Three Essays in Applied Econometrics

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Submitted to the graduate degree program in Economics and the
Faculty of the Graduate School of the University of Kansas
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy

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Three Essays in Applied Econometrics

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Abstract

This dissertation includes three essays in Applied Econometrics. Each essay explores an interesting and important question in the real economic world. In the course of investigating the nature of each question, appropriate techniques are combined in order to overcome the problems of previous methods. It is not a simple application of textbook techniques. Rather, advanced techniques recently developed are appropriately combined so that our understanding of the question becomes deeper and improved.

The first essay is regarding the assessment of the effects of neighborhood land uses on residential house values. It is widely recognized that a nuclear plant or a prison, for example, often has an adverse effect on the property values of the nearby houses, while a park or a university usually has a beneficial effect. Such effects are estimated using a nonparametric regression method together with some advanced techniques in order to deal with potential problems.

The second essay considers the assessment of the sources of the economic growth in East Asia countries. East Asian countries experienced phenomenal economic growth from the 1970s to 1997, the so called "Asian Miracle," which ended when a financial crisis hit in 1997. There is a fundamental question with

regard to the Asian Miracle. Which is the prime source of the rapid growth between capital accumulation and productive improvements? Our approach to the question utilizes a nonparametric derivative estimation method so that we do not need the strong assumptions used by previous approaches.

The third essay assesses the effectiveness of IMF lending programs. When a member country of the IMF faces external payment problems rooted in macroeconomic and/or structural imbalances, the country may ask the IMF for financial assistance to normalize external payments and correct underlying macroeconomic imbalances. Our approach is based on a vector autoregressive model with regime switching so that it provides a dynamic feature of evaluation over the wide range time horizon. Our approach also provides a way to estimate not only the total effect of IMF programs, but also the loan effect and the policy advice effect. This kind of separation is often very important in policy discussion.

Acknowledgments

Before starting this dissertation, I read other people's acknowledgements in their dissertations. At the time, I felt that their gratitude to advisers and family members was over exaggerated. No, it is not over exaggeration. This is my feeling now. I feel that I would not have finished the dissertation without the support and encouragement from advisers, family members, and other people around me. I would like to say "Thank you" to all these people from the bottom of my heart.

I am especially grateful to Dr. Shigeru Iwata. He encouraged me tremendously and was very patient with my slow work. He has been my constant source of guidance, motivation, and encouragement throughout my study. Our meetings over the years, even during the holidays, are now memorable moments in my life.

I also would like to extend my heartfelt thanks to the other members of my dissertation committee, Dr. Elizabeth Asiedu, Dr. Gautam Bhattacharyya, Dr. Ted Juhl, and Dr. Tailan Chi. Their comments and encouragement helped me a lot.

Finally, I would like to express my gratitude to my family members, especially to my wife, Marina Murao. Without her support and encouragement, it was impossible to finish my study. I also got mental support from the other members of my family including my children, Emmi and Juna. Their laughter and smiles make me happy and gave me energy to complete the dissertation. I love you all.

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Chapter 1

Introduction

This dissertation includes three essays in Applied Econometrics. Each of them deals with an interesting and important question in the real economic world. Investigating the nature of each question and the problems of previous methods, appropriate techniques are combined so that our understanding of the question becomes deeper and improved. It is not a simple application of textbook techniques. Rather, advanced techniques recently developed are appropriately combined in order to deal with potential problems. The following sections of this chapter provide the brief descriptions of the essays.

1.1 First Essay

The first essay is title as "Nonparametric Assessment of the Effect of Neighborhood Land Uses on Residential House Values." It is widely recognized that a nuclear plant or a prison, for example, often has an adverse effect on the property values of the nearby houses, while a park, a museum, or a university usually has a beneficial effect. The effect of a land use defined as a function of distance between the land use factor and a particular house is inherently nonlinear and the use of a simple linear regression method could lead to a misleading conclusion.

The purpose of this essay is to estimate the land use effect function by using a nonparametric regression method. There are three important features of our model. First, it is a semiparametric model, which keeps a conventional linear form with respect to the dwelling attributes of the house, but treats its location characteristics in a nonlinear fashion. Second, unlike the usual nonparametric regression, it keeps additive structure in the nonparametric component, so that it retains much of the interpretative features of the linear models. Third, it uses the local linear smoother, which is superior to other smoothers.

The standard semiparametric model can be written as

$$y_i = x_i'\beta + f(z_i) + u_i \tag{1.1}$$

In our application y_i stands for the natural log of the sales price of the i-th house, x_i is a vector of the dwelling characteristics of the house, z_i is a vector of the location characteristics including distance to the land use factors, and $f(z_i)$ stands for an arbitrary function of z_i. Dwelling characteristics (x-variables) are variables that describe the characteristics of a house, including the age of the house, the land size, the number of rooms. Location characteristics (z-variables) are variables that describe the characteristics of a real estate site, such as distances to various land use factors. In our application, four location characteristics are considered: golf course, university, nitrogen plant, site elevation.

The nonparametric part $f(z_i)$ is assumed to be an additive form.

$$f(z_i) = \alpha + \sum_{j=1}^{p} f_j(z_{ji}) \tag{1.2}$$

where z_{ji} is the j-th component of vector z_i and p is the number of location characteristics. An underlying assumption here is that different land use factors do not have interactive effects on the house values. There are three distinctive merits for the above specification. First, it can avoid what is called the "curse of dimensionality" problem that plagues standard non- or semiparametric methods. Second, it provides a simple interpretation similar to one for the parametric linear models. Third, it makes computation easy with the help of the "backfitting algorithm."

Each component of the nonparametric part is estimated with a type of the local polynomial estimator. The use of the local polynomial estimator provides two merits. First, it has high asymptotic efficiency among all possible linear smoothers.

Second, it does not require any modification to deal with so called “boundary effect,” while the usual nonparametric kernel method suffers a large bias at boundary points. Its disadvantage is its computational cost. For our application, the local linear estimator is used.

We estimated the effects of three land use factors: golf courses, a university, and a nitrogen plant, as well as site elevation, on the neighborhood home values in Lawrence Kansas. The data are on the residential houses with 6,400 observations over the period from 1986 to 1995.

Our use of a semiparametric additive model with a local linear smoother enabled us to reveal salient features of the price effect curves of the golf courses, the university, the nitrogen plan, and elevation. Our results are consistent with our natural expectations. Since the results are shown in detail in Chapter 2, one of them is explained as illustrated here. The house directly adjacent to the university has a value 40% higher than the comparable house located 2,000 meters or more away from it. As the distance to the university gets large, the positive effect of the university declines rapidly and then at a more moderate pace. It disappears around 1,800 meters. A reason for the university effect to disappear around 1,800 meters seems to be that the walking distance of 20 minutes is likely to be the maximum for the usual person to choose to commute on foot.

1.2 Second Essay

The second essay is titled as" Sources of Economic Growth in East Asia: A Nonparametric Assessment." East Asian countries had an experience of phenomenal economic growth from the 1970s to 1997, the so called "Asian Miracle," which ended when a financial crisis hit in 1997. There is a fundamental question with regard to the Asian Miracle. Which is the prime source of the rapid growth of theses economies between capital accumulation and productivity improvements?

With regard to the Asian Miracle, there are opposite views: "accumulation view" and "assimilation view." The proponents of the accumulation view would argue that the rapid growth of theses economies had come primarily from capital accumulation and increasing labor participation rather than from productivity improvements. Therefore, the rapid growth is bound to slow down eventually. If the accumulation view is correct and growth is mainly based on capital formation, then the rapid growth will not be sustainable for long because the law of diminishing returns will eventually prevail.

On the other hand, the proponents of the assimilation view would argue that these countries can get back to their pre-crisis long-run growth paths since their economic growth originated from improvements in productivity. These countries have incorporated ideas from abroad and have improved in productivity. If growth originates from a narrowing of the "idea gap" as the assimilation view claims, no significant opportunity costs needed to be incurred to incorporate ideas from abroad, and therefore it is possible to get back to rapid growth paths. Both groups can point to empirical evidence for a variety of countries that supports their respective cases.

Productivity improvement originated from technological change can be measured as a change in total factor productivity (TFP). If Y represents output, K and L represent capital and labor, respectively, and t indicates time, then an aggregate production function in Hicks neutral form can be written as

$$Y(t) = A(t)F[K(t), L(t)] \tag{1.3}$$

where $A(t)$ stands for an index of the state of technology and called as total factor productivity or TFP. This leads to the following relationship

$$\frac{\dot{Y}}{Y} = \varepsilon_K \frac{\dot{K}}{K} + \varepsilon_L \frac{\dot{L}}{L} + \frac{\dot{A}}{A} \tag{1.4}$$

where $\dot{X} = dX / dt$ is the time derivative of the respective variable; ε_K and ε_L stand for the elasticities of output with respect to capital and labor, respectively. Here $\dot{A}/A$ represents TFP growth. If ε_K and ε_L were known, then TFP growth can be simply calculated by subtraction. An important question in the literature is how to estimate ε_K and ε_L. There are two approaches developed in the literature. The first approach assumes the perfect competition in factor markets so that the output elasticities of capital and labor are equal to the income shares of capital and labor (v_K and v_L), respectively. Under constant to returns to scale, $v_K + v_L = \varepsilon_K + \varepsilon_L = 1$. With this replacement, TFP growth can be calculated as the "Sollow residual." This method is called the growth accounting method. The second approach assumes a particular parametric form for an aggregate production function and estimates the production function by running a regression. Then, its elasticity estimates are used in the above formula to calculate TFP growth. Neither assumption, however, is particularly attractive when dealing with developing economies. First, capital and labor markets in these economies are likely to be far from perfectly competitive. Second, there is no guarantee that any particular functional form of the production function is appropriate for these economies.

We propose a third approach to estimate TFP growth. The output elasticities of capital and labor can be estimated if we apply a nonparametric derivative estimation method to an aggregate production function. For this approach, we do not need the assumption of perfectly competitive factor markets, nor do we need to assume any particular functional form of the aggregate production function. We construct a nonparametric derivative estimation method with utilizing a type of high efficiency estimator.

Using annual data for 1960-1995 or 1960-1990, TFP growth rates are estimated for nine East Asian countries: Hong Kong SAR, Indonesia, Korea, Malaysia, Philippines, Singapore, Taiwan Province of China, Thailand, and China.

Our findings, based on the new estimation procedure, include that Hong Kong, Korea, Singapore, and Taiwan all have very similar TFP growth of 3.4-3.9 percent over the period 1960-1995. There results provide little support for the strong version of the accumulation hypothesis. We also find that the output elasticities of capital and labor are quite different from the income shares of those factors in the East Asian countries. The estimated capital elasticity appears to be much smaller than the measured income shares of capital, resulting in misleadingly high contribution of capital growth to output growth in conventional growth-accounting exercises. On the basis of our new estimates, we would argue that East Asian growth reflects a combination of the accumulation and assimilation views of economic growth.

1.3 Third Essay

The third essay is titled as “Are IMF Lending Programs Effective? A Panel VAR Approach.” A member country of the IMF may ask financial assistance to the IMF when the country faces external payment problems rooted in macroeconomic and/or structural imbalances. One of the main functions of the IMF is to provide short term financial assistance to its member countries to deal with temporary balance-of-payments disequilibria. Upon an agreement between the two parties, an IMF lending program is implemented for the country. The IMF’s assistance to the participating countries in the program is typically two fold. First, the IMF provides a loan to the participating country in order to correct its balance-of-payments problem and restore conditions for strong economic growth. Second, the IMF demands the country to comply with its policy advice, which is known as the IMF conditionality. While the IMF’s role is widely regarded as both necessary and useful, one important question that is often raised is whether IMF programs are effective on the program country’s economic performance.

By now there is a quite large empirical literature that attempts to evaluate the effectiveness of IMF lending programs on the program country’s economy. Economists outside the IMF tend to find that IMF programs have no effect or even negative effect on the country’s economic growth and that programs appear to have a positive impact on current account and balance of payments but the effects last only in a short term. On the other hand, the IMF staff economists tend to find somewhat more positive effect of programs.

After reviewing previous approaches and their problems, we provide another approach based on a vector autoregression (VAR) model with a switching policy reaction function, and estimate the system together with a program participation equation. Our VAR approach is quite different from the single equation approach in the past studies. We treat all endogenous variables equally with multiple equations and estimate the multiple equations with panel data. This feature is crucially important to take into account a variety of shock encountered by the economy. Our policy reaction function switches between the two regimes depending on whether the county is "in" or "out" of the IMF program. This feature is also quite different from the dummy variable approach in the previous studies. When the program agreement includes some types of policy shifts, the country's policy makers are expected to respond to a variety of economic shocks differently from before the agreement. This kind of policy shift is difficult to capture by the program dummy alone. The dummy variable approach also lacks the dynamic features of evaluation crucially needed for any macro-economic programs. The effectiveness of the IMF program has to be evaluated not a few points in time but over the wide range of time horizon after its implementation. Under our VAR approach with regime switching, the effectiveness of the IMF program is evaluated over the wide range of time horizon time. More specifically the program effectiveness assessment is conducted in two ways: First by taking difference of two conditional predictions over the appropriate time horizon, and second by calculating impulse response functions generated from the program shock.

Another important feature where our approach is different from those in the literature is that we can estimate the loan effect and the policy advice effect separately. The dummy variable approach in the previous studies attempts to capture the total effect of the IMF program as the coefficient value of the program dummy, and hence it fails to evaluate the loan provision and the policy advice separately. Under our approach the total effect of the IMF program can be break down to the loan effect and the policy advice effect. This kind of separation is often very important in policy discussion.

Our data set is the panel data of annual observations for 79 countries covering Asia, Latin America, and Africa over the period of 28 years from 1976 through 2003. It contains 377 IMF programs actually implemented.

We find that, with IMF programs, output growth of the country increases, and the balance of payments as well as the government fiscal balance improves. Our findings are quite consistent with those in the literature except two important points. First, surprisingly, the effectiveness of IMF programs appears to come largely from the policy shifts rather than from the loan itself. Second, we observe, like many other studies, that IMF programs have only short-term effects on the country's economy. Other studies find this is due to the weakness of the programs. Our results suggest that the short lived effects of IMF programs may be due to the program country's failure in adhering to the new policy rules set under the programs.

Chapter 2

First Essay

Nonparametric Assessment of the Effects of Neighborhood Land Uses on Residential House Values

2.1 Introduction

The effect of nearby land uses on residential property values has long been a popular topic among a variety of agents such as city designers, property tax collectors, housing developers, and possible house buyers as well as sellers. It is widely recognized that a nuclear plant or a prison, for example, may have an adverse effect on the property value of the nearby houses, while a park, a museum, or a university usually has a beneficial effect. Assessment of such effects is essential for designing public projects, evaluating property tax of nearby houses, planning housing development and setting bid and ask prices of the houses in the market.

The impact of land uses on house prices often cannot be appropriately described by a simple linear function of distance. For instance, the houses located close enough to overlook a golf course entertain direct beneficial impact (wide open view, clean air, etc.) on their property values. This direct impact is expected to decline rapidly and becomes zero at a certain point, as distance gets large. This, however, is not the end of the story. The above group of houses generates a 'good neighborhood,' which in turn has a beneficial effect on the houses located further away from the golf course. This secondary impact is expected to decline much more slowly as distance grows.

Estimating such a nonlinear effect of a land use factor is complicated by the need to control for many other factors including a variety of dwelling characteristics of the house such as the size of the house and the number of the bedrooms, etc., as well as other land use factors.

This essay introduces a partly linear and partly nonparametric regression procedure that treats its nonparametric part in additive manner and therefore provides a convenient framework for analysis of this problem. A traditional approach to the house value assessment in economics is based on the hedonic price model (see e.g. Rosen 1974), in which the value of a house is viewed as a sum of the values of its dwelling attributes. What lacks in this approach is the appropriate evaluation of the location characteristics of the house. The approach adopted by this essay retains a linear structure of the hedonic price model with respect to the dwelling characteristics of the house, while it models the location characteristics in nonparametric but additive fashion. In this way the model preserves an important interpretation feature of the linear model that would be lost with the usual nonparametric regression models. In particular, the nature of the effect of a variable on the response surface does not depend on the values of the other variables. Therefore, we can plot the function for each coordinate separately to examine the roles of the variables in predicting the response.

2.2 Literature Review

There are several studies which attempted to quantify the effect of land uses empirically. Nelson et al. (1992) estimate the effect of one Minnesota landfill on the values of 708 nearby homes located within 2 miles of the landfill. Do and Grudnitski (1995) estimate the effect on the values of 717 houses in San Diego when they are directly adjacent to golf courses. They both found evidence of the presence of the land use effects (see also Waddell et al. 1993). Their investigations, however, are restricted to the analysis based on conventional linear regression with dummy variables, which allows them to capture only qualitative aspects of the land use effect. Stock (1989, 1991), on the other hand, uses a semiparametric regression to estimate the effect of removing hazardous waste on house prices. McMillen and Thorsnes (1999) construct a house price index using a semiparametric regression (see also McMillen 1996). Other applications of nonparametric or semiparametric estimation techniques to the hedonic price model include Meese and Wallace (1991), Pace (1993, 1998), Goetzmann and Spiegel (1995), and Anglin and Gencay (1996).

2.3 Overview of the Essay

This essay identifies the effect of land uses on the value of a particular house as an unrestricted function of distance to the land use factor, estimates this function by using recently developed techniques of nonparametric regression, and assesses the effects in detail. Specifically, the goal of this essay is to make a nonparametric assessment of the effects of three land use factors: (1) golf courses, (2) a university (a major employment and education center of the city) and (3) a nitrogen plant (the main polluter), on the nearby home values in Lawrence, Kansas.

The organization of the rest of the paper is as follows: In Section 2.4, the semiparametric additive model is introduced and described for this application.

Section 2.5 discusses the data, Section 2.6 explains the estimation procedure and Section 2.7 gives the results. A brief conclusion is given in Section 2.8.

2.4 The Semiparametric Additive Model

2.4.1 Semiparametric Model

To describe the semiparametric procedure, suppose that the i-th observation is given by a $(k+p+1)\times 1$ vector $(y_i, \mathbf{x}_i', \mathbf{z}_i'), i = 1, \ldots, n$, which is generated by the model

$$y_i = f(\mathbf{z}_i) + g(\mathbf{x}_i, \beta) + u_i \tag{2.1}$$

where $f(\mathbf{z})$ is an arbitrary function of $\mathbf{z}$, while $g(\mathbf{x}, \beta)$ is a known parametric function of $\mathbf{x}$ and a vector of unknown parameters β. The disturbance term u_i is assumed to satisfy

$$E(u_i | \mathbf{x}_i, \mathbf{z}_i) = 0 \tag{2.2}$$

and

$$E(u_i u_j | \mathbf{x}_i, \mathbf{x}_j, \mathbf{z}_i, \mathbf{z}_j) = \sigma^2 \quad \text{if} \quad i = j$$

$$E(u_i u_j | \mathbf{x}_i, \mathbf{x}_j, \mathbf{z}_i, \mathbf{z}_j) = 0 \quad \text{otherwise} \tag{2.3}$$

The most popular functional form of $g(\bullet,\bullet)$ is linear, that is,

$$g(\mathbf{x}, \beta) = \mathbf{x}'\beta \tag{2.4}$$

In our application y_i stands for the natural log of the sale price of the house, $\mathbf{x}_i$ is a vector of the dwelling characteristics of the house, and $\mathbf{z}_i$ is a vector of the location characteristics including distance to the land use factors. Rather than considering an arbitrarily chosen parametric form, such as polynomials, for $f(\bullet)$, we estimate it by a nonparametric function.

There are by now a variety of techniques available for applied researchers to estimate a nonparametric regression model (see e.g. Härdel 1990 and Eubank 1988). These techniques have much in common and may be referred to as "smoothers." They are characterized in essence by local averaging, that is, averaging the y-values of observations having predictor values $\mathbf{z}$ close to a target value. Smoothers differ mainly in their method of averaging. We restrict our attention to linear smoothers; that is smoothers that are linear in y. Examples of the linear smoothers include the Kernel, spline, and orthogonal series regression estimators (see Eubank 1988 and Härdel 1990).

Now let $\mathbf{P}$ denote the projection matrix $\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'$ and $\mathbf{S}$ be a linear smoothing operator, where $\mathbf{X}$ is an $n \times k$ matrix with its i-th row equal to $\mathbf{x}_i'$. For example, for the Nadaraya-Watson kernel regression estimator, the (i, j) element of $\mathbf{S}$ is given by $S_{ij} = K(z_i - z_j)/\sum_j K(z_i - z_j)$ for $i, j = 1, \ldots, n$ where

$K(\bullet)$ is a kernel function, which generates the weights with a maximum at zero and satisfies certain moment conditions. Write equation (2.1) in matrix form

$$\mathbf{y} = \mathbf{f} + \mathbf{g} + \mathbf{u} \tag{2.5}$$

where $\mathbf{y}, \mathbf{f}, \mathbf{g}$, and $\mathbf{u}$ are $n \times 1$ vectors with the i-th element equal to $y_i, f(\mathbf{z}_i), g(\mathbf{x}_i, \beta)$ and u_i. Assuming equations (2.2), (2.3), and (2.4), the estimators of $\mathbf{f}$ and $\mathbf{g}$ are given by

$$\hat{\mathbf{f}} = \mathbf{S}(\mathbf{y} - \hat{\mathbf{g}}) = \mathbf{S}(\mathbf{y} - \mathbf{X}\hat{\beta})$$

$$\hat{\mathbf{g}} = \mathbf{P}(\mathbf{y} - \hat{\mathbf{f}}) = \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'(\mathbf{y} - \hat{\mathbf{f}}) = \mathbf{X}\hat{\beta}$$

Combining the above two equations, we obtain the following equations (Green, Jennison, and Seheult 1985).

$$\hat{\beta} = [\mathbf{X}'(\mathbf{I} - \mathbf{S})\mathbf{X}]^{-1}\mathbf{X}'(\mathbf{I} - \mathbf{S})\mathbf{y} \tag{2.6}$$

$$\hat{\mathbf{f}} = \mathbf{S}(\mathbf{y} - \mathbf{X}\hat{\beta}) \tag{2.7}$$

Under some regularity conditions on the bandwidth parameter, $\hat{\beta}$ and $\hat{\mathbf{f}}$ are consistent estimators of β and $\mathbf{f} = E(\mathbf{y} - \mathbf{X}\beta | \mathbf{Z})$, respectively. In particular, it is well known that the convergence rate of $\hat{\beta}$ as $n \to \infty$ is the same as in the parametric case (see e.g. Robinson 1988 for this property and its limit distribution; see Bierens 1987 for the limit distribution of the kernel estimator).

2.4.2 Additive Model

We now make a further assumption that nonparametric part $\mathbf{f}$ in equation (2.1) or (2.5) takes an additive form, that is,

$$f(\mathbf{z}_i) = \alpha + \sum_{j=1}^{p} f_j(z_{ji}) \tag{2.8}$$

where z_{ji} is the j-th components of vector $\mathbf{z}_i$. An underlying assumption here is that different land use factors do not have interactive effects on the house values. A simple test for the validity of this assumption will be discussed in the later section.

There are three distinctive merits for the above specification (see Hastie and Tibshirani 1989, 1990). First, it can avoid what is called the "curse of dimensionality" problem that plagues standard non- or semi-parametric methods; that is, far large sample size is required to obtain a reasonable estimate of $\mathbf{f}$ with high dimensions of $\mathbf{z}$. The additive model specification converts a high dimension problem into that of a single dimension, thereby getting around this problem.

Second, it provides a simple interpretation. Economists tend to ask ceteris paribus questions: What is the impact of z_j (the j-th variable of $\mathbf{z}$) on the left hand variable if all other variables are kept unchanged? The additive model gives an immediate answer to such questions. Because the impact of z_j on y does not depend on all other z_k's ($k \neq j$), we can plot the p-coordinate functions separately to examine the roles of the variables in predicting y.

Third, it makes computation easy. With the help of the "backfitting algorithm" developed by Friedman and Stuetzle (1981), estimation of the additive model becomes especially attractive.

We refer to the model consisting of equations (2.5) and (2.8) as the "semi-parametric additive model", which is a version of the "generalized additive model" introduced originally by Hastie and Tibshirani (1986). Under this specification the property value of a house is explained by a linear combination of conventional dwelling characteristics plus a sum of the unrestricted functions of distance to each factor.

2.4.3 Smoother

Among linear smoothers most popular are probably kernel smoothers and spline smoothers. We adopt a special type of kernel smoother in our application. The reason for choosing it is simply the availability of relatively more complete theoretical results than other smoothers. In fact, many linear smoothers can be expressed as kernel smoothers.

It is sometimes useful to view kernel smoothers as local polynomial fits.

Consider a small neighborhood $N(z)$ of z and let $z_i \in N(z)$ for $i = 1, \ldots, n$. Then, assuming the existence of the q-th derivative of $f(z)$, we have a Taylor series approximation

$$f(z_i) \approx b_0 + b_1(z_i - z) + \cdots + b_q(z_i - z)^q \qquad (2.9)$$

where $b_j = \partial^j f(z) / \partial z^j$ for $j = 1, \ldots, q$. The problem of estimating $f(z)$ is therefore equivalent to that of estimating b_0 in a local polynomial regression that minimizes

$$\sum_{i=1}^{n} [y_i - b_0 - b_1(z_i - z) - \cdots - b_q(z_i - z)^q]^2 K\left(\frac{z_i - z}{\lambda}\right) \qquad (2.10)$$

where $K(\bullet)$ stands for a kernel function and λ is the bandwidth parameter. When $q = 0$, the solution $\hat{f}(z)$ is known as the Nadaraya-Watson (NW) estimator

$$\hat{f}_{NW}(z) = \frac{\sum_{i=1}^{n} K\left(\frac{z_i - z}{\lambda}\right) y_i}{\sum_{i=1}^{n} K\left(\frac{z_i - z}{\lambda}\right)} \qquad (2.11)$$

which is probably the most popular kernel regression estimator. It, however, often suffers a large bias. When $q = 1$, the estimator $\hat{f}(z)$ is referred to as the local linear (LL) estimator (Fan 1992, Fan and Gijbels 1996) and is given by

$$\hat{f}_{LL}(z) = \frac{\sum_{i=1}^{n} \left[\hat{s}_2(z) - \hat{s}_1(z)(z_i - z)\right] K\left(\frac{z_i - z}{\lambda}\right) y_i}{\sum_{i=1}^{n} \left[\hat{s}_2(z) - \hat{s}_1(z)(z_i - z)\right] K\left(\frac{z_i - z}{\lambda}\right)} \qquad (2.12)$$

where $\hat{s}_k(z) = \sum_{i=1}^{n} (z_i - z)^k K(z_i - z / \lambda)$ for $k = 1,2$. The LL estimator simply provides a higher order approximation than the NW estimator. There are two advantages of using this estimator. First, it has high asymptotic efficiency among all possible linear smoothers (Fan 1992). Second, it does not require any modifications at boundary points, where the usual kernel estimator suffers a large bias. Its disadvantage is its computational cost (n^2 iterations are required, compared to n iterations in NW case).

2.5 Data

Our data are on the residential houses in Lawrence, Kansas (see Figure 2.1 for a map and Appendix A.1 for a brief description). Table 2.1 summarizes our data on dwelling attributes ("x-variables") and location characteristics ("z-variables"), which are two fundamental determinants of house price ("y-variable"). Dwelling attributes are a set of variables that describe the characteristics of a house. Age of a house, total square footage, and number of rooms are typical examples of dwelling attributes. Location characteristics measure the characteristics of a real estate site, such as proximity to various land uses or facilities. Four location characteristics: golf course, university, nitrogen plant, and site elevation were evaluated. All three golf courses in Lawrence are located in western part of the city. Houses around the golf courses are usually priced higher than the city average. The university, located at the center of the city, is the primary employment center; students and university employees accounted for approximately one third of the city population. The nitrogen plant, at the east edge of the city, is the major industrial establishment and is perceived as a pollution source. Land elevation is an indicator of flood potential. Part of the residents can be victimized by rainstorms in a normal year, let alone the flood of 1993. This last location variable was apparently not explicitly evaluated in previous research.

House sale data were obtained from Douglas County Appraisal Office and site investigations. The data include the dwelling attributes and sale values of each residential transaction in Douglas County from January 1986 to May 1995. Douglas County TIGER (composed in 1990) file was used as the basic coverage. Lawrence was clipped out as the study area. Address matching was accomplished in PC Arc/Info to identify the house locations. Boundaries of golf courses, university and nitrogen plant were digitized. The Geographic Information System (GIS) is then used to determine the distance of each house to a land use boundary (see Aronoff 1989). Eventually, 6,415 residential sales were available for our analysis with a set of variables necessary for modeling. The dependent variable is the logarithm of the sales price of each property at the date of sale. Independent variables, summarized in Table 2.1, include multiple measures of dwelling attributes and four location characteristics: golf course, university, nitrogen plant, and elevation. Dwelling characteristics include the log of the living area, log of the lot area, log of the finished living area, the age of the house in order to estimate an age depreciation effect, and dummy variables for the number of full and half baths, the number of bedrooms, the story height, the presence and type of fireplace, heating and cooling. The main city is on the south side of Kansas River; a dummy variable for whether a house falls in this side of the river is included to measure an expected positive transportation convenience.

Three important variables---crime rate, school quality, and jurisdictional tax rates---are not included. The omissions are mainly due to the consideration that Lawrence is relatively homogeneous in these factors. We expect that the absence of these Tiebout variables would not diminish our results.

One limitation of our data is that the distances to the land use factors were recorded only for the houses located within the preselected maximum distance from the factors: 1,000 meters for the golf courses, 4,000 meters for the university, and 8,000 meters for the nitrogen plant, respectively (those are 43.4%, 99.8%, and 79.1%

of the total observations). Those numbers were selected because, on the basis of the preliminary examination of a small subset of the data, the price effect of a land use factor appears to be negligible for those located beyond that distance. For each of such observations, a random distance larger than the maximum was assigned; namely, a randomly generated number between 1,000 and 6,000 for the golf courses, 4,000 and 5,000 for the university, and 8,000 and 9,000 for the nitrogen plant, respectively. In fact, the impacts of the factors were empirically found dying out within the distance of 50–60% of the above maximum to the factors: about 600 meters, 2 kilometers, and 5 kilometers for the golf courses, the university, and the nitrogen plant, respectively. See Figure 2.3(A)–(C).

2.6 Estimation and Computation

The model we shall estimate is given by

$$y_{it} = \alpha_t + \mathbf{x}'_{it}\beta + \sum_{j=1}^{p} f_j(z_{jit}) + u_{it} \tag{2.13}$$

for $i = 1,\dots,n,$ and $t = 1,\dots,T,$ where y_{it} is the value of the house, $\mathbf{x}_{it}$ is a vector of the dwelling characteristics of the house (such as the size of the house, the number of bedrooms and etc.), z_{jit} is the j-th location characteristics including distance to the land use factors, and u_{it} is an unknown disturbance term.

The parametric part $\mathbf{x}_{it}'\beta$ corresponds to the conventional hedonic price model, while $\sum f_j(z_{jit})$ represents the nonparametric part. The individual function $f_j(\bullet)$ is not restricted to any functional form except that it is smooth, but the whole nonparametric part is restricted to be additive. A most popular computational approach (among economists) to such a model appears to be a two-step estimation procedure (e.g. Robinson 1988). In this procedure, the first step consists of the usual nonparametric regressions of $\mathbf{y}$ on $\mathbf{z}$, and $\mathbf{x}$ on $\mathbf{z}$, respectively, and the second step is the ordinary least squares (OLS) regression of the residuals of the former regression on those of the latter to obtain the "semiparametric estimate" of $\hat{\beta}$ of β. To obtain the estimate of $\mathbf{f}$, we run the nonparametric regression of $\mathbf{y} - \mathbf{x}\hat{\beta}$ on $\mathbf{z}$.

The actual computation goes as follows: after estimating $E(y_i|\mathbf{z}_i)$ and $E(\mathbf{x}_i|\mathbf{z}_i)$ with any usual nonparametric regression techniques, we calculate the "residuals" $e_i^y \equiv y_i - \hat{E}(y_i|\mathbf{z}_i)$ and $\mathbf{e}_i^{\mathbf{x}} \equiv \mathbf{x}_i - \hat{E}(\mathbf{x}_i|\mathbf{z}_i)$. The estimator $\hat{\beta}$ in equation (2.6) may be obtained by regressing e_i^y on $\mathbf{e}_i^{\mathbf{x}}$ with the ordinary least squares. Our goal is then to estimate $\hat{f} \equiv \hat{E}(e_i|\mathbf{z}_i)$ with constraint (2.8), where $e_i \equiv y_i - \mathbf{x}_i'\beta$. To this end, we follow the steps below:

1. We first approximate each f_j by a step function and use it as a starting value for the iteration:

(a) Let c_{jh} denote the appropriately chosen equally spaced points in the support of z_j for $h=1,\ldots,H_j$ and $j=1,\ldots,p$ with $c_{j0}=0$. Define the location dummy $d_{jh}=1(z_j \in (c_{j,h-1}, c_{jh}])$, which takes the value unity when z_j falls into the h-th interval.

(b) Regress e_i linearly on d_{jhi}'s with constant and obtain the fitted value of e_i given by $\hat{e}_i = \hat{\theta} + \sum_{j=1}^{p}\sum_{h=1}^{H}\hat{\theta}_{jh} d_{jhi}$. Write the fitted regression in the first step as $y_i = \hat{\alpha} + \mathbf{x}'_j \widetilde{\beta} + \sum_j \mathbf{d}_{ji}\widetilde{\theta}_j + \hat{u}_i \equiv \hat{\alpha} + \mathbf{x}'_i \widetilde{\beta} + e_i^0$, where $\mathbf{d}_{ji}$ is a $H_j \times 1$ vector of j-th location dummies and $\hat{\alpha}$, $\widetilde{\beta}$ and $\widetilde{\theta}_j$ are OLS estimates.

2. We now apply the iterative procedure known as the backfitting algorithm, which is explained briefly as follows:

(a) Set the initial values $s_j^0(\bullet) = \sum_{h=1}^{H_j}\widetilde{\theta}_{jh} d_{jh}$ for $j=1,\ldots,p$. This is the step for $m=0$.

(b) The m-th iteration is described as follows: Starting with $j=1$, set $r_{ji}^m = y_i - \hat{\alpha} + \mathbf{x}'_t \hat{\beta}_{j-1}^m - \sum_{l=1}^{j-1} s_l^m(z_{li}) - \sum_{l=j+1}^{p} s_l^{m-1}(z_{li})$ where $\hat{\beta}_j^0 = \widetilde{\beta}$ for $j=1,\ldots,p$, and estimate $s_j^m(z_{ji}) = \hat{E}(r_{ji} | z_{ji})$ with some nonparametric regression techniques.

(c) Compute $\hat{\beta}_j^m = \left[\sum_{i=1}^{n}\mathbf{x_i}\mathbf{x}'_i\right]^{-1}\sum_{i=1}^{n}\mathbf{x}_i\left[y_i - \sum_{l=1}^{j} s_l^m(z_{li}) - \sum_{l=j+1}^{p} s_l^{m-1}(z_{li})\right]$.

(d) Repeat this step from $j=1$ to p, and repeat the entire p-steps until

$$ESS = \sum_{i=1}^{n}\left[y_i - s_0 - \sum_{j=1}^{p} s_j^m(z_{ji})\right]^2 \text{ fails to decrease.}$$

Clearly the error sum of squares (ESS) does not increase at any step of the algorithm and therefore converges. Breiman and Friedman (1985) show that $\sum_{j=1}^{p} s_j^{\infty}(z_{ji})$ is unique and provides the best additive approximation to the nonparametric part or $f = E(y_i - \mathbf{x}_i'\beta | z_i)$ in our model. This does not mean, however, that the individual functions $f_j(\bullet)$'s are uniquely estimated. Buja et al. (1989) show that if the smoothers S_j are symmetric with eigenvalues in $[0,1)$ such as the cubic spline smoother, the normal equations corresponding to the algorithm are consistent for every $\mathbf{y}$.

The essential idea of this algorithm is to reduce computation of multiple regression to that of successive simple regressions. We use a local linear estimator described in Section 2.4 with the Epanechnikov kernel [1] given by $K(u) = 0.75(1-u^2)I(|u| \le 1)$. The cross-validation functions (see Appendix A.2) are computed to guide the selection of the bandwidth.

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[1] The Epanechnikov kernel is frequently used because of certain optimality properties, such as minimizing mean integrated squared error.

2.7 Empirical Results

We first show the result of the parametric linear model and then report nonparametric estimation results.

2.7.1 Parametric Estimates

The left columns of Table 2.2 reports the estimates based on the linear regression with dummy variables for equally spaced intervals of z_j's. The results suggests that the most important three dwelling attributes of the house (in terms of statistical significance) are the size of the total living area (LVG_AREA), the size of the land (LAND), and the age of the house (AGE). The age has a nonlinear effect on the house value, which declines at a decreasing rate as the house gets older. Other important characteristics are the number of full bathrooms (FL_BATH), whether the basement is at least half-finished (BASEMT), whether it has central heating system (HEAT) and or air conditioner (HEAT_AIR), and the number of openings of brick fireplaces (BRICK). The number of bedrooms (BED_RMS) is totally insignificant, and the number of family rooms (FAM_RMS) has a negative effect. These results might sound odd but it is not unreasonable that when LVG_AREA variable is included in the regressors, BED_RMS variable does not have any additional explanatory power. Also, given LVG_AREA, an increase in FAM_RMS could lower the house value, because many family rooms often imply that the house is for rent to multifamily tenants, in particular to a group of students, and usually such a house is likely to be of low quality. The coefficients of the year dummies measure the time effect of each year from 1986 to 1994 with 1995 as the base year. The estimates show the upward movement from 1986 to 1988, followed by the downward movement from 1989 to 1991, which is followed again by the upward movement from 1992 to 1995. This trend roughly coincides with the local business cycle of the real estate market in the Midwest during the period. In any case, most of the results above are quite standard in empirical studies of the hedonic price of a house.

2.7.2 Semiparametric Estimates and Bandwidth Selection

We now estimate equation (2.13) according to the procedure outlined in Section 2.4. The first important step is the choice of the bandwidth, λ, which determines how much to smooth. There is a well-known trade-off in kernel estimation between the bias and variance of the estimate: The use of a small λ reduces the bias but generates a large variance, while choosing a large value of λ will reduce the variance at the expense of introducing bias into the estimation. Although there are many approaches to this problem (see, for example, Eubank 1988, Härdel 1990, and Silverman 1986), we use the cross validation procedure, which is described in Appendix A.2. The idea of this procedure is to compute the squared prediction errors for each selected value of λ by sample reuse techniques. We compute the cross-validation function separately for four location characteristics: (i) distance to the nearest golf course (z_1), (ii) distance to the university (z_2), (iii) distance to the nitrogen plant (z_3), and (iv) land elevation (z_4), for a range of values of each λ_j and plot them in Figure 2.2(A)-(D).

Figure 2.2 provides data driven criteria for bandwidth selection. In addition to this automatic criteria, we also have our own subjective criteria. Although we do not have prior information about the exact shape of each regression curve, our natural expectation is summarized as follows: (i) All curves are reasonably smooth, (ii) $f_1(z_1)$ and $f_2(z_2)$ are monotone decreasing functions of z_1 and z_2, respectively, (iii) $f_3(z_3)$ is a monotone increasing function of z_3, (iv) $f_4(z_4)$ is expected to be strictly increasing at least up to some point and then possibly may go down.

Each bandwidth is then selected by combining the automatic criteria with our subjective criteria. More specifically, starting from the bottom point of each cross-validation curve in Figure 2.2, we search for the value of λ_j ($j = 1,\ldots,4$) closest to the bottom value that satisfies four subjective criteria described above. Each of the selected bandwidth for $f_j(z_j)$ is marked along the respective cross-validation curves in Figures 2.2(A)-(D). As we can see, the bandwidths selected for all but the golf-course effect exceed that suggested by the mechanical cross-validation procedure. These sizes of smoothing are needed for removing spurious noise such as the effect of arterial streets.

The nonparametrically estimated effects of three land use factors and elevation on the property value of the house are displayed in Figure 2.3(A)-(D). For comparison purpose, a polynomial function based on the cubic curve fit and a step function estimated using dummy variables are superimposed in each figure. The step function, although not smooth, can capture rough shapes of the true curve. As we can observe in Figure 2.3, the kernel estimates smooth out the discontinuity of the step function without losing important local features. The polynomial estimates, on the other hand, tend to mask the local details of the curve in favor of the overall fit.

The vertical axis of each figure measures the proportional change in house values. For example, according to the kernel estimates, the house located 100 meters away from the nearest golf course is expected to value 6 percentage point higher than the comparable house located 200 meters away ($\hat{f}_1(100) - \hat{f}_1(200) = 0.06$). The 95% pseudo confidence bands of each kernel regression curve is shown in Figure 2.4(A)-(D). Strictly speaking, these bands are not exactly the confidence bands because the function estimates $\hat{f}(z_j)$ are asymptotically biased.

2.7.3 Nonparametric Assessment

In the following we summarize the assessment of the effects of neighborhood land uses on the residential house values on the basis of nonparametric regression curves.

2.7.3a Golf-Course Effect and University Effect

All four curves in Figures 2.3 and 2.4 look very reasonable. The positive effects of the golf courses and the university are quite sizable; the house directly adjacent to one of the golf courses has a value more than 20% higher than the comparable house 600 meters or more away from it, while the house directly adjacent to the university has a value more than 40% higher than the comparable house located 2,000 meters or more away from it. As the distance to the golf course or the university gets large, such effects initially declines rapidly and then in a more moderate pace. The parametric and nonparametric regression curves are quite close in both cases.

In the golf course case, about 22% price premium at 0 meter declines to 12% at 100 meters and to just 6% at 200 meters. This sharp decline stops around 200 meters, which is followed by a more gradual decline. In particular, between 300 and 450 meters, the curve has a plateau of 2.5% price premium. In the university case, the initial 42% price premium declines to 28% at 200 meters and to 15% at 400 meters. In this range the curve is close to linear with a slope equal to minus 6.5% per 100 meters. Then the decline becomes much gradual; 8% price premium at 500 meters and 3% at 1,000 meters—the slope in this range is minus 1% per 100 meters.

The main source of the price effect of the golf course appears to be the direct and physical benefits that a house can entertain from the golf course, namely those such as big open space, attractive view, and fresh air. The upper limit of the distance that allows such benefits seems to be about 200 meters. The small but positive price premium in the range of 300 to 450 meters, therefore, should have a different source. It is commonly observed that the houses located close to the golf courses tend to form a good neighborhood. The latter, in turn, has a positive effect on the price of the houses located near but not so close to the golf courses. The reason for this kind of 'good neighborhood effect' to disappear around 500-600 meters is most likely to be a wide street which cuts the otherwise continuous residential area and prevents the effect to continue to spread.

The price premium for the houses near the university appears to have a different source. It is true that the direct physical benefits similar to those described in the golf course case also apply to the houses near the university. However, this explains only a fraction of total price premium for the university. The major source of the price effect appears to be simply the length of time required to travel to the university. The university is the center of activities for 27,000 students as well as an employment center of many workers. A reason for the university effect to disappear around 1,800 meters seems to be that the walking distance of twenty minutes is likely to be the maximum for the usual person to choose to commute on foot.

2.7.3b Nitrogen-Plant Effect

The negative effect of the nitrogen plant, a pollution source of the city, is sizable as well as wide spread. The house located 1,500 meters from the plant values 17% lower than the comparable house located 6,000 meters or more from it. The negative price premium decreases almost constantly by 2% per 500 meters from minus 11% at 2,000 meters to minus 4% at 4,000 meters and then the pace slows down. Although the thick smoke produced by the plant is sometimes visible from the center of the city, its negative externality is not likely to be entirely based on the measured pollution level.

2.7.3c Elevation Effect

As seen in Figure 2.3(D), the discrepancy between parametric and semiparametric estimates is largest for the elevation effect. The parametric estimates show a large variation of the effect; the house at the lowest elevation values 16% lower than the house at the highest elevation, whereas the semiparametric estimates suggest much smaller variation, just 6% difference. A reason for this discrepancy appears to be that our subjective criteria make us to choose a rather wide bandwidth, which flattens the curve.

2.7.3d Stability of the Effects

So far we have implicitly assumed that the price effects of the four location characteristics are time invariant. To check their stability, the model was estimated separately for 1986, 1990, and 1994 (the number of observations are 868, 595, and 655 for 1986, 1990, and 1994, respectively). The results are displayed in Figure 2.5(A)-(D).

The most stable among the four characteristics is clearly the university effect, for which there appears to be no structural change over time between 1986 and 1994.

Interesting cases are the effects of the golf course and nitrogen plant. The golf course effect looks relatively stable over time in the range of distance between 200 and 600 meters, whereas there seems to be a large negative shift in the effect on the houses within 200 meters from the golf course. The house adjacent to a golf course values 24% higher in 1986 but only 16% higher in 1994. This seems to reflect a specific situation on the supply side in that a new area next to one of the golf courses had been rapidly developed for housing during 1990 and 1995. The effect of the nitrogen plant exhibits a little different pattern of change over time. There is an upward shift in the estimated regression curve from 1984 to 1990, while the curve for 1994 is not much different from that for 1990. The negative effect of the nitrogen plant appears to have decreased during this period. A possible explanation is that the plant became less pollutant.

2.7.4 Specification Tests and Prediction Performance

Two specification tests for checking the validity of the underlying assumptions of our semiparametric additive model given by equation (2.13) are conducted.[2] The first test examines the additivity assumption (2.8), whereas the

[2] Another potentially important misspecification is the omission of any major centers (land uses), which would cause spatial autocorrelation of the errors. To test this possibility, a

second one tests the semiparametric model against the linear model.

A simple diagnostic test to check the additivity assumption, proposed by Hastie and Tibshirani (1990), is to regress the residuals from the semiparametric regression (2.13) on the interaction terms of estimated f_j 's and examine the significance of each. More specifically, we run the regression

$$\hat{u}_i = \sum_{\substack{j,k=1 \\ j<k}}^{4} \gamma_{jk} \hat{f}_{ji} \hat{f}_{ki} + e_i \tag{2.14}$$

where $\hat{u}_i = y_i - \hat{\alpha} - \mathbf{x}_i' \hat{\beta} - \sum \hat{f}_{ji}$ is the residual of semiparametric regression (2.13), $\hat{f}_{ji} = \hat{f}(z_{ji})$, and γ_{jk} is the unknown parameter. If the coefficient γ_{jk} were found to be significantly different from zero from conventional standard, we would suspect that location characteristics z_j and z_k have enough interaction to prevent the additive specification (2.8). A preferred model in such a case would be

$$f(\mathbf{z}_i) = \alpha + \sum_{h \neq j,k} f_h(z_{hi}) + f_{jk}(z_{ji}, z_{ki}) \tag{2.15}$$

rather than equation (2.8), where $f_{jk}(\bullet)$ is an unknown function of z_j and z_k. The result of the regression of the residuals on six interaction terms using 1993 data is reported in Table 2.3. None of the terms is found significant at the 1 % level, providing support for the additivity assumption (2.8).

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standard test (such as Moran I) for spatial autocorrelation can be used. Such a test, however, is not conducted in this essay.

Next, to test the linear specification (H_0) against the semiparametric specification, we conduct a simple Wu-Hausman test, which is described in Robinson (1988). The test is based on the contrast between the OLS estimate $\tilde{\beta}$ and the semiparametric estimate $\hat{\beta}$. If H_0 is true, that is, the linear specification is correct, then $\tilde{\beta}$ is consistent and more efficient than $\hat{\beta}$, while $\hat{\beta}$ is consistent whether or not H_0 is true. Although our primary interest is in estimation of $\mathbf{f}$ rather than β, this test provides a simple and convenient way to examine the validity of the semiparametric specification. Since $\hat{\beta}$ is $\sqrt{n}$ consistent, the test statistic has the usual limit distribution and the test may be conducted in the manner same as in the parametric case. The test statistic is given by

$$\eta = (\hat{\beta} - \beta)'[\mathrm{var}(\hat{\beta}) - \mathrm{var}(\tilde{\beta})]^{-1}(\hat{\beta} - \tilde{\beta}) \tag{2.16}$$

which, under H_0, has chi-squared distribution with degrees of freedom equal to the dimension of β. The right hand columns of Table 2.2 presents the semiparametric estimates of the coefficients of the dwelling attributes (x-variables). The Wu-Hausman statistic computed from the 1993 data is 240.47. Since the 99 % quantile of the chi-squared distribution with 27 degrees of freedom is 46.96, the consistency of the OLS regression estimates is rejected, providing support for our semiparametric model.

We may also compare the semiparametric regression with the OLS regression in terms of prediction performance. For this purpose, we use 1993 observations $(y_j, \mathbf{x}_j, \mathbf{z}_j)$ to predict 1994 prices of houses, y_i^*, given their dwelling attributes, $\mathbf{x}_i^*$, as well as location characteristics, $\mathbf{z}_i^*$. The detailed prediction procedure is described in Appendix A.3. After obtaining $\hat{y}_i^*$'s, the measures of prediction accuracy are computed for a subset of 1994 houses that are located near either one of golf courses, the university, or the nitrogen plant (more specifically, $z_1 < 1{,}000$, $z_2 < 4{,}000$ and $z_3 < 8{,}000$). The total number of such houses is 158. The results are reported in Table 2.4. As shown in Table 2.4, the prediction performance of the semiparametric regression is slightly better than the OLS regression.

2.8 Conclusion

We estimated the effects of three land use factors and elevation on the residential house values without assuming any parametric restrictions on the functional forms of the distances. Our use of a semi-parametric additive model with a local linear smoother enabled us to reveal salient features of the price effect curves of the golf courses, the university, the nitrogen plant, and the elevation, which are consistent with our natural expectations. Our procedure can be applied to a broad range of similar studies.

Table 2.1 List of Variables

Type of Variable	Variable Name	Description	Mean	Std.	Min	Max
y-variable	HOUSE_VALUE	The sale price of the house in 1983 dollars (log)	10.88	0.46	8.2 1	12.59
x-variables	AGE	The number of years after the house was built	24.87	25.87	0	135
	AGE_SQ	Square of AGE	1287.68	2437.39	0	18225
	REMODL	A dummy variable for remodeling (1 if the house is remodeled)	0.08	0.27	0	1
	AGERM	The number of years after the house was remodeled	0.75	3.98	0	61
	AGERM_SQ	Square of AGERM	16.38	136.71	0	3721
	LVG_AREA	The size of the total living area (log of square feet)	7.33	0.39	5.95	8.70
	LAND	The size of the primary site (log of square feet)	9.10	0.47	6.74	12.21
	BED_RMS	The number of bedrooms	3.08	0.74	1	7
	FAM_RMS	The number of family rooms	0.36	0.49	0	2
	FL_BATH	The number of full bathrooms (any three fixtures)	1.67	0.66	0	4
	HLF_BATH	The number of half bathrooms (any two fixtures)	0.39	0.52	0	3
	HEIGHT	A dummy variable for story height (1 if the story height is 20 feet or higher)	0.15	0.35	0	1

Table 2.1 Continued

Type of Variable	Variable Name	Description	Mean	Std.	Min	Max
x-variables	BASEMT	A dummy variable for basement (1 if the basement is either half- or full- finished)	0.62	0.49	0	1
	HEAT	A dummy variable for central heating (1 if the house is equipped with central heating)	0.13	0.34	0	1
	HEAT_AIR	A dummy variable for central heating and air conditioning (1 if the house is equipped with both)	0.84	0.37	0	1
	BRICK	The number of openings of brick fireplaces	0.42	0.63	0	4
	METAL	The number of openings of metal fireplaces	0.25	0.45	0	3
	NORTH	A dummy variable for north (1 if the house is in North Lawrence)	0.04	0.20	0	1
	YEAR86-94	Dummy variables for each year 1986 to 1994				
z-variables	GOLF	Distance from the house to the nearest golf course (meters)	2176.69	1862.29	0.03	5997
	UNIV	Distance from the house to the university (meters)	2290.68	934.57	42	4991
	NITRO	Distance from the house to the nitrogen plant (meters)	5954.43	2125.33	1504	9000
	ELEV	Elevation of the house site (meters)	277.01	19.78	247	322

Table 2.2 Parameter Estimates of the Linear Model with Dummy Variables versus the Semiparametric Model

	Parametric Regression			Semiparametric Regression		
Variable	Estimate	Standard Error	t-value	Estimate	Standard Error	t-value
Constant	6.23735	0.09033	69.045			
AGE	-0.00905	0.00041	-22.275	-0.00724	0.00039	-18.686
AGE_SQ	0.00005	0.00000	15.090	0.00004	0.00000	12.026
REMODL	0.07403	0.01292	5.729	0.07706	0.01275	6.043
AGERM	-0.00462	0.00183	-2.532	-0.00491	0.00181	-2.713
AGERM_SQ	0.00007	0.00004	1.581	0.00008	0.00004	1.833
LVG_AREA	0.44103	0.01206	36.573	0.42861	0.01183	36.233
LAND	0.13607	0.00579	23.516	0.13502	0.00558	24.186
BED_RMS	-0.00263	0.00427	-0.062	-0.00083	0.00417	-0.199
FAM_RMS	-0.03812	0.00585	-6.513	-0.02079	0.00580	-3.581
FL_BATH	0.07138	0.00590	12.104	0.06713	0.00580	11.576
HLF_BATH	0.03666	0.00572	6.414	0.03337	0.00559	5.972
HEIGHT	0.06824	0.00774	8.815	0.05844	0.00761	7.683
BASEMT	0.09533	0.00591	16.127	0.08273	0.00571	14.498
HEAT	0.21144	0.01513	13.978	0.22396	0.01492	15.015
HEAT_AIR	0.28632	0.01524	18.784	0.31337	0.01504	20.830
BRICK	0.06884	0.00533	12.915	0.07103	0.00520	13.668
METAL	0.02519	0.00683	3.686	0.02006	0.00664	3.021
NORTH	-0.17328	0.01958	-8.849	-0.15891	0.01740	-9.134
YEAR86	-0.11726	0.01503	-7.802	-0.09985	0.01490	-6.702
YEAR87	-0.07820	0.01511	-5.173	-0.06265	0.01498	-4.182
YEAR88	-0.05507	0.01512	-3.636	-0.04291	0.01498	-2.864
YEAR89	-0.05519	0.01554	-3.552	-0.04808	0.01540	-3.123
YEAR90	-0.07758	0.01552	-4.999	-0.07645	0.01536	-4.978
YEAR91	-0.10881	0.01557	-6.986	-0.10392	0.01545	-6.726
YEAR92	-0.11395	0.01529	-7.487	-0.10821	0.01508	-7.173
YEAR93	-0.08632	0.01519	-5.681	-0.08050	0.01505	-5.347
YEAR94	-0.04366	0.01526	-2.860	-0.03890	0.01512	-2.574

Table 2.3 Regression of Residuals on Interaction Terms

Variable	Estimate	Standard Error	t-value
FGFK	-0.676729	1.98228160	-0.341
FGFN	1.719703	3.95649979	0.435
FGFE	-11.854903	10.04750721	-1.180
FKFN	1.870161	4.24298318	0.441
FKKE	4.361601	10.84225800	0.402
FNFE	-4.346213	10.89307381	-0.399
R^2	0.0033		

Notes: The regression does not include an intercept term, and R^2 is computed in uncorrected form. FGFK stands for the interaction term between the golf-course effect and the university effect, that is, $FGFK = \hat{f}_1 \cdot \hat{f}_2$. Similarly, $FGFN = \hat{f}_1 \cdot \hat{f}_3$, $FGFE = \hat{f}_1 \cdot \hat{f}_4$, $FKFN = \hat{f}_2 \cdot \hat{f}_3$, $FKFE = \hat{f}_2 \cdot \hat{f}_4$, $FNFE = \hat{f}_3 \cdot \hat{f}_4$. To compute the above regression, 1993 year data are used. The sample size is 693.

Table 2.4 Prediction Performance of Parametric vs. Semiparametric Regressions

Measures of Prediction Accuracy	Parametric regression	Semiparametric regression
Root Mean Square Error	0.1959051	0.1904084
Root Mean Square Percentage Error	0.0174042	0.0168488
Theil's U Statistic	0.0177319	0.0172344

Notes: Both linear and semiparametric regressions were first run using 1993 data with 693 observations and then those estimates were used for predicting 1994 house sales prices. To compute the measures of prediction accuracy, only 158 observation points of 1994 data that are located near the land use factors were utilized. Measures of prediction accuracy are defined as follows:

(A) Root mean square error (RMSE)

$$RMSE = \sqrt{(1/n)\sum_{t=1}^{n}(\hat{y}_t - y_t)^2}$$

(B) Root mean square percentage error (RMSPE)

$$RMSPE = \sqrt{(1/n)\sum_{t=1}^{n}[(\hat{y}_t - y_t)/y_t]^2}$$

(C) Theil's U statistic

$$U_1 = \sqrt{\sum_{t=1}^{n}(y_t - \hat{y}_t)^2 / \sum_{t=1}^{n} y_t^2}$$

Figure 2.1 City Map

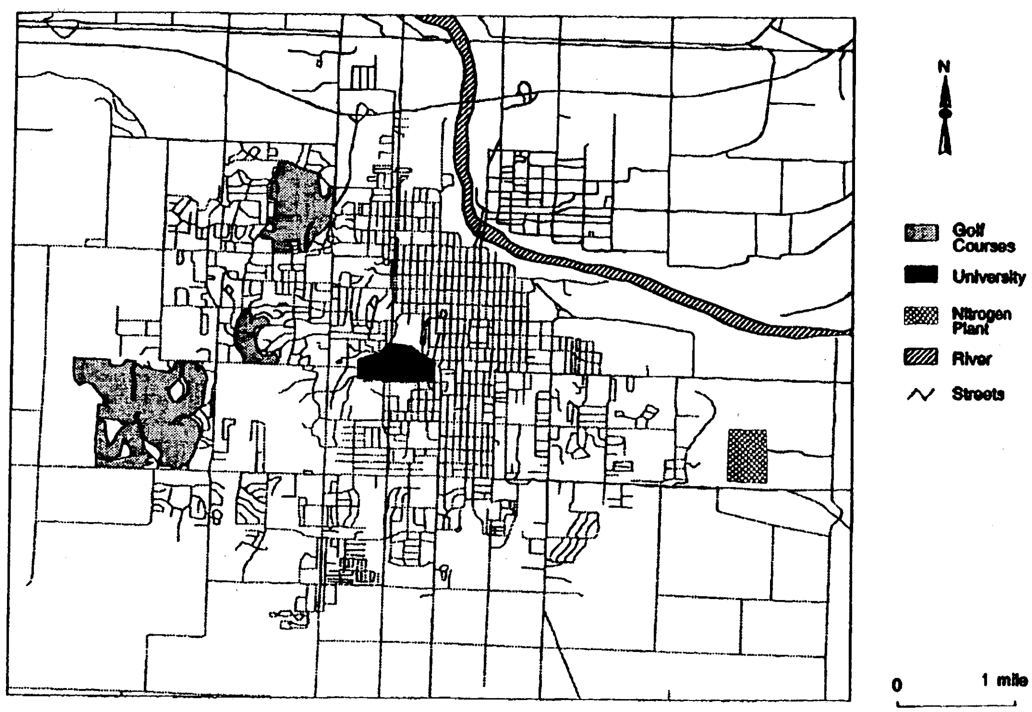
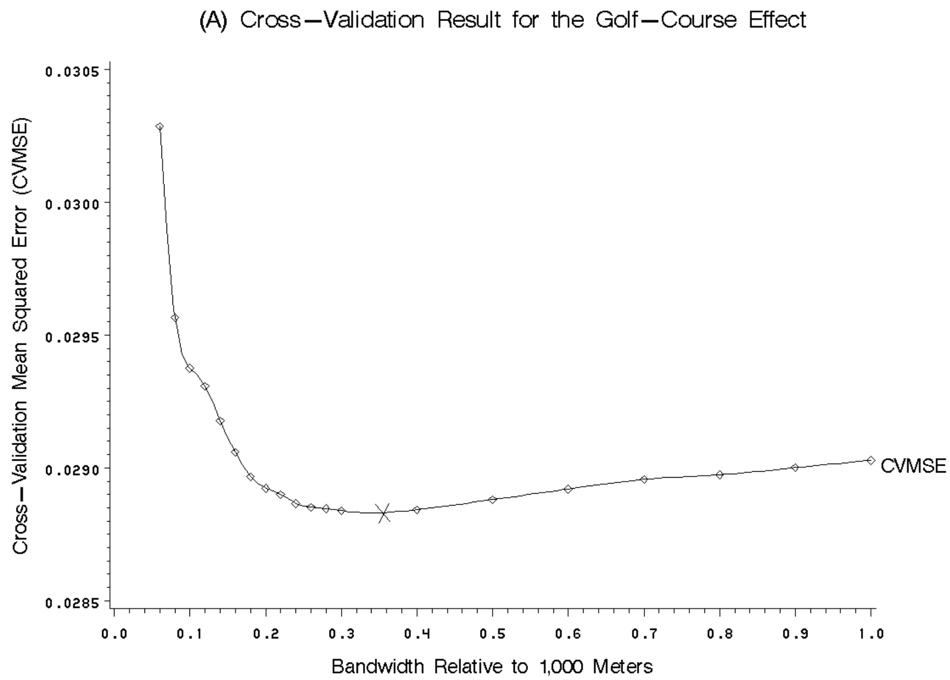


Figure 2.2 Cross-Validation Curves



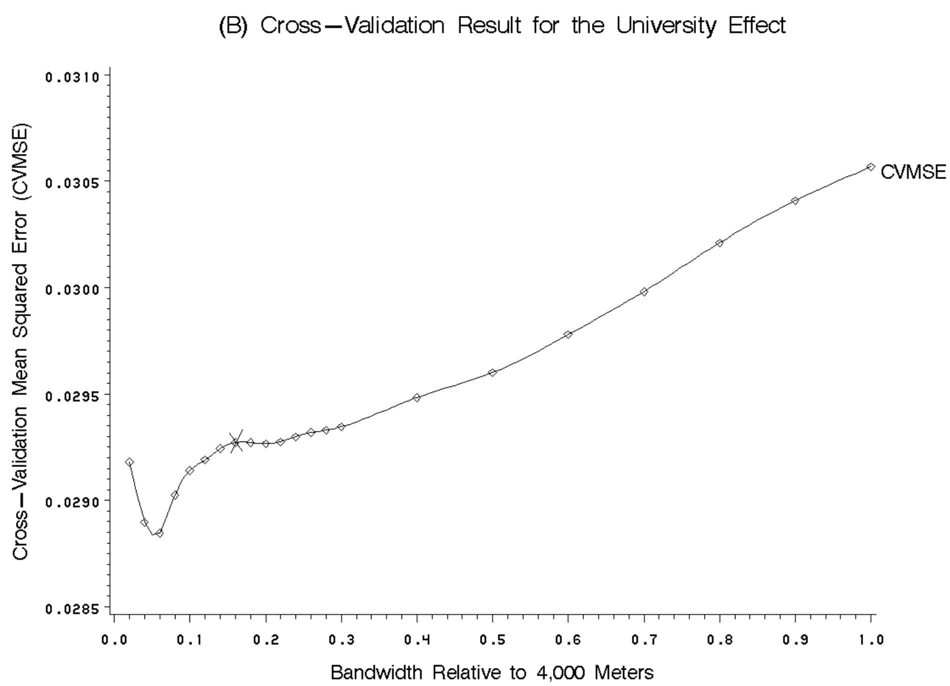
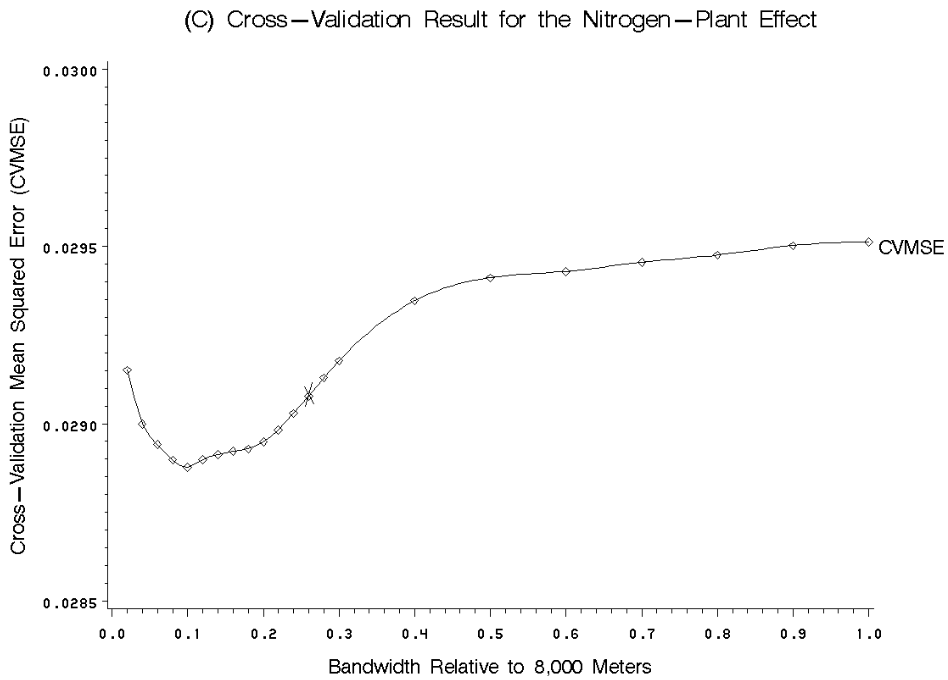


Figure 2.2 Continued



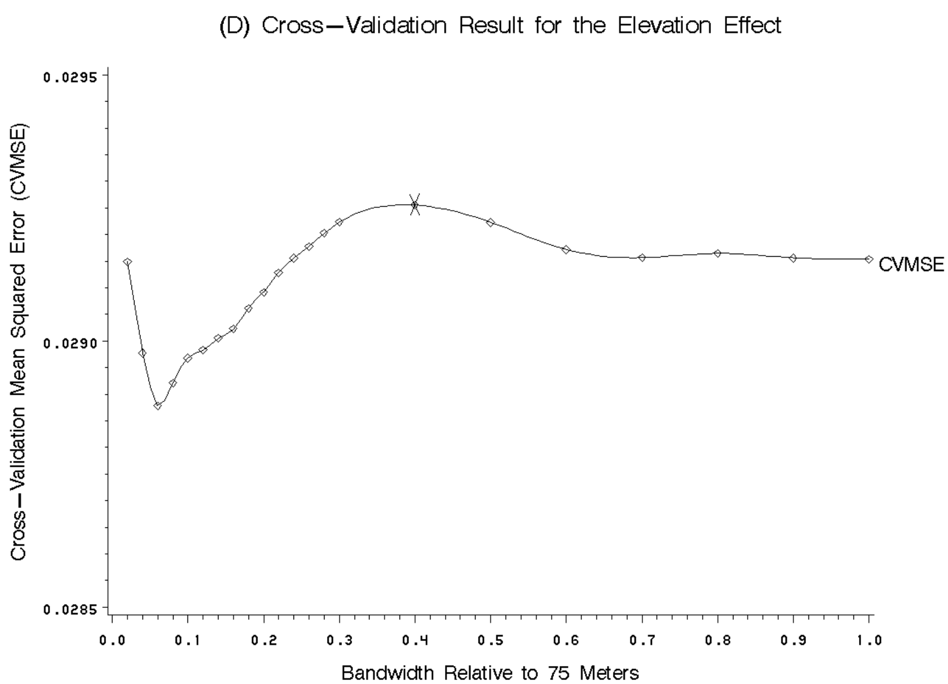
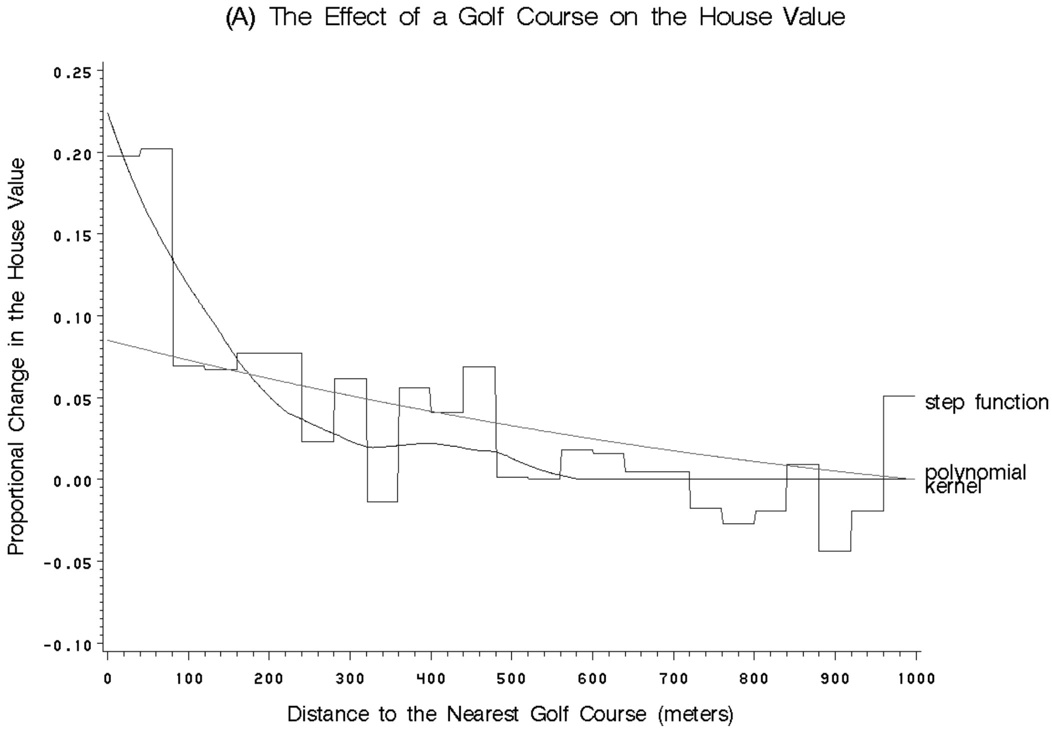


Figure 2.3 Nonparametric Estimates of the Effects of Location Characteristics



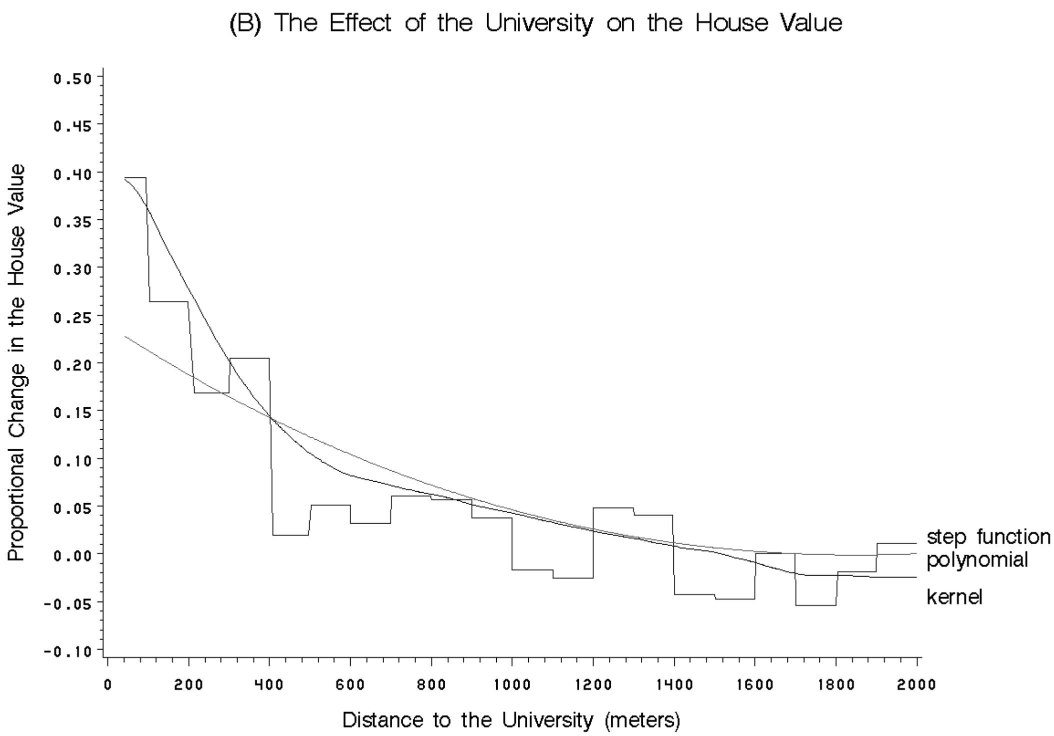
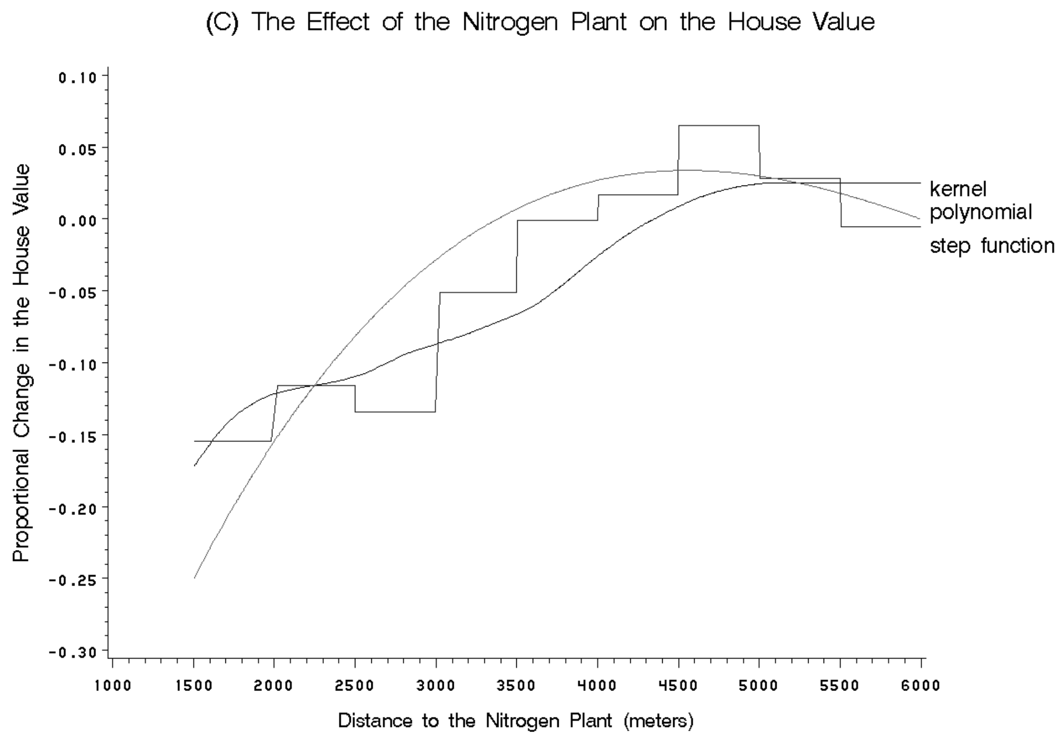


Figure 2.3 Continued



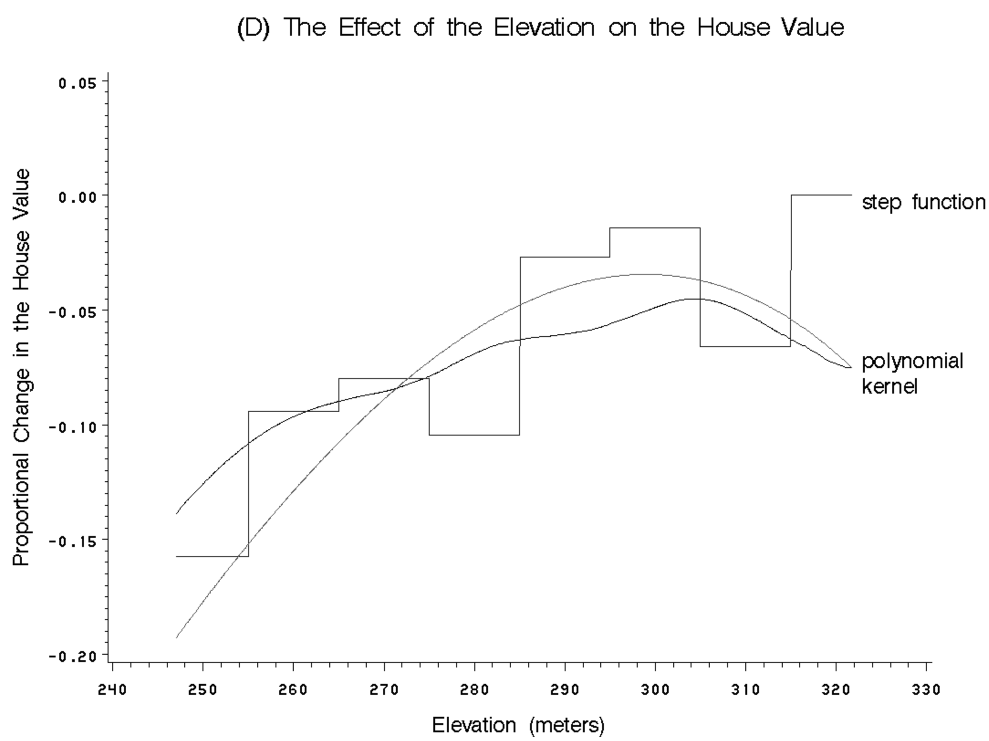
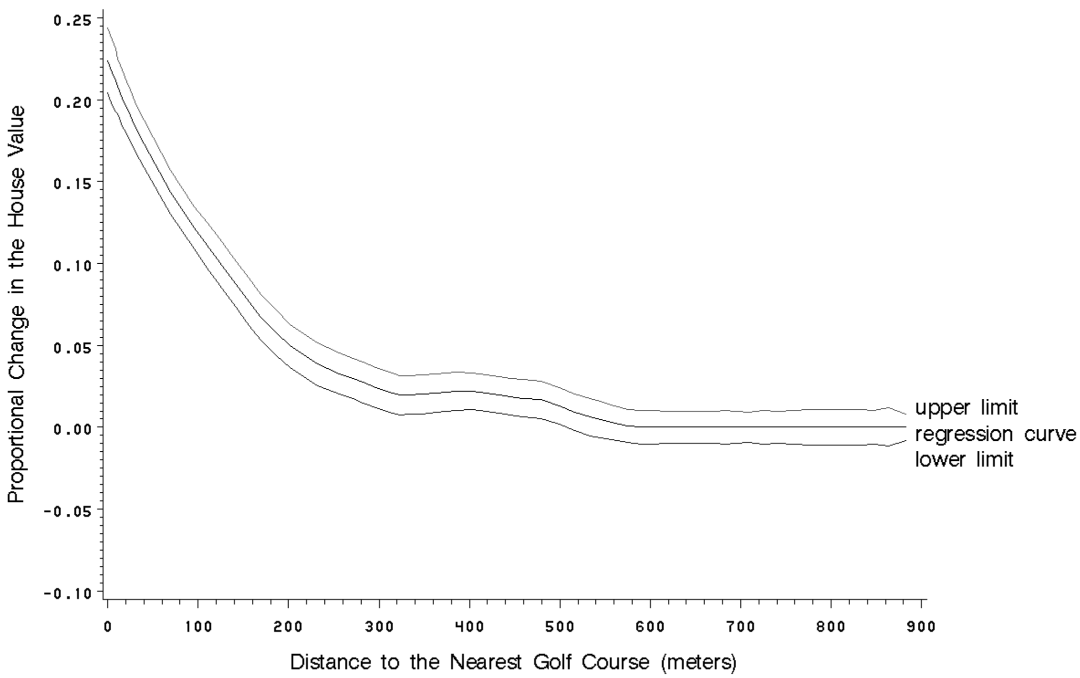


Figure 2.4 Confidence Bands of Nonparametric Estimates

(A) 95 Percent Confidence Interval for the Golf–Course Effect



(B) 95 Percent Confidence Interval for the University Effect

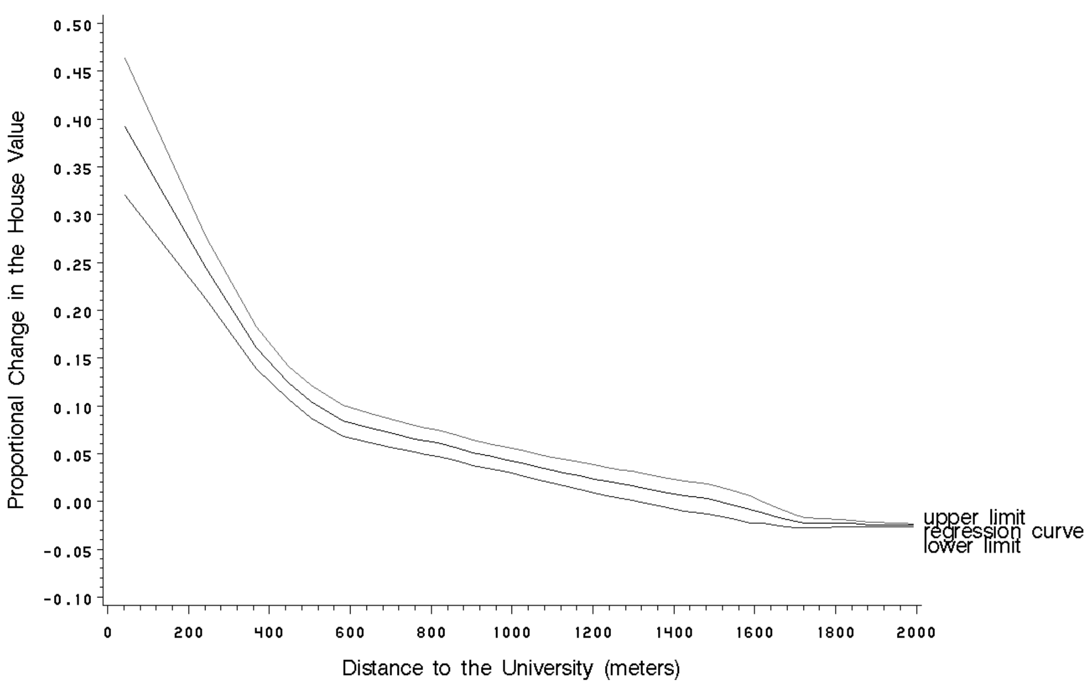
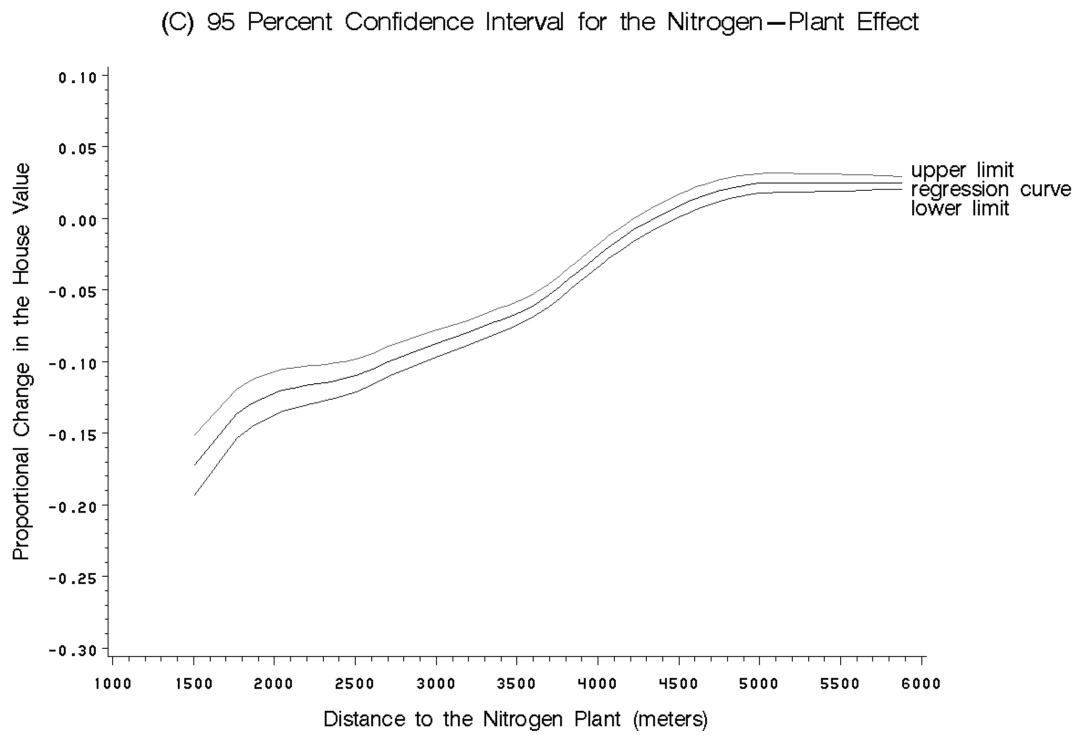


Figure 2.4 Continued



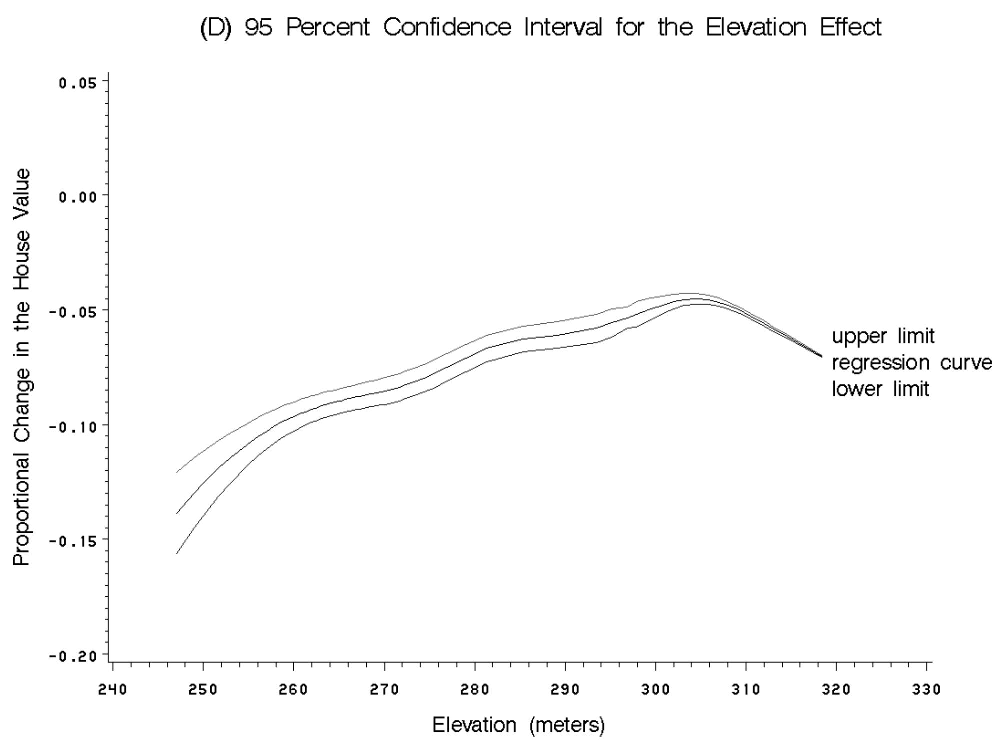
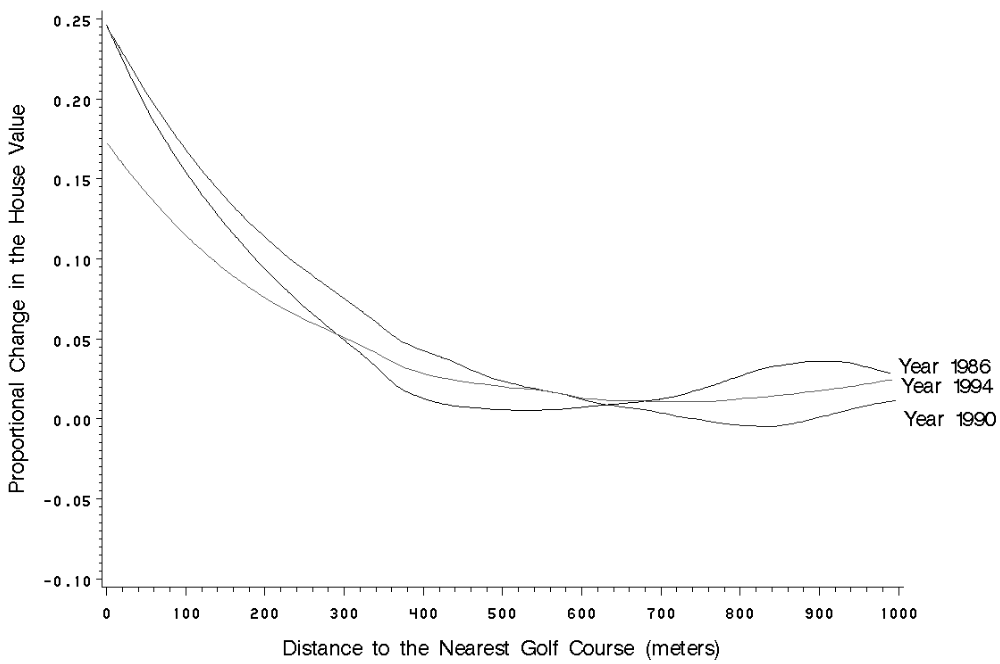


Figure 2.5 Year Comparison

(A) Year Comparison for the Golf—Course Effect



(B) Year Comparison for the University Effect

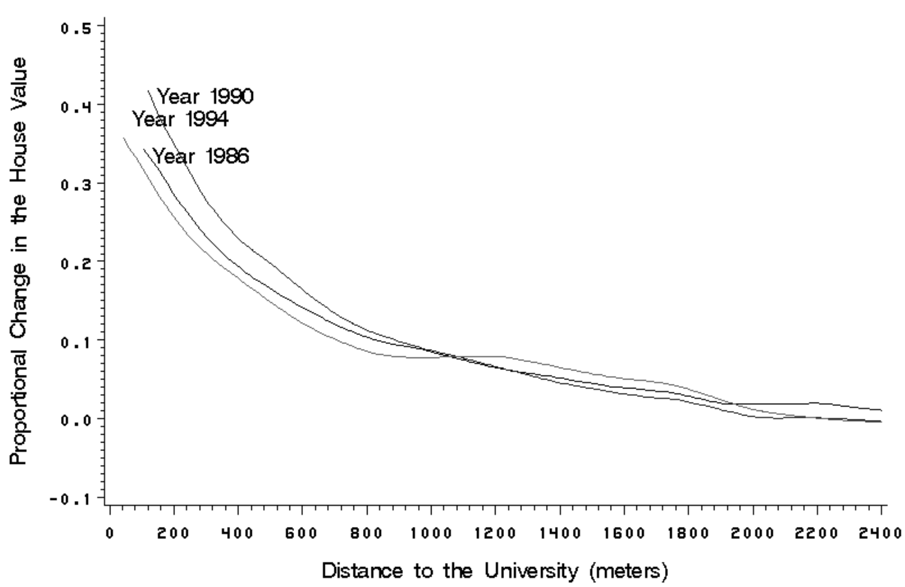
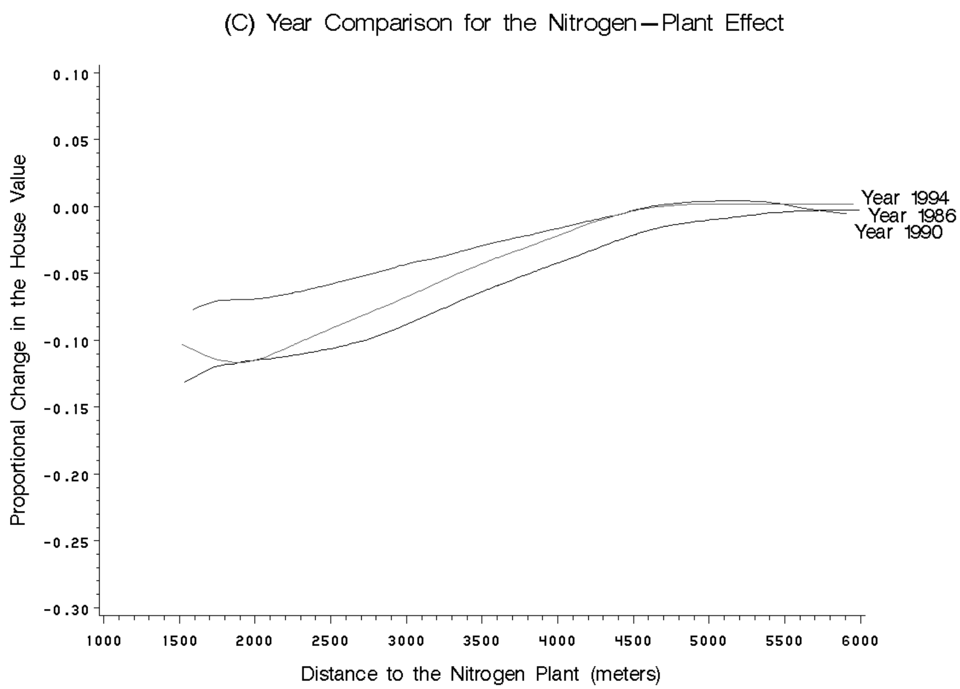
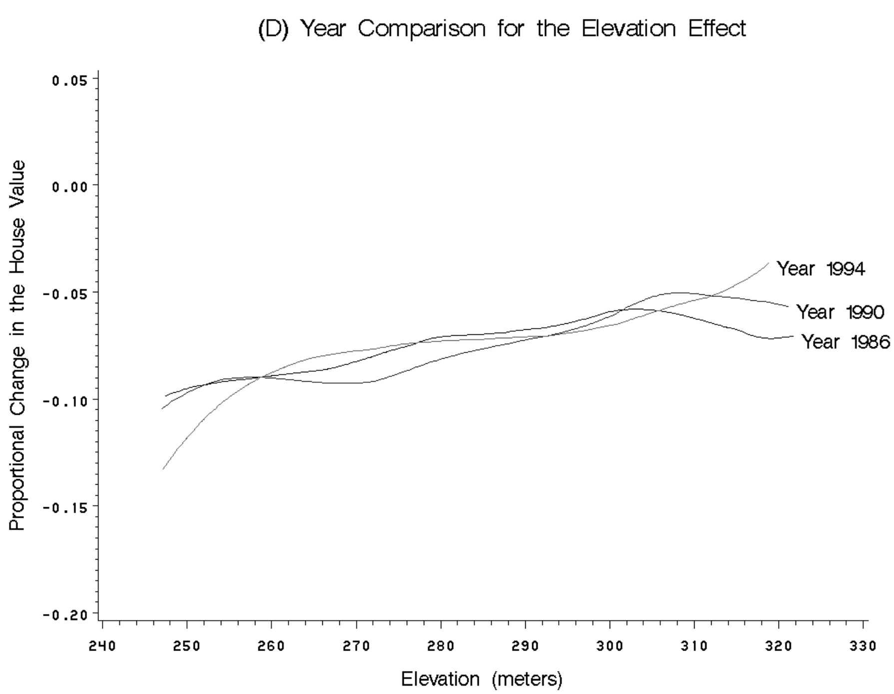


Figure 2.5 Continued





Chapter 3

Second Essay

Sources of Economic Growth in East Asia: A Nonparametric Assessment

3.1 Introduction

For more than a quarter century since the early 1970s, the countries in East Asia grew at phenomenal rates, leading observers to dub the period as the "Asian Miracle." The rapid growth came to an abrupt end when the financial crisis hit in 1997, with many of the high-performing countries in the region falling into painful recessions and facing the distinct possibility that the miracle, if indeed there had been one, was over.

Clearly the Asian financial crisis was an unprecedented event and was unforeseen by virtually everyone. But what is more troubling is that a decline in growth in East Asian countries, even abstracting from the effects of the financial crisis, was already being predicted by some. Paul Krugman (1994) in particular, using the results of Young (1992, 1995), argued persuasively that the rapid growth of the East Asian economies over the past three decades had come primarily from capital accumulation, increasing labor force participation, and improving labor quality, rather than from improvements in productivity. As such, the rate of growth of these countries was bound to slow down eventually. Even though Krugman did not see the Asian financial crisis coming, he certainly saw an end to the so-called Asian miracle—presumably the crisis only made the end come faster.

3.2 Literature Review

The Young (1992) and Krugman (1994) papers set off a heated debate on the sources of economic growth in East Asia.[1] One group, subscribing to the "accumulation view", claimed that growth in East Asian countries was mainly driven by high rates of capital formation.[2] The second group adheres to the "assimilation view," arguing that the essential component of East Asian high growth was the acquisition and mastery of foreign technology.[3] In other words, high growth resulted largely, although not exclusively, from gains in efficiency and productivity.

Whether the accumulation or assimilation view of growth is a more accurate characterization of the East Asian miracle has important implications for growth strategies. If the accumulation view is correct and growth is mainly based on capital formation, it will not be sustainable for long because the law of diminishing returns (to capital) will eventually prevail. As Krugman (1994) puts it rather dramatically, the East Asian economies with their high rates of investment would end up looking

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[1] See the extremely useful survey by Craft (1999) and Felipe (1999).

[2] This group includes Young (1992, 1995), Kim and Lau (1994), Krugman (1994), Collins and Bosworth (1997), Sarel (1997), and Senhadji (2000), among others.

[3] This second group includes, for example, Romer (1993), Nelson and Pack (1996), Klenow and Rodriguez-Clare (1997), and Easterly and Levine (2000).

like the former Soviet Union! Following this logic, the future looks quite bleak for the East Asian countries even when they recover from the fallout of the financial crisis; growth rates in the future will be permanently below those experienced in earlier years. The practical implication for growth-enhancing strategies under the accumulation view is that to improve living standards requires investment, which has to be paid for in large part through foregone consumption.

On the other hand, the assimilation view would point to a more optimistic outcome. The proponents of this view would argue that, following the downturn resulting from the financial crisis, East Asian countries can get back to their pre-crisis long-run growth paths. And, if growth indeed originates from a narrowing of the "idea gap" as the assimilation view claims, no significant opportunity costs need to be incurred to incorporate ideas from abroad (Romer 1993). Instead, ideas can be transmitted to the mutual benefit of producers and no sacrifice of current consumption for future growth is required.

Both groups can point to empirical evidence for a variety of countries that support their respective cases.[4] Most of the studies associated with the accumulation view use time-series data and follow the conventional growth-accounting method based on the Solow (1957) model. This growth-accounting method relies on the assumption of competitive factor markets, enabling one to replace output elasticities (with respect to capital and labor), with the respective income shares of these factors.

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[4] International comparisons of the sources of growth have been made by Dougherty and Jorgenson (1996); see also Islam (1999).

While the use of income shares may well be a reasonable approximation in industrial countries,[5] this procedure is more questionable for developing countries, including the East Asian countries, where the capital and labor markets are unlikely to be perfectly competitive. The assimilation view on the other hand is generally supported by cross-country empirical growth analysis where the values of the output elasticities of capital and labor are estimated rather than imposed. These estimated elasticities are then used to calculate productivity changes. To do the cross-country regression analysis, however, requires assuming a particular form for the underlying aggregate production function, which may or may not be valid. Indeed, as Hulten (2000) points out, the original growth-accounting formulation due to Solow (1957) is completely nonparametric, and thus assuming any particular form for the production function is basically incorrect.

3.3 Overview of the Essay

This essay proposes a new method of estimating the sources of economic growth and the growth of total factor productivity (TFP) using nonparametric derivative estimation techniques. This method requires no specific assumptions on the competitive state of factor markets or the form of the underlying aggregate production function. Applying this methodology to East Asian countries over the period 1960–95 yields estimates of output elasticities with respect to capital and labor, as well as TFP growth. Two main results emerged from the analysis. First, the

[5] See Oulton and Young (1996).

estimated output elasticities of capital and labor tend to be quite different from their respective income shares, casting some doubt on the conventional growth-accounting model assumption of competitive factor markets. Second, the growth rates of TFP turn out in many cases to be similar to those obtained in other studies, yet in certain important cases are much higher, lending some support to the assimilation view of sources of economic growth.

The rest of the paper proceeds as follows: Section 3.4 discusses the basic framework used to analyze the sources of economic growth. Section 3.5 describes the nonparametric derivative estimation method, and Section 3.6 reports the estimation results. The final section provides a brief conclusion.

3.4 Estimating the Sources of Economic Growth

In the context of the neoclassical growth model, we start with an aggregate production function, which typically is specified as

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

where Y is output, K and L are capital and labor inputs, and t indicates time. The aggregate production function approach is an analytical simplification that makes it possible to summarize detailed information about the complex process of economic growth within a simple unified framework (for a review of the neoclassical growth model, see, for example, Barro and Sala-i-Martin, 1995). Differentiating the logarithm of (3.1) with respect to t, we obtain

$$\frac{\dot{Y}}{Y} = \frac{\partial \underline{F}}{\partial K}\frac{K}{\underline{F}}\frac{\dot{K}}{K} + \frac{\partial \underline{F}}{\partial L}\frac{L}{\underline{F}}\frac{\dot{L}}{L} + \frac{\partial \underline{F}}{\partial t}\frac{1}{\underline{F}} \tag{3.2}$$

where $\dot{X} = dX/dt$ is the time derivative of the respective variable.

Function (3.1) is often specified more explicitly in Hicks neutral form

$$\underline{F}(K(t), L(t), t) = A(t)F(K(t), L(t)) \tag{3.3}$$

where A(t) is called total factor productivity or TFP, and measures the shift in the production function $\underline{F}$ at given levels of capital and labor. In this form, taking log derivatives of (3.3) with respect to time yields

$$\frac{\dot{Y}}{Y} = \frac{\partial F}{\partial K}\frac{K}{F}\frac{\dot{K}}{K} + \frac{\partial F}{\partial L}\frac{L}{F}\frac{\dot{L}}{L} + \frac{\dot{A}}{A} \tag{3.4}$$

The last term on the right hand side of (3.2) is interpreted in (3.4) as the growth rate of TFP.[6] Since (3.3) is the form typically assumed in the literature, we base our discussion on this specification throughout this essay. Equation (3.4) can be written as

$$\begin{pmatrix}\text{growth rate}\\ \text{of GDP}\end{pmatrix} = \varepsilon_K \times \begin{pmatrix}\text{growth rate}\\ \text{of capital}\end{pmatrix} + \varepsilon_L \times \begin{pmatrix}\text{growth rate}\\ \text{of labor}\end{pmatrix} + \begin{pmatrix}\text{growth rate}\\ \text{of TFP}\end{pmatrix}$$

where ε_K and ε_L stand for the elasticity of output with respect to capital and labor, respectively. Since the growth rates of GDP, capital, and labor are available in the national income accounts data of most countries, TFP growth rates are obtained by subtracting from GDP growth the sum of the growth rates of capital and labor with

[6] A little caution is necessary here because the last term on the right hand side of (3.2) is the partial derivative of *F* with respect to time so that it depends on the values of *K* and *L*. Here it is assumed that $(\partial F / \partial t) = 0$.

appropriate weights ε_K and ε_L. An obvious problem with this procedure is that ε_K and ε_L are unknown parameters depending on the functional form of $F(\cdot,\cdot)$ and it is these parameters that are critical in calculating TFP growth.

The question then is how to estimate ε_K and ε_L. There are two approaches developed in the literature. The first approach assumes that the factor markets are perfectly competitive so that the necessary equilibrium conditions are given by equalities between the income shares of capital and labor in GDP (v_K and v_L) and the elasticities of output. The rental price of capital, *r*, and the wage rate, *w*, are then given by $r = A \cdot \partial F / \partial K$ and $w = A \cdot \partial F / \partial L$ so that $\varepsilon_K \equiv (\partial F / \partial K)(K / F) = rK/Y = v_K$ and $\varepsilon_L \equiv (\partial F / \partial L)(L / F) = wL/Y = v_L$. In other words, ε_K and ε_L are equal to the income share of each factor (v_K and v_L). Under constant to returns to scale, $v_K + v_L = \varepsilon_K + \varepsilon_L = 1$. Thus, with this replacement, the growth rate of TFP may be calculated by simple subtraction. The result is what is known as the "Solow residual."[7] The second approach assumes a particular parametric form of (3.1) and estimates the production function by running a regression either in level or difference form. The output elasticities are constructed using the parameter estimates and TFP growth is again calculated as a residual.

Neither assumption, however, is particularly attractive when dealing with

[7] Hsieh (1997) calculates the dual measure of TFP growth by comparing the growth of output prices with the growth of the weighted average of capital and labor input prices. This method is very data intensive and difficult to use. For a critique of the Hsieh approach, particularly as applied to Singapore, see Young (1998).

developing economies. For one thing, capital and labor markets in these economies are likely to be far from perfectly competitive. Furthermore, there is no guarantee that any particular functional form of the production function is appropriate for these economies (see Hulten, 2000). The simplest form used has been the Cobb-Douglas function, which involves estimating a single parameter, and then using the constant returns to scale assumption, calculating the other elasticity.[8] The parametric form that became popular in 1970s is the translog function,[9] which essentially attempts to estimate the second-order Taylor approximation of general function (3.3). However, a straightforward application of a translog production function often results in severe collinearity problems when using time series data. Kim and Lau (1994) apply a common translog form to all the East Asian countries they studied, with some parameter variations allowed for each country.[10] Furthermore, as pointed out by White (1980), least squares does not provide a proper approximation to the unknown function, and hence, the resulting estimates are often misleading.[11]

This essay proposes a third approach that has not been utilized in this context. For this approach, we do not need the assumption of perfectly competitive factor markets. Nor do we need to assume any particular functional form of the

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[8] See Senhadji (2000) who uses this form to estimate output elasticities for a large number of countries.

[9] See Christensen et al. (1980) for a comprehensive review of the translog function.

[10] Hu and Khan (1997) substitute income shares for the elasticities of output in the translog function to calculate TFP growth in China.

[11] Barro (1998) also questions the appropriateness of the regression approach.

aggregate production function. All that is needed is only some kind of smoothness of the production function. The proposed approach is based on non-parametric kernel derivative estimation techniques developed recently in the statistics and econometrics literature (see Härdle 1990, and Pagan and Ullah 1999). The logarithmic transformation of (3.1) and (3.3) with the addition of a stochastic term is

$$\ln Y(t) = a(t) + F^{*}(\ln K(t), \ln L(t)) + u(t) \tag{3.5}$$

where $a(t) \equiv \ln A(t)$ is an unknown function of *t*, $F^{*}(x_1, x_2) = \ln F(e^{x_1}, e^{x_2})$, and *u(t)* is an error term satisfying $E[u(t) \mid \ln K(t), \ln L(t), t] = 0$. The idea behind the estimation procedure is as follows. Note that output elasticities ε_K and ε_L are simply the partial derivatives of the systematic part of (3.5) with respect to the first two arguments. Hence, application of nonparametric derivative estimation techniques yields the estimates $\hat{\varepsilon}_K$ and $\hat{\varepsilon}_L$, which are plugged in (3.4) to get the estimate of TFP growth as a residual.

The nonparametric regression method has been usefully applied in many areas of economics.[12] In particular, a semi-parametric regression model, in which the function is partly parametric (usually linear) and partly nonparametric, has been implemented by Engle, Granger, Rice, and Wise (1986), Stock (1989), and Iwata, Murao, and Wang (2000), among others. Another popular variant is the nonparametric estimation of derivatives of a regression function. Examples of nonparametric estimation of derivatives include Rilstone (1992), who applied the techniques to examine the properties of a production function, and Rilstone (1991), in order to estimate average uncompensated price elasticities. Also, Lewbel (1993) provides nonparametric estimates of average compensated price elasticities, while Lewbel (1995) nonparametrically tests demand constraints and compares them with those yielded by the standard parametric test, assuming that the demand system has the quadratic, almost ideal, form. But, as far as we are aware, the nonparametric derivatives method has not been utilized to calculate the sources of growth or TFP growth.

3.5 Estimation Method

In order to estimate output elasticities ε_K and ε_L, first note that the conditional expectation of $\ln Y(t)$ in (3.5) is given by

$$m(\ln K, \ln L, t) \equiv E[\ln Y \mid \ln K, \ln L, t] = a(t) + F^*(\ln K, \ln L), \tag{3.6}$$

which we call the mean function. This additive separability form imposes structure on the conditional mean, which can improve the efficiency of estimation of derivatives. Note that

$$\varepsilon_K \equiv \frac{\partial \ln F}{\partial \ln K} = \frac{\partial F^*}{\partial \ln K(t)}$$

$$\varepsilon_L \equiv \frac{\partial \ln F}{\partial \ln L} = \frac{\partial F^*}{\partial \ln L(t)}$$

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[12] For a very useful survey of nonparametric methods of estimation, see Delgado and Robinson (1992).

are the partial derivatives of the mean function $m(x_1, x_2, x_3)$ with respect to the first two arguments, or the slopes of the regression curve (3.5).

We now introduce the nonparametric estimation approach. The idea of the nonparametric regression is simply local averaging, that is, averaging the y values of observations having predictor values $\mathbf{x} = (x_1, x_2, x_3)$ close to a target value. As you include more distant observations for averaging, the resulting curve would be smoother and smoother until all observations are included for averaging, in which case the curve would be a straight line. This is the case of a linear regression. On the other hand, if only the closest observations are averaged, the resulting curve would become less smooth. How smooth the function should be is controlled by the parameter called bandwidth (h).

Below we essentially focus on estimation of the average TFP growth performance over the whole sample period. This focus is reasonable for two reasons. First, unlike the point estimation, the average estimator can attain the same speed of convergence as when the parametric model is used. Second, comparison with the previous estimates using the conventional method is straightforward.

To estimate the average TFP growth, we tried three different methods. The first approach is to estimate the TFP growth rate at each observation point and then average them over the whole period. The second approach is to estimate directly the average derivatives and then get the corresponding TFP growth. The third approach is an extension of the first, assuming some kind of trend in the derivatives. We outline each in turn.

To see how to estimate the derivatives in the first method, it is helpful to consider nonparametric estimation of the mean function F^* first.[13] Let $K(\mathbf{z})$ be the kernel function satisfying $\int K(\mathbf{z})d\mathbf{z} = 1$. The well-known Nadaraya-Watson kernel regression estimator of $m(\mathbf{x})$ is given by

$$\hat{m}(\mathbf{x}) = \hat{g}(\mathbf{x}) \big/ \hat{f}(\mathbf{x})$$

where

$$\hat{g}(\mathbf{x}) = \frac{1}{nh_1h_2h_3}\sum_{i=1}^{n} K(\mathbf{z}_i)y_i \,, \quad \hat{f}(\mathbf{x}) = \frac{1}{nh_1h_2h_3}\sum_{i=1}^{n} K(\mathbf{z}_i) \tag{3.7}$$

$\mathbf{x} = (x_1, x_2, x_3) = (\ln K, \ln L, t)$, $\mathbf{z}_i = \big((x_{1i} - x_1)/h_1, (x_{2i} - x_2)/h_2, (x_{3i} - x_3)/h_3\big)$, and h_j indicates the bandwidth for variable x_j for $j = 1,2,3$. This is a standard technique of non-parametric regression, from which our non-parametric derivative estimation method is derived. Since F^* is time invariant, we have $\frac{1}{T}\int m(x_1, x_2, t)dt = \frac{1}{T}\int a(t)dt + F^*(x_1, x_2)$. Therefore, it is natural to consider an estimator of F^* by taking a time average of $\hat{m} - a(t)$, or $\hat{F}^*(x_1, x_2) = (1/T)\sum_{t=1}^{T}[\hat{m}(x_1, x_2, t) - a(t)]$, which is a type of estimator discussed by Chen et al. (1996). Although this estimator itself is not operational because $a(t)$ is unknown, the derivatives of F^* like ε_K and ε_L are estimable in the following

13 For a comprehensive review of nonparametric regression procedures including the kernel method, see Delgado and Robinson (1992), Eubank (1988), Härdle (1990), and Pagan and Ullah (1999).

manner. Vinoid and Ullah (1988) show an estimate of the derivative of F^* is obtained by analytically differentiating $\hat{F}^*$. This simple estimator turns out to be free of $a(t)$ in the above context and hence, the estimation is fairly straightforward. That is,

$$\hat{\varepsilon}_K(x_1, x_2) = \frac{1}{T}\sum_{t=1}^{T}\frac{\partial}{\partial x_1}\hat{m}(x_1, x_2, t)$$

and

$$\hat{\varepsilon}_L(x_1, x_2) = \frac{1}{T}\sum_{t=1}^{T}\frac{\partial}{\partial x_2}\hat{m}(x_1, x_2, t)$$

where

$$\frac{\partial \hat{m}(\mathbf{x})}{\partial x_j} = \left[\hat{g}_j(\mathbf{x}) - \hat{f}_j(\mathbf{x})\hat{m}(\mathbf{x})\right] \big/ \hat{f}(\mathbf{x})$$

$$\hat{g}_j(\mathbf{x}) = -\frac{1}{nh_1h_2h_3h_j}\sum_{i=1}^{n}K_j(\mathbf{z}_i)y_i$$

$$\hat{f}_j(\mathbf{x}) = -\frac{1}{nh_1h_2h_3h_j}\sum_{i=1}^{n}K_j(\mathbf{z}_i) \qquad (3.8)$$

$K_j(\mathbf{z}_i) = \partial K(\mathbf{z}_i) \big/ \partial z_{ji}$ and z_{ji} is the j-th element of $\mathbf{z}_i$ for $j = 1,2$. This gives a pointwise derivative at each observation point. The growth rate of TFP is then calculated as a residual after substituting $\hat{\varepsilon}_K$ and $\hat{\varepsilon}_L$ into equation (3.4).[14] The model (3.5) is substantially general and allows one to test whether the factor markets

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[14] The probability bands for the estimated residual $(\hat{\dot{A}}(t) \big/ A(t))$ are constructed based on the joint sampling distribution of $\hat{\varepsilon}_K$ and $\hat{\varepsilon}_L$. Appendix B gives the asymptotic α% pointwise error bands.

are actually competitive and whether a specific parameterization of the production function is correct.

The second approach is based on the average derivative estimation developed by Härdle and Stoker (1989). In this method, we estimate the global behavior of the elasticities[15]

$$E[\varepsilon_j(\mathbf{x})] = -E\left[m(\mathbf{x}) \cdot f_j(\mathbf{x}) \big/ f(\mathbf{x})\right]$$

by its sample counterpart

$$-(1/T)\sum_{t=1}^{T} \ln Y_t \cdot \hat{f}_j(\mathbf{x_t}) \big/ \hat{f}(\mathbf{x_t}).$$

Then the average TFP growth is obtained from the Solow formula, using the average growth rates of output, capital and labor.

The third approach is based on the idea of locally weighted regression. Basically the regular kernel estimator assumes that the conditional expectation is a constant in a neighborhood of the estimation point and this justifies the averaging. But we might expect that the function be better approximated with a lower order polynomial around that point. Instead of using a linear or quadratic relation as a global approximation (which yields a Cobb-Douglas and Translog function, respectively), the method uses them locally. It then reduces to a so-called local linear or quadratic estimator (Fan 1992, Härdle and Linton 2000).

[15] This relation follows from

$$E[\varepsilon_j(\mathbf{x})] = \int_{\mathbf{x}} \left[\partial m(\mathbf{x}) \big/ \partial x_j\right] f(\mathbf{x}) d\mathbf{x} = -\int_{\mathbf{x}} m(\mathbf{x}) \cdot \partial f(\mathbf{x}) \big/ \partial x_j d\mathbf{x} = -E\left[m(\mathbf{x}) \cdot f_j(\mathbf{x}) \big/ f(\mathbf{x})\right]$$

where the second equality follows by integration by parts.

In implementing the above procedures, we need to choose a kernel function and the bandwidth. The accuracy of kernel smoothers as estimators of *m* (the mean function) or derivatives of *m* is a function of the kernel *K* and the bandwidth *h*. In practice, the accuracy depends mainly on the bandwidth *h* (Härdle 1990). Appendix B.3 describes how the selection is made based on the cross validation method.

The large sample properties of the above estimators are well established. When the sample size is small, however, a large sample approximation may be misleading. To find out how reliable the estimators are in a situation like ours, we conducted a small Monte Carlo experiment with the CES production function, which is reported in Appendix B.4.[16] The result indicates that even with a sample size as small as ours, the nonparametric derivative estimates look superior, in terms of bias, to the parametric estimates such as the Cobb-Douglas and Translog models. On the other hand, (as expected) the variances of the nonparametric estimators are found to be larger than the parametric ones. The standard errors reported in the tables in the next section, therefore, should be interpreted with a degree of caution.[17]

3.6 Estimation Results

Using the procedures outlined in the previous section, we estimate TFP

[16] Note that Rilstone (1991, 1992) also utilized the nonparametric regression methods for sample sizes ranging between 25-44 observations.

[17] In our case, the results reported in the tables are the overall sample averages of the estimated derivatives rather than a point derivative estimate at any particular point. This increases the speed of convergence by factor of root n because the point estimates are asymptotically uncorrelated.

growth rates for nine East Asian countries: Hong Kong SAR, Indonesia, Korea, Malaysia, Philippines, Singapore, Taiwan Province of China, Thailand, and China. We use two data sets for this study: First, the data set based on the Penn World tables covering the period 1960–1990, and second, the data set constructed by Collins and Bosworth (1996) which covers the period 1960–1995. Each of the data sets is described in Appendix B.1. The data for Hong Kong SAR are only available in the Penn data set.

Before presenting our nonparametric estimates of TFP growth rates, we summarize the results obtained with the conventional methods in Table 3.1. Because the results using two data sets are similar, only the estimates with the Collins data set are reported here. Table 3.1 reports the conventional growth accounting estimates of TFP growth rates for the nine East Asian countries. The estimates in the column labeled with “Young” are reported for Hong Kong SAR, Korea, Singapore, and Taiwan Province of China, using weighted labor shares calculated by Young (1995). In the column labeled “Collins” are the TFP growth estimates based on the constant labor and capital shares equal to 0.65 and 0.35 respectively, which serve as a benchmark.[18] As can be seen from Table 3.1, differences between the Young and the Collins estimates are quite small in three of the countries that are common to both

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[18] The income shares were assumed to be the same across countries by Collins and Bosworth (1996). In an interesting paper, Sarel (1997) uses international evidence to estimate technologically-determined coefficients for each major sector of activity and then derives a weighted average for each country according to their output composition. Sarel’s estimates for the capital share are between 0.28 - 0.35, which are close to the Collins-Bosworth value of 0.35.

studies. The exception is Singapore, where the difference is substantial. This result follows directly from the relatively small income share estimate of labor used by Young.[19]

We now present the results of nonparametric estimation. Among the three estimation methods, the results of the first two (the average of pointwise derivative estimates and the average derivative estimates) are reported in Tables 3.2 and 3.3, respectively. The third method (local linear and quadratic estimation) fails to yield reasonable point estimates in terms of the stability of elasticities over time (although their averages turn out quite close to the results of the first method). As such, we do not report these last results here. The reason of the failure is unclear, although it is possible that the local linear and quadratic estimation is sometimes sensitive to the size of the sample.

Table 3.2 presents the nonparametric TFP growth estimates averaged over the whole time period,[20] together with estimated output elasticities for nine East Asian countries.[21] There is no important difference between the nonparametric

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[19] Young uses 0.51 as the average labor share for Singapore, compared to 0.63 for Hong Kong SAR, 0.70 for Korea, and 0.74 for Taiwan Province of China. The growth rate of capital in Singapore during 1960-90 is 12 percent, which is about the same as in Korea and Taiwan Province of China, so Young's very large income share estimate of capital makes TFP growth for Singapore less than a half percentage point. Collins and Bosworth (1998) use a labor share of 0.65 for Singapore (common across countries). Senhadji (2000) finds the output elasticity of capital for Singapore to be 0.48 (in levels) and 0.3 (in differences). Sarel (1997) uses an estimate of 0.35 for Singapore.

[20] This is equivalent to the TFP growth estimates obtained by first averaging the pointwise derivatives (elasticities) and then calculating the residuals with the average data on output and input growth.

[21] The bandwidth used for each estimate is reported in Appendix B.3.

estimates using the different data sets (not reported in the table). However, the nonparametric estimation methods yield quite different estimates of the TFP growth rate, as compared to the conventional methods. Except for the cases of Hong Kong SAR and China, our estimates of TFP growth over the period 1960-1995 are higher than the estimates obtained using the "Young" and "Collins" methods. Table 3.2 also reports the estimated output elasticities of capital and labor. All the estimates are highly significant based on the values of their asymptotic standard errors.

Table 3.3 presents nonparametric TFP growth estimates based on the average derivative method. The estimated TFP growth rates are a little larger (5-8% larger in most cases) than those estimated with the pointwise derivative method reported in Table 3.2, but the standard errors are almost twice as large as the first method. Therefore, in what follows, we focus on the results of the first method only, namely averaging local estimates of the derivatives, and refer them to simply as nonparametric estimates.

Table 3.4 provides the comparison of the conventional estimates and the nonparametric estimates for four East Asian countries: Hong Kong SAR, Korea, Singapore, and Taiwan Province of China. We find that the nonparametric "residual" estimates and the conventional estimates using Young's weighted labor shares ("Residual" and "Young" in Table 3.4) are quite similar to each other for Hong Kong SAR, Korea and Taiwan Province of China, but very different for Singapore. These results indicate that the Young and Collins-Bosworth estimates are validated, except for Singapore. But TFP growth in Singapore turns out to be much higher than would be the case using the "Young" and "Collins" methods. The estimate here results from the fact that the labor elasticity (0.63) is higher than that used by Young, and in fact close to that of Collins and Bosworth (1996). However, the estimated capital elasticity (0.17) is considerably smaller than the income share (0.35) assumed by Collins and Bosworth.

A comparison of factor elasticities and factor shares reveals three interesting points. First, in most East Asian countries, the estimated capital elasticity is smaller than the capital share, while the estimated labor elasticity is larger than the labor share.[22] Second, the difference between the labor share and the estimated labor elasticity is quite large in the East Asian countries. Third, the sum of the capital and labor elasticity is not far away from unity in most East Asian countries, seemingly verifying the constant returns to scale assumption.

The above results have an intuitive appeal. The first point above implies that capital is compensated higher than its marginal product, while labor is compensated less than its marginal product. This finding is in line with the typical government policy in many East Asian countries that taxes labor and subsidizes capital in order to attract foreign investment. It is interesting to observe that this pattern is not applicable to Hong Kong SAR, which is known as a free capitalist economy, as compared to government-led capitalist economies like Korea and Singapore. The second point is consistent with the view that the equality of the factor elasticity and

[22] The estimated capital elasticities for Korea, Singapore, and Taiwan Province of China are respectively 0.18, 0.17, and 0.18, whereas the corresponding capital shares of those countries are 0.30, 0.49, and 0.26.

the factor income share is unlikely to hold in developing countries. This casts doubt on the validity of the conventional procedure of the growth accounting calculation. The third point suggests that the aggregate production functions of most East Asian economies exhibit constant returns to scale.[23]

It is fairly common to assume that the aggregate production function exhibits constant returns to scale. Therefore, we next estimate elasticities by explicitly imposing this restriction. More specifically, with constant returns to scale, equation (3.1) together with (3.3) is replaced by

$$Y/L = A \cdot F(K/L, 1) = A \cdot f(K/L),$$

while (3.5) is replaced by

$$\ln(Y/L) = a + f^{*}(\ln(K/L)) + u.$$

The elasticities are then obtained as

$$\varepsilon_K \equiv \frac{\partial \ln F}{\partial \ln K} = \frac{\partial f^{*}}{\partial \ln(K/L)} \quad \text{and} \quad \varepsilon_L = 1 - \varepsilon_K .$$

Table 3.5 presents the results of this constrained nonparametric derivative estimation. Comparing the results in Table 3.5 and Table 3.2, we find that the constrained estimates of TFP growth are very close to the unconstrained ones. In particular, the constrained growth estimates for Hong Kong SAR, Korea, Taiwan Province of China, and China lie within one standard error from the unconstrained

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23 For all eight countries: Hong Kong SAR, Indonesia, Korea, Malaysia, Singapore, Taiwan Province of China, Thailand, and China, the 95 percent confidence intervals of the sum of the two elasticities roughly contain unity, suggesting constant returns to scale technology. The only exception is the Philippines, whose corresponding interval is (0.40, 0.63).

estimates. The estimates for Singapore and Thailand lie within two standard errors. The constrained and unconstrained estimates are significantly different from each other only in the cases of Indonesia, Malaysia, and the Philippines.

Overall, our estimates are quite similar to the Young's modified estimates (Young 1995) with one major exception. Our TFP growth estimate for Singapore (3.6–3.7 percent) turns out to be much larger than Young's (0.3–0.5 percent). This is interesting because Hsieh (2002) calculates the dual measure of TFP growth and found the value to be similar to ours. Klenow and Rodriguez-Clare (1997) also report a similar number (3.3 percent) for Singapore.

3.7 Conclusion

This essay develops a new method of estimating the growth rate of TFP that does not require such strong assumptions that are needed for the conventional growth-accounting method. Our findings based on the new estimation procedure can be summarized as follows. First, we find that Hong Kong SAR, Korea, Singapore, and Taiwan Province of China all have very similar TFP growth of 3.4–3.9 percent over the period 1960–1995, which represents 44–47 percent of output growth of each country during that period. On the other hand, capital growth contributes only 25–28 percent of output growth in these countries. These results provide little support for the strong version of the accumulation hypothesis.

Second, we find that the output elasticities of capital and labor are quite different from the income shares of those factors in the East Asian countries. The actual capital elasticity appears to be much smaller than the measured income share of capital, resulting in a misleadingly high contribution of capital growth to output growth in conventional growth-accounting exercises.

In conclusion, our findings appear to suggest an alternative view about East Asian economic growth that is somewhat different from either the strict “accumulation” or “assimilation” views. On one hand, as the “assimilation” view suggests, economic growth in East Asian countries appears to come from productivity improvements rather than only capital accumulation. On the other hand, in order to attract foreign investment through which new technology is transferred to the country’s economy, the government has to encourage a higher capital compensation and a lower labor compensation than what is economically justified. As a result, there is likely to have been excessive capital investment. Therefore, according to this scenario, unlike what the pure assimilation view would predict, there appear to be some opportunity costs associated with a narrowing of the “idea gap.” All in all, on the basis of the new estimates, we would argue that East Asian growth reflects a combination of the accumulation and assimilation views of economic growth.

Table 3.1 Conventional Estimates of TFP Growth of East Asian Countries (1960-95)

Country	TFP growth estimate (in percent)		Labor share (Young)	Growth (in percent)		
	Young	Collins		Output	Capital	Labor
Hong Kong SAR	4.1	4.1	0.63	7.7	5.2	2.6
Indonesia	-	1.4	-	5.9	8.2	2.5
Korea	2.8	2.3	0.71	8.2	11.8	2.7
Malaysia	-	1.5	-	6.8	9.6	3.0
Philippines	-	-0.1	-	3.8	5.7	2.9
Singapore	0.5	1.8	0.51	8.0	12.1	3.1
Taiwan Province of China	3.4	2.6	0.74	8.3	11.4	2.7
Thailand	-	2.1	-	7.5	10.3	2.7
China	-	3.1	-	6.8	6.9	2.0

Notes: "Young" and "Collins" indicate, respectively, the estimates based on the income share of labor from Young (1995), and the income share set equal to 0.65 as in Collins and Bosworth (1996). "Labor share" is the income share of labor used in Young (1995). "Growth (in percent)" is the actual growth rate of each variable.

Table 3.2 Nonparametric Estimates of TFP Growth of East Asian Countries (1960-95)

Country	TFP growth estimate (in percent)	Elasticity estimates		Growth (in percent)		
		Capital	Labor	Output	Capital	Labor
Hong Kong SAR	3.4	0.41	0.71	7.7	5.2	2.6
	(0.41)	(0.058)	(0.098)			
Indonesia	2.6	0.18	0.64	5.9	8.2	2.5
	(0.30)	(0.025)	(0.087)			
Korea	3.7	0.18	0.81	8.2	11.8	2.7
	(0.42)	(0.025)	(0.114)			
Malaysia	3.2	0.19	0.58	6.8	9.6	3.0
	(0.34)	(0.026)	(0.080)			
Philippines	1.7	0.17	0.34	3.8	5.7	2.9
	(0.21)	(0.025)	(0.053)			
Singapore	3.7	0.17	0.63	8.0	12.1	3.1
	(0.39)	(0.024)	(0.089)			
Taiwan Province	3.8	0.19	0.76	8.3	11.4	2.7
of China	(0.41)	(0.027)	(0.105)			
Thailand	3.7	0.19	0.67	7.5	10.3	2.7
	(0.40)	(0.029)	(0.099)			
China	2.8	0.28	0.95	6.8	6.9	2.0
	(0.43)	(0.043)	(0.146)			

Notes: Figures in parentheses are the standard errors. The values of the elasticity of capital and labor are estimated by a nonparametric method. "Growth (in percent)" is the actual growth rate of each variable.

Table 3.3 Estimates of TFP Growth Based on Average Derivative Estimation (1960-95)

Country	TFP growth estimate (in percent)	Elasticity estimates		Growth (in percent)		
		Capital	Labor	Output	Capital	Labor
Hong Kong SAR	3.7 (1.06)	0.50 (0.135)	0.52 (0.189)	7.7	5.2	2.6
Indonesia	2.6 (0.43)	0.18 (0.036)	0.73 (0.108)	5.9	8.2	2.5
Korea	3.9 (0.82)	0.18 (0.051)	0.80 (0.185)	8.2	11.8	2.7
Malaysia	3.4 (0.47)	0.18 (0.040)	0.54 (0.083)	6.8	9.6	3.0
Philippines	1.9 (0.43)	0.15 (0.040)	0.35 (0.119)	3.8	5.7	2.9
Singapore	3.9 (0.86)	0.20 (0.055)	0.53 (0.142)	8.0	12.1	3.1
Taiwan Province of China	4.1 (0.67)	0.23 (0.047)	0.59 (0.120)	8.3	11.4	2.7
Thailand	3.4 (0.77)	0.24 (0.067)	0.57 (0.097)	7.5	10.3	2.7
China	3.2 (0.39)	0.28 (0.045)	0.95 (0.072)	6.8	6.9	2.0

Notes: Figures in parentheses are the standard errors, calculated according to Hardle and Stoker (1989). The values of the elasticity of capital and labor are estimated by the nonparametric average derivative method. “Growth (in percent)” is the actual growth rate of each variable.

Table 3.4 Comparison of Estimates

Country	TFP growth estimate (in percent)			Capital		Labor	
	Conventional		Non-para-metric	Elasticity	Income share	Elasticity	Income share
	Young	Collins					
Hong Kong SAR	4.1	4.1	3.4	0.41	0.37	0.71	0.63
Korea	2.8	2.3	3.7	0.18	0.29	0.81	0.71
Singapore	0.5	1.8	3.7	0.17	0.49	0.63	0.51
Taiwan Province of China	3.8	2.1	3.8	0.19	0.26	0.76	0.74

Notes: "Young" and "Collins" indicate, respectively, the conventional estimates based on the income share of labor from Young (1995), and the income share set equal to 0.65 as in Collins and Bostworth (1996). Nonparametric estimates are based on the pointwise nonparametric derivative method. The values of the elasticity of capital and labor are estimated by a nonparametric method. The income shares of labor are the values used in Young (1995).

Table 3.5 Nonparametric Estimates of TFP Growth of East Asian Countries with Constant Returns to Scale (1960-95)

Country	TFP growth estimate (in percent)	Elasticity estimates		Growth (in percent)		
		Capital	Labor	Output	Capital	Labor
Hong Kong SAR	3.5	0.51	0.49	7.7	5.2	2.6
	(0.125)	(0.0230)				
Indonesia	1.9	0.25	0.75	5.9	8.2	2.5
	(0.035)	(0.0044)				
Korea	3.3	0.24	0.76	8.2	11.8	2.7
	(0.054)	(0.0047)				
Malaysia	2.3	0.23	0.77	6.8	9.6	3.0
	(0.043)	(0.0045)				
Philippines	0.5	0.13	0.87	3.8	5.7	2.9
	(0.034)	(0.0061)				
Singapore	3.1	0.20	0.80	8.0	12.1	3.1
	(0.052)	(0.0045)				
Taiwan Province	3.4	0.25	0.75	8.3	11.4	2.7
of China	(0.057)	(0.0051)				
Thailand	3.0	0.23	0.77	7.5	10.3	2.7
	(0.058)	(0.0055)				
China	3.0	0.36	0.64	6.8	6.9	2.0
	(0.068)	(0.0095)				

Notes: Figures in parentheses are the standard errors. The values of the elasticity of capital and labor are estimated by the pointwise nonparametric derivative method. "Growth (in percent)" is the actual growth rate of each variable.

Chapter 4

Third Essay

Are IMF Lending Programs Effective? A Panel VAR Approach

4.1 Introduction

The International Monetary Fund (IMF) was established to administer the Bretton Woods system of pegged exchange rates at the end of World War II. When President Nixon finally closed the Gold window in 1973, the system effectively broke down and the currencies of most developed countries started floating. With the end of the system of quasi-fixed exchange rates, the IMF had lost its major purpose as the guarantor of an exchange rate system and since then it has been struggling to find a role for itself. Major upheavals in the international system in the 1970's through 90's --- the oil crisis of the 1970's, the developing country debt crisis of 1982, the transition of formerly planned economy to the market, and the 1997 Asian currency crisis --- led to surges in lending, providing an opportunity of surviving as a financial institution. However, the recent increasingly rapid development of international capital markets creates the situation in which not only do private capital flows dwarf IMF resources, but so do official holdings of foreign currency reserves.[1] Moreover, use of IMF resources has fallen recently to minimal levels that have never been seen before. There are critics who contend the IMF's useful time has passed in the environment of exchange flexibility and open capital markets. Even those who support the institution find its reform inevitable.

Certainly only the most optimistic people can confidently believe that the recent unusual calmness in worldwide financial markets is not a temporary phenomenon but reflects the permanent shift to the period of stability. It is more likely that the period of crises will return soon, and the IMF is needed to play a role once again. However, even in such a case, it is important more than ever to correctly access the efficacy of the core function of the IMF in order to think about the reform of the institution.

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[1] In 2005, eight Asian countries (Japan, Singapore, Indonesia, China, Malaysia, the Philippines, Thailand, and South Korea) command reserves worth about ten times as large as the IMF total.

By now there is a quite large empirical literature that attempts to evaluate the effectiveness of IMF lending programs on the program country's economy. Economists outside the IMF tend to find that Fund programs have no effect or even negative effect on the country's economic growth and that programs appear to have a positive impact on current account and balance of payments but the effects last only in a short term (e.g. Conway 1997, Barro & Lee 2006). On the other hand, the IMF staff economists tend to find somewhat more positive effect of programs (e.g. Dicks-Mireaux et al, 2000).

Most of the literature defines "program effectiveness" as the difference between the actual macroeconomic performance that was observed under the program and the hypothetical performance that would have occurred if the program had not been implemented. Since hypothetical performances are not observed, various econometric approaches have been taken to construct counterfactual outcomes.[2] Construction of counterfactuals is a considerably difficult task especially in macroeconomic context, where many key variables involved are endogenous, and dynamic time-series aspects of movement of variables are crucial for analysis.

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[2] Khan (1990) and Ul Haque and Khan (1998) provide excellent surveys of the literature.

4.2 Overview of the Essay

In this essay we develop a new approach that takes account of the dynamic nature of the problem in the following two senses. First, all the variables involved are endogenous and jointly determined in a system. A standard way to handle them is to use a vector autoregressive (VAR) model. Variables are classified into two groups. One group consists of the economic variables that are targeted in IMF program agreements, such as the GDP growth rate, the inflation rate, and the overall balance of payments (as a percent of GDP). The general practice in the literature is to focus on these macroeconomic performance variables. Another group consists of policy instruments such as money supply, fiscal balance, and exchange rate changes. The equations expressing these policy instruments may be viewed as policy reaction functions.

Second, program effects cannot be appropriately captured in a dynamic context by a simple program dummy variable. Conditionality attached to IMF agreements forces the program country to make policy shifts. This leads to a change in policy reaction functions. For example, in response to a negative BOP shock the country under an agreement has to undertake tighter monetary and fiscal policy than when it usually does without such an agreement. This type of policy shifts needs to be expressed by a switch from one reaction function to another. Use of a program dummy variable is not appropriate because it allows for a change in the intercept only.

In this essay we do not use the program dummy to capture the program effects. The effects of the IMF program have two aspects: the effect of loan itself and the effect of policy shifts induced by IMF agreements. We call these the loan effect and the policy effect, respectively. We let policy reaction function to switch from one regime to another regime, depending on whether or not the country enters into the agreement. Under our identification restrictions, we can estimate two effects separately from the data.

Another point where our approach is different from those in the literature is treatment of the selectivity problem. A simple comparison between program countries and non-program countries shows that macroeconomic performance of program countries is almost always worse than that of non-program countries. But this does not automatically imply that the IMF program has a negative economic effect. To avoid a common mistake of attributing a patient's sickness to the treatment of a doctor, many authors address the problem of the self-selectivity by incorporating in their regressions the correction term obtained form the Probit model run separately. Unfortunately this popular approach often fails to yield a significant coefficient estimate, which implies that the selectivity bias does not appear to be present. We attack the problem differently by using the partial likelihood method based on the Tobit model.

The results generated from our new approach to the IMF program effectiveness suggest that the selectivity bias is a serious problem when evaluating the program effects, which makes the effect look smaller than it actually is. When properly taking account of the selectivity problem, contrary to the literature, the net effect of the IMF program on economic growth is found clearly positive. With the IMF program, the inflation is found to decline, the fiscal deficits to shrink, and the BOP to improve. Our finding agrees with the literature, however, that all these effects are short lived and last only for a few years after the program terminates.

The rest of the paper is organized as follows. The next section reviews the program evaluation approaches taken by the previous studies in the literature and propose our new approach. Section 4.4 describes the data and overviews the stylized facts in the data. Section 4.5 outlays our econometric model and describes how we access the program effect based on the model. Section 4.6 reports empirical results and discusses their implications. Section 4.7 concludes.

4.3 Background

The econometric approaches used in the literature can be divided into four basic groups: (a) the “before-after” approach, (b) the “with-without” or “control-group” approach, (c) the generalized evaluation estimation approach, and (d) the instrumental variable approach. The “before-after” approach compares macroeconomic performance during a program with performance prior to the program. A change in the measure of macroeconomic performance between the two regimes is considered as the program effect. This approach provides unbiased estimates of program effects so long as the economic environment of the country under consideration remains unchanged over time periods. However, this kind of other-things-equal assumption tends to be violated in practice. Such external shocks to developing countries includes large changes in world oil prices, large year-to-year changes in industrial country real gross national product, significant shifts in real interest rates, and the like. A change in such factors leads to biased estimates of program effects under this approach.

The “with-without” or “control-group” approach compares macroeconomic performance between non-program countries and program countries. The group of non-program countries is called the “control group,” and the group of program countries is called the “experimental group” or “treatment group” in the literature of program evaluation. A difference in the measure of macroeconomic performance between the two groups is considered as the program effect. This approach provides unbiased estimates of program effects so long as members in both groups are drawn randomly from the same population. However, participation in an IMF program typically reflects different circumstances between program and non-program countries, and hence it is unreasonable to assume that members in both groups are drawn randomly from the same population. Neglecting the non-random selection of program countries leads to biased estimation.

The “generalized evaluation estimation” approach, which was introduced by Goldstein and Montiel (1986), attempts to correct bias that is caused by the non-random selection of program countries. Their framework has several important features, including the previous two approaches as special cases of this approach. However, their estimation method is a single equation method with a substitution of one equation into another. This substitution presupposes the recursive structure of policy and target variables.[3] In addition, due to the estimation method, their program effect is estimated as the total program effect which combines the impact of the IMF loan and the impact of IMF policy advice to program countries.

An instrumental variable approach, which was developed by Barro and Lee (2005), attempts to cope with the selectivity bias problem, using the instrumental variable technique. They use political and institutional variables that, they claim, affect countries' decisions of selecting one of the two regimes but not influence economic performance. If their claim is right, then the instrumental variables approach is a catch-all method to take care of all endogenuity problems including selectivity without contemplating the structural relationship of variables that brings on endogenuity. However, this claim is not testable. Another problem with Barro and

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[3] Goldstein and Montiel (1986) implicitly assume that policy variables do not react to the contemporaneous target variables but do so with delay.

Lee (2005) is that their program evaluation is based on the standard cross-country growth regression with 5 years average data, which might be good for capturing long-run outcomes of the IMF program but is not appropriate for examining the short to medium term impact on the economy of the program.

Although there has been a great deal of progress made toward understanding the effectiveness of IMF stabilization programs, important methodological issues remain. It is the common practice in the empirical literature to estimate the effectiveness of IMF programs as the size and significance of the coefficient on a program dummy in a single regression equation. This approach produces major limitations for all studies in the literature reviewed above. Although it is the standard approach to the program evaluation in labor economics, the dummy variable procedure is not a good choice when the program may affect the outcome through a shift in reaction function as is the case in many policy reform programs in macroeconomic context. When the program agreement includes some type of policy shifts, the country's policy makers are expected to respond to a variety of economic shocks differently from before the agreement. This kind of policy shift is difficult to capture by the program dummy alone.

Our approach outlined in the next section is based on a vector autoregression model using panel data across countries. This is quite different from the single equation approach in the past studies. We treat all endogenous variables equally with multiple equations and estimate the multiple equations in panel. This feature is crucially important to take into account a variety of shock encountered by the economy.

We then examine the two different channels through which the IMF works: the loan and the IMF policy advice. The IMF policy advice affects the target economic performance indirectly through a change in the macroeconomic policies. On the other hand, the IMF loan may have direct impact on the target economic performance either by reducing the debt burden or through a possible recovery of confidence among investors or both. Since the IMF policy advice often aims at a systematic change in the pattern of policy reaction of the government, our policy reaction functions are assumed to switch between two regimes: in-program and out-program. Our intention is to capture the impact of the IMF policy advice as differences in parameter values between the two regimes.

4.4 Data

Our data set is the panel data of annual observations for 79 countries covering Asia, Latin America, and Africa over the period of 28 years from 1976 through 2003. It contains 377 IMF programs actually implemented, including Stand by Arrangements and Extended Fund Facilities (the former consists of 84% of all programs and the latter consists of the remaining 16%). Panel (A) of Figure 4.1 displays the distribution of the duration of programs implemented over 28 years. The sample mode is 4 quarters (59% of the episodes) and 84% of the all cases fall between 4 and 8 quarters. Panel (B) shows the distribution of the loan amount per program as a percentage of GDP. The sample mean and median of the loan are 1.42% and 0.77% of GDP, respectively. Panel (C) shows the distribution of the number of program participations of a given country.

The data also contain basic macroeconomic variables such as GDP growth, inflation, government fiscal balance, balance of payments, exchange rate, etc. Table 4.1 gives a list of variables, and Appendix C.1 provides the descriptions and sources of the data. The summary statistics of main variables are reported in Table 4.2 for the whole sample as well as for the two sub periods separately depending on whether or not countries participate in the IMF programs. Since the distributions are heavily skewed for some of the variables, the medians appear to be more appropriate summary of central tendency than the means. Simple comparisons of median values under two regimes in Table 4.2 reveal the conventional observation about the effectiveness of the IMF program. The economic growth rates tend to be lower in the program countries (or periods) than in the non-program countries (or periods).[4] Similarly, we observe higher inflation rates, larger government budget deficits, as well as larger depreciation of national currencies in program countries (or periods).

Of course this simple comparison of unconditional central tendencies (such as means or medians) does not tell much about the program effectiveness. The bad macroeconomic performance of the program countries (or periods) is the reason why they chose to participate in the program in the first place rather than the consequence of the program.

Distinction between pre-existing conditions and treatment effects is seldom

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[4] For example, Przeworski and Vreeland (2000) classify countries in the IMF program into four groups depending on whether they have good or bad reserve as well as deficit conditions, and find, in all cases, the countries participating in the programs grow slower than those not participating in the programs.

easy to make but it is a most crucial step to correctly evaluate the effectiveness of the IMF programs. A more useful insight into this sample selectivity aspect of the problem is gained if we look at Table 4.3, which tracks down the changes in the key variables before and after the program treatment. Panel (A) of Table 4.3 depicts how the median values of the major macroeconomic variables have moved along the time line from 3 years to 1 year before the program implementation, while Panel (B) shows the movements of the median values of the same variables from 1 year to 3 years after the exit. The balances of payments as well as the budget deficits of the typical program country deteriorate at an accelerating rate for this period before it finally asks for help. After the program period, the GDP growth rate, inflation rate, and the balance of payments of the typical program country get back to the normal levels observed when deterioration started around 3 years before the program initiation.   In contrast, the government budget deficits get slightly better.

This gives quite different but still partial a picture of the impact of the program on macroeconomic variables over time. It is still partial because it does not tell how much of the before-after differences is attributable to the IMF programs and how much is simply the outcome of business cycle fluctuations.

4.5 Model and Estimation

4.5.1 Model of Program Effects

Our model consists of three groups of equations. The first two groups of equations describe the behavior of what we call the policy variables and the target variables, while the third equation describes the selection mechanism for the IMF loan program.

The policy variables are a set of policy instruments that the government can control through its monetary, fiscal and exchange rate policies. They are fiscal deficits (DEF), a change in domestic credit (ΔDC), and a change in exchange rate (ΔEX). The target variables are the country's macroeconomic performance variables such as output growth (ΔY), inflation (ΔP), and the balance of payments (BOP).

The third equation mimics the IMF's selection criterion that determines whether a given country in a given period is "in" or "out" of the IMF program, on the basis of the historical records of the country's target variables as well as other political considerations.

As pointed out previously, the IMF program has two major aspects: the loan provision and the policy advice. To distinguish the two different channels through which the IMF program possibly operates, we make the following specification. Since the policy advice often aims at a systematic change in the pattern of the policy reaction of the government, the policy equation is assumed to switch between two regimes: in-program and out-program. The economic variables are affected by the IMF policy advice indirectly through a change in the policy reaction function. For example, following the IMF's advice to cut deficits and tighten money (a shift in the policy equations), the country's balance of payments improves. The IMF financial assistance or loans, on the other hand, may have a direct impact on the economic performance variables either through reducing the debt burden or through a possible recovery of confidence among investors.[5] This impact likely depends upon the size of the loan made during the given time period.

To formally introduce our model, we define the following variables.

$\mathbf{y}_{it}^{P} =$ an $m^{P} \times 1$ vector of policy variables in country i in period t,

$\mathbf{y}_{it}^{T} =$ an $m^{T} \times 1$ vector of target variables in country i in period t,

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[5] Marchesi (2002) shows the adoption of the IMF program signals "good intent" of a country which is rewarded with the debt relief.

d_{it} = a program dummy taking on the value 1 or 0 depending on the IMF program is in effect in country i in period t,

L_{it} = the amount of the IMF loan (as a percent of GDP) to country i in period t.

Let $\mathbf{y}_{it} = [\mathbf{y}_{it}^{P}{}', \mathbf{y}_{it}^{T}{}']'$, which is an $m \times 1$ vector with $m = m^P + m^T$. Then the structural model for $\mathbf{y}_{it}^{P}$ and $\mathbf{y}_{it}^{T}$ is given by

$$\mathbf{A}_{11}\mathbf{y}_{it}^{P} = \mathbf{a}_{i}^{Pd} + \mathbf{A}_{y1}^{Pd}\mathbf{y}_{i,t-1} + \cdots + \mathbf{A}_{yp}^{Pd}\mathbf{y}_{i,t-p} + \boldsymbol{\varepsilon}_{it}^{P} \tag{4.1a}$$

$$\mathbf{A}_{22}\mathbf{y}_{it}^{T} = \mathbf{a}_{i}^{T} + \mathbf{A}_{12}\mathbf{y}_{it}^{P} + \mathbf{A}_{y1}^{T}\mathbf{y}_{i,t-1} + \cdots + \mathbf{A}_{yp}^{T}\mathbf{y}_{i,t-p} + \mathbf{a}_{L0}^{T}L_{it} + \cdots + \mathbf{a}_{Lp}^{T}L_{i,t-p} + \boldsymbol{\varepsilon}_{it}^{T} \tag{4.1b}$$

for $d = 1,0$, where $\mathbf{A}_{11}$, $\mathbf{A}_{22}$ and $\mathbf{A}_{12}$ are $m^P \times m^P$, $m^T \times m^T$ and $m^T \times m^P$ matrices, $\mathbf{A}_{yj}^{Pd}$ and $\mathbf{A}_{yj}^{T}$ are $m^P \times m$, $m^T \times m$ matrices of parameters for $j = 1,\ldots,p$, and $\mathbf{a}_{Lj}^{T}$ is an $m^T \times 1$ vector of parameters for $j = 0,\ldots,p$. The first equation above is a set of policy reaction functions that switch between two regimes: in-program (d = 1) and out-program (d = 0). The second equation describes each target variable as a function of contemporaneous policy variables, the amount of IMF loan, and all lagged variables. This model specification is based on the assumption that the policy variables cannot respond to the target variables instantly while the target variables reflect a change in policy variables without delay. This assumption is justified by the following considerations. The delay in policy reaction is caused by the information delay and slow responses of the policy makers. In many developing countries the information about even basic economic statistics is not available quickly, and policy makers' reactions are often quite slow. In particular, at the time of currency or financial crisis, which is an especially important period for our study, deteriorations of macroeconomic performance variables are so rapid that policy responses necessarily tend to lag behind. We also test the hypothesis that the coefficients on $\mathbf{y}_t^T$ are zero in the policy equation based on its instrumental variables estimates, using their own lags $\mathbf{y}_{t-j}^T$ for $j = 3, \cdots, 6$ as the instruments. We find that the F-test cannot reject the null.[6] In a later section, we try two alternative specifications. The country specific intercept and variance covariance matrix of the error terms in equations (4.1a) and (4.1b) introduce individual heterogeneity into the above panel VAR.[7]

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[6] The p-values are 0.999, 1.000, and 0.998 for the government balance equation, the domestic credit growth equation, and the exchange rate depreciation equation, respectively.

[7] There is criticism against the use of a panel VAR model with cross-country data in general. Pesaran and Smith (1995) point out that a panel VAR model does not yield the average dynamics of members when homogeneity of dynamics across countries is suspect. However,

Note that the IMF loan variable is excluded from the policy equation (4.1a). The IMF's policy advice in practice is based on a highly standardized formula as a function of the current and target values of several key macro variables, independent of the actual amount of loan provided. This does not imply, however, that its policy advice is formulated irrespective of the loan amount, but that the amount of loan required to achieve policy goal is already taken into account when the loan decision is made.

We now turn to the selection mechanism. The program participation by a country is a product of interactions between the desire of the country for financial help and the IMF's willingness to lend, which in turns are related to the country's underlying macroeconomic situations. In this sense it is no doubt that the program participation is endogenously determined. This mechanism is usually characterized by a probit selection model. That is, the program participation (d =0 or 1) is directly estimated as a function of underlying macroeconomic and other variables. However, the amount of loan (L_{it}) is observable and the IMF program dummy (d_{it}) is 1 only

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our sample is limited and without restrictions we would not be able to estimate a model with reasonable complications.

when L_{it} is positive. A more efficient way to model the selection process is, therefore, to use a Tobit model. Let L^*_{it} be the potential loan amount implied by the IMF standardized formula, which can be observed only when L^*_{it} is positive. We then postulate that the selection process is governed by

$$L^*_{it} = \mathbf{w}_{i,t-1}'\theta + v_{it} \tag{4.2}$$

where $\mathbf{w}_{i,t-1}$ is a vector of historical records on the target, policy, and other variables. Since the actual loan amount offered by the IMF might reflect a given country's influence on the decision process inside the IMF, we include institutional variables such as the IMF quota size.[8] The actual observed loan and the IMF program dummy are given by

$$L_{it} = L^*_{it} d_{it} \quad \text{and} \quad d_{it} = 1(L^*_{it} > 0) \tag{4.3}$$

Our assumption here is that the loan amount as a percentage of GDP represents the quantity measuring the plausibility of a given country in a give time period would participate in the IMF program. Rewriting (4.1a) and (4.1b), we have

$$\mathbf{y}^P_{it} = \mathbf{b}^{Pd}_i + \mathbf{B}^{Pd}_{y1}\mathbf{y}_{i,t-1} + \cdots + \mathbf{B}^{Pd}_{yp}\mathbf{y}_{i,t-p} + \mathbf{u}^P_{it} \tag{4.4a}$$

[8] These variables are suggested by Barro and Lee (2005), who used them as instrumental variables for the IMF program dummy.

$$\mathbf{y}_{it}^T = \mathbf{b}_i^T + \mathbf{B}_{12}\mathbf{y}_{it}^P + \mathbf{B}_{y1}^T\mathbf{y}_{i,t-1} + \cdots + \mathbf{B}_{yp}^T\mathbf{y}_{i,t-p} + \mathbf{b}_{L0}^T L_{it} + \cdots + \mathbf{b}_{Lp}^T L_{i,t-p} + \mathbf{u}_{it}^T \quad (4.4b)$$

where $\mathbf{b}_i^{Pd} = \mathbf{A}_{11}^{-1}\mathbf{a}_i^{Pd}$, $\mathbf{B}_{yj}^{Pd} = \mathbf{A}_{11}^{-1}\mathbf{A}_{yj}^{Pd}$, $\mathbf{b}_i^T = \mathbf{A}_{22}^{-1}\mathbf{a}_i^T$, $\mathbf{B}_{12} = \mathbf{A}_{22}^{-1}\mathbf{A}_{12}$, $\mathbf{B}_{yj}^T = \mathbf{A}_{22}^{-1}\mathbf{A}_{yj}^T$ for $j = 1,\ldots,p$, and $\mathbf{b}_{Lj}^T = \mathbf{A}_{22}^{-1}\mathbf{a}_{Lj}^T$ for $j = 0,\ldots,p$. The error term v_{it} in the selection equation (4.2) represents the information that is not observed by the econometrician but relevant to the selection process, for example, information not published but observed by at least one party. The error term v_{it} is assumed to be correlated with the shocks to the system $\mathbf{u}_{it} = [\mathbf{u}_{it}^P{}', \mathbf{u}_{it}^T{}']'$. We can write the error terms $\mathbf{u}_{it}$ and v_{it} jointly as

$$\begin{bmatrix} \mathbf{u}_{it}^P \\ \mathbf{u}_{it}^T \\ v_{it} \end{bmatrix} = \begin{bmatrix} \mathbf{A}_{11}^{-1} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{A}_{22}^{-1} & \mathbf{0} \\ \mathbf{c}_P{}' & \mathbf{c}_T{}' & c_L \end{bmatrix} \begin{bmatrix} \varepsilon_{it}^P \\ \varepsilon_{it}^T \\ \varepsilon_{it}^L \end{bmatrix} \equiv \Gamma \boldsymbol{\varepsilon}_{it} \quad (4.5)$$

where $\varepsilon_{it} \sim \mathrm{iid}(\mathbf{0}, \mathbf{I})$ is a vector of structural shocks. The term ε_{it}^L stands for an exogenous shock to the IMF loan. The zero restrictions on matrix Γ in (4.5) imply that $\mathbf{y}_{it}$ is not affected contemporaneously by this shock. This assumption simply reflects the notion that the effect of the loan would not be materialized immediately. This obviously does not rule out the possibility that the shock will have influence on all variables in $\mathbf{y}_{it}$ with delay. On the other hand, the IMF loan decision is affected by all contemporaneous exogenous shocks to all variables in $\mathbf{y}_{it}$. A sudden deterioration of a country's balance of payment position, for example, can lead to a quick decision by the IMF.

Assuming at least either $\mathbf{c}_P \neq \mathbf{0}$ or $\mathbf{c}_T \neq \mathbf{0}$, we can write the likelihood function of the model and maximize it with respect to its parameters to get the ML estimates. We do not follow this approach, however, because it does not work well with large number of parameters.

4.5.2 Estimation

Instead of using the maximum likelihood method, we employ the recursive estimation procedure based on the partial likelihood approach (Vella 1992). Note that the conditional expectations of $\mathbf{y}_{it}^P$ and $\mathbf{y}_{it}^T$ in (4.4) given v_{it} and d_{it} together with the lagged $\mathbf{y}_{it}$ are given by

$$
\begin{aligned}
E(\mathbf{y}_{it}^P \mid \mathbf{y}_i^{t-1}, v_{it}, d_{it}) &= \mathbf{b}_i^{Pd} + \mathbf{B}_{y1}^{Pd}\mathbf{y}_{i,t-1} + \cdots + \mathbf{B}_{yp}^{Pd}\mathbf{y}_{i,t-p} + \gamma_P^d v_{it} \\
E(\mathbf{y}_{it}^T \mid \mathbf{y}_i^{t-1}, v_{it}, \mathbf{u}_{it}^P, d_{it}) &= \mathbf{b}_i^T + \mathbf{B}_{12}\mathbf{y}_{it}^P + \mathbf{B}_{y1}^T\mathbf{y}_{i,t-1} + \cdots + \mathbf{B}_{yp}^T\mathbf{y}_{i,t-p} \\
&\quad + \mathbf{b}_{L0}^T L_{it} + \ldots + \mathbf{b}_{Lp}^T L_{i,t-p} + \gamma_T v_{it} + \delta\mathbf{u}_{it}^P
\end{aligned}
\tag{4.6}
$$

where $\mathbf{y}_i^{t-1} = \{\mathbf{y}_{i,t-1}, \mathbf{y}_{i,t-2}, \ldots\}$, $\gamma_P = \mathbf{c}_P / \sigma_{VV}$, $\gamma_T = \mathbf{c}_T / \sigma_{VV}$, $\delta = \mathbf{B}_{12}\mathbf{A}_{11}^{-1}$ and $\sigma_{VV} = \mathbf{c}_P{}'\mathbf{c}_P + \mathbf{c}_T{}'\mathbf{c}_T + c_L^2$. In other words, we can obtain consistent estimates of the parameters of equation (4.4a), free of selectivity bias, by running separate regressions for $d = 0$ and 1 when including v_{it} as an additional regressor. Also, we can avoid the endogeneity problem of $\mathbf{y}_{it}^{P}$ and L_{it} for the regression (4.4b), if we include v_{it} and $\mathbf{u}_{it}^{P}$ as additional regressors. Of course v_{it} and $\mathbf{u}_{it}^{P}$ are unobservable, but they can be estimated. First, we estimate θ from the selection equation (4.2) by maximizing the Tobit likelihood. Then we obtain $\hat{v}_{it} = L_{it} - \mathbf{w}_{i,t-1}'\hat{\theta}$. Next, we run the OLS regression of $\mathbf{y}_{it}^{P}$ on $\mathbf{y}_{i,t-1}$ and $\hat{v}_{it}$, and then compute $\hat{\mathbf{u}}_{it}^{P} = \mathbf{y}_{it}^{P} - \hat{\mathbf{b}}_{i}^{Pd} - \hat{\mathbf{B}}_{y1}^{Pd}\mathbf{y}_{i,t-1} - \ldots - \hat{\mathbf{B}}_{yp}^{Pd}\mathbf{y}_{i,t-p} - \hat{\gamma}_{P}\hat{v}_{it}$. Finally, we run the OLS regression of $\mathbf{y}_{it}^{T}$ on $\mathbf{y}_{i,t-1}$, $\hat{v}_{it}$, and $\hat{\mathbf{u}}_{it}^{P}$. The resulting estimates of $\mathbf{b}_{i}^{P}$, $\mathbf{b}_{i}^{T}$, $\mathbf{B}_{12}$ $\mathbf{B}_{yj}^{Pd}$, $\mathbf{B}_{yj}^{T}$, and $\mathbf{b}_{Lj}^{T}$ are all consistent (Rivers and Vuong 1998). These regression results can also be used for testing the selectivity bias as well as endogeneity of $\mathbf{y}_{it}^{P}$. We can test the selectivity bias in (4.4a) by testing a hypothesis that each component of γ_{P} equal zero by a simple t-test (Vella 1992). Also endogeneity of $\mathbf{y}_{it}^{P}$ and L_{it} can be tested by testing hypotheses $\delta = \mathbf{0}$ and $\gamma_{T} = 0$ by a simple F-test and t-test.

4.5.3 How Do We Evaluate the IMF Programs?

All the previous studies evaluate the effectiveness of IMF programs by estimating a single parameter on the program dummy variable. This conventional approach, however, has at least two fatal shortcomings. First, even after taking into account the selectivity and endogeneity problems, this approach lacks the dynamic features of evaluation crucially needed for any macro-economic programs. The effectiveness of the IMF programs has to be evaluated not at a few points in time but over the wide range of time horizon after its implementation. Second, it does not provide any hint about the channels through which the program affects the economic performances. With the conventional approach, we cannot separately evaluate the loan provision and the policy advice, which are often very important in policy discussion.

This essay provides a remedy to the above weakness in the previous studies. We show three approaches to measure the effects of the IMF program on the country's macroeconomic performance over time.

4.5.3a Standard Program Evaluation

The first procedure does not require the structural model and is close to the conventional static program evaluation procedure. We set first the benchmark levels of $\mathbf{y}$, L, and $\mathbf{w}$ at $\overline{\mathbf{y}}^{\mathbf{t-1}}$, $\overline{L}^{t}$, and $\overline{\mathbf{w}}^{t}$, where t stands for the start year of the program and $\mathbf{w}^{t} = \{\mathbf{w}_{t}, \mathbf{w}_{t-1}, \ldots\}$. They might be the median values across all program countries, or can be set on the basis of some historic episode such as the Mexican Peso crisis of 1994. Starting from this benchmark, we calculate four types of the predicted values of the performance variables given by

$\hat{\mathbf{y}}^{T}_{t+h}(L>0, d=1)$, $\hat{\mathbf{y}}^{T}_{t+h}(L=0, d=1)$, $\hat{\mathbf{y}}^{T}_{t+h}(L>0, d=0)$ and $\hat{\mathbf{y}}^{T}_{t+h}(L=0, d=0)$

for horizon $h = 0,1,2,\cdots$. They are the values of the macro performance in *h* years after the program implementation predicted by the model in the following four different cases: (a) with both loan and policy advice (L>0, *d* = 1), (b) with advice but without loan (L = 0, *d* = 1), (c) with loan but without advice (L>0, *d* = 0) and (d) without loan nor advice (L = 0, *d* = 0). By comparing four values each corresponding to alternative scenarios in the wide range of horizon *h*, we can address a variety of interesting questions that the conventional single program dummy variable model was not able to answer. For example, the total effect of the IMF program on a typical recipient country after *h* years from its implementation is estimated to be $\hat{\mathbf{y}}^{T}_{t+h}(L>0, d=1) - \hat{\mathbf{y}}^{T}_{t+h}(L=0, d=0)$. For the effect of the policy advice alone, there are two cases. Assuming the country is already given the loan from the IMF, the incremental effect from its policy advice is measured by

$\hat{\mathbf{y}}^T_{t+h}(L>0, d=1) - \hat{\mathbf{y}}^T_{t+h}(L>0, d=0)$. On the other hand, when the country is given only policy advice without any loan, the effect is measured by

$\hat{\mathbf{y}}^T_{t+h}(L=0, d=1) - \hat{\mathbf{y}}^T_{t+h}(L=0, d=0)$.

4.5.3b Program Evaluation Based on the Impulse Response Functions

Although the above procedure provides a sensible way to measure the program effect, there is an alternative way to do so based on impulse response functions. We first choose the benchmark level of the initial condition $\overline{\mathbf{y}}^{\mathbf{t-1}}, \overline{\mathbf{x}}^t, \overline{L}^t$, and $\overline{\mathbf{w}}^t$ to be the median values for the countries when L^*_t is close to zero. That is, to make a story realistic, we start with the border-line situation between d =0 and 1 for the country. We next calculate the dynamic responses of $\mathbf{y}^T$ to an exogenous shock to loan decision equation (4.2). This gives the marginal effect of the IMF program on the performance variables $\mathbf{y}^T$ for a border-line country.

4.5.3c Program Evaluation after a Hypothetical Shock

In the third procedure, we consider the hypothetical case in which a certain negative shock hits a country's economy such as the one in the balance of payment (BOP) crisis. This would usually trigger the IMF rescue effort by means of the provision of loans and policy advice. So we start our exercise by subjecting the system to an exogenous shock to the BOP and construct the impulse response functions of $\mathbf{y}_{t+h}^{T}$ under the four different scenarios similar to the first evaluation scheme above. Based on the results, we can answer the questions such as what would happen to the country's BOP level if the IMF provides loans but no policy intervention at the crisis.

4.6 Empirical Results

4.6.1 Selectivity Bias

The results of the maximum likelihood estimation of the Tobit selection model given in equation (4.2) are reported in Table 4.4.[9] We can observe the selection mechanism pretty clearly where a country with low economic growth and high balance of payment deficits in the past is more likely to participate in the IMF

[9] We choose the lag length in our VAR: p equal to 2 based on the AIC.

program. A proper treatment of these pre-existing conditions is crucial in evaluating the program effectiveness. How serious is the resulting selectivity bias may be examined by testing the hypothesis that γ_P and γ_T in equation (4.6) are equal to zero jointly in the set of the policy equations and the target equations, respectively. Table 4.5 reports the results of the F-tests. Essentially, these tests examine the size of σ_{uv} in equation (4.5). The results suggest that the selectively bias appears quite serious.

Most previous studies use the probit selection equation to investigate the sample selection issue in the IMF program evaluation. They find the tests fail to reject the absence of selectivity and some economists conclude that selectivity is not important in this evaluation (e.g. Dicks-Mireaux et al , 2000). In contrast, our results show the selectivity bias is really serious and has to be properly dealt with to correctly evaluate the program effectiveness.

4.6.2 Policy Reaction Functions

In order to get the loan, the country needs to comply with the policy shifts recommended by the IMF economists. This is often referred to as the IMF conditionality and is the major component of the IMF supported stabilization programs. In our model, the country switches its policy reaction function from one form to another, depending on whether or not it is participating in the program. We first conduct a test whether there are actually two policy regimes. The standard F-test rejects no regime switching.[10] We next try to see how different are policy reactions under two regimes. Figure 4.2 displays the dynamic responses of (A) fiscal, (B) monetary and (C) exchange rate policies, respectively, to a negative balance of payment shock. The size of the shock is set equal to one standard error in each case. The solid line in each panel indicates the policy reaction under the program regime while the broken line indicates that under the non-program regime. Panels (A) and (B) in Figure 4.2 show that with the IMF program, the country responds to a negative BOP shock by much tighter fiscal and monetary policies (less fiscal spending and less money supply increase) than it does without the program. What is more remarkable is that the exchange rate completely stops to depreciate after 3 years with

[10] The p-value for the government balance equation is 0.00004, the p-value for the domestic credit growth equation is 0.02135, and the p-value for the exchange depreciation equation is 0.000000. Thus, the null hypothesis of no regime switching can be rejected at 5 percent significance for each equation.

the IMF program. In contrast, it continuously depreciates for a long period of time after the BOP shock without the program. This stark contrast of the policy responses under two regimes is perfectly consistent with what is expected from the IMF guideline.

4.6.3 How Effective Are IMF Programs?

4.6.3a Standard Program Evaluation

Figure 4.3 presents the program effects on the key macroeconomic variables over time in a manner close to the standard average treatment effect estimation. We set the values of the variables in the start year of the program at the median values in the start year of all the episodes in the reference group, and estimate the average treatment effects for the typical program country over the appropriate time horizon.[11] The reference group is defined as the cases in which a country currently participates in the IMF program but was not in the program for the previous three years.

Panels (A) – (D) of Figure 4.3 display the expected impacts of the program

[11] This is so called "average treatment effect of the treated" in the literature on treatment effects.

on key macro variables over the 10 years horizon. We assume that the country is in the IMF program for two years. The size of the loan is set at the median value of 0.859% of GDP in the start year and 0.853% of GDP in the following year. The narrow broken line in each panel indicates the effect of the loan only, while the wide broken line indicates the effect of the policy advice only. The total effect of the IMF program is shown by the solid line.

We can see from the total effect curves in four panels in Figure 4.3 that the typical program country is clearly benefited from the IMF stabilization program in all four macro performance variables. The total effect curve in Panel (A) tells us that output grows at a rate from 0.5% to 1.5% higher over three years with a program than when it would do without the program. Similarly Panel (B) indicates that the inflation rate declines substantially with the IMF program than without it. It falls by more than 10% in the peak year and keeps falling for 5 -6 years after the completion of the program. Balance of payments relative to GDP also improves significantly with the program, which increases by more than 2% after one year, but the effect quickly disappears as the program completes. Net government deficits relative to GDP shrinks by 2-3% after one year and keeps shrinking for as long as 3 years after the completion of the program.

Figure 4.3 also depicts the dynamic average treatment effects of the loan and the policy advice separately. The most important finding here is that the effectiveness of the IMF program appears to come largely from the policy shifts observed at the stage of the program implementation. Although we simply call it the IMF policy advice, it often means that under the IMF pressure the government of a program country can adopt a tough policy that is right but so unpopular to implement otherwise.

In particular, it is striking that reduction of inflation and net government deficits are almost entirely attributable to the policy advice with little impacts of the loan. On the other hand, both the loan and the policy advice contribute equally to increases in output growth and balance of payments. The results are contrary to the popular view that the IMF's main role is lending money when it is needed rather than providing policy advices.

4.6.3b Evaluation via Impulse Responses

We now look at a picture from a slightly different angle. We consider a typical country whose economic condition is on the border line in the sense that, according to the participation equation (4.2), the country has an equal chance of participating in the program and not. In other words, it is the case in which the systematic part of equation (4.2) is equal to zero. We then examine dynamic responses of key macro variables to an exogenous shock on the participation equation. This procedure yields the marginal effect of the IMF program on macro performance variables over the horizon in the same manner as the effect of monetary policy is examined through the dynamic response to a monetary policy shock.

This measure of the program effect is quite different from the one reported in the previous subsection. Here we try to answer the question: What kind of improvements are expected to be brought in when the IMF program is exogenously applied to a country's economy that is not either as bad or as good?

The size of the shock is set equal to one standard deviation of its distribution. The simulation is designed in such a way that it reproduces the empirical distribution of the actual program duration by adjusting the duration of the shock. Namely, 41.5% of the cases are less than or equal to 1 year, 43.1% are between 1 and 2 years, 12.6% are between 2 and 3 years, and 2.8% are between 3 and 4 years.

The result is reported in Figure 4.4. The impacts of the IMF program on the output growth, inflation, and balance of payments over the horizon have the pattern similar to the average treatment effects depicted in Figure 4.3. Output growth increases, inflation declines, and balance of payments as well as its fiscal balance improve within one to two years after the start of the program and the effects disappear after 4-5 years. The impact on output is not accurately captured here. The impact on the balance of payments is clearer.

4.6.4 Alternative Specifications

Our base line specification given in (4.1) and (4.2) is based on the assumption that policy variables do not respond to macroeconomic performance instantly while the latter variables reflect policy variables without any delay. We now consider two alternative model specifications. First, we switch the roles of policy and target variables and consider the mirror image of the base line specification. Namely we assume that policy variables respond to macro performance variables without delay, while the latter do not reflect policy variables instantly. Figure 4.5 presents the average treatment effects under this specification.

Compared to Figure 4.3, there are two major differences in the figure. First, we see that output growth declines at the initial phase of the program implementation but rises subsequently [see the solid line in Panel (A)]. Similarly inflation rises initially before falling after the second year [see the solid line in Panel (B)]. Second, the loan effect and the policy effect work in the opposite direction in the cases of output growth, inflation, and government fiscal balance. In particular, the IMF loan reduces output growth, raises inflation, and worsens government fiscal situation. Although loans could have a negative impact on the economy, for example, through the Dutch disease phenomenon, the timing of the effects in the figure is a little difficult to interpret. When a country is hit by a currency or financial crisis, the economy often deteriorates so rapidly that policy makers can respond to the new developments only with delay. If we ignore this sort of delay in reaction, the negative macroeconomic developments would be attributed to the program itself. Under the current model specification, policy is expected to react to the contemporaneous macroeconomic situation instantly. That is probably why the loan effect in Figure 4.5 picks up negative impacts on output growth, inflation, and fiscal balance.

Another model specification is to discard the recursive structure entirely and allow for the full simultaneity of $\mathbf{y}$. In particular, we include contemporaneous $\mathbf{y}^T$ variables on the right hand side of the $\mathbf{y}^P$ equations, and contemporaneous $\mathbf{y}^P$ variables on the right hand side of the $\mathbf{y}^T$ equations. To estimate this model, we use, as instrumental variables, all right hand side variables in the selection equation (4.2) as well as $\mathbf{y}^P$ and $\mathbf{y}^T$ lagged by 3 – 6 years, respectively. Since we are not entirely confident of the use of these lagged variables as instruments, the following results should be regarded as only reference. The results are shown in Figure 4.6. Except the initial negative effects on the balance of payments, the total program effects in Figure 4.6 are similar to those in Figure 4.3. Output grows higher over 3-4 years with a program than without it [Panel (A)]. The inflation rate declines substantially, and with the IMF program the balance of payments as well as the fiscal balance improves clearly [Panels (B)-(D)].

Despite some differences described above, both Figures 4.5 and 4.6 share two important features with Figure 4.3. First, the policy effect dominates the loan effect. Second, the net total effect on output growth is positive in the sense that the total effect curves in Panel (A) in Figures 4.3, 4.4, and 4.5 all integrate to positive numbers.

4.6.5 Why the Effect Doesn't Last?

We see in the previous section that our results suggest more strongly positive effect of IMF programs on the country's economy than the existing studies in the literature. However, our results share with other studies one important observation. That is, the IMF program has almost always has only a short-term effect. This is also one of the main points the critics of the IMF emphasize. So, it is quite interesting to know what interpretation our results can offer to this issue.

For this purpose we assume the following hypothetical situation. Suppose that the typical program country analyzed in Figure 4.3, after receiving the loan and policy advice for two years, decides to keep the same policy rule in successive years after the end of the program instead of switching back to the policy rule it was using before asking the IMF for help. Figure 4.7 shows what would happen in this situation, which is implied by our estimation results. The answer is striking. As expected, the loan effect has no change from Figure 4.3. The policy advice on the other hand as now the long-term impacts on all macroeconomic variables after the lending is finished. Economic growth would be 1.5% higher, inflation 20% lower, the

BOP-GDP ratio 1.4% higher, and the fiscal balance-GDP ratio 3% higher than when the country does not participate in the IMF program. This finding may suggest that the lack of adherence to the new policy rules after the program finishes rather than the weakness of the program itself might explain why the program effects do not last well beyond the program period.

4.7 Conclusion

In this essay we develop a new approach to evaluate the effectiveness of IMF lending programs on the program country's economy. Instead of including a program dummy in a static regression model in a conventional fashion, we set up a vector autoregression (VAR) model with a switching policy reaction function and estimate the system together with the program participation equation. In this way, we can estimate the loan effect and the policy advice effect separately. The program effectiveness assessment is then conducted in two ways: First by taking difference of two conditional predictions over the appropriate time horizon, and second by calculating impulse response functions generated from the program shock.

We find that, with IMF programs, output growth of the country increases, and the balance of payments as well as the government fiscal balance improves. Our findings are quite consistent with those in many previous studies except two important points. First, surprisingly, the effectiveness of IMF programs appears to come largely from the policy shifts rather than from the loan itself. Second, we observe, like many other studies, that IMF programs have only short-term effects on the country's economy. Other studies find this is due to the weakness of the programs. Our results suggest that the short lived effects of IMF programs may be due to the program country's failure in adhering to the new policy rules set under the programs.

Table 4.1 List of Variables

Variable name	Description
GDP growth	The growth rate of real GDP
Inflation	The inflation rate based on the consumer price index
Balance of payments	The balance of payment as a percentage of GDP
Government balance	The government fiscal surplus as a percentage of GDP
Domestic credit growth	The growth rate of domestic credit
Exchange depreciation	The depreciation rate of the local currency against the dollar
IMF loan	The amount of the IMF loan as a percentage of GDP
IMF quota	The country's IMF quota as a percentage of the total
Armed conflict	The dummy for civil wars and interstate armed conflicts
Latin America	The dummy for Latin American countries
Asia	The dummy for Asian countries including India and Pakistan
Africa	The dummy for African countries

Table 4.2 Summary Statistics

Variable	Whole sample			Non-program regime			Program regime		
	Mean	Median	Std. dev.	Mean	Median	Std. dev.	Mean	Median	Std. dev.
GDP growth (%)	2.77	3.52	5.72	3.14	3.79	5.99	2.12	3.06	5.15
Inflation (%)	49.07	8.81	429.76	49.69	7.70	471.98	47.98	11.11	344.51
Balance of payments (%)	0.86	0.43	3.29	0.71	0.30	3.21	1.10	0.61	3.41
Government balance (%)	-4.47	-3.67	5.52	-4.45	-3.50	5.67	-4.52	-3.90	5.22
Domestic credit growth (%)	27.97	15.51	185.22	28.99	15.35	227.37	26.38	15.98	85.79
Exchange depreciation (%)	50.64	5.97	725.37	63.23	4.88	909.28	28.70	7.82	82.18
IMF loan (%)	0.26	0	0.86	0	0	0	0.73	0.38	1.31

Table 4.3 Macro Performance Variables along the Time Line

(A) Before the Program

Variable	Three years before	Two years before	One year before
GDP growth (%)	3.8	2.6	1.4
Inflation (%)	10.2	9.7	9.1
Balance of payments (%)	0.30	0.0	-0.56
Government balance (%)	-4.0	-5.0	-5.7
Domestic credit growth (%)	18.1	18.1	18.8
Exchange depreciation (%)	3.1	0.0	6.8

(B) After the Program

Variable	One year after	Two years after	Three years after
GDP growth (%)	3.3	4.1	3.4
Inflation (%)	9.4	8.4	7.7
Balance of payments (%)	0.27	0.31	0.0
Government balance (%)	-3.8	-3.3	-3.1
Domestic credit growth (%)	13.7	13.0	11.7
Exchange depreciation (%)	3.2	3.9	5.7

Note: The median of the sample distribution is reported.

Table 4.4 Tobit ML Estimates of the Loan Equation

Explanatory variable	Coefficient	Standard error
GDP growth(-1)	-0.061***	0.009
GDP growth(-2)	-0.036***	0.009
GDP growth(-3)	-0.022**	0.009
Balance of payments(-1)	-0.007	0.014
Balance of payments (-2)	-0.006	0.015
Balance of payments (-3)	-0.050***	0.015
IMF quota (-1)	0.188*	0.106
Armed conflicts (-1)	-0.182	0.115
Latin America	-0.279**	0.142
Asia	-0.032	0.178
Africa	-0.341**	0.143
Constant	-0.226*	0.135
R^2	0.50	
Fraction of positive observations	0.318	

Notes

1. '***', '**', and '*' indicate that the coefficients are significant at 1 percent, 5 percent, and 10 percent level, respectively.
2. The R-squared is calculated based on the generalized residuals (Gourieroux et al. 1987).
3. The countries outside of the above geographic regions include the former socialist countries, Middle East countries, China, and Papua New Guinea.
4. The result changes little when including the following potential explanatory variables: the ratio of international reserve to imports, the international reserve, and the intensity of trade with the US.

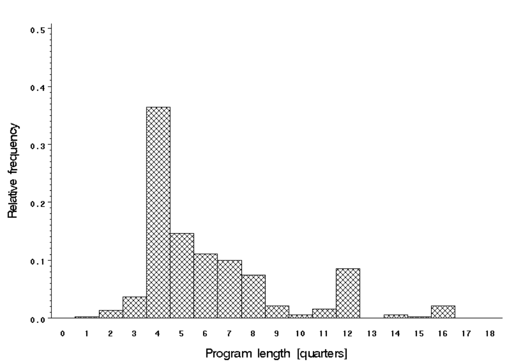
Table 4.5 Tests for Selectivity

Null hypothesis (H_0)	F-value	5% critical value	p-value
$\gamma_P = \mathbf{0}$	10.68	2.10	0.00000
$\gamma_T = \mathbf{0}$	0.49	2.61	0.69
$\gamma = \mathbf{0}$	7.21	1.88	0.00000

Note: $\gamma_P = [\gamma_P^0{}', \gamma_P^1{}']'$ and $\gamma = [\gamma_P{}', \gamma_T{}']'$. The above figures are based on the F test statistics, which has a typical form as $F = \frac{1}{J}\hat{\gamma}'[\hat{V}ar(\hat{\gamma})]^{-1}\hat{\gamma}$ where J is the number of restrictions.

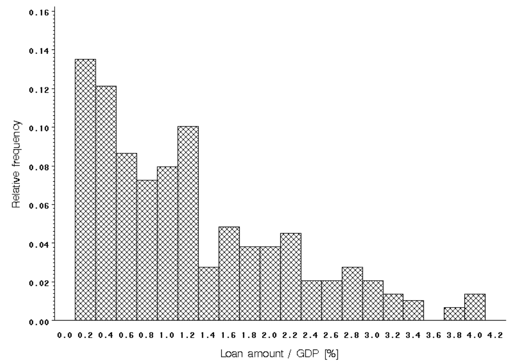
Figure 4.1 Basic Statistics of IMF Programs

(A) Program Duration



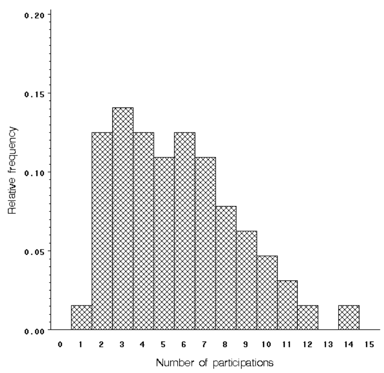
(mean=6.1 quarters, standard deviation=3.0 quarters)

(B) Loan Amount



(mean=1.42 % , standard deviation=2.53 %)

(C) Number of Program Participations

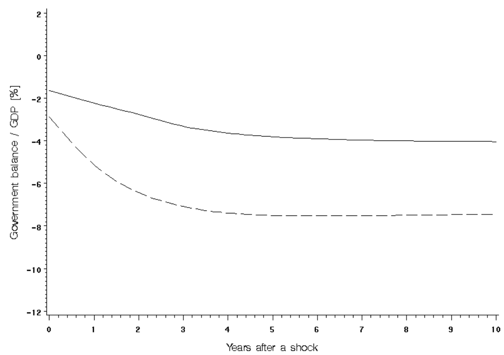


(mean=5.66 times, standard deviation=2.89 times)

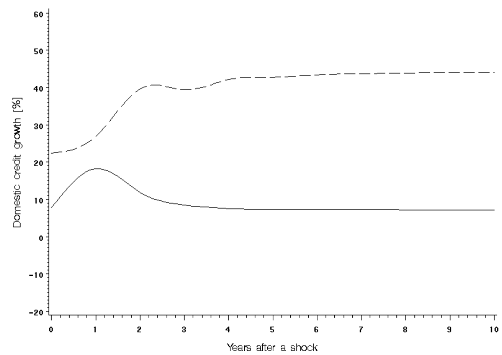
Note: The horizontal axis in Panel A measures the number of quarters of the program duration. The horizontal axis in Panel B measures the amount of the loan made for each program divided by the country's GDP. The vertical axis in Panel A and B measures the relative frequency of programs. The 7% of the total observations have the loan amount larger than 4.1% of GDP. The horizontal axis in Panel C measures the number of times each country participated in the IMF program during the sample period. The vertical axis in Panel C measures the relative frequency of countries. The top seven countries in terms of the number of participations are: Uruguay (14 times), Argentina (12 times), Panama (11 times), Jamaica (11 times), Costa Rica (10 times), Peru (10 times), and Philippines (10 times).

Figure 4.2 Policy Reaction Functions under Two Regimes

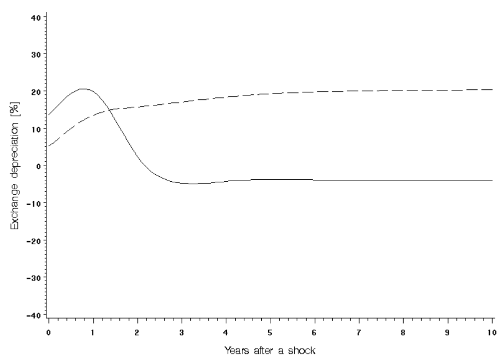
(A) Government Balance



(B) Domestic Credit Growth

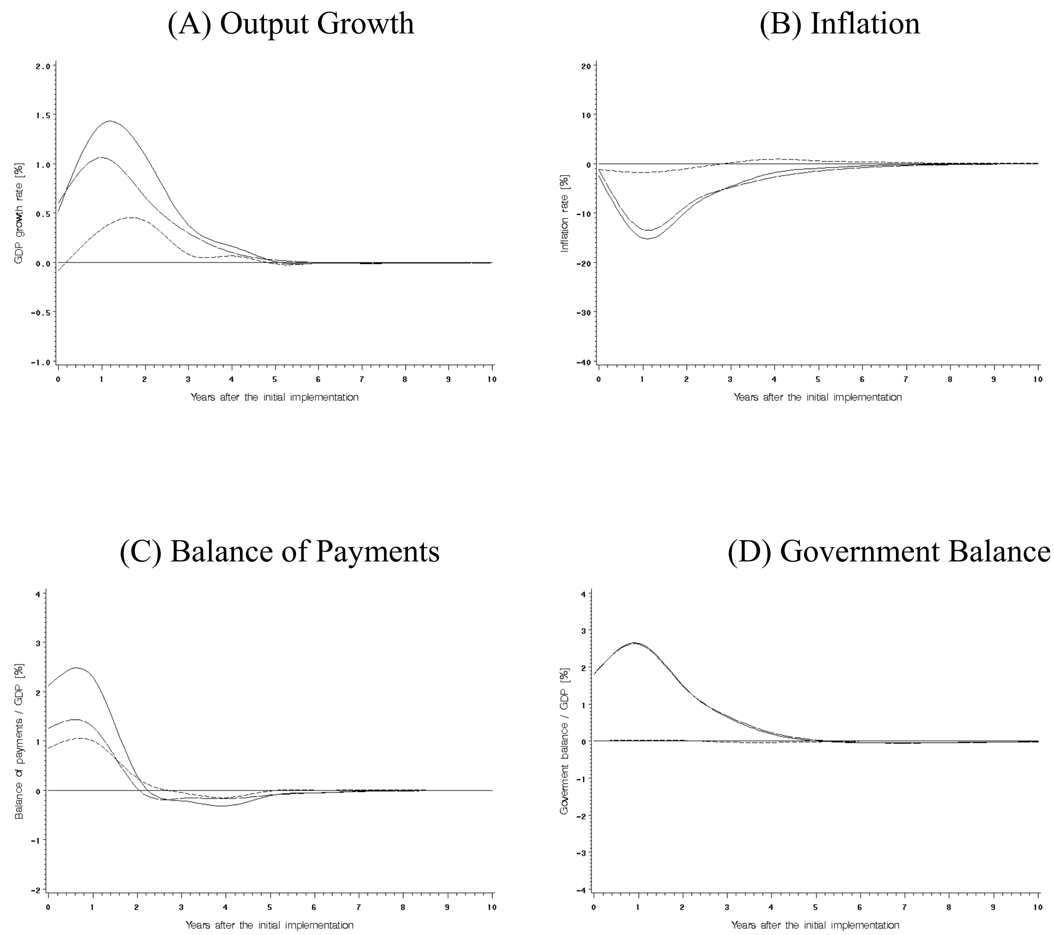


(C) Exchange Depreciation



Note: Each figure presents the dynamic response of respective policy variable to a negative balance of payment shock of one standard deviation. The solid line indicates the response with the IMF program and broken line indicates the response without the program.

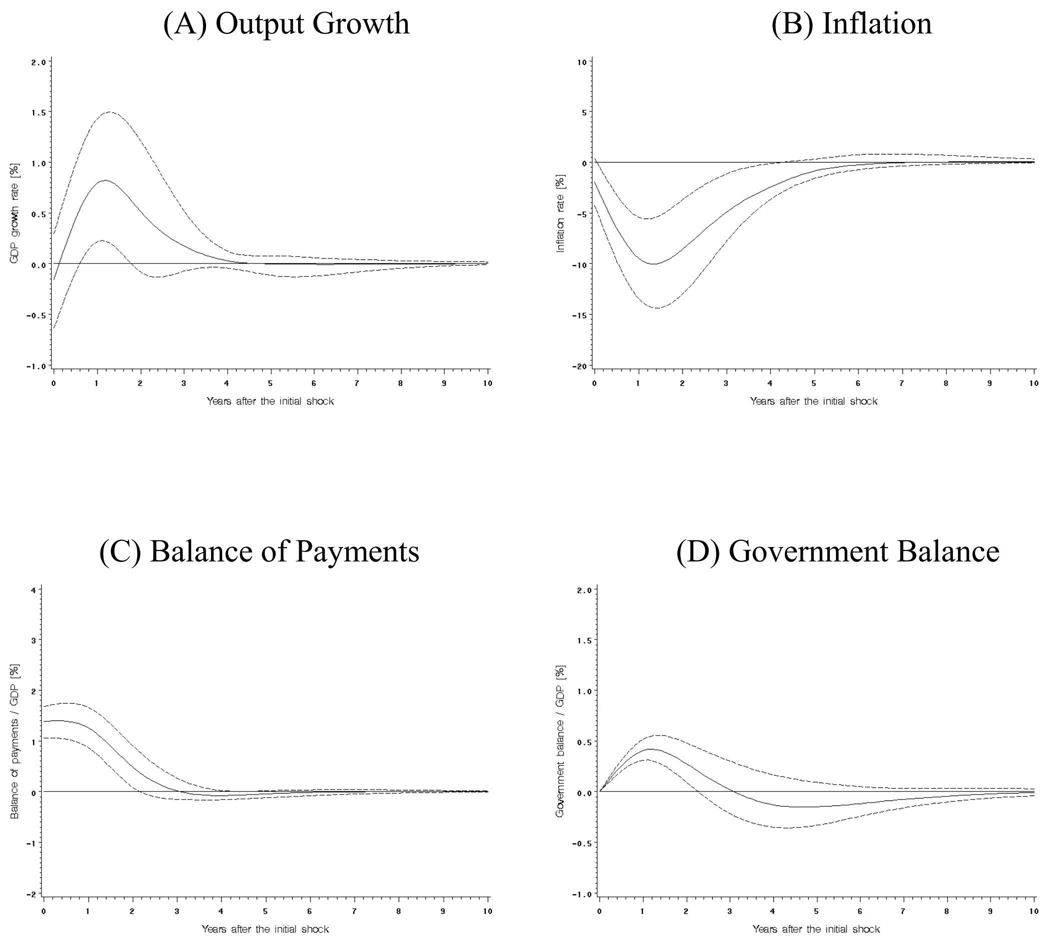
Figure 4.3 Dynamic Average Treatment Effects of the IMF Program



Notes

1. The country is assumed to be in the IMF program for two years. The size of loan is set at the median value, i.e. at 0.859% of GDP in the start year and 0.853% of GDP in the following year.
2. The short-dashed line indicates the effect of the loan only, while the long-dashed line indicates the effect of the policy advice only. The total effect of the IMF program is shown by the solid line.
3. For the input data set of simulation we select years such that a country participates to the IMF program and it is out of the program for the pervious three years. The median of each variable in the input data set is used as the initial value for simulation.

Figure 4.4 Dynamic Responses of Macro Performance Variables

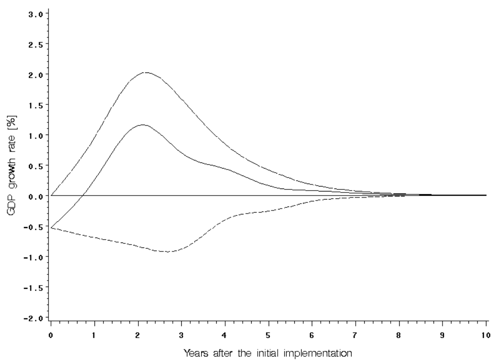


Notes

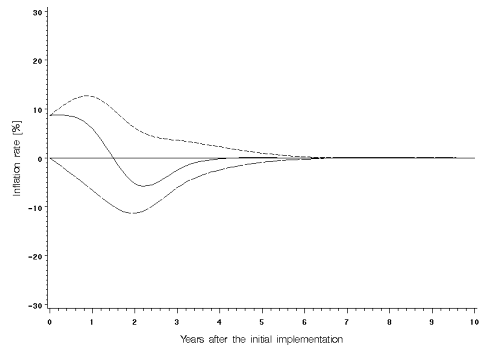
1. The figures show dynamic responses of macro performance variables to a shock on the participation equation (4.2).
2. The solid line indicates the median of the distribution of dynamic response of the respective variable at each time horizon in each panel, while two broken lines indicate one standard error bands.

Figure 4.5 Dynamic Average Treatment Effects of the IMF Program under Alternative Model Specification 1

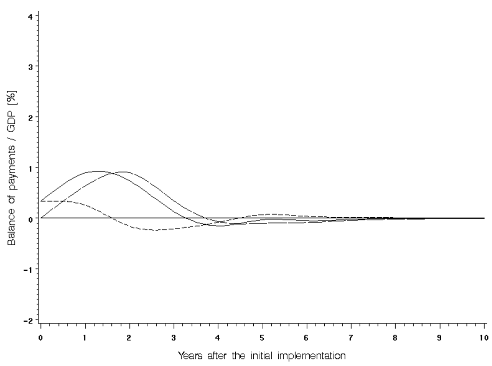
(A) Output Growth



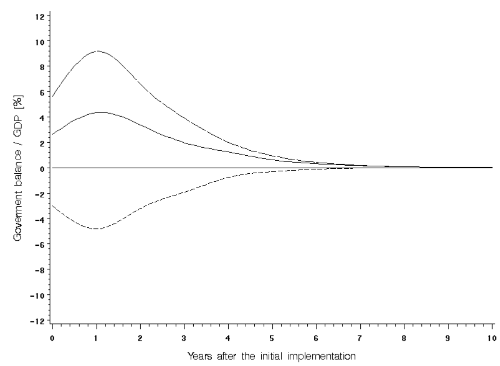
(B) Inflation



(C) Balance of Payments



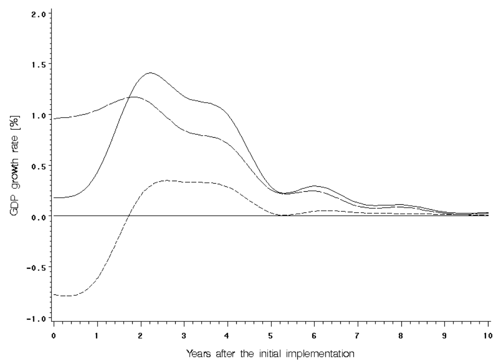
(D) Government Balance



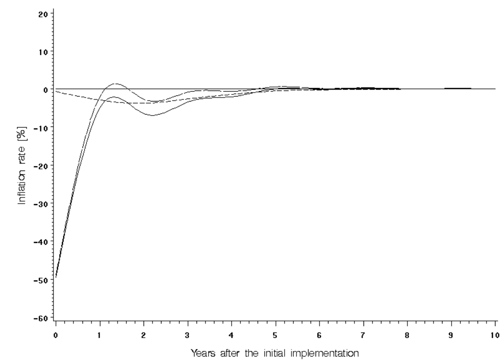
Note: Under this model specification, the contemporaneous policy variables are included in the right hand side of the target equations while the contemporaneous target variables are not included as the arguments in the policy reaction functions.

Figure 4.6 Dynamic Average Treatment Effects of the IMF Program under Alternative Model Specification 2

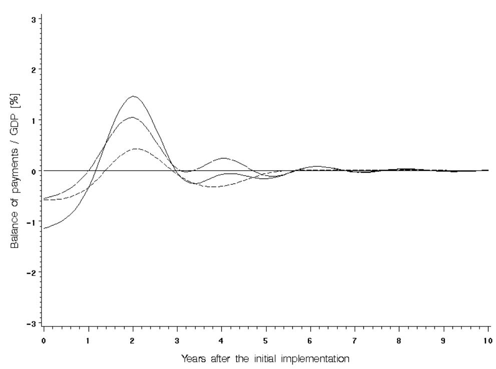
(A) Output Growth



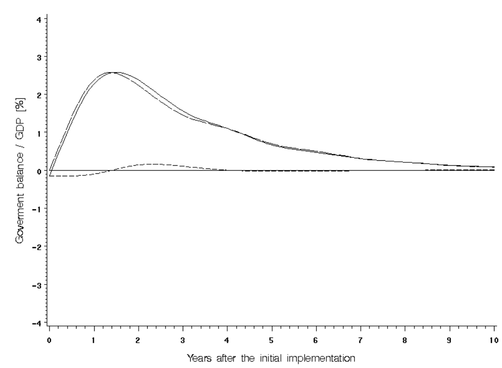
(B) Inflation



(C) Balance of Payments



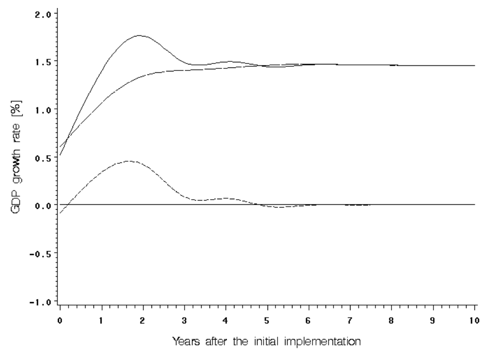
(D) Government Balance



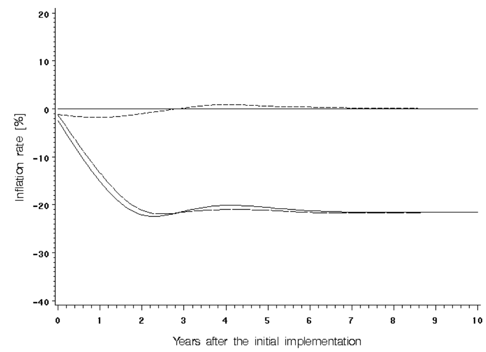
Note: Under this model specification, the contemporaneous target variables are included in the right hand variables of the policy reaction functions, and the contemporaneous policy variables are in the target equations.

Figure 4.7 Dynamic Treatment Effects with Permanent Stay in the Program Regime

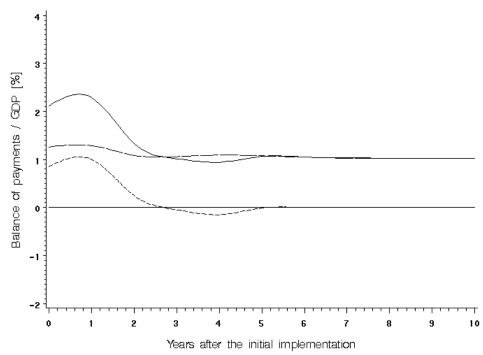
(A) Output Growth



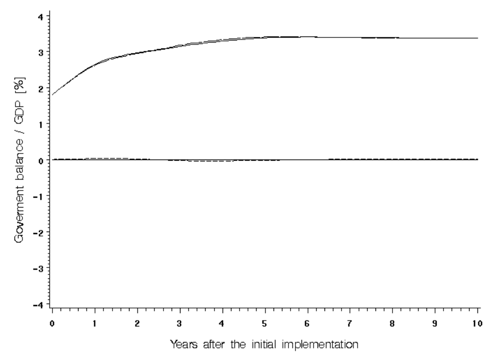
(B) Inflation



(C) Balance of Payments



(D) Government Balance



Note: The country is assumed to receive IMF loan for two years and stay in the program regime permanently. The rest is the same as the conditions used for Figure 4.3.

Chapter 5

Concluding Remarks

This dissertation includes three essays in Applied Econometrics. Each essay attempts to answer an interesting and important question in the real economic world. Advanced techniques recently developed are appropriately combined so that our understanding of the question becomes deeper and improved.

5.1 First Essay

The first essay is regarding the assessment of the effects of neighborhood land uses on residential house values. The effects of land uses on residential property values are crucial when evaluating costs and benefits of land projects for the purpose of public policy prescription or business decision making. It is widely recognized that a nuclear plant or a prison, for example, may often have an adverse effect on the property values of the nearby houses, while a park, a museum, or a university usually has a beneficial effect. The effect of a land use defined as a function of distance between the locations of the land use factor and a particular house is, however, inherently nonlinear (in an unknown form) and the use of a simple linear regression method could lead to a misleading conclusion.

The first essay estimates the land use effect function by using the state of the art techniques of nonparametric regression method. There are three important features of our statistical model. First, it is a semiparametric model, which keeps a conventional linear form with respect to the dwelling attributes of the house just like in the popular hedonic model, but treats its location characteristics in a nonparametric fashion using the kernel method. Second, unlike the usual nonparametric regression, it keeps additive structure in the nonparametric component so that it retains much of the interpretative features of the linear models. Third, it uses the local linear smoother, which is superior to other smoothers in terms of avoiding the boundary effect and other features.

Our statistical model enabled us to reveal salient features of the price effect curves of the golf courses, the university, the nitrogen plant, and the elevation, which are consistent with our natural expectations. Our procedure can be applied to a broad range of similar studies.

5.2 Second Essay

The second essay considers the assessment of the sources of the economic growth in East Asia. There is a fundamental question with regard to the Asian Miracle. Which is the prime source of the rapid growth of theses economics between capital accumulation and productive improvements? The conventional growth-accounting approach to estimating the sources of economic growth requires unrealistically strong assumptions about either competitiveness of factor markets, or the form of the underlying aggregate production function.

The second essay outlines a new approach utilizing nonparametric derivative estimation techniques that does not require imposing these restrictive assumptions. The results for East Asian countries show that output elasticities of capital and labor tend to be different from the income shares of these factors, and that the growth of total factor productivity over the period 1960–95 has been an important factor in the overall growth performance of these countries.

5.3 Third Essay

The third essay explores the assessment of the effectiveness of IMF lending programs on the program country's economy. We develop a new approach to evaluate the effectiveness of IMF programs. Instead of including the program dummy in a static regression model in a conventional fashion, we set up a vector autoregression (VAR) model with a switching policy reaction function and estimate the system together with a program participation equation. The program effectiveness assessment is conducted in two ways: First by taking difference of two conditional predictions over the appropriate horizon, and second by calculating impulse response functions generated from the program shock.

We find that, with IMF programs, output growth of the country increases, and the balance of payments as well as the government fiscal balance improves. Our findings are quite consistent with those in the literature except two important points. First, surprisingly, the effectiveness of IMF programs appears to come largely from the policy shifts rather than from the loan itself. Second, we observe, like many other studies, that IMF programs have only short-term effects on the country's economy. Other studies find this is due to the weakness of the programs. Our results suggest that the short lived effects of IMF programs may be due to the program country's failure in adhering to the new policy rules set under the programs.

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Appendices

Chapter 2: First Essay

Appendix A.1 Description of the City of Lawrence

Lawrence is located in the northeast corner of the State of Kansas, about 40 miles west of Kansas City and about 30 miles east of Topeka, the state capital. Lawrence is a university town with the University of Kansas being the center of the city. The city has a population of about 75,000 and the university has more than 27,000 students. Its geological size is about 5 to 6 miles in each direction (see also Figure 2.1).

Appendix A.2 Cross-Validation

The problem of deciding how much to smooth is of great importance in nonparametric regression. The choice of a bandwidth or smoothing parameter has frequently a more important impact on the shape of the regression curve than the choice of a kernel has. To guide our bandwidth selection, we compute the cross-validation function

$$CV(\lambda_1,\ldots,\lambda_p)=\frac{1}{n}\sum_{i=1}^{n}\left[y_i-\mathbf{x}_i'\hat{\beta}-\sum_{j=1}^{p}\hat{f}_{\lambda_j j}^{(i)}(z_{ji})\right]^2 \tag{A.1}$$

for an appropriate range of values of λ_j, $j=1,\ldots,p$, where the estimate of the j-th function is given by

$$\hat{f}_{\lambda_j j}^{(i)}(z_{ji})=\frac{\sum_{k\neq i;k=1}^{n}K\left(\frac{z_{ji}-z_{jk}}{\lambda_j}\right)r_{ji}}{\sum_{k\neq i;k=1}^{n}K\left(\frac{z_{ji}-z_{jk}}{\lambda_j}\right)} \tag{A.2}$$

$$\hat{\beta}_{(i)}=[\mathbf{X}_{(i)}'\mathbf{X}_{(i)}]^{-1}\mathbf{X}_{(i)}'\mathbf{y}_{(i)}-\sum_{j=1}^{p}\hat{\mathbf{f}}_j^{(i)}(\mathbf{z}_j)$$

where $\mathbf{X}_{(i)}$ and $\mathbf{y}_{(i)}$ stand for $\mathbf{X}$ and $\mathbf{y}$ with i-th rows are removed.

In practice, 1,164 observations were randomly chosen out of 6,415 total observations and this subset was used for the cross-validation. The bandwidth selection depends on the sample size and it must be rescaled for the whole data set.

Appendix A.3 Prediction Procedure

Denote 1993 observations by $(y_i,\mathbf{x}_i',\mathbf{z}_i')$ for $i=1,\ldots,n$, and 1994 observations by $(y_i^*,\mathbf{x}_i^{*\prime},\mathbf{z}_i^{*\prime})$ for $i=1,\ldots,n$. Let $r_i=y_i-\hat{\alpha}-\mathbf{x}_i'\hat{\beta}$ where $\hat{\alpha}$ and $\hat{\beta}$ are the semiparametric regression estimates based on 1993 data. Now compute successively

$$\hat{f}_k(z^*_{ji}) = \frac{\sum_{h=1}^{n} \left[\hat{s}_{j2}(z^*_{ji}) - \hat{s}_{j1}(z^*_{ji})(z_{jh} - z^*_{ji})\right] K\left(\frac{z_{jh} - z^*_{ji}}{\lambda_j}\right) r^j_h}{\sum_{h=1}^{n} \left[\hat{s}_{j2}(z^*_{ji}) - \hat{s}_{j1}(z^*_{ji})(z_{jh} - z^*_{ji})\right] K\left(\frac{z_{jh} - z^*_{ji}}{\lambda_j}\right)} \tag{A.3}$$

$$r^j_h = y_h - \hat{\alpha} - \mathbf{x}'_h \hat{\beta} - \sum_{k=0}^{j-1} \hat{f}_k(\mathbf{z}_{kh})$$

from $j = 1$ to p, where $\hat{s}_{jk}(z) = \sum_{i=1}^{n} (z_{ji} - z)^k K(z_{ji} - z / \lambda_j)$ for $k = 1,2$, and $\hat{f}_0(z_{kh}) \equiv 0$.

The predicted value of y^*_i based on 1993 data is given by

$$\hat{y}^*_i = \hat{\alpha} + \mathbf{x}^{*\prime}_i \hat{\beta} + \sum_{j=1}^{p} \hat{f}_j(z^*_{ji}) \tag{A.4}$$

and the root mean squared error is given by

$$RMSE = \left[(1/n^*) \sum_{i=1}^{n^*} \left(\hat{y}^*_i - y^*_i\right)^2 \right]^{1/2} .$$

Chapter 3: Second Essay

Appendix B.1 Data Description

Two data sets, referred to as “Penn” and “Collins”, were constructed. The Penn data set is based on the Penn World Tables Mark 5.6. The Penn World Tables Mark 5.6 covers the period from 1950 to 1992. The output measure is Gross Domestic Product expressed in international prices. The labor data are extracted from the Penn World Tables. Although the capital data are available in the Penn World Tables, many East Asian countries have missing observations in the early years. We therefore obtained the capital data from Nehru and Dhareshwar (1993) (available at http://www.worldbank.org/research/growth/ddhehdha.htm), which cover the period from 1950 to 1990 for most of the East Asian countries except Hong Kong SAR. The capital data for Hong Kong SAR are extracted from the Penn World Tables.

The Collins data set is based on Collins and Bosworth (1996) (available at http://www.brookings.edu/es/research/project/develop/develop.htm), which cover the period from 1960 to 1996. The output measure is an index of Real Gross Domestic Product (GDP) based on World Bank data. The labor input measure is an index of total labor force based on OECD employment or International Labor Organization. The capital stock is an index of capital stock from Nehru and Dhareshwar (1993) data.

Two types of conventional estimates are calculated under the labels: “Collins” and “Young”, depending on the source of labor share data. The “Collins” method uses the labor share set equal to 0.65 as in Collins and Bosworth (1996). The “Young” method uses the labor share estimates used in Young (1995).

Young's estimates are available for Hong Kong SAR, Korea, and Singapore, and Taiwan Province of China up to 1990.

Appendix B.2 Distribution of Output Elasticities

It can be shown that the limiting distribution of $(\hat{\varepsilon}_K, \hat{\varepsilon}_L)$ in equation (3.8) is given by

$$\begin{bmatrix} (nh_1^3 h_2)^{1/2} & 0 \\ 0 & (nh_1 h_2^3)^{1/2} \end{bmatrix} \begin{bmatrix} \hat{\varepsilon}_K(\mathbf{x}) - \varepsilon_K(\mathbf{x}) \\ \hat{\varepsilon}_L(\mathbf{x}) - \varepsilon_L(\mathbf{x}) \end{bmatrix} \xrightarrow{L} N\big(\mathbf{0}, \mathbf{\Omega}(\mathbf{x})\big)$$

where

$$\mathbf{\Omega}(\mathbf{x}) = \begin{bmatrix} \omega_{11}(\mathbf{x}) & \omega_{12}(\mathbf{x}) \\ \omega_{12}(\mathbf{x}) & \omega_{22}(\mathbf{x}) \end{bmatrix}$$

$$\omega_{ii}(\mathbf{x}) = \frac{\sigma_u^2(\mathbf{x})}{f(\mathbf{x})} \int K_i(\mathbf{z})^2 \, d\mathbf{z} = \frac{\sigma_u^2(\mathbf{x})}{16\pi^{3/2} f(\mathbf{x})} \qquad \text{for } i = 1,2$$

$$\omega_{12}(\mathbf{x}) = \frac{\sigma_u^2(\mathbf{x})}{f(\mathbf{x})} \int K_1(\mathbf{z}) K_2(\mathbf{x}) d\mathbf{z} = 0 \, .$$

Therefore, the asymptotic α% point-wise error bands are given by

$$\Delta Y_t / Y_t - \hat{\varepsilon}_K (\Delta K_t / K_t) - \Delta \hat{\varepsilon}_L (\Delta L_t / L_t) \pm z_{(1-\alpha)/2} s$$

where $z_{(1-\alpha)/2}$ stands for the upper $(1-\alpha)/2$ quantile of the standard normal distribution and *s* is the standard error of the estimate given by

$$s(\mathbf{x}) = \frac{1}{4\pi^{3/4}\sqrt{nh_1h_2}}\left(\frac{\hat{\sigma}^2(\mathbf{x})}{\hat{f}(\mathbf{x})}\right)^{1/2}\sqrt{\frac{1}{h_1^2}\left(\frac{\Delta K_t}{K_t}\right)^2 + \frac{1}{h_2^2}\left(\frac{\Delta L_t}{L_t}\right)^2}$$

where $\hat{\sigma}^2(\mathbf{x}) = \sum_{i=1}^{n}[y_i - \hat{m}(\mathbf{x}_i)]^2 K(\mathbf{z}_i) / \sum_{i=1}^{n} K(\mathbf{z}_i)$ and $\hat{f}(\mathbf{x})$ is given in equation (3.7). The above bands are not strictly the classical asymptotic α % confidence interval since the non-parametric regression estimator is not asymptotically unbiased in general.

Appendix B.3 Kernel Function and Bandwidth Selection

To implement the procedures described in Section 3.5, we use the second order Gaussian product kernel

$$K(\mathbf{z}_i) = (1/8)\prod_{j=1}^{3}(3 - z_{ij}^2)\phi(z_{ij}),$$

to reduce the bias, the derivative of which is given by

$$K_j(\mathbf{z}_i) = -(1/8)z_{ij}(5 - z_{ij}^2)\phi(z_{ij})\prod_{k\neq j}(3 - z_{ik}^2)\phi(z_{ik})$$

for $j = 1,2,3$, where $\phi(\cdot)$ stands for the standard normal density function. The selection of bandwidth h_j is made on the basis of the cross validation method outlined below.

Taking into account

$$d \ln Y = da(t) + (\partial F^* / \partial \ln K) d \ln K + (\partial F^* / \partial \ln L) d \ln L \text{ ,}$$

we select the bandwidth *h* so as to minimize the cross validation function

$$CV(h) = (T-1)^{-1} \sum_{t=2}^{T} [\Delta \ln Y_t - (d/dt)\hat{a}(t) - \hat{\varepsilon}_K \Delta \ln K_t - \hat{\varepsilon}_L \Delta \ln L_t]^2 \text{ .}$$

In the above, the estimates $(d/dt)\hat{a}(t)$, $\hat{\varepsilon}_K$ and $\hat{\varepsilon}_L$ are the "leave-two-out" estimators, that is, they are estimated using all observations except those at time *t* and *t*-1. The CV-function validates the ability to predict $\{\Delta \ln Y_t\}$ across the subsamples $\{(\ln Y_t - \ln Y_{t-1}, \mathbf{X}_s)_{s \neq t-1, s \neq t}\}$ (Stone 1974).

The bandwidth of (capital, labor, time) used for estimation is (0.75, 0.45, 14.6) for Hong Kong, (1.78, 0.51, 19.5) for Indonesia, (2.42, 0.54, 19.5) for Korea, (1.87, 0.60, 19.5) for Malaysia, (1.18, 0.57, 19.5) for Philippines, (2.44, 0.67, 19.5) for Singapore, (2.29, 0.58, 19.5) for Taiwan, (1.93, 0.56, 19.5) for Thailand, and (1.43, 0.42, 19.5) for China.

Appendix B.4 A Monte Carlo Experiment

The purpose of this Monte Carlo experiment is to ascertain how well the nonparametric estimates of derivatives perform with small samples. In this experiment, the true form of the regression function is known, and the data are drawn from a known population. The original model and data set was initially constructed by White (1980) and used by Byron and Bera (1983) and Rilstone (1989) (the latter result is reproduced in Table 4.1 of Pagan and Ullah, 1999). We modified the model by adding a time trend assuming the Hicks neutral form.

The true model is a stochastic CES production function

$$y_t = (x_{t1}^{-5} + 2x_{t2}^{-5})^{-1/5} \exp(p(t) + u_t)$$

or

$$\ln y_t = -(1/5)\ln[\exp(-5\ln x_{t1}) + \exp(-5\ln x_{t2})] + p(t) + u_t \quad \text{for} \quad t = 1, \ldots, T,$$

where y_t, x_{t1}, and x_{t2} stand for the values of output, capital, and labor, respectively. The time trend of output $p(t)$ is set equal to the third degree polynomial, estimated from the data by regressing output on its first lag as well as the trend. The terms $\ln x_{i1}$ and $\ln x_{i2}$ are generated from an estimated second-order autoregression fitted to the data for log capital and labor and then transformed it to have mean equal to (0.5, 0.5) and each variance equal to 1/12, while u_t are generated independently from a normal distribution with mean zero and variance 0.01.

Our goal is to estimate derivatives or elasticities $\partial \ln y / \partial \ln x_j$. In the literature on production economics, the parametric approximations often used for this purpose are the following two types.

(1) CD: Cobb-Douglas function

$$\ln y_t = \beta_0 + \beta_1 \ln x_{t1} + \beta_2 \ln x_{t2} + \beta_3 t + u_t$$

(2) TL: Translog function

$$\ln y_t = \beta_0 + \beta_1 \ln x_{it} + \beta_2 \ln x_{t2} + \beta_3 (\ln x_{t1})^2 + \beta_4 \ln x_{t1} \ln x_{t2} + \beta_5 (\ln x_{t2})^2 + \beta_6 t + \beta_7 t^2 + u_t$$

Table B.1 presents three sets of estimates of the output elasticities $b_j(x_1, x_2) = \partial \ln y / \partial \ln x_j$ for j = 1, 2 at the mean point ($\ln x_1$, $\ln x_2$) = (0.5, 0.5), using OLS estimation assuming (i) the Cobb-Douglas (CD) and (ii) Translog (TL) forms of production function as well as (iii) nonparametric estimation (NP). The sample size is 200. It is clear that in terms of bias, the nonparametric estimates are much superior to the parametric counterparts. The standard errors for the Cobb-Douglas and Translog estimates, however, are somewhat smaller compared to the nonparametric standard errors. This may reflect the slow speed of convergence of nonparametric estimates.

Table B.2 presents the same comparison using only 35 observations, which is equal to the sample size in our study. The result is strikingly similar to Table B.1, except the standard errors are larger. The nonparametric estimates remain less biased for elasticities.

Table B.1 Monte Carlo Experiment (sample size 200)

$b(x)$	CD	TL	NP	True value
$\hat{b}_1$	0.3563	0.3556	0.3368	0.3333
	(0.0386)	(0.0392)	(0.0682)	
$\hat{b}_2$	0.6441	0.6453	0.6646	0.6667
	(0.0367)	(0.0385)	(0.0666)	

Notes: The estimates are mean values of $b_1(x_1, x_2, t)$ and $b_2(x_1, x_2, t)$ based on 300 samples of size 200. Standard errors are in parentheses.

Table B.2 Monte Carlo Experiment (sample size 35)

$b(x)$	CD	TL	NP	True value
$\hat{b}_1$	0.3593	0.3553	0.3350	0.3333
	(0.1027)	(0.1124)	(0.1661)	
$\hat{b}_2$	0.6495	0.6492	0.6588	0.6667
	(0.0955)	(0.1053)	(0.1890)	

Notes: The estimates are mean values of $b_1(x_1, x_2, t)$ and $b_2(x_1, x_2, t)$ based on 300 samples of size 35. Standard errors are in parentheses.

Chapter 4: Third Essay

Appendix C.1 Data Description

Macroeconomic data are obtained from the World Economic Outlook Database and the International Financial Statistics constructed by the IMF. Data related with IMF loans and IMF quota sizes are also obtained from the IMF. Data related with armed conflicts are obtained from the Armed Conflict Dataset prepared by the International Peace Research Institute, Oslo. Its website is: http://www.prio.no/cscw/armedconflict. These data sets are merged so the resulting data set covers 28 years of time periods form 1976 to 2003. In the process of creating new variables, missing values are generated from the computation of growth rates and their lagged values. Some countries are deleted due to many missing values and other reasons. As a result, our data set is an unbalanced panel data set with 79 countries. Each country has observations somewhere between 10 years and 24 years for estimation.

Appendix C.2 Standard Program Evaluation

(1) Set the benchmark levels of the initial condition: $\mathbf{y}_{t_0-1},\ldots,\mathbf{y}_{t_0-p+1}$ and

$L_{t_0},\ldots,L_{t_0+T}$ at the average values of all the episodes, where t_0 is the start year of the program and T is the duration of the typical program.

(2) Calculate the one-step-ahead forecasts

$$\hat{\mathbf{y}}^{P}_{t_0+h} = \hat{\mathbf{b}}^{Pd} + \hat{\mathbf{B}}^{Pd}_{y1}\hat{\mathbf{y}}_{t_0+h-1} + \cdots + \hat{\mathbf{B}}^{Pd}_{yp}\hat{\mathbf{y}}_{t_0+h-p} \tag{C.1}$$

$$\hat{\mathbf{y}}^{T}_{t_0+h} = \hat{\mathbf{b}}^{T} + \hat{\mathbf{B}}_{12}\hat{\mathbf{y}}^{P}_{t_0+h} + \hat{\mathbf{B}}^{T}_{y1}\hat{\mathbf{y}}_{t_0+h-1} + \cdots + \hat{\mathbf{B}}^{T}_{yp}\hat{\mathbf{y}}_{t_0+h-p} + \hat{\mathbf{B}}^{T}_{L0}\overline{L}_{t_0+h} + \hat{\mathbf{B}}^{T}_{Lp}\overline{L}_{t_0+h-p} \tag{C.2}$$

successively for $h = 0,1,\ldots,H$, where $\hat{\mathbf{y}}_{t_0+h-l} = \overline{\mathbf{y}}_{t_0+h-l}$ for $h < l$. In the above forecasts, we set $d_t = 1$ for $t = t_0,\ldots,t_0+T$, and $d_t = 0$ otherwise. Set also $L_t = 0$ for $t \neq t_0,\ldots,t_0+T$.

(3) $\hat{\mathbf{y}}^{T}_{t+h}(L>0, d=1)$ is now obtained by applying (C.1) and (C.2) successively with $d_{t_0+h} = 1$ and $L_{t_0+h} > 0$ for $h = 0,1,\ldots,T$. Similarly, $\hat{\mathbf{y}}^{T}_{t+h}(L=0, d=1)$ is obtained with $d_{t_0+h} = 1$ for $h = 0,1,\ldots,T$ and $L_{t_0+h} = 0$ for all $h \geq 0$, while $\hat{\mathbf{y}}^{T}_{t+h}(L>0, d=0)$ is obtained with $L_{t_0+h} > 0$ for $h = 0,1,\ldots,T$ and $d_{t_0+h} = 0$ for all $h \geq 0$. Lastly $\hat{\mathbf{y}}^{T}_{t+h}(L=0, d=0)$ is obtained with $d_{t_0+h} = 0$ and $L_{t_0+h} = 0$ for all $h \geq 0$.

Appendix C.3 Program Evaluation via Impulse Responses

(1) For this procedure we need first to estimate the following auxiliary regressions to

forecast $\mathbf{w}_t$.

$$\mathbf{w}_{it} = \mathbf{c}_0 + \sum_{j=1}^{p} \mathbf{C}_{1j} \mathbf{w}_{i,t-j} + \sum_{j=1}^{p} \mathbf{C}_{2j} \mathbf{y}_{i,t-j} + \mathbf{u}_{it}^{w} \tag{C.3}$$

(2) Set the levels of the initial condition $\mathbf{y}_{t_0-1},\ldots,\mathbf{y}_{t_0-p+1}$ and $\mathbf{w}_{t_0-1},\ldots,\mathbf{w}_{t_0-p+1}$ at the average values ($\mathbf{y}_{t_0-1},\ldots,\mathbf{y}_{t_0-p+1}$ are the same as in the previous procedure).

(3) Set $\varepsilon_{t_0}^{L} = 1$ and $\varepsilon_{t_0+h}^{L} = 0$ for $h = 1,\ldots T$, together with $\varepsilon_{t_0+h}^{P} = \mathbf{0}$ and $\varepsilon_{t_0+h}^{T} = \mathbf{0}$ for $h = 0,1,\ldots$.

(4) Calculate forecasts (C.1) and (C.2) successively for $h = 0,1,\ldots,H$. Instead of setting the values of L_{t_0+h} at the historical averages as in the previous procedure, we generate the series according to

$$L_{t_0+h} = L_{t_0+h}^{*} 1(L_{t_0+h}^{*} > 0) \quad \text{and} \quad L_{t_0+h}^{*} = \hat{\mathbf{w}}_{t_0+h-1}\hat{\theta},$$

where $\hat{\mathbf{w}}_{t_0+h} = \hat{\mathbf{c}}_0 + \sum_{j=}^{p} \hat{\mathbf{C}}_{1j} \hat{\mathbf{w}}_{t_0+h-j} + \sum_{j=1}^{p} \hat{\mathbf{C}}_{2j}(\mathrm{L}) \hat{\mathbf{y}}_{t_0+h-j}$ and $1(\cdot)$ is the indicator function. More specifically, for $h = 0$,

$$\hat{\mathbf{y}}_{t_0}^{P} = \hat{\mathbf{b}}^{Pd} + \hat{\mathbf{B}}_{y1}^{Pd} \hat{\mathbf{y}}_{t_0-1} + \cdots + \hat{\mathbf{B}}_{yp}^{Pd} \hat{\mathbf{y}}_{t_0-p}$$

$$\hat{\mathbf{y}}_{t_0}^{T} = \hat{\mathbf{b}}^{T} + \hat{\mathbf{B}}_{12} \hat{\mathbf{y}}_{t_0}^{P} + \hat{\mathbf{B}}_{y1}^{T} \hat{\mathbf{y}}_{t_0-1} + \cdots + \hat{\mathbf{B}}_{yp}^{T} \hat{\mathbf{y}}_{t_0-p} + \hat{\mathbf{B}}_{L0}^{T} \hat{L}_{t_0} + \cdots + \hat{\mathbf{B}}_{Lp}^{T} \hat{L}_{t_0-p}$$

where $\hat{L}_{t_0} = \hat{\mathbf{w}}_{t_0-1}'\hat{\theta} + \sigma_{vv}\varepsilon_{t_0}^{L}$. For $h = 1,2,\ldots$, use (C.1) and (C.2) successively.

(5) Calculate the impulse response at horizon h as

$$
\begin{aligned}
IRF(h) = {} & E(\mathbf{y}^T_{t_0+h} \mid \varepsilon^L_{t_0+\tau} = 1, \varepsilon^P_{t_0+\tau} = \mathbf{0}, \varepsilon^T_{t_0+\tau} = \mathbf{0} \text{ for } \tau = 0,1,\ldots,T) \\
& - E(\mathbf{y}^T_{t_0+h} \mid \varepsilon^L_{t_0+\tau} = 0, \varepsilon^P_{t_0+\tau} = \mathbf{0}, \varepsilon^T_{t_0+\tau} = \mathbf{0}).
\end{aligned}
$$