POVERTY, THE COUP TRAP, AND THE SEIZURE OF EXECUTIVE POWER

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I. Introduction

THE transfer of executive power through the use or threat of force, the coup d'état, has become commonplace. As is the case with snowflakes and sunsets, no two such transfers are exactly alike. Various studies have described the nuances and idiosyncrasies of particular coups in great detail.[1] Underlying the interesting particulars of colonels overthrowing generals and of upwardly mobile drill sergeants taking up residence in presidential palaces, however, there is a common denominator among coups: poverty.

We agree with Luttwak and with Finer that economic backwardness is close to being a necessary condition for coups.[2] Coups are almost nonexistent in developed countries. To assess the interrelationship between economic privation (as measured by per capita income) and the incidence of coups d'état, we have analyzed political and economic data from 121 countries between 1950 and 1982. We find a pronounced inverse relationship between coups and income: coups are 21 times more likely to occur among the poorest countries in our sample than among the wealthiest.

To carry out our study, we constructed a model that enables us to assess the separate influences of income growth, the level of income, and a country's past history of coups, as well as the interdependence of coups and income growth. Because the data are organized by country over time, we are able to employ time-series analysis to discriminate between

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[1] See, for example, Henry Bienen, ed., *The Military Intervenes: Case Studies in Political Development* (New York: Russell Sage Foundation, 1968); and Samuel Decalo, *Coups and Army Rule in Africa* (New Haven: Yale University Press, 1976).

[2] Edward Luttwak, *Coup d' Etat: A Practical Handbook* (New York: Knopf, 1969); Samuel E. Finer, *The Man on Horseback* (London: Pall Mall, 1962).

the long- and short-term effects of coups d'état. Zuk and Thompson exploited a similar data structure to analyze postcoup military spending over time.[3] By contrast, most previous work is cross-sectional in nature.[4]

Huntington argued that "modernity breeds stability, but modernization breeds instability,"[5] while Olson contended more narrowly that economic growth is destabilizing.[6] Needler asserts, however, that "a successful coup or revolt is less likely when economic conditions are improving."[7] Our model enables us to simultaneously assess the impact of the rate of economic growth and the level of per capita income on one form of political instability: the coup d'état. We find that a high level of income dramatically inhibits coups; so does a high rate of economic growth, to the extent that it exerts an influence independent of the level of income. According to Huntington, "The more man wages war against 'his ancient enemies: poverty, disease, ignorance' the more he wages war against himself."[8] If that is true, the coup d'état is not man's weapon of choice.

Our model also indicates that the political aftereffects of a successful coup are substantial. A successful coup continues to elevate the propensity for yet another coup for up to six years. This finding comports with Finer's assertion that the "political culture" of a country suffers serious erosion in the wake of a coup.[9] Once the ice is broken, more coups follow.[10] And once the structures of civilian authority and constitutional procedures are torn down, many years are required to rebuild them. This elevated coup propensity is consistent with the recent finding by Bienen and Van De Walle that African leaders who acquire power by extralegal

[3] Gary Zuk and William R. Thompson, "The Post-coup Military Spending Question: A Pooled Cross-Sectional Time Series Analysis," *American Political Science Review* 76 (March 1982), 60-74.

[4] Robert W. Jackman, "Politicians in Uniform: Military Governments and Social Change in the Third World," *American Political Science Review* 70 (December 1976), 1078-97; Rosemary O'Kane, "A Probabilistic Approach to the Causes of Coups d'Etat," *British Journal of Political Science* 11 (July 1981), 287-308; Rosemary O'Kane, "Towards an Examination of the General Causes of Coups d'Etat," *European Journal of Political Research* 11 (March 1983), 27-44; Pat McGowan and Thomas H. Johnson, "African Military Coups d'Etat and Underdevelopment: A Quantitative Historical Analysis," *Journal of Modern African Studies* 22 (December 1984), 633-66; Thomas H. Johnson, Robert O. Slater, and Pat McGowan, "Explaining African Military Coups d'Etat, 1960-1982," *American Political Science Review* 78 (September 1984), 622-40.

[5] Samuel P. Huntington, *Political Order in Changing Societies* (New Haven: Yale University Press, 1968), 41.

[6] Mancur Olson, "Rapid Growth as a Destabilizing Force," *Journal of Economic History* 23 (December 1963), 529-52.

[7] Martin C. Needler, "Political Development and Military Intervention in Latin America," *American Political Science Review* 60 (September 1966), 616-26, at 617.

[8] Huntington (fn. 5), 41.

[9] Finer (fn. 2).

[10] McGowan and Johnson (fn. 4), 639; O'Kane (fn. 4, 1983), 34.

means are more likely to be ousted than their legally appointed counterparts, at least during the first years of their rule.[11]

Despite the dramatic effect of economic performance on the probability of coups, the reverse is not true: a country's past coup history has little discernible effect on its economy. We find no evidence that either the recent history of coups or the current propensity for a coup d'état significantly affect the growth rate.

In section II, we describe the data used in this analysis. Section III provides a preliminary analysis of the interrelationships among coups, per capita income, and political instability. In section IV we subject the data to a parametric analysis that accounts for the joint endogeneity of coups and economic growth. Concluding remarks appear in section V.

II. The Data

Our political data are provided by *The World Handbook of Political and Social Indicators*;[12] the economic data were compiled by Summers and Heston.[13] The *World Handbook* provides annual political data for 148 countries during the period 1948-1982; Summers and Heston provide annual economic data for 130 countries between 1950 and 1985. After matching the two data sets, we are left with annual observations for 121 countries from 1950 to 1982. We do not include years prior to a country's independence; therefore our data for some countries begin after 1950. (For example, our first observation for Algeria is dated 1962.) The matched data set includes 3,036 observations; each consists of political and economic information for a given country during a particular year.

The political data include riots, elections, political executions, deaths from domestic political violence, successful irregular transfers of executive power (that is, successful coups), and unsuccessful attempts at irregular transfers of executive power (failed coups). The political variables were compiled for the *World Handbook* from published sources such as the *New York Times Index* and *Keesing's Contemporary Archives*. Some of

[11] Henry Bienen and Nicolas Van De Walle, "Time and Power in Africa," *American Political Science Review* 83 (March 1989), 19-34, at 26, 30.

[12] This information was made available by the Inter-University Consortium for Political and Social Research, Ann Arbor, MI. The data for the *World Handbook of Political and Social Indicators III, 1948-1982* (New Haven: Yale University Press, 1983), were originally collected by Charles Lewis Taylor. Neither the collector of the original data nor the Consortium bear any responsibility for the analyses or interpretations presented here.

[13] Robert Summers and Alan Heston, "A New Set of International Comparisons of Real Product and Prices: Estimates for 130 Countries, 1950-1985" *The Review of Income and Wealth* 34 (April 1988), 1-25.

these measures of political unrest undoubtedly suffer from serious underreporting: the South African government does not invite the press to hangings of political prisoners. The data on irregular transfers (coups) are quite reliable, however, as even critics of the use of the elite press as a source of political events data acknowledge.[14]

To measure income, we use real gross domestic product (GDP) per capita. Summers and Heston provide two measures of real income, one using "chain prices," the other reporting incomes in constant 1980 prices. Comparisons of real income across time and between developed and developing countries are hampered by differences in culture and technology.[15] Real GDP as measured in 1980 U.S. dollars has the advantage of expressing all values of real income in terms of a common base year: it is therefore the measure we have adopted. The 1980 measure of real GDP makes the inter-country, inter-year comparisons of real income easier to interpret; using the "chain price" as a measure yields essentially similar results.

For both measures of real income, Summers and Heston compute separate price deflators for consumption, investment, and government spending. To calculate real income per capita, they divide nominal GDP in each sector by the sector-specific price index and combine the resulting constant dollar values. They assert that this approach provides a more reliable indicator of real income then could be obtained by using a single price deflator.

III. Preliminary Data Analysis

Table 1 reports the means and standard deviations of the political and economic variables that form the basis of our analysis. This table indicates that riots, elections, and deaths from domestic political violence are common events; each occurs in about one-third of all country/years. Coups (whether successful or not) and political executions are less common; they occur in fewer than one-tenth of the country/years in our sample. The mean of real gross domestic product per capita is just under $3,000 measured in 1980 U.S. dollars, or about 27 percent of U.S. per capita GDP for 1980.

Table 2 reports the Pearson correlation coefficients between population, income, and six political variables: riots, unsuccessful coup at-

[14] Mort Rosenbloom, *Coups and Earthquakes: Reporting the World for America* (New York: Harper & Row, 1979).

[15] A cogent discussion of these issues in relation to the Summers and Heston data is contained in Robert E. Lucas, "On the Mechanics of Economic Development," *Journal of Monetary Economics* 22 (July 1988), 3-42, at 3-4.

TABLE 1
DESCRIPTION OF VARIABLES USED IN THE ANALYSIS

	Mean	*Standard Deviation*	*Non-zero Observation as a Fraction of Total Observations*
Population[a]	22.335	60.081	100.0%
Per capita income[b]	2,939.000	3,877.000	100.0%
Riots	2.705	8.861	34.6%
Failed coups	0.084	0.368	6.4%
Successful coups	0.060	0.282	5.1%
Elections	0.342	0.623	28.6%
Political executions	4.011	70.751	7.8%
Deaths from domestic political violence	1,046.681	27,250.329	33.2%

[a] In millions
[b] In 1980 US dollars

tempts, successful coups, elections, political executions, and deaths from domestic political violence. The entries above the diagonal are the zero-order Pearson correlation coefficients; second-order correlation coefficients among the political variables (controlling for per capita income and population) appear below the diagonal. Standard errors appear in parentheses; they were calculated using Efron's bootstrap technique,[16] with 1,024 replications. This procedure allows us to estimate the probability distribution of the correlation coefficients; it does not impose an a priori distribution.

Per capita income exhibits a negative correlation with coup attempts (successful or otherwise) and with two of our other measures of political instability: political executions and deaths from domestic political violence. It is positively correlated with elections and, to a statistically insignificant extent, with riots.

Because coups, deaths from domestic political violence, and political executions are all negatively correlated with income, there is a danger that the positive correlations among these variables may be spurious. To avoid such an error, we examine the partial correlations among these variables, controlling for population and income (entries below the diagonal in Table 2).

The correlation of coups with riots and political executions remains positive even after correcting for the common influences of income and

[16] Bradley Efron, "Bootstrap Methods: Another Look at the Jack-Knife," *Annals of Statistics* 7 (January 1979), 1-26.

TABLE 2

CORRELATION COEFFICIENTS BETWEEN POPULATION, INCOME, AND POLITICAL VARIABLES[a]

	Population	*Per Capita Income*[a]	*Riots*	*Failed Coups*	*Successful Coups*	*Elections*	*Political Executions*	*Deaths from Domestic Political Violence*
Population	1.000	−0.008	0.348	−0.042	−0.029	0.083	0.000	0.029
		(0.015)[b]	(0.037)	(0.005)	(0.006)	(0.024)	(0.004)	(0.008)
Per capita income	·	1.000	0.029	−0.068	−0.090	0.107	−0.021	−0.024
			(0.018)	(0.011)	(0.007)	(0.019)	(0.007)	(0.005)
Riots	·	·	1.000	0.103	0.066	0.094	0.018	0.016
				(0.041)	(0.020)	(0.024)	(0.017)	(0.020)
Failed coups	·	·	0.138[c]	1.000	0.183	0.004	0.070	0.023
			(0.040)		(0.038)	(0.016)	(0.031)	(0.036)
Successful coups	·	·	0.094	0.194	1.000	0.001	0.075	0.016
			(0.020)	(0.038)		(0.016)	(0.033)	(0.026)
Elections	·	·	0.081	0.045	0.043	1.000	0.028	−0.020
			(0.025)	(0.016)	(0.016)		(0.029)	(0.004)
Political executions	·	·	0.022	0.074	0.078	0.038	1.000	0.004
			(0.017)	(0.031)	(0.033)	(0.029)		(0.014)
Deaths from domestic political violence	·	·	0.008	0.026	0.018	−0.015	0.004	1.000
			(0.020)	(0.035)	(0.026)	(0.003)	(0.014)	

[a] Standard errors are shown in parentheses.
[b] The entries above the diagonal are zero-order Pearson correlation coefficients.
[c] The entries below the diagonal are second-order Pearson correlations controlling for per capita income and population.

population. The correlation between successful coups and deaths from domestic political violence remains insignificant, and the correlation between coups and elections becomes significantly positive (although small) once the effects of population and income are controlled for.

The pattern of partial correlations between successful coups and the other political variables is almost identical to the corresponding pattern for failed coups. This is not surprising; in view of the penalties for failure, we may expect that coup participants will set their plans in motion only when they expect to succeed.

Table 3 shows that the relationship between successful coups and per capita income is nonlinear. The incidence of coups is approximately constant among countries in the three lowest quintiles of income for our sample (up to per capita income of about $2,300 measured in 1980 U.S. dollars). At income levels above $2,300, the incidence of coups drops off dramatically. The coup rate for countries in the highest income quintile (above $4,800) is only about 0.3 percent per year, or twenty-one times lower than the average for the three lowest quintiles.

A notable feature of Table 3 is that high income seems to inhibit successful coups more effectively than it does failed coups. This may be the result of reporting bias: in poor countries, some failed coup attempts may not be reported. Although we are confident that few successful coups go unreported, we are less sure of the data on coup *attempts*. Reporting bias

TABLE 3
INCIDENCE OF POLITICAL EVENTS BY INCOME QUINTILE

	Percentage of Observations with at Least One Occurrence of					
Quintile of per Capita Income	*Successful Coup*	*Failed Coup*	*Riot*	*Death from Domestic Political Violence*	*Election*	*Political Execution*
1. Less than $575	7.4	6.3	26.9	35.0	16.9	12.9
2. Between $575 and $1,079	7.3	10.2	30.4	34.3	24.8	8.3
3. Between $1,079 and $2,294	7.3	8.8	41.2	42.2	29.5	7.5
4. Between $2,294 and $4,804	3.1	5.4	41.4	32.7	32.7	8.3
5. At least $4,805	0.3	1.5	33.3	22.2	38.9	2.3
Overall	5.1	6.4	34.6	33.2	28.6	7.8

is not the only problem; another one is the very definition of the term "failed coup attempt." As Needler put it, "The categories of coups that were aborted, suppressed, or abandoned melt into each other and into a host of other non-coup phenomena so as to defy accounting."[17]

The economic variables have a much stronger effect than the political variables. For example, among the political variables, unsuccessful coups have the strongest association with successful coups: the probability of a successful coup, conditional on a failed coup occurring in the same year, is four times the unconditional mean probability. The influence of income on the probability of a coup is much more dramatic: the conditional probability of a coup where per capita GDP is in the highest quintile of the sample (i.e., in excess of $4,805) is only one-fifteenth of the unconditional probability.

The inverse relationship between income and the coup propensity in Table 3 is a mirror image of the positive correlation described by Lipset between income and democratic stability. Lipset relied upon GNP per capita in 1949, as calculated by the UN statistical office. We reconstruct his analysis using Summers and Heston's real GDP measures for 1950, the earliest year for which they are available. Lipset calculated mean incomes for four groups of countries, classified by the degree to which they enjoyed a democratic political culture.[18]

Using the countries within Lipset's classes for which Summers and Heston's data are available, we find that the average incomes during 1950, as measured in constant 1980 U.S. dollars, were: $4,284 for "European and English-Speaking Stable Democracies"; $2,210 for "European and English-Speaking Unstable Democracies and Dictatorships"; $1,719 for "Latin American Unstable Democracies and Dictatorships"; and $1,249 for "Latin American Stable Dictatorships." The means of all categories except European and English-Speaking Stable Democracies (which is near the top of the fourth quintile) fall into the middle quintile of per capita income for our sample. This suggests that the level of income at which the incidence of coups begins to decline is about the same as that identified by Lipset as the level at which "stable democracy" emerges.

The two variables that are central to the remainder of our analysis, coups and per capita incomes, exhibit considerable interregional heterogeneity. Region-specific means for the annual coup probability, the an-

[17] Needler (fn. 7), 617.

[18] Seymour Martin Lipset, "Some Social Requisites of Democracy: Economic Development and Political Legitimacy," *American Political Science Review* 53 (March 1959), 69-105, at 75-77.

nual growth rate of per capita income, and the level of per capita income are shown in Table 4. South America has the highest rate of coups, followed by Africa (the poorest and slowest-growing region). Europe/North America (the richest region), and Oceania have the lowest coup rates. These interregional comparisons are broadly consistent with the negative association between income and coups indicated in Table 3. However, the high rate of coups in South America does not seem entirely attributable to low income or slow growth: the countries of Africa are poorer and have slower rates of growth, but experience a lower rate of coups.

TABLE 4
SELECTED STATISTICS BY REGION, 1950

	Fraction of Observations with at least one Coup d'Etat	*Annual Per Capita Income Growth Rate*	*Per Capita Income (1980 U.S.$)*
South America	12.7%	1.8%	2,157
Africa	7.8%	1.3%	612
Central America and the Caribbean	6.6%	1.8%	1,678
Asia	5.9%	2.9%	1,702
Europe and North America	1.4%	3.3%	4,826
Oceania	1.0%	2.2%	3,311

The pronounced negative association between coups and high income is consistent with the findings of some authors that—controlling for various political variables—a weak economy makes coups more likely.[19] This leaves several questions unanswered: Do coups cause poor economic performance, or does poor economic performance cause coups? What is the effect of political instability, in the form of coups d'état, on the *rate* of economic growth, controlling for the *level* of economic attainment? What explains the high rate of coups in South America despite that region's relatively advanced economic development? In section IV, we construct a parametric framework in which we assess the nature and degree of feedback between coups and economic performance. The parametric approach also enables us to distinguish between the effects of the level of income and the rate of income growth, and to incorporate the aftereffects of past coups into our analysis.

[19] Jackman (fn. 4), 1084; O'Kane (fn. 4, 1983), 34; Johnson, Slater, and McGowan (fn. 4), 635; McGowan and Johnson (fn. 4), 658.

IV. Parametric Analysis

We begin our analysis by constructing a probit model of coups. This model reveals that poverty and a past history of coups significantly increase the risk that a coup will occur. Rapid growth does not emerge as a source of coups: to the extent that it matters independently of the *level* of income, the *rate* of income growth is coup-*inhibiting*.

The relationship between coups and income raises the question: Does low income cause coups, or is it the other way around? To find the answer, we employ a simultaneous equations framework that allows for the joint endogeneity of coups and income. The model we have constructed indicates that disturbances to the GDP growth equation are correlated with shocks to the coup equation. Unanticipated low growth is associated with an elevated coup probability. It appears to be easier for the military to seize power when the current government is doing badly than when it is doing well. The aftereffects of a successful coup, however, are felt for many years in the form of a heightened risk of yet further coups.

A. A Model of Coups

From a data-analytic point of view, coups are a discrete phenomenon; there is no such thing as a "half a coup." To account for the all-or-nothing nature of coups, we use a probit model to analyze their occurrence. In this model, there is an underlying propensity to have a coup during year t in country i. We denote this propensity as z^*_{it}. When z^*_{it} is positive, at least one successful coup occurs; when it is negative or zero, there is no successful coup. We let δ_{it} denote the indicator variable for a successful coup. If at least one successful coup occurs during year t in country i, $\delta_{it} = 1$; otherwise $\delta_{it} = 0$.

The model is completed by specifying the process that generates z^*_{it}. Here we assume that it is of the form:

$$z^*_{it} = \mathbf{x}'_{it}\theta - \eta_{it} \qquad (1)$$

where the disturbance term is normally distributed with zero mean and variance σ^2_η. In latent variable models of this type, one can identify the θ parameter only up to a factor of proportionality, namely $1/\sigma_\eta$. We follow the usual custom by imposing the convenient but arbitrary normalization $\sigma_\eta = 1$. The vector $\mathbf{x}_{it}$ consists of variables that are predetermined with respect to z^*_{it} during year t in country i.[20] These variables may include

[20] Robert F. Engle, David F. Hendry, and Jean-François Richard, "Exogeneity," *Econometrica* 51 (March 1983), 277-304, at 280.

time-varying regressors, such as past values of per capita GDP, as well as fixed regressors, such as variables that indicate geographic region.

We begin with a distributed lag model in which the latent coup propensity depends solely upon the occurrence of previous coups:

$$z^*_{it} = \theta_0 + \sum_{s=1}^{T} \theta_s c_{it-s} - \eta_{it} \tag{2}$$

where c_{it} denotes the number of coups that actually occurred in country i during year t. Equation (2) specifies that the propensity for a coup to occur during the current year depends upon the number of coups in each of the preceding T years. In this model, the effects of a past coup depend on the time that has elapsed since its occurrence. The parameter θ_s represents the impact of a coup that occurred s years ago on the current propensity for a coup. The error term in equation (2) is serially uncorrelated and homoscedastic.

In principle, we would like to make T as large as possible and place no additional restrictions on the θ_s terms. As a practical matter, we have only 3,036 observations, with no more than 33 consecutive annual observations for any given country. It is therefore impossible for us to estimate the impact of coups that lie more than thirty-two years in the past. Moreover, we observe complete thirty-three-year histories for only 48 of the 119 countries in our data set. The median country contributes 24 observations. Thus, if we required complete T-year histories to estimate equation (2), we would have to discard most of our data if T were large. For instance, only 414 of our 3,036 observations include complete twenty-four-year coup histories; so, for $T = 24$, we could use only 14 percent of our data. An alternative to this approach would be to impose hypothesized values for the pre-sample coup histories. We could set $c_{it} = 0$ for all pre-sample values of t. Although this approach seems sensible for newly independent countries, it is less appealing for countries that were independent for a long time prior to 1948, such as Argentina, which gained independence in 1816, or Bolivia, which has been independent since 1825.

To operationalize the model, we set $T = 13$. Half of our observations (1,524 data points) contain complete thirteen-year histories. Our choice of T enables us to examine possible time dependence in the coup process over more than a decade while still leaving us with a relatively large number of observations. Column one of Table 5 reports the parameter estimates for equation (2). We see that the estimated impact coefficients are, with one exception (the fourth lag), positive and significant up to six years into the past; moreover, with one exception (the ninth lag), they are individually insignificant beyond six years.

Table 5
The Effect of Past Coups and Recent Independence on the Likelihood of a Current Coup[a]

	Equation (2)	Equation (3)	Equation (4)	Equation (4) (revised)
Intercept	−1.926	−1.909	0.825	−1.926
	(0.086)	(0.084)	(4.033)	(0.100)
Coup History				
Recent coups				
Most recent 6 years		0.261	0.263	0.262
		(0.058)	(0.059)	(0.059)
Distant coups		0.128	0.132	0.125
More than 6 years past		(0.055)	(0.055)	(0.055)
Coups lagged 1 year	0.406			
	(0.145)			
Coups lagged 2 years	0.365			
	(0.160)			
Coups lagged 3 years	0.375			
	(0.138)			
Coups lagged 4 years	−0.351			
	(0.302)			
Coups lagged 5 years	0.316			
	(0.137)			
Coups lagged 6 years	0.289			
	(0.154)			
Coups lagged 7 years	0.179			
	(0.181)			
Coups lagged 8 years	0.043			
	(0.129)			
Coups lagged 9 years	0.458			
	(0.136)			
Coups lagged 10 years	0.141			
	(0.159)			
Coups lagged 11 years	−0.060			
	(0.201)			
Coups lagged 12 years	−0.277			
	(0.276)			
Coups lagged 13 years	0.274			
	(0.201)			
Recent Independence				
Age (since independence)			−0.016	
			(0.138)	
Age^2			−0.404	
			(0.598)	
Age^3			0.020	
			(0.028)	
Post-1950 independence			−0.0003	0.050
			(0.0004)	(0.117)
Log of the likelihood function	−259.007	−268.332	−267.008	−268.245

[a] Standard errors are shown in parentheses.

A more parsimonious representation of the coup data is provided by model (3), in which the error term is serially uncorrelated and homoscedastic:

$$z_{it}^* = \gamma_0 + \gamma_1 \sum_{s=1}^{L} c_{it-s} + \gamma_2 \sum_{s=L+1}^{T} c_{it-s} - \eta_{it} \tag{3}$$

In this model, all recent coups (those that occurred within the past L years) have a common effect, measured by γ_1 on the coup propensity; γ_2 measures the common effect of coups in the more distant past (those that occurred between $L + 1$ and T years ago). Because the estimated individual impact coefficients become individually insignificant after six lags, we set $L = 6$, and estimate model (3). The resulting parameter estimates are reported in column two of Table 5.

A model in which the aftereffects of a coup decay geometrically is also estimated:

$$z_{it}^* = \theta_0 + \theta_1 \sum_{s=1}^{T} \beta^s c_{it-s} + \eta_{it}$$

According to this model, a coup occurring $s + 1$ years in the past has β^s times the impact of a coup occurring last year. The estimated β is 0.89, indicating that the aftereffect of coups wears off geometrically with a half-life of about six years. The log of the likelihood functions is essentially the same for both model (3) and this model.

Model (3) provides a parsimonious representation of the coup data while preserving the overall fit of the model. However, the change in the log of the likelihood function (which falls by only 9.33 as a result of 11 independent restrictions) cannot form the basis of a classical hypothesis test because the parameter consolidation embodied in model (3) is informed by previous examination of the data.

A key implication of model (3) is that a past history of coups makes further coups more likely. The impact coefficients for recent coups, γ_1, and for coups in the more distant past, γ_2, are significant and positive; though recent coups have a greater impact on the current propensity to a coup.

It has been suggested that recent independence inhibits coups.[21] To test the hypothesis that newly independent countries are at a reduced risk of a coup, we extend the specification of equation (3) by incorporating the amount of time elapsed since independence into equation (4). Because the effect of time since independence may be nonlinear, we add

[21] O'Kane (fn. 4, 1981), 289-96.

a cubic polynomial in this variable, a_{it}. That is, we estimate a separate coefficient for a_{it}, a_{it}^2, and a_{it}^3. We also add an indicator, a_i, which takes on a value of 1 if country i gained autonomy after 1950; otherwise it equals 0. This yields the following equation:

$$z_{it}^* = \delta_0 + \delta_1 \sum_{s=1}^{L} c_{it-s} + \delta_2 \sum_{s=L+1}^{T} c_{it-s} + \delta_3 a_{it} + \delta_4 a_{it}^2 + \delta_5 a_{it}^3 + \delta_6 a_i + \eta_{it} \quad (4)$$

Estimates of equation (4) are reported in column three of Table 5. The hypothesis that the effects of newly gained independence are constant corresponds to $\delta_s = 0$ for $s \in \{3, 4, 5\}$. To test this hypothesis, we reestimate the model, omitting the a_{it} terms. This amounts to imposing three independent restrictions on model (4) and implies that the effects of post-1950 independence, as measured by δ_6, are constant over time. These estimates are reported in column four of Table 5.

The likelihood ratio test statistic for the null hypothesis of no change has an asymptotic χ_3^2 distribution. The test statistic assumes a value of 2.47, corresponding to a p-value of 0.480. At the $\alpha = 0.05$ significance level, this indicates acceptance of the null hypothesis that the effects of recent (that is, post-1950) independence do not change over time. Moreover, the estimates of the restricted version of equation (4) reported in column four of Table 4 indicate that recent independence has no effect at all. The impact of post-1950 independence on the coup propensity is measured by δ_6. Our estimate of this parameter is smaller than its standard error. Although the "recent independence" effect is discussed at length in the literature, our data do not suggest that, controlling for a country's past history of coups, post-1950 independence makes a country any more or less disposed toward a coup.

We complete our analysis of coups by adding past economic performance and regional indicator variables to our model:

$$z_{it}^* = \lambda_0 + \lambda_1 (\sum_{s=1}^{6} c_{it-s}) + \lambda_2 (\sum_{s=7}^{T} c_{it-s}) + \lambda_3 y_{it-1} + \lambda_2 \Delta y_{it-1} + \sum_{j=5}^{9} \lambda_j r_{ij} - \eta_{it} \quad (5)$$

where y_{it-1} denotes the log of per capita income in country i during year $t-1$, Δy_{it-1} is the change in the log of per capita income between $t-2$ and $t-1$, and r_{ij} is a zero/one variable that indicates whether country i is located in region j. For example, in the case of Algebra, the indicator for Africa assumes a value of 1, while all other region indicators are set to 0.

The parameter λ_1 measures the cumulative impact of coups during the recent past (no more than six years ago) on the current coup propensity; λ_2 measures the aftereffects of coups in the more distant past; λ_3 measures the impact of the previous period's level of per capita income; and λ_4 measures the effects of the last period's growth. The remaining parameters measure regional effects: λ_5 measures the effect of location in Africa; λ_6 and λ_7 measure the effects of location in Europe/North America and in South America, respectively; λ_8 and λ_9 measure the effects of location in the Caribbean/Central America and in Oceania respectively. The Asia effect is subsumed into the intercept term, λ_0.

To estimate model (5), we use all 2,798 observations for which complete two-year histories are available. The resulting estimates appear in column one of Table 6. The effect of the last period's income as measured by λ_3 is consistent with the results in the preceding section; income has a large and statistically significant coup-inhibiting effect. All else being equal, for a country at the sample mean, a doubling of per capita income leads to a 37.4 percent reduction in the annual probability of a coup, from 0.0615 to 0.0385. The average probability of a coup in our subsample of 2,798 observations for which two-year histories are available is 0.0615, slightly higher than the 0.0507 mean probability for the entire sample of 3,036.

The estimated parameters for this model also include some surprises. For example, the estimated coefficient of the last period's growth rate, λ_4, is imprecisely estimated and insignificant. Several of the region-specific coefficients are also insignificant. Notably, the coefficient estimated for Africa differs insignificantly from zero. African countries are more susceptible to coups because they are poor, not because they are African.[22]

The only regional effect that is significant is that for South America. Many South American countries became independent well before 1950, however, and are notorious for having suffered coups during the 1930s and 1940s.[23] Thus, the "South America effect" may really be the aftereffect of coups occurring before 1950. An adequate resolution of this question will require collection of pre-1950 coup data for the countries that were independent at the beginning of our sample period.

As indicated by the significant and positive coefficient for recent coups, a past history of successful coups puts a country at greater risk of yet further coups. This past-coup effect, however, appears to wear off with the passage of time. This comports with the recent finding of Bienen and Van De Walle that African leaders who acquire power by

[22] McGowan and Johnson (fn. 4), 652-60.

[23] Cf. the discussion in Finer (fn. 2), 154-57, in which he describes the specialized Spanish vocabulary developed in Latin America for coups d'état.

TABLE 6
PARAMETER ESTIMATES FOR MODELS (5) AND (7)[a]

	Dependent Variable	
	Coup d'Etat[b]	*Change in per capita GDP*[c]
Intercept	0.878 (0.608)	0.074 (0.012)
Recent coups	0.181 (0.046)	0.0004 (0.0015)
Past coups	0.040 (0.034)	−0.003 (0.001)
Last period's (log of) per capita income	−0.374 (0.087)	−0.007 (0.002)
Last period's growth rate	−1.000 (0.651)	0.168 (0.019)
Africa	−0.145 (0.136)	−0.018 (0.004)
Europe and North America	0.002 (0.188)	0.012 (0.004)
South America	0.575 (0.148)	−0.004 (0.004)
Central America and Caribbean	0.135 (0.156)	−0.007 (0.004)
Oceania	−0.385 (0.474)	0.002 (0.006)
Number of observations	2,798	2,798
Log of the likelihood function	−510.502	3894.0985
r-square		0.172
Standard error of the estimate		0.057

[a] Standard errors are shown in parentheses.
[b] Estimated by probit.
[c] Estimated by ordinary least squares.

extralegal means stand at increased risk of losing power during the first two years of their rule.[24] Further research by Bienen and Van De Walle, based on a larger sample of leaders, indicates that, although nonconstitutional entry places leaders at greater risk of losing power during the beginning of their rule, this risk falls over time. Beyond four years, the risk of losing power is actually lower for them than for leaders who acquire power by constitutional means.[25] This finding aligns with the

[24] Bienen and Van De Walle (fn. 11), 30-31.
[25] Bienen and Van De Walle, "Of Time and Power," mimeo (Princeton: Princeton University, 1989), chap. 5, pp. 24 and 25, and Table 8.

insignificant coefficient in Table 6 for coups that occurred more than six years in the past.

Our model of coups is constructed "from the ground up," beginning with a simple autoregressive model of coups, and then adding economic and regional variables. This method raises the concern that our results might have been different if we had first estimated model (5), which includes regional and economic variables, and *then* tested (a) O'Kane's recent independence hypothesis; and (b) our restrictions on the lag structure of coups. For example, the results of the test of O'Kane's hypothesis could differ due to correlation between omitted economic and regional variables, on the one hand, and age since independence, on the other.

To guard against the possibility that our results might be an artifact of bias created by omitted variables, we reran our tests including the economic and regional variables. Even though this procedure does not constitute an independent set of tests, it is reassuring to know that the results did not change. The alternative approach did not uncover evidence of any "new independence" effect; nor did the restriction of the lag structure for coups to "recent coups" and "coups in the more distant past" lead to significant erosion of the goodness of fit. To be specific, the likelihood ratio test of the null hypotheses that the "new independence effect" is constant over time (zero coefficients for a_{it}, a_{it}^2, and a_{it}^3), and that there is no "new independence effect" (a coefficient of zero for a_i) were 6.073 and 0.487 respectively, generating p-values of 0.194 and 0.485, which indicate acceptance at all conventional levels.

B. A Model of Income

The dependence of coups on income raises the important question whether low income can be said to cause coups or whether coups cause poor economic growth. The parameter estimates in column one of Table 6 certainly indicate that income "Granger-causes" coups,[26] in the sense that including both past income and a country's past history of coups among the explanatory variables improves the fit obtained when only lagged coups are included in the model. In order to learn about the contemporaneous effect of coups on growth and of growth on coups, however, we must construct a model that accounts for joint endogeneity of economic growth and coups d'état.

A necessary first step toward such a model is the construction of a simple model of per capita GDP. Since it is known that output is strongly correlated over time, we fit an autoregressive model of per capita GDP

[26] C.W.J. Granger, "Investigating Causal Relations by Econometric Models and Cross-Spectral Methods," *Econometrica* 37 (July 1969), 424-38; Engle, Hendry, and Richard (fn. 20), 280.

$$\Delta y_{it} = \alpha_0 + \alpha_1 y_{it-1} + \sum_{j=1}^{T-1} \alpha_{j+1} \Delta y_{it-j} + \epsilon_{it} \tag{6}$$

where y_{it} is the natural logarithm of per capita GDP during year t for country i, and Δy_{it} is the change in per capita GDP in country i between year $t-1$ and year t.

Notice that equation (6) is algebraically equivalent to the "levels" specification

$$y_{it} = \beta_0 + \sum_{j=1}^{T} \beta_j y_{it-j} + \epsilon_{it}$$

where $\beta_0 = \alpha_0$, $\beta_1 = 1 + \alpha_1 + \alpha_2$, $\beta_j = \alpha_{j+1} - \alpha_j$, for $1 < j < T$, and $\beta_T = -\alpha_T$. Because per capita income exhibits a high degree of serial persistence, this specification yields falsely reassuring values of R^2 (above 0.99), whereas the challenge is to predict the change of per capita income. Accordingly, we have chosen to work with equation (6).

We obtain an adequate representation of the process generating per capita income by setting $T = 2$. The likelihood ratio test statistic against inclusion of Δy_{it-2} is 2.4652, well below the 5 percent asymptotic critical value of 3.84. The errors from our estimates of equation (7) generated a Durbin-Watson statistic of 1.9805 and a first-order autocorrelation of 0.0059, with a standard error of 0.0566. These results indicate that there is no correlation remaining in the residuals. This precludes our having to use instrumented estimates of Δy_{it-1}, a procedure employed by Zuk and Thompson to study the impact of coups on military spending.[27]

Because our data are a cross section of time series, we can employ standard techniques to test the null hypothesis of a zero coefficient for y_{it-1} despite the nonstationarity of the GDP process under this hypothesis. If we had only a single long time series, the coefficient of y_{it-1} would not be asymptotically normally distributed, and we would have to resort to alternative testing procedures.[28]

Next, we consider a model that incorporates the effect of other predetermined variables, such as a country's past experience with coups, and regional indicator variables introduced in the analysis of the coup propensity in the preceding subsection; namely

$$\begin{aligned}\Delta y_{it} = \beta_0 + \beta_1\left(\sum_{s=1}^{6} c_{it-s}\right) + \beta_2\left(\sum_{s=7}^{32} c_{it-s}\right) + \beta_3 y_{it-1} \\ + \beta_4 \Delta y_{it-1} + \sum_{j=5}^{9} \beta_j r_{ij} + \epsilon_{it}\end{aligned} \tag{7}$$

[27] Zuk and Thompson (fn. 3), 65.

[28] David A. Dickey and Wayne A. Fuller, "Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root," *Econometrica* 49 (July 1981), 1057-72.

Estimated parameter values for this model appear in column two of Table 6. Recent coups have a statistically insignificant coefficient, but coups in the distant past have a slight, statistically significant growth-inhibiting effect. However, we lack a convincing explanation for the delayed emergence of economic aftershocks with such a long lag.

Lagged income has a small growth-inhibiting effect. All else being equal, per capita income grows at a slower rate in wealthy countries than in poor ones, as would be the case if there were decreasing returns to scale in the growth technology. Barro also estimates a small but significant negative coefficient for per capita income in an income-growth equation for a cross section of countries.[29] As a check against the possibility that the small negative coefficient of y_{it-1} is merely the product of short-sample bias,[30] we reestimate our model using only countries for which we have data for all thirty-three years of the sample period. The degree of short-sample bias will be reduced in this subsample. Yet, even in this subsample of countries, the coefficient of y_{it-1} remains significantly negative.

The regional indicators play a significant role in our model. In general, African countries have substantially slower rates of growth than Asian countries.[31] Central America and the Caribbean are also plagued by slow growth. Western Europe and North America grow somewhat more rapidly (controlling for their high per capita incomes) than the Asian countries. The significance of the regional indicators suggests that there may be interregional heterogeneity among the other parameters of our model. This question is addressed in the context of the joint model we develop in the next section.

A theoretical case can be made for including population and population growth among the explanatory variables in the growth equation.[32] When we estimate population growth and income growth as a system of Seemingly Unrelated Regression Equations[33] we find that shocks to the population-growth and income-growth equations are correlated (we estimate $\rho = -0.092$). However, the coefficients of lagged population and lagged population growth are insignificant in the GDP growth equation.

[29] Robert J. Barro, "A Cross-Country Study of Growth, Saving, and Government," *National Bureau of Economic Research Working Paper Series* 2855 (February 1989), 27.

[30] See F.H.C. Marriott and J. A. Pope, "Bias in the Estimation of Autocorrelations," *Biometrika* 41 (December 1954), 390-402; and M. G. Kendall, "Note on Bias in the Estimation of Autocorrelation," *Biometrika* 41 (December 1954), 403-4.

[31] McGowan and Johnson (fn. 4), 655.

[32] Barro (fn. 29), 12-17.

[33] See A. C. Harvey, *The Econometric Analysis of Time Series* (Oxford: Phillip Allan, 1981), 67-73, for a discussion of Seemingly Unrelated Regression Equations.

C. A Simultaneous Model of Coups and Income

Our attention now turns to the construction of a model that accounts for the joint endogeneity of income growth and the propensity for a coup d'état. Because the coup variable is discrete, we cannot imbed this analysis in a standard simultaneous equations framework. Instead, we use a latent variable model pioneered by Heckman.[34] In this model, the discrete variable—in our case an indicator for whether a coup occurs—is generated by a continuous latent variable crossing a threshold, as in the probit model analyzed at the beginning of this section. Unlike the probit model, Heckman's framework accounts for the simultaneity of continuous and discrete variables; in our case, these are the current rate of growth of income and the occurrence of a coup, respectively.

As in the previous section, we let Δy_{it} denote the first difference in the natural logarithm of per capita income (as measured by gross domestic product) in country i between years $t-1$ and t; $\Delta y_{it} = y_{it} - y_{it-1}$. As before, we define z_{it}^* as the propensity of country i to have a coup during year t, while $\delta_{it} \in \{0,1\}$ is an indicator variable that assumes a value of 1 if a coup occurs in country i during year t; if not, it is equal to zero. The occurrence of a coup d'état, δ_{it}, and the propensity for a coup, z_{it}^*, are linked by the following relationship: $\delta_{it} = 1$ if $z_{it}^* > 0$, and $\delta_{it} = 0$ if $z_{it}^* < 0$. In other words, whenever z_{it}^* exceeds zero, a coup occurs; otherwise, there is no coup.

In this model, the propensity for a coup and the rate of economic growth are jointly determined by a pair of simultaneous equations of the following form:

$$\Delta y_{it} = \mathbf{x}_{1it}\boldsymbol{\alpha}_{11} + \mathbf{x}_{wit}\boldsymbol{\alpha}_{1w} + z_{it}^*\gamma_1 + u_{1it} \tag{8a}$$
$$z_{it}^* = \mathbf{x}_{wit}\boldsymbol{\alpha}_{2w} + \mathbf{x}_{2it}\boldsymbol{\alpha}_{22} + \Delta y_{it}\gamma_2 + u_{2it} \tag{8b}$$

According to this specification, the current growth rate, Δy_{it}, is systematically affected by the current coup propensity, z_{it}^*, as well as some predetermined variables, $\mathbf{x}_{1it}$ and $\mathbf{x}_{wit}$.[35] Similarly, the model allows for a direct impact on the coup propensity of the current growth rate (measured by γ_2), as well as another (potentially different) set of predetermined variables, $\mathbf{x}_{wit}$ and $\mathbf{x}_{2it}$. A key feature of this specification is the potential exclusion of a subset of k_1 variables, $\mathbf{x}_1$, from the coup equation, and another subset, consisting of k_2 variables, $\mathbf{x}_2$, from the GDP growth equation. The error terms (u_{1it} and u_{2it}) are distributed according to a

[34] James J. Heckman, "Dummy Endogenous Variables in a Simultaneous Equation System," *Econometrica* 46 (July 1978), 931-59.

[35] Using the definition given by Engle, Hendry, and Richard (fn. 20), 280.

bivariate normal probability distribution with zero mean, and a variance-covariance matrix Ω (whose i,j^{th} element we denote ω_{ij}).

Equations (8a) and (8b) depart from the univariate models of the preceding sections in two important ways. First, they allow for correlation of the disturbance terms of the coup and growth equations. Second, they allow for simultaneous feedback between the coup propensity and the rate of growth.

The first question to be addressed in this framework is whether either series is predetermined with respect to the other.[36] If the error terms are correlated with one another, this will not be the case. If income growth were predetermined with respect to coups, we could consistently estimate its impact by simply including it among the explanatory variables in the coup equation (as has been done by others).[37] In the absence of predeterminedness, however, estimates that treat income as an exogenous variable on the right-hand side of a coup equation (or coups as an exogenous variable on the right-hand side of an income-growth equation) will be biased.

Failure of coups and income to be predetermined with respect to one another may simply be a result of common shocks to both processes. For example, an unsuccessful foreign war may hobble economic growth and simultaneously precipitate a coup d'état. By contrast, lowered income may trigger a coup directly rather than merely stem from a common cause. Our model allows for more direct feedback between the two processes via the parameters γ_1 and γ_2, and includes previous coups and lagged income among the predetermined variables in each equation.

Ideally, we would like to include all of the right-hand side variables from the stand-alone coup model, equation (5), and the stand-alone income-growth model, equation (7), in both the coup and income-growth equations of our simultaneous system. However, if we do so, we will fail to identify the model fully.[38]

One means of identifying the model is to impose the restrictions $\gamma_1 = 0$ and $\gamma_2 = 0$. Identification can also be achieved by excluding from the coup equation at least one predetermined variable that appears in the growth equation, and excluding from the growth equation at least one predetermined variable that appears in the coup equation (e.g., setting $k_1 \geq 1$, and $k_2 \geq 1$). In order to *test* our model, we require at least one

[36] *Ibid.*

[37] Jackman (fn. 4); O'Kane (fn. 4, 1981 and 1983); McGowan and Johnson (fn. 4); Johnson, Slater, and McGowan (fn. 4).

[38] Thomas J. Rothenberg, "Efficient Estimation with a priori Information," *Cowles Foundation Monograph* 23 (New Haven: Yale University Press, 1973), provides a comprehensive discussion of identification in models with endogenous explanatory variables.

overidentifying restriction in addition to the two restrictions needed to identify the model fully.

Fully efficient estimates of equations (8a) and (8b) can be obtained by using the joint two-stage Amemiya's Generalized Least Squares (AGLS) estimation method, which is shown by Newey to be asymptotically equivalent to Full Information Maximum Likelihood estimation (FIML).[39] This procedure requires that we first estimate a reduced-form version of (8a) and (8b) in which all of the exogenous right-hand side variables are included in both equations.

$$\Delta y_{it} = x_{1it}\pi_{11} + x_{wit}\pi_{1w} + x_{2it}\pi_{12} + v_{1it} \tag{9a}$$
$$z^*_{it} = x_{1it}\pi_{21} + x_{wit}\pi_{2w} + x_{2it}\pi_{22} - v_{2it} \tag{9b}$$

Because we cannot observe the coup propensity directly, but only whether it is positive, we can identify the parameters of the model only up to a factor of proportionality. To identify the model, we impose an arbitrary but convenient normalization of the variance of the disturbance term (u_{2it}) in the coup equation (8b):

$$\omega_{22} = 1 - 2\gamma_1\gamma_2 + \gamma_1^2\gamma_2^2 - \gamma_2^2\omega_{11} - 2\gamma_2\omega_{12}$$

This normalization is convenient because it implies that the variance of v_{2it} in equation (9b) equals 1; namely, $\sigma_{22} = 1$. After the reduced-form equations are estimated by maximum likelihood, the structural parameters of equations (8a) and (8b)—α_{11}, α_{1w}, α_{2w}, α_{22}, γ_1, and γ_2—are recovered from the reduced-form parameters using Newey's version of the AGLS procedure.[40] Estimates of the standard error of the disturbance term of the income-growth equation, and the correlation between the disturbances to the income-growth equation and the coup equation, emerge directly from the estimation of the reduced-form equations and are not conditional on the restrictions used to identify the parameters of the structural model.

Estimates of the parameters of the reduced-form model appear in Table 7. The correlation coefficient between the two shocks has an estimated value of 0.1323, and is almost three times as large as its standard deviation. This indicates rejection of the null hypothesis that the shocks are uncorrelated at all standard significance levels. As discussed above, correlation between the shocks implies that coups cannot be treated as predetermined in the income equation, nor is income predetermined for

[39] Whitney K. Newey, "Efficient Estimation of Limited Dependent Variable Models with Endogenous Explanatory Variables," *Journal of Econometrics* 36 (November 1987), 231-50.

[40] *Ibid.* See Appendix.

TABLE 7
JOINT MAXIMUM LIKELIHOOD ESTIMATION OF THE REDUCED FORM EQUATIONS[a]

Dependent Variable	*Coups d'Etat*		*Change in per capita GDP*
Intercept	0.866 (0.427)		0.076 (0.013)
Recent coups	0.184 (0.043)		0.0007 (0.0016)
Past coups	0.041 (0.032)		−0.0033 (0.0016)
Last period's (log of) per capita income	−0.367 (0.061)		−0.007 (0.002)
Last period's growth rate	−1.102 (0.743)		0.160 (0.032)
Africa	−0.184 (0.111)		−0.017 (0.003)
Europe and North America	−0.034 (0.001)		0.013 (0.003)
South America	0.539 (0.131)		−0.003 (0.004)
Covariance parameters		$\hat{\rho}$ = 0.1323 (0.0453) $\hat{\sigma}$ = 0.0571 (0.0028)	
Number of observations		2,798	
Log of the likelihood function		3533.083	

[a] Standard errors are shown in parentheses.

the purposes of estimating the coup equation. Estimation techniques that fail to account for this joint endogeneity will result in biased estimates.

Our next question is whether the correlation between coups and income is simply the result of common influences on both (such as wars, or natural disasters), or whether they are linked by a more fundamental feedback. We begin by imposing the following restrictions: that there is no direct contemporaneous feedback between coups and income ($\gamma_1 = 0$ and $\gamma_2 = 0$), and that the past history of coups has no effect on income growth. (The latter entails omitting recent coups as well as coups in the more distant past from the growth equation.) This set of restrictions is sufficient to identify both the coup and income equations; in addition, it provides us with two overidentifying (and hence testable) restrictions.

Parameter estimates of the restricted model obtained by Newey's

AGLS technique are reported in Table 8. The χ^2 test of the overidentifying restrictions generates a test statistic whose value is 4.419, indicating acceptance even at the α = 10 percent significance level. Our restricted model embodies the strong result that coups do not Granger-cause income growth;[41] moreover, even the current coup propensity does not affect the rate of income growth. This means that, while coups and income appear to be affected by common influences, there is no evidence that income growth is affected by coups.

Next, we test the hypothesis that income does not affect coups. Conditional on the restrictions of the previous model, in which coups do not affect income, this hypothesis imposes two additional overidentifying restrictions. That is, it calls for the exclusion of lagged income growth and

TABLE 8
SIMULTANEOUS ESTIMATION USING NEWEY'S JOINT AGLS[a]

Dependent Variable	*Coups d'Etat*	*Change in per capita GDP*
Intercept	0.830 (0.428)	0.0675 (0.0126)
Recent coups	0.189 (0.035)	[b]
Past coups	0.035 (0.034)	[b]
Last period's (log of) per capita income	−0.359 (0.061)	−0.0062 (0.0017)
Last period's growth rate	−1.097 (0.750)	0.1485 (0.0317)
Africa	−0.184 (0.111)	−0.0173 (0.0034)
Europe and North America	−0.052 (0.117)	0.0127 (0.0032)
South America	0.533 (0.129)	−0.0061 (0.0036)
Current growth rate	[b]	[b]
Current coup propensity	[b]	[b]
Number of overidentifying restrictions	2	
Chi-squared Statistic	4.419	

[a] Standard errors are shown in parentheses.
[b] Constrained to equal zero.

[41] Engle, Hendry, and Richard (fn. 20), 280.

the lagged level of income from the coup equation. This model was also estimated by Newey's AGLS technique, and generated a χ^2 statistic of 35.569 for the two additional overidentifying restrictions, indicating rejection at all levels of standard significance. Per capita income has a highly significant coup-inhibiting effect.

There is a marked similarity between the structural coefficients reported in Table 8 and the stand-alone estimates presented in Table 6. Income influences the coup propensity, but only with a lag. The previous year's per capita GDP plays a significant coup-inhibiting role. Likewise, the previous year's growth rate has an imprecisely estimated coup-inhibiting effect. At least for one form of political instability, the coup d'état, the much-discussed positive association with the rate of economic growth fails to materialize.[42]

Our results indicate that the probability of a coup depends not only on past income, but also on a country's past coup experience. We find compelling evidence of the existence of a "coup-trap": once a country has experienced a coup d'état, it has a much harder time avoiding further coups. This is consistent with the assertion that the political culture of a country is severely eroded by a successful coup, and that it takes a long time for recovery to set in.[43]

While coups inflict long-term political damage, the linkage between low income and the threat of a coup provides an incentive even for authoritarian governments to promote economic growth. In democracies, elections are used to motivate governments to spur economic growth; those that fail are likely to be turned out of office by the voters. In nondemocratic countries, the threat of a coup appears to play a similar role.

In contrast to the marked influence of economic performance on the propensity for a coup, coups occurring in the recent past have no systematic effect on the rate of income growth. This finding, and the inability to reject the model reported in Table 8, which embodies the restriction that coups do not Granger-cause income growth,[44] is analogous to McCallum's conclusion that U.S. presidential elections do not significantly affect the growth rate.[45]

Alesina observes that McCallum's results are consistent with the hypothesis that the election of Republican presidents causes slower-than-average growth, while election victories by Democratic presidential

[42] Olson (fn. 6).
[43] Finer (fn. 2).
[44] Engle, Hendry, and Richard (fn. 20), 280.
[45] Bennett McCallum, "The Political Business Cycle: An Empirical Test," *Southern Economic Journal* 44 (January 1978), 504-15.

candidates spur above-normal growth.[46] The estimated value of the regression coefficient for elections will be a weighted average of supernormal growth following Democratic election victories and subnormal growth after Republican ones. These two effects may cancel each other, resulting in an estimated coefficient of zero.

In a similar vein, the insignificant coefficient for recent coups in the growth equation may be the result of averaging coups staged by pro-growth factions and those staged by factions whose policies retard the rate of economic growth. Lacking a way to distinguish these two types of coups from one another on a priori grounds, we cannot use the coefficient of lagged coups to distinguish decisively between the hypothesis that coups have no effect and the alternative that there is a bimodal population of coups, some of which enhance growth while others retard it.

The coefficient on lagged coups is not the only means of distinguishing the "coups-have-no-effect" hypothesis from the "bimodal population" hypothesis. If coups are really a bimodal population, we should expect greater variation of the residuals from the growth equation in coup years than in noncoup years. By contrast, the coups-have-no-effect hypothesis implies homoscedastic errors that are equally dispersed in coup and noncoup years. When we calculate separate standard errors for the coup years and the noncoup years, we find that the standard error of the growth equation (estimated on the whole sample) is 40 percent higher (0.0784) in years in which there is a coup d'état than in years in which there is none (0.0558). This is consistent with the bimodal population hypothesis.

Governments that come to power through a coup can influence the rate of economic growth, just as popularly elected governments can. Our results indicate, however, that the coup itself does not significantly affect the rate of growth; nor are governments that are newly installed via a coup systematically different from other governments in their effect on growth (although there are other undeniable differences).

The lack of systematic short-term economic effects resulting from coups highlights the distinction between revolutions, which cause major disruption and reorganization of societies, and coups, which frequently involve the seizure of the preexisting power structure but not its destruction.

The significance of the region-specific effects raises the possibility that there are differences in the effects of coups and income in different

[46] Alberto Alesina, "Macroeconomics and Politics," in Stanley Fisher, ed., *National Bureau of Economic Research Macroeconomics Annual 1988* (Cambridge: MIT Press, 1989).

regions as well. That is, the π parameters in equations (9a) and (9b) may differ among regions. The Hausman test provides a suitable framework to detect the presence of interregional heterogeneity in the parameters of our model.[47] If there is no heterogeneity, then the estimates obtained for the sample as a whole are efficient; estimating the parameters separately for different regions results in consistent but inefficient estimates. If interregional heterogeneity is present, however, the estimates for the sample as a whole will be biased, while the separate region-specific estimates will remain consistent. This puts our problem squarely within the framework of the Hausman test.

Another, more extreme, form of heterogeneity would result if each country had its own parameters, so that the growth and coup parameters for, say, Argentina would be different from the parameters for Bolivia or Indonesia. Unfortunately, if we attempted to estimate a separate set of parameters for each country, our results would be biased due to the well-known "parameter proliferation problem."[48] Although we are therefore unable to test directly for this form of heterogeneity, parameter proliferation does not prevent us from consistently estimating the degree of interregional heterogeneity.

We conduct Hausman tests of the null hypothesis of no interregional heterogeneity in the coefficients on past coups and income in the coup equation. When we estimate the parameters for Africa separately, we obtain a test statistic of 2.128 for the hypothesis of no difference from the parameters for the sample as a whole, corresponding to a p-value of 0.952. This indicates acceptance at conventional levels. Likewise, when we estimate the parameters for South America separately, they generate a Hausman test statistic of 0.150, with a p-value of 0.999, also indicating acceptance at conventional levels. When the growth equations for the OECD and non-OECD countries are allowed to have separate parameters, we obtain a test statistic of 3.770, corresponding to a p-value of 0.806. Once again, we fail to reject the hypothesis of no heterogeneity.

V. Conclusion

Our analysis indicates that the probability that a government is overthrown by a coup d'état is substantially influenced by the rate of eco-

[47] J. A. Hausman, "Specification Tests in Econometrics," *Econometrica* 46 (November 1978), 1251-71.

[48] For discussion of this problem, see Stephen Nickell, "Biases in Dynamic Models with Fixed Effects," *Econometrica* 49 (November 1981), 1417-26; see also the discussion by Gary Chamberlin, "Panel Data," in Zvi Grilliches and M. Intrilligator, eds., *The Handbook of Econometrics: Volume II* (Amsterdam: North Holland, 1983), 1248-1318, at 1256.

nomic growth. The negative association between successful coups and income is more pronounced than any of the interrelationships among the political variables in our data. We construct a parametric model of the coup process and uncover some surprises: the effect of recent independence, often considered to be an important inhibitor of coups, is found to be insignificant.

When the simultaneity of income and coups is accounted for, we find that coups spawn countercoups. The probability of a coup is increased markedly when previous governments have been overthrown. This is consistent with Finer's view that coups have substantial political aftereffects.

The coup-inhibiting effect of income is dramatic. For this reason, even authoritarian governments have powerful incentives to promote economic growth, not out of concern for the welfare of their citizens, but because failure to deliver adequate economic performance may lead to their own downfall. By contrast, we uncover little evidence of feedback from coups to income growth. Our findings are consistent with the hypothesis that poverty spawns coups, but that coups do not have economic effects.

Huntington asserted that political instability is negatively related to "modernity," but provoked by "modernization."[49] We agree with Jackman that a meaningful empirical assessment of the interrelationships among such "umbrella concepts" must "focus on their separate components."[50] Our analysis represents one empirical piece of the "political instability and modernization" puzzle. We find that although Huntington's assertion may be true in general, for our narrowly defined variables, coups d'état (one facet of instability) are negatively related to *both* the level of income (one component of modernity) *and* the rate of economic growth (one dimension of modernization).

APPENDIX

Estimation of the Joint Model of Section IV

This appendix provides details of the technique used to estimate the simultaneous equations model given by equations (8a) and (8b). To begin with, we employ some simplifying notation. We let J denote the number of countries in our sample, indexed by $i \in \{1, \ldots, J\}$, with country i providing T_1 annual observations, indexed by $t \in \{1, \ldots, T_i\}$. Denote the 1 by 2 vector

[49] Huntington (fn. 5), 41.

[50] Robert W. Jackman, "Cross-Sectional Statistical Research and the Study of Comparative Politics," *American Journal of Political Science* 29 (February 1985), 161-82, at 169.

$(\Delta y_{it}, z^*_{it})$ by $\mathbf{y}_{it}$, and define δ_{it} as $\delta_{it} \equiv 1_{\{z^*_{it}>0\}}$, a function that assumes a value of "1" if z^*_{it} is positive, and equals zero otherwise. Denote by $\mathbf{x}_{it}$ the 1 by $(k_1 + k_w + k_2)$ vector $(\mathbf{x}_{1it}, \mathbf{x}_{wit}, \mathbf{x}_{2it})$, which consists of all the variables that enter either equation (8a) or equation (8b). We define the 1 by 2 disturbance vector $\mathbf{u}_{it}$ as $\mathbf{u}_{it} \equiv (u_{1it}, u_{2it})$, and the $1 \times (2 + k_1 + 2k_w + k_2)$ row vector α is defined as

$$\alpha \equiv (\gamma_1, \gamma_2, \alpha_{11}, \alpha_{1w}, \alpha_{2w}, \alpha_{22}).$$

Recall that γ_1, and γ_2 are scalars, α_{11} is a 1 by k_1 vector, α_{22} is a 1 by k_2 vector, while α_{1w} and α_{2w} are 1 by k_w row vectors. Let $K = k_1 + k_w + k_2$ and let $E(\mathbf{uu}') = \mathbf{\Omega}$. Define the vector functions $\Gamma(\alpha)$, and $\mathbf{A}(\alpha)$ as follows:

$$\Gamma(\alpha) = \begin{bmatrix} 1 & -\gamma_2 \\ -\gamma_1 & 1 \end{bmatrix} \quad \mathbf{A}(\alpha) = \begin{bmatrix} \alpha'_{11} & \mathbf{0}' \\ \alpha'_{1w} & \alpha'_{2w} \\ \mathbf{0}' & \alpha'_{22} \end{bmatrix}$$

where $\Gamma(\alpha)$ is a 2 by 2 matrix, and $A(\alpha)$ is a K by 2 matrix, and the zero vectors are defined conformably.

Using this notation, we can write equations (8a) and (8b) in the more streamlined form:

$$\mathbf{y}_{it}\mathbf{\Gamma}(\alpha) = \mathbf{x}_{it}\mathbf{A}(\alpha) + \mathbf{u}_{it} \tag{A.1}$$

Postmultiplying both sides of equation (A.1) by $[\mathbf{\Gamma}(\alpha)]^{-1}$ results in a convenient expression for equations (9a) and (9b):

$$\mathbf{y}_{it} = \mathbf{x}_{it}\mathbf{\Pi}(\alpha) + \mathbf{v}_{it} \tag{A.2}$$

where $\mathbf{\Pi}(\alpha) = \mathbf{A}(\alpha)[\mathbf{\Gamma}(\alpha)]^{-1}$ is the K by 2 matrix of reduced form parameters. For convenience, let $\pi_1(\alpha)$ denote the first column of $\pi(\alpha)$, and $\pi_2(\alpha)$ the second column. Notice that the vector of disturbances from equation (A.2) satisfies: $\mathbf{v} = \mathbf{u}[\mathbf{\Gamma}(\alpha)]^{-1}$.

If we let Σ denote the variance-covariance matrix for the reduced form parameters, then we obtain:

$$\Sigma = ([\mathbf{\Gamma}(\alpha)]^{-1})'\mathbf{\Omega}([\mathbf{\Gamma}(\alpha)]^{-1}).$$

We let ω_{ij} and σ_{ij} denote the $(i,j)^{th}$ elements of $\mathbf{\Omega}$ and Σ respectively. To simplify the estimation, we impose the restriction that $\sigma_{22} = 1$. This results in a fairly messy normalization of ω_{22}; namely

$$\omega_{22} = 1 - 2\gamma_1\gamma_2 + \gamma_1^2\gamma_2^2 - 2\gamma_2\omega_{12} - \gamma_2^2\omega_{11}.$$

This allows us to write Σ in the form:

$$\Sigma = \begin{bmatrix} \sigma^2 & \rho\sigma \\ \rho\sigma & 1 \end{bmatrix}$$

Here we let ρ denote the correlation between v_{1it} and v_{2it}, and σ^2 is the variance of v_{1it}.

We assume that v_{it} has a normal probability distribution. So, the joint density of v_1 and v_2 (where we suppress the (i,t) part of the subscript to avoid cluttered notation) is given by:

$$\phi(v) = \frac{1}{2\pi\sigma\sqrt{(1-\rho^2)}} \exp\left(-\frac{1}{2} v\Sigma^{-1}v'\right)$$

$$\phi(v) = \frac{1}{2\pi\sigma\sqrt{(1-\rho^2)}} \exp\left(-\frac{1}{2\sigma^2(1-\rho^2)}(v_1^2 - 2\rho\sigma v_1 v_2 + \sigma^2 v_2^2)\right).$$

Completing the square, this expression simplifies to:

$$\phi(v) = \frac{1}{2\pi\sigma\sqrt{1-\rho^2}} \exp\left\{-\frac{1}{2(1-\rho^2)\sigma^2}(v_1^2(1-\rho^2) + (\sigma v_2 - \rho v_1)^2)\right\}.$$

Now, define:

$$\phi(z;\tau) = \frac{1}{\sqrt{2\pi\tau}} \exp\left\{-\frac{z^2}{2\tau^2}\right\}$$

and the corresponding cumulative density function as:

$$\Phi(z,\tau) = \int_{-\infty}^{z} \phi(v^*;\tau)dv^*.$$

This allows $\phi(v)$ to be factorized into:

$$\phi(v) = \phi(v_1;\sigma)\phi(v_2 - (\rho/\sigma)v_1;(1-\rho^2)^{1/2}).$$

Accordingly, the contribution of the $(i,t)^{th}$ observation to the likelihood function is:

$$l_{it} = \delta_{it}\ln\left(\int_{-\infty}^{\mathbf{x}_{it}\pi_2(\alpha)} \phi(v_{1it};\sigma)\phi(v^* - \rho/\sigma v_{1it};(1-\rho^2)^{1/2})dv)^*\right)$$

$$+ (1-\delta_{it})\ln\left(\int_{\mathbf{x}_{it}\pi_2(\alpha)}^{\infty} \phi(v_{1it};\sigma)\phi(v^* - \rho/\sigma v_{1it};(1-\rho^2)^{1/2})dv^*\right)$$

where $v_{1it} = \Delta y_{it} - \mathbf{x}_{it}\pi_1(\alpha)$.

These integrals can be more simply written by using a change of variables, namely:

$$w^* = (v^* - \rho/\sigma v_{1it})/\sqrt{1-\rho^2}.$$

This leads to the simplified expression:

$$l_{it} = \delta_{it}\ln\Phi((\mathbf{x}_{it}\pi_2(\alpha) - (\rho/\sigma)v_{1it})/(1-\rho^2)^{1/2};1) \\ + (1-\delta_{it})\ln[1-\Phi((\mathbf{x}_{it}\pi_2(\alpha) - (\rho/\sigma)v_{1it})/(1-\rho^2)^{1/2};1)] \\ + \ln\phi(v_{it};\sigma) \quad (A.3)$$

with $v_{1it} = \Delta y_{it} - \mathbf{x}_{it}\pi_1(\alpha)$. We shall adopt the streamlined notation:

$$l^*(\alpha,\rho,\sigma) = l(\Pi(\alpha),\rho,\sigma) = \sum_{i=1}^{J}\sum_{t=1}^{T_i} l_{it}. \quad (A.4)$$

Notice that $l^*(\alpha,\rho,\sigma)$ depends on the parameter α directly, whereas $l(\Pi(\alpha),\rho,\sigma)$ depends on α only *indirectly,* through the Π-matrix. This distinction must be borne in mind in what follows.

Having defined the likelihood function, we could proceed to maximize it directly. However, as a practical matter, the function $l^*(\alpha,\rho,\sigma)$ is fairly impervious to standard maximization techniques. We employ the practical alternative of Amemiya's GLS technique, as refined by Newey (fn. 39). We proceed in two stages. In Stage 1, we maximize $l(\Pi,\rho,\sigma)$ with respect to Π, ρ, σ. In Stage 2, we use a variant of the minimum χ^2 technique to recover α from our estimate of Π.

Stage 1: Estimating the "Reduced Form" Parameters: Π

First, we exploit the fact that our likelihood function factors into the product of the likelihood function corresponding to the growth equation, whose log is given by:

$$\ln\phi(v_{1it};\sigma)$$

and the likelihood function of a probit model that corresponds to the coup equation, amended by the addition of v_{1it} to the other conditioning variables:

$$\delta_{it}\ln\Phi((\mathbf{X}_{it}\pi_2(\alpha) - (\rho/\sigma)v_{1it};1)/((1-\rho^2)^{1/2}) \\ + (1-\delta_{it})\ln[1-\Phi((\mathbf{X}_{it}\pi_2(\alpha) - (\rho/\sigma)v_{1it};1)/((1-\rho^2)^{1/2})].$$

This enables us to obtain our estimates of Π, ρ, and σ in three steps:
(1) Run an ordinary least squares (OLS) regression of Δy_{it} on $\mathbf{x}_{it}$. Let ψ_1 denote the estimated K by 1 parameter vector from this regression, and let e_{it} denote the residual: $e_{it} = \Delta y_{it} - \mathbf{x}_{it}\psi_1$. The standard error of this regression is:

$$\tau = [[\sum_{i=1}^{J}\sum_{t=1}^{T_i} e_{it}^2]/[\sum_{i=1}^{J} T_i]]^{1/2}$$

(2) Estimate a probit model with ξ_{it} as the dependent variable, where $\xi_{it} \equiv 1_{\{z_{it}^*>0\}}$, and $\mathbf{x}_{it}$, and e_{it} are the independent variables. Let ψ_2 denote the vector of coefficients of $\mathbf{x}_{it}$, and ζ the coefficient of e_{it}.

Notice that in equation (A.3), the argument of the normal cumulative density functions is:

$$(\mathbf{x}_{it}\pi_2(\alpha) - (\rho/\sigma)v_{1it})/(1-\rho^2)^{1/2}.$$

In the probit model estimated in this step of the procedure, the arguments of the standard normal cumulative density functions in the probit likelihood are $\mathbf{x}_{it}\psi_2 + \zeta e_{it}$.

(3) Let $\hat{\pi}_1 = \psi_1$, $\hat{\sigma} = \tau$, $\hat{\pi}_2 = \psi_2/(1 + \zeta^2\tau^2)^{1/2}$,
$\hat{\rho} = \zeta\tau/(1 + \zeta^2\tau^2)^{1/2}$, and $\hat{\Pi} = (\hat{\pi}_1|\hat{\pi}_2)$.

These parameters *are* the maximum likelihood estimators of the reduced form parameters; Π, σ, and ρ. To be precise, $\hat{\Pi}$, σ, and $\hat{\rho}$ solve:

$$\max_{\Pi,\rho,\sigma} \quad l(\Pi,\rho,\sigma).$$

This leaves us with the problem of recovering the α parameters from the $\hat{\Pi}$-matrix.

Stage 2: Recovering the "Structural Parameters" from the Π-matrix

The standard procedure for achieving this (see, for example, Rothenberg, fn. 38) is to use minimum χ^2 estimation. That is, to solve:

$$\min_{\alpha} \; [\text{vec}(\Pi(\alpha)) - \text{vec}(\hat{\Pi})]'\Delta_{\pi}^{-1}[\text{vec}(\Pi(\alpha)) - \text{vec}(\hat{\Pi})]$$

where for any matrix Z, vec(Z) is a column vector consisting of the columns of Z, "stacked" one atop the other, with the first column at the top, and the last at the bottom. The matrix Δ_{π} denotes the variance-covariance matrix of the estimated reduced form parameter vector: vec($\hat{\Pi}$). The minimum χ^2 technique was shown by Rothenberg (fn. 38) to be equivalent to direct maximum likelihood estimation of the structural parameters (e.g., α). However, the relation between α and vec($\hat{\Pi}$) is nonlinear, making minimum chi-squared estimation somewhat complicated.

Newey (fn. 39) establishes that the following adaptation of AGLS estimation is equivalent to minimum chi-squared estimation. To begin, we adopt the following notation: $\mathbf{0}$ denotes the 1 by K matrix of zeros, I_{2K} is the $2K$ by $2K$ identity matrix, and we denote by $I[a{:}b]$ the submatrix of I_{2K} consisting of columns a through b. Now, define

$$\mathbf{g}_1 = \begin{bmatrix} \pi_2' \\ \hline \mathbf{0}' \end{bmatrix}, \quad \mathbf{g}_2 = \begin{bmatrix} \mathbf{0}' \\ \hline \pi_1' \end{bmatrix},$$

and let
$$\begin{aligned} \mathbf{H}_{11} &= \mathbf{I}[1{:}k_1], \\ \mathbf{H}_{1w} &= \mathbf{I}[(k_1+1){:}(k_1+k_w)], \\ \mathbf{H}_{2w} &= \mathbf{I}[(K+k_1+1){:}(K+k_1+k_w)], \\ \mathbf{H}_{22} &= \mathbf{I}[(K+k_1+k_w+1){:}2K]. \end{aligned}$$

To estimate α, we run the following regression using generalized least squares (GLS):

$$\text{vec}(\hat{\Pi}) = \mathbf{g}_1\gamma_1 + \mathbf{g}_2\gamma_2 + \mathbf{H}_{11}\alpha_{11} + \mathbf{H}_{1w}\alpha_{1w} + \mathbf{H}_{2w}\alpha_{2w} + \mathbf{H}_{22}\alpha_{22}.$$

That is, we regress vec($\hat{\Pi}$) on $\mathbf{g}_1, \mathbf{g}_2, \mathbf{H}_{11}, \mathbf{H}_{1w}, \mathbf{H}_{2w}$, and $\mathbf{H}_{22}$ using GLS. To employ GLS, we require a consistent estimator for the variance-covariance matrix of the error. We construct this as follows:

(1) We estimate the variance-covariance matrix of vec($\hat{\Pi}$), Δ_π, via Efron's bootstrap technique (fn. 16), with 1,024 replications.
(2) We obtain consistent estimates of γ_1 and γ_2 by running the regression of vec($\hat{\Pi}$) on $\mathbf{g}_1, \mathbf{g}_2, \mathbf{H}_{11}, \mathbf{H}_{1w}, \mathbf{H}_{2w}$, and $\mathbf{H}_{22}$ using OLS. The coefficients of $\mathbf{g}_1$ and $\mathbf{g}_2$ (which we denote γ_1^* and γ_2^* respectively) are consistent (but not efficient) estimators of γ_1 and γ_2.

$$\text{Let } \mathbf{\Gamma}^* = \begin{bmatrix} 1 & -\gamma_1^* \\ -\gamma_2^* & 1 \end{bmatrix}$$

(3) Let $\Sigma_\pi = (\mathbf{I}_K \otimes \mathbf{\Gamma}^*)\Delta_\pi(\mathbf{I}_K \otimes \mathbf{\Gamma}^*)'$, where I_K is the K by K identity matrix. We use Σ_π as our estimator of the variance-covariance matrix for the GLS regression.

Newey shows that the resulting estimate of α is fully efficient, and that the standard errors from the GLS estimator are the true standard errors.

Finally, let pred[vec($\hat{\Pi}$)] denote the predicted value of vec($\hat{\Pi}$) from the GLS regression of vec($\hat{\Pi}$) on $\mathbf{g}_1, \mathbf{g}_2, \mathbf{H}_{11}, \mathbf{H}_{1w}, \mathbf{H}_{2w}, \mathbf{H}_{22}$. Then, if there are m overidentifying restrictions imposed on the model,

$$(\text{pred}[\text{vec}(\hat{\Pi})] - \text{vec}(\hat{\Pi}))'\Delta_\pi^{-1}(\text{pred}[\text{vec}(\hat{\Pi})] - \text{vec}(\hat{\Pi}))$$

has (asymptotically) a χ^2 distribution with m degrees of freedom, permitting an easy test of our model.