EMPIRICAL MODELING AND DATA PROBLEMS IN DEVELOPMENT

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Abstract. This entry reviews econometric and simulation models as applied to developing countries. Both micro and macroeconomic models are discussed. It is seen that data problems common to empirical modeling in developing countries are severe. This may explain the increased popularity computable general equilibrium and household simulation techniques have recently enjoyed.

1. Empirical Modeling

Quantitative models aid in the clarification of propositions in economics. What can appear as self-contradictory or open-ended statements in a narrative may be easily resolved by way of a numerical balance between opposing forces or a convergent infinite series. Narratives carry nuances that may block effective communication between policymakers attempting reach consensus.

There are two general approaches to empirical models of developing countries, econometric and simulation modeling.[1] Econometric models derive their power from classical and Bayesian statistical theory (Greene, 2003). In classical econometric models, characteristics of a population are inferred from a sample of observations on values of random variables. Once a governing probability distribution is assumed, typically a *students t* or *normal* distribution, rigorous conclusions can be drawn concerning the reliability of the inference. Nothing, however, can be said about the quality of the data. The application of Bayesian statistical methods to developing countries is still in its infancy.[2]

Sadoulet and De Janvry review a wide range of *microeconomic* policy models, including demand, profit function, supply response and various household models under a range of assumptions about agent behavior (Sadoulet and de Janvry, 1995). These models essentially tally social and private costs and benefits in an effort to guide sectoral or regional policymaking. The authors also consider models of international trade and distortions from a partial equilibrium point of view, as well as computable general equilibrium (CGE) models.

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[1]There are many excellent general references for the application of empirical models to developing economies. See, for example, Sadoulet and de Janvry (1995), Taylor (1979) and Blitzer et al. (1975).

[2]For an example, see Sala-i-Martin et al. (2004). For Bayesian methods, see Greene (2003), chapter 16.

Economywide models are usually based on either aggregate data from national income and product accounts or more disaggregated input-output tables.[3] Regional models may link regional input-output models, analogous to international trade models. The informal sector can also be treated in the same way, operating along side the formal economy and trading with it (Gibson, 2005).

1.1. **Econometric models.** Econometric models have been applied to developing economies at both the micro and macroeconomic levels. Microeconomic models describe individual consumer and producer behavior. Data on consumer behavior is often supplied by household, income and expenditure surveys, while producer data might be gleaned from a manufacturing census, input-output studies, tax records, or direct questionnaires administered by governments, non-governmental organizations (NGOs) and independent researchers.[4]

Econometric models, as applied to developing countries, suffer from more extreme violations of the underlying assumptions of the classical linear regression model than in the more stable environment of advanced countries. Strictly speaking, time-series econometric models would only apply to a self-replicating stationary state in which nothing of fundamental importance changed over the estimation period.[5] In particular, the assumption of repeated samples drawn from independent and identical conditional probability distributions (i.i.d.) for each value of the independent variable is severely compromised. This is well-known, of course, and tests and corrections for heteroskedasticity are widely available and widely applied.[6] In time-series models, the i.i.d. assumption implies *structural stability* and is violated as a matter of course in developing economies, since structural change, rather than stability, is the explicit objective of most development policies.[7] Beyond the violation of the most fundamental assumption of structural stability and heteroskedasticity, econometric models suffer from simultaneity bias, omitted variables and other model misspecifications, selectivity bias, as well as measurement and censored and cluster error.[8]

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[3]An early, rigorous treatment of economy-wide models is Blitzer et al. (1975). For an introduction, see Chowdhury and Kirkpatrick (1994). See also Dervis et al. (1982), Robinson (1995) and Taylor (1990).

[4]For a survey of the experience with household consumer surveys see Grosh and Glewwe (2000).

[5]This is a common criticism of econometric methodology, one, as Kennedy points out, "most econometricians usually ignore" (Kennedy, 1998, p. 99). The techniques used for coping with the problem when it is not include (1) regime switching, (2) adding additional equations to the model and (3) using a random coefficient method that allows for coefficients to have their own assumed probability distribution.

[6]See, for example, chapter of 11 of Greene (2003).

[7]The well known "Lucas critique" is a weaker variant of the same argument. The assumption of structural stability is violated by the very existence of government policy, since agent behavior adjusts endogenously to it (Lucas, 1976). There is debate as to whether the critique is econometrically significant. On the other hand, there were 625 phones in Indonesia in 1965 and some five years later, after the launch of a communications satellite, 233,000 phones were in place. This is by far a more fundamental change in the underlying nature of society and could be expected to alter expectations in a more fundamental way than even monetary and fiscal policy.

[8]Deaton usefully surveys causes and corrections for these maladies, in the context of developing countries, at both the micro and macroeconomic level (Deaton, 1995).

Apart from problems of statistical inference, complaints about the use of macroeconometric models in the context of poor data go back at least to the 1970s.[9] Aggregative econometric models, it was argued, were of limited value since (1) time series were too short (2) revisions too frequent and (3) and data too unreliable.[10] Although corrections do exist for data measured inaccurately, under the assumption that the measurement error is random, there is no econometric test or correction for unreliable, or biased, data. Ultimately, it is a matter of judgement, confidence, plausibility, cross check and correlation, with subjectively determined weights.[11]

Econometric models transplanted from developed to developing economies often ignore structural rigidities such as foreign exchange and skilled labor shortages and the presence of a large informal sector (Behrman and Hanson, 1979).[12] Policy and coordination problems are also overlooked, as are various endogeneities peculiar to developing economies, such as credit flows, human capital formation and even monetary and fiscal policy when authorities lack independence.

Macroeconometric models could be made to track data, but have often failed to predict turning points. These models are sometimes regarded as better at analysis than prediction, to the extent that their adjustment mechanisms are transparent and reasonable.[13] One reason large econometric macromodels have fallen out of favor is that the correlation and high t-statistics observed in earlier macro models were due to the lack of *stationarity* of the time series. Many macroeconomic time series are highly correlated as result of a common time trend. Removing the trend by taking first differences puts the framework on much more solid basis but weakens the predictive power of the models. The setback has been attributed to the inherent weakness of macroeconomic theory, problems of aggregation, and the resulting ad hoc nature of principal macroeconomic behavioral relationships.

Together with the "Lucas critique", these obvious and fundamental problems caused some researchers to abandon macroeconomics altogether and refocus econometric attention on microeconomic models. Others turned to models with little or no theoretical content in an effort to improve short-term forecasts.[14] Models with lagged dependent variables and the even more radical vector autoregression (VAR) models performed well, not because they possessed desirable statistical properties (which they do not) but because they were arguably more realistic. As such, the

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[9]Before that, econometricians, according to Kennedy were "too busy doing econometrics" to worry about underylying principles (Kennedy, 1998).

[10]See Shourie (1972). The last problem is the most important. Shourie notes, for example that in Sri Lanka, value added in the construction industry is usually estimated in the national accounts as a function of imported inputs. A regression that purported to show that construction value added was determined by imports would produce highly confident, but useless estimates.

[11]See section 2 below.

[12]Behrman and Hansen presents a prototype macroeconometric model for developing economies and draws a number of important conclusion about typical shortcomings (Behrman and Hanson, 1979, p. 28).

[13]Indeed, by the 1980s, large-scale econometric models used for private sector forecasting fell out of favor. Staffs of econometricians were replaced by staffs of MBAs who could hedge against an uncertain future rather than trying to predict it. Kennedy mentions "Goodhart's law" that holds that all econometric models break down when used for policy (Kennedy, 1998, p. 7). See also, in this regard, Summers (1991).

[14]See Sims (1980).

VAR framework can be seen as the first step in abandoning the inferential approach for one more grounded in reality.[15]

Microeconometric models also faced many of the same estimation problems, but researchers have, by and large, found ingenious ways to adapt their models and to correct for deficiencies. The corrective procedures for models with heteroskedasticity, bias introduced by pooling time series and cross sectional data, selection, clustering or other data deficiencies can cause collateral damage to the inferential process. Often, bias disappears only when the sample size grows large, a luxury usually unafforded in developing country data sets.[16]

To combat these and other problems of estimation, researchers attempt to construct *robust* models. Robustness means that the same qualitative conclusion emerges from a variety of different model specifications.[17] Robust conclusions are more credible and convincing to consumers of econometric studies and disable much of the criticisms leveled at the models. Ultimately, however, robustness is subjective, thereby widening the gap between classical statistical theory and useful model conclusions.

1.2. **Simulation models.** Simulation models take the last step and abandon classical statistical theory all together. They therefore cannot be rigorously evaluated.[18] Since no inference from sample to population is involved, it is meaningless to ask how well any given simulation model reflects its parent population relative to say, some other simulation model. Simulation models instead rely on a less precise criterion of validity. The principal means of validation is its perceived realism; that is, does it resemble the object it is supposed to simulate.[19] If it does, then the model is validated, but the procedure does not stop there. A model that expands and covers accurately ever expanding dimensions of the economy is better than a model that covers only a subset of the same data. This is only true when the models are non-recursive so that the model must be calibrated as a whole. In non-recursive models, errors in one component will propagate into the rest of the model, such that mistakes multiply rather than cancel out. In recursive models, the calibration procedure can mask error.

Simulation models are based on the notion that good models do not contain results that are widely at variance with reality in any of their *computable properties*. The notion of computable properties, as used here, is broader than the properties

[15]For the standard critique of the VAR method, see Cooley and LeRoy (1985). The VAR approach was developed by Sims in response to weak macroeconomic theory, that is, ungrounded in the rational model, as well as the enormous subjective judgement required to implement, adjust and forecast with structural models. Kennedy suggests that VAR models may be seen as an "evolutionary step along the road to more adequate dynamic modeling" (Kennedy, 1998, p. 168). For a "horse race" with the VAR, structural and co-integration, error correction models see Adams and Ratcliffe (1995).

[16]Efficiency of estimation is quite another matter. The the corrections for heteroskedasticity, for example, all assume that the functional form of the heteroskedasticity can be properly calibrated. In fixed effects models, for example, it necessarily takes an additive form.

[17]Robust models are not to be confused with robust estimators, which are said to be robust with respect to "fat tails" i.e., outliers.

[18]Viewed from the optic of classical statistical theory, simulation models rely on *judgement* rather than *random* samples. A judgement sample involves subjective evaluation of the data, selecting the most representative for further scrutiny and analysis.

[19]This criterion has been referred to as the "duck test" (Gibson, 2003).

of a given model that might be presented as a result of in- or out-of-sample forecasts properties. Computable properties include derivatives of presented properties and may reveal otherwise undetected inaccuracies in the model.[20] Rational actor models, for example, especially those that deal with expectations of the future, may well have some computable properties that differ substantially from the perceptions of how an actual economy behaves.[21]

Empirical modeling based on a general equilibrium approach avoids some of the problems of aggregation discussed above. General equilibrium imposes consistency on the decisions of rational actors, but consistency is achieved in a wide variety of ways. It is probably fair to say that all models combine, in varying proportions, elements of *agency* and *structure.*[22] Economists tend to favor agency, despite the deep problem of the self-validation of rational actor models. Policymakers, however, typically place more weight on structure than agency in evaluating the realism of a model. Thus, models that over-emphasize agency are subject to the Lucas critique, and can be seen to lack realism. Models that over- emphasize structure, on the other hand, are guilty of the opposite excess. Policy becomes unrealistically effective, simply because agents are assumed not to adjust their behavior. In this way, planning models of the 1950s through the 1970s were too optimistic about the effects of government policy and are now considered to have "failed"(Chowdhury and Kirkpatrick, 1994, p. 3).

Policymakers and other consumers often reject empirical models in which the the causal mechanisms at work are obsucre. They cannot be blamed for shying away from "black box" models that even their authors fail to fully comprehend (Dervis et al., 1982, p. 3), (Karchere and Kuh, 1982). When there are several adjustment mechanisms at work in the same economy, such as with competitive markets in some sectors and oligopolistic in others, formal as well as informal agricultural or service sectors or segmented labor markets, numerically calibrated simulation models place explicit weights on each of the various mechanisms. Sensitivity analysis can then be undertaken with respect not just to agent behavior, but also the overall structure of the economy.

Does robustness play a role in simulation modeling? Simulation models are usually subjected to *sensitivity analysis*, a procedure that aims at robustness. Model conclusions that are dependent on one or two critical parameters are obviously not as convincing as those which are robust to reasonable changes in those parameters. Model structure, is of course, a different matter; models with different closures, as discussed in the next section, can have entirely different comparative static and dynamic properties.

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[20] An example might be a forecast of output growth of 2% over a period of 20 years for a given country or region. Employment growth is also forecast by the model at 3% for the same time period. A simple example of computable property is productivity growth, which here is -1%. This estimate may or may not be deemed realistic, but since it can be computed from the data of the model, it must be considered as part of the forecast.

[21] This is the "gap", to which Dervis *et al.* refer, between the realm of pure theory and the real world facing policymakers (Dervis et al., 1982).

[22] The neoclassical general equilibrium is perhaps at one extreme of the spectrum, imparting maximal weight to agency, while minimizing the effect of structure. Thus, tastes, technology and the endowment are the familiar structural givens of the neoclassical theory of market behavior. The von Neumann growth model, on the other hand, might be thought of as maximizing the role of structure while minimizing that of agency. Other models, including Keynesian and non-Walrasian constructs, fall somewhere between the two extreme cases.

1.3. **Macro simulation models.** CGE models are usually multisectoral, economy-wide models, which may static or dynamic.[23] They are usually calibrated to a Social Accounting Matrix (SAM) and exhibit a wide range of adjustment mechanisms, from closed, purely competitive, Walrasian models to macro structuralist models in which foreign exchange availability determines the level of output in some key sectors.[24] CGE models have even been compiled at the village level (Taylor et al., 1999).

Sen describes a particularly simple accounting framework in which the number of equations is one short of the number of unknowns. Formally speaking the model cannot be solved, or "closed", until an additional equation is found and justified as part of the macroeconomic system (Sen, 1963).[25] Closure then refers to selection of parameters and variables, specifically around the relationship between savings and investment. In a neoclassical closure, for example, the quantity of savings determines the level of investment. In a Keynesian closure, an independent investment function is present and savings adjusts to it through changes in output. A foreign exchange constrained closure is similar to the neoclassical, except that instead of factors of production as the ultimate constraint on production, it is rather the level of foreign exchange for imported intermediates and capital goods. Closure is related to but not the same thing as a "gap" model, in which there are specific targets for output and employment and either a savings, foreign or fiscal constraint binds (Bacha, 1990), (Taylor, 1994). The gap is determined by the amount by which the constraint would have to be shifted so that internal and external policy objectives could be met.

An algebraically indeterminate system may also be closed by some maximization procedure, with the marginal equality that results providing the needed additional equation. Planning models, for example, may try to maximize employment by choosing a sectoral pattern of output consistent with a foreign exchange constraint or some other supply side limitation. One of the most well-known models in economics endogenizes the savings rate in order to maximize the discounted value of future consumption (Ramsey, 1928). Formally speaking, this closure is as acceptable as any other, provided of course that it passes the test of realism.

Most of the earlier applied CGE models were static and reconciled flows of supply and demand in any one period of time. But with the availablity of highly efficient microcomputer programs, such as GAMS and GEMPACK, dynamic models have become much more common. They may be solved recursively or simultaneously and can be close by way some some optimization criterion. They may be solved in level terms or in growth rates as did Johansen in the original CGE model (Johansen, 1960). In this regard, CGEs have come to compete directly with large econometric models.

Solving a dynamic model means finding a solution path for the each of the endogenous variables of the model. The computational characteristics of the model

[23] The literature on CGEs is large. Particularly useful are Robinson (1995) and the introductory chapter to Taylor (1990). Some other references are Dervis et al. (1982), De Maio et al. (1999) and Gunning and Keyzer (1995).

[24] For a Walrasian approach, see Scarf and Shoven (1983); for some early and relatively simple examples of various other closures, see Rattso (1982) and Gibson (1985).

[25] Closure in this sense is not to be confused with Leontief open and closed models. Final demand is taken as given in open models, while all or part of final demand is endogenized as a function of the levels of output in the closed model.

may show that some endogenous variables, or their ratio, reach a steady-state in which there is no further change.[26] Many dynamic models of developing countries are calibrated to time periods far away from the steady state and the absence or presence of smooth convergence seems hardly to affect their prestige in the eyes of policymakers and other users. The issue is similar to the i.i.d. problem discussed above; since development is itself about changing the fundamental parameters underlying the economy, it hardly seems desirable to project a distant future based on current values. The transient or transitionary phase of the solution to the dynamic model is of considerably more interest.

1.4. **Calibrating empirical models and policy.** Sadoulet and De Janvry note that there are two steps in using quantitative models for policy analysis, (1) calibration and verification, and (2) forecasts and analysis (Sadoulet and de Janvry, 1995, p. 7). The calibration phase can be done formally in econometric models, the coefficient of variation, R^2, determining the goodness of fit.[27] Despite textbook admonition against the practice, policy oriented econometric models are calibrated much in the same way as simulation models, with variables added, deleted, combined, lagged, or algebraically transformed until the goodness of fit reaches an acceptable level. In the process of calibration, econometric models can lose rather than gain transparency, since the model itself changes during calibration. The changes are theoretically rationalized, but lead to subtle and complex interactions that result in computational characteristics that are omitted or suppressed in the presentation of results.

In contrast, transparency of simulation models is usually (although not always) unaffected by the calibration procedure. Calibration has many pitfalls of its own however, and is sometimes called "guesstimation."[28] Guesstimation refocuses attention on the realism of the final product, not the secondary issues of inference as noted above. Indeed, econometric models also have their own brand of guesstimation, but it rather concerns the model specification and is done behind doors as tightly closed as those of simulation modelers.[29] It is safe to say the first-level regressions are *never* published. Estimation is thus "guesstimation" at some fundamental level, and significance, as McCloskey rightly points out, is not a property of the model in regard to the economy it tries to represent, but of the *calibration* of the model to the sample data (McCloskey, 1997).

[26] There is debate as to the relevance of the steady state in simulation models. One of the most well-known models in economics is due to Solow and can solved for both transient and steady-state paths of the endogenous variables (Solow, 1956). If, as in the Solow model, the half-life or distance to half of the steady state values of the model is many years and even decades away, the steady-state part of the path might be of limited value to policymakers (Barrow and Sala-i-Martin, 2004).

[27] For an interesting discussion of calibration in macro models see Canova and Ortega (2000).

[28] This pejorative implies that no estimation procedure is involved, which may or may not be correct. In principle, full information, maximum likelihood estimation of all the structural parameters of a model is possible and even desirable, under the assumption of structural stability (Jorgenson, 1984, p. 3).

[29] Kennedy, citing Hendry and Richard (1983) notes three problems: (1) "the data generation process is complicated, data are scarce and of uncertain relevance, experimentation is uncontrolled and available theories are highly abstract and rarely uncontroversial"; (2) "most econometricians would agree that specification is an innovative and imaginative process that cannot be taught...It is simply 'lore.'" (3) There is no accepted way of finding the best specification (Kennedy, 1998, p. 74).

2. Data Problems

According to Deaton

> The news...is dismal. National income and growth comparisons across countries are plagued by conceptual index number problems, and by immense practical difficulties. Many frequently used data from LDCs are of poor quality, or only pretend to exist, having their only reality in the mind of bureaucrats in New York and Washington. (Deaton, 1995, p. 1814)

Data in developing countries can be reliable, noisy and/or unreliable according to whether there are errors in the data collection process and whether these errors tend to cancel out.[30] Errors in the data collection process result from their being "made up" by interpolation, extrapolation and falsification. Errors also result from changing definitions as well as the standard index number problem. But the existence of noisy or unreliable data is a meta-problem in science generally and not specific to developing economies.[31] There is no econometric test for unreliable data.

In economics, data problems exist most fundamentally because of aggregation.[32] Populations tend to be more heterogeneous in developing countries, because of race, religion and ethnic identity. Income is often badly distributed. Thus, aggregating rich and poor can distort data in developing countries (at the top of the Kuznets curve) more significantly than in more egalitarian societies.

In developing economies, data problems are also more likely to occur because the social structure is rapidly changing. Apart from the processes involved in development, macroeconomic imbalances, stagnation and crisis, can cause emigration or social conflict which biases or causes large gaps in data collection. Consistency problems are multiplied when regions differ significantly or when political structure is regionally fragmented.

In these ways, the aggregation problem is probably more severe in developing than in stable, developed countries. Moreover, governments and NGOs often lack budgets to do an adequate job of collecting, cross checking and validating data. In

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[30] See the special issue of the *Journal of Development Economics* devoted to data problems in developing countries. An overview is provided in Srinivasan (1994).

[31] Deaton points out that there is no reason to believe the backwardness itself is responsible for poor quality survey data. He notes that Indian statisticians have played leading roles in developing survey methodology and survey data in India is "second to none" (Deaton, 1995, p. 1799).

[32] The principal problem has little to do with the fact that social science studies *humans* rather "natural" processes. Intentionality is crucial to data saying anything about the way subjects behave. But so long as intentionality is constant, and this is admittedly a big assumption, data should be able to be gathered about behavior, in the same way as, say biologists gather information about the behavior of a particular species when it is confronted with mutually exclusive alternatives, satisfying hunger or the sex drive. The problem arises when economists aggregate behavior of different species, say elephants and mice. This is particularly important in developing countries. Elephants (think of the very rich) respond and adapt to their environment in ways that differ significantly from the response of mice (the poor or the informal sector). Aggregating behavior of the two species is not impossible, but without knowing the relevant weights, and how they change over time, models can produce nonsense. Macroeconomists are always subject to this problem of aggregation; it is part of the nature of macroeconomics. One can only hope that the relative weights remain constant over time and recognize the need to change the model when they do not. Deaton, for example, argues that if regression coefficients differ by strata, population-weighted OLS estimate are still biased and inconsistent and separate regressions must be run (Deaton, 1995, p. 1797).

household surveys, for example, respondents should be chosen randomly, but some live in inaccessible areas and researchers may literally risk their lives in war-torn or crime ridden regions. Representativeness problems would be less severe if data were even collected in a consistent fashion over time, effectively creating proxies, but they are usually not.[33]

The existence of a large informal or traditional sector also causes significant problems for developing country data. The informal sector in agriculture can make up more than half the economy and is typically understudied. Developing economies are often only semi-monetized, with barter playing an important role, especially in the rural sector, so that autoconsumption, and certainly investment, can be important. Investment in the informal sector is particularly difficult to track, often appearing in the national accounts as consumption. Smaller on-farm construction projects such as clearing, informal roads and irrigation canals or terracing are missed by government officials who concentrate on licenses, building permits and capital import authorizations to estimate investment in the national accounts (Taylor, 1979, p. 23).

With technocrats are in short supply, data gathering may be hampered by poorly trained or untrained field workers. Democratic institutions, which would support objective collection and analysis of data, are not always in place. Local accounting procedures may themselves be part of the problem. If we interpret "book value" as "replacement value" then clearly the capital stock will be underestimated.[34]

Specific data problems include stratification and cluster bias, groups of individuals with similar unobservable characteristics, ability or entrepreneurship, weather, tastes or prices. There is also selectivity bias and other sampling difficulties; there may be non-random reasons why some individuals enter a given sample and this usually introduces bias. Respondents may also incorrectly report data when civil or criminal liability is an issue, such as "unregistered" labor contracts. Respondents may lie for privacy or political purposes or in an attempt to conform to perceptions of researchers' expectations.

Futher, uncertainty and inefficiency in tax laws may cause inaccurate reporting. This occurs in two ways: first, if tax liability is presumed to increase, information will be withheld from government officials. Conversely, if there are no tax or regulatory implications of investment projects, government data collection is more likely to overlook the activity, thereby underestimating the conceptual category. There may also be principal-agent problems, in which respondents misrepresent their objective conditions when it is in their interest to do so.

Finally, a subjective or post-modernist effect may cause some respondents to report conditions that vary greatly from others when all are attempting to be objective.

Corrective methods to statistically compensate for problems mentioned above are available and have become central to much of the literature on developing economies. But in each case, the corrective procedure comes at the cost of precision and often require strong assumptions to justify their application in any case.

[33]Deaton notes that holding precision constant, any cost-minimizing sample design will lead to over-sampling of urban households (Deaton, 1995, p. 1790).

[34]Taylor observes that in inflationary regimes, the government may well require that LIFO (last-in-first-out) accounting be applied to inventory evaluation as an anti-inflationary device (Taylor, 1979, p. 23).

In every case, the researcher faces a trade-off between the loss of credibility of uncorrected procedures and the implausibility of the assumptions required to "fix" the problems encountered.[35]

2.1. **Data problems specific to macroeconomic models.** Data is collected and processed by different agencies or ministries with different missions, budgets, effectiveness and capabilities. In principle, each agency is estimating a different aspect of the same economy and thus should report broadly consistent magnitudes. In practice the magnitudes can vary substantially.

Most developing countries base their gross domestic product (GDP) estimates on the production rather than demand side.[36] These estimates could be cross checked by demand side surveys or census data. In practice this is not often done and satellite measurement may well turn out to provide the most reliable estimates.[37]

The Central Statistical Office (CSO) is typically responsible for the national accounts in units of local currency. If the estimates are based on "flow of product" concepts, the underlying information will determine the accuracy of the final figure. Unfortunately, this will vary from sector to sector, with the reliability of the information dropping off with the square the distance between the CSO and respondents. In other words, rural data will be collected with less frequency and lead to more between-year extrapolation. Sectoral data based on industrial census may be refreshed the most often, with other data scaled to these results. In general demand-side data, based on flow of product, is weaker than data based on value added, for which there might be fiscal interests at stake (Taylor, 1979, p. 22).

The Ministry of Trade or Central Bank may compile balance of payments data in hard currencies. In practice balance of payments data may not agree with national accounts for exports and imports. Problems were no doubt more widespread when currency controls and import licensing were widespread policy interventions. Underinvoicing of exports and overinvoicing of imports became important sources of foreign exchange for some in some developing countries, and transfer pricing as a tax-minimizing strategy could significantly distort foreign trade data.

The Ministry of Finance typically compiles government expenditure data with help from the World Bank, IMF or regional development banks. Ministry of Finance data for government expenditure may not agree with national accounts data for government expenditure. The Ministry of Interior or Labor may handle household surveys with help from the World Bank, International Labor Organization (ILO) or NGOs. Household surveys are often inconsistent with data for consumption in national accounts. Finally, the Environmental Ministry may also be relevant, especially if environmental problems are seen as linked to growth, international trade in tourism and income distribution.

2.2. **Addressing data problems in developing countries.** The two generally accepted methods of dealing with data problems in developing countries are cross

[35]These trade-offs are subjective in nature and center on the question of sampling and inference, rather than model building per se. Once resolved, fundamental questions still remain. For example, consider the basic assumption that the *means* of a conditional probability distribution all lie on a straight line. Why must it be the mean and not, say, the *median?* Quantile regression techniques exist but since the equations cannot solved in closed form, collateral statistical analysis is difficult to perform.

[36]See Heston (1994) and Wiese (1995).

[37]See Sutton and Costanza (2002) and references cited therein.

check and correlation. *Cross check* exploits the dual nature of transactions. Correlation is more elaborate and integrates econometric methods into the process of consistent data generation.

Taylor notes that CGE modelers make a "fetish" out of accounting consistency (Taylor, 1990, p. 7). But there are good reasons for bowing to this god. As noted above, if policymakers or other consumers of the model detect evidence that the model's results are at substantial variance with the economy as they see it, it may be difficult to sustain trust in the results. SAMs themselves are not models but can be used to create data that is free of the inconsistencies arising from their various sources.[38] SAM methodology is a simple, but thorough, example of the cross check method.[39]

Once a SAM is constructed, it is still possible to cross check it with other data. Cross checking reports on working conditions and environmental problems from different sources, workers and political entities.[40] The difficulty with cross checking as a standardized methodology is that it requires a significant degree of qualitative knowledge, not only with respect to available data, sources and methods, but with respect to the country and region under study (Sastry, 1975). Patterns of growth data can also be sometimes be used to comb out inconsistencies (Taylor, 1979, p. 47).

A sequence of dynamic SAMs can also cross check investment and capital accumulation. Financial data from balance sheets from firms and central banks can be used for cross checking although this is in its infancy. Data from agencies regulating financial practices, labor standards and environmental compliance can sometimes be used for cross checking.

Correlation in cross sectional or panel data shows that some measures are "better" than others. Gruben and McLeod note, for example, that data problems prevent our saying whether poverty in developing countries has increased or not. as is done in Gruben and McLeod (2002). In this case, the question is whether household surveys, on which poverty estimates are made, are consistent with national income and product accounts. In principle, a household survey would be representative of the cross section of the consuming population. Hence the mean consumption per capita should be highly correlated with the consumption per capital in the national accounts. Bhalla points out that this is not the case (Bhalla, 2002). Consumption data should be should then be cross checked for consistency with correlation analysis.

3. Some final observations

The foregoing suggests an explanation for the increasing popularity of simulation models, in both macro and microeconomic applications, compared to traditional econometric modeling. In the latter, the nessary restrictions for indentification are often "incredible." The assumptions required to make valid inferences are strained

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[38] They can usually be estimated rather quickly, as Taylor notes, within a week or so and often represent time well spent in understanding how an economy works (Taylor, 1979, p. 46).

[39] Some researchers refuse to force consistency on their models and introduce various objects such as "phantom taxes" or explicit residuals (Dixon and Rimmer, 2002). The South African Reserve Bank publishes a residual between the income and expenditure measures of GDP.

[40] Verite, an NGO that certifies labor conditions in developing countries, notes that data consistently shows that working conditions as reported by employers and workers are different and ILO pay package checks confirm discrepancies.

by the very process of development. If repeated samples of i.i.d. random variables were possible, there would be no reason to use simulation models. Their popularity derives from the fact that opportunities for clean sampling are rare and especially unavailable in developing economies.

Models based on unreliable data are themselves unreliable, despite any other attractive properties they may possess. Unreliable data is data measured with error, but the error is not necessarily random and therefore may not cancel out. Unreliable data is the product of judgement sampling. Since it can be and often is produced by individuals who lack knowledge of proper sampling procedures, or indeed with political or self-interested motives, no corrective procedures are available. Biased data is bad data and must be recognized as such but the defintion of "good" or "reliable" data remains subjective.

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