A New Approach to Causality and Economic Growth

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1. Introduction

The renaissance of growth theory in economics in the last decade has been accompanied by a host of empirical papers using cross-country data to attempt to analyze the factors that cause economic growth. These papers have looked at a variety of factors. A partial list would include alternative measures of human capital, fiscal policy, the level and composition of public and private investment, monetary policy and inflation, as well as a host of political and demographic factors. The December 1993 special issue of the *Journal of Monetary Economics,* based on a World Bank conference, provides a representative collection of papers illustrating this diversity.

The large number of papers on the causes of economic growth, however, is also a signal that there is little substantive agreement. As an example, in a series of papers, DeLong and Summers (1991, 1992, 1993) argue that equipment investment is a key determinant of economic growth and the social returns from equipment investment exceed its private returns. Auerbach, Hassett, and Oliner (1994) vigorously dispute both claims. Virtually all other studies do not even include the composition of private investment as a variable.

Faced with a bewildering and indecisive literature, one natural temptation is to deny that anything serious can be learned from cross-sectional studies of economic growth. According to this view, unobserved differences or heterogeneity across countries, vast differences in the sizes of countries, spillover effects across countries, poor data for less developed countries, and a relatively small number of observations, collectively pose insurmountable problems for empirical work in this area. Inferences in this statistical environment will necessarily be "fragile."

While these statistical problems are real and possibly important, we do not believe that the existing literature has taken the most profitable statistical framework to investigate these issues. Two clear deficiencies are present in much work in this area. First, there is typically a proliferation of variables purporting to measure the same underlying factors. For example, several different proxies for human capital may be used, even in the same study. Second, insufficient attention is given to questions of causality. Single-equation models are the norm in cross-section growth investigations. The dependent variable is always the growth rate and all the other variables are taken as independent causal determinants of economic growth.

The first problem - the proliferation of proxies for the same underlying factors - can be addressed by using models with latent variables. In a latent variable framework, proxies can be used as noisy indicators of underlying, unobserved latent variables. Using latent variables helps to avoid the collinearity and errors-in-variables problems that occur when several proxies are used as explanatory variables, and it provides a parsimonious representation of statistical relationships. Bollen (1989) provides a comprehensive discussion of latent variable models that connects directly to traditional econometric approaches.

The second problem - causality - is more vexing. We agree with DeLong and Summers (1994, pp. 806-807) that inferences may be fragile because "the direction of causation and the isolation of other possible influences is extremely difficult." Both DeLong and Summers (1991) and Easterly and Rebelo (1993) provide some discussion of causal issues in their papers.[1] Yet, few attempts have been made to examine a richer set of model specifications, including alternative specifications of causal structures.[2]

Schooled in the Cowles Commission simultaneous equations tradition, economists tend to believe that causal and structural issues must be dealt with *a priori* through identification assumptions. However, there are at least two broad, generic approaches to inferring causal structure from the data themselves with limited a priori information. These are the "invariance approach" and a method recently developed by philosophers and computer scientists which we call the "instrumental variable approach."

The invariance approach is based on the idea that external interventions will have different effects on marginal or conditional distributions, depending on the underlying causal structure. For example, suppose that taxes were a cause of government spending but government spending did not cause taxes. In this case, a major shock to the process for government spending (such as a war) would not have an effect on the marginal distribution for taxes. Hoover (1991) and Hoover and Sheffrin (1992) outline and apply this method for determining causal structure. However, only the broad direction of causal influence (e.g., does A cause B or B cause A) and not precise details of causal structure can be determined through these methods.

In principle, we can learn more details about causality and structure through the "instrumental variables" approach. Economists are familiar with instrumental variables as an econometric tool. The idea behind instrumental variables is that the identification and estimability of parameters can be changed with the addition of further variables. Spirtes, Glymour, and Scheines (SGS) (1993) show that this same principle can be used, within well-defined limits, to identify causal structure. Their work builds on the ideas of statisticians and computer scientists developed during the 1980s, especially Pearl (1988) and his colleagues. While it is impossible to infer causal structure from the mere correlation between two variables A and B, statements about the causal relationship between A and B can sometimes be made with the addition of other variables.

SGS provide a series of algorithms and search procedures to aid inferences about causal structure both with and without latent variables. In our work we use these algorithms to suggest several possible models that are consistent with the data. We then estimate these models, using latent variables, and test several alternatives as well.

Section 2 presents the statistical theory behind the SGS approach that we use in our work. The results from the search procedure applied to a standard cross-sectional data set are presented in Section 3. The search procedure results in strong claims about the underlying causal structure. We explain carefully the nature and logic of these claims. In Section 4 we estimate our preferred models and compare them to reasonable alternatives. Finally, we conclude with some thoughts on the applicability of our methods in economic contexts.

2. Inferring Causal Structure From Data

In order to make inferences about the nature of causal structure from the data, there need to be connections between the properties of causal models and probability structures in the data. The SGS approach that we use in our work links the structure of causal models to conditional independence relations among the variables in the model. The essential idea is that tests for independence and conditional independence among the variables in a model can be informative about the structure of models.

Although the underlying theory is more general, we will present it for the case of linear, recursive models with multivariate normal variables. If the underlying models are simultaneous, the methods that we use will be uninformative as to causal direction. While the recursive case is somewhat limiting, as we illustrate in our work below, the outcome from these procedures can be a starting point for investigating simultaneous structures as well.

Any linear, recursive simultaneous model can be represented by a directed, acyclical graph denoted $<V,E>$ where V is the set of vertices of the graph and E is the set of directed edges. The vertices represent variables and the directed edges represent causal linkages. Figure 1 presents an example of such a graph. Directed edges or arrows represent causal direction, for example, x_1 causes x_3; x_2 causes x_3 and x_4; and x_3 and x_4 cause x_5. All variables that have a directed edge into them also have associated with them an independent, normal error term, although these are not shown in the graphs. A graph is acyclical if no causal chains come back to the same variable - this rules out simultaneous structures. The graph in Figure 1 represents the three-equation linear model:

$$x_3 = a\,x_1 + b\,x_2 + \varepsilon_1$$

$$x_4 = c\,x_2 + \varepsilon_2$$

$$x_5 = d\,x_3 + e\,x_4 + \varepsilon_3$$

where a, b, c, d and e are coefficients and the three error terms are independent and normally distributed. In this framework, variables that do not have arrows into them, such as x_1 and x_2, are assumed to be normally distributed and uncorrelated.

To develop the theory, we need some terminology from graph theory. The *parents* of a variable are its direct causes. For example, x_1 and x_2 are parents of x_3. If a variable q can be reached on a causal chain from another variable p, then q is a *descendant* of p. In Figure 1, x_3 and x_5 are descendants of x_1. Two variables, p and q, are *adjacent* if either p is a direct cause of q or q is a direct cause of p. For example, x_1 and x_3 are adjacent but x_3 and x_4 are not adjacent. Finally, if p and q both cause r but p and q are not adjacent, then r is an *unshielded collider*. In Figure 1, x_5 is an unshielded collider because it is directly caused by two non-adjacent variables, x_3 and x_4.

In analyzing the causal relationships in a data set, a crucial question is whether or not the set of measured variables is *causally sufficient*. A set of variables that includes all common causes for the variables within the set is causally sufficient; otherwise, it is causally insufficient. It is not difficult to see why this distinction is important. In a causally sufficient set of two variables, correlation between the two would imply causation from one variable to the other. If the set is not causally sufficient, the two variables could have a common cause.

Two axioms, the *Markov Condition* and *Faithfulness*, provide the links between causal models and conditional independence of a probability structure. The Markov Condition spells out the independence relations among a set of causally sufficient variables that we expect to hold in a causal structure:

Markov Condition: Let v be an element of a causally sufficient set of variables V, and P be a probability distribution over V. Then v is independent of every set of variables that does not contain its descendants, conditional on its parents (v is independent of all variables in the set $V \backslash [\text{Descendants}(v) \cup \text{Parents}(v)]$ given the Parents(v)).

We illustrate the Markov condition in Figure 2. For example, applying the Markov condition to the variable v, we see that v is independent of x_3 conditional on x_1 and x_2 or, in symbols, $v \perp x_3 \mid \{x_1, x_2\}$. Similarly, the Markov condition also implies that $x_3 \perp \{x_2, x_4, x_5, v\} \mid x_1$. It is important to note that these independence relations hold for all values of the coefficients (the parameters) in our representation.

The Markov condition is based on the following common sense principles: (1) an effect is independent of its indirect causes, conditional on its direct causes, and (2) variables are independent conditional on their common causes. While these are very intuitive principles, there has been extensive discussion of this axiom. Spirtes, Glymour, Scheines (1993, pp. 57-70) provide an extensive review of the debate. While the Markov condition will hold for a broad class of data-generating mechanisms, examples of situations where the Markov condition does not hold include: (1) the existence of causal relations between different members of the population (which would be especially common in time series analysis), and (2) a mixture of members in a population in which causal paths go in conflicting directions.

In recursive, linear models, the Markov condition, and independence relations that can be derived from them, characterize virtually all the conditional independence relations. However, for particular configurations of the parameters it is possible that there could be additional independence relations among the variables. For example, in Figure 1, x_2 will in general be correlated with x_5. However, the coefficients along the two paths leading from x_2 to x_5 could be such that they exactly cancel each other. In linear, recursive models this can only occur on a set of measure zero. Nonetheless, we want to rule this possibility out and require that all independence relations among the variables correspond to directed edges in the underlying graph. We say that a graph G is *faithful* to a probability distribution P if and only if all of the independence relations in P are implied by the Markov condition applied to G.

Under the Markov condition and Faithfulness, the conditional independence relations among a set of variables are implied by the graph of the causal model. In general, more than one model will imply the same conditional independence relations. How large is the class of graphs that imply a given set of conditional independence relations? Pearl (1988) provided the answer to this question. He discovered a convenient, graphical characterization of all of the independence relations implied by the Markov conditions called d-separation. Using this idea, it is possible to describe the equivalence class of models that imply the same independence relations. Following Spirtes, Scheines, Meek, and Glymour (1994), we call this the Markov Equivalence Theorem.[3]

Markov Equivalence Theorem: Two faithful, acyclic graphs over the same variables entail the same conditional independence relations if and only if (a) they have the same adjacencies and (b) the same unshielded colliders.

Figure 3 illustrates this theorem. Graphs (a) and (b) are Markov equivalent because they both have x_3 as an unshielded collider and the same adjacencies. Note, however, that they do differ in causal directions among x_1, x_2, and x_4. Graph (c) is not Markov equivalent to (a) because it lacks an unshielded collider. Graph (d) is also not Markov equivalent to (a) because it lacks an adjacency.

One implication of this theorem is that definitive statements about the causal direction between any two variables require that the independence relations produce unshielded colliders somewhere within the graph. Suppose there are only three variables in our universe, x_1, x_2, and x_3. We are interested in finding the causal direction between x_1 and x_2 , which we know are causally connected. Suppose we find that x_3 is independent of x_1 but correlated with x_2. We now show that this pattern of correlations leads to a situation in which x_2 is an unshielded collider. Since x_1 and x_3 are uncorrelated, they cannot be adjacent, so x_2 must lie between them as in Figure 4. Of all the four possible configurations, only (d) preserves the independence between x_3 and x_1. Thus, x_2 is an unshielded collider. This means that x_1 must cause x_2.

We can give an instrumental variables interpretation to this chain of reasoning. We can roughly think of x_3 as being an instrument for x_2 in a regression of the form $y = a x_2 + x_1$ for some variable y. While we could not consistently estimate the coefficient "a" by ordinary least squares since the error term (x_1) is correlated with the right-hand-side variable, we could estimate this equation with x_3 as an instrument. From a causal modeling point of view, this means that it is possible to change the value for x_2 without changing the value of x_1. That could not be possible if x_2 was a cause of x_1. Since the variables are causally connected, it must be the case that x_1 causes x_2.

SGS construct algorithms to move from empirical, conditional independence relations in the data to Markov equivalent classes of models. Users of the algorithms need to specify whether or not a set of variables is causally sufficient. Naturally, stronger inferences can be drawn when the set is assumed to be causally sufficient. As explained in the next section, we always assume that the set of variables is causally insufficient. The algorithm for the causally sufficient case is the easiest to understand. It operates in three stages. First, applying the Markov condition, it uses tests for conditional independence to remove adjacencies from a complete totally undirected graph. An adjacency is removed between two variables if they are independent conditional on any other variables in the set. Second, it looks at the set of potentially unshielded colliders x, y, and z such that x and z are not adjacent but x and y and y and z are adjacent. Let S be a set such that x and z are independent conditional on S. From the theory of d-separation, y is a collider on the path from x to z if and only if y is not a member of any such set S. Therefore, we can determine whether y is a collider by testing for this condition. The third and final step is to determine if any additional edges can be oriented based on the knowledge that some orientations would create unshielded colliders when they are not, in fact, unshielded colliders. This algorithm and the more complex algorithm that does not assume causal sufficiency are discussed in detail in SGS (1993).

In implementing these algorithms, statistical decisions must be made about conditional independence. Under the assumption of multivariate normality, tests for partial correlation are also tests for conditional independence. The partial correlation is the correlation coefficient conditional on a set of variables. As

Whittaker (1990) also emphasizes, the off-diagonal elements of the standardized inverse of the correlation matrix for a set of variables are the negatives of the partial correlations between the corresponding variables, conditional on the remaining variables. For a specified significance level, the algorithms test for a zero partial correlation using Fisher's z.[4]

In linear models, in the presence of unmeasured or latent variables there may be additional constraints on the correlation matrix of a set of variables implied by a directed, acyclical graph. An important subset of these constraints involve four distinct correlation coefficients and are known as *tetrads* or tetrad differences. For example, suppose we observe four variables (x_1, x_2, x_3, and x_4) which have all been caused by a single unmeasured variable. Also suppose no other causal connections exist between the variables. In this case, every pair of observed variables is dependent conditional on all other variables. Yet, constraints are nonetheless imposed by the model. Letting ρ_{12} denote the correlation between variables x_1 and x_2, then there are three tetrad constraints:

$$\rho_{13}\,\rho_{24} - \rho_{14}\,\rho_{23} = 0$$

$$\rho_{12}\,\rho_{34} - \rho_{14}\,\rho_{23} = 0$$

$$\rho_{13}\,\rho_{24} - \rho_{12}\,\rho_{34} = 0$$

The tetrad constraints can be used to check for causal sufficiency for a set of variables. For example, if the first tetrad constraint holds, then in the graph either (1) ρ_{13} or $\rho_{24} = 0$ and ρ_{14} or $\rho_{23} = 0$ or (2) there must exist a set of variables Q such that all the partial correlations $\rho_{ij} \mid Q = 0$. If our set of variables originally included only x_1, x_2, x_3, and x_4, and the simple correlations were not equal to zero, then we would be able to infer the existence of a latent variable. Tests for the existence of latent variables as well as related specification tests for these additional constraints are contained in the TETRAD II program developed by SGS.

In using the algorithms, it is important to remember that it performs a series of tests and the significance level for the overall result will not equal the significance level for the individual tests. Since the procedure works by eliminating adjacencies unless the partial correlations are high enough, there are naturally possibilities for Type II errors. To ensure that are results our robust, we re-run the algorithms at higher significance levels to see if any other causal information emerges. Finally, it is possible to input a priori information about causal structure into the algorithms.

3. Applying the Search Procedures to Cross-Sectional Growth Data

The first stage of our empirical analysis is to study the pattern of correlations and partial correlations in a cross-country data set of growth related variables. This allows us, using the algorithm developed by SGS, to reject the existence of causal paths connecting some of the variables. Our data come from 68 countries, and include information on growth rates, equipment and non-equipment investment, openness of the economy, political stability, and human capital. Summary statistics and variable definitions are shown in Table 1. The data are generally drawn from recent papers on economic growth; details concerning our data sources and data set construction are available from the authors.

In applying the SGS methodology, we do not assume that our set of variables is causally sufficient. Recall that in order to be causally sufficient a set of variables must contain all common causes of all of the variables in the set. In our context, an example would be that there could not exist any factors not included in our data set which cause both equipment investment and economic growth. This seems likely to be a false assumption, since we do not have measures in our data set of such factors as how well developed capital markets are or of the level of entrepreneurship. Such factors would plausibly have a direct causal influence on both equipment investment and economic growth. Scanning the list of variables in Table 1, it is easy to think of other examples that might result in causal insufficiency.

In applying the SGS algorithm, one must select a significance level to use in testing the hypotheses that the various correlations and partial correlations are equal to zero. As the significance level increases, the critical values for failing to reject the hypothesis that a given correlation is equal to zero decrease in magnitude, and we will generally fail to reject the null hypothesis (that the correlation is equal to zero) in a larger number of cases. Thus, the number of causal paths that are rejected will generally decrease as the significance level rises. The causal paths that cannot be ruled out when specifying a 0.05 significance level for the correlation hypothesis tests are shown in Figure 5, while Figure 6 displays the causal paths which cannot be rejected when the significance level is set at 0.20. The graphs in Figures 5 and 6 are examples of what SGS call partially oriented inducing path graphs (POIPG). The edges should be interpreted as follows: (i) a single-headed arrow pointing from x_1 to x_2 is a cause (either direct or indirect) of x_2 but x_2 does not cause x_1; (ii) a double-headed arrow connecting x_1 and x_2 means that there is a latent (unmeasured in our data set) common cause of x_1 and x_2; (iii) a single-headed arrow with a circle at its base pointing from x_1 to x_2 (o→) indicates either that x_1 is a cause of x_2 or that there is a common latent cause of x_1 and x_2, or both; (iv) an edge between x_1 and x_2 with circles at both ends (o—o) indicates that one or more of the following conditions holds: x_1 causes x_2, x_2 causes x_1, or there is a common latent cause of x_1 and x_2.

The most notable, and surprising, finding in this analysis concerns the causal relationship between economic growth and equipment investment. Growth may cause equipment investment or there may be a common unmeasured (in our data) cause of growth and equipment investment, but we can rule out the possibility that equipment investment causes growth. Given the importance of this relationship, and the fact that previous work has assumed that equipment investment does cause growth, it is worth exploring in some detail how we are able to reject the possibility that causation runs in this direction.

The correlation between the growth and openness variables is insignificant at both the 0.05 and 0.20 levels, but the correlation between growth and equipment investment and the correlation between equipment investment and openness are significant at both levels.[5] Any causal ordering of growth and equipment investment must be consistent with this pattern of correlations. Figure 7 shows two graphs that would lead to growth and openness being correlated. In the top graph, openness causes equipment investment and equipment investment causes growth. This causal ordering would induce a non-zero correlation between growth and openness and is therefore inconsistent with our data. In the bottom graph, growth causes equipment investment and equipment investment causes openness. This would also induce a correlation between growth and openness and is inconsistent with the data.

Figure 8 shows some causal structures that are consistent with the observed pattern of correlations. In the top graph, growth and openness both cause equipment investment. The next graph shows a causal structure where growth causes equipment investment and where a latent variable (T) causes both equipment investment and openness. In this case, the correlation between equipment investment and growth is not due to a causal relationship between the two, but instead due to some unmeasured common causal factor (for example, how developed the country's financial markets are). The bottom two graphs also involve latent variables. Note that none of the possible causal structures show equipment investment causing growth. A causal link running in this direction will always induce a non-zero correlation between growth and openness and will be inconsistent with the data. In terms of the terminology developed in section 2, equipment investment is an unshielded collider in all of the graphs that are consistent with the observed correlation pattern.

The role of openness deserves further comment. Harrison (1991) surveys a fairly extensive empirical literature that posits that openness directly affects the rate of economic growth. She finds that direct links between openness and growth are sensitive to measures of openness. Our results suggest that this direct causal mechanism may not be operative, although that may be partly due to the particular measure of openness which we employ.

Aside from the causal relationship between equipment investment, growth, and openness, the other causal orderings shown in Figure 5 are not too surprising. The initial level of development (as measured by Y/L) causes schooling (or has a latent cause in common with schooling). Secondary schooling and equipment investment have a common latent cause. This might be due to the secondary school enrollment rate being a noisy indicator of human capital per worker, and human capital being a cause of equipment investment. Assassinations, war casualties, and coups are linked together but are not connected to the other variables. It makes sense that these variables are grouped together, but, unlike Barro (1991), we did not find that growth was positively related to political stability in our sample. Government consumption and investment spending are linked together (perhaps both caused by a latent variable capturing attitudes toward public spending) but are unrelated to other variables.

Some of the causal links shown in Figure 6 (where the significance level is 0.20) seem unlikely. In particular, it seems implausible that equipment investment and secondary school enrollment rates actually cause the initial level of development (Y/L). To circumvent this problem, we reapplied the SGS algorithm after specifying that the initial level of development is determined prior to the other variables and cannot be caused by them. The POIPG produced by this modification is shown in Figure 9. The implausible links have now disappeared, and the resulting graph is very similar to that produced when the significance level was much lower (in Figure 5). It is noteworthy that the direction of causality between equipment investment and growth does not seem very sensitive to the significance level or to whether Y/L is specified as being predetermined.

The search procedure described above provides information that can guide us in specifying an econometric model of economic growth, but it does not dictate exactly what the specification is. The search results suggest that equipment investment does not cause economic growth, but they also tell us that it is possible that either growth causes equipment investment or that a common latent cause of both variables exists. Judgment must be used in deciding how this information should be used in specifying a model.

Some of the specifications suggested by the search may be subjected to further analysis to test their plausibility. The initial empirical analysis suggests primary and secondary schooling may be jointly caused by a latent variable. This suggests the hypothesis that both of these variables are noisy indicators of a latent unmeasured variable we might call "human capital."

$$\text{primary}_i = \lambda_1 \text{ human capital}_i + \varepsilon_{1i}$$
$$\text{secondary}_i = \lambda_2 \text{ human capital}_i + \varepsilon_{2i}$$

where i is an index of observations (countries) and the ε's are independent normally distributed errors. In practice, one of the λ's must be set equal to a fixed value (usually one) in order for the model to be identified. The advantage of a latent variable specification is that it allows one to cleanly incorporate hard-to-measure conceptual variables, such as human capital, into an econometric specification without having to directly include multiple "proxy'' variables in the structural equations. In similar fashion, we can construct a latent variable for "political instability" for which assassinations, war casualties, and coups and revolutions are noisy indicators.[6]

As outlined in section 2, measurement models for latent variables generally imply that certain tetrad equations must hold, and it is possible to test whether this is true. We jointly tested all of the tetrad equations implied by the latent variable structure for "human capital" and "political instability," and found that we failed to reject the hypothesis that all six of the tetrad equations implied by this measurement structure hold at the 0.75 significance level.[7] Since the data are largely supportive of our hypothesized measurement model for the human capital and political instability latent variables, we adopted this specification in estimating the growth models described in the next section.

Jones (1994) found that equipment prices (rather than quantities) were related to growth. We re-ran the algorithms using equipment and non-equipment prices in place of the quantities.[8] The causal output of our algorithms was quite similar: In no case did equipment prices cause growth. Either growth causes equipment prices or there is a joint cause. If prices and quantities were both entered into the algorithm, no causal conclusions were possible.[9]

4. Estimating Causal Models of Economic Growth

Using the results of our search procedure as a guide, we estimated several specifications for causal models of economic growth. Our strategy is to start with simple specifications and then augment the model. Figure 10 illustrates our structure. Our first specification is a bare bones recursive model suggested by the POIPG displayed in Figure 9. Equipment investment is modeled as a function of growth, the human capital latent variable, and openness. Non-equipment investment is modeled as a function of growth. Finally, the human capital latent variable is assumed to be a linear function of the initial development level. Coefficients for these regression equations were estimated jointly with the factor loadings (the λ parameters) for the measurement models for the political stability and human capital latent variables by maximum likelihood under the assumption that the measured variables were drawn from a multivariate normal distribution.[10] Parameter estimates are shown in Table 2.

The results are as expected. Growth, openness, and human capital all have a positive impact on equipment investment. Growth has a positive effect on non-equipment investment, and the initial development level has a positive impact on human capital. The factor loading on the secondary school enrollment rate variable is close to one, suggesting that primary and secondary school enrollment are capturing largely the same human capital effects. The factor loadings for the political instability latent variable are all positive, providing some support for the view that the assassinations, coups, and war casualties variables are appropriate indicators. Since our search procedure did not provide strong support for including the political instability latent variable in the structural equations, we omitted it in our initial specification.

While the results of our search procedure and the estimation results reported in Table 2 provide strong support that growth does affect equipment investment, they are unlikely to convince a skeptic who has a strongly held prior belief that equipment investment has a strong effect on growth. To address this concern, we next augment the model with an equation in which growth is the dependent variable, thus moving to a simultaneous equation framework with latent variables.

Our causal search procedure was predicated on the assumption that the underlying data-generating process is recursive, so the results displayed in the POIPGs are less helpful in model specification once we entertain the possibility of bi-directional causality.

We specify growth to be a linear function of equipment investment, Y/L, and human capital. The system is identified through the exclusion of Y/L in the equipment investment equation and openness in the growth equation. The exclusion of openness from the growth equation is supported by the results of our search procedure (although, as mentioned above, this assumed the model was recursive). The search procedure does not support including the initial development level (Y/L) in either equation, but economic theory suggests that Y/L should have an effect on growth rates. One additional change to the specification is the inclusion of the political instability latent variable in the growth and investment equations.

The estimates of the extended model are reported in Table 3. The results provide strong support for our prior causality search. The key finding is that equipment investment has a very small and statistically insignificant effect on growth. As expected, growth rates decrease with the initial level of development and increase with the level of human capital. The political instability latent variable has negative coefficients in the growth and both investment equations, but all three coefficients are insignificant. Somewhat surprisingly, the growth coefficient in the non-equipment investment equation, which was positive and significant in the initial specification, now is negative and insignificant. The other coefficients are very close to those presented in Table 2.

We are able to explain why the initial development level was significant in the econometric model but was not uncovered through the search algorithm. In theory, if two variables in a graph are adjacent, they should be dependent conditional on <u>all</u> sets of other variables (including the null set) in the model. To avoid an exponential search, the algorithm eliminates adjacencies if it finds independence for any set of variables. In this case, the simple correlation between growth and initial development level is virtually zero, and the algorithm eliminated an adjacency between these variables in the first round of its search. However, the correlation conditional on other variables is actually negative and significant. The algorithm incorrectly eliminated the adjacency in its search procedure.[11]

We estimated additional models in order to test the sensitivity of our results. Tables 4 and 5 present the results of two variants of the specification reported in Table 3. Government consumption and public investment are added to the growth and investment equations in the specification reported in Table 4. Public investment is estimated to have a positive impact on growth and non-equipment investment, although it has no discernible effect on equipment investment. This suggests that the complementarities between infrastructure investment and private non-equipment investment are greater than those between infrastructure and private equipment investment. However, we need to emphasize that we have not yet investigated the consequences of treating public investment as endogenous. As with private equipment investment, it may be the case that causality instead runs largely from growth to investment.

Strikingly, in the specification reported in Table 4 we again find that growth has a positive and statistically significant effect on equipment investment, while equipment investment has no discernible effect on growth. This result holds up over all of the specifications we investigated and appears to be quite robust.

In Table 5, we report results from a specification with different identifying assumptions. We now let the openness variable enter the growth equation, but omit political instability. This does not change our basic finding that growth has a significant effect on equipment investment and, as before, we fail to reject the hypothesis that equipment investment has no effect on growth (the point estimate of the equipment investment coefficient is negative in the growth equation, with a standard error larger than the coefficient). The openness variable has a positive estimated coefficient in the growth equation, but has a standard error larger that the coefficient. The other coefficients are very similar to those in Table 4. Overall, our results do not appear to be very sensitive to changes in the specification of the model.

5. Conclusion

Our results are indirectly foreshadowed in DeLong and Summers (1993). They report the results of instrumental variables regressions in Table 5 of their paper. Using savings or equipment prices as instruments for equipment investment did not change the OLS results. But when a measure of tariff and non-tariff barriers is used as an instrument, the effect of equipment investment on growth becomes close to zero and statistically insignificant.[12] Tariff and non-tariff barriers, of course, are closely tied to the openness variable that we highlight.

Our method effectively uncovered the instruments that rendered the coefficient on equipment investment in the growth equation to be zero and insignificant. To put it another way, our work indicates that given the cross-sectional data set, the DeLong and Summers equation with equipment investment as exogenous in a growth equation cannot be viewed as a structural equation in a recursive model of economic growth. The models we estimate are consistent with the full set of correlations in the data. They are broadly consistent with growth models augmented for human capital as in Mankiw et al. (1992).

This approach inevitably points to considering models of economic growth within a complete structural model rather than with single equations. The approach taken in this paper cannot deliver a fully identified simultaneous equation model a priori - no method can - but it can narrow down the classes of models that should be seriously considered. In actual practice, model specification in economics moves back and forth between theory and measurement. The methods in this paper bring some additional discipline to this process from the measurement side.

Endnotes

[1]DeLong and Summers argue that the negative correlation of equipment prices and quantities suggest that growth cannot cause equipment because changes in demand would cause a positive correlation (along a supply curve) of prices and quantities. We discuss this point below but note that the negative correlation may be due to measurement error. Easterly and Rebelo argue that the causal direction runs from public investment to growth because only some types of public investment are correlated with growth. However, there is no a priori reason why different types of public investment may not respond differentially to growth.

[2]Blomstrom (1993) et al. use Granger causality tests on five year averages of data to look at the causality of fixed investment and growth. For a discussion of limitations of Granger causality, see Hoover and Sheffrin (1992).

[3]This result was originally developed by Verma and Pearl (1990) and Frydenberg (1989).

[4] See Anderson (1984) or Spirtes, Scheines, Meek and Glymour (1994) for an exposition of Fisher's z.

[5]The sample correlation between growth and openness is 0.12. Assuming these variables are drawn from a bivariate normal distribution, there is a 0.35 probability of observing a sample correlation that large under the null hypothesis that the population correlation equals zero. Although the discussion in the text focuses on openness, growth causes equipment investment without the openness variable as long as both measures of schooling are included in the data.

[6] The data suggest that a latent variable may also exist for which government consumption and public investment are noisy indicators.

[7]The test is due to Bollen (1990) and uses the Bonferroni adjustment to "correct" the single equation critical values for the fact that multiple tetrad equations are being simultaneously tested.

[8]To maintain a reasonable sample size, we omitted the public investment variable from our search. The sample size was 58. Chad Jones kindly supplied the relative price data.

[9]In our sample, there was a strong negative correlation of -0.74 between equipment prices and quantities, suggesting they carry very similar information. In

our view, this strong negative correlation may be due to measurement error; given nominal values, errors in deflators will produce a negative correlation between prices and real quantities.

[10]The estimator of the coefficients is consistent under more general conditions; see Bollen (1989) for a general discussion. The estimates were obtained using the procedure CALIS in SAS.

[11] Simple regressions reveal this pattern. A regression of growth on the initial development level alone will not lead to a significant coefficient. But in a multivariate regression, the coefficient on the initial development level is negative and significant. The algorithm can make mistakes because of correlation patterns of this sort in the data. As long as the faithfulness property holds, this problem would eventually disappear as the sample size increases.

[12]Similar, although less dramatic results from instrumental variables estimation are reported in Jones (1994).

References

Anderson, T., 1984, *An Introduction to Multivariate Statistical Analysis*, New York: Wiley.

Auerbach, Alan J., Kevin A. Hassett, and Stephen Oliner, 1994, "Reassessing the Social Returns to Equipment Investment," *Quarterly Journal of Economics*, 109, 789-802.

Barro, Robert J., 1991, "Economic Growth in a Cross Section of Countries," *Quarterly Journal of Economics*, 106, 407-443.

Blomstron, Magnus, Robert E. Lipsey, and Mario Zejan, 1993, "Is Fixed Investment the Key to Economic Growth?" NBER Working Paper No. 4336.

Bollen, Kenneth A., 1989, *Structural Equations with Latent Variables*, New York: Wiley.

______, 1990, "Outliner Screening and a Distribution-Free Test for Vanishing Tetrads," *Sociological Methods and Research*, 19, 80-92.

DeLong, J. Bradford and Lawrence H. Summers, 1991, "Equipment Investment and Economic Growth," *Quarterly Journal of Economics*, 1991, 445-502.

______, 1992,"Equipment Spending and Economic Growth: How Strong Is the Nexus?," *Brookings Papers on Economic Activity* 1992:2, 157-199.

______, 1993, "How Strongly Do Developing Countries Benefit from Equipment Investment?" *Journal of Monetary Economics*, 32, 395-416.

______,1994, "Equipment Investment and Economic Growth: A Reply," *Quarterly Journal of Economics*, 109, 803-807.

Easterly, William and Sergio Rebelo, 1993, "Fiscal Policy and Economic Growth: An Empirical Examination," *Journal of Monetary Economics*, 32, 417-458.

Frydenberg, M., 1989, "The Chain Graph Markov Property," Technical Report 186, Department of Theoretical Statistics, University of Aarhus, Denmark.

Harrison, Ann, 1991, "Openness and Growth: A Time Series, Cross-Country Analysis for Developing Countries," Working Paper for the World Development Report, The World Bank.

Hoover, Kevin D., 1991, "The Causal Direction Between Money and Prices: An Alternative Approach," *Journal of Monetary Economics*, 27, 381-423.

Hoover, Kevin D. and Steven M. Sheffrin, 1992, "Causation, Spending, and Taxes: Sand in the Sandbox or Tax Collector for the Welfare State?" *American Economic Review*, 82, 225-248.

Jones, Charles I., 1994, "Economic Growth and the Relative Price of Capital," *Journal of Monetary Economics*, 34,3, 359-382.

Mankiw, N. Gregory, D. Romer, and D. Weil, 1992, "A Contribution to the Empirics of Economic Growth," *Quarterly Journal of Economics*, 107, 2, 407-437.

Pearl, Judea, 1988, *Probalistic Reasoning in Intelligent Systems*, Morgan and Kaufman: San Francisco.

Spirtes, Peter, Clark Glymour, and Richard Scheines, 1993, *Causation, Prediction, and Search*, New York and Berlin: Springer-Verlag.

Spirtes, Peter, Richard Scheines, Christopher Meek, and Clark Glymour, 1994, *Tetrad II: Tools for Causal Modeling, User's Manual*, 1994

Verma, T.S. and Judea Pearl, 1990, "Equivalence and Synthesis in Causal Models," Proceedings of the 6th Conference on AI, pp. 220-227.

Whittaker, Joe, 1990, *Graphical Models in Applied Multivariate Statistics*, New York: Wiley.

Figure 1

An Acyclical Directed Graph

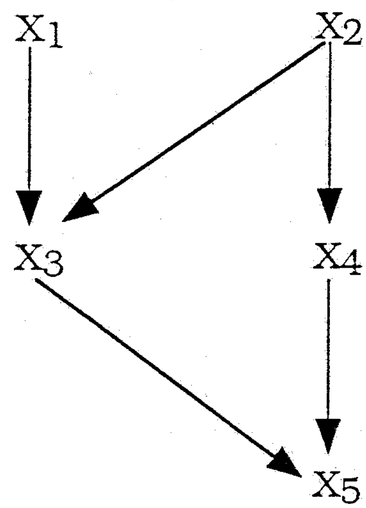
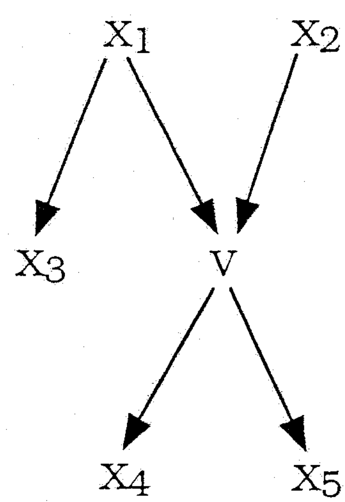


Figure 2

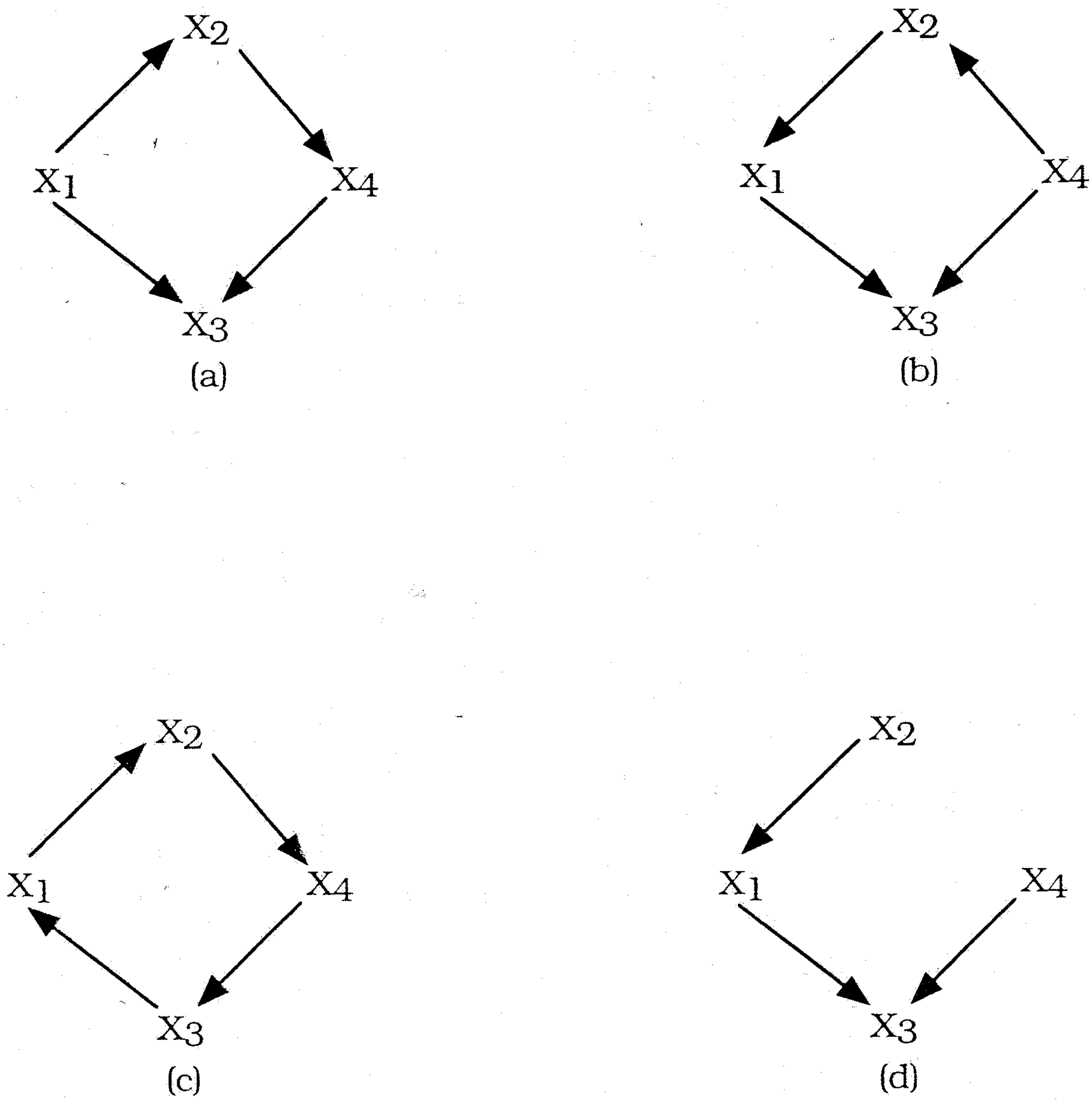
The Markov Condition



$$V \perp X_3 \mid (X_1, X_2)$$
$$X_3 \perp (X_2, X_4, X_5, V) \mid X_1$$

Figure 3

The Markov Equivalence Theorem



Graphs (a) and (b) are Markov equivalent. Graph (c) is not equivalent to (a) because it lacks an unshielded collider. Graph (d) is not equivalent to (a) because it lacks an adjacency.

Figure 4

Instrumental Variables Interpretation

$$X_1 \longrightarrow X_2 \longrightarrow X_3$$

(a)

$$X_1 \longleftarrow X_2 \longrightarrow X_3$$

(b)

$$X_1 \longleftarrow X_2 \longleftarrow X_3$$

(c)

$$X_1 \longrightarrow X_2 \longleftarrow X_3$$

(d)

Only in graph (d) will X_1 and X_3 both be correlated with X_2 but not correlated with each other.

Figure 5.

POIPG, 0.05 significance level

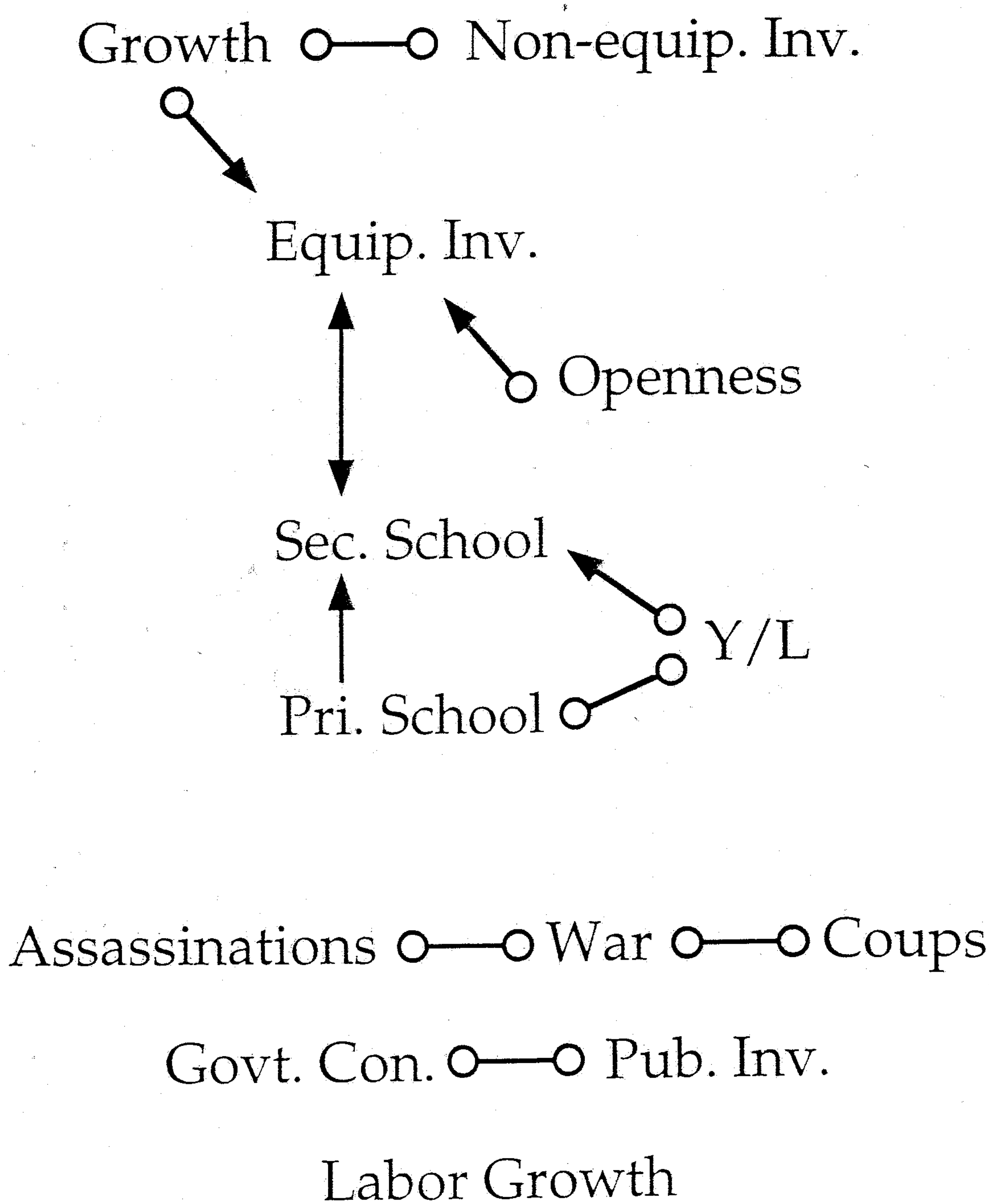


Figure 6.

POIPG, 0.20 significance level

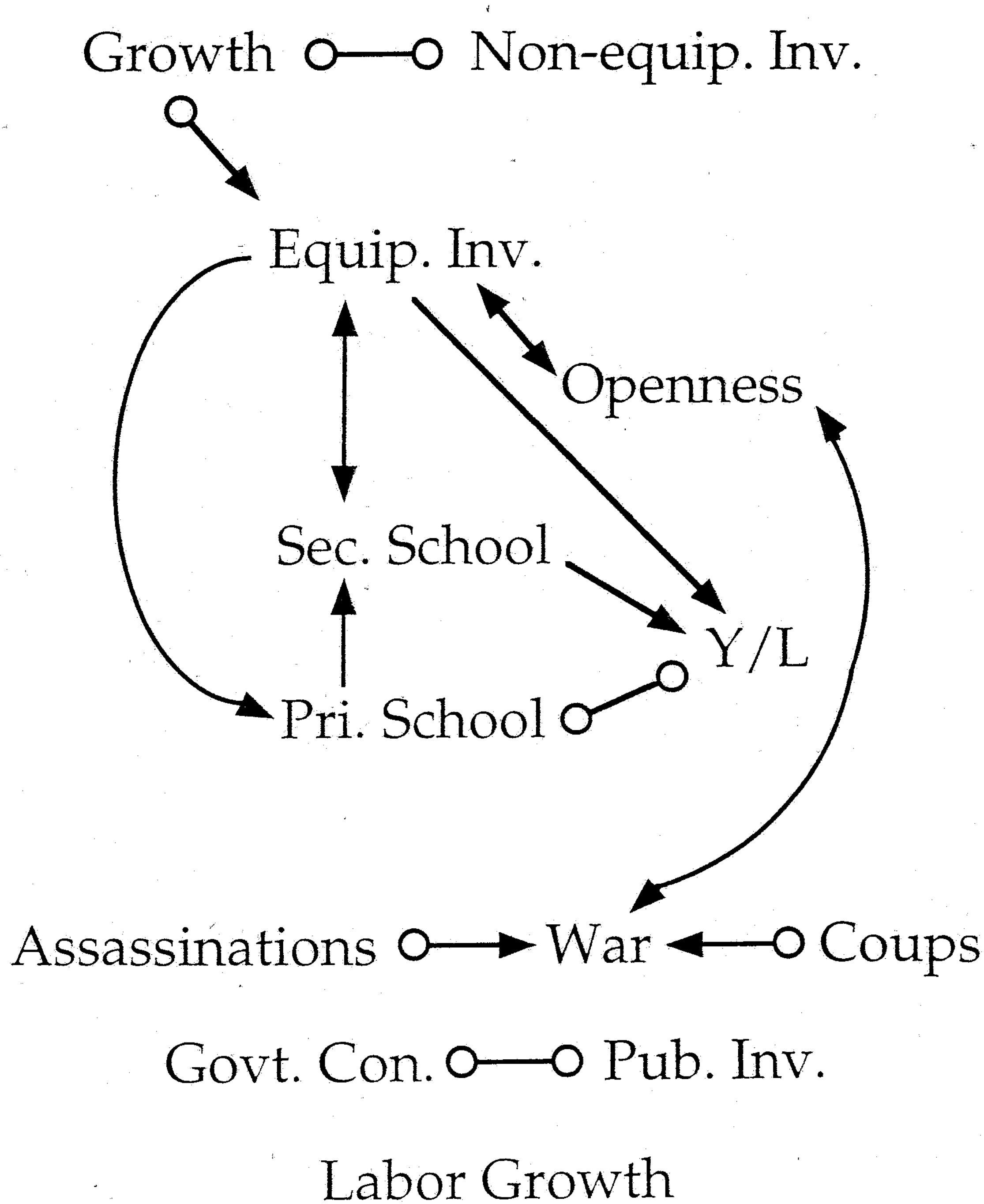


Figure 7.

Rejected Causal Orderings

Openness $\longrightarrow$ Equip. Inv. $\longrightarrow$ Growth

Growth $\longrightarrow$ Equip. Inv. $\longrightarrow$ Openness

Figure 8.

Possible Causal Orderings

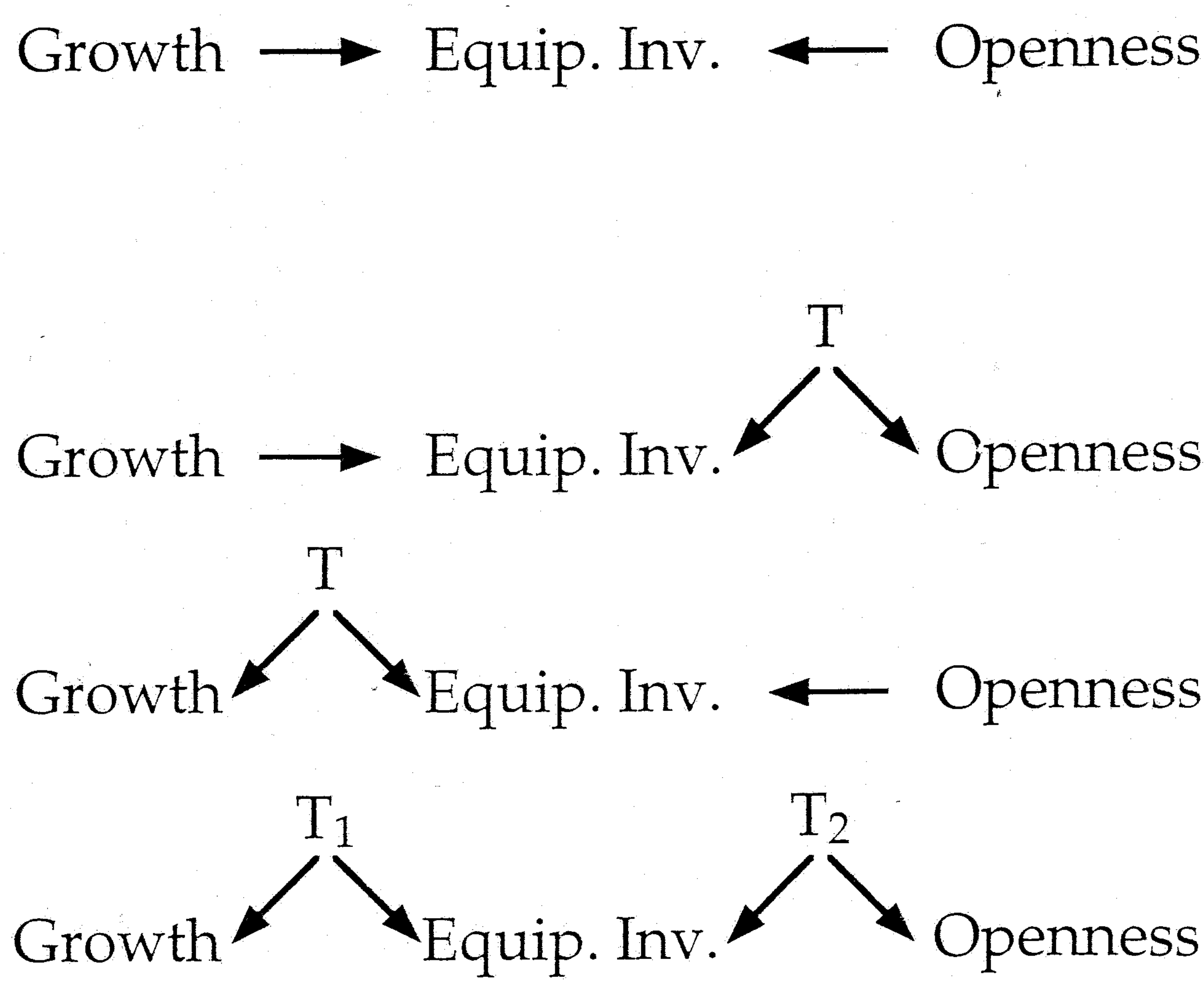


Figure 9.

POIPG, 0.20 significance level with
Y/L specified as predetermined.

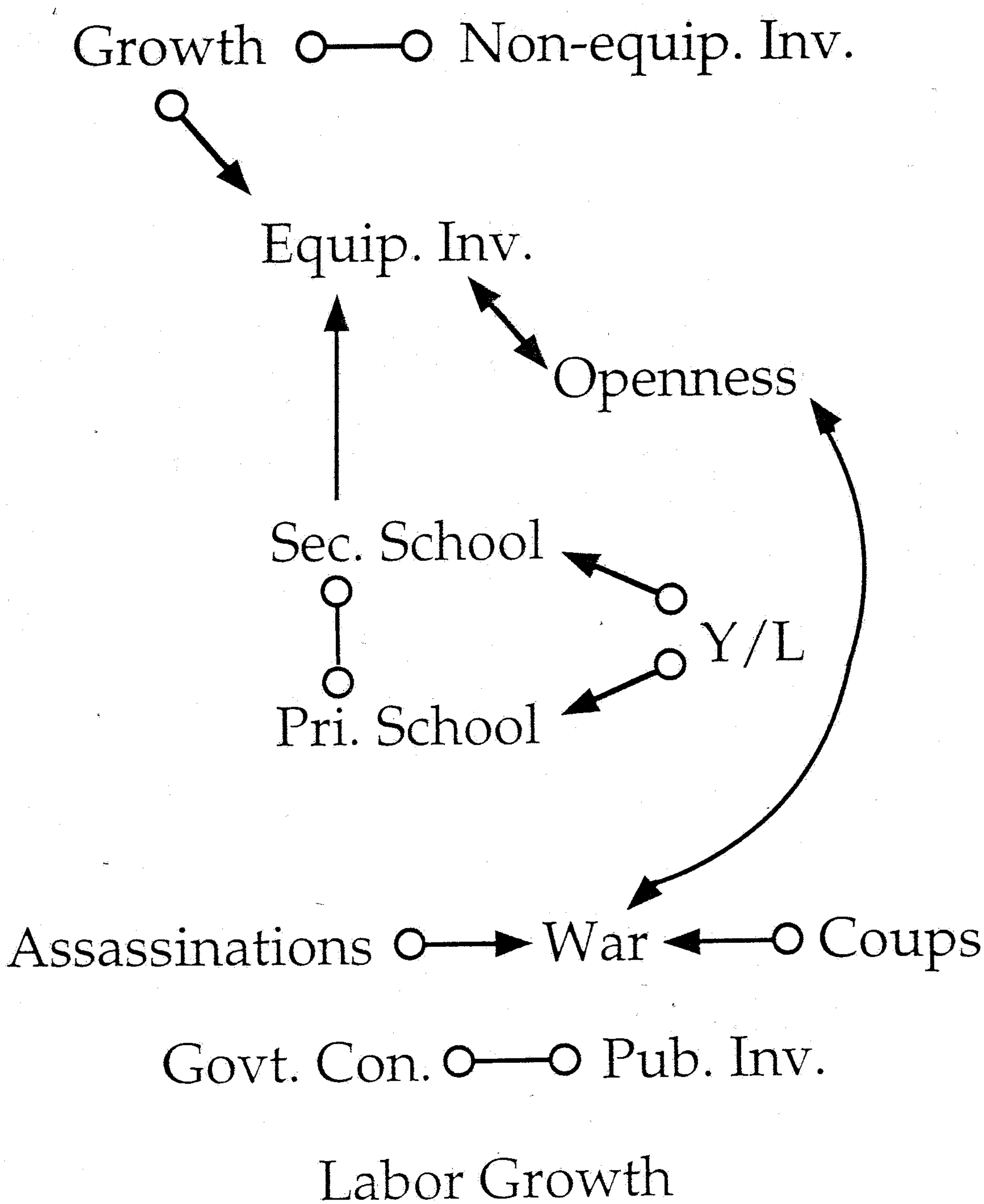
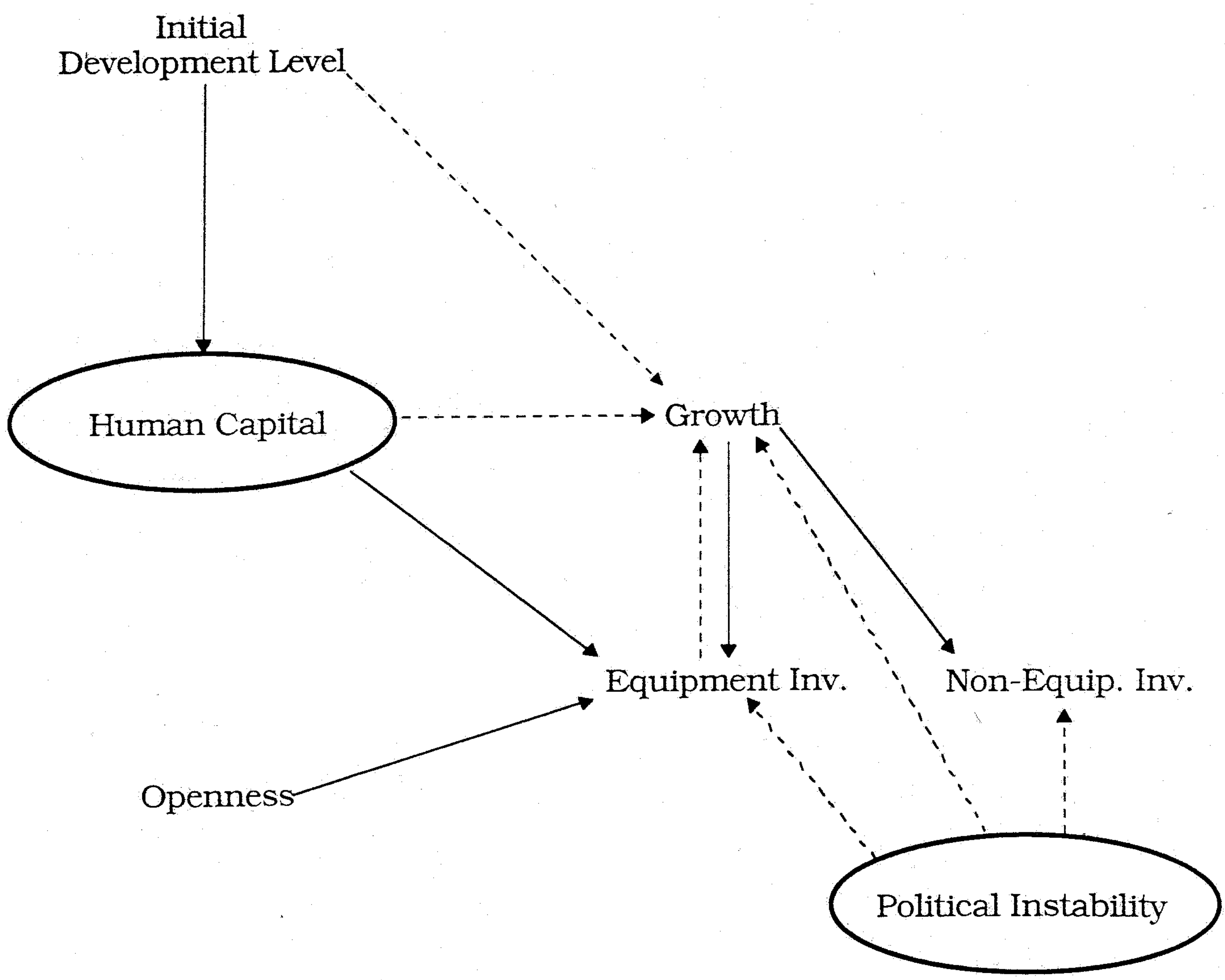


Figure 10

Empirical Models



Base Model in solid arrows.
Initial Simultaneous Model adds dotted arrows.

Table 1

Descriptive Statistics

Variable Name	*Description - all variables scaled*	*Mean*	*Standard Deviation*
Y/L	ln (1960 Y/L) relative to the U.S.	–1.938	0.868
Growth	Y/L growth 1960-85	0.020	0.016
Non-equipment investment	non-equipment investment (fraction of GDP)	0.131	0.059
Equipment investment	equipment investment (fraction of GDP)	0.041	0.033
Assassination	assassinations	0.038	0.112
Casualties	war casualties	0.106	0.336
Government consumption	government consumption (fraction of GDP)	0.184	0.069
Coups	revolution and coups	0.222	0.292
Openness	imports and exports (fraction of GDP)	0.246	0.195
Public investment	total public investment (fraction of GDP)	0.084	0.051
Primary school	primary school gross enrollment rate	0.801	0.294
Secondary school	secondary school gross enrollment rate	0.274	0.233

Table 2

Basic Model Parameter Estimates
(standard errors in [parentheses)

Structural Equations

	Equipment Investment	Non-Equipment Investment	Human Capital
Growth	0.866 (0.174)	1.333 (0.378)	
Openness	0.055 (0.015)		
Y/L			0.240 (0.029)
Human Capital	0.033 (0.014		

Measurement Models

	Human Capital
Primary School Enrollment	1.000
Secondary School Enrollment	0.850 (0.109)

	Political Instability
Assassination	1.000
Coups	2.927 (1.254)
War Casualties	4.091 (1.909)

Table 3

Simultaneous Model
(standard errors in parentheses)

Structural Equations

	Growth	Equipment Investment	Non-Equipment Investment	Human Capital
Growth		0.808 (0.299)	-0.326 (1.396)	
Equipment Investment	-0.036 (0.121)			
Non-equipment Investment	0.149 (0.164)			
Openness		0.057 (0.015)	0.018 (0.030)	
Y/L	-0.014 (0.006)			0.243 (0.028)
Human Capital	0.039 (0.034)	0.027 (0.014)	0.135 (0.030)	
Political Instability	-0.041 (0.068)	-0.119 (0.086)	-0.309 (0.200)	

Measurement Models

	Human Capital
Primary School Enrollment	1.000
Secondary School Enrollment	0.831 (0.100)

	Political Instability
Assassinations	1.000
Coups	3.049 (1.246)
War Casualties	4.389 (1.815)

Table 4

Specification Including Public Consumption and Investment

(standard errors in parentheses)

Structural Equations

	Growth	Equipment Investment	Non-Equipment Investment	Human Capital
Growth		1.005 (0.354)	0.868 (0.820)	
Equipment Investment	-0.134 (0.195)			
Non-equipment Investment	-0.055 (0.166)			
Openness		0.050 (0.015)	-0.013 (0.026)	
Y/L	-0.023 (0.012)			0.240 (0.028)
Government Consumption	-0.042 (0.033)	0.060 (0.045)	-0.013 (0.080)	
Public Investment	0.154 (0.083)	-0.017 (0.072)	0.262 (0.139)	
Human Capital	0.103 (0.068)	0.032 (0.014)	0.136 (0.026)	
Political Instability	-0.070 (0.074)	-0.094 (0.079)	-0.123 (0.131)	

Measurement Models

	Human Capital
Primary School Enrollment	1.000
Secondary School Enrollment	0.849 (0.103)

	Political Instability
Assassinations	1.000
Coups	3.134 (1.316)
War Casualties	4.262 (1.855)

Table 5

Specification with Alternative Identifying Assumptions
(standard errors in parentheses)

Structural Equations

	Growth	Equipment Investment	Non-Equipment Investment	Human Capital
Growth		1.288 (0.456)	0.466 (0.670)	
Equipment Investment	-0.293 (0.309)			
Non-equipment Investment	0.036 (0.129)			
Openness	0.018 (0.020)	0.048 (0.016)	-0.007 (0.026)	
Y/L	-0.026 (0.013)			0.239 (0.029)
Government Consumption	-0.041 (0.036)	0.072 (0.049)	-0.034 (0.080)	
Public Investment	0.149 (0.080)	-0.036 (0.083)	0.296 (0.131)	
Human Capital	0.108 (0.069)	0.032 (0.014)	0.136 (0.026)	
Political Instability		-0.063 (0.073)	-0.129 (0.124)	

Measurement Models

	Human Capital
Primary School Enrollment	1.000
Secondary School Enrollment	0.858 (0.104)

	Political Instability
Assassinations	1.000
Coups	2.897 (1.218)
War Casualties	3.953 (1.744)