligned} \tag{4.18}$$

Collection of terms in (4.18) leads to:

$$\begin{aligned}\omega_{it+\tau} = (1/h_i)\Big\{&[\phi_i/(1-\theta_i)]\Big[(1-d_i a_t) - \theta_i^\tau\,(1-d_i a_t\theta_i) \\ &+(1-d_i a_t)\sum_{\upsilon=0}^{\infty}(a_t\mu_i)^\upsilon - \theta_i^\tau\,(1-d_i a_t\theta_i)\sum_{\upsilon=1}^{\infty}(a_t\mu_i\theta_i)^\upsilon\Big] \\ &+[\theta_i^\tau\,(1-d_i a_t\theta_i)]\Big[1+\sum_{\upsilon=1}^{\infty}(a_t\mu_i\theta_i)^\upsilon\Big]q_{it}\Big\}\ , \\ &\tau = 0,1,2,\ldots\,;\ i = 1,2\ldots,N\,.\end{aligned} \tag{4.19}$$

Equation (4.19) contains two geometric series:

(a) $\sum_{\upsilon=1}^{\infty}(a_t\mu_i)^\upsilon$, which has the solution $a_t\mu_i/(1-a_t\mu_i)$ – providing $|a_t\mu_i| < 1\,\forall\, i$; and

(b) $\sum_{\upsilon=1}^{\infty}(a_t\mu_i\theta_i)^\upsilon$, which has the solution $a_t\mu_i\theta_i/(1-a_t\mu_i\theta_i)$ – providing $|a_t\mu_i\theta_i| < 1\,\forall\, i$.[6]

Sucessive substitutions with (ii) mean that (i) and (4.17) simplify to

$$q^e_{it+\tau} = \theta_i^\tau q_{it}\ . \tag{iii}$$

[6]Solution (a) is ensured when $|a\mu_i| < 1$, the necessary condition for which, as noted earlier, is that $h_i > 1/(2+\rho)$. On the other hand, for solution (b), only sufficient

With solutions (a) and (b), (4.19) simplifies to:

$$\omega_{it+\tau} = (1/h_i)[\phi_i/(1-\theta_i)]\left\{(1-d_ia_t)/(1-a_t\mu_i) - \theta_i^\tau(1-d_ia_t\theta_i)/(1-a_t\mu_i\theta_i)\right\} \tag{4.20}$$

$$+(1/h_i)\left[\theta_i^\tau(1-d_ia_t\theta_i)/(1-a_t\mu_i\theta_i)\right] q_{it}$$

$$\tau = 0,1,2,\ldots;\ i = 1,2\ldots,N\,.$$

Since, for estimation purposes, the only year of interest is year t (i.e. for $\tau = 0$), the user cost for efficiency-adjusted inputs can be further simplified and expressed in more compact notation as:[7]

$$\omega_{it} = \Theta_{0it} + \Theta_{1it}q_{it}\ \ ,\ i = 1,2,...,N, \tag{4.21}$$

where:

$$\Theta_{0it} = (1/h_i)[\phi_i/(1-\theta_i)]\left\{(1-d_ia_t)/(1-a_t\mu_i) - (1-d_ia_t\theta_i)/(1-a_t\mu_i\theta_i)\right\}$$

and

$$\Theta_{1it} = (1/h_i)(1-d_ia_t\theta_i)/(1-a_t\mu_i\theta_i).$$

Notice that Θ_{0it} and Θ_{1it} are not fixed parameters, but vary over time due to that fact that the discount rate used to determine the minimum expected acquisition and hiring cost of the production plan also varies over time.

Unlike traditional user costs, ω_{it} as defined by equation (4.21) cannot be evaluated prior to estimation since values for the parameters μ_i, ϕ_i and θ_i cannot be observed. This aspect of the model is addressed in the estimation section.

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conditions on the components of the product $a\mu_i\theta_i$ can be established, namely (i) that $h_i > 1/(2+\rho)$ and (ii) that $|\theta_i| < 1$.

Note that the geometric series $\sum_{\iota=0}^{\infty} m^\iota$, where $m \in \Re$, has the solution $1/(1-m)$ if $|m| < 1$. The solution to the same series with the first element ($m^0 = 1$) removed, i.e. $\sum_{\iota=1}^{\infty} m^\iota$ is therefore $[1/(1-m)] - 1 = m/(1-m)$.

[7] Note that, in the case of expectations where $\phi_i = 0\ \forall i$, $\Theta_{0it} = 0\ \forall i$ and $\forall t$, and (4.21) reduces to $\omega_{it} = \Theta_{1it}q_{it}$.

Additionally by allowing the prices to be estimated we are not avoiding the direct use of IT equipment price indexes which appear problematic.

4.4.3 Elasticities

Elasticities of input demand and production cost with respect to input prices, output quantity and disembodied technical change are important elements when analyzing the effects of changes in market conditions and government policies on producers.

This section presents the elasticities of efficiency-adjusted and observed input demands for each input i with respect to:

- own and cross user costs of efficiency-adjusted inputs (ω_i, ω_j), and acquisition or hiring prices (q_i, q_j) ;
- output quantity (y);
- disembodied technical change (t).

Price Elasticities of Demand for Efficiency-Adjusted Inputs

Elasticities with Respect to User Costs The elasticity of demand for efficiency-adjusted input i with respect to the user cost of this input, ω_{it}, evaluated in year t, is:

$$\epsilon^{z\omega}_{iit} = \left[\partial Z_i \binom{\cdot}{t} / \partial \omega_{it}\right] (\omega_{it}/z^*_{it}) \ , \quad i = 1, 2, ..., N. \qquad (4.22)$$

where: $Z_i \binom{\cdot}{t}$ is the demand function defined by (4.14) and z^*_{it} is the value of this function (i.e. the optimal demand) in year t.

Similarly, the elasticity of demand for efficiency-adjusted input i with respect to the user cost of input j, ω_{jt} $(j \neq i)$, and evaluated in year t, is:

$$\epsilon_{ijt}^{z\omega} = \left[\partial Z_i \begin{pmatrix} \cdot \\ t \end{pmatrix} / \partial \omega_{jt}\right] (\omega_{jt}/z_{it}^*) \quad , \quad i, j = 1, 2, ..., N \; ; \; j \neq i. \tag{4.23}$$

Elasticities with Respect to Acquisition or Hiring Prices To determine the elasticity of demand for efficiency-adjusted input i with respect to the acquisition or hiring price for that input, q_{it}, note that by (4.21), $\partial\omega_{it}/\partial q_{it} = \Theta_{1it}$. This result allows a definition of this elasticity in year t, as:

$$\begin{aligned} \epsilon_{iit}^{zq} &= \left[\partial Z_i \begin{pmatrix} \cdot \\ t \end{pmatrix} / \partial \omega_{it}\right] (\partial\omega_{it}/\partial q_{it}) (q_{it}/z_{it}^*) \\ &= \epsilon_{iit}^{z\omega} (q_{it}/\omega_{it}) \Theta_{1it} \quad , \quad i = 1, 2, ..., N. \end{aligned} \tag{4.24}$$

Using the same reasoning, the elasticity of demand for efficiency-adjusted input i with respect to the acquisition or hiring of input j, q_{jt} $(j \neq i)$, in year t, is:

$$\epsilon_{ijt}^{zq} = \epsilon_{ijt}^{z\omega} (q_{jt}/\omega_{jt}) \Theta_{1jt} \; , \; i, j = 1, 2, ..., N \; ; \; j \neq i. \tag{4.25}$$

Elasticities of Efficiency-Adjusted Input Demand to Non-Price Variables

The following derivations are with respect to (4.14). In particular, the elasticity of demand for efficiency-adjusted input i with respect to output quantity is defined as:

$$\epsilon_{it}^{zy} = \left[\partial Z_i \begin{pmatrix} \cdot \\ t \end{pmatrix} / \partial y_t\right] (y_t/z_{it}^*) \quad , \quad i = 1, 2, ..., N. \tag{4.26}$$

The elasticity of efficiency-adjusted input i with respect to disembodied technical change is:

$$\epsilon_{it}^{zt} = \left[\partial Z_i \begin{pmatrix} \cdot \\ t \end{pmatrix} / \partial t\right] (1/z_{it}^*) \; , \; i = 1, 2, ..., N. \tag{4.27}$$

Elasticities of Observed Input Demand to Non-Price Variables

The following derivations are with respect to (4.15). The elasticity of observed input demand i to a change in output is:

$$\begin{aligned} \epsilon_{iyt}^{vy} &= (1/h_i)\left[\partial Z_i\begin{pmatrix} \cdot \\ t \end{pmatrix}/\partial y_t\right](y_t/v_{it}) \\ &= \epsilon_{it}^{zy}\left[z_{it}^*/(h_i v_{it})\right], \quad i = 1, 2, ..., N. \end{aligned} \tag{4.28}$$

Finally, the elasticity of observed demand for input i to technical change is defined as:

$$\begin{aligned} \epsilon_{it}^{vt} &= (1/h_i)\left[\partial Z_i\begin{pmatrix} \cdot \\ t \end{pmatrix}/\partial t\right](1/v_{it}) \\ &= \epsilon_{it}^{zt}\left[z_{it}^*/(h_i v_{it})\right] \qquad, \quad i = 1, 2, ..., N. \end{aligned} \tag{4.29}$$

Elasticities of Cost with Respect to Non-Price Variables

From (4.13) the cost of optimal efficiency-adjusted inputs in year t is[8]

$$c_t^* = \sum\nolimits_{i=1}^{N} \omega_{it} z_{it}^* = C\begin{pmatrix} \cdot \\ t \end{pmatrix},$$

where $C\begin{pmatrix} \cdot \\ t \end{pmatrix} = C(\omega_{1t}, \omega_{2t}, ..., \omega_{Nt}, y_t, t)$. Given this definition, the elasticity of cost with respect to output is

[8] Note that the elasticity of cost with respect to prices is already captured, since by Shephard's lemma, $\partial C\begin{pmatrix} \cdot \\ t \end{pmatrix}/\partial\omega_{it} = z_{it}^*$ – see (14).

Also, note that since $c_t^* = \sum_{i=1}^{N} \omega_{it} z_{it}^*$,

$$\partial C\begin{pmatrix} \cdot \\ t \end{pmatrix}/\partial y_t = \sum\nolimits_{i=1}^{N} \omega_{it} \partial Z_i\begin{pmatrix} \cdot \\ t \end{pmatrix}/\partial y_t.$$

In other words, the elasticity of cost with respect to any non-price variable (in this case y_t) can be expressed a multiplicative transformation of the efficiency-adjusted input demand functions.

$$\epsilon_t^{cy} = \left[\partial C \binom{\cdot}{t} / \partial y_t\right] (y_t / c_t^*) = \sum\nolimits_{i=1}^{N} c_{it}^* \epsilon_{it}^{zy} \ , \tag{4.30}$$

where: $c_{it}^* = \omega_{it} z_{it}^* / c_t^*$, i.e. the cost elasticity can be expressed as a expenditure share-weighted average of the elasticities of demand for efficiency-adjusted inputs with respect to output.[9]

The elasticity of cost to disembodied technical change is:

$$\epsilon_t^{ct} = \left[\partial C \binom{\cdot}{t} / \partial t\right] (1 / c_t^*) = \sum\nolimits_{i=1}^{N} c_{it}^* \epsilon_{it}^{zt} \ . \tag{4.31}$$

4.5 Empirical Model

4.5.1 Functional Form

Several flexible functional forms could be used to estimate the model developed in the previous section. Of these, the chosen form – the symmetric generalized McFadden (SGM) cost function – allows concavity to be imposed without at the same time reducing flexibility.

The SGM cost function, with five inputs (skilled (S), unskilled labor (U), IT (IT), non-IT capital (K) and intermediate inputs (M)) one output, and trend, has the following form:

[9] The fact that the cost elasticity can be derived from the input elasticities is important when the cost function is not actually estimated (i.e. when only the input demand equations are estimated). The same is true for the other cost elasticity derivations that follow.

$$C^{SGM}(\omega_{1t},\omega_{2t},\omega_{3t},\omega_{4t},\omega_{5t},y_t,t)= \tag{4.32}$$

$$[\sum_{i=1}^{5}\beta_i\omega_{it}+\frac{0.5\sum_{i=1}^{5}\sum_{j=1}^{5}\beta_{ij}\omega_{it}\omega_{jt}}{\sum_{i=1}^{5}b_i\omega_{it}}$$
$$+\sum_{i=1}^{5}\beta_{it}\omega_{it}t+\beta_{tt}\left(\sum_{i=1}^{5}b_i\omega_{it}\right)(t)^2]y_t \tag{4.33}$$
$$+\alpha_t\left(\sum_{i=1}^{5}b_i\omega_{it}\right)t+\sum_{i=1}^{5}\alpha_i\omega_{it}+\alpha_{yy}\left(\sum_{i=1}^{5}b_i\,\omega_{it}\right)y_t^2$$
$$,\ t=1,2,\ldots,T,$$

where: $\beta_{ij}=\beta_{ij}\forall i,j$, and the each b_i $(i=1,2,\ldots,5)$ is a fixed exogenous weight.

Efficiency-adjusted input demands are obtained from the SGM cost function:

$$Z_i^{SGM}(\omega_{1t},\omega_{2t},\omega_{3t},\omega_{4t},\omega_{5t},y_t,t)= \tag{4.34}$$
$$\beta_i+\left(\sum_{j=1}^{5}\beta_{ij}\omega_{jt}\Big/\sum_{i=1}^{5}b_i\omega_{it}\right)y_t$$
$$-(1/2)\left(b_i\sum_{i=1}^{5}\sum_{j=1}^{5}\beta_{ij}\omega_{it}\omega_{jt}\Big/\left(\sum_{i=1}^{5}b_i\omega_{it}\right)^2\right)y_t$$
$$+\beta_{it}ty_t+\beta_{tt}b_it^2y_t$$
$$+\alpha_tb_it+\alpha_i+\alpha_{yy}b_iy_t^2$$
$$i=1,2,...,5\ \ ,\ t=1,2,\ldots,T.$$

Since, taken together, these demand functions contain all of the coefficients in the cost function, it is possible to estimate the system of demand equations without losing any information.

4.5.2 Estimation

The variables z_{it} are unobservable, so direct estimation of demand equations (4.34) is not possible. Instead the estimated equations are:

$$v_{it}=(1/h_i)\,Z_i^{SGM}\binom{\cdot}{t}+\mu_iv_{it-1}\ . \tag{4.35}$$

Equations (4.35) allow estimation of the coefficients in (4.34) using observed data.

Concavity is imposed on equations (4.34)[10]. With the simplification that $\phi_i = 0 \forall i$, expression (4.21) becomes[11]

$$\omega_{it} = \frac{1}{h_i} \left[(1 - d_i a \theta_i) / (1 - a \mu_i \theta_i) \right] q_{it} \ . \ , \tag{4.36}$$

where $d_i = 1 - \delta_i$.

Finally, to reduce any possible heteroskedasticity and to make calculations with the results more tractable, the resulting version of equation (4.35) is divided through by output (y_t).

Once the concavity and user cost elements are incorporated in the demand equations for efficiency-adjusted inputs, the outcome is a set of equations that are very nonlinear in coefficients.

These demand equations are estimated as a system along with the expectations equations:

$$q_{it+1} = \theta_i q_{it} + e^q_{it+1} \ , \ i = 1, 2, 3; \ t = 1, 2, \ldots, T-1 \tag{4.37}$$

where e^q_{it+1} is a random disturbance associated with the expectations equation for acquisition price i. The properties of the disturbances are discussed in the next section.

[10] See Appendix E for details on imposing concavity.

[11] With $\phi_i = 0 \forall i$, the expectations process given by (4.16) simplifies to (for three inputs):

$$q^e_{it+1} = \theta_i q_{it} \ , \ i = 1, 2, 3 \, .$$

Two things come about with this restriction. First, the only restriction on θ_i implied by the theory, i.e. that $\theta_i \neq 1 \ \forall i$, is no longer needed.Second, it means that the ratio of two expected prices will always be directly proportional to the observed ratio of these prices.

4.5.3 Econometric issues

Since the demand for each efficiency-adjusted input is determined by the same processors and since the errors on these demands are generated in part by random deviations from the optimal levels of these inputs, there is likely to be some correlation between the error in the demand equation for one input and in that for another. Similarly, since expectations are made by the same processors, the expectations errors – between $E_t(q_{ut+1})$ formed in year t and the realization of this variable, q_{ut+1}, in year $t+1$ – are assumed to be correlated with the optimization errors and vice versa. Thus, since the errors across equations are assumed to be correlated within any year, and since each equation shares some coefficients with the others, the econometric problem is to estimate a set of non-linear seemingly unrelated equations with lagged dependent variables. The system of equations may therefore be specified in the general notation as:

$$
\begin{align}
v_{y1} &= \Phi_1(\beta', X) + e_1^v \ , \notag \\
v_{y2} &= \Phi_2^v(\beta', X) + e_2^v \notag \\
v_{y3} &= \Phi_3^v(\beta', X) + e_3^v \notag \\
v_{y4} &= \Phi_4^v(\beta', X) + e_4^v \tag{4.38} \\
v_{y5} &= \Phi_5^v(\beta', X) + e_5^v \tag{4.39} \\
q_1 &= \Phi_1^q(\beta', X) + e_1^q \notag \\
q_2 &= \Phi_2^q(\beta', X) + e_2^q \notag \\
q_3 &= \Phi_3^q(\beta', X) + e_3^q \notag \\
q_4 &= \Phi_4^q(\beta', X) + e_4^q \tag{4.40} \\
q_5 &= \Phi_5^q(\beta', X) + e_5^q \tag{4.41}
\end{align}
$$

where: v_{yi} and q_i , $i = 1, 2, 3, 4, 5$, are vectors of observations on the dependent variable, β' is a vector of coefficients to be estimated, X is a matrix of observations on the regressors, and $e_1, .., e_{10}$ are vectors of disturbances.

The disturbances are assumed to have the following features:

$$\begin{aligned}
E(e^v_{it}e^v_{js}) &= \sigma^2_{vvij} \text{ for } t = s \text{ and zero otherwise;} \\
E(e^q_{it+1}e^q_{js+1}) &= \sigma^2_{qqij} \text{ for } t = s \text{ and and zero otherwise;} \\
E(e^v_{jt}e^q_{is+1}) &= \sigma^2_{vqij} \text{ for } t = s \text{ and and zero otherwise.}
\end{aligned}$$

The system of nonlinear equations can be estimated using a generalized least squares method that minimizes the sum of squared errors using pseudoregressors obtained from a linearization of each equation. Since the linearization still requires the evaluation of gradients at a point, and since these gradients are a non-linear function of the coefficients that comprise β, numerical methods must be used to find a solution to the least squares problem. There are a variety of algorithms that could solve the problem, but success (convergence to a vector $\hat{\beta}$ that gives a a global minimum) may depend upon the algorithm chosen. When convergence is reached, the resulting $\hat{\beta}$ computed is consistent and asymptotically efficient.

Consistent estimation of the coefficient vector $\hat{\beta}$ and of the asymptotic covariance matrix of these parameters does not require that a distribution for the disturbances be specified. In fact, it is possible to say that $\hat{\beta}$ is asymptotically normal and efficient as well, without assuming anything about the distribution for the disturbances. Here the equations are jointly estimated by the Nonlinear Seemingly Unrelated Regression estimator applied to data for 42 US industries over the period from 1983 to 2001[12].

[12]We also assumed for simplicity constant returns to scale.

4.5.4 Estimation Results

The choice of values for the exogenous constants b_1, b_2, b_3, b_4, b_5 is essentially up to the researcher, although these are usually set to the sample mean levels. Here, b_i is computed prior to estimation using sample averages of observed data:

$$b_i = \; v_i^{ave} \Big/ \sum\nolimits_{k=1}^{5} v_k^{ave}$$

where: $v_i^{ave} = \sum\nolimits_{t=1}^{T} v_{it}/T$, $t = 1, 2, \ldots, T$, $i = 1, 2, 3, 4, 5$; i.e., this is the average observed constant-dollar level of input i over the sample.

The initial starting values for the coefficients were set to levels that seemed plausible; in part, these were chosen to obtain convergence in early runs of the model.

With these settings and adjustments, the system converged. The resulting coefficient estimates are presented in Table 4.1[13].

[13] Industry dummies were also included in the estimation.

Table 4.1: Regression Results with Efficiency Change

Parameter	Estimate	Std. Error
β_{UU}	-0.0562	5.50E-03
β_{UK}	4.20E-03	1.50E-03
β_{UI}	0.0292	2.70E-03
β_{US}	6.30E-03	1.80E-03
β_{UM}	0.0800	1.03E-02
β_{KK}	-3.10E-04	2.20E-04
β_{KI}	-2.20E-03	8.00E-04
β_{KS}	-4.60E-04	2.10E-04
β_{KM}	-5.90E-03	2.10E-03
β_{II}	-1.79E-01	2.80E-03
β_{IS}	5.50E-03	1.40E-03
β_{IM}	-4.75E-02	4.80E-03
β_{SS}	-2.82E-02	6.60E-03
β_{SM}	9.90E-03	7.20E-03
β_{MM}	-1.27E-01	2.40E-02
β_{U}	5.20E-06	1.50E-02
β_{K}	4.18E-02	6.50E-03
β_{I}	4.83E-02	8.40E-03
β_{S}	-1.07E-02	3.70E-03
β_{M}	4.73E-01	2.83E-02

Table 4.1(continue): Regression Results with Efficiency Change

Parameter	Estimate	Std. Error
β_{UT}	4.70E-03	1.30E-03
β_{KT}	-4.00E-05	2.70E-04
β_{it}	-3.30E-03	5.10E-04
β_{ST}	1.10E-03	3.20E-04
β_{MT}	-5.90E-03	1.90E-03
β_{TT}	-1.00E-04	1.50E-04
h_U^{-1}	0.5610	0.0137
h_K^{-1}	0.4704	0.0121
h_I^{-1}	0.2613	0.0119
h_S^{-1}	0.4166	0.0704
h_M^{-1}	0.6779	0.0216
θ_U	0.0293	0.0377
θ_K	0.8583	0.0188
θ_I	0.8305	0.0130
θ_S	0.7198	0.0261
θ_M	0.1621	0.0362
Equation	Std. Error	R^2
Unskilled Labor	0.0198	0.9740
Non-IT capital	3.20E-03	0.9970
IT capital	4.60E-03	0.9960
Skilled labor	2.60E-03	0.9980
Int. inputs	0.0324	0.9870
Log of L.F	18817.9	

The estimates of the efficiency parameters suggest that technical efficiency levels increase with factor addition. Moreover because $h_i = 1$ implies that efficiency does not change, the rate of efficiency growth for the it$h$ input can be expressed as $h_i - 1$. Significant adjustment costs would occur if efficiency parameters were below 1, implying negative rates of efficiency growth. These rates are estimated to be 0.78% for unskilled labor, 1.12% for non-IT capital, 2.82% for IT capital, 1.4% for skilled labor and 0.48% for intermediate inputs.

With respect to labor, our results indicate that the efficiency gains arising from new skilled labor are higher than those from new unskilled labor. The efficiency gains from new skilled labor are not offset by the efficiency eroding adjustment costs. The estimated rates of efficiency growth for intermediate inputs and for non-IT capital accumulation indicate that new intermediate inputs and new non-IT capital are more efficient than their current levels.

The results in this chapter indicate that technical efficiency levels rise with new IT capital inputs. From the estimation results we observe that IT capital has the larger rate of efficiency growth among all inputs. Therefore the efficiency gains from IT capital improvements are not offset by the reductions in efficiency arising from IT capital adjustment costs.

The large efficiency effect of IT capital relative to the other inputs could mean that, over the sample, where there were net increases in every year, the contribution of this input in production increased not only because of net additions, but also because those net additions had a higher marginal product than IT capital already in use or that was just replaced.

4.5.5 Elasticities

The formulas for the elasticities are derived from the specific form presented in (4.22) and are the empirical counterpart of the equations presented in the theoretical part of this work.

The question we want to answer in this paper is whether IT causes SBTC. Based on the results from the system estimation presented in Table 4.1 we observe that the efficiency coefficients are statistically significant. In this section we report the elasticities for each input and each industry with respect to own and cross user costs of efficiency adjusted inputs. The results are presented in Appendix F.

Over the sample, the demands for efficiency adjusted inputs were negatively affected by their own user cost prices, so they appear to have the correct sign.

Before we analyze the relationship between the price of IT capital and the demands for skilled and unskilled labor, here are the results concerning the other inputs included in this analysis.

For most of the industries, the cross elasticities with respect to the user cost of non-IT capital indicate that this inputs price and IT capital, skilled labor and in fewer cases intermediate inputs were complements in production. That is, since the elasticities appear to be negative, an increase of the price of non-IT capital causes the demand of non-IT capital to decrease along with the demand of IT-capital, skilled labor and in some industries intermediate inputs. Similar results exist in the case of intermediate inputs, even though the price of intermediate inputs seems to have a negative effect on both types of labor depending on the industry under investigation.

The cross elasticities with respect to the user costs of unskilled labor appear positive, except in some industries when the demand for intermediate inputs is concerned. That means that an increase in the wage of unskilled labor causes the relative demand of IT-capital, non-IT capital and skilled labor to rise.

Finally the cross elasticities with respect to skilled labor are negative with both non-IT and IT capital, positive with unskilled labor and intermediate inputs. That is an increase in the wage of skilled labor causes the demand for IT and non-IT capital to decrease and the demand for unskilled labor to rise.

In this chapter we are interested in whether IT causes SBTC. So we are going to focus on the cross elasticities with respect to the user cost of IT capital and analyze the case of decreasing IT prices since this is the picture in the US economy during the last decade.

The cross effect of IT prices on the demand for non-IT capital appears to be negative for a large fraction of the industries in the sample. This implies that a decrease in the price of IT capital will cause the demand for non-IT capital to rise. Next, the cross effect of the IT price on the demand for intermediate inputs seems to vary depending on the industry under investigation. For some industries the effect is positive and therefore a decrease in the user cost of IT reduces the demand for intermediate inputs and in others the effect is negative implying the opposite. A safe conclusion to be made is that this relationship depends on the industry under examination, its investment in IT equipment as well as its investment in intermediate inputs.

Now taking a quick glance of the tables, the answer to the question on whether IT causes SBTC is in the affirmative. More analytically, for most industries the cross elasticities of unskilled labor with respect to the user cost of IT capital appear positive. Based on that we can conclude that the dramatic decrease in the price of IT equipment that has been happening this last decade has caused a reduction in the demand of unskilled labor.

Furthermore, the negative sign of the cross elasticities of skilled labor with respect to the user cost of IT indicates that the reduction in the price of IT equipment has led to an increase in the demand for skilled labor.

Based on the above, we can conclude that the dramatic decline in the IT equipment price has indeed caused the relative demand for skilled workers to rise and the demand for unskilled labor to decrease.

To summarize, based on the results from the elasticities we can conclude that IT causes SBTC. The results indicate that IT capital and skilled labor are complements in production. The same holds for IT and non-IT capital and, in some cases, intermediate inputs. The analysis also suggests that IT capital substitutes for low-skill work.

Finally, the dramatic decline in the price of IT equipment that has appeared in the US economy during the last decade has indeed caused the demand to shift away from unskilled to skilled, educated, labor and it will continue to do so as long as there exists a reduction in IT prices[14].

[14] Another way to see the effect of IT capital on labor is to determine the effect of IT capital on the wages of skilled and unskilled labor. Assuming that the quantities are fixed and using the implicit fuction theorem we obtain from equation (4.34): $\frac{\partial Z_i}{\partial W_{it}}\frac{dW_{it}}{dW_{ITt}} + \frac{\partial Z_i^*}{\partial W_{ITt}} = 0$ where i can be either skilled or unskilled labor. In form of elasticities of efficiency adjusted inputs with respect to user costs we get that: $\frac{dW_{it}}{dW_{jt}}\frac{W_{jt}}{W_{it}} = -\frac{\varepsilon^{zw}_{iITt}}{\varepsilon^{zw}_{iit}}$. Based on that we can construct using the demand elasticities an indication of the effect of the price of IT on the wages of skilled and unskilled. For instance a 1% decrease on average in the price of IT, decreases the wages of unskilled labor by 1.6% and increases by 1.5% the wages of skilled labor. Therefore, the gap of the wage between skilled and unskilled labor increases by 3%, i.e. $\frac{d[W_s - W_u]}{dW_{IT}} = 3\%$.

4.6 TFPG Measurement and Decomposition

Total factor productivity growth ($TFPG$) is defined as the change in the quantity of output less the change in the quantity of input. This variable provides a useful way to measure economic performance, since if $TFPG$ is positive, fewer resources are used in the production of a given level of output in each future year. Similarly, provided that $TFPG$ is positive, the resource cost of achieving any particular level of economic growth will fall over time.

There are several possible sources of $TFPG$. A common explanation for productivity growth is technical change, since the adoption of new production technologies leads to resource savings. Another explanation is that for technologies with increasing returns to scale, increases in output require relatively fewer additional resources because these technologies operate more effectively at higher levels of output.

This section presents the framework needed to measure $TFPG$.

4.6.1 Measurement of TFPG

$TFPG$ between years t and t', measured with cost-minimizing efficiency-adjusted input quantities, is defined as:

$$TFPG^z_{t,t'} = [y_{t'}/y_b - y_t/y_b] - [z^*_{t'} - z^*_t] \quad , \; 1 \leq t < t' \leq T \tag{4.42}$$

where:

$$z^*_t = \Phi^z(\omega_{1b}, \ldots, \omega_{Nb}, \omega_{1t}, \ldots, \omega_{Nt}; z^*_{1b}, \ldots, z^*_{Nb}, z^*_{1t}, \ldots, z^*_{Nt}) \; ;$$

$\Phi^z : \Re_+^{4N} \rightarrow \Re_+$ is a function that aggregates efficiency-adjusted input quantities into a single quantity index that is equivalent to a ratio of the aggregate input in year t (or t') to that in the reference year b, i.e. it is a measure of growth in the input aggregate between year b and t (or t'), and y_b, ω_{ib}, and z_{ib}^* are reference output, reference user cost for efficiency-adjusted input i, and optimal efficiency-adjusted reference quantity of input i, respectively.[15] The reference point is comprised of 'base values' that in this case are averages of the observations in year t and t'.

4.6.2 Decomposition of TFPG

A change in cost between year t and t' can be represented in terms of the cost function $\tau = 0$. Provided that the cost function is a second-order approximation, with second-order terms that are time invariant, it is possible to express this change using only the first-order derivatives of the cost function. In particular, the difference between the value of the cost function in year in t and that in t' is

$$\begin{aligned} & C\binom{\cdot}{t'} - C\binom{\cdot}{t} = \\ & (1/2)\left\{\sum_{i=1}^{N}\left[\partial C\binom{\cdot}{t'}\Big/\partial\omega_{it'} + \partial C\binom{\cdot}{t}\Big/\partial\omega_{it}\right](\omega_{it'} - \omega_{it})\right. \\ & \quad + \left[\partial C\binom{\cdot}{t'}\Big/\partial y_{t'} + \partial C\binom{\cdot}{t}\Big/\partial y_t\right](y_{t'} - y_t) \\ & \quad\quad \left. + \left[\partial C\binom{\cdot}{t'}\Big/\partial t' + \partial C\binom{\cdot}{t}\Big/\partial t\right](t' - t) \right\} \quad . \end{aligned} \tag{4.43}$$

The use of Shephards Lemma allows the following derivations

$$\partial C\binom{\cdot}{\upsilon}/\partial\omega_{i\upsilon} = z_{i\upsilon}^* \quad , \quad \upsilon = t\,,\, t' \;\; ; i = 1, 2, ..., N \;, \tag{4.44}$$

[15] Note that while the analysis is limited to five inputs, the more general number (N) is used in the various derivations in this chapter to make the theory more generally useful.

where z_{iv}^{*} is the optimal level of efficiency-adjusted input i in year v. In addition, since

$$c_v = C\begin{pmatrix} \cdot \\ v \end{pmatrix} = \sum\nolimits_{i=1}^{N} \omega_{iv} z_{iv}^{*} \ , \ v = t\,,\, t', \tag{4.45}$$

substitution of (4.45) and (4.44) into (4.43) and use of the elasticity definitions leads to the following:

$$\begin{aligned} &\sum\nolimits_{i=1}^{N} \omega_{it'} z_{it'}^{*} - \sum\nolimits_{i=1}^{N} \omega_{it} z_{it}^{*} = \\ &\quad (1/2) \sum\nolimits_{i=1}^{N} \left[z_{it'}^{*} + z_{it}^{*}\right] (\omega_{it'} - \omega_{it}) + DC\begin{pmatrix} \cdot \\ t, t' \end{pmatrix}\ , \end{aligned} \tag{4.46}$$

where $DC\begin{pmatrix} \cdot \\ t,t' \end{pmatrix}$ denotes

$$\begin{aligned} (1/2)\Big\{ &\left[\epsilon_{t'}^{Cy}(c_{t'}/y_{t'}) + \epsilon_{t}^{Cy}(c_t/y_t)\right](y_{t'} - y_t) \\ &+ \left[\epsilon_{t'}^{Ct} c_{t'} + \epsilon_{t}^{Ct} c_t\right](t' - t) \ , \end{aligned}$$

i.e. $DC\begin{pmatrix} \cdot \\ t,t' \end{pmatrix}$ is the set of terms in (4.43) that involve partial derivatives of the cost function $C(\cdot)$ with respect to non-price variables, expressed in terms of elasticities.

The terms involving z_{iv}^{*} and ω_{iv} $(v = t\,,\, t'; i = 1, 2, \ldots, N)$ in (4.46) can be decomposed so that:

$$\begin{aligned} &\Big[(1/2) \sum\nolimits_{i=1}^{N} \omega_{it'} z_{it'}^{*} + (1/2) \sum\nolimits_{i=1}^{N} \omega_{it'} z_{it'}^{*} \\ &\quad -(1/2) \sum\nolimits_{i=1}^{N} \omega_{it} z_{it}^{*} - (1/2) \sum\nolimits_{i=1}^{N} \omega_{it} z_{it}^{*}\Big] \\ &- \Big\{(1/2) \sum\nolimits_{i=1}^{N} \omega_{it'} z_{it}^{*} + (1/2) \sum\nolimits_{i=1}^{N} \omega_{it'} z_{it'}^{*} \\ &-(1/2) \sum\nolimits_{i=1}^{N} \omega_{it} z_{it}^{*} - (1/2) \sum\nolimits_{i=1}^{N} \omega_{it} z_{it'}^{*}\Big\} \ = DC\begin{pmatrix} \cdot \\ t, t' \end{pmatrix} \end{aligned} \tag{4.47}$$

where the terms in the square brackets in (4.47) are just the left-hand side of (4.46) re-expressed somewhat differently, and the terms in parentheses are the expansion of the first set of terms on the right-hand side of 4.46).

Eliminate and combine terms in (4.47) to get:

$$\begin{aligned} &\sum\nolimits_{i=1}^{N}\Big[(\omega_{it'}+\omega_{it})/2\Big]\,z_{it'}^{*}- \\ &\sum\nolimits_{i=1}^{N}\Big[(\omega_{it'}+\omega_{it})/2\Big]\,z_{it}^{*}=DC\begin{pmatrix} \cdot \\ t,t' \end{pmatrix}. \end{aligned} \tag{4.48}$$

Now define the variables that comprise the reference point, namely the average values:

$$\begin{aligned} \omega_{ib} &= (\omega_{it'}+\omega_{it})/2 \quad , \quad i=1,2,\ldots,N; \\ z_{ib}^{*} &= (z_{it'}^{*}+z_{it}^{*})/2 \quad , \quad i=1,2,\ldots,N; \\ y_{b} &= (y_{t'}+y_{t})/2 \ ; \end{aligned}$$

Reference-point total cost is thus $c_b=\sum_{i=1}^{N}\omega_{ib}z_{ib}^{*}$ and the reference-point cost share for each input i is $s_{ib}=(\omega_{ib}z_{ib}^{*})/c_b$, $i=1,2,\ldots,N$.

Define the index of efficiency-adjusted input quantity growth (relative to the reference point b) for year υ as:

$$\begin{aligned} z_{\upsilon}^{*} &= \Big(\sum\nolimits_{i=1}^{N}\omega_{ib}z_{i\upsilon}^{*}\Big)\Big/\Big(\sum\nolimits_{i=1}^{N}\omega_{ib}z_{ib}^{*}\Big) \\ &= \sum\nolimits_{i=1}^{N}\Big[(\omega_{ib}z_{ib}^{*})/\Big(\sum\nolimits_{i=1}^{N}\omega_{ib}z_{ib}^{*}\Big)\Big](z_{i\upsilon}^{*}/z_{ib}^{*}) \\ &= \sum\nolimits_{i=1}^{N}s_{ib}(z_{i\upsilon}^{*}/z_{ib}^{*}), \quad \upsilon=t,t' \ . \end{aligned} \tag{4.49}$$

Multiply each element of the summations in (4.48) by $(c_b z_{ib}^{*})\,/\,(c_b z_{ib}^{*})$ and note that the result matches (4.49), so that (4.48) becomes:

$$\begin{aligned} c_b\,(z_{t'}^{*}-z_{t}^{*}) \equiv (1/2)\Big\{&\Big[\,\epsilon_{t'}^{Cy}(c_{t'}/y_{t'})+\epsilon_{t}^{Cy}(c_t/y_t)\Big](y_{t'}-y_t) \\ &+\Big[\epsilon_{t'}^{Ct}c_{t'}+\epsilon_{t}^{Ct}c_t\Big](t'-t)\Big\} \ . \end{aligned} \tag{4.50}$$

Multiply the first set of terms in (4.50) by y_b/y_b.Multiply through the resulting expression by $-(1/c_b)$ and add $(y_{t'} - y_t)/y_b$ to both sides of the subsequent equation to get the following:

$$
\begin{aligned}
&[y_{t'}/y_b - y_t/y_b] - (z^*_{t'} - z^*_t) = (y_{t'} - y_t)/y_b \\
&\quad -(1/2)\left\{\left[\epsilon^{Cy}_{t'}(c_{t'}/c_b)/(y_{t'}/y_b) + \epsilon^{Cy}_{t}(c_t/c_b)/(y_t/y_b)\right](y_{t'} - y_t)/y_b \right. \\
&\qquad \left. + \left[\epsilon^{Ct}_{t'}(c_{t'}/c_b) + \epsilon^{Ct}_{t}(c_t/c_b)\right](t' - t)\right\} \ .
\end{aligned} \tag{4.51}
$$

And arrive at:

$$
\begin{aligned}
TFPG^{z}_{t,t'} = (1 - \epsilon^{Cy}_{t,t'})&(y_{t'} - y_t)/y_b \\
&-\epsilon^{Ct}_{t,t'}(t' - t) \ ,
\end{aligned} \tag{4.52}
$$

where:

$\epsilon^{Cy}_{t,t'} = (1/2)\left[\epsilon^{Cy}_{t'}(c_{t'}/c_b)/(y_{t'}/y_b) + \epsilon^{Cy}_{t}(c_t/c_b)/(y_t/y_b)\right]$;

$\epsilon^{Ct}_{t,t'} = (1/2)\left[\epsilon^{Ct}_{t'}(c_{t'}/c_b) + \epsilon^{Ct}_{t}(c_t/c_b)\right]$.

Note that the terms $\epsilon^{Cy}_{t,t'}$ and $\epsilon^{Ct}_{t,t'}$ can be viewed as weighted averages of the corresponding elasticities in t' and t, with the weights measured relative to the reference point.

Expression (4.52) shows $TFPG^{z}_{t,t'}$ to be equal to the sum of two components. The first component measures the effect of changes in scale[16] on $TFPG^{z}_{t,t'}$ and the second component measures the effect of changes in disembodied technology on $TFPG^{z}_{t,t'}$.

[16]In our case this effect of changes in scale is set to zero since we have assumed Constant Returns to Scale

To estimate the size of the difference between $TFPG$ measured with efficiency-adjusted input indexes and that measured with observed input indexes, note that the latter is defined as:

$$TFPG^{v}_{t,t'} = [y_{t'}/y_b - y_t/y_b] - [v_{t'} - v_t] \quad , \; 1 \leq t < t' \leq T \; , \tag{4.53}$$

where

$$v_v = \Phi^v(\omega_{1b}, \ldots, \omega_{Nb}, \omega_{1v}, \ldots, \omega_{Nv}; v_{1b}, \ldots, v_{Nb}, v_{1v}, \ldots, v_{Nv}) \; , \; v = t', t$$

and $\Phi^v : \Re^{4N}_{+} \rightarrow \Re_{+}$ is a function that aggregates observed quantities into a single quantity index that is equivalent to a ratio of the aggregate observed input in year t to that at the reference point b.

Rearrange (4.53) to isolate the output growth term $[y_{t'}/y_b - y_t/y_b]$ – which is common to both measures of $TFPG$ – and substitute this rearranged version:

$$TFPG^{v}_{t,t'} = TFPG^{z}_{t,t'} + [z^{*}_{t'} - z^{*}_{t}] - [v_{t'} - v_t] \quad , \; 1 \leq t < t' \leq T \; . \tag{4.54}$$

In other words, $TFPG$ measured with observed inputs (column 2 in table 4.3) is comprised of the same two components identified above (which together make $TFPG^{z}_{t,t'}$- column 3, table 4.3), plus a third component, namely the difference between efficiency-adjusted input growth and observed input growth – this is the total input/factor efficiency effect (column 4, table 4.3). If $[z^{*}_{t'} - z^{*}_{t}] - [v_{t'} - v_t] <$ 0, measured productivity growth rates will be lower than efficiency adjusted TFP growth.

Table 4.3: TFP Growth and Decomposition

			Factor Efficiency Effect					
	Observed	Technical						
CODE	TFP	Change	Total	U	K	M	S	IT
1	-0.0303	0.0094	-0.0397	-0.0037	-0.0013	-0.0305	-0.0008	-0.0034
2	0.0622	0.0127	0.00495	0.0235	-0.0005	0.0295	0.0021	-0.0051
3	-0.1133	0.0077	-0.121	-0.0799	-0.0011	-0.034	-0.0022	-0.0038
4	0.083	0.0078	0.0752	0.0852	-0.0006	-0.0051	-0.0012	-0.0031
5	-0.0109	0.0081	-0.019	0.01	-0.0008	-0.0239	-0.0005	-0.0037
6	-0.036	0.0083	-0.0444	-0.0046	-0.0002	-0.036	-0.00005	-0.034
7	-0.097	0.0094	-0.1072	-0.0109	-0.0007	-0.0919	0.0003	-0.0038
8	-0.0286	0.0088	-0.037	-0.017	-0.0006	-0.014	-0.00003	-0.0045
9	-0.12	0.009	-0.129	-0.035	-0.0009	-0.082	-0.0007	-0.0096
10	0.039	0.0079	0.0312	0.0319	-0.0015	0.01	0.0024	-0.011
11	-0.248	0.0091	-0.257	-0.019	-0.0028	-0.224	-0.0008	-0.01
12	0.287	0.0107	0.276	0.036	-0.0005	0.2599	-0.0091	-0.0104
13	0.3248	0.0112	0.3136	0.1218	-0.0012	0.1962	0.0024	-0.0056
14	-1.094	0.0086	-1.033	-0.1317	-0.0019	-0.9643	-0.0004	-0.005
15	1.8906	0.008	1.8825	0.2174	0.002	1.6659	-0.00009	-0.0027
16	-0.3512	0.0079	-0.3591	-0.1195	-0.0005	-0.2375	0.0011	-0.0028
17	0.0191	0.0086	0.0105	0.0096	0.001	0.0025	0.0069	-0.0033
18	-0.1786	0.0091	-0.1877	-0.0341	-0.0021	-0.1489	0.0015	-0.0041
19	-0.0873	0.0102	-0.0975	-0.0476	-0.0016	-0.0383	0.0004	-0.0103
20	-0.1759	0.0126	-0.1885	-0.0055	-0.0031	-0.1633	-0.002	-0.0145
21	0.1252	0.0111	0.1141	0.0747	-0.0007	0.0451	0.0002	-0.0051
22	0.1113	0.0077	0.1036	-0.0177	0.00003	0.121	0.0005	-0.0002

Table 4.3(continue): TFP Growth and Decomposition

			Factor Efficiency Effect					
	Observed	Technical						
CODE	TFP	Change	Total	U	K	M	S	IT
23	2.6207	0.0109	2.6098	0.6512	0.0068	1.9412	-0.0008	0.0113
24	-4.943	0.0091	-4.952	-2.965	-0.0967	-1.869	0.0023	-0.0228
25	-3.0484	0.0018	-3.0502	-0.5398	-0.0046	-0.3278	0.00005	-2.1359
26	0.5362	0.0182	0.518	0.1418	-0.0972	-0.0556	-0.0008	0.529
27	-0.2031	0.0145	-0.2177	-0.3468	-0.0047	-0.0627	-0.0028	0.1992
28	-0.3571	0.0084	-0.3655	-0.2734	-0.002	-0.0754	-0.0011	-0.0134
29	-0.0024	0.0099	-0.0123	0.0787	-0.0075	-0.0126	-0.0045	-0.0664
30	0.0211	0.0105	0.0106	0.1923	-0.0067	-0.1374	-0.0057	-0.0318
31	-0.1968	0.0096	-0.2065	0.0521	-0.0292	-0.1981	-0.0022	-0.029
32	0.2015	0.0097	0.1918	0.0867	-0.0151	0.1319	-0.0019	-0.0097
33	0.6969	0.0081	0.6887	0.0321	0.0567	0.6094	-0.0017	-0.0078
34	-0.5162	0.0074	-0.5237	-0.3861	-0.0041	-0.1078	-0.0079	-0.0175
35	-0.1484	0.0074	-0.1559	-0.0594	-0.0075	-0.0795	-0.0016	-0.0077
36	0.9974	0.0078	0.9896	0.9063	-0.002	0.1002	0.0013	-0.0162
37	0.3156	0.0058	0.3097	0.3103	-0.0053	0.0186	-0.0052	-0.0086
38	-0.2796	0.0079	-0.2875	-0.143	-0.0037	-0.1254	-0.0027	-0.0126
39	-2.3317	0.0081	-2.3398	-1.9798	-0.0061	-0.3113	-0.0203	-0.0222
40	-0.1458	0.0127	-0.1586	-0.0755	-0.0036	-0.0364	-0.0295	-0.0136
41	0.4326	0.012	0.4206	0.4432	-0.0032	-0.0009	-0.0155	-0.0029
42	-0.2667	0.0143	-0.2811	-0.0706	-0.0032	-0.1503	-0.0283	-0.0286

Two sources of the productivity wedge are usually identified: input mismeasurement and output mismeasurement. The first component occurs when inputs are growing and exhibiting efficiency gains. Measured input growth will be underestimated and therefore the measured productivity growth will exceed the efficiency adjusted rate. The second one occurs from higher input efficiency inducing greater output. This effect causes efficiency adjusted productivity growth to rise above the typically measured rate. Here, a third source arises from input aggregation in the calculation of measured productivity growth. The weights used are based on observed cost shares. However, efficiency adjusted cost shares differ from measured shares, and consequently efficiency adjusted input growth differs from measured growth in the calculation of productivity growth rates.

The total factor efficiency effect included two components and it depends on which of the two dominates. The first is the input adjustment effect (difference between observed and adjusted input growth using observed cost shares to construct input growth) and the second is the aggregation effect (which captures the effect from the different cost shares). For the input adjustment effect, one would expect that as inputs are growing, efficiency gains imply a positive effect, that is measured productivity growth overstates efficiency adjusted growth. But, even with positive efficiency growth rate, input changes must be increasing over time for the input adjustment effect to be positive. The aggregation component is expected to be negative. Efficiency-adjusted cost shares decline more for faster growing inputs. This causes a reduction in efficiency adjusted input growth and therefore the efficiency adjusted productivity growth will exceed the typical measured rate.

It is possible to evaluate the total factor efficiency effect, which causes the productivity gap between efficiency adjusted and measured productivity growth, according to the contribution of each input separately. The decomposition of the total factor efficiency effect according to the contribution of each input is also presented in table 4.3 (columns 5-9).

From table 4.3 we observe that technical change appears to have a positive contribution to productivity in all industries of the sample.

In 17 out of 42 industries the averaged observed TFP is positive while in the rest is negative. With respect to the latter case, measured productivity growth rates averaged below efficiency based growth as observed inputs growth exceeded efficiency adjusted growth (as observed from the total factor efficiency effect in Table 4.3, column 4). As mentioned it is possible to evaluate the productivity gap according to the contribution of each input.

Clearly the efficiency growth associated with new intermediate inputs accounts for most of the difference between efficiency adjusted and measured productivity in all US industries (they have the largest share in production and cost). Unskilled labor appears to have an important contribution to the gap, but this could be due to the fact that the share of unskilled labor is decreasing in production.

Efficiency adjusted IT growth is the third important contributors for the productivity gap. This could imply that the productivity gap could result from the decline in the efficiency adjusted IT cost shares relative to observed shares coupled with high growth rates of IT inputs.

Based on the above, efficiency adjusted productivity growth, in most of the industries, averaged above measured growth. The gap between efficiency-adjusted and measured productivity growth arises from using observed and not efficiency adjusted inputs and cost shares in production. Efficiency growth associated with new intermediate inputs and new IT capital were the main sources of this productivity gap.

4.7 Conclusion

An issue rising in the literature on IT has been the substitution of IT equipment for other forms of capital and labor inputs. A number of papers investigate the relationship between IT and labor demand. They indicate that IT causes the relative demand for more highly educated workers to rise. IT-based production processes also causes substitution of low skill human work, referred to in the literature as SBTC. Some economists argue that SBTC has caused the wage inequality that has appeared in world economies and particularly the US economy. This effect appears to go both ways, since education or skill is required for successful adoption of new technology.

Another issue in this literature is the non-existence of constant quality price indexes which are essential for identifying the change in price for a given level of performance. Price indexes which do not hold performance constant present a distorted picture of IT equipment prices as well as their output and investment. Unfortunately constant quality price indexes have not yet been developed for all IT equipment or not yet incorporated in the US national accounts.

Here we use a framework general enough to be able to capture all the issues mentioned above, avoiding some pitfalls in the use of IT equipment price indexes which appear problematic. The empirical analysis is based on a more general production function which allows efficiency gains to arise when new inputs generate an improvement in technical efficiency that is not fully offset by costs of adjustment. Specifically, we are estimating a system of factor demands derived from a general cost function along with some price expectation processes from which we are able to obtain the effect from IT capital prices on the demand of both skilled and unskilled labor.

For this estimation, data from various sources are combined to create a database that includes skilled, unskilled labor, IT, non-IT capital and intermediate inputs for 42 US industries over the period 1983-2001.

From the analysis we find that the efficiency gains from IT capital are very large and significant and can not be offset from any costs of adjustment. The efficiency gains parameter of IT capital is the largest amongst all inputs included in the model. New IT capital inputs improves technical efficiency.

The question of this chapter on whether IT causes SBTC is answered through the estimated elasticities of efficiency adjusted inputs. The cross elasticities suggest that IT causes SBTC. That is, a decrease in the price of IT equipment, a fact that has been indeed happening in the last decade, causes the demand for skilled workers to rise and the demand for unskilled ones to decrease.

Chapter 5

Conclusion

The economics of growth became a fundamental question in the recent economic literature. As Temple (1999) stated, a better understanding of what generates economic growth can make a huge contribution to human welfare. The last years have seen an outpouring of empirical work intended to explain what causes economic growth.

Financial markets and institutions are considered in the literature as a source of economic growth. Specifically, a question exists in the literature on whether financial development exerts a positive influence on economic growth. Recent empirical evidence suggest a positive first-order relationship between financial development and economic growth. Evidence also suggest that the level of financial development is a good predictor of future rates of economic growth, capital accumulation and technological change. Recently, nonlinearities became an issue in the relationship of financial development and economic growth. Recent studies, find that the effect of financial development on growth may vary in different groups of countries or may vary according to the level of financial development of the country.

Based on the above, the second chapter of this thesis examines whether and how indicators of financial intermediary development influences economic growth. Methodologically, we use both parametric and nonparametric techniques to establish whether financial development is a determinant of economic growth and whether this relationship is nonlinear. We apply both techniques using the Levine, Loayza and Beck (2000) data set, while we allow for three determinants (namely: initial per capita income, human capital and the financial index) of economic growth to be treated nonlinearly. We find that when the nonlinearities between initial income and human capital, on the one hand and economic growth, on the other, are taken into consideration, the effect from financial intermediary development indices on economic growth will be linear and significantly positive.

In recent years, attention has turned to another issue: the slowdown in productivity that started some time in the late 1960s or early 1970s. This issue has never been resolved satisfactory, despite a significant research effort. This has been supplanted by yet another mystery: why hasn't the widely touted information revolution reversed the productivity slowdown? This is best captured by Solow (1957) who suggested that: "You can see the computer age everywhere but in the productivity statistics".

Economists have observed a rapid diffusion of information technology and its related equipment, especially computers, in world economies, and they suggest that this fact is a direct consequence of the dramatic decline in the price of computer-related equipment which has a very significant impact on economic growth. This view, along with the Solow productivity paradox, has become a rising issue in economics and has created a debate among economists.

In the third chapter we investigate the impact of IT capital on productivity and, hence, the process of economic growth in the presence of adjustment costs. We accomplish the above by constructing an index of TFP growth for traditional inputs, and by using this index to evaluate the impact of IT capital on TFP via semiparametric methods that allow the effect of IT capital on TFP to be nonlinear. In order to do so, data are used, for 42 U.S industries over the period 1984 to 2001, which are obtained from several sources (BEA and BLS publications). The results indicate that IT has a positive effect on productivity that varies among industries and time. Adjustment costs are important when identifying this effect since their omission tends to understate the effect of IT capital on economic performance. Finally, the relationship appears to be nonlinear, a result fist appearing in the IT literature.

Another issue arising in the literature on IT, has been the substitution of information technology for other forms of capital and labor inputs. A number of papers in the literature investigate the relationship between IT and labor demand. They indicate that IT causes the relative demand for more highly educated and experienced workers, as well as the relative demand for highly skilled workers to rise. IT-based production processes also causes substitution for low skill human work. This is referred in the literature as skill-biased technical change (SBTC).

In the fourth chapter we examine the labor demands for skilled and unskilled workers, and how these are affected by the IT capital growth. The question on whether IT causes SBTC is answered through a framework, which allows efficiency gains in production to arise when new inputs generate an improvement in technical efficiency that is not fully offset by costs of adjustment. To do so, we use data from various sources and from publications that allow us to separate the labor force into skilled and unskilled workers and break the capital into IT and non-IT capital. The empirical analysis is based on a "dynamic" system of factor demand equations for a U.S private industries derived from a general cost function along with some price expectation processes in order to avoid the use of IT equipment price indexes which appear problematic. From the estimation analysis we find that the efficiency gains arising from new IT capital are very large and significant. The cross elasticities estimated suggest that a decline in the price of IT equipment causes the demand for skilled labor to rise and substitutes for low-skill human work.

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Gmm dynamic panel results

Table A1: Private Credit and Growth: GMM System Estimator

Regressors	Coefficient	t-statistic
Constant	4.723	4.92
Initial Income per Capita	-0.363	-2.92
Government size	-1.373	-5.63
Trade Openness	0.212	1.98
Inflation	-1.274	-4.21
Average years of schooling	0.127	1.32
Black market premium	-0.741	-8.54
Private credit	1.608	14.76
Dummy 71-71	-1.012	-12.38
Dummy 76-80	-1.152	-7.83
Dummy 81-85	-3.039	-18.49
Dummy 86-90	-2.182	-15.90
Dummy 91-95	-2.791	-17.42
Sargan test (p-value): 0.537		
Serial correlation test (p-value): 0.520		

Table A2: Liquid liabilities and Growth: GMM System Estimator

Regressors	Coefficient	t-statistic
Constant	-0.253	-0.30
Initial Income per Capita	-0.573	-3.41
Government size	-0.756	-2.09
Trade Openness	0.096	0.39
Inflation	0.073	0.15
Average years of schooling	0.319	2.19
Black market premium	-1.787	-14.13
Liquid liabilities	2.641	12.27
Dummy 71-71	-0.938	-15.66
Dummy 76-80	-0.964	-8.87
Dummy 81-85	-2.939	-16.18
Dummy 86-90	-2.221	-12.27
Dummy 91-95	-2.909	-18.24
Sargan test (p-value): 0.620		
Serial correlation test (p-value): 0.404		

Table A3: Commercial-Central and Growth: GMM System Estimator

Regressors	Coefficient	t-statistic
Constant	-7.440	-9.78
Initial Income per Capita	-0.115	-1.03
Government size	-0.695	-2.92
Trade Openness	0.322	1.38
Inflation	-2.470	-8.33
Average years of schooling	0.396	2.98
Black market premium	-0.779	-9.16
Commercial vs Central bank	2.793	10.78
Dummy 71-71	-0.953	-9.82
Dummy 76-80	-0.792	-7.20
Dummy 81-85	-2.585	-18.23
Dummy 86-90	-1.778	-12.71
Dummy 91-95	-2.491	-14.43
Sargan test (p-value): 0.416		
Serial correlation test (p-value): 0.726		

Table A4: SEMIPARAMETRIC ESTIMATION: PRIVATE CREDIT AND GROWTH (CONDITIONED ON INITIAL INCOME AND HUMAN CAPITAL)

Regressors	Coefficient	t-statistic
Government Size	-0.362	-0.89
Trade Openness	0.122	0.46
Inflation	-1.789	-2.13
Black Market Premium	-0.424	-1.28
Private Credit	1.368	4.56
Dummy 71-75	-0.858	-1.73
Dummy 76-80	-0.906	-1.84
Dummy 81-85	-3.306	-6.78
Dummy 86-90	-2.242	-4.52
Dummy 91-95	-2.138	-4.30

Table A5: Semiparametric estimation: Liquid liabilities and Growth (conditioned on initial income and human capital)

Regressors	Coefficient	t-statistic
Government Size	-0.407	-0.99
Trade Openness	-0.048	-0.18
Inflation	-1.187	-1.34
Black Market Premium	-0.946	-3.04
Liquid liabilities	1.781	4.48
Dummy 71-75	-0.800	-1.62
Dummy 76-80	-0.943	-1.91
Dummy 81-85	-3.403	-6.93
Dummy 86-90	-2.298	-4.61
Dummy 91-95	-2.268	-4.57

Table A6: Semiparametric estimation: Commercial-Central and Growth (conditioned on initial income and human capital)

Regressors	Coefficient	t-statistic
Government Size	-0.419	-1.02
Trade Openness	0.077	0.29
Inflation	-2.303	-2.82
Black Market Premium	-0.513	-1.58
Commercial-Central bank	2.816	4.25
Dummy 71-75	-0.571	-1.16
Dummy 76-80	-0.329	-0.68
Dummy 81-85	-2.786	-5.78
Dummy 86-90	-1.829	-3.78
Dummy 91-95	-1.942	-3.90

Table A7: Semiparametric Estimation:
Private Credit and Growth
(conditioned only on initial income)

Regressors	Coefficient	t-statistic
Government Size	-0.481	-1.17
Trade Openness	0.273	1.05
Inflation	-1.595	-1.93
Black Market Premium	-0.362	-1.10
Private Credit	1.639	5.30
Secondary Schooling	0.546	2.89
Dummy 71-75	-1.178	-2.38
Dummy 76-80	-1.183	-2.41
Dummy 81-85	-3.430	-6.99
Dummy 86-90	-2.467	-4.92
Dummy 91-95	-2.087	-4.17

Table A8: Semiparametric Estimation: Liquid liabilities and Growth (conditioned only on initial income)

Regressors	Coefficient	t-statistic
Government Size	-0.456	-1.11
Trade Openness	0.065	0.25
Inflation	-0.973	-1.12
Black Market Premium	-0.998	-3.22
Liquid liabilities	2.027	4.96
Secondary Schooling	0.569	3.02
Dummy 71-75	-1.114	-2.26
Dummy 76-80	-1.120	-2.44
Dummy 81-85	-3.484	-7.06
Dummy 86-90	-2.488	-4.94
Dummy 91-95	-2.289	-4.58

Table A9: SEMIPARAMETRIC ESTIMATION:
COMMERCIAL-CENTRAL BANK AND GROWTH
(CONDITIONED ONLY ON INITIAL INCOME)

Regressors	Coefficient	t-statistic
Government Size	-0.560	-1.36
Trade Openness	0.192	0.74
Inflation	-2.375	-2.95
Black Market Premium	-0.495	-1.53
Commercial-Central bank	3.121	4.62
Secondary Schooling	0.653	3.46
Dummy 71-75	-0.838	-1.71
Dummy 76-80	-0.506	-1.05
Dummy 81-85	-2.846	-5.89
Dummy 86-90	-1.940	-3.98
Dummy 91-95	-1.961	-3.91

MARGINAL INTEGRATION AND THE PARTIALLY LINEAR MODEL

For comparison purposes we have used marginal integration, conditioning on only two variables: one is the financial intermediary index and the other is either the logarithm of initial income or human capital, respectively.

Below you can see the results obtained when marginal integration is applied in the partially additive linear model using liquid liabilities and commercial versus central bank assets as the financial intermediate index respectively.

The analysis followed is the same as with private credit. The graphical analysis presented here is when estimating the semiparametric partially additive linear

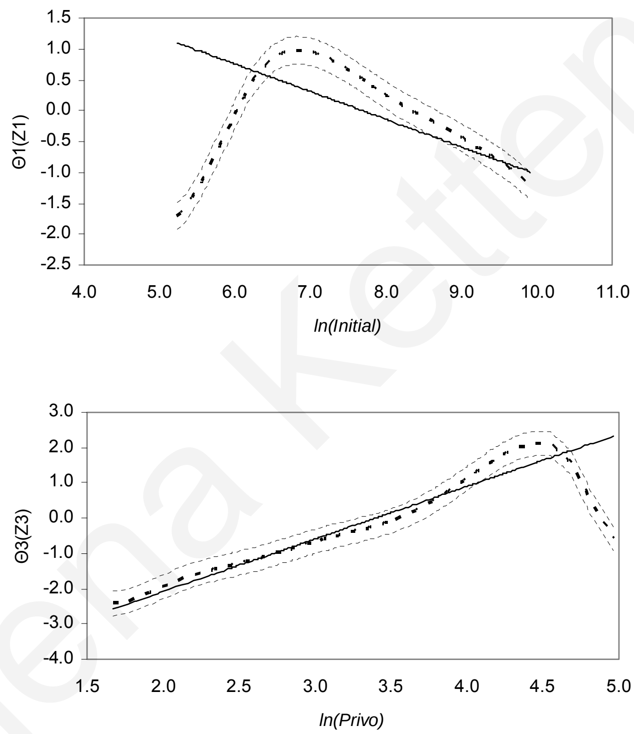

Figure 5.1: Semiparametric PLR model conditioned on initial income and private credit.

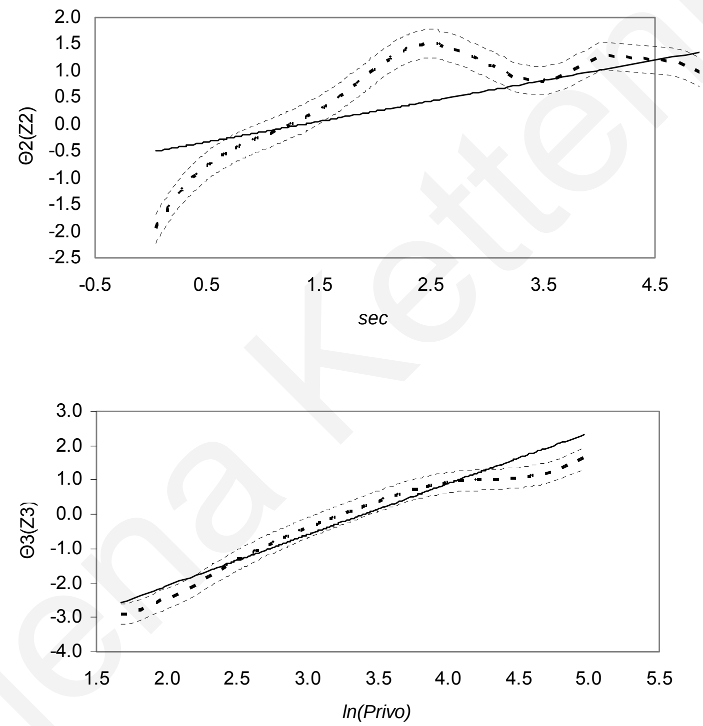

Figure 5.2: Semiparametric PLR model conditioned on human capital and private credit.

model with initial income, secondary schooling and the financial index as nonlinear regressors. This graphical analysis will dive further support to the results presented earlier with private credit.

Firstly, we place the graphs obtained from the estimation using liquid liabilities as the financial index.

From the graphs the results based on private credit are verified with liquid liabilities as well. We observe that the relationship between initial income as well as human capital with economic growth is nonlinear. The relationship between liquid liabilities and economic growth appears to be positive and linear.

Secondly, we place the results from marginal integration using commercial versus central bank assets as the financial index.

Based on that, we can observe that the same results hold as in the case of the other two financial intermediary development indices.

Finally, we conclude that when the nonlinearities between initial income and growth, and human capital and growth, are ignored we obtain a nonlinear relationship between financial development and economic growth. If the nonlinearities are taken into consideration we observe a positive linear relationship between finance and growth.

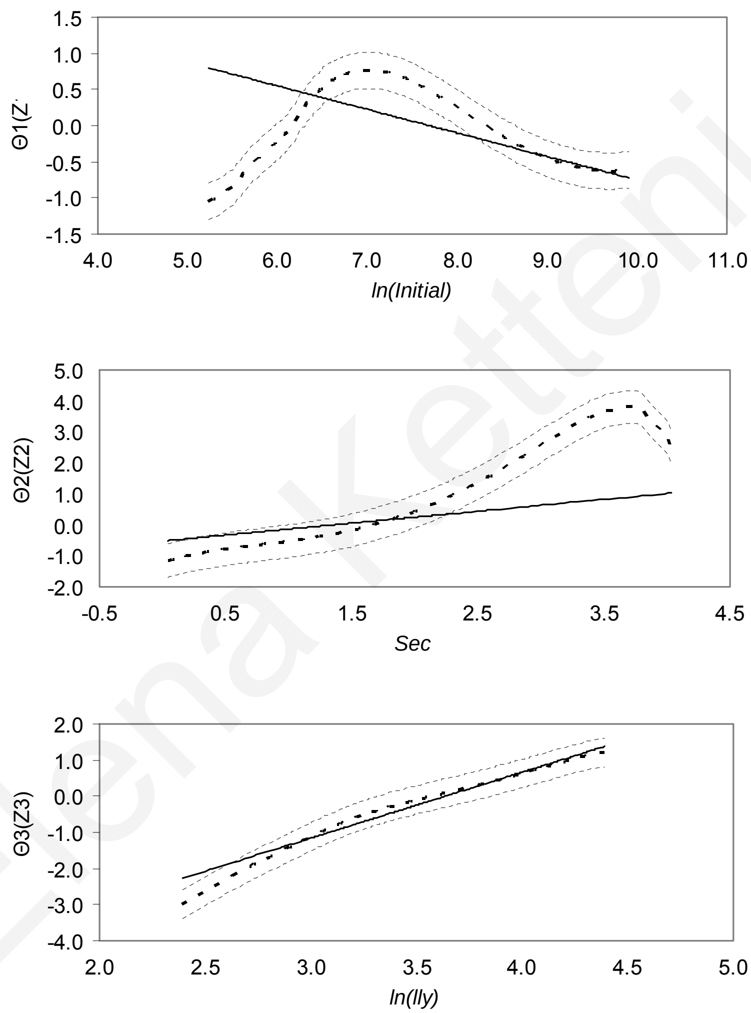

Figure 5.3: Semiparametric PLR model conditioned on initial income, human capital and liquid liabilities.

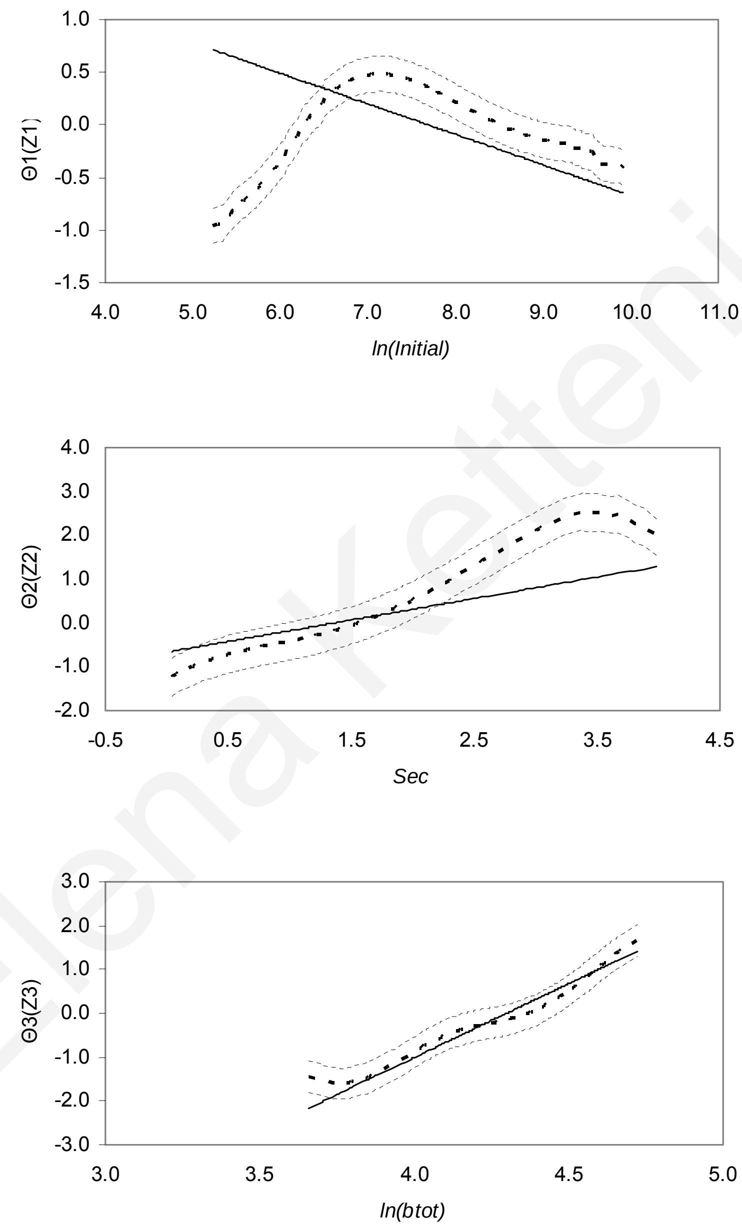

Figure 5.4: Semiparametric PLR model conditioned on initial income, human capital and commercial versus central bank assets.

specification tests: interaction terms

Table A10: GMM with interaction terms

System Estimator

Regressors	Coefficient	*t*-statistic
Constant	-12.483	-4.06
Initial Income per Capita	2.719	5.71
Government size	-1.059	-3.27
Trade Openness	0.173	1.15
Inflation	-1.495	-2.88
Average years of schooling	-0.391	-0.73
Black market premium	-0.823	-7.95
Private credit	4.027	6.01
*Initial income *private credit*	-0.932	-6.44
*schooling * private credit*	0.157	1.25
*Initial income *schooling*	0.690	6.26
Dummy 71-71	-1.079	-10.66
Dummy 76-80	-1.090	-6.96
Dummy 81-85	-3.059	-14.36
Dummy 86-90	-2.236	-10.73
Dummy 91-95	-2.872	-15.03
Sargan test (p-value): 0.322		
Serial correlation test (p-value): 0.685		

Table A11: GMM (interaction and nonlinear terms)

System Estimator

Regressors	Coefficient	t-statistic
Constant	405.99	1.76
Initial Income per Capita	-221.52	-1.73
Government size	0.082	0.16
Trade Openness	0.925	3.71
Inflation	-1.631	-2.47
Average years of schooling	2.404	1.67
Black market premium	-0.730	-3.94
Private credit	-1.223	-0.77
*Initial income *private credit*	0.021	0.38
*Schooling * private credit*	-0.733	-1.16
*Initial income *schooling*	0.611	1.05
(Initial income)^2	43.83	1.68
(Initial income)^3	-3.739	-1.59
(Initial income)^4	0.116	1.48
(Schooling)^2	-0.513	-0.65
(Schooling)^3	0.195	1.49
Dummy 71-71	-0.727	-5.65
Dummy 76-80	-0.709	-3.45
Dummy 81-85	-3.085	-10.99
Dummy 86-90	-1.868	-8.47
Dummy 91-95	-2.551	-9.57
Sargan test (p-value): 0.268		
Serial correlation test (p-value): 0.883		

Appendix B. Decomposition of TFP with Adjustment Costs

Following Morrison (1992) and Nadiri and Prucha (1989, 1999), we denote the production function as:

$$Y = F(X_t, IT_t, I_t, t)$$

where X denotes the variable inputs included in the model (in this case $X = K, L, M$). IT refers to the IT-capital entering the production function as a quasi-fixed input. Instead of IT_t we could also use the IT_{t-1}. And I refers to the investment in IT, included in the production function to capture potential adjustment costs. Adjustment costs as mentioned in the paper can also be included using ΔIT_t.

Total differentiation of Y and division with output yields:

$$\frac{\dot{Y}}{Y} = \sum \frac{\partial F}{\partial X_t} \frac{X_t}{Y} \frac{\dot{X}_t}{X_t} + \frac{\partial F}{\partial IT_t} \frac{IT_t}{Y} \frac{\dot{IT}_t}{IT_t} + \frac{\partial F}{\partial I_t} \frac{I_t}{Y} \frac{\dot{I}_t}{I_t} + \frac{\partial F}{\partial t} \frac{1}{Y}$$

where $\cdot$ indicates derivative with respect to time.

From cost minimization the first order condition yield (omission of subscript t for convenience):

$w = \mu \frac{\partial F}{\partial X} \Longrightarrow \frac{wX}{Y} = \mu \frac{\partial F}{\partial X} \frac{X}{Y}$

From the envelope theorem we know that $\mu = \frac{\partial C}{\partial Y}$.

Then:

$\frac{wX}{Y} = \frac{\partial C}{\partial Y} \frac{\partial F}{\partial X} \frac{X}{Y} \Longrightarrow \frac{wX}{C} = \varepsilon_{cy}(\frac{\partial F}{\partial X} \frac{X}{Y})$.

Also from the FOC we have that:

$\frac{\partial C}{\partial Z} = -\mu \frac{\partial F}{\partial Z}$ where $Z = IT, I$ and $\frac{\partial C}{\partial Z} \prec 0$

$\frac{\partial C}{\partial Z} = \frac{\partial C}{\partial Y}\frac{\partial F}{\partial Z} \Longrightarrow \frac{\partial F}{\partial Z}\frac{Z}{Y} = \frac{1}{\varepsilon_{cy}}(\frac{\partial C}{\partial Z}\frac{Z}{C})$.

Additionally from Shephards Lemma we have that:

$\frac{\partial F}{\partial X} = w$

Based on the above we now have:

$$\frac{T\dot{F}P}{TFP} = \frac{\dot{Y}}{Y} - \frac{1}{\varepsilon_{cy}}[\sum \frac{w_t X_t}{C}\frac{\dot{X}_t}{X_t} + \theta(.)\frac{I\dot{T}_t}{IT_t} + \delta\frac{\dot{I}_t}{I_t}]$$

The conventional TFP approach gives us that:

$\frac{T\dot{F}P}{TFP} = \frac{\dot{Y}}{Y} - \sum \frac{w_t X_t}{C}\frac{\dot{X}_t}{X_t}$

Combining the two measures of TFP we get that the new measure with adjustment costs and scale effect can be written as (decompose the TFP growth into scale effect, effect from IT, effect from adjustment costs and technical change):

$\frac{T\dot{F}P}{TFP} = (\frac{1}{\varepsilon_{cy}} - 1)\sum \frac{w_t X_t}{C}\frac{\dot{X}_t}{X_t} + \theta(.)\frac{I\dot{T}_t}{IT_t} + \delta\frac{\dot{I}_t}{I_t} + technical - change$

Appendix C. Industry Codes

The industries used in our analysis are presented in Table C.1.

Table C.1: INDUSTRY CODES

Industry	Code	Industry	Code
Agriculture, forestry and fishing	1	Leather and leather products	23
Mining	2	Transportation	24
Construction	3	Communication	25
Lumber and wood products	4	Electric, gas, and sanitary services	26
Furniture and fixtures	5	Wholesale trade	27
Stone, clay,and glass products	6	Retail trade	28
Primary metal industries	7	Bank and security	29
Fabricated metal products	8	Insurance	30
Industrial machinery and equipment	9	Real estate	31
Electronic, other electric equipment	10	Hotels and other lodging places	32
Transportation equipment	11	Personal services	33
Instruments and related products	12	Business services	34
Misc. manufacturing industries	13	Auto repair, services, and parking	35
Food and kindred products	14	Miscellaneous repair services	36
Tobacco products	15	Motion pictures	37
Textile mill products	16	Amusement and recreation services	38
Apparel and other textile products	17	Health services	39
Paper and allied products	18	Legal services	40
Printing and publishing	19	Educational services	41
Chemicals and allied products	20	Other services	42
Petroleum and coal products	21		
Rubber and misc. plastics products	22		

Appendix D. IT and Economic Performance

Here we present the results from all other specifications used in the analysis of IT and economic performance.

the output elasticity of IT-capital

When estimating the nonparametric component of the smooth coefficient function we obtain the output elasticity of IT-capital.

According to Figure 5.5, the effect of IT-capital is not constant across industries and time but varies considerably. Also we can state that the relationship between IT-capital and productivity appears to be nonlinear especially in the case where adjustment costs are included in the model. The output elasticity appears to increase with the level of IT capital. Then at a certain level of IT it starts decreasing up to a point and it begins increasing again at very high levels of IT capital.

The two graphs give credence to the argument that the omission of adjustment costs understates the effect of IT-capital on productivity. We can see from Figure 5.5 that the output elasticities from the models with adjustment costs appear to be greater than the output elasticities from the model without adjustment costs. The vast majority of the output elasticity estimates from the model with adjustment costs lie in the range of 0.04-0.07, while for the model without from 0.03-0.05. However, the differences between the two are not large. This may be due to the fact that adjustment costs do not appear to be statistically significant enough to offset any gains from IT capital, even though they do exist.

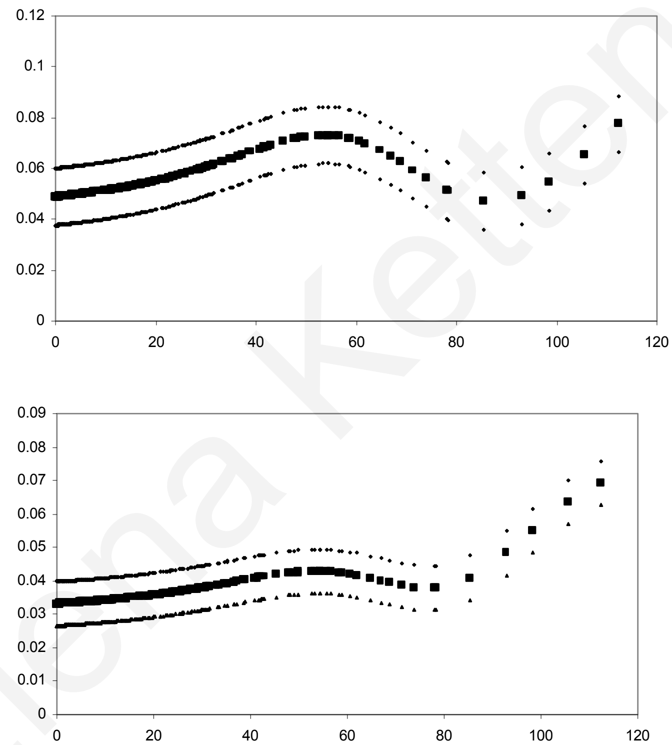

Figure 5.5: IT-capital Output Elasticity with $\theta(IT_{it})$ and $\hat{IT}_{it}$

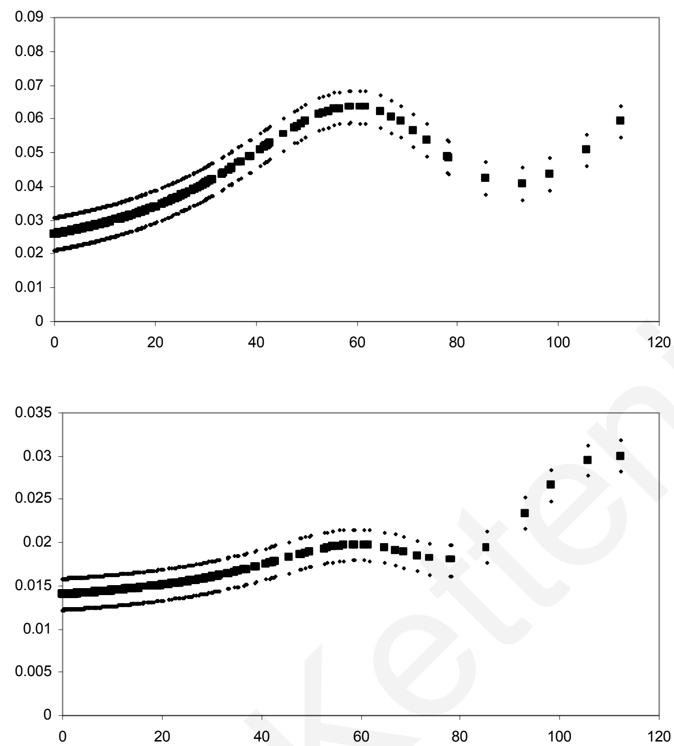

Figure 5.6: IT Capital Output Elasticity: $\theta(IT_{it})$ and $I\hat{T}_{it-1}$

The results from the smooth coefficient model (with and without adjustment costs) for the function θ when $I\hat{T}_{t-1}$ is used, are presented in Figure 5.6. As before, the first graph was obtained from the model with adjustment costs and the second from the one without.

Figure 5.6 also shows that the effect of IT-capital is not constant across industries. Furthermore, the relationship between IT and productivity appears to be nonlinear as before, especially in the model with adjustment costs. Here, the elasticity estimates from the models with and without adjustment costs lie in the range of 0.025-0.05 and 0.015-0.03 respectively, something that suggests again that the output elasticities of IT-capital obtained from the model with adjustment costs are larger than the ones from the model without. The output elasticities when $I\hat{T}_{it}$ is used are higher than the ones with the end of the period IT capital stock.

The average output elasticity ($\theta(IT_t)$) for each industry is reported in Table D1 along with the average IT-capital stock in order to examine in detail what happens at the industry level. The results in Table D1 are from the model using $I\hat{T}_t$. Column 3 reports the elasticities from the model with adjustment costs and column 4 from the one without.

Table D1: Output elasticities (Average by Industry)

Code	IT	$\theta(IT_t) - Adj.$	Std. Error	$\theta(IT_t) - NoAdj.$	Std. Error
1	2.379	0.049	0.004	0.033	0.0002
2	4.919	0.05	0.0004	0.034	0.0002
3	3.697	0.05	0.0009	0.034	0.0004
4	0.769	0.049	0.0001	0.033	0.0001
5	0.588	0.049	0.0001	0.033	0.0001
6	1.303	0.049	0.0002	0.033	0.0001
7	1.797	0.049	0.0001	0.033	0.0001
8	2.962	0.049	0.0004	0.033	0.0001
9	13.754	0.053	0.0034	0.035	0.0014
10	15.387	0.053	0.0028	0.035	0.0011
11	7.199	0.051	0.0007	0.034	0.0003
12	9.75	0.051	0.0015	0.034	0.0006
13	0.713	0.049	0.0001	0.033	0.0001
14	3.94	0.05	0.0005	0.034	0.0002
15	0.379	0.049	0.0002	0.033	0.0001
16	1.016	0.049	0.0001	0.033	0.0001
17	0.764	0.049	0.0001	0.033	0.0001
18	2.256	0.049	0.0002	0.033	0.0001
19	8.545	0.051	0.0019	0.034	0.0007
20	7.354	0.051	0.0012	0.034	0.0005
21	0.781	0.049	0.0001	0.033	0.0001
22	1.616	0.049	0.0003	0.033	0.0001

Table D1continue: OUTPUT ELASTICITIES

Code	IT	$\theta(IT_t) - Adj.$	Std. Error	$\theta(IT_t) - NoAdj.$	Std. Error
23	0.098	0.049	0.0001	0.033	0.0001
24	34.92	0.06	0.0071	0.038	0.0028
25	67.078	0.069	0.0039	0.046	0.0019
26	26.977	0.059	0.0036	0.037	0.0014
27	58.537	0.067	0.0171	0.045	0.0126
28	26.787	0.059	0.0077	0.037	0.0031
29	73.499	0.07	0.0176	0.047	0.0127
30	20.843	0.057	0.0079	0.036	0.0031
31	30.977	0.061	0.0074	0.038	0.0029
32	2.086	0.049	0.0001	0.033	0.0001
33	1.035	0.049	0.0002	0.033	0.0001
34	55.098	0.069	0.0195	0.045	0.0142
35	1.857	0.049	0.0002	0.033	0.0001
36	1.451	0.049	0.0003	0.033	0.0001
37	4.742	0.05	0.0009	0.034	0.0004
38	1.501	0.049	0.0002	0.033	0.0001
39	6.541	0.05	0.0013	0.034	0.0006
40	4.385	0.05	0.0006	0.034	0.0002
41	0.785	0.049	0.0002	0.033	0.0001
42	17.285	0.055	0.0057	0.036	0.0023

The average elasticities from the model with adjustment costs lie within a range: 0.048 to 0.069. As expected the average elasticities from the model without adjustment costs are lower and lie in the range 0.033 and 0.045. There is no large variation in the elasticity estimates across industries. They are larger for the industries with high levels of IT-capital (IT-intensive industries), a result consistent with the previous literature. Also we can observe that for industries with low levels of IT-capital the output elasticities remain approximately the same. But when industries increase their IT-capital stock, these elasticities seem to increase and by a large amount. So the effect of IT on productivity is larger in industries with high levels of IT-capital. Also note that we observe larger elasticities outside the manufacturing sector and particularly in the service sector. The same results hold as well in the case where $I\hat{T}_{t-1}$ is used in the estimation model, even though the output elasticities are smaller (see Table D2).

Table D2: Output elasticities (Average by Industry)

Code	$\theta(IT_t) - Adj.$	Std. Error	$\theta(IT_t) - NoAdj.$	Std. Error
1	0.025	0.0005	0.014	0.00006
2	0.026	0.0005	0.014	0.00006
3	0.026	0.0012	0.014	0.0002
4	0.025	0.0001	0.014	0.00002
5	0.025	0.0001	0.014	0.00001
6	0.025	0.0002	0.014	0.00003
7	0.025	0.0002	0.014	0.00002
8	0.025	0.0006	0.014	0.00008
9	0.03	0.0045	0.015	0.0006
10	0.031	0.0036	0.015	0.0005
11	0.027	0.0011	0.014	0.0001
12	0.028	0.0019	0.014	0.0002
13	0.025	0.0001	0.014	0.00001
14	0.026	0.0007	0.014	0.00009
15	0.025	0.0001	0.014	0.0001
16	0.025	0.0002	0.014	0.00002
17	0.025	0.0002	0.014	0.00001
18	0.025	0.0003	0.014	0.00004
19	0.028	0.0025	0.014	0.0003
20	0.027	0.0016	0.014	0.0002
21	0.025	0.0001	0.014	0.00002
22	0.025	0.0004	0.014	0.00004

Table D2continue: Output elasticities

Code	$\theta(IT_t) - Adj.$	Std. Error	$\theta(IT_t) - NoAdj.$	Std. Error
23	0.024	0.0001	0.014	0.00005
24	0.042	0.0121	0.017	0.0018
25	0.057	0.0052	0.021	0.0039
26	0.038	0.0047	0.016	0.0006
27	0.051	0.0138	0.02	0.0049
28	0.039	0.0121	0.016	0.0018
29	0.057	0.0115	0.021	0.0044
30	0.035	0.0113	0.016	0.0016
31	0.041	0.0116	0.016	0.0018
32	0.025	0.0003	0.014	0.00003
33	0.025	0.0002	0.014	0.00003
34	0.05	0.0136	0.019	0.0055
35	0.025	0.0003	0.014	0.00003
36	0.025	0.0004	0.014	0.00005
37	0.026	0.0012	0.014	0.0002
38	0.025	0.0002	0.014	0.00002
39	0.027	0.0018	0.014	0.0002
40	0.026	0.0008	0.014	0.0001
41	0.025	0.0002	0.014	0.00002
42	0.033	0.0075	0.015	0.001

This model supports the argument that the output elasticities from the model with adjustment costs are higher, leading to a larger effect from IT-capital on productivity. Another conclusion that we can draw from both tables is the fact that when industries increase their IT-capital this immediately increases the output elasticity of IT-capital. For low levels of IT the output elasticity remains the same.

Next, we obtain a new figure in which the new smooth coefficient function is $\theta(IT_{it}, \bar{K}, \bar{L}, \bar{M})$. Figure 5.7 presents the output elasticities with IT capital in the end of the period. As before the first graph refers to the model with adjustment costs and the second to the model without.

From figure 5.7 we also observe that the output elasticities and therefore the effect of IT-capital on economic performance are understated when adjustment costs are not included in the model. The results are quite similar with the case in which the smooth coefficient function depends only on IT capital stock and with the results from our preferred specification. These graphs provide further verification to the nonlinear relationship among IT-capital and productivity. And the nonlinearity is more obvious when adjustment costs are included in the model. Very similar results are obtained for the average output elasticity as well when $\theta(IT_{it}, K_{it}, L_{it}, M_{it})$ and are presented in Table D3.

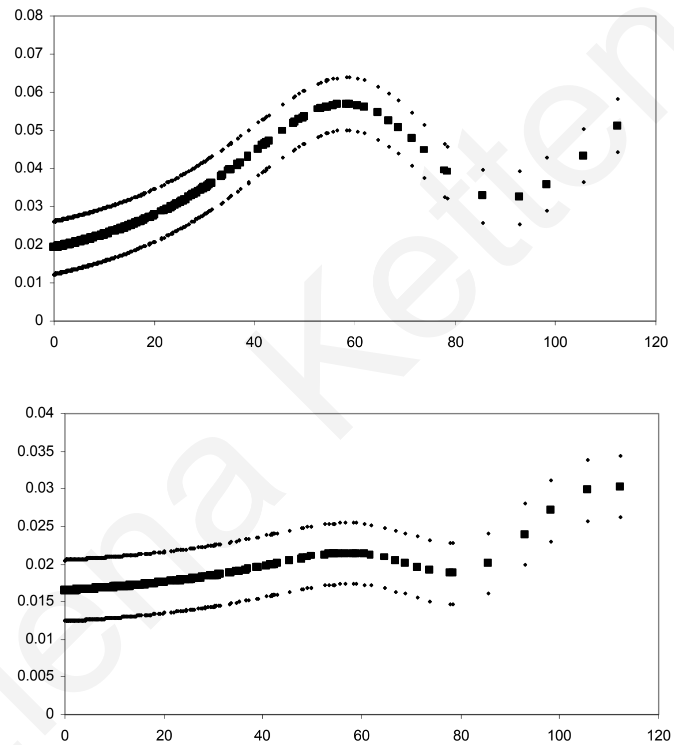

Figure 5.7: IT Output Elasticity: $\theta(IT_{it}, \bar{K}, \bar{L}, \bar{M})$ and $I\hat{T}_{it-1}$

Table D3: Output elasticities (Averages by Industry)

Code	Elast-Adj.	Std. Error	Elast-No Adj.	Std. Error
1	0.055	0.0011	0.024	0.0013
2	0.048	0.003	0.02	0.0025
3	0.023	0.0123	0.073	0.0086
4	0.017	0.0008	0.019	0.0001
5	0.013	0.0008	0.019	0.0001
6	0.016	0.0006	0.019	0.0001
7	0.023	0.0006	0.021	0.0004
8	0.024	0.0012	0.02	0.0004
9	0.043	0.0112	0.022	0.0068
10	0.041	0.0168	0.023	0.0053
11	0.034	0.0129	0.033	0.0205
12	0.022	0.0007	0.02	0.0002
13	0.011	0.0004	0.018	0.0001
14	0.017	0.0087	0.025	0.0012
15	0.01	0.0006	0.018	0.0001
16	0.016	0.0004	0.019	0.0001
17	0.015	0.0006	0.019	0.0001
18	0.021	0.0003	0.02	0.0002
19	0.023	0.0002	0.02	0.00001
20	0.055	0.0057	0.025	0.0013
21	0.02	0.0003	0.021	0.0002
22	0.020	0.0008	0.020	0.0003

Table D3continue: Output elasticities

Code	Elast-Adj.	Std. Error	Elast-No Adj.	Std. Error
23	0.01	0.0003	0.018	0.00001
24	0.044	0.0218	0.034	0.0169
25	0.045	0.11	0.03	0.024
26	0.034	0.0024	0.029	0.0021
27	0.047	0.0466	0.035	0.064
28	0.051	0.049	0.036	0.052
29	0.055	0.0085	0.035	0.0014
30	0.044	0.0052	0.018	0.0027
31	0.065	0.0152	0.02	0.0151
32	0.021	0.0016	0.019	0.0001
33	0.015	0.0012	0.019	0.0001
34	0.042	0.028	0.027	0.0058
35	0.019	0.0014	0.019	0.0003
36	0.011	0.0011	0.018	0.0001
37	0.012	0.0022	0.018	0.0001
38	0.017	0.003	0.019	0.0004
39	0.043	0.0096	0.012	0.0101
40	0.022	0.0017	0.021	0.0003
41	0.021	0.0022	0.021	0.0004
42	0.055	0.0071	0.015	0.0044

Sources of output growth

Table D4 presents the results of the model using $\theta(IT_{it})$ without adjustment costs while Table D5 gives the results from the model with adjustment costs. From both tables the contribution of other inputs is excluded since it remains the same as the one presented in Table 3.2.

Table D4: Sources of output growth, 1985-2001 (%)

Industry Code	Output Growth	Contribution of IT capital	Exogenous technical change
1	2.32	0.48	0.22
2	0.33	0.12	0.99
3	1.05	0.89	-0.87
4	1.15	0.39	-0.89
5	1.97	0.4	-0.25
6	0.97	0.32	0.16
7	0.83	0.16	0.73
8	1.45	0.4	0.09
9	5.88	0.35	2.91
10	10.4	0.32	5.52
11	1.84	0.26	0.003
12	1.93	0.41	-1.05
13	2.05	0.36	0.77
14	1.57	0.34	-0.55
15	-1.45	0.13	-4.99
16	0.35	0.34	0.37
17	-0.17	0.31	0.63
18	0.97	0.29	-0.26
19	0.32	0.51	-1.37
20	2.16	0.38	0.52
21	0.59	0.21	-0.12
22	4.23	0.49	0.59

Table D4continue: Sources of output growth

Industry Code	Output Growth	Contribution of IT capital	Exogenous technical change
23	-3.02	0.35	0.54
24	3.32	0.47	0.66
25	6.99	0.79	3.25
26	1.02	0.2	0.33
27	4.14	0.68	2.11
28	4.8	0.46	0.65
29	5.57	0.82	1.91
30	1.49	0.52	-0.38
31	2.9	0.44	-0.59
32	2.15	0.25	-0.55
33	2.59	0.49	-1.13
34	7.62	0.61	0.02
35	3.09	0.3	-0.99
36	2.39	0.59	-1.93
37	4.9	0.59	-1.22
38	5.11	0.15	-0.75
39	3.19	0.5	-1.37
40	2.35	0.38	-0.74
41	3.06	0.44	-0.84
42	4.78	0.5	-0.51

Table D5: Sources of output growth, 1985-2001 (%)

Industry Code	Output Growth	Contribution of IT capital	Contribution adjustment cost	Exogenous technical change
1	2.32	0.72	0.07	-0.08
2	0.33	0.17	-0.12	1.05
3	1.05	1.33	-0.66	-0.65
4	1.15	0.58	0.05	-1.14
5	1.97	0.59	0.05	-0.5
6	0.97	0.48	-0.37	0.38
7	0.83	0.24	0.03	0.62
8	1.45	0.58	0.05	-0.16
9	5.88	0.54	0.05	2.67
10	10.4	0.49	0.01	5.33
11	1.84	0.39	-0.11	-0.02
12	1.93	0.61	0.06	-1.32
13	2.05	0.53	0.05	0.55
14	1.57	0.51	0.02	-0.73
15	-1.45	0.19	-0.001	-5.05
16	0.35	0.49	-0.13	0.34
17	-0.17	0.47	-0.36	0.84
18	0.97	0.44	-0.22	-0.18
19	0.32	0.75	0.04	-1.66
20	2.16	0.57	-0.21	0.55
21	0.59	0.3	0.03	-0.25
22	4.23	0.72	-0.25	0.6

Table D5continue: Sources of output growth

Industry Code	Output Growth	Contribution of IT capital	Contribution adjustment cost	Exogenous technical change
23	-3.02	0.52	0.06	0.31
24	3.32	0.76	0.07	0.3
25	6.99	1.48	0.06	2.51
26	1.02	0.31	0.02	0.19
27	4.14	1.04	0.06	1.68
28	4.8	0.72	0.06	0.32
29	5.57	1.43	-0.59	1.89
30	1.49	0.81	0.07	-0.75
31	2.9	0.69	0.07	-0.93
32	2.15	0.37	0.04	-0.72
33	2.59	0.73	0.08	-1.44
34	7.62	0.88	0.07	-0.32
35	3.09	0.45	-0.33	-0.79
36	2.39	0.87	-0.2	-2
37	4.9	0.87	0.05	-1.55
38	5.11	0.22	-0.48	-0.34
39	3.19	0.75	0.07	-1.69
40	2.35	0.56	0.06	-0.98
41	3.06	0.64	0.06	-1.11
42	4.78	0.77	0.07	-0.86

Similar to the previous analysis, we find that adjustment costs have either a negative or a small positive, close to zero, effect on output growth. Again, all industries's output growth is positively influenced by IT-capital, and the industries with the largest IT capital contribution appear to be communication and bank and security. Bank and security appear to also have large negative adjustment costs not captured in the previous analysis. In this case, we clearly observe that the contribution of IT-capital in output growth is larger when adjustment costs are included in the model. So here too the omission of adjustment costs provides us a smaller effect from IT-capital to growth.

We also provide support to the fact that IT promotes growth in all industries, even to the ones which experience output reduction. The contribution in some industries is approximately the same as in the case with the more general smooth coefficient function. But in others the contribution here appears to be smaller. Especially in those previously referred as IT-intensive industries.

Table D6 presents the results from the model in which the smooth coefficient function depends on all inputs, but without adjustment costs,

Table D6: Sources of output growth, 1985-2001 (%)

Industry Code	Output Growth	Contrib. of capital	Contrib. of labor	Contrib. of interm. inputs	Contrib. of IT capital	Exogenous technical change
1	2.32	-0.006	0.36	1.26	0.79	-0.09
2	0.33	-0.08	-0.71	0.008	0.17	0.93
3	1.05	0.05	1.11	-0.13	0.49	-0.47
4	1.15	-0.01	0.21	1.46	0.21	-0.71
5	1.97	0.04	0.13	1.64	0.16	-0.004
6	0.97	0.07	-0.06	0.48	0.16	0.32
7	0.83	-0.08	-0.31	0.33	0.11	0.78
8	1.45	0.03	-0.005	0.94	0.27	0.2
9	5.88	0.03	-0.21	2.79	0.45	2.81
10	10.4	0.2	-0.27	4.62	0.37	5.46
11	1.84	0.05	-0.19	1.72	0.26	0.005
12	1.93	0.06	-0.49	3.01	0.26	-0.91
13	2.05	0.02	0.05	0.86	0.12	1.00
14	1.57	0.05	0.08	1.65	0.18	-0.39
15	-1.45	-0.02	-0.42	3.87	0.03	-4.9
16	0.35	-0.04	-0.57	0.25	0.16	0.54
17	-0.17	0.003	-1.16	0.05	0.14	0.79
18	0.97	0.09	-0.09	0.94	0.19	-0.16
19	0.32	0.03	0.15	1.01	0.34	-1.21
20	2.16	0.13	-0.04	1.16	0.63	0.28
21	0.59	-0.02	-0.14	0.67	0.13	-0.04
22	4.23	0.14	0.36	2.66	0.3	0.78

Table D6continued: Sources of output growth, 1985-2001 (%)

Industry Code	Output Growth	Contrib. of capital	Contrib. of labor	Contrib. of interm. inputs	Contrib. of IT capital	Exogenous Technical change
23	-3.02	-0.05	-2.18	-1.69	0.06	0.84
24	3.32	0.09	0.72	1.38	1.16	-0.02
25	6.99	0.37	0.23	2.35	2.84	1.2
26	1.02	0.43	-0.06	-0.33	0.13	0.85
27	4.14	0.15	0.32	0.63	1.08	1.95
28	4.8	0.2	1.15	1.12	1.38	0.96
29	5.57	0.4	0.3	2.14	1.02	1.71
30	1.49	0.25	0.45	0.66	0.64	-0.5
31	2.9	0.44	0.1	2.51	0.72	-0.87
32	2.15	0.39	0.86	1.21	0.16	-0.46
33	2.59	0.05	0.59	2.6	0.21	-0.85
34	7.62	0.16	2.65	4.13	0.68	-0.003
35	3.09	0.58	1.06	2.13	0.17	-0.85
36	2.39	0.05	0.31	3.36	0.18	-1.52
37	4.9	0.25	1.9	3.37	0.21	-0.84
38	5.11	0.26	1.96	3.49	0.1	-0.71
39	3.19	0.12	1.84	2.11	0.52	-1.39
40	2.35	0.03	1.49	1.19	0.24	-0.6
41	3.06	0.05	1.74	1.68	0.28	-0.69
42	4.78	0.08	1.93	2.77	0.74	-0.75

Appendix E. Imposing Concavity - Cost Function

The SGM cost function is not necessarily concave in user costs of efficiency-adjusted inputs, ω_{it}. In particular, the symmetric matrix in the case we have 5 inputs.

$$B = \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} & \beta_{14} & \beta_{15} \\ \beta_{12} & \beta_{22} & \beta_{23} & \beta_{24} & \beta_{25} \\ \beta_{13} & \beta_{23} & \beta_{33} & \beta_{34} & \beta_{35} \\ \beta_{14} & \beta_{24} & \beta_{34} & \beta_{44} & \beta_{45} \\ \beta_{15} & \beta_{25} & \beta_{35} & \beta_{45} & \beta_{55} \end{bmatrix},$$

which is comprised of the coefficients β_{ij} in the demand equations, may not be negative semi-definite. This property is imposed on B by triangularization, i.e. by imposing the equality $B = -AA'$, where A is a lower triangular matrix.

Define the transpose of A as:

$$A' = \begin{bmatrix} a_{11} & a_{12} & a_{13} & \alpha_{14} & \alpha_{15} \\ 0 & a_{22} & a_{23} & \alpha_{24} & \alpha_{25} \\ 0 & 0 & a_{33} & \alpha_{34} & \alpha_{35} \\ 0 & 0 & 0 & \alpha_{44} & \alpha_{45} \\ 0 & 0 & 0 & 0 & \alpha_{55} \end{bmatrix}.$$

which means that each β_{ij} in B is replaced with the corresponding element of $-AA'$:

$\beta_{11} = -a_{11}^2$

$\beta_{12} = -a_{11}a_{12}$

$$\beta_{13} = -a_{11}a_{13}$$

$$\beta_{14} = -a_{11}a_{14}$$

$$\beta_{15} = -a_{11}a_{15}$$

$$\beta_{22} = -(a_{12}^2 + a_{22}^2)$$

$$\beta_{23} = -(a_{12}a_{13} + a_{22}a_{23})$$

$$\beta_{24} = -(a_{12}a_{14} + a_{22}a_{24})$$

$$\beta_{25} = -(a_{12}a_{15} + a_{22}a_{25})$$

$$\beta_{33} = -(a_{13}^2 + a_{23}^2 + a_{33}^2)$$

$$\beta_{34} = -(a_{13}a_{14} + a_{23}a_{24} + a_{33}a_{34})$$

$$\beta_{35} = -(a_{13}a_{15} + a_{23}a_{25} + a_{33}a_{35})$$

$$\beta_{44} = -(a_{13}^2 + a_{23}^2 + a_{33}^2 + a_{44}^2)$$

$$\beta_{45} = -(a_{14}a_{15} + a_{24}a_{25} + a_{34}a_{35} + a_{44}a_{45})$$

$$\beta_{55} = -(a_{13}^2 + a_{23}^2 + a_{33}^2 + a_{44}^2 + a_{55}^2)$$

Appendix F. Elasticities of Efficiency Adjusted Inputs with respect to user costs

Table F1: Elasticities by industry

	CODE=1						CODE=2				
	WU	WK	WM	WS	WIT		WU	WK	WM	WS	WIT
U	-0.0312	-0.0125	-0.0092	0.0141	0.0328	U	-0.0005	-0.00008	0.0365	0.0011	0.0062
K	-0.0066	-0.0026	-0.0013	0.0032	-0.0064	K	-0.0005	-0.0011	0.0237	-0.0004	-0.0032
M	-0.0016	-0.0007	-0.0104	-0.0028	-0.0099	M	0.0145	0.0014	-0.0196	-0.0007	-0.0479
S	0.0831	0.0332	-0.0476	-0.0627	-0.0285	S	0.0037	-0.0015	0.0296	-0.002	-0.0004
IT	0.0878	0.0341	0.0897	-0.0153	-0.1457	IT	0.0007	0.0004	-0.0003	-0.0007	-0.0004
	CODE=3						CODE=4				
	WU	WK	WM	WS	WIT		WU	WK	WM	WS	WIT
U	-0.0315	0.0121	0.0123	0.0183	0.0574	U	-0.0042	-0.0039	-0.0194	0.0053	0.0208
K	0.0202	-0.0848	-0.0141	-0.0015	-0.00103	K	-0.0201	-0.002	0.0043	-0.0012	-0.0636
M	0.067	-0.0355	-0.0274	0.0045	-0.00234	M	-0.0064	0.0241	-0.0154	0.048	0.0782
S	0.0212	-0.0697	-0.0118	-0.0152	-0.0159	S	0.0031	-0.0002	0.0001	-0.0005	-0.0008
IT	0.0149	0.0588	0.0578	-0.00604	-0.0039	IT	0.0002	-0.0046	0.0001	-0.0003	-0.0009
	CODE=5						CODE=6				
	WU	WK	WM	WS	WIT		WU	WK	WM	WS	WIT
U	-0.0751	-0.0445	0.0001	-0.0128	-0.0358	U	-0.062	0.0157	0.0589	-0.0006	0.0134
K	-0.0217	-0.0132	0.0036	-0.0408	-0.0949	K	0.0702	-0.0179	-0.0677	0.0127	0.0192
M	0.0293	0.0171	-0.0518	0.0476	0.0016	M	0.0251	-0.064	-0.0332	0.0682	0.0355
S	-0.0874	-0.056	0.0002	-0.0321	-0.0015	S	-0.0757	0.0368	0.0021	-0.0014	-0.0061
IT	0.0002	0.0063	-0.0004	-0.0869	-0.00023	IT	0.0252	0.0814	0.0016	-0.001	-0.0041

Table F1continue: Elasticities

	CODE=7						CODE=8				
	WU	WK	WM	WS	WIT		WU	WK	WM	WS	WIT
U	-0.0108	0.0158	-0.0013	-0.0022	0.0405	U	-0.0708	0.0011	-0.0028	0.0097	0.0004
K	0.0053	-0.078	0.0059	0.0183	-0.0017	K	0.0003	-0.0004	0.0001	-0.0041	0.0016
M	-0.0438	0.0602	-0.001	0.0109	0.0403	M	-0.0011	0.0016	-0.0046	0.0075	0.0012
S	-0.0233	0.0567	0.0033	-0.095	-0.0015	S	0.0013	-0.0022	0.003	-0.0502	-0.0058
IT	0.0083	-0.0011	0.0002	-0.0302	-0.0011	IT	0.0009	-0.0031	0.0019	0.0192	-0.0042

	CODE=9						CODE=10				
	WU	WK	WM	WS	WIT		WU	WK	WM	WS	WIT
U	-0.0125	0.051	-0.069	0.0224	0.0054	U	-0.0005	-0.0175	0.0275	-0.0006	0.0035
K	0.0033	-0.0029	0.0003	-0.0002	0.0006	K	-0.0452	-0.0022	0.0003	-0.088	0.004
M	-0.018	0.0018	-0.0226	0.0795	-0.0251	M	0.0051	0.0225	-0.0356	0.0327	-0.0045
S	0.0634	-0.07	0.0077	-0.0061	-0.0005	S	-0.0008	-0.0917	0.0048	-0.0394	-0.0034
IT	0.0395	0.0051	-0.0034	-0.0007	-0.001	IT	0.0002	0.0057	-0.0083	-0.0004	-0.0001

	CODE=11						CODE=12				
	WU	WK	WM	WS	WIT		WU	WK	WM	WS	WIT
U	-0.0206	0.001	-0.0799	0.0092	0.0168	U	-0.0661	-0.0017	0.0019	0.0671	0.0126
K	0.0039	-0.0002	0.0002	-0.0018	0.0034	K	-0.0009	-0.0003	0.0003	0.0001	-0.0755
M	-0.0128	0.0707	-0.0595	0.0161	-0.0144	M	0.043	0.0151	-0.0202	-0.03	0.0384
S	0.0377	-0.002	0.0403	-0.0039	-0.0015	S	0.0654	0.0251	-0.0162	-0.0013	-0.0012
IT	0.0004	-0.0002	0.0002	-0.0009	-0.0001	IT	0.0141	-0.0285	0.0043	-0.002	-0.0002

	CODE=13						CODE=14				
	WU	WK	WM	WS	WIT		WU	WK	WM	WS	WIT
U	-0.0486	0.0013	0.0111	0.0635	0.0017	U	-0.0771	0.0018	-0.0852	0.0196	0.0435
K	0.0001	-0.0321	-0.0256	-0.0014	-0.004	K	0.0066	-0.0016	0.0061	-0.0018	-0.0064
M	0.0761	-0.0214	-0.0235	-0.0105	-0.0205	M	-0.0118	0.0233	-0.0367	0.0025	-0.0241
S	0.0248	-0.0702	-0.0597	-0.0328	-0.0852	S	0.0012	-0.003	0.001	-0.0333	-0.0011
IT	0.0014	0.0041	-0.0529	-0.0011	-0.0011	IT	0.0038	-0.0003	-0.0008	-0.0702	-0.0013

Table F1continue: Elasticities

CODE=15

	WU	WK	WM	WS	WIT
U	-0.0785	-0.0118	0.0095	0.0214	-0.0712
K	-0.0935	-0.0141	0.0001	0.0234	-0.0859
M	0.0003	0.0044	-0.0004	0.004	0.0033
S	0.002	0.0278	0.0001	-0.0018	-0.0382
IT	-0.0041	-0.0627	0.0005	-0.0254	-0.041

CODE=16

	WU	WK	WM	WS	WIT
U	-0.0021	0.003	-0.0013	0.0494	-0.0031
K	0.0004	-0.0006	0.0003	-0.0001	0.0024
M	-0.0598	0.0871	-0.0412	0.0174	-0.0034
S	0.0012	-0.0017	0.0092	-0.0013	-0.0001
IT	-0.0415	0.0032	-0.0013	-0.0098	-0.0001

CODE=17

	WU	WK	WM	WS	WIT
U	-0.0554	-0.0862	0.0118	0.0419	0.0184
K	-0.0957	-0.0015	0.0021	0.0072	-0.0034
M	0.0391	0.0614	-0.0121	0.0026	0.0178
S	0.0047	0.0074	0.0935	-0.0013	-0.0507
IT	-0.0518	-0.0082	0.0014	-0.0012	-0.0026

CODE=18

	WU	WK	WM	WS	WIT
U	-0.0493	0.0708	-0.0207	-0.0079	0.0002
K	0.002	-0.0029	0.0527	0.0498	0.025
M	-0.0062	0.0055	-0.0557	0.0296	0.0344
S	-0.0011	0.0024	0.0013	-0.0873	-0.0902
IT	0.0047	0.0016	0.0022	-0.0012	-0.0014

CODE=19

	WU	WK	WM	WS	WIT
U	-0.0236	-0.0573	0.0726	0.0392	0.0533
K	-0.0435	-0.0015	0.0093	-0.0083	0.0019
M	0.0252	0.0431	-0.0042	-0.0057	-0.0011
S	0.0065	-0.0132	-0.002	-0.0032	-0.062
IT	0.0055	0.0044	-0.0005	-0.0007	-0.0019

CODE=20

	WU	WK	WM	WS	WIT
U	-0.0306	0.00309	-0.0025	0.0374	0.0021
K	0.0039	-0.0041	0.0035	-0.0612	-0.0028
M	-0.0367	0.0399	-0.0486	0.0225	0.0214
S	0.0733	-0.0965	0.003	-0.0478	-0.0017
IT	0.0012	-0.0012	0.0001	0.0056	-0.0015

Table F1continue: ELASTICITIES

CODE=21

	WU	WK	WM	WS	WIT
U	-0.0002	-0.0004	-0.0189	0.0002	0.0191
K	-6E-05	-0.0005	0.0252	-0.0111	-0.0141
M	-0.0012	0.0003	-0.0018	0.006	0.0012
S	0.0003	-0.0002	0.0088	-0.0361	-0.0528
IT	0.0021	-0.0002	0.00255	-0.0555	-0.0201

CODE=22

	WU	WK	WM	WS	WIT
U	-0.0159	0.0007	0.0018	0.0007	0.0692
K	0.0042	-0.0008	-0.0228	-0.0004	0.0177
M	0.0647	-0.001	-0.0109	-0.0001	0.0051
S	0.01	-0.0008	-0.0058	-0.0012	-0.0068
IT	0.0271	0.0088	0.0064	-0.0069	-0.0516

CODE=23

	WU	WK	WM	WS	WIT
U	-0.0933	0.0116	0.0709	-0.0251	0.0131
K	0.0114	-0.0143	-0.0854	0.0153	-0.0155
M	0.0351	-0.0433	-0.03	0.0493	-0.0611
S	-0.0162	0.0103	0.0641	-0.0642	-0.0221
IT	0.0109	-0.0115	-0.0927	-0.0293	-0.0364

CODE=24

	WU	WK	WM	WS	WIT
U	-0.0788	-0.0121	-0.0303	-0.0214	0.0748
K	-0.0221	-0.0344	-0.0101	-0.0061	0.0212
M	-0.0173	-0.0037	-0.0733	0.0177	0.0645
S	-0.0128	-0.0205	0.0194	-0.0725	0.0121
IT	0.0145	0.0244	0.0359	0.0019	-0.0164

CODE=25

	WU	WK	WM	WS	WIT
U	-0.0867	-0.0337	0.0183	-0.0729	0.0448
K	-0.0695	-0.0299	0.0157	-0.0652	-0.0417
M	0.0908	0.0398	-0.0366	-0.0541	0.0196
S	-0.0123	-0.0563	-0.0187	-0.0562	-0.0347
IT	-0.0101	-0.0437	0.0776	-0.0421	-0.0551

CODE=26

	WU	WK	WM	WS	WIT
U	-0.0009	-0.0004	0.0004	-0.0001	-0.0001
K	-0.0001	-0.0008	0.0001	-0.0001	-0.0003
M	-0.0004	0.0001	-0.0025	0.0016	0.0041
S	-0.0002	-0.0011	0.0237	-0.0153	-0.0393
IT	-0.0003	-0.0006	0.0013	-0.0008	-0.0022

CODE=27

	WU	WK	WM	WS	WIT
U	-0.0132	0.0041	0.0375	0.0009	0.0799
K	0.0531	-0.0183	-0.0151	-0.0494	0.0103
M	0.0541	-0.0175	-0.0152	0.0019	0.0122
S	0.0018	0.0016	0.0051	-0.0947	-0.0331
IT	-0.0031	0.0029	0.0394	-0.0291	-0.0185

CODE=28

	WU	WK	WM	WS	WIT
U	-0.0146	-0.0559	0.0526	0.0008	0.0791
K	-0.0469	-0.0188	0.0168	0.023	-0.0226
M	0.0451	0.0173	-0.0223	0.0844	-0.0317
S	0.0065	0.0241	0.0962	-0.018	-0.0185
IT	0.0068	-0.0226	0.0307	-0.0181	-0.0607

Table F1continue: Elasticities

CODE=29

	WU	WK	WM	WS	WIT
U	-0.0033	0.0015	-0.0014	0.0054	0.0053
K	0.0884	-0.0389	0.0037	-0.0141	-0.0014
M	-0.023	0.0084	-0.0832	0.0294	0.0347
S	0.0035	-0.0159	0.0154	-0.0057	-0.0057
IT	0.0019	-0.0735	0.0723	-0.0025	-0.0031

CODE=30

	WU	WK	WM	WS	WIT
U	-0.0081	-0.0904	-0.0024	0.0012	0.0352
K	-0.0077	-0.0011	-0.0038	-0.0195	0.0491
M	-0.0086	-0.0146	-0.0806	0.0491	0.0042
S	0.0031	-0.0001	0.0031	-0.0934	-0.0271
IT	0.0555	0.0002	-0.0023	0.0001	-0.0181

CODE=31

	WU	WK	WM	WS	WIT
U	-0.0085	-0.0012	0.0111	0.0275	0.0063
K	-0.0039	-0.0586	0.0507	-0.0128	0.0031
M	0.0015	0.0023	-0.0227	0.0113	-0.0011
S	0.0011	-0.0171	0.0033	-0.0479	-0.003
IT	0.0098	0.0147	-0.0114	-0.0113	-0.0085

CODE=32

	WU	WK	WM	WS	WIT
U	-0.0071	0.0029	0.0891	0.0111	0.0021
K	0.0083	-0.0345	-0.0011	-0.0182	-0.0023
M	0.0679	-0.0268	-0.0457	0.0449	-0.0265
S	0.0011	-0.0691	0.0063	-0.0964	-0.0027
IT	0.0306	-0.0126	-0.0515	-0.0031	-0.0108

CODE=33

	WU	WK	WM	WS	WIT
U	-0.0041	-0.0003	-0.0002	0.0373	0.0019
K	-0.0003	-0.0051	0.0191	-0.0459	-0.0401
M	-0.0015	-0.0014	-0.094	-0.0104	0.0844
S	0.0028	-0.0121	0.0129	-0.0115	-0.0026
IT	0.0403	0.0011	0.0285	-0.0762	-0.0301

CODE=34

	WU	WK	WM	WS	WIT
U	-0.0771	-0.0758	0.0031	0.0469	0.001
K	-0.0033	-0.0033	0.0001	0.0024	0.0039
M	0.0037	0.0003	-0.0185	0.0002	-0.0695
S	0.0013	0.0001	0.0052	-0.0236	-0.0767
IT	0.0033	0.0003	-0.0188	0.0009	-0.0985

Table F1continue: ELASTICITIES

	CODE=35						CODE=36				
	WU	WK	WM	WS	WIT		WU	WK	WM	WS	WIT
U	-0.0209	-0.0012	0.0029	0.0033	0.0486	U	-0.0321	-0.0081	0.0062	0.0161	0.0115
K	-0.0015	-0.0965	0.0021	-0.0241	-0.0392	K	-0.0614	-0.0595	0.0001	-0.0283	0.0022
M	0.0012	0.0803	-0.0805	-0.0299	-0.0196	M	0.0361	0.0351	-0.0747	0.0636	-0.0135
S	-0.0002	-0.0157	-0.0587	-0.0125	-0.0751	S	0.0281	-0.0025	0.0019	-0.0176	-0.0169
IT	-0.0008	-0.0491	0.0082	-0.0154	-0.0194	IT	0.0181	-0.0191	-0.0391	-0.0123	-0.0124
	CODE=37						CODE=38				
	WU	WK	WM	WS	WIT		WU	WK	WM	WS	WIT
U	-0.0027	0.0164	-0.055	0.0126	0.0231	U	-0.0101	0.0013	-0.0017	0.0124	0.0028
K	0.0147	-0.0173	0.0005	-0.0953	-0.0189	K	0.0057	-0.0845	0.0098	-0.0708	-0.0015
M	-0.0226	0.0024	-0.0886	0.0258	0.0029	M	-0.0664	0.0826	-0.0017	0.0009	0.0051
S	0.0329	-0.0291	0.0016	-0.0761	-0.0451	S	0.055	-0.0748	0.0012	-0.0756	-0.0184
IT	0.0432	-0.0294	0.0087	-0.0199	-0.0155	IT	-0.0199	0.0036	0.0015	-0.0569	-0.0151
	CODE=39						CODE=40				
	WU	WK	WM	WS	WIT		WU	WK	WM	WS	WIT
U	-0.0003	-0.0003	0.0008	0.0003	0.0028	U	-0.0005	-0.0048	-0.0115	0.0188	0.0034
K	0.0015	-0.0016	-0.0043	0.0017	-0.0086	K	-0.0077	-0.0288	0.0004	-0.0182	-0.0057
M	0.0008	0.0009	-0.0024	0.0011	-0.0081	M	-0.0095	0.0002	-0.0161	0.0015	-0.0015
S	-0.0009	-0.0011	0.0031	-0.0021	-0.0015	S	0.0165	-0.0881	-0.0001	-0.0142	-0.0016
IT	0.0001	-0.0001	-0.0001	-0.0002	-0.0002	IT	0.0016	-0.0106	-0.0042	-0.0042	-0.0022
	CODE=41						CODE=42				
	WU	WK	WM	WS	WIT		WU	WK	WM	WS	WIT
U	-0.0996	0.0178	-0.0245	0.0185	0.0009	U	-0.0056	0.0021	-0.0018	0.0197	0.0408
K	0.0117	-0.0214	-0.0107	-0.0228	0.0007	K	0.0517	-0.0245	-0.0317	-0.0204	-0.0227
M	0.0021	0.0012	-0.0144	-0.0201	-0.0056	M	-0.0013	-0.0176	-0.0491	-0.0921	-0.0409
S	0.0068	-0.0013	-0.0891	-0.0024	-0.0025	S	0.0338	-0.0015	-0.0019	-0.0134	-0.0289
IT	0.0042	-0.0017	-0.0738	-0.0103	-0.0038	IT	0.0671	-0.0297	-0.0046	-0.0364	-0.0533