PRACTICAL PANEL MODELLING

With Applications in Islamic Banking and Finance Research

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Assalamualaikum Warahmatullahi Wabarakatuh

Bismillahirrahmanirrahim

Alhamdulillahirabbil'alamin, all praise and gratitude to Allah SWT. Alhamdulillah in 2022 the National Committee for Islamic Economics and Finance (KNEKS) launched a book entitled Practical Panel Modelling (With Applications in Islamic Banking and Finance Research).

Today's Islamic economy has experienced rapid growth at the global and national levels where it is predicted to grow around USD 3.2 trillion by 2024 and has become a potential investment area for investors. Investment in the Islamic economy sectors rose to 399 percent in 2018, with a value of USD 1.2 billion. The growth of several Islamic economic and financial institutions in several developed and developing countries confirms this. The State of Global Economic Report 2020/2021 report states that there are more than 1.8 billion Muslim residents who are consumers of halal products. Consumption of halal products increases by 5.2 percent annually with total consumer spending reaching USD 2.2 Trillion US Dollars in 2019 and will continue to grow to reach USD 3.2 Trillion in 2024. This figure comes from food and beverage consumption. halal, followed by, Muslim friendly tourism, Muslim fashion, halal medicines and cosmetics and recreation/media. This potential is expected to continue to increase in line with the increasing growth of the Muslim population at the global level.

Indonesia, which is one of the countries with the largest Muslim population in the world, which is around 240 million people, has huge Islamic economic potential. With abundant natural resources (SDA) and human resources (HR) that continue to increase in quantity and quality, Indonesia has a large capital to become the world's leading Islamic economic center. Indonesia is also a very decisive market in the world trade in halal products. Indonesia is the largest consumer of halal food and beverage products in the world with a consumption value of US$114 billion in 2020.

To increase the competitiveness of the Indonesian nation, the development of aspects of natural resources (SDA) and human resources (HR) alone is not enough. It is necessary to develop research and innovation aspect as the backbone of the nation's progress in order to drive Indonesia to become a developed country in the world. Islamic economy in Indonesia needs to be supported by research and innovation pillars that are strategic, effective, have a major impact on the development of the industrial world, of international quality, and are based on the latest technological developments in various fields of Islamic economy and finance sector, the Islamic social finance sector, as well as Islamic business and entrepreneurship sector.

This book entitled Practical Panel Modelling (With Applications in Islamic Banking and Finance Research) is an effort made by the National Committee for Islamic Economics and Finance (KNEKS) to foster the development of research and innovation in the Islamic economic and finance sector, especially the Islamic Banking and Finance areas. It is hoped that this book can contribute to increase the capacity of researchers in Indonesia, which still has to be improved both in terms of quantity and quality of publications as well as the quality of research outputs. In the future, with the more advanced progress of research in the Islamic economic and finance areas, it is expected that the output will strengthen national economic resilience and realize Indonesia's vision as a leading Islamic economic center in the world.

Thank you
Wabillahitaufik Walhidayah
Wassalamu'alaikum Warahmatullahi Wabarakaatuh

Jakarta, September 2022

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Bismillahirrahmanirrahiim
Assalamu'alaikum Warahmatullahi Wabarakaatuh

Praise and gratitude for the presence of Allah SWT because of His grace and blessing, this book entitled Practical Panel Modelling (With Applications in Islamic Banking and Finance Research). Sholawat and greetings are always poured out to our beloved Prophet Muhammad SAW.

Currently, the Islamic economy has become a new attraction in the global economy, this is supported by the trend of the global Muslim population that continues to increase, where by 2030, the world's Muslim population is predicted to exceed a quarter of the global population. The State of Global Economic Report 2020/2021 has reported that there are more than 1.8 billion Muslim residents who are consumers of halal products. Consumption of halal products increases by 5.2 percent annually with total consumer spending reaching USD 2.2 Trillion US Dollars in 2019 and will continue to grow to reach USD 3.2 Trillion in 2024. This figure comes from food and beverage consumption. Halal, followed by Muslim fashion, Muslim-friendly tourism, Halal media and recreation, and Halal medicines and cosmetics. With the continued increase in the global Sharia economy, Indonesia as a country with the largest Muslim population should also be able to take advantage of this growth potential, especially in the halal industry sector by boosting exports of halal products, which currently have a very small contribution compared to the total demand for the world halal industry market.

Meanwhile, the Islamic economy and finance sector with an interest-free system is allegedly more stable and resistant to crisis shocks. Many studies have been conducted by researchers from various countries to prove this. For this reason, theory and practice in this field must be enforced in parallel in order to create a strong foundation for the system's sustainability. Unfortunately, the Islamic economic and finance system still has many shortcomings in practice. The imbalance between theory and practice has given rise to many unresolved problems to date. Thus, the development of scientific research related to the Islamic economic and financial sector must continue to be encouraged. Findings from these various studies can be key in solving problems to integrate theory and practice of Islamic economics and finance.

In the future, Indonesia still needs a lot of research and innovation related to the Islamic economics, particularly in the Islamic economic and finance areas. Alhamdulillah, in 2022, KNEKS has launched a book entitled Practical Panel Modelling (With Applications in Islamic Banking and Finance Research). This book constitutes the nature and theory of econometrics by providing the basics of empirical research that would facilitate understanding of econometric techniques, i.e. panel data modelling with applications in Islamic banking and finance. Hopefully, this book can contribute to the development of research and innovation in the field of Islamic economics and finance areas especially to increase the capacity of researchers in Indonesia, which still has to be improved both in terms of quantity and quality of publications as well as the quality of research output.

Thank you
Wabillahitaufik Walhidayah
Wassalamu'alaikum Warahmatullahi Wabarakaatuh

Jakarta, September 2022

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CONTENTS

THE NATURE OF ECONOMETRICS

"...an attempt to increase the sum of what is known, usually referred to as 'a body of knowledge', by the discovery of new facts or relationships through a process of systematic inquiry, the research process."

(Macleod Clark and Hockey, 1989)

1.1 INTRODUCTION

Testable implications or hypotheses arising from economic and financial theories generally involve relationships between variables. Generally, when (i) measurement is relevant and possible, (ii) statistical generalizations are to be made, and (iii) hypothesis testing is involved, econometric techniques are called for.

This introductory chapter discusses the nature of econometrics by providing the basics of empirical research that would facilitate understanding of econometric techniques deliberated in the book, i.e. panel data modelling with applications in Islamic banking and finance. These include the meaning of econometrics, steps in econometric analysis or empirical research, and data structure. The chapter then ends with a synopsis of chapters in the book.

1.2 WHAT IS ECONOMETRICS?

Succinctly stated, econometrics is measurement of economic theories. It forms the basis of empirical research to answer research questions or to address research hypotheses under study. In economics and related disciplines, theories and hypotheses are developed to explain certain behavior or phenomena. For instances,

- The simple Keynesian consumption theory postulates a positive relation between consumption and income with the increase in consumption to be less than proportionate to the increase in income. That is, the marginal propensity to consume is between 0 and 1,
- The neoclassical growth theory (Mankiw et al., 1992) hypothesizes (i) a positive relation between output per labor and investment ratio, (ii) a positive relation between output per labor and human capital, and (iii) convergence of income across countries,
- The "too-big-to-fail" hypothesis views bank size to be the driver of bank risk-taking behavior,
- The bank lending channel states that small, less capitalized and less liquid banks are more strongly affected by monetary policy tightening, and
- The real sector connectivity and risk sharing of Islamic banking operations make Islamic banks to be more stable.

These theories, and others in economics and related fields, prescribe specific relations between outcome variables and their determinants. However, most likely, there are also competing theories or alternative theoretical explanation of the behavior or phenomena under study. For examples, the permanent income hypothesis states that consumption is not related to current income but to permanent income. The endogenous growth theory admits divergence in the level of economic development or per capita income across countries. Increasing bank size may not necessarily lead to higher risk as banks can benefit from economies of scale. Also, there may be more factors that explain the bank lending channel, among which include bank risk, securitization, and market structure. Finally, Islamic banks may be less stable as a result of contractual complexity and risks unique only to Islamic banking businesses.

Econometrics takes these (contradicting) theoretical predictions as a starting point and then applies mathematics and statistics to data to verify which theoretical prediction tends to describe the behavior of the outcome variables. Theories provide qualitative predictions, e.g. the increase in X is associated with the increase (or decrease) in Y, where Y is the outcome variable and X is its determinant. Econometrics verifies or refutes the predictions and, above that, provides measurements to allow for example the following statement to be made – the increase in X by 1 unit is associated with the expected increase (decrease) in Y by 0.7 unit, all else equal.

Maddala and Lahiri (2009, p. 3) aptly sum up Econometrics as:

> *The application of statistical and mathematical methods to the analysis of economic data, with the purpose of giving empirical content to economic theories and verifying them or refuting them.*

From these, it is clear that an econometric analysis would involve theories and hypotheses, a mathematical function that links the outcome variable and its determinants, an estimable statistical model and its assumptions, estimation of the model, hypothesis testing, and inferences. In doing so, it requires a systematic procedure and rigor such that convincing inferences can be made and implications can be drawn for policies and decision making.

1.3 STEPS IN EMPIRICAL RESEARCH

Econometrics as explained above delineates the following steps in empirical research, given that relevant data are available:

Step 1: Statements of Hypotheses
Step 2: Model Specification
Step 3: Model Estimation
Step 4: Diagnostic Tests
Step 5: Hypothesis Testing
Step 6: Inferences and Implications

These steps are detailed below:

1.3.1 Statements of Hypotheses

As we emphasize above, econometrics starts with theories and hypotheses, which is based on the well-known notion that "measurement without theory is meaningless". Founded on a theory or theories, a hypothesis is a statement/supposition made concerning a particular aspect of the subject or issue under study, which usually involves the relationships among the variables. For an example, in assessing Islamic banks vis-à-vis conventional banks, Ibrahim and Rizvi (2018) state among others the following hypotheses:

- *There is no effect of financing/lending growth of Islamic and conventional banks on future bank risk,*

- *There is no significant difference in the effect of financing/lending growth of Islamic and conventional banks on future bank risk, and*
- *Financing growth of Islamic banks during the crisis period is not related to excessive risk.*

Ibrahim and Rizvi (2018, p. 35)

As another example, Du et al. (2018) postulate the following hypotheses in their analysis of foreign banks in Chile:

- *Foreign banks will decrease the net interest margin,*
- *Foreign banks will decrease a bank's volatility of net interest margin and the volatility of return on assets. In addition, foreign banks will decrease the z-score, and*
- *Foreign banks will have a positive effect on bank's commercial, consumption, and housing loans.*

Du et al. (2018, p.170)

Note that Ibrahim and Rizvi (2018) state the hypotheses of no significant relations among the variables while Du et al. (2018) explicitly indicate directional (negative or positive) relations between the variables.

Principally, statements of hypotheses comprise the null hypothesis and the alternative hypothesis. The null hypothesis is basically the statement that a researcher holds it to be true unless there is sufficient evidence to conclude otherwise. Meanwhile, the alternative hypothesis is the complement (or negation) of the null hypothesis that the researcher seeks to uncover evidence for. The research hypothesis in empirical research, which is based on the theoretical prediction, constitutes the alternative hypothesis. This means that it is incumbent on the researcher to find sufficient evidence to support it and in the process nullifies the null hypothesis. Since the null and alternative hypotheses are mutually exclusive and exhaustive, we may state only the null hypothesis, only the alternative hypothesis, or both. In the above examples, Ibrahim and Rizvi (2018) state the null hypotheses while Du et al. (2018) the alternative hypotheses. Below, explanation will be given on how inferential statistics is applied to distinguish the two hypotheses, i.e. which hypothesis is supported by the data.

1.3.2 Model Specification

Model specification comprises three essential aspects – variables to be included, functional form, and statistical assumptions.

The first aspect involves the variables to be included to explain the outcome or dependent variable of interest. By virtue of being a "model", an econometric model involves abstraction or simplification. However, it cannot be too simplistic. That is, we must strike a balance between being too oversimplified and being too realistic by including all variables deemed relevant. The former runs the risk of omitting relevant variables and hence omitted variable bias. The latter results in the loss of degrees of freedom and inefficiency in the estimation or even inability to obtain precise estimates.

The guideline in deciding whether the variables are to be included is to categorize them on the basis of the research objectives and theories into focal variables and controlled variables. The focal variables are the variables stated in the research hypotheses to explain the dependent variable of interest, e.g. lending growth in Ibrahim and Rizvi (2018) and foreign banks in Du at al. (2018) as stated above. These variables must be included. The controlled variables are other variables that either must be included or are deemed relevant. The "must-be-included" variables are the variables strongly suggested by theories or past literature to be important or consistently important. They together with the focal variables would normally form the so-called a "baseline" model. Then, the "deemed relevant" variables can be used to assess whether the "baseline" results prevail when they are included in the regressions. In essence, they will be useful for robustness checks of the findings related to the research objectives.

Let denote y as the outcome/dependent variable of interest, whose behavior or variations we seek to explain, x_1 is the focal variable, x_2 and x_3 are the controlled variables. Collectively, x_1, x_2, and x_3 are called the independent or explanatory variables. The second aspect of model specification involves the functional form that links y to x_1, x_2, and x_3. The standard function is the linear function (or log-linear function, where the variables are expressed in natural log). That is,

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \qquad (1).$$

In (1), $\beta_0, \beta_1, \beta_2$ and β_3 are the parameters of the model to be estimated.

It should be noted that, statistically, the requirement is for the function to be linear in the parameters and not in the independent variables. For example, if the hypothesis posits that y is non-linearly related to x_1 we may include the squared x_1 in the model. Additionally, if the hypothesis states that the relation between y and x_1 is conditioned on x_2, we can include their interaction in the model. Respectively, these are written as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_1^2 \qquad (2)$$

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 (x_1 \times x_2) \qquad (3)$$

While these functions are non-linear in x_1, they are linear in the parameters.

Models (1)-(3) are mathematical models, which are impossible to fit the data collected for y, x_1, x_2, and x_3. Thus, we need to turn these mathematical models into statistical/econometric models by adding the error term. Using (1), we have:

$$y = \beta_0 + \beta_1 y_1 + \beta_2 y_2 + \beta_3 y_3 + \varepsilon \qquad (4),$$

where ε is the error term. It can be thought of all other variables not included in the model because they are of minor importance, unobservable, or data on these variables are unavailable. It also reflects the degree of our ignorance in that, impossibly, we can explain 100% the variations in y. In (4), $\beta_0 + \beta_1 y_1 + \beta_2 y_2 + \beta_3 y_3$ is the explained or predicted value of y and ε is its unexplained portion.

Obviously, the parameters need to be estimated. This brings the third aspect in model specification, the statistical assumptions. We have made two assumptions without stating them explicitly as the model assumptions – the variables included are adequate in that there are no relevant variables excluded and no irrelevant variables included and the model is linear in the parameters. In addition to these two assumptions, the standard assumptions in the linear regression/econometric model are:

(i) The error terms have a mean of 0, $E(\varepsilon) = 0$ [Zero Mean],
(ii) The error terms have a constant variance, $V(\varepsilon) = \sigma^2$, [Homoskedasticity],
(iii) The error terms are normally distributed, [Normality],
(iv) The error terms are independent of each other, $Cov(\varepsilon_i \varepsilon_j) = 0$ for $i \neq j$ [No Serial Correlation or Auto Correlation],
(v) The error terms are independent of the explanatory variables, $Cov(X, \varepsilon) = 0$ [Exogeneity], and
(vi) There are no changes in the parameters of the model [Structural Stability]

These assumptions together (except the normality assumption) are the classical assumptions of the linear regression model. They are essential for valid inferences to be made and, consequently, their violations require remedies. Thus, it should be expected that, diagnostic tests to verify the validity of the assumptions are a part of the empirical research.

1.3.3 Model Estimation

Once a model is specified, it is fitted to the data to provide the estimates of the model parameters, namely the estimates of $\beta_0, \beta_1, \beta_2$ and β_3 in (1). An estimation method provides a formula based on certain criteria to compute the estimates of the model's parameters.

The basic estimation method, which hinges on the validity of the classical assumptions, is the ordinary least squares (OLS) estimation method. As the name implies, it is based on minimizing the sum of the squared errors:

$$Min \sum_{i=1}^{N} \varepsilon_i^2 = \sum_{i=1}^{N} (y_i - [\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i}])^2 \qquad (5).$$

The OLS estimates have desirable statistical properties, given that the classical assumptions are valid. These properties are summarized as BLUE, which stands for Best Linear Unbiased Estimates. Due to this, the least squares-based estimation methods remain the key estimation methods in econometrics.

Apart from the standard OLS estimation method, there are various estimation methods available. Among them include robust estimation method, maximum likelihood estimation method, and the generalized method of moments (GMM) estimation methods. Readers may refer to standard econometrics textbooks on the estimation methods.

1.3.4 Diagnostic Tests

Once a model is estimated, we have to assess its overall performance and its validity before inferences are drawn. The overall performance refers to the model's explanatory power as indicated by R-squared or adjusted R-squared and the F test for overall significance. There are various diagnostic statistics available. It is a good econometric practice to present together with the estimation results diagnostic statistics relevant to the model under study.

The diagnostic statistics for the standard linear regression model estimated via the OLS method relates mainly to verification of whether the classical assumptions are valid. Examples are:

(i) The Jargue-Bera statistics for error normality,
(ii) The White statistics for heteroscedasticity,
(iii) The Engle's ARCH statistics for the autoregressive conditional heteroscedasticity (ARCH) effect,
(iv) The LM statistics for the absence of autocorrelation,
(v) The RESET statistics for model mis-specification, and
(vi) The CUSUM and CUSUMSQ statistics for structural stability.

Again, readers are referred to standard statistical texts for the details of these statistics. Given the importance of the diagnostic statistics to affirm the model validity, the discussion on relevant diagnostic statistics will appear throughout the book.

1.3.5 Hypothesis testing

The evaluation of diagnostic statistics as highlighted above necessarily involves hypothesis testing. Likewise, once diagnostic tests are conducted and remedies are made when relevant, hypotheses under study must be statistically tested before inferences can be drawn.

Hypothesis testing starts with statements of hypotheses, whether they are related to the research objectives (Section 1.3.1) or model assumptions (Section 1.3.4). Then, we need to set the significance levels of the test. Normally, we employ 1%, 5%, and 10% significance levels such that we can state whether the null hypothesis is rejected at 1%, 5%, or 10% significance level. Take the significance level as our tolerance of making mistake. It reflects the probability of rejecting the true null hypothesis. Associated with each significance level is the critical value of the test, which is a cutoff point for rejection or non-rejection of the null hypothesis. Take note that the critical value must correspond to the test statistic employed.

The test statistic refers to the value derived from the estimation. Among the standard test statistics are z-statistic, t-statistic, chi-squared statistic and F-statistic. Associated with each test statistic is the p-value, which represents the probability of observing the value above the computed test statistic (in absolute value). In other words, the p-value represents the area under the tail(s) of the corresponding distribution (e.g. t-distribution or F-distribution). Based on these, the decision rule is:

- Reject the null hypothesis if the test statistic is equal or above the critical value (in absolute term), or alternatively
- Reject the null hypothesis if the p-value is equal or below the significance level

The non-rejection or rejection of the null is the basis for drawing inferences and implications, which is the final step of the empirical research.

1.3.6 Inferences and implications

The final component in empirical research is inferences and implications. There are two parts of inferences – (i) significance and (ii) intuition and importance. The first follows directly from hypothesis testing of the hypotheses under study. Failure to reject the null hypothesis means that the evidence to support the alternative hypothesis is not sufficient or not strong enough. Stated differently, the rejection of the null hypothesis provides indication that the alternative hypothesis is supported, i.e. it is most likely true. It should be noted that the statistical "significance" or "insignificance" inferred from estimation results would not be informative if unaccompanied by intuition and economic importance. At least, once the null is rejected, the estimated coefficient values pertaining to the research hypotheses should be given economic meaning as well as economic importance and, to be complete, should be viewed in the context of existing theories and findings. Finally, any empirical research must answer "so what" question. In other words, the research should suggest implications from the findings.

1.4 DATA STRUCTURE

Empirical research or econometric analyses necessarily involve measurements or data. There are basically three (3) data structures that we may work with. These are cross-sectional data, time series data, and panel data.

Cross-Sectional Data: Cross-sectional data are measurements or data observed at a given time period across individual units, e.g. individuals, households, firms, and countries. Montoro and Rojas-Suarez (2015) is a good example of banking and finance studies that employ cross-sectional data. They gather bank-level data of 124 banks from 6 Latin American countries, i.e. Argentina, Brazil, Chile, Colombia, Mexico, and Peru, to test which initial bank-specific and country-specific characteristics explain credit growth during the crisis.

Time-Series Data: Time-series data are measurements or data over time for a unit or subject under study. As an example, Sukmana and Ibrahim (2017) test whether Islamic deposit rates follow closely conventional deposit rates for the case of Malaysia over the period January 1999 – November 2016.

Panel Data: Panel Data combine the cross-sectional and time-series dimensions of the data. The examples of banking and financing studies using panel data are abundant and, given the focus of this book on practical econometrics using panel data, they will be cited throughout the books.

1.5 SYNOPSIS

This book aims to provide practical guides for empirical or econometric-based research using panel data. Every chapter is self-contained in that it deals with a specific econometric method that can be readily applied to test hypotheses that are appropriate to the method without the need to refer to other chapters, though it is advisable that readers do refer to standard econometrics textbooks for elementary concepts and methods.

It contains four main chapters, three of which deal with basic panel data modelling and one on handling and interpreting interaction terms in econometrics. The three panel data topics are Traditional Panel Models (Chapter 2), Dynamic Panel Models – GMM (Chapter 3), and Panel VAR (Chapter 4). Then, we include a chapter on Interaction Terms (Chapter 5) due to its wide application in econometric models using panel data. We conclude the book with Chapter 6 by motivating the need to have R.I.C.E. (Robustness, Identification, Clarity and Ethics) in empirical Islamic banking and finance research.

In each of these four main chapters, we present model specification and statistical issues. While our approach is to avoid the technical details, we believe that sufficient statistical or econometric foundations underlying each panel data modelling is necessary. Apart from this, the common features across all chapters are examples of empirical studies employing corresponding modelling approaches, which we exclusively focus on empirical banking and finance studies, and demonstration of STATA implementation. Each chapter, where relevant, also provides suggestions on how to deal with statistical issues that might arise.

TRADITIONAL PANEL MODELS

The use of panel data provides major benefits for econometric estimation in at least three areas: (1) the identification of economic models and discrimination between competing economic hypotheses; (2) the elimination or reduction of estimation bias and (3) the reduction of problems of data multicollinearity.

(Hsiao, 1985)

2.1 INTRODUCTION

Panel data contain observations of multiple units (e.g. countries, provinces, firms, individuals) over periods of time. They have been used extensively in empirical analyses of various issues including economic growth and convergence, firm investment behavior and bank-level performance. Employing panel data offers several advantages, which include:

Data variability: there is obviously increasing variability in the variables under study by pooling cross-sectional and time series data. This has two advantages. First, in econometric modelling, variability in explanatory variables is essential for the precision of the estimates. That is, the larger the variability of an independent variable, the lower the standard error of its estimated coefficient. And second, the cross-sectional variability of a variable allows evaluation of factors/determinants that are time-invariant. There are certain variables that do not vary over time for a cross-sectional unit. The examples, among many, include the fraction of population adhering to religion for a country, governance structure of a firm, and banking regulation. However, these factors may be important - religion for credit risk, board composition for firm performance, and bank regulation for bank lending activity – but cannot be incorporated as explanatory variables in time series setting due to lack of data variability.

Normality and Degree of Freedom: closely related to data variability is data availability or number of observations. Especially for developing countries, data availability is a major constraint to a thorough analysis. Take the issue of income inequality as an example. Data on income inequality for a developing country not only are limited but also exhibit little variability over time, making econometric analyses of income inequality for the country unreliable. As another example, if one is interested in assessing the comparative performance of Islamic and conventional commercial banks for the case of Malaysia, he/she will have a small sample size if the cross-sectional data are used. The typical statistical problems arising from a small sample size are non-normality, multicollinearity and lack of degree of freedom. By employing panel data, these problems are subdued.

Heterogeneity, Dynamics and Omitted Variable Bias: modelling using cross-sectional data is unable to capture (unobserved) heterogeneity across units and dynamic behavior of a variable under study. Hence, estimation of an empirical model using a cross-sectional dataset may suffer from omitted variable bias. There are likely factors specific to but varied across individual units that may affect the variable under study. For instance, in addition to standard determinants, lending activity by banks may likely be affected by the (unobserved) degree of risk aversion and managerial style of banks' top management. The lending by banks may also be dynamic in nature as banks have a target for lending based on past lending. This means that omission of these variables would render the estimation biased, the so-called omitted variable bias. Employing panel data would enable incorporating heterogeneity across units and dynamics in the modelling and, consequently, circumvent the omitted variable bias.

Disaggregation and Aggregation Bias: the use of aggregate data in empirical analyses using time series may fail to unearth information or insight specific to each component in the aggregate. For instance, many early studies have assessed the bank lending channel of monetary transmission using aggregate loans. While this can offer an aggregate look into the issue, it fails to unearth potential difference in the responses of loans by each bank to monetary policy changes. It is conceivable from a theoretical point of view that large banks may not reduce lending in responses to interest rate hike while small banks may curtail their lending substantially. This difference is impossible to verify by using the aggregate data. In other words, there is a need for a bank-level panel dataset.

These advantages of panel data notwithstanding, panel data inherit statistical weaknesses of cross-sectional data and time-series data. The normal problems in cross-sectional data are heteroskedastic errors and potential error correlation, the so-called cross-sectional dependence. Meanwhile, the main statistical issues in time-series are autocorrelation and non-stationarity. Apart from these issues, the endogeneity problem may also be a concern. Proper modelling of panel data requires taking into consideration of these statistical issues.

Addressing these issues depends in great part on the panel data structure and on whether the behavior of a variable under study is static or dynamic. Baltagi (2013) classifies panel data into two – micro panels and macro panels. Micro panels refer to panel data of many cross-sectional units (in hundreds or thousands) over a short time period. Meanwhile, macro panels are panel data of cross-sectional units over a long time period (usually more than 20 years). Further, panel data can be balanced (cross-sectional units with the same time period) or unbalanced (cross-sectional units with different numbers of observations, i.e. different time spans). It is notable that whether the panel data are balanced or unbalanced is of less relevant since in most cases the modelling can cater for both.

This chapter focuses on static/traditional panel modelling and makes no distinction between micro panels and macro panels. More precisely, it deliberates pooled OLS, fixed-effects, and random-effects panel estimators and then the two-stage least squares (2SLS) and Hausman-Taylor (HT) panel estimators. In banking and finance (including Islamic banking and finance), recent examples of empirical studies utilizing the traditional panel models include:

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- Alqahtani, F., Mayes, D. G., Brown, K., 2016. Economic turmoil and Islamic banking: Evidence from the Gulf Cooperation Council. Pacific-Basin Finance Journal 39, 44-56.
- Abedifar, P., Hasan, I., Tarazi, A., 2016. Finance-growth nexus and dual-banking systems: Relative importance of Islamic banks. Journal of Economic Behavior & Organization 132, 198-215.
- Zins, A., Weill, L., 2017. Islamic banking and risk: the impact of Basel II. Economic Modelling 64, 626-637.

- Bitar, M., Pukthuanthong, K., Walker, T., 2018. The effect of capital ratios on the risk, efficiency and profitability of banks: Evidence from OECD countries. Journal of International Financial Markets, Institutions & Money 53,227-262.
- Ibrahim, M.H., Rizvi, S.A.R., 2018. Banking lending, deposits and risk-taking in times of crisis: A panel analysis of Islamic and conventional banks. Emerging Markets Review 35, 31-47.

The next section presents traditional panel model specification and estimation. Various statistical tests are also provided in the same section. Then, section 2.3 briefly reviews applications of the traditional panel models in scholarly journal publications. This is followed by the implementation of the traditional panel models using STATA in section 2.4. Section 2.5 deals with the endogeneity issue by means of the instrumental variable techniques using the two-stage least squares and Hausman-Taylor estimators. Finally, section 2.6 concludes with our recommendations.

2.2 SPECIFICATION AND ESTIMATION

A typical or generic static panel model is written as:

$$y_{it} = \beta x_{it} + u_i + \varepsilon_{it} \tag{1}$$

where y_{it} is the dependent variable, x_{it} is an explanatory variable or a vector of explanatory variables, u_i is the individual specific effects, and ε_{it} is the standard error term. The individual specific effects are to capture (unobserved) heterogeneity or factors impacting on the dependent variable. The time specific effects can also be added to account for time-varying factors exerting common impacts on all cross-sectional units.

The estimation of (1) depends on the treatment of the individual specific effects, whether they are assumed to be (i) constant and common across units, (ii) constant but varying across units, or (iii) random. In the first case, given that the error term fulfills the classical assumptions, the ordinary least squares (OLS) estimation method can be used. This is known as the pooled OLS estimator. The second and third cases call for respectively the fixed-effects panel estimator and the random-effects panel estimator. The explanation of these three traditional panel estimators that follows is based heavily on Maddala and Lahiri (2009). For ease of illustration, the panel model contains only one explanatory variable, i.e. a bivariate panel model.

2.2.1 Pooled OLS

If the individual specific effects are treated as a constant and common across countries, then the model would be:

$$y_{it} = u + \beta x_{it} + \varepsilon_{it} \tag{2}$$

where $u_i = u$. Given that ε_{it} fulfills all classical assumptions, equation (2) can be estimated using the standard ordinary least squares estimation method or pooled OLS (POLS) estimator. The estimated slope coefficient of (2) using the POLS is:

$$\hat{\beta}_{POLS} = T_{xx}^{-1} T_{xy} \quad (3)$$

where $T_{xy} = \sum_{i,t}(x_{it} - \bar{x})(y_{it} - \bar{y})$, $T_{xx} = \sum_{i,t}(x_{it} - \bar{x})^2$, and $\bar{y}$ and $\bar{x}$ are respectively the grand means of *y* and *x*. The POLS estimates are best linear unbiased insofar as the classical assumptions are met. The main statistical issues in the use of the POLS are (i) the failure to account for heterogeneity across units and hence model mis-specification and (ii) whether the classical assumptions such as absence of autocorrelation, cross-sectional independence, and homoscedasticity are met.

2.2.2 Fixed-Effects Panel Estimator

The fixed-effects panel model takes the individual specific effects to be fixed for a cross-sectional unit but varying across units, i.e.:

$$y_{it} = \beta x_{it} + u_1 + u_2 + \cdots + u_N + \varepsilon_{it} \quad (4)$$

This amounts to having intercept dummies for all cross-sectional units in the sample. As in the case of the POLS, equation (4) can be estimated using the standard ordinary least squares estimation method given that ε_{it} fulfills all classical assumptions, which is known as the least squares dummy variable (LSDV) estimator. However, its implementation can be cumbersome for large N. The degree of freedom may also be an issue.

Accordingly, it is more practical to filter out first the individual specific effects. This can be achieved by using within-transformation of (4) as:

$$(y_{it} - \bar{y}_i) = \beta(x_{it} - \bar{x}_i) + \epsilon_{it} \quad (5)$$

where $\bar{y}_i$ and $\bar{x}_i$ are the group means, i.e. $\bar{y}_i = \frac{1}{T}\sum_t y_{it}$ and $\bar{x}_i = \frac{1}{T}\sum_t x_{it}$, and $\epsilon_{it} = (\varepsilon_{it} - \bar{\varepsilon}_i)$. Define $W_{xy} = \sum_{i,t}(x_{it} - \bar{x}_i)(y_{it} - \bar{y}_i)$ and $W_{xx} = \sum_{i,t}(x_{it} - \bar{x}_i)^2$. The least squares estimation of (5) is known as the fixed-effects estimator or, alternatively, the within estimator or LSDV estimator. Based on (5), the estimate of the slope coefficient is:

$$\hat{\beta}_{Within} = \hat{\beta}_{LSDV} = W_{xx}^{-1} W_{xy} \quad (6).$$

The fixed-effects estimator yields consistent estimates regardless of whether there is a correlation between the explanatory variable and the error term or not. However, it is not efficient in the absence of correlation between them since it relies only on within variations. Another disadvantage of the estimator is its inability to incorporate time-invariant variables (for example, Islamic bank dummy) into the model since they will be filtered out through within-transformation.

2.2.3 Random-Effects Panel Estimator

The individual specific effects can be specified as random, hence the random-effects panel model. It is stated as:

$$y_{it} = \beta x_{it} + u_i + \varepsilon_{it}; u_i \sim IID(0, \sigma_u^2) \quad \varepsilon_{it} \sim IID(0, \sigma_\varepsilon^2) \qquad (7)$$

and u_i and ε_{it} are not correlated. Note that, in the random-effects panel model, the error correlation of individual i for different time periods is no longer zero. More precisely,

$$E(\epsilon_{it}\epsilon_{is}) = \begin{cases} \sigma_u^2 + \sigma_\varepsilon^2 \ \ for\ t = s \\ \sigma_u^2\ for\ t\ \neq s \end{cases} \qquad (8)$$

where $\epsilon_{it} = u_i + \varepsilon_{it}$. With the variance-covariance matrix whose off-diagonals are not zero, equation (7) is estimated using the generalized least squares estimation method:

$$\hat{\beta}_{GLS} = \frac{W_{XY} + \theta B_{XY}}{W_{XX} + \theta B_{XX}} \qquad (9)$$

where $B_{XY} = T_{XY} - W_{XY}$ and $B_{XX} = T_{XX} - W_{XX}$ (they are between variations). θ is the ratio of σ_ε^2 to $T\sigma_u^2 + \sigma_\varepsilon^2$:

$$\theta = \frac{\sigma_\varepsilon^2}{T\sigma_u^2 + \sigma_\varepsilon^2} \qquad (10)$$

Thus, it is clear that $\hat{\beta}_{GLS}$ will be closer to $\hat{\beta}_{POLS}$ if σ_u^2 approaches zero, i.e. there is not much variation in the individual specific effects. It will be closer to $\hat{\beta}_{Within}$ when T gets larger.

This random-effects panel model is suited when the objective is to draw inferences about the population of the subject under study, where the sample is drawn from. In addition, unlike the fixed-effects panel model, it allows inclusion of time-invariant variables (e.g. Islamic bank dummy and bank ownership). However, the random-effects panel estimator yields biased estimates if the error term (i.e. $\epsilon_{it} = u_i + \varepsilon_{it}$) is correlated with the right-hand-side variables.

2.2.4 Which Estimator?

Given three different treatments of the individual specific effects and hence three different estimators, i.e. Pooled OLS, Fixed-Effects Panel (Within or LSDV), and Random-Effects Panel (GLS) estimators, the choice of an estimator for a (static) panel model becomes relevant. From the foregoing discussion, the choice of the estimator depends on the following questions:

- Are inferences intended for only the cross-sectional units under study or for the population from which the cross-sectional units are drawn?
- Is there heterogeneity across cross-sectional units?
- Is there correlation between explanatory variables and the error terms?

The answer to the first question will direct to the use of either the fixed-effects panel estimator or the random-effects estimator. In most statistical analyses, the aim is to draw inferences about the population. Accordingly, the random-effects estimator should be used. Alternatively, the fixed-effects panel estimator is appropriate when the inferences are intended for or confined only to the cross-sectional units under study.

While the assumption of homogeneity (or absence of unobserved individual heterogeneity) is hardly tenable, i.e. it is almost always "yes" to the second question, it is advisable to run a statistical test whether $\sigma_u^2 = 0$. This is a test of poolability, which we can employ the Breusch-Pagan Lagrangian Multiplier (LM) test (Breusch and Pagan, 1980). Under the null hypothesis that $\sigma_u^2 = 0$, the Breusch-Pagan LM statistics is computed as:

$$LM = \frac{NT}{2(T-1)}\left[\frac{\sum_{i=1}^{N}\left(\sum_{t=1}^{T}\hat{\varepsilon}_{it}\right)^2}{\sum_{i=1}^{N}\sum_{t=1}^{N}\hat{\varepsilon}_{it}^2} - 1\right]^2 \qquad (11)$$

where $\hat{\varepsilon}_{it}$ is the residuals from the least squares regression. The statistic is chi-squared distributed with one degree of freedom. The rejection of the null hypothesis (i.e. $\sigma_u^2 = 0$) suggests that there is individual heterogeneity and hence the use of pooled OLS is not appropriate.

The third question is related to the choice between the fixed-effects panel estimator and the random-effects panel estimator. As noted earlier, the fixed-effects estimator is consistent regardless whether u_i is correlated with x_{it} or not. In the absence of their correlation, however, the fixed-effects estimator is not efficient while the random-effects estimator is consistent and efficient. This leads to the following hypotheses:

H_0: u_i is not correlated with x_{it}
H_1: u_i is correlated with x_{it}

In distinguishing between these two hypotheses, the Hausman test is usually applied. The non-rejection of the null hypothesis suggests that the random-effects estimator is preferred. Its rejection, on the other hand, points to the fixed-effects estimator.

2.2.5 Other Tests

Apart from the above tests, there are several diagnostic tests for the static panel. These include tests for heteroskedasticity, serial correlation, cross-sectional dependence, and time effects. While there are various tests that have been developed for each case, we present here the commonly used diagnostic tests.

Heteroskedasticity: The cross-sectional setting of panel data means that heteroscedasticity is very likely. A modified Wald statistic for groupwise heteroscedasticity tests whether the residuals of a fixed-effects model have constant variance or varying variances across cross-sectional units, i.e. $H_0: \sigma_i^2 = \sigma^2, i = 1, \ldots, N$ where N is the number of cross-sectional units. Under the null of homoscedasticity, the statistic is Chi-squared distributed with N degrees of freedom.

Serial Correlation: The presence of serial correlation renders the results less efficient. Accordingly, it is advisable to conduct a serial correlation test. While there are various tests for serial correlation, Drukker (2003) demonstrates that the Wooldridge's (2002) test exhibits good size and power properties with samples of moderate size. As explained in Drukker (2003), the Wooldridge's test is based on regressing the residuals obtained from the panel model (fixed-effects panel model or random-effects panel model) in first differences on their lags. The test amounts to testing the coefficient of the lagged residuals equal to -0.5, whose statistic is F-distributed.

Cross-sectional dependence: Another statistical problem is the presence of cross-sectional dependence. This can be examined using the Breusch-Pagan's (1980) LM test or the Pesaran's (2004) CD test for cross-sectional dependence. The null hypothesis is that the residuals of cross-sectional units are not correlated. These tests are implemented after the estimation of a fixed-effects panel model. According to Baltagi (2013), the cross-sectional dependence of the error terms is more a problem in macro panels. In panel data with few years but large cross-sectional units, i.e. micro panels, the cross-sectional dependence would not be much of a problem.

Time Effects: A test also can be conducted whether time-specific effects should be included when estimating a fixed-effects model. This can be done easily by performing the restricted F-test on the coefficients of time dummies in the regression.

2.3 APPLICATIONS

The traditional panel estimators particularly the fixed-effects and random-effects panel estimators remain applicable. Examples of their recent applications to banking and finance research, including Islamic banking and finance, are given below.

Example I	Bertay, A. C., Demirguc-Kunt, A., Huizinga, H., 2013. Do we need big banks? Evidence on performance, strategy and market discipline. Journal of Financial Intermediation 22, 532-538.

Bertay et al. (2013) assess the implications of bank size on (i) bank risk and return, (ii) activity mixes and funding strategies, and (iii) market discipline using bank-level data from 90 countries over the years 1991- 2011. In the analysis, a distinction is made between absolute bank size and systemic bank size, respectively measured as the natural logarithm of total assets and the ratio of bank liabilities to GDP. They allow for country specific effects and time specific effects and employ least squares estimation.

The findings from their analysis indicate that absolute size and systemic size exert different impacts on bank return. Namely, return on assets (ROA) and return on equity (ROE) are directly related to bank absolute size but negatively related to systemic size. Interestingly, bank size (absolute or systemic) does not seem to exert any bearing on bank stability. In addition, a larger bank in terms of its assets tends to have a larger share of non-interest income and a larger share of non-deposit or wholesale funding. By contrast, systemically larger banks are relatively more traditional, having relatively small share of non-interest income and depending more on deposit funding. Finally, they document evidence suggesting increasing sensitivity of interest costs to capitalization rate when banks become systemically larger. Meanwhile, the interest costs do decline with systemic size, except for those banks with low capitalization levels.

Example II	Abedifar, P., Hasan, I., Tarazi, A., 2016. Finance-growth nexus and dual-banking systems: Relative importance of Islamic banks. Journal of Economic Behavior & Organization 132, 198-215.

Abedifar et al. (2016) assess the impacts of Islamic banking presence on (i) aggregate financial intermediation, (ii) economic growth, (iii) income inequality and poverty alleviation, and (iv) efficiency of conventional banks using country-level and bank-level panel data of 22 dual-banking countries over the period 1999 – 2011. These impacts are examined for the cases of (i) predominantly Muslim countries, (ii) low income countries, (iii) high uncertainty avoidance countries, (iv) more religiously diverse countries, (v) high inflation countries, and (vi) crisis and non-crisis periods. They employ the fixed-effects panel estimator with standard errors clustered at the country level.

The findings point to positive contributions of Islamic banking presence especially of medium-size Islamic banks to financial intermediation and financial deepening and to economic welfare, which are particularly apparent in predominantly Muslim countries, in low income countries, and high uncertainty avoidance countries. At the bank level, they indicate the efficiency gains by conventional banks in predominantly Muslim countries with the presence of large Islamic banks.

Example III	Alqahtani, F., Mayes, D. G., Brown, K., 2016. Economic turmoil and Islamic banking: Evidence from the Gulf Cooperation Council. Pacific-Basin Finance Journal 39, 44-56.

Alqahtani et al. (2016) perform a comparative analysis of Islamic and conventional banks in terms of CAMEL (Capital Adequacy, Asset Quality, Management Efficiency, Earning, and Liquidity) measures during the recent global financial crisis and subsequent economic recessions. They re-evaluate Beck et al.'s (2013) findings that there are few differences between Islamic and conventional banks. Using a panel of 101 banks from the GCC, they build static panel models for CAMEL measures and specify the individual specific effects as fixed based on the Hausman test, i.e. the fixed-effects panel models. The robust standard errors are employed.

Their results indicate more differences between Islamic and conventional banks, as compared to those documented by Beck et al. (2013). Namely, Islamic banks perform better during the initial stages of the global financial crisis in terms of capitalization, profitability, and liquidity. However, once the crisis propagated to the real sector, they perform worse in terms of capitalization, profitability and efficiency. Accordingly, Islamic banks are not immune to economic shocks, although they seem resilient in the wake of financial shocks.

Example IV	Ibrahim, M.H., Rizvi, S.A.R., 2018. Banking lending, deposits and risk-taking in times of crisis: A panel analysis of Islamic and conventional banks. Emerging Markets Review 35, 31-47.

Ibrahim and Rizvi (2018) compare lending growth and deposit growth of Islamic banks vis-à-vis conventional banks during the 2008/2009 global financial crisis using a panel sample of 25 Islamic banks and 114 conventional banks from 10 dual-banking countries. They opt for static panel specifications of loan and deposit growth equations and estimate the equations using the random-effects panel estimator for a combined sample of Islamic and conventional banks due to the presence of the time-invariant Islamic bank dummy. However, when they estimate the equations separately for Islamic banks and conventional banks, they also experiment with the fixed-effects estimator for robustness.

Their results indicate that Islamic banks were able to sustain Islamic financing during the crisis period and, comparatively, witnessed higher financing growth as compared to credit growth of conventional banks. As regards deposits, they document no discernable difference between Islamic banks and conventional banks. Noting that the strong financing growth of Islamic banks was not accompanied by strong deposit growth, they proceed to assess whether the Islamic financing growth during the period reflects increasing risk-taking of Islamic banks using a dynamic panel model. They find no evidence of excessive risk taking by Islamic banks during the crisis period.

2.4 TRADITIONAL PANEL IN STATA

This section illustrates STATA implementation of the following static panel model:

$$\begin{aligned} dloan_{it} = \beta_1 lnta_{it-1} + \beta_2 npl_{it-1} + \beta_3 eqa_{it-1} + \beta_4 liqta_{it-1} \\ +\beta_5 gdpg_{it} + u_i + \varepsilon_{it} \end{aligned} \tag{12}$$

where *dloan* is the growth rate of gross loans, *lnta* is the natural logarithm of total assets, *npl* is non-performing loan ratio, *eqa* is equity to asset ratio, *liqta* is liquid asset to total asset ratio and *gdpg* is real GDP growth. The data are in *DualBank.xlsx*. We first illustrate the estimation of (12) using the pooled OLS, fixed-effects panel, and the random-effects panel estimators. Then, we conduct relevant tests for the static panel models.

2.4.1 Estimation

Once the data are placed in STATA, we must set the panel structure using:

tsset *code year.*

In addition, the following variables need to be constructed:

gen *lgloan = ln(grossl)*
gen *dloan = (lgloan – l.lgloan)*100*
gen *lnta = ln(ta)*
gen *liqta = (liquid/ta)*100*

Other variables can be used directly.

<u>Pooled OLS</u>

Syntax: reg *depvar indepvars, options*

```
. reg dloan l.lnta l.npl l.eqa l.liqta gdpg

      Source |       SS       df       MS              Number of obs =    1823
-------------+------------------------------           F(  5,  1817) =   41.88
       Model |  76435.9688     5  15287.1938           Prob > F      =  0.0000
    Residual |  663281.565  1817  365.042138           R-squared     =  0.1033
-------------+------------------------------           Adj R-squared =  0.1009
       Total |  739717.534  1822   405.99206           Root MSE      =  19.106

------------------------------------------------------------------------------
       dloan |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        lnta |
         L1. |  -2.141997   .2902902    -7.38   0.000    -2.711335    -1.57266
             |
         npl |
         L1. |  -.4464612   .0463103    -9.64   0.000    -.5372882   -.3556341
             |
         eqa |
         L1. |   .0085806   .0598715     0.14   0.886    -.1088436    .1260047
             |
       liqta |
         L1. |   .0699312   .0296226     2.36   0.018     .0118333    .1280292
             |
        gdpg |   .9823568   .1233278     7.97   0.000     .7404777    1.224236
       _cons |   43.99894   4.786144     9.19   0.000     34.61202    53.38586
------------------------------------------------------------------------------
```

<u>Fixed-Effects Panel Model</u>

Syntax: xtreg *depvar indepvars, fe options*

```
. xtreg dloan l.lnta l.npl l.eqa l.liqta gdpg, fe

Fixed-effects (within) regression               Number of obs      =      1823
Group variable: code                            Number of groups   =       139

R-sq:  within  = 0.1504                         Obs per group: min =         8
       between = 0.0428                                        avg =      13.1
       overall = 0.0629                                        max =        14

                                                F(5,1679)          =     59.45
corr(u_i, Xb)  = -0.6850                        Prob > F           =    0.0000
```

```
------------------------------------------------------------------------------
       dloan |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        lnta |
         L1. |  -7.372018   .7190188   -10.25   0.000    -8.782285    -5.96175
             |
         npl |
         L1. |  -.5927842   .0680652    -8.71   0.000    -.7262857   -.4592827
             |
         eqa |
         L1. |     .34297   .1187292     2.89   0.004     .1100972    .5758427
             |
       liqta |
         L1. |   .2102266   .0428236     4.91   0.000     .1262333    .2942199
             |
        gdpg |   .8536246   .1296015     6.59   0.000     .5994272    1.107822
       _cons |    116.961   11.68642    10.01   0.000      94.0395    139.8824
-------------+----------------------------------------------------------------
     sigma_u |  12.635099
     sigma_e |  17.933843
         rho |  .33171869   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0:     F(138, 1679) =     2.78           Prob > F = 0.0000
```

Random-Effects Panel Model

Syntax: xtreg *depvar indepvars, re options*

```
. xtreg dloan l.lnta l.npl l.eqa l.liqta gdpg, re

Random-effects GLS regression                   Number of obs      =      1823
Group variable: code                            Number of groups   =       139

R-sq:  within  = 0.1204                         Obs per group: min =         8
       between = 0.1566                                        avg =      13.1
       overall = 0.1008                                        max =        14

                                                Wald chi2(5)       =    214.60
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000

------------------------------------------------------------------------------
       dloan |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        lnta |
         L1. |  -2.676123   .3487775    -7.67   0.000    -3.359715   -1.992532
             |
         npl |
         L1. |  -.4754937   .0502933    -9.45   0.000    -.5740668   -.3769206
             |
         eqa |
         L1. |   .0264184   .0677783     0.39   0.697    -.1064247    .1592616
             |
       liqta |
         L1. |   .1236792   .0324259     3.81   0.000     .0601256    .1872328
             |
        gdpg |   .9766285   .1246752     7.83   0.000     .7322697    1.220987
       _cons |    50.7604   5.722015     8.87   0.000     39.54546    61.97534
-------------+----------------------------------------------------------------
     sigma_u |  4.1135241
     sigma_e |  17.933843
         rho |  .04998195   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

The results from the three estimators are re-presented in the Table below:

	POLS	FE	RE
L.lnta	-2.142***	-7.372***	-2.676***
	(0.000)	(0.000)	(0.000)
L.npl	-0.446***	-0.593***	-0.475***
	(0.000)	(0.000)	(0.000)
L.eqa	0.009	0.343***	0.026
	(0.886)	(0.004)	(0.697)
L.liqta	0.070**	0.210***	0.124***
	(0.018)	(0.000)	(0.000)
Gdpg	0.982***	0.854***	0.977***
	(0.000)	(0.000)	(0.000)
_cons	43.999***	116.961***	50.760***
	(0.000)	(0.000)	(0.000)
N	1823	1823	1823
N_g		139	139
r2	0.103	0.150	0.101

p-values in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

2.4.2 Tests in Traditional Panel Models

Is Pooled OLS adequate?

To answer this question, we can test whether the variance of individual specific effects is zero. The null hypothesis is it is zero.

This test can be done by running the random-effects panel model first. Then, the following command is used:

```
. xttest0
Breusch and Pagan Lagrangian multiplier test for random effects

        dloan[code,t] = Xb + u[code] + e[code,t]

        Estimated results:
                         |       Var     sd = sqrt(Var)
                ---------+-----------------------------
                   dloan |   405.9921       20.14924
                       e |   321.6227       17.93384
                       u |   16.92108       4.113524

        Test:   Var(u) = 0
                            chibar2(01) =    46.94
                         Prob > chibar2 =   0.0000
```

The statistic rejects the null hypothesis that the variance of the individual-specific effects is zero. Accordingly, allowance must be made for heterogeneity by including the individual specific effects in the model. In other words, the pooled OLS specification is rejected.

Is Fixed- or Random-Effects Model?

This can be answered using the Hausman test. The null hypothesis is that the individual specific effects are not correlated with X. In this case, the random-effects (GLS) estimator is consistent and efficient. The rejection of the null hypothesis suggests the use of fixed-effects estimators.

For the purpose, the following string of commands needs to be used

xtreg *dloan l.lnta l.npl l.eqa l.liqta gdpg, fe*
est store fixed
xtreg *dloan l.lnta l.npl l.eqa l.liqta gdpg, re*
hausman fixed

```
. hausman fixed

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-
V_B))
             |     fixed          .          Difference          S.E.
-------------+----------------------------------------------------------
-
      L.lnta |   -7.372018    -2.676123       -4.695894        .6287625
       L.npl |   -.5927842    -.4754937       -.1172905        .0458633
       L.eqa |      .34297     .0264184        .3165515        .0974818
     L.liqta |    .2102266     .1236792        .0865474        .0279719
        gdpg |    .8536246     .9766285       -.1230039        .0353927
------------------------------------------------------------------------
-
       b = consistent under Ho and Ha; obtained from xtreg
       B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(5) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =      141.56
                Prob>chi2 =      0.0000
```

The statistic rejects the null hypothesis of no correlation between the error term and the explanatory variables. Accordingly, the fixed-effects panel model is suggested.

Are Errors Heteroskedastic?

In this case, *xttest3* command is used after running the fixed-effects panel model. In STATA, this test must be installed if this command is not available. To install, type the following instruction: *ssc install xttest3*. The null hypothesis of the test is the errors are homoscedastic or have a constant variance.

After running the fixed-effects panel model, type *xttest3*.

```
. xttest3
Modified Wald test for groupwise heteroscedasticity in fixed effect regression
model
H0: sigma(i)^2 = sigma^2 for all i
chi2 (139)   =  11203.24
Prob>chi2 =       0.0000
```

The statistic suggests that the errors are heteroscedastic. The null hypothesis is rejected at 1% significance level.

Are Errors Auto-correlated?

The Wooldridge's test for serial correlation is implemented using the following command: *xtserial depvar indepvar*. The null hypothesis is the absence of serial correlation. The command must be installed if it is not available. This can be done using *ssc install xtserial* or *use findit xtserial* and install from there. Take note that the lag operator (i.e. *l.x*) cannot be used to run xtserial. Accordingly, the lagged variable must be generated first (e.g. *gen lagx = l.x*).

```
. xtserial dloan laglnta lagnpl lageqa lagliqta gdpg
Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      138) =     17.832
           Prob > F =      0.0000
```

The statistic rejects the null hypothesis. Accordingly, the error terms are serially correlated.

Are Errors Cross-Sectional Dependent?

The cross-sectional dependence of the error terms can be tested using the Breusch-Pagan's LM test and the Pesaran's CD test. The null hypothesis is there is no cross-sectional dependence in the error term. For the Breusch-Pagan's LM test, the command *xttest2* is used after running the fixed-effects model. For the Pesaran's CD test, the following can be implemented after the fixed-effects estimation:

```
. xtcsd, pesaran abs
 Pesaran's test of cross sectional independence =    20.628, Pr = 0.0000
 Average absolute value of the off-diagonal elements =     0.266
```

The test rejects the null hypothesis of no cross-sectional dependence.

Should Time-Specific Effects be Included?

In testing whether the time specific effects should be included, we run the fixed-effects model including the time specific effects and then perform the F-restricted test on the joint significance of the coefficients of the time dummies. The null hypothesis is the coefficients jointly equal zero, i.e. there are no time-specific effects in the model. The implementation of the test can be done using:

. **xtreg** *dloan l.lnta l.npl l.eqa l.liqta gdpg i.year, fe*
. **testparm** *i.year*

```
. xtreg dloan l.lnta l.npl l.eqa l.liqta gdpg i.year, fe
Fixed-effects (within) regression               Number of obs      =      1823
Group variable: code                            Number of groups   =       139
R-sq:  within  = 0.2088                         Obs per group: min =         8
       between = 0.0266                                        avg =      13.1
       overall = 0.0507                                        max =        14

                                                F(18,1666)         =     24.43
corr(u_i, Xb)  = -0.8409                        Prob > F           =    0.0000

------------------------------------------------------------------------------
       dloan |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        lnta |
         L1. |  -12.69046   1.416635    -8.96   0.000    -15.46903   -9.911885
             |
         npl |
         L1. |  -.4496269   .0689267    -6.52   0.000     -.584819   -.3144349
             |
         eqa |
         L1. |   .1396602   .1199821     1.16   0.245    -.0956714    .3749919
             |
```

```
       liqta |
         L1. |    .260653   .0427777     6.09   0.000     .1767493    .3445568
             |
        gdpg |     .47776   .1563399     3.06   0.002     .1711167    .7844033
             |
        year |
       2002  |  -.2928765   2.497993    -0.12   0.907    -5.192412    4.606659
       2003  |   3.505725   2.534744     1.38   0.167    -1.465894    8.477344
       2004  |   6.413322   2.638213     2.43   0.015      1.23876    11.58788
       2005  |   14.69795   2.630321     5.59   0.000     9.538867    19.85703
       2006  |   11.92551   2.806075     4.25   0.000     6.421706    17.42932
       2007  |    21.5198   2.874737     7.49   0.000     15.88133    27.15828
       2008  |   15.12554   3.030701     4.99   0.000     9.181161    21.06993
       2009  |   8.909062    3.11223     2.86   0.004     2.804769    15.01335
       2010  |   17.16588   3.257279     5.27   0.000     10.77709    23.55467
       2011  |   10.60985   3.409238     3.11   0.002      3.92301    17.29669
       2012  |   19.21745    3.45435     5.56   0.000     12.44213    25.99278
       2013  |   16.68743    3.58428     4.66   0.000     9.657262     23.7176
       2014  |   17.46842   3.696762     4.73   0.000     10.21764    24.71921
             |
       _cons |   187.3521   20.53305     9.12   0.000     147.0788    227.6254
-------------+----------------------------------------------------------------
     sigma_u |  19.420593
     sigma_e |  17.373758
         rho |  .55545744   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0:     F(138, 1666) =     2.72           Prob > F = 0.0000

. testparm i.year

 ( 1)  2002.year = 0
 ( 2)  2003.year = 0
 ( 3)  2004.year = 0
 ( 4)  2005.year = 0
 ( 5)  2006.year = 0
 ( 6)  2007.year = 0
 ( 7)  2008.year = 0
 ( 8)  2009.year = 0
 ( 9)  2010.year = 0
 (10)  2011.year = 0
 (11)  2012.year = 0
 (12)  2013.year = 0
 (13)  2014.year = 0

       F( 13,  1666) =    9.46
            Prob > F =    0.0000
```

The test, thus, indicates that the time-specific effects are jointly significant and, accordingly, they should be included in the model.

2.4.3 Robust Standard Errors

The presence of non-constant variance (heteroscedasticity), autocorrelation, and cross-sectional dependence calls for remedial measures such that valid inferences can be drawn. An approach normally adopted in the literature is the use of robust standard errors. This is similar to the classical linear regressions where, in the presence of heteroscedasticity and/or autocorrelation problems, White or Newey-West robust variance-covariance matrix is used.

If the error terms exhibit non-constant variance or within-panel autocorrelation, we could employ the robust standard errors by using the option *vce(robust)*. These robust standard errors are based on the Huber/White /sandwich VCE estimator. Thus, using the fixed-effects panel model above, the estimation of the model with robust standard errors is:

```
. xtreg dloan l.lnta l.npl l.eqa l.liqta gdpg, fe vce(robust)

Fixed-effects (within) regression               Number of obs     =      1823
Group variable: code                            Number of groups  =       139

R-sq:  within  = 0.1504                         Obs per group: min =         8
       between = 0.0428                                        avg =      13.1
       overall = 0.0629                                        max =        14

                                                F(5,138)          =     51.28
corr(u_i, Xb)  = -0.6850                        Prob > F          =    0.0000

                               (Std. Err. adjusted for 139 clusters in code)
------------------------------------------------------------------------------
             |               Robust
       dloan |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        lnta |
         L1. |  -7.372018     1.0312    -7.15   0.000    -9.411013   -5.333022
             |
         npl |
         L1. |  -.5927842   .1062778    -5.58   0.000    -.8029276   -.3826408
             |
         eqa |
         L1. |     .34297   .2422283     1.42   0.159    -.1359889    .8219289
             |
       liqta |
         L1. |   .2102266   .0589381     3.57   0.000      .093688    .3267652
             |
        gdpg |   .8536246   .1278107     6.68   0.000     .6009041    1.106345
       _cons |    116.961   16.35158     7.15   0.000     84.62893     149.293
-------------+----------------------------------------------------------------
     sigma_u |  12.635099
     sigma_e |  17.933843
         rho |  .33171869   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Note that using the option *vce(cluster panelid)*, where *panelid* is the variable that identifies the cross-sectional units, provides identical robust standard errors as above. That is, the following command will generate identical results:

. **xtreg** *dloan l.lnta l.npl l.eqa l.liqta gdpg, fe vce(cluster code)*

Further, clustering on the panel variable (i.e. *panelid*) requires that there are many clusters and there are no error correlations across the clusters. When there is cross-sectional dependence in the model, it is suggested that the Driscoll and Kraay standard errors be used (Hoechle, 2007). This requires the estimation of the panel model using **xtscc** as explained in Hoechle (2007). Finally, while the estimation above is for the fixed-effects panel model, the robust standard errors are also available for the random-effects panel model using the option *vce(robust)* or *vce(cluster panelid)*.

2.5 ENDOGENEITY IN TRADITIONAL PANEL MODELS

Let rewrite the traditional panel model as:

$$y_{it} = \beta_1 x1_{it} + \beta_2 x2_{it} + u_i + \varepsilon_{it}; \varepsilon_{it} \sim IID(0, \sigma_\varepsilon^2) \quad (13)$$

where $x1_{it}$ is a $k_1 \times 1$ vector of explanatory variables specified to be endogenous, $x2_{it}$ is a $k_2 \times 1$ vector of explanatory variables taken to be exogenous and $x_{it} = [x1_{it}\ x2_{it}]$. These mean that ε_{it} is not correlated with the variables in $x2_{it}$ but it is allowed to be correlated with $x1_{it}$. The individual specific effects, i.e. u_i, can be fixed or random. An interesting case that might arise is some variables in $x1_{it}$ and/or $x2_{it}$ are time-invariant. In this case, it is impossible to estimate the coefficients of these time-invariant variables using the within estimator. Meanwhile, the GLS random-effects estimator is inconsistent if some of the explanatory variables are correlated with the individual specific effects. In this section, we introduce the instrumental variable estimation techniques, namely the two-stage least squares estimator (*xtivreg*) and the Hausman-Taylor estimator (*xthlaylor*), to deal with the endogeneity problem.

2.5.1 IV and Two-Stages Least Squares Estimators

The two-stage least squares (2SLS) estimators deal with the endogeneity issue in (13) by employing instrumental variables to instrument the endogenous explanatory variables. The number of instruments must be equal or more than the number of the endogenous explanatory variables for the order condition to be satisfied. There are several 2SLS estimators depending on the assumption made on the individual specific effects. If u_i is assumed to be fixed and is correlated with $x2_{it}$, then the fixed-effects or within estimator is efficient. Meanwhile, if u_i is assumed to be random and is uncorrelated with $x2_{it}$, the random-effects estimators will be more efficient and consistent. In essence, these 2SLS within and random-effects estimators are the generalizations of the traditional fixed- and random-effects estimators to deal with the endogeneity problem.

In STATA, *xtivreg* implements the 2SLS estimators in traditional panel models with endogenous explanatory variables. These are illustrated below.

Model

Let say we are interested in the following model:

$$npl_{it} = \alpha_1 lnta_{it} + \alpha_2 dloan_{it} + \alpha_3 gdpg_{it} + u_i + \varepsilon_{it} \tag{14}$$

where the variables are as defined above. Applying the fixed-effects panel estimator yields the following results:

```
. xtreg npl lnta dloan gdpg, fe

Fixed-effects (within) regression               Number of obs      =      1823
Group variable: code                            Number of groups   =       139

R-sq:  within  = 0.1721                         Obs per group: min =         8
       between = 0.0818                                        avg =      13.1
       overall = 0.1041                                        max =        14

                                                F(3,1681)          =    116.44
corr(u_i, Xb)  = -0.2709                        Prob > F           =    0.0000

------------------------------------------------------------------------------
         npl |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        lnta |  -3.240732    .208823   -15.52   0.000    -3.650313   -2.831152
       dloan |  -.0811244   .0073719   -11.00   0.000    -.0955835   -.0666652
        gdpg |  -.1194721   .0417058    -2.86   0.004    -.2012729   -.0376713
       _cons |   57.80072   3.217494    17.96   0.000        51.49    64.11144
-------------+----------------------------------------------------------------
```

```
     sigma_u |  8.4600292
     sigma_e |  5.7370504
         rho |  .68499323   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0:     F(138, 1681) =    21.50           Prob > F = 0.0000
```

2SLS Fixed-Effects/Within Estimator

Suppose we have reasons to believe that *dloan* is endogenous, i.e. it is correlated with ε_{it}. Moreover, we take *dloan* to be a function of AR, where AR is the activity restriction index. Taking the individual specific effects as fixed, we can apply the 2SLS estimator. The syntax or command in STATA is:

Syntax: xtivreg *depvar varlist₁ (varlist₂ = varlistᵢᵥ), fe options*

The options available are:

- vce*(vcetype)* specifies the standard errors reported. The default is the variance estimator from the generalized least-squares regression. We may also opt for bootstrap or jackknife methods in deriving the standard errors using respectively vce*(bootstrap)* and vce*(jackknife)*,
- *first* reports the first-stage regression, and
- level*(#)* specifies the confidence level. The 95% confidence level is the default

The application of the 2SLS within estimator to the above model using AR as the instrument for *dloan* yields:

```
. xtivreg npl lnta gdpg (dloan = ar), fe

Fixed-effects (within) IV regression         Number of obs      =       1823
Group variable: code                         Number of groups   =        139

R-sq:  within  =      .                      Obs per group: min =          8
       between = 0.1973                                     avg =       13.1
       overall = 0.1295                                     max =         14

                                             Wald chi2(3)       =     876.52
corr(u_i, Xb)  = -0.2831                     Prob > chi2        =     0.0000

------------------------------------------------------------------------------
         npl |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       dloan |  -.5016913     .15202    -3.30   0.001     -.799645   -.2037377
        lnta |  -4.367314   .5410354    -8.07   0.000    -5.427724   -3.306904
        gdpg |   .3343995   .1784275     1.87   0.061    -.0153121     .684111
       _cons |    79.1132   9.451618     8.37   0.000     60.58837    97.63803
-------------+----------------------------------------------------------------
     sigma_u |  8.3385763
     sigma_e |  9.8305486
         rho |  .41843419   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F  test that all u_i=0:     F(138,1681) =     6.49        Prob > F    = 0.0000
------------------------------------------------------------------------------
Instrumented:   dloan
Instruments:    lnta gdpg ar
------------------------------------------------------------------------------
```

Note that for the model to be identified, there must be at least as many instruments (varlist$_{IV}$) not in the regression (*varlist₁*) as there are instrumented variables (*varlist₂*). The challenge in implementing the 2SLS is to identify these instruments.

2SLS Random-Effects Estimators

The 2SLS random-effects estimators are more efficient and consistent when u_i is random and is uncorrelated with $x2_{it}$. The STATA command for implementing the 2SLS random-effects estimators is:

Syntax: xtivreg *depvar varlist$_1$ (varlist$_2$ = varlist$_{iv}$), re options*

The implementation of the model with u_i specified to be random requires estimation of the variance of u_i and the variance of ε_{it}. The default is the Swamy-Arora method. An alternative method is the variance-component estimators by Baltagi and Chang (2000), which is applied when *nosa* option is specified. Using either estimator of the variance components, we may apply the generalized 2SLS or G2SLS estimator, which is the default, or the Baltagi's EC2SLS random-effects estimator by specifying the option *ec2sls*. They differ in the ways the instruments are constructed from the exogenous and instrumental variables. The *options* listed under the 2SLS fixed-effects estimator, i.e. vce(*vcetype*), *first*, and level(#), can also be used.

The estimation of equation (14) using the G2SLS with Swamy-Arora method to estimate the variance components is:

```
. xtivreg npl lnta gdpg (dloan = ar), re
G2SLS random-effects IV regression               Number of obs      =      1823
Group variable: code                             Number of groups   =       139

R-sq:  within  = 0.0957                          Obs per group: min =         8
       between = 0.2009                                         avg =      13.1
       overall = 0.1291                                         max =        14

                                                 Wald chi2(3)       =    102.27
corr(u_i, X)       = 0 (assumed)                 Prob > chi2        =    0.0000

------------------------------------------------------------------------------
         npl |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       dloan |  -.4669586   .1391954    -3.35   0.001    -.7397766   -.1941407
        lnta |  -3.956037   .4561654    -8.67   0.000    -4.850105   -3.061969
        gdpg |   .2979294   .1636553     1.82   0.069    -.0228292     .618688
       _cons |   72.53876   8.151547     8.90   0.000     56.56203     88.5155
-------------+----------------------------------------------------------------
     sigma_u |  16.750348
     sigma_e |  9.8305486
         rho |  .74380663   (fraction of variance due to u_i)
------------------------------------------------------------------------------
Instrumented:   dloan
Instruments:    lnta gdpg ar
------------------------------------------------------------------------------
```

The estimation using the G2SLS using Baltagi-Chang's variance-component estimator is:

```
. xtivreg npl lnta gdpg (dloan = ar), re nosa
G2SLS random-effects IV regression               Number of obs      =      1823
Group variable: code                             Number of groups   =       139

R-sq:  within  = 0.0957                          Obs per group: min =         8
       between = 0.2010                                         avg =      13.1
       overall = 0.1291                                         max =        14

                                                 Wald chi2(3)       =    102.45
corr(u_i, X)       = 0 (assumed)                 Prob > chi2        =    0.0000
```

```
------------------------------------------------------------------------------
         npl |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       dloan |  -.4660708    .139032    -3.35   0.001    -.7385686   -.1935731
        lnta |  -3.946005   .4546423    -8.68   0.000    -4.837088   -3.054923
        gdpg |   .2969875   .1634686     1.82   0.069    -.0234051      .61738
       _cons |   72.37706   8.123826     8.91   0.000     56.45465    88.29947
-------------+----------------------------------------------------------------
     sigma_u |  16.499528
     sigma_e |  9.8217883
         rho |  .73835907   (fraction of variance due to u_i)
------------------------------------------------------------------------------
Instrumented:   dloan
Instruments:    lnta gdpg ar
------------------------------------------------------------------------------
```

Finally, the estimation using the Baltagi's EC2SLS yields:

```
. xtivreg npl lnta gdpg (dloan = ar), re ec2sls

EC2SLS random-effects IV regression             Number of obs      =      1823
Group variable: code                            Number of groups   =       139

R-sq:  within  = 0.1083                         Obs per group: min =         8
       between = 0.1743                                        avg =      13.1
       overall = 0.1337                                        max =        14

                                                Wald chi2(3)       =     81.82
corr(u_i, X)       = 0 (assumed)                Prob > chi2        =    0.0000

------------------------------------------------------------------------------
         npl |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       dloan |  -.3641041   .1109944    -3.28   0.001    -.5816492    -.146559
        lnta |  -3.871708   .4597589    -8.42   0.000    -4.772819   -2.970598
        gdpg |   .1821632   .1321523     1.38   0.168    -.0768505    .4411769
       _cons |   70.25286   7.806185     9.00   0.000     54.95302     85.5527
-------------+----------------------------------------------------------------
     sigma_u |  16.750348
     sigma_e |  9.8305486
         rho |  .74380663   (fraction of variance due to u_i)
------------------------------------------------------------------------------
Instrumented:   dloan
Instruments:    lnta gdpg ar
------------------------------------------------------------------------------
```

2.5.2 Hausman-Taylor (HT) Estimator

Suppose that we have the following model, which is the extension of the specification written in (13):

$$y_{it} = \beta_1 x1_{it} + \beta_2 x2_{it} + \theta z_{it} + u_i + \varepsilon_{it}; \varepsilon_{it} \sim IID(0, \sigma_\varepsilon^2) \quad (15)$$

where z_{it} is a vector of time-invariant variables. Some of these time-invariant variables are allowed to be endogenous. Obviously, the within estimator will not be able to estimate the coefficients of the time-invariant variables since they will be filtered out through within transformation. Thus, in the presence of time-invariant variables, the random-effects panel estimators would be the natural option. The assumption is $u_i \sim IID(0, \sigma_u^2)$ and it is uncorrelated with ε_{it}. The main issue is the above model contains some endogenous explanatory variables, i.e. $x1_{it}$. The *xtivreg* or 2SLS estimators as described above assume that these endogenous explanatory variables are correlated with the idiosyncratic error ε_{it}.

Similar to the 2SLS estimators, the Hausman-Taylor (HT) estimator employs the method of instrumental variables (Hausman and Taylor, 1981). However, it assumes that the endogenous explanatory variables are correlated with the individual-specific random effects, u_i and none of the explanatory variables are correlated with ε_{it}. The HT is designed to estimate a panel model having time-invariant explanatory variables and, at the same time, to address the non-zero correlation between some explanatory variables and the individual specific effects. In STATA, this is achieved by using **xthtaylor**.

Without going into the technical details, the HT estimation steps are as follows:

- Applying the within estimator to estimate β_1 and β_2 and obtain the within residuals. Note that the within estimator will filter out the time-invariant variables. Thus, at this stage, we will not be able to estimate the coefficients of the time-invariant explanatory variables,
- Regressing the within residuals on the time-invariant explanatory variables. If there are endogenous time-invariant explanatory variables in the model, they must be instrumented by the exogenous time-varying variables ($x2_{it}$) and exogenous time-invariant variables. The order condition for identification requires that the number of exogenous time-varying variables must be at least as many as the number of time-invariant endogenous variables,
- Using the within and overall residuals based on these estimates to derive the variance components, and
- GLS transforming each variable using the estimated variance components,
- Running the HT estimator using the GLS-transformed variables and employing the within-transformed of the time-varying variables, within-panel mean of the time-varying variables, and the exogenous time-invariant variables as instruments.

To illustrate, let extend equation (14) to include a time-invariant dummy variable as:

$$npl_{it} = \beta_1 lnta_{it-1} + \beta_2 dloan_{it-1} + \beta_3 gdpg_{it} + \theta IB_i + u_i + \varepsilon_{it} \quad (16)$$

where IB is the Islamic bank dummy. Note that, in (16), the bank-specific variables are lagged one to address the concern that the contemporaneous bank-specific variables might be correlated with ε_{it}. In the above model, lagged-one *dloan* is assumed to be correlated with u_i. Obviously, the reasons underlying this assumption must be convincing. However, since our purpose is to illustrate the application of the HT estimator, we take that there are convincing reasons.

The syntax for implementing the HT estimator is:

- **xthtaylor** *depvar indepvars*, **endog**(*varlist*) [*options*] where *depvar* is the dependent variable, *indepvars* is the explanatory variables, **endog**(*varlist*) is the required option that specifies the endogenous variables, and *options* are other options available under **xthtaylor**. These include among others *noconstant* to suppress the constant term, vec(*vcetype*) where *vcetype* = *conventional, bootstrap*, or *jackknife* to specify the type of standard errors, and level(#) to set the confidence level. If these options are not specified, the constant will be included and *conventional* GLS standard errors and 95% confidence level are used.

The HT estimator applied to the above model yields:

```
. xthtaylor npl l.dloan l.lnta gdpg ib, endo(l.dloan)

Hausman-Taylor estimation                       Number of obs      =      1684
Group variable: code                            Number of groups   =       139

                                                Obs per group: min =         7
                                                               avg =      12.1
                                                               max =        13

Random effects u_i ~ i.i.d.                     Wald chi2(4)       =    172.33
                                                Prob > chi2        =    0.0000

------------------------------------------------------------------------------
         npl |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
TVexogenous  |
        lnta |
         L1. |  -2.055771   .2026963   -10.14   0.000    -2.453048   -1.658494
        gdpg |  -.1325506   .0426755    -3.11   0.002    -.2161929   -.0489082
TVendogenous |
       dloan |
         L1. |   -.063745   .0073313    -8.69   0.000    -.0781141   -.0493759
TIexogenous  |
          ib |   .1921206   1.636882     0.12   0.907     -3.01611    3.400351
             |
       _cons |   39.03263   3.219413    12.12   0.000      32.7227    45.34257
-------------+----------------------------------------------------------------
     sigma_u |  7.1270207
     sigma_e |    5.52284
         rho |  .62480698   (fraction of variance due to u_i)
------------------------------------------------------------------------------
Note:  TV refers to time varying; TI refers to time invariant.
```

The studies that have adopted the HT estimator include:

- Hou, X., Wang, Q., 2013. Implications of banking marketization for the lending channel of monetary policy transmission: Evidence from China. Journal of Macroeconomics 38, 442-451.
- Bouvatier, V., 2014. Heterogeneous bank regulatory standards and the cross-border supply of financial service. Economic Modelling 40, 342-354.
- Shehzad, C.T., De Haan, J., 2015. Supervisory powers and bank risk taking. Journal of International Financial Markets, Institutions & Money 39, 15-24.

2.6 CONCLUSION

This chapter deals with the traditional/static panel models. They remain applicable under certain settings and are still widely applied in the analyses of panel data. In the estimation of the static panel models, the choice of the estimators need to be made and it depends crucially on the assumptions governing the error components as well as whether the key explanatory variables are time invariant, which is summarized below:

Model: $y_{it} = \beta x_{it} + u_i + \varepsilon_{it}$

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">Presence of Time-Invariant Variables</td></tr>
<tr><td>NO</td><td>YES</td></tr>
<tr><td rowspan="4">The error-component assumptions</td><td>u_i and ε_{it} are not correlated with the variables in x_{it},</td><td>Random-Effects Estimator (RE)</td><td>Random-Effect Estimator (RE)</td></tr>
<tr><td>u_i is correlated with some variables in x_{it}, ε_{it} is not correlated with all variables in x_{it}.</td><td>Fixed-Effects Estimator (FE)</td><td>Hausman-Taylor Estimator (HT)</td></tr>
<tr><td>u_i is not correlated with some variables in x_{it}, ε_{it} is correlated with some variables in x_{it}.</td><td>2SLS Random-Effects Estimator (G2SLS, EC2SLS)</td><td>2SLS Random-Effects Estimator (G2SLS, EC2SLS)</td></tr>
<tr><td>u_i and ε_{it} are correlated with some variables in x_{it}.</td><td>2SLS Fixed-Effects Estimator (2SLS)</td><td>2SLS Random-Effects Estimator (G2SLS, EC2SLS)</td></tr>
</table>

Apart from above, it is advisable that the robust standard errors are employed to address the problems of heteroscedasticity, serial correlation, and/or cross-sectional dependence. Further, given the uncertainty regarding the assumptions of the error components, we should apply various estimators for robustness.

DYNAMIC PANEL MODELS

Due to the various endogeneity problems ..., least squares based inference methods, i.e. fixed effects or random effects estimators, are biased and inconsistent. Hence, it has become standard practice nowadays to use Instrumental Variables (IV) methods or the Generalized Method of Moments (GMM), which produce consistent parameter estimates for a finite number of time periods, T, and a large cross-sectional dimension, N.

(Bun and Sarafidis, 2013)

3.1 INTRODUCTION

The (theoretical) acknowledgement of potential dynamic behavior or persistence of a variable under study leads naturally to its incorporation in the modelling of the variable. Underlined by the availability of panel data across countries, states, firms, households, individuals etc., there has been proliferation of empirical studies based on dynamic panel model specification covering such issues as economic growth (Fufa and Kim, 2018), firm investment (Ratti et al., 2008), capital structure (Ebrahim et al., 2014), carbon emissions (Ibrahim and Law, 2014), and many others. It is normally applied to micro panels, i.e. panel data with large N (in hundreds or thousands) and short T (mostly less than 10).

The empirical banking and finance literature adopting dynamic panel models is voluminous. In the case of Islamic banking and finance, notable examples are:

- Daher, H., Masih, M., Ibrahim, M., 2015. The unique risk exposures of Islamic banks' capital buffers: A dynamic panel data analysis. Journal of International Financial Markets, Institutions & Money 36, 36 – 52.
- Imam, P., Kpodar, K., 2016. Islamic banking: Good for growth? Economic Modelling 59, 387 – 401.
- Ibrahim, M. H., Rizvi, S. A. R., 2017. Do we need bigger Islamic banks? An assessment of bank stability. Journal of Multinational Financial Management 40, 77 – 91.
- Yanikkaya, H., Gumus, N., Pabuccu, Y. U., 2018. How profitability differs between conventional and Islamic banks: A dynamic panel data approach. Pacific-Basin Finance Journal 48, 99 – 111.
- Ahmed, W.M.A., 2018. How do Islamic versus conventional equity markets react to political risk? Dynamic panel evidence. International Economics 156, 284-304.

This chapter covers dynamic panel modelling and estimation using generalized method of moments (GMM) estimators. It first explains dynamic panel model specification and deliberates the endogeneity concern in dynamic panel models. Then, it proceeds to two commonly used GMM estimators, i.e. the first difference GMM estimator and system GMM estimator. This is followed by examples of GMM applications of the dynamic panel models in banking and finance. The next section illustrates the GMM estimation of dynamic panel models using STATA based on the commands **xtabond2**, **xtabond**, and **xtdpdsys**. The final section concludes.

3.2 SPECIFICATION AND ISSUES

3.2.1 Specification

The dynamic panel model specification is to capture persistence or partial adjustments due to for example the presence of adjustment costs. In its simple form, we write the model as:

$$y_{it} = \rho y_{it-1} + \beta x_{it} + u_i + \varepsilon_{it} \qquad (1)$$

where y_{it} and y_{it-1} are the dependent variable and lagged dependent variable, x_{it} is an explanatory variable or a vector of explanatory variables, u_i is the individual specific effects, and ε_{it} is the standard error term.

The dynamic of the variable under study is captured by the inclusion of the lagged dependent variable. The coefficient of y_{it-1} measures the degree of persistence of the dependent variable or the speed at which it returns to its long-run conditional mean. It is expected that $0 < \rho < 1$, the higher the value, the more persistent the variable would be. Alternatively, we may also state that the higher the value, the slower the adjustment of y_{it} to its long run mean once hit by shocks. Apart from this, the inclusion of the lagged dependent variable or the dynamic term allows interpretation/measurement of temporal impacts of the explanatory variables on the dependent variable. In (1), β measures the contemporaneous change in y due to a unit change in x. Meanwhile, the full long run impact of x on y is $\beta/(1-\rho)$.

3.2.2 Endogeneity Concern

There are various statistical issues related to the estimation of (1), the main of which is endogeneity. Statistically, the endogeneity problem arises when the right-hand-side variables are correlated with the error terms. In (1), there are two sources of endogeneity, namely from (i) the correlation between the explanatory variables (x_{it}) and the error terms ($u_i + \varepsilon_{it}$) and (ii) the correlation between the lagged dependent variable and the error terms. While the former may be the result of reverse causality or omission of relevant variables, the latter arises by construction. That is, since y_{it-1} contains the individual specific effects u_i, $cov(y_{it-1}, u_i + \varepsilon_{it}) \neq 0$. This concern adds to the problems of heteroskedasticity, serial correlation, cross-sectional dependence/contemporaneous correlation, which are potential in panel settings.

The statistical consequence of endogeneity, when estimated using the traditional panel estimators, is biased estimated coefficients of the "endogenous" right-hand-side variables and potentially of variables correlated with the endogenous variables. Accordingly, in the presence of endogeneity, statistical inferences will be misleading.

Reverse causality arises when the dependent variable (y_{it}) causes an independent variable (x_{it}) resulting in non-zero correlation between the error term (i.e. shocks in y_{it}) and the independent variable concerned. In banking literature, several studies have assessed the impact of bank-specific variables (such as bank capital and bank size) on bank performance (such as profitability and risk). By appealing to "economies of scale" and "too-big-too fail" theses, for example, bank size is obviously a key determinant of bank risk. Still, it is conceivable that undertaking risk may likely lead a bank to increase its size and market share. The same can be said regarding the causal nexus between bank capital and bank profitability; i.e. banks may be less profitable if they keep high levels of capital and more profitable banks are able to keep higher levels of capitals. In bank-level studies, a commonly adopted approach to address the endogeneity concern arising from reverse causality is to use lagged-one instead of contemporaneous values of explanatory variables.

In econometric modelling, there is always uncertainty regarding explanatory variables other than the variables under focus that should be included. In essence, econometric modelling requires striking a balance between having too many explanatory variables and hence runs the risk of including irrelevant variables and too few explanatory variables and hence runs the risk of omitting relevant variables. The latter is a source of endogeneity leading to biased estimates, the so-called omitted variable bias.

Allowing for heterogeneity by including the individual specific-effects does address the omitted variable bias arising from (unobserved) time-invariant characteristics of the individuals or panels under study. Further, it is common in empirical implementation that robustness of the results pertaining to the focus variables or key research theses are evaluated using alternative sets of (controlled) explanatory variables to minimize the problem of omitted variable bias:

(i) Classify the explanatory or independent variables into three categories:
   - Focal explanatory variables: the explanatory variables under the study focus
   - Core explanatory variables: basic core variables that must be included on the basis of theories or past studies to explain the dependent variable
   - Conditional explanatory variables: additional variables that might be relevant for explaining the dependent variable

(ii) Estimate the baseline specification, which includes only the focal and core explanatory variables

(iii) Add the conditional variables, one at a time or one set or category at a time, into the regression and then assess the robustness of the baseline results, the ones related to the focal variables.

A scan to existing empirical studies would reveal that the above practical approach to econometric analysis is widely adopted. The research is mainly interested in the focal variables. Given the uncertainty of what should be in the list of independent variables, experimenting with alternative sets would add credibility by minimizing the omitted variable bias and demonstrating robustness or lack thereof of the key variables in explaining the dependent variable.

More formally, regardless of the sources of endogeneity, the endogeneity problem can be addressed using an instrumental variable technique. The availability of various instrumental variable – based estimation methods means that understanding statistical issues underlying the methods is important. The generalized method of moments (GMM) estimators, which are the focused in this chapter, are detailed in the next section.

3.3 GMM ESTIMATION

There are two GMM estimators for dynamic panel model (1) – the first difference GMM estimator by Arellano and Bond (1991) and the system GMM estimator by Arellano and Bover (1995) and Blundell and Bond (1998). The common feature of these estimators is the use of instruments to address the endogeneity issue. The requirements for the instruments are:

- They must exhibit strong enough correlation with the endogenous regressors, and
- They must exhibit no correlation with the error terms.

We deliberate in this section the two GMM estimators in details. Then, we discuss relevant diagnostics for the consistency of the estimates.

3.3.1 First-Difference GMM

The first difference GMM approach to dynamic panel model estimation developed by Arellano and Bond (1991) is based on (i) filtering out individual specific effects in equation (1) through differencing and (ii) using instruments to address the correlation between the transformed error terms and the explanatory variables, the so-called endogeneity issue.

While there are many ways of differencing to remove the individual-specific effects, first differencing seems most common. The other differencing methods are within-transformation and forward differencing (Helmert transformation). By first differencing, we have:

$$(y_{it} - y_{it-1}) = \rho(y_{it-1} - y_{it-2}) + \beta(x_{it} - x_{it-1}) + (\varepsilon_{it} - \varepsilon_{it-1}) \qquad (2)$$

Based on (2), it is clear that the minimum time dimension for the GMM implementation using first-differencing is 3 periods as further illustrated below.

Period	First-differenced equation
1	Not applicable
2	Not applicable
3	$(y_{i3} - y_{i2}) = \rho(y_{i2} - y_{i1}) + \beta(x_{i3} - x_{i2}) + (\varepsilon_{i3} - \varepsilon_{i2})$
4	$(y_{i4} - y_{i3}) = \rho(y_{i3} - y_{i2}) + \beta(x_{i4} - x_{i3}) + (\varepsilon_{i4} - \varepsilon_{i3})$
5	$(y_{i5} - y_{i4}) = \rho(y_{i4} - y_{i3}) + \beta(x_{i5} - x_{i4}) + (\varepsilon_{i5} - \varepsilon_{i4})$
6	$(y_{i6} - y_{i5}) = \rho(y_{i5} - y_{i4}) + \beta(x_{i6} - x_{i5}) + (\varepsilon_{i6} - \varepsilon_{i5})$

Note that first-differencing, while removing the individual specific effects, induces the correlation between the lagged dependent variable $(y_{it-1} - y_{it-2})$ and the transformed error term $(\varepsilon_{it} - \varepsilon_{it-1})$ since y_{it-1} is a function of ε_{it-1} as stated in equation (1). That is, cov$[(y_{it-1} - y_{it-2}),(\varepsilon_{it} - \varepsilon_{it-1})] \neq 0$. To resolve this, the GMM approach to dynamic panel model estimation utilizes instruments for the lagged dependent variable. As stated, they must exhibit strong enough correlation with the endogenous regressors, that is, $(y_{it-1} - y_{it-2})$ but must exhibit no correlation with the error term.

To illustrate the application of the instruments or moment conditions in the first-difference GMM estimator, we write equation (2) for $t = 3$,

$$(y_{i3} - y_{i2}) = \rho(y_{i2} - y_{i1}) + \beta(x_{i3} - x_{i2}) + (\varepsilon_{i3} - \varepsilon_{i2}) \tag{3}$$

From (3), y_{i1} is a good candidate for the instrument to be used since it is correlated with $(y_{i2} - y_{i1})$ but is uncorrelated with the future error term $(\varepsilon_{i3} - \varepsilon_{i2})$.

Then, for $t = 4$, we have

$$(y_{i4} - y_{i3}) = \rho(y_{i3} - y_{i2}) + \beta(x_{i4} - x_{i3}) + (\varepsilon_{i4} - \varepsilon_{i3}) \tag{4}$$

In (4), y_{i1} and y_{i2} are good candidates for the instruments since they are correlated with $(y_{i3} - y_{i2})$ but are uncorrelated with the future error term $(\varepsilon_{i4} - \varepsilon_{i3})$.

Expanding the list of instruments for all time periods in the panel data, we would have:

Period	First-differenced equation	Instruments
1	Not applicable	--
2	Not applicable	--
3	$(y_{i3} - y_{i2}) = \rho(y_{i2} - y_{i1}) + \beta(x_{i3} - x_{i2}) + (\varepsilon_{i3} - \varepsilon_{i2})$	y_{i1}
4	$(y_{i4} - y_{i3}) = \rho(y_{i3} - y_{i2}) + \beta(x_{i4} - x_{i3}) + (\varepsilon_{i4} - \varepsilon_{i3})$	y_{i1}, y_{i2}

5	$(y_{i5} - y_{i4}) = \rho(y_{i4} - y_{i3}) + \beta(x_{i5} - x_{i4}) + (\varepsilon_{i5} - \varepsilon_{i4})$	y_{i1}, y_{i2}, y_{i3}
6	$(y_{i6} - y_{i5}) = \rho(y_{i5} - y_{i4}) + \beta(x_{i6} - x_{i5}) + (\varepsilon_{i6} - \varepsilon_{i5})$	$y_{i1}, y_{i2}, y_{i3}, y_{i4}$

Under the Arellano-Bond first difference GMM, the deeper lags of level variables are ingeniously used as instruments for the endogenous variables. More precisely, under the assumptions that the idiosyncratic error term ε_{it} is not autocorrelated and the explanatory variables x_{it} are (weakly) exogenous (they are uncorrelated with future realizations of the error term), the first difference GMM estimator employs the following moment conditions:

$$\mathrm{E}[y_{it-s}(\varepsilon_{it} - \varepsilon_{it-1})] = 0 \quad \text{for } s \geq 2, t = 3, \ldots, T \tag{5}$$
$$\mathrm{E}[x_{it-s}(\varepsilon_{it} - \varepsilon_{it-1})] = 0 \quad \text{for } s \geq 2, t = 3, \ldots, T \tag{6}$$

The first-difference GMM can be implemented as a one-step estimator or a two-step estimator. The one-step first difference GMM assumes the error terms to be both independent and homoscedastic across units and over time. The two-step first difference GMM relaxes the assumptions of independence and homoscedasticity by utilizing the residuals from the first-step GMM to consistently construct the variance-covariance matrix in the second step. It is worth noting that the standard errors of the two-step first difference GMM are severely downward biased and, hence, it is customary in the estimation to employ Windmeijer's (2005) finite sample corrected standard errors.

The Arellano-Bond first difference GMM has at least three shortcomings. First, while filtering out the individual specific effects, differencing removes information contained in the level of the variables. This would decrease the signal-to-noise ratio and hence may worsen the measurement error bias (Griliches and Hausman, 1986). Second, the strength of the lagged level variables as instruments depends crucially on their temporal properties. More specifically, as noted by Blundell and Bond (1998), they are weak instruments if they exhibit persistent behavior. The consequence of weak instruments is substantial bias especially when T is small (Alonso-Borrego and Arellano, 1999). And finally, as illustrated above, the number of instruments increases quadratically as T increases. This would lead to the problem of instrument proliferation and consequently affect the estimation (Roodman, 2009a).

3.3.2 System GMM

Arellano and Bover (1995) and Blundell and Bond (1998) extend the first difference GMM to resolve the problems of instrument weakness and the loss of information in the level of the variables by estimating (1) and (2) as a system. The instruments for the regression in first difference are similar to those under the first difference GMM. As for the regression in level, the lagged difference of the corresponding variables is suggested as the instruments.

To illustrate, we rewrite the regression in level:

$$y_{it} = \rho y_{it-1} + \beta x_{it} + u_i + \varepsilon_{it}$$

As explained above, $cov(y_{it-1}, u_i + \varepsilon_{it}) \neq 0$. Accordingly, an instrument variable is needed. Note that, although y_{it-1} is correlated with the individual specific effects u_i, $y_{it-1} - y_{it-2}$ will not. The same can be said for the explanatory variables. This means that the following moment conditions can be employed:

$$\mathrm{E}[(y_{it-s} - y_{it-s-1})(u_i + \varepsilon_{it})] = 0 \quad \text{for } s = 1 \tag{7}$$
$$\mathrm{E}[(x_{it-s} - x_{it-s-1})(u_i + \varepsilon_{it})] = 0 \quad \text{for } s = 1 \tag{8}$$

The system GMM offers improvements over the first-difference GMM especially when the regressors are persistent. As in the case of the first-difference GMM, the system GMM can be implemented as a one-step estimator or a two-step estimator. Likewise, in the two-step system GMM, the Windmeijer's (2005) finite sample corrected standard errors are normally used. It should be noted that, under the system GMM, the problem of instrument proliferation remains potential.

3.3.3 Diagnostics

The consistency of the parameter estimates by the GMM estimators depends critically on the absence of serial correlation in ε_{it} and the validity of the instruments. In addition, in using the GMM estimators, we also should be mindful of the problem of too many instruments.

The serial correlation in ε_{it} is evaluated using the Arellano-Bond serial correlation test on the residuals generated from (2), i.e. the regression in first difference. Take note that, if ε_{it} is serially uncorrelated, $(\varepsilon_{it} - \varepsilon_{it-1})$ will be correlated of order 1:

$$E[(\varepsilon_{it} - \varepsilon_{it-1})(\varepsilon_{it-1} - \varepsilon_{it-2}) \neq 0 \tag{9}$$
$$E[(\varepsilon_{it} - \varepsilon_{it-1})(\varepsilon_{it-2} - \varepsilon_{it-3}) = 0 \tag{10}$$

Accordingly, for the error term in (1) to be serially uncorrelated, the test for AR(2) must be insignificantly different from zero. In other words, the null hypothesis of serial correlation of order 2 should not be rejected.

The validity of the instruments or the moment conditions as stated in (5)-(8) can be tested using the Hansen's (1982) J statistic. It is applicable when the number of instruments is larger than the number of included endogenous variables so that over-identifying restrictions can be employed to evaluate whether the instruments are correlated with the error terms. The Hansen's J statistic is distributed as a chi-square distribution with the degree of freedom equals to the number of over-identifying restrictions. The rejection of the null hypothesis indicates that the instruments are not valid. Another test for instrument validity is the Sargan's (1958) test, which is the special case of the

Hansen's J test under the assumption of conditional homoscedasticity (Baum et al., 2003). As in the case of the Hansen's J test, the null hypothesis is the instruments are orthogonal to the error term.

Finally, in using the GMM estimators, we should be mindful of the number of instruments. As noted above, the number of the instruments employed in the GMM estimators increases quadratically, leading to potential instrument proliferation. In his discussion on the theme of too many instruments, Roodman (2009a) demonstrates that they can overfit the endogenous variables and bias the coefficient estimates. In addition, the Hansen's J test for instrument validity is weakened by the presence of too many instruments. Practically, it is suggested that the number of instruments should be lower than the number of cross-sections by restricting the lags or by collapsing the instruments (Roodman, 2009a). See Tabak et al. (2011) and the next section for citations of this practical rule in limiting the number of instruments.

3.3.4 Which Estimator?

Given the two alternative GMM estimators, i.e. the first difference GMM and the system GMM estimators, a natural question that might arise is: which estimator is to be used as basis of inferences? The choice between the first difference GMM and system GMM is immaterial if they yield similar results leading to the same inferences. It is however non-trivial when their results are markedly different.

Based on the discussion above, the system GMM is preferred when the variables under study exhibit persistence or are near unit root or random walk process. In this case, as noted above, the lagged level variables are poor instruments for their first differences. In addition, the system GMM is applicable even if there are time-invariant variables in the models. Meanwhile the first difference GMM in unable to estimate the coefficients of the time-invariant variables.

Apart from these, we may use the Pooled OLS and fixed-effects estimators as a yardstick, as done by Marrero (2010) and most recently Jha (2019). The Pooled OLS estimation of a dynamic panel model yields an upward bias of the coefficient of the lagged dependent variable. By contrast, the fixed-effects estimator results in a downward bias. This means that the consistent estimate should be between the two. In his study, Marrero (2010) finds the coefficient of the lagged dependent variable to be between the values from the Pooled OLS and the fixed-effects estimators. However, he also finds that the autoregressive coefficient from the first difference GMM estimator is too close to the one by the fixed-effects estimator. He reasons that the estimates from the first difference GMM are potentially biased due to weak instruments. Based on this reason, he opts for the system GMM as a basis of inferences.

3.4 APPLICATIONS

The first difference and system GMM estimators have become a very popular tool to estimate a dynamic panel model with small T and large N. Illustrative examples of the GMM applications are given below:

Example I	Imam, P., Kpodar, K., 2016. Islamic banking: Good for growth? Economic Modelling 59, 387 – 401.

Imam and Kpodar (2016) employ a panel of 52 countries, 29 of which are OIC countries, covering the period 1990-2000 to assess the impact of Islamic banking development on economic growth. The development of Islamic banking is measured by Islamic bank financing to GDP ratio, Islamic bank assets to GDP ratio and Islamic bank deposits to GDP ratio. They use the system GMM estimator based on the argument that it is consistent and relatively more efficient as compared to the first difference GMM estimator. The one-step system GMM with robust standard errors is used. However, they footnote that the two-step method with Windmeijer's correction yields similar results. Further, to minimize overfitting the endogenous variables in the model from too many instruments, they limit the instruments to the first lag for the predetermined and endogenous variables. The Arellano-Bond autocorrelation and Hansen's J tests are performed to verify the consistency of the model.

The results suggest that, after controlling for standard determinants of economic growth, Islamic banking development contributes positively to economic growth. The main channels of the documented positive contribution of Islamic banking are capital accumulation and financial inclusion. The recommendation from the study is clear – the development of Islamic banking should be further promoted as a catalyst for economic growth especially in low growth Muslim countries.

Example II	Ibrahim, M. H., Rizvi, S. A. R., 2017. Do we need bigger Islamic banks? An assessment of bank stability. Journal of Multinational Financial Management 40, 77 – 91.

Ibrahim and Rizvi (2017) address the debate on whether Islamic banks should be small as they are or should be bigger by assessing the impact of Islamic bank size on Islamic bank stability. Their analysis is based on a panel sample of 45 Islamic banks from 13 countries from 2000 to 2014. According to Ibrahim and Rizvi (2017), since their model is dynamic, the fixed-effects and random-effects estimators would not be appropriate. The two-step system GMM with Windmeijer's finite-sample correction is used. Noting that they have small N, they limit the number of instruments such that it is less than the number of cross-sectional units, i.e. 45. As a robustness check, they also implement the bias-corrected LSDV estimator.

The results suggest that bigger Islamic banks are more stable. A further analysis emphasizes the importance of bank regulation in shaping the size – stability relations for Islamic banks. More specifically, activity restrictions and capital stringency tend to strengthen the positive relation between bank size and bank stability. However, it is weakened by more private monitoring and supervisory power. Thus, Islamic banks should be bigger but need to be accompanied by regulation in the forms of activity restrictions and capital stringency such that the benefits of being big can be more effective.

Example III	Yanikkaya, H., Gumus, N., Pabuccu, Y. U., 2018. How profitability differs between conventional and Islamic banks: A dynamic panel data approach. Pacific-Basin Finance Journal 48, 99 – 111.

Yanikkaya et al. (2018) examine the dynamics of Islamic and conventional bank profitability using a panel sample of 74 Islamic and 354 conventional commercial banks from the OIC countries and the U.K. over the period 2007-2013. They adopt the two-step system GMM estimator and apply Windmeijer's (2005) finite-sample correction. Noting that the number of Islamic banks is small (between 60 to 74 banks), they use the "collapse" option to deal with the problem of instrument proliferation when the GMM estimator is applied to the panel data of Islamic banks.

They document evidence suggesting different determinants of bank profitability as measured by the net interest margin and return on assets for Islamic banks and conventional banks. Thus, according to them, the profitability dynamics of these two types of banks are different. For Islamic banks, in particular, they find that the share of risk-sharing financial products contributes positively to their performance. Thus, promotion of these products is recommended.

Example IV	Jha, C.K., 2019. Financial reforms and corruption: Evidence using GMM Estimation. International Review of Economics and Finance 62, 66-78.

Jha (2019) assesses the impact of financial reforms and financial liberalization on corruption using a panel sample of 87 countries over the period 1984-2005. To measure corruption, he uses the International Country Risk Guide's (ICRG) corruption index. Meanwhile, the financial reforms and financial liberalization measures are based on the work by Abiad et al. (2010). He incorporates in the model the natural log of real GDP per capita, government size, and openness as controlled variables. In the analysis, he uses both the two-step first difference and system GMM estimators and applies Windmeijer's (2005) finite sample corrected standard errors. The followings are notable in their econometric implementation:

- It is acknowledged in the paper that political and cultural factors are potential determinants of corruption. However, since they are fixed across times for each countries, they are omitted. It is argued that their effects on corruption are picked up through the country specific effects or country dummies. As a result, the omission of these relevant factors should not be a concern.
- He treats the controlled variables as endogenous

- Acknowledging the problem of too many instruments, he collapses the instruments and, alternatively, uses only up to two lags as instruments.
- Finally, he also estimates the model using the Pooled OLS and Fixed-effects estimators. Obviously, these estimators yield biased estimates. More specifically, the coefficient of the lagged dependent variable is upward biased under the Pooled OLS and it is downward biased under the fixed-effects estimator. This provides a useful check. That is, the consistent estimate of the coefficient of the autoregressive term should be between these two estimates. Marrero (2010) deliberates on how to use this to choose between the first difference GMM and system GMM estimators.

The results from the analysis suggests that financial reforms robustly reduce corruption and there is no indication that legal origins influence the effectiveness of financial reforms in reducing corruption.

3.5 GMM ESTIMATORS USING STATA

This section demonstrates STATA commands related to the estimation of a dynamic panel using the GMM estimators. The model is:

$$npl_{it} = \rho npl_{it-1} + \beta_1 lnta_{it} + \beta_2 dloan_{it} + \beta_3 gdpg_{it} + u_i + \varepsilon_{it} \qquad (11)$$

where *npl* is the non-performing loan ratio as a measure of credit risk, *lnta* is the natural logarithm of total assets, *dloan* is the growth rate of the gross loan, and *gdpg* is real GDP growth. The data are in *DualBank.xlsx*.

Once the data are entered into STATA, we must set the panel structure using:

tsset *code year*

In addition, the following variables need to be generated:

gen *lgloan = ln(grossl)*
gen *dloan = (lgloan – l.lgloan)*100*
gen *lnta = ln(ta)*

Other variables (*npl* and *gdpg*) can be used directly.

We first demonstrate the first difference GMM and then proceed to the system GMM, both with the assumption that the explanatory variables are exogenous. We prefer the **xtabond2** command. However, we will also demonstrate **xtabond** and **xtdpdsys**. Then, we relax the assumption of exogeneity of (some) explanatory variables. We also show how to limit the instruments to deal with the problem of instrument proliferation.

3.5.1 First-Difference GMM

<u>**One-Step First Difference GMM**</u>

Syntax: **xtabond2** *depvar l.depvar indepvars*, **gmm**(*l.depvar*) **iv**(*indepvars*) *options*

where **gmm**() lists the endogenous and predetermined variables, **iv**() the strictly exogenous variables, and *options* are the options available for **xtabond2**. The above command assumes that the explanatory variables are exogenous.

The following command estimates the one-step first difference GMM with robust standard errors clustered at the bank level:

```
. xtabond2 npl l.npl lnta dloan gdpg, gmm(l.npl) iv(lnta dloan gdpg) nolevel
robust

Favoring speed over space. To switch, type or click on mata: mata set matafavor
space, perm.
Warning: Two-step estimated covariance matrix of moments is singular.
  Using a generalized inverse to calculate robust weighting matrix for Hansen
test.
  Difference-in-Sargan/Hansen statistics may be negative.

Dynamic panel-data estimation, one-step difference GMM
----------------------------------------------------------------------------
--
Group variable: code                            Number of obs      =      1684
Time variable : year                            Number of groups   =       139
Number of instruments = 94                      Obs per group: min =         7
Wald chi2(4)   =    326.99                                     avg =     12.12
Prob > chi2    =     0.000                                     max =        13
----------------------------------------------------------------------------
--
             |               Robust
         npl |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+--------------------------------------------------------------
--
         npl |
         L1. |   .7096738   .0406315    17.47   0.000     .6300375    .7893101
             |
        lnta |  -.6706229   .5219363    -1.28   0.199    -1.693599    .3523535
       dloan |   -.032195    .010149    -3.17   0.002    -.0520867   -.0123034
        gdpg |  -.1621074   .0419066    -3.87   0.000    -.2442429    -.079972
----------------------------------------------------------------------------
--
Instruments for first differences equation
  Standard
    D.(lnta dloan gdpg)
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L(1/14).L.npl
----------------------------------------------------------------------------
--
Arellano-Bond test for AR(1) in first differences: z =  -4.74  Pr > z =  0.000
Arellano-Bond test for AR(2) in first differences: z =  -1.09  Pr > z =  0.274
----------------------------------------------------------------------------
--
Sargan test of overid. restrictions: chi2(90)   = 306.24  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(90)   = 103.85  Prob > chi2 =  0.151
  (Robust, but weakened by many instruments.)

Difference-in-Hansen tests of exogeneity of instrument subsets:
  iv(lnta dloan gdpg)
    Hansen test excluding group:     chi2(87)    =  88.88  Prob > chi2 =  0.424
    Difference (null H = exogenous): chi2(3)     =  14.98  Prob > chi2 =  0.002
```

Note that the Arellano-Bond test for AR(1) is rejected while for AR(2) is not rejected. Thus, the model (equation 11) does not suffer from the serial correlation problem. In addition, the Hansen's J test suggests the validity of the instruments. The option *nolevel* requests the use of first-difference GMM while *robust* asks for the robust standard errors clustered at the bank level. Note that the command **iv**(*var1 var2 var2*) generates one column per variable and the strictly exogenous variables instrument themselves.

The equivalent **xtabond** command is:

```
. xtabond npl lnta dloan gdpg, robust noconstant

Arellano-Bond dynamic panel-data estimation  Number of obs         =      1684
Group variable: code                        Number of groups      =       139
Time variable: year
                                             Obs per group:    min =         7
                                                               avg           =
12.11511
                                                               max =        13

Number of instruments =     94              Wald chi2(4)          =    326.99
                                             Prob > chi2           =    0.0000
One-step results
                                   (Std. Err. adjusted for clustering on code)
-----------------------------------------------------------------------------
--
             |               Robust
         npl |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+---------------------------------------------------------------
--
         npl |
         L1. |   .7096738   .0406315    17.47   0.000     .6300375    .7893101
             |
        lnta |  -.6706229   .5219363    -1.28   0.199    -1.693599    .3523535
       dloan |   -.032195    .010149    -3.17   0.002    -.0520867   -.0123034
        gdpg |  -.1621074   .0419066    -3.87   0.000    -.2442429    -.079972
-----------------------------------------------------------------------------
--
Instruments for differenced equation
        GMM-type: L(2/.).npl
        Standard: D.lnta D.dloan D.gdpg
```

The option *noconstant* can be excluded since under first difference GMM, the constant is filtered out by first differencing.

<u>Two-Step First Difference GMM</u>

Syntax: **xtabond2** *depvar l.depvar indepvars*, **gmm**(*l.depvar*) **iv**(*indepvars*) *twostep options*

The following command estimates the two-step first difference GMM with Windmeijer's finite sample correction clustered at the bank level:

```
. xtabond2 npl l.npl lnta dloan gdpg, gmm(l.npl) iv(lnta dloan gdpg) nolevel
robust twostep
Favoring speed over space. To switch, type or click on mata: mata set matafavor
space, perm.
Warning: Two-step estimated covariance matrix of moments is singular.
  Using a generalized inverse to calculate optimal weighting matrix for two-
step estimation.
  Difference-in-Sargan/Hansen statistics may be negative.
```

```
Dynamic panel-data estimation, two-step difference GMM
------------------------------------------------------------------------------
--
Group variable: code                            Number of obs      =      1684
Time variable : year                            Number of groups   =       139
Number of instruments = 94                      Obs per group: min =         7
Wald chi2(4)    =    331.31                                    avg =     12.12
Prob > chi2     =     0.000                                    max =        13
------------------------------------------------------------------------------
--
             |              Corrected
         npl |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
--
         npl |
         L1. |   .7112546   .0406959    17.48   0.000      .631492    .7910172
             |
        lnta |  -.5850687   .4926176    -1.19   0.235    -1.550582    .3804442
       dloan |  -.0311381   .0105446    -2.95   0.003    -.0518052   -.0104711
        gdpg |  -.1431662   .0395233    -3.62   0.000    -.2206304    -.065702
------------------------------------------------------------------------------
--
Instruments for first differences equation
  Standard
    D.(lnta dloan gdpg)
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L(1/14).L.npl
------------------------------------------------------------------------------
--
Arellano-Bond test for AR(1) in first differences: z =  -4.22  Pr > z =  0.000
Arellano-Bond test for AR(2) in first differences: z =  -1.13  Pr > z =  0.260
------------------------------------------------------------------------------
--
Sargan test of overid. restrictions: chi2(90)   = 306.24  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(90)   = 103.85  Prob > chi2 =  0.151
  (Robust, but weakened by many instruments.)

Difference-in-Hansen tests of exogeneity of instrument subsets:
  iv(lnta dloan gdpg)
    Hansen test excluding group:     chi2(87)    =  88.88  Prob > chi2 =  0.424
    Difference (null H = exogenous): chi2(3)     =  14.98  Prob > chi2 =  0.002
```

Note that to implement the two-step estimator, the option *twostep* is added. The equivalent **xtabond** command is:

```
. xtabond npl lnta dloan gdpg, robust noconstant twostep

Arellano-Bond dynamic panel-data estimation  Number of obs        =      1684
Group variable: code                        Number of groups     =       139
Time variable: year
                                             Obs per group:    min =         7
                                                               avg          =
12.11511
                                                               max =        13

Number of instruments =     94              Wald chi2(4)         =    331.31
                                             Prob > chi2          =    0.0000
Two-step results
                                   (Std. Err. adjusted for clustering on code)
------------------------------------------------------------------------------
--
             |              WC-Robust
         npl |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
--
         npl |
         L1. |   .7112546   .0406959    17.48   0.000      .631492    .7910172
             |
        lnta |  -.5850687   .4926176    -1.19   0.235    -1.550582    .3804442
       dloan |  -.0311381   .0105446    -2.95   0.003    -.0518052   -.0104711
        gdpg |  -.1431662   .0395233    -3.62   0.000    -.2206304    -.065702
```

```
------------------------------------------------------------------------------
--
Instruments for differenced equation
        GMM-type: L(2/.).npl
        Standard: D.lnta D.dloan D.gdpg
```

For the two-step estimator, the option *robust* invokes Windmeijer's finite sample correction.

3.5.2 System GMM

One-Step System GMM

Syntax: **xtabond2** *depvar l.depvar indepvars*, **gmm**(*l.depvar*) **iv**(*indepvars*) *options*

The system GMM is the default under the **xtabond2**, i.e. when the option *nolevel* is not included.

The following command estimates the one-step system GMM with robust standard errors clustered at the bank level:

```
. xtabond2 npl l.npl lnta dloan gdpg, gmm(l.npl) iv(lnta dloan gdpg, eq(diff))
robust

Favoring speed over space. To switch, type or click on mata: mata set matafavor
space, perm.
Warning: Two-step estimated covariance matrix of moments is singular.
  Using a generalized inverse to calculate robust weighting matrix for Hansen
test.
  Difference-in-Sargan/Hansen statistics may be negative.

Dynamic panel-data estimation, one-step system GMM
------------------------------------------------------------------------------
--
Group variable: code                            Number of obs      =      1823
Time variable : year                            Number of groups   =       139
Number of instruments = 108                     Obs per group: min =         8
Wald chi2(4)    =     383.46                                   avg =     13.12
Prob > chi2     =      0.000                                   max =        14
------------------------------------------------------------------------------
--
             |               Robust
         npl |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
--
         npl |
         L1. |   .7623601   .0463546    16.45   0.000     .6715068    .8532134
             |
        lnta |    .063807   .4490087     0.14   0.887    -.8162338    .9438479
       dloan |  -.0381922   .0111539    -3.42   0.001    -.0600534   -.0163309
        gdpg |  -.1577199   .0412784    -3.82   0.000     -.238624   -.0768158
       _cons |   1.512881   7.149006     0.21   0.832    -12.49891    15.52467
------------------------------------------------------------------------------
--
Instruments for first differences equation
  Standard
    D.(lnta dloan gdpg)
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L(1/14).L.npl
Instruments for levels equation
  Standard
    _cons
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    D.L.npl
```

```
------------------------------------------------------------------------------
--
Arellano-Bond test for AR(1) in first differences: z =  -4.50  Pr > z =  0.000
Arellano-Bond test for AR(2) in first differences: z =  -1.13  Pr > z =  0.257
------------------------------------------------------------------------------
--
Sargan test of overid. restrictions: chi2(103)  = 545.98  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(103)  = 121.19  Prob > chi2 =  0.106
  (Robust, but weakened by many instruments.)

Difference-in-Hansen tests of exogeneity of instrument subsets:
  GMM instruments for levels
    Hansen test excluding group:     chi2(90)   = 106.37  Prob > chi2 =  0.115
    Difference (null H = exogenous): chi2(13)   =  14.83  Prob > chi2 =  0.318
  iv(lnta dloan gdpg, eq(diff))
    Hansen test excluding group:     chi2(100)  = 103.58  Prob > chi2 =  0.383
    Difference (null H = exogenous): chi2(3)    =  17.62  Prob > chi2 =  0.001
```

Note that *nolevel* is excluded in the system GMM. Moreover, the **eq***(diff)* is added in **iv***(.)*. As in the first difference GMM, the command **iv**(*var1 var2 var2*) generates one column per variable and the strictly exogenous variables instrument themselves. However, different patterns of arrangement can be requested, one option of which is **eq***(diff)*. See Roodman (2009b) for details.

The one-step system GMM using **xtdpdsys** command is:

```
. xtdpdsys npl lnta dloan gdpg, vce(robust)

System dynamic panel-data estimation         Number of obs        =      1823
Group variable: code                         Number of groups     =       139
Time variable: year
                                              Obs per group:    min =         8
                                                                avg           =
13.11511
                                                                max =        14

Number of instruments =    108               Wald chi2(4)         =    472.35
                                              Prob > chi2          =    0.0000
One-step results
------------------------------------------------------------------------------
--
             |               Robust
         npl |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
--
         npl |
         L1. |    .772451   .0395914    19.51   0.000     .6948533    .8500486
             |
        lnta |   .2372348   .3288861     0.72   0.471     -.40737     .8818397
       dloan |  -.0427759   .0126565    -3.38   0.001    -.0675822   -.0179695
        gdpg |  -.1653823   .0505159    -3.27   0.001    -.2643917   -.0663729
       _cons |  -1.090734   5.194839    -0.21   0.834    -11.27243    9.090965
------------------------------------------------------------------------------
--
Instruments for differenced equation
        GMM-type: L(2/.).npl
        Standard: D.lnta D.dloan D.gdpg
Instruments for level equation
        GMM-type: LD.npl
        Standard: _cons
```

A close look at the above results, the **xtabond2** and **xtdpdsys** do not yield identical results. This stems from different construction of variance-covariance matrices in the two commands, the matrix **H** in Roodman (2009b). Again, readers are referred to Roodman (2009b) for technical details. To have identical results, the option *h(2)* needs to be specified for xtabond2:

```
. xtabond2 npl l.npl lnta dloan gdpg, gmm(l.npl) iv(lnta dloan gdpg, eq(diff))
robust h(2)
Favoring speed over space. To switch, type or click on mata: mata set matafavor
space, perm.
Warning: Two-step estimated covariance matrix of moments is singular.
  Using a generalized inverse to calculate robust weighting matrix for Hansen
test.
  Difference-in-Sargan/Hansen statistics may be negative.

Dynamic panel-data estimation, one-step system GMM
----------------------------------------------------------------------------
--
Group variable: code                            Number of obs      =      1823
Time variable : year                            Number of groups   =       139
Number of instruments = 108                     Obs per group: min =         8
Wald chi2(4)   =     472.35                                    avg =     13.12
Prob > chi2    =      0.000                                    max =        14
----------------------------------------------------------------------------
--
             |              Robust
         npl |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+--------------------------------------------------------------
--
         npl |
         L1. |    .772451   .0395914    19.51   0.000     .6948533    .8500486
             |
        lnta |   .2372348   .3288861     0.72   0.471      -.40737    .8818397
       dloan |  -.0427759   .0126565    -3.38   0.001    -.0675822   -.0179695
        gdpg |  -.1653823   .0505159    -3.27   0.001    -.2643917   -.0663729
       _cons |  -1.090734   5.194839    -0.21   0.834    -11.27243    9.090965
----------------------------------------------------------------------------
--
Instruments for first differences equation
  Standard
    D.(lnta dloan gdpg)
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L(1/14).L.npl
Instruments for levels equation
  Standard
    _cons
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    D.L.npl
----------------------------------------------------------------------------
--
Arellano-Bond test for AR(1) in first differences: z =  -4.63  Pr > z =  0.000
Arellano-Bond test for AR(2) in first differences: z =  -1.13  Pr > z =  0.260
----------------------------------------------------------------------------
--
Sargan test of overid. restrictions: chi2(103)   = 522.87  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(103)   = 120.63  Prob > chi2 =  0.113
  (Robust, but weakened by many instruments.)

Difference-in-Hansen tests of exogeneity of instrument subsets:
  GMM instruments for levels
    Hansen test excluding group:     chi2(90)    = 108.28  Prob > chi2 =  0.092
    Difference (null H = exogenous): chi2(13)    =  12.35  Prob > chi2 =  0.499
  iv(lnta dloan gdpg, eq(diff))
    Hansen test excluding group:     chi2(100)   = 101.96  Prob > chi2 =  0.427
    Difference (null H = exogenous): chi2(3)     =  18.67  Prob > chi2 =  0.000
```

Two-Step System GMM

Syntax: **xtabond2** *depvar l.depvar indepvars*, **gmm**(*l.depvar*) **iv**(*indepvars) twostop options*

The following command estimates the two-step system GMM with Windmeijer's finite sample correction:

```
. xtabond2 npl l.npl lnta dloan gdpg, gmm(l.npl) iv(lnta dloan gdpg, eq(diff))
robust h(2) twostep
Favoring speed over space. To switch, type or click on mata: mata set matafavor
space, perm.
Warning: Two-step estimated covariance matrix of moments is singular.
  Using a generalized inverse to calculate optimal weighting matrix for two-
step estimation.
  Difference-in-Sargan/Hansen statistics may be negative.

Dynamic panel-data estimation, two-step system GMM
----------------------------------------------------------------------------
--
Group variable: code                            Number of obs      =      1823
Time variable : year                            Number of groups   =       139
Number of instruments = 108                     Obs per group: min =         8
Wald chi2(4)   =    472.27                                     avg =     13.12
Prob > chi2    =     0.000                                     max =        14
----------------------------------------------------------------------------
--
             |              Corrected
         npl |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+--------------------------------------------------------------
--
         npl |
         L1. |   .7713315   .0398913    19.34   0.000      .693146     .849517
             |
        lnta |   .2067765   .3215948     0.64   0.520    -.4235378    .8370908
       dloan |  -.0423708   .0128752    -3.29   0.001    -.0676056    -.017136
        gdpg |  -.1605278   .0499978    -3.21   0.001    -.2585216   -.0625339
       _cons |   -.695162   5.143535    -0.14   0.892    -10.77631    9.385981
----------------------------------------------------------------------------
--
Instruments for first differences equation
  Standard
    D.(lnta dloan gdpg)
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L(1/14).L.npl
Instruments for levels equation
  Standard
    _cons
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    D.L.npl
----------------------------------------------------------------------------
--
Arellano-Bond test for AR(1) in first differences: z =  -4.42  Pr > z =  0.000
Arellano-Bond test for AR(2) in first differences: z =  -1.15  Pr > z =  0.249
----------------------------------------------------------------------------
--
Sargan test of overid. restrictions: chi2(103)  = 522.87  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(103)  = 120.63  Prob > chi2 =  0.113
  (Robust, but weakened by many instruments.)

Difference-in-Hansen tests of exogeneity of instrument subsets:
  GMM instruments for levels
    Hansen test excluding group:     chi2(90)   = 108.28  Prob > chi2 =  0.092
    Difference (null H = exogenous): chi2(13)   =  12.35  Prob > chi2 =  0.499
  iv(lnta dloan gdpg, eq(diff))
    Hansen test excluding group:     chi2(100)  = 101.96  Prob > chi2 =  0.427
    Difference (null H = exogenous): chi2(3)    =  18.67  Prob > chi2 =  0.000
```

The equivalent **xtdpdsys** command is:

```
. xtdpdsys npl lnta dloan gdpg, vce(robust) twostep

System dynamic panel-data estimation         Number of obs         =      1823
Group variable: code                        Number of groups      =       139
Time variable: year
                                             Obs per group:    min =         8
                                                               avg           =
13.11511
                                                               max =        14
```

```
Number of instruments =    108              Wald chi2(4)          =    472.27
                                             Prob > chi2           =    0.0000
Two-step results
----------------------------------------------------------------------------
--
             |              WC-Robust
         npl |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+--------------------------------------------------------------
--
         npl |
         L1. |   .7713315   .0398913    19.34   0.000      .693146     .849517
             |
        lnta |   .2067765   .3215948     0.64   0.520    -.4235378    .8370908
       dloan |  -.0423708   .0128752    -3.29   0.001    -.0676056    -.017136
        gdpg |  -.1605278   .0499978    -3.21   0.001    -.2585216   -.0625339
       _cons |   -.695162   5.143535    -0.14   0.892    -10.77631    9.385981
----------------------------------------------------------------------------
--
Instruments for differenced equation
        GMM-type: L(2/.).npl
        Standard: D.lnta D.dloan D.gdpg
Instruments for level equation
        GMM-type: LD.npl
        Standard: _cons
```

3.5.3 Endogeneity of Explanatory Variables

In the model, it can be argued that *lnta* and *dloan* can be predetermined or potentially endogenous. As the name implies, a predetermined variable is a variable whose value is predetermined. Econometrically, this means that its current and past values are not correlated with the current error term. However, their future values and the current error term can be correlated. An endogenous variable is a variable whose current value is correlated with the error term, for example as a results of reverse causality.

If we treat both *lnta* and *dloan* as predetermined, the xtabond2 command is:

```
. xtabond2 npl l.npl lnta dloan gdpg, gmm(l.npl lnta dloan) iv(gdpg,
eq(diff)) robust h(2) twostep
Favoring speed over space. To switch, type or click on mata: mata set
matafavor space, perm.
Warning: Number of instruments may be large relative to number of
observations.
Warning: Two-step estimated covariance matrix of moments is singular.
  Using a generalized inverse to calculate optimal weighting matrix for two-
step estimation.
  Difference-in-Sargan/Hansen statistics may be negative.

Dynamic panel-data estimation, two-step system GMM
----------------------------------------------------------------------------
--
Group variable: code                          Number of obs      =      1823
Time variable : year                          Number of groups   =       139
Number of instruments = 328                   Obs per group: min =         8
Wald chi2(4)   =    597.84                                   avg =     13.12
Prob > chi2    =     0.000                                   max =        14
----------------------------------------------------------------------------
--
             |              Corrected
         npl |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+--------------------------------------------------------------
--
         npl |
         L1. |    .760384   .0396922    19.16   0.000     .6825887    .8381792
             |
        lnta |    .029521   .2411635     0.12   0.903    -.4431508    .5021929
       dloan |  -.0518367   .0117999    -4.39   0.000    -.0749641   -.0287093
        gdpg |  -.1465034   .0378873    -3.87   0.000    -.2207612   -.0722456
       _cons |   2.196724   3.816045     0.58   0.565    -5.282587    9.676035
```

```
------------------------------------------------------------------------------
--
Instruments for first differences equation
  Standard
    D.gdpg
  GMM-type (missing=0, separate instruments for each period unless
collapsed)
    L(1/14).(L.npl lnta dloan)
Instruments for levels equation
  Standard
    _cons
  GMM-type (missing=0, separate instruments for each period unless
collapsed)
    D.(L.npl lnta dloan)
------------------------------------------------------------------------------
--
Arellano-Bond test for AR(1) in first differences: z =  -4.46  Pr > z =  0.000
Arellano-Bond test for AR(2) in first differences: z =  -1.12  Pr > z =  0.262
------------------------------------------------------------------------------
--
Sargan test of overid. restrictions: chi2(323)  = 829.17  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(323)  = 137.75  Prob > chi2 =  1.000
  (Robust, but weakened by many instruments.)

Difference-in-Hansen tests of exogeneity of instrument subsets:
  GMM instruments for levels
    Hansen test excluding group:     chi2(283)  = 134.78  Prob > chi2 =  1.000
    Difference (null H = exogenous): chi2(40)   =   2.96  Prob > chi2 =  1.000
  iv(gdpg, eq(diff))
    Hansen test excluding group:     chi2(322)  = 135.71  Prob > chi2 =  1.000
    Difference (null H = exogenous): chi2(1)    =   2.04  Prob > chi2 =  0.153
```

Note that *lnta* and *dloan* are now include in **gmm**(.).

If both are assumed to be endogenous, the command and results would be:

```
. xtabond2 npl l.npl lnta dloan gdpg, gmm(l.npl l.lnta l.dloan) iv(gdpg,
eq(diff)) robust h(2) twostep
Favoring space over speed. To switch, type or click on mata: mata set
matafavor speed, perm.
Warning: Number of instruments may be large relative to number of
observations.
Warning: Two-step estimated covariance matrix of moments is singular.
  Using a generalized inverse to calculate optimal weighting matrix for two-
step estimation.
  Difference-in-Sargan/Hansen statistics may be negative.

Dynamic panel-data estimation, two-step system GMM
------------------------------------------------------------------------------
--
Group variable: code                            Number of obs      =      1823
Time variable : year                            Number of groups   =       139
Number of instruments = 300                     Obs per group: min =         8
Wald chi2(4)    =     527.31                                   avg =     13.12
Prob > chi2     =      0.000                                   max =        14
------------------------------------------------------------------------------
--
             |              Corrected
         npl |      Coef.   Std. Err.      z    P>|z|     [95% Conf.
Interval]
-------------+----------------------------------------------------------------
--
         npl |
         L1. |   .7459653   .0401767    18.57   0.000     .6672204    .8247102
             |
        lnta |  -.2548182   .2174895    -1.17   0.241    -.6810897    .1714534
       dloan |  -.0569597   .0166477    -3.42   0.001    -.0895885   -.0243308
        gdpg |  -.1553388   .0282854    -5.49   0.000    -.2107772   -.0999004
       _cons |   6.739439   3.579769     1.88   0.060    -.2767796    13.75566
------------------------------------------------------------------------------
--
```

```
Instruments for first differences equation
  Standard
    D.gdpg
  GMM-type (missing=0, separate instruments for each period unless
collapsed)
    L(1/14).(L.npl L.lnta L.dloan)
Instruments for levels equation
  Standard
    _cons
  GMM-type (missing=0, separate instruments for each period unless
collapsed)
    D.(L.npl L.lnta L.dloan)
---------------------------------------------------------------------------
--
Arellano-Bond test for AR(1) in first differences: z =  -4.46  Pr > z =  0.000
Arellano-Bond test for AR(2) in first differences: z =  -1.09  Pr > z =  0.277
---------------------------------------------------------------------------
--
Sargan test of overid. restrictions: chi2(295)   = 743.73  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(295)   = 131.97  Prob > chi2 =  1.000
  (Robust, but weakened by many instruments.)

Difference-in-Hansen tests of exogeneity of instrument subsets:
  GMM instruments for levels
    Hansen test excluding group:     chi2(257)   = 132.72  Prob > chi2 =  1.000
    Difference (null H = exogenous): chi2(38)    =  -0.75  Prob > chi2 =  1.000
  iv(gdpg, eq(diff))
    Hansen test excluding group:     chi2(294)   = 129.34  Prob > chi2 =  1.000
    Difference (null H = exogenous): chi2(1)     =   2.62  Prob > chi2 =  0.105
```

Note that now, the one-lagged *lnta* and *dloan* are entered in **gmm**(.). See Roodmand (2009b), page 124 on the **gmm**(.) for the predetermined and endogenous variables.

Note also that the Hansen's J statistic for both results has the p-value of 1. As explained by Labra and Torrecillas (2018) in reference to Roodman (2009a), the p-value close to 1 means that the asymptotic properties of the test have not been applied. In this case, the null of instrument validity must be rejected. They further note that the p-value should be between 0.05 and 0.80 , with the range from 0.10 to 0.25 to be optimal. In the above results, the problem may be from too many instruments, which we are now turn to.

3.5.4 Instrument Proliferation

A quick look at the results in the previous section reveals that, by specifying *lnta* and *dloan* as predetermined or endogenous, the number of instruments substantially exceeds the number of cross-sectional units or group. Thus, we need to limit the number of instruments by restricting the lags for the instruments or using the option *collapse*.

We may restrict the lags to 2 using the option *lag(1 2)* in the **gmm**(.):

```
. xtabond2 npl l.npl lnta dloan gdpg, gmm(l.npl lnta dloan, lag(1 2)) iv(gdpg,
eq(diff)) robust h(2) twostep
Favoring speed over space. To switch, type or click on mata: mata set matafavor
space, perm.
Warning: Two-step estimated covariance matrix of moments is singular.
  Using a generalized inverse to calculate optimal weighting matrix for two-
step estimation.
  Difference-in-Sargan/Hansen statistics may be negative.
```

```
Dynamic panel-data estimation, two-step system GMM
------------------------------------------------------------------------------
--
Group variable: code                            Number of obs      =      1823
Time variable : year                            Number of groups   =       139
Number of instruments = 118                     Obs per group: min =         8
Wald chi2(4)   =    523.61                                     avg =     13.12
Prob > chi2    =     0.000                                     max =        14
------------------------------------------------------------------------------
--
             |              Corrected
         npl |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
--
         npl |
         L1. |   .7877507   .0442597    17.80   0.000     .7010033    .8744981
             |
        lnta |   .2224767   .2654771     0.84   0.402    -.2978488    .7428022
       dloan |  -.0518004   .0111867    -4.63   0.000     -.073726   -.0298749
        gdpg |  -.1173323   .0377981    -3.10   0.002    -.1914152   -.0432494
       _cons |   -1.10311   4.226558    -0.26   0.794    -9.387012    7.180791
------------------------------------------------------------------------------
--
Instruments for first differences equation
  Standard
    D.gdpg
  GMM-type (missing=0, separate instruments for each period unless
collapsed)
    L(1/2).(L.npl lnta dloan)
Instruments for levels equation
  Standard
    _cons
  GMM-type (missing=0, separate instruments for each period unless
collapsed)
    D.(L.npl lnta dloan)
------------------------------------------------------------------------------
--
Arellano-Bond test for AR(1) in first differences: z =  -4.39  Pr > z =  0.000
Arellano-Bond test for AR(2) in first differences: z =  -1.15  Pr > z =  0.251
------------------------------------------------------------------------------
--
Sargan test of overid. restrictions: chi2(113)  = 502.61  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(113)  = 130.77  Prob > chi2 =  0.121
  (Robust, but weakened by many instruments.)

Difference-in-Hansen tests of exogeneity of instrument subsets:
  GMM instruments for levels
    Hansen test excluding group:     chi2(73)    =  96.93  Prob > chi2 =  0.032
    Difference (null H = exogenous): chi2(40)    =  33.83  Prob > chi2 =  0.743
  iv(gdpg, eq(diff))
    Hansen test excluding group:     chi2(112)   = 128.82  Prob > chi2 =  0.132
    Difference (null H = exogenous): chi2(1)     =   1.95  Prob > chi2 =  0.163
```

As may be observed above, the number of instruments is now 118. This is less than the number of groups, which is 139. The p-value of the Hansen's J statistics is now 0.121.

We may also use the option *collapse* in **gmm**(.):

```
xtabond2 npl l.npl lnta dloan gdpg, gmm(l.npl lnta dloan, collapse) iv(gdpg,
eq(diff)) robust h(2) twostep
Favoring speed over space. To switch, type or click on mata: mata set matafavor
space, perm.
Warning: Two-step estimated covariance matrix of moments is singular.
  Using a generalized inverse to calculate optimal weighting matrix for two-
step estimation.
  Difference-in-Sargan/Hansen statistics may be negative.
```

```
Dynamic panel-data estimation, two-step system GMM
------------------------------------------------------------------------------
--
Group variable: code                            Number of obs      =      1823
Time variable : year                            Number of groups   =       139
Number of instruments = 45                      Obs per group: min =         8
Wald chi2(4)   =    466.19                                     avg =     13.12
Prob > chi2    =     0.000                                     max =        14
------------------------------------------------------------------------------
--
             |              Corrected
         npl |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
--
         npl |
         L1. |   .7777864   .0498828    15.59   0.000     .6800179     .875555
             |
        lnta |  -.0120299   .2059031    -0.06   0.953    -.4155925    .3915327
       dloan |  -.0368143   .0099341    -3.71   0.000    -.0562848   -.0173438
        gdpg |  -.1098972   .0307331    -3.58   0.000    -.1701331   -.0496614
       _cons |   2.142626   3.354489     0.64   0.523    -4.432052    8.717304
------------------------------------------------------------------------------
--
Instruments for first differences equation
  Standard
    D.gdpg
  GMM-type (missing=0, separate instruments for each period unless
collapsed)
    L(1/14).(L.npl lnta dloan) collapsed
Instruments for levels equation
  Standard
    _cons
  GMM-type (missing=0, separate instruments for each period unless
collapsed)
    D.(L.npl lnta dloan) collapsed
------------------------------------------------------------------------------
--
Arellano-Bond test for AR(1) in first differences: z =  -4.23  Pr > z =  0.000
Arellano-Bond test for AR(2) in first differences: z =  -1.17  Pr > z =  0.241
------------------------------------------------------------------------------
--
Sargan test of overid. restrictions: chi2(40)   = 175.61  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(40)   =  55.04  Prob > chi2 =  0.057
  (Robust, but weakened by many instruments.)

Difference-in-Hansen tests of exogeneity of instrument subsets:
  GMM instruments for levels
    Hansen test excluding group:     chi2(37)   =  46.65  Prob > chi2 =  0.133
    Difference (null H = exogenous): chi2(3)    =   8.38  Prob > chi2 =  0.039
  iv(gdpg, eq(diff))
    Hansen test excluding group:     chi2(39)   =  52.64  Prob > chi2 =  0.071
    Difference (null H = exogenous): chi2(1)    =   2.39  Prob > chi2 =  0.122
```

Note that the option collapse reduces the number of instruments substantially. In addition, the p-value of the Hansen's J statistic is 0.057. Thus, at 5% significance level, the null that the instruments are valid cannot be rejected.

3.5.5 Comparing Estimators

Before we end this section, we compare the two GMM estimators with the Pooled OLS and fixed-effects estimators. More specifically, we estimate the two-step first difference and system GMM estimators assuming that the explanatory variables are strictly exogenous (see Sections 5.1 and 5.2). The results are tabulated below:

	Pooled OLS	Fixed-Effects	DIFF GMM	SYS GMM
L.npl	0.823***	0.681***	0.711***	0.772***
	(24.31)	(16.76)	(17.48)	(19.51)
lnta	-0.141**	-0.268	-0.585	0.237
	(-2.28)	(-1.14)	(-1.19)	(0.72)
dloan	-0.0448***	-0.0457***	-0.0311***	-0.0428***
	(-5.23)	(-4.83)	(-2.95)	(-3.38)
gdpg	-0.125***	-0.142***	-0.143***	-0.165***
	(-5.26)	(-5.89)	(-3.62)	(-3.27)
_cons	4.124***	7.190*		-1.091
	(3.73)	(1.90)		(-0.21)
N	1823	1823	1684	1823

t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Take note of the coefficients of the autoregressive term estimated using the GMM estimators. They are between the autoregressive coefficient of the Pooled OLS, which is upward biased, and the autoregressive coefficient of the fixed-effects estimator, which is downward biased. This should be expected for the GMM estimates to be consistent. In our example, the first difference GMM and system GMM results lead to similar inferences. Thus, the selection of which estimator to be used should not be an issue. In other words, the results are robust to alternative GMM estimators.

3.6 CONCLUSION

The GMM estimators are widely applied in empirical research to estimate dynamic panel models. The main strength of the approach is its ability to address the endogeneity problem, whether it arises from reverse causality or by construction via the inclusion of the lagged independent variable. It is also convenient since we do not need to search for instruments to be used, which is practically difficult. The instruments must fulfill the conditions that they must be strongly correlated with the instrumented variables but must not be correlated with the error term. The first difference GMM estimators ingeniously exploit the lagged values of the endogenous variables in level as instruments for the corresponding variables in first difference. The system GMM adds the variables in first difference to be instruments of the corresponding variables in level. They arguably fulfill the conditions of the instrument variables.

It should be noted that the GMM estimators are practically appealing when the panel comprises large N and short T, preferably less than 10. In a panel sample with small N, the problem of too many instruments naturally arises. The key to addressing this problem is to limit the number of instruments to be less than N. While we have options to do so by either limiting the lags of the instruments or collapsing the instruments, we should note that the GMM estimators may not be optimal in small sample.

PANEL VAR

This technique combines the traditional VAR approach, which treats all the variables in the system as endogenous, with the panel-data approach, which allows for unobserved individual heterogeneity.

(Love and Zicchino, 2006)

4.1 INTRODUCTION

Panel vector autoregression (Panel VAR) modelling, as Love and Zicchino (2006) note, combines the advantages of the vector autoregression (VAR) and panel data modelling. The VAR modelling, despite its parsimony, allows specification of (some) variables as endogenous and hence enables evaluation of causal interactions among them. Meanwhile, the panel data modelling controls for individual heterogeneity and accordingly circumvents the problem of omitted variable bias.

Since its introduction by Holtz-Eakin et al. (1998), the Panel VAR has been applied to address various issues, among which include Investment Behavior (Love and Zicchino, 2006), Consumption Behavior (Shen et al., 2015, Simo-Kengne et al., 2013), Monetary Transmission Mechanisms (Carpenter and Demiralp, 2012), and Finance and Shadow Economy (Berdiev and Saunoris, 2016). In the field of Banking and Finance (including Islamic Banking and Finance), some examples are:

- Ibrahim, M. H., 2019. Oil and macro-financial linkages: Evidence from the GCC countries. The Quarterly Review of Economics and Finance 72, 1-13.
- Jaremski, M., Sapci, A., 2017. Understanding the cyclical nature of financial intermediation costs. Southern Economic Journal 84(1), 181-201.
- Kabir, M.N., Worthington, A.C., 2017. The 'competition-stability/fragility' nexus: A comparative analysis of Islamic and conventional banks. International Review of Financial Analysis 50, 111-128.
- Khandelwal, P., Miyajima, K., Santos, A., 2016. The impact of oil prices on the banking system in the GCC. IMF Working Paper #WP/16/161.
- Love, I., Turk-Ariss, R., 2014. Macro-financial linkages in Egypt: A panel analysis of economic shocks and loan portfolio quality. Journal of International Financial Markets, Institutions and Money 28, 158-181.

This chapter explains the panel VAR and its implementation in steps using the STATA code made available by Inessa Love, University of Hawaii at Manoa. These steps include panel VAR lag order specification, panel VAR estimation, panel VAR stability, panel VAR Granger causality, and panel VAR impulse-response functions and variance decompositions.

4.2 PANEL VAR MODELLING

This section presents panel VAR model specification and discusses statistical and interpretation issues related to its implementation.

4.2.1 Specification

For the ease of illustration, the panel VAR model of order 1, or PVAR(1), comprising of two endogenous variables is used:

$$y_{it} = \alpha_1 y_{it-1} + \alpha_2 x_{it-1} + u_{1i} + \varepsilon_{1it} \tag{1}$$

$$x_{it} = \beta_1 y_{it-1} + \beta_2 x_{it-1} + u_{2i} + \varepsilon_{2it} \tag{2}$$

where *y* and *x* are the endogenous variables, $u_{.i}$ is the individual specific effects to capture (unobserved) individual heterogeneity, and ε_{it} is the standard error term. A vector of exogenous variables impacting on the endogenous variables may also be included in the system.

It is well noted that, in dynamic panel modelling, the traditional panel estimators such as the fixed-effects and random-effects estimators yield biased estimates due to the presence of non-zero correlation between the lagged endogenous variables and the individual-specific effects. It is also equally well noted that, in VAR modelling, the estimated coefficients of (1) and (2) are hard to interpret. In the implementation of a panel VAR, these issues of estimation and interpretation are addressed through respectively the GMM estimator and simulation of impulse-response functions and variance decompositions, which are detailed below and demonstrated in a later section.

4.2.2 Issues in Panel VAR

The implementation of a panel VAR model involves the following issues: lag order selection, estimation, and interpretation.
Lag order selection: The specification of the Panel VAR entails the selection of the lag order. Unfortunately, the empirical implementation in many studies is silent on how the lag order is selected. Love and Zicchino (2006), Love and Turk-Ariss (2014) and Kabir and Worthington (2017) employ panel VAR lag order 1 in their studies. Meanwhile, other studies have opted for longer lags (Brana et al. (2012), Shen et al. (2014), and Atems and Jones (2015)). Abrigo and Love (2016) describe the lag selection procedure using the moment and model selection criteria (MMSC) developed by Andrews and Lu (2001). In addition to selecting the optimal lag order of the panel VAR, the MMSC also suggests the lag order for the moment conditions. Georgoutsos and Maratis (2017) adopt and report the MMSC in their study.

Estimation: As in a dynamic panel model, there is an endogeneity issue in panel VAR modelling due to non-zero correlation between lagged dependent variables and the individual fixed effects. Accordingly, the least squares estimation method would yield biased estimates even with large N. To address the endogeneity issue, the panel VAR is estimated using the GMM estimator. It involves (i) filtering out individual fixed effects and (ii) employment of instrumental variables.

Filtering out individual fixed effects can be through either first differencing or forward orthogonal transformation (also known as Helmert transformation). Using (1) as an example, first differencing yields:

$$(y_{it} - y_{it-1}) = \alpha_1(y_{it-1} - y_{it-2}) + \alpha_2(x_{it-1} - x_{it-2}) + (\varepsilon_{1it} - \varepsilon_{1it-1}) \quad (3)$$

Meanwhile, Helmert transforming (1) leads to:

$$y^*_{it} = \alpha_1 y^*_{it-1} + \alpha_2 x^*_{it-1} + \varepsilon^*_{it}, \quad m^*_{it} = (m_{it} - \overline{m_{it}})\sqrt{T_{it}/(T_{it}+1)} \quad (4)$$

where $m = y$ and x, $\overline{m}_{it}$ is the average of all available future observations and T_{it} is the number of all available future observations. In the empirical implementation, the Helmert transformation seems to be preferred. As compared to differencing, the Helmert transformation minimizes data loss in the presence of gap in the data. In addition, unlike in (3), $y_{it-1}$is not correlated with the Helmert-transformed error term and hence can readily be used as an instrument for y^*_{it-1}. Like the GMM estimation of dynamic panel data models, deeper lags of endogenous variables can also be added as instruments.

Take note that the GMM estimator suffers from the problem of weak instruments when the regressors exhibit persistence or are near unit root. To avoid the weak instrument problem, Abrigo and Love (2016) suggests differencing non-stationary regressors. In other words, it is advisable to conduct unit root tests to identify the stationarity property of each variable under investigation and then, in the presence of unit root, differencing the variable concerned. It needs mentioning that spurious regression is less serious in panels (Phillips and Moon, 1999), which explains why it is not necessary to conduct panel cointegration test in the applications of panel VAR.

Interpretation: The estimated coefficients of a panel VAR are hard to interpret. As standard in VAR modelling, they are summarized by means of Granger causality, impulse-response functions, and variance decompositions. In the case that an exogenous variable is included in the panel VAR specification, the temporal effect of one unit change in the exogenous variable can also be traced through dynamic multipliers.

There are two requirements related to the generation of impulse-response functions and variance decompositions: stability and shock identification. The stability of a panel VAR system requires that the moduli of the eigenvalues of the dynamic matrix be within the unit circle, which must be checked for good econometric practices. As for shock identification, the standard scheme used in empirical studies is Cholesky factorization. This requires ordering of the variables in the panel VAR system according to their relative endogeneity. The variable ordered first is taken to be affected by other variables in the system with lags, but it affects them immediately. It is the most exogenous or more correctly least endogenous in the system. The variable ordered last is most responsive to shocks in other variables in the system. Since the results can be driven by the variable ordering, it is a good econometric practice to experiment with alternative plausible orderings for robustness as is done in Love and Turk-Ariss (2014).

4.3 PANEL VAR APPLICATIONS

This section provides examples of studies in banking and finance utilizing panel VAR modelling as an empirical approach to address their research objectives. The focus is not only on the objectives and findings but also on how they address various statistical issues related to the implementation of panel VAR as discussed in the preceding section.

Example I	Kabir, M.N., Worthington, A.C., 2017. The 'competition-stability/fragility' nexus: A comparative analysis of Islamic and conventional banks. International Review of Financial Analysis 50, 111-128.

Kabir and Worthington (2017) analyze the competition – stability versus competition – fragility hypotheses for a sample of banks from 16 dual banking countries (i.e. countries that have both conventional banks and Islamic banks). Arguing that the degree of competition and bank stability are potentially endogenous, they adopt a panel VAR to allow for potential feedbacks between the two variables. Their panel VAR system comprises of 4 variables. In addition to competition (the Lerner index) and stability (Z-score, NPL ratio and Merton's Distance to Default) measures, they include GDP growth and the natural log of total assets. From the panel VAR results, they conclude in support of the competition – fragility hypothesis for both Islamic and conventional banks.

They set the lag order of panel VAR to 1 based on the Lagrange multiplier (LM) test for autocorrelation and the Schwarz information criteria (SIC). The model is estimated using the GMM estimator where the individual fixed effect is filtered using the Helmert transformation. From the estimated Panel VAR models, they simulate impulse-response functions and variance decompositions by adopting the Cholesky decomposition with the following ordering: GDP growth, log of total assets, bank competition, and bank stability.

Example II	Khandelwal, P., Miyajima, K., Santos, A., 2016. The impact of oil prices on the banking system in the GCC. IMF Working Paper #WP/16/161.

Khandelwal et al. (2016) assess the impact of oil prices on bank risk for the GCC banking sector. In addition to dynamic panel models, they employ a panel VAR system comprising real oil price growth, real equity price growth, NPL ratios, real credit growth, and real deposit growth for 42 GCC banks to disentangle feedback loops among them. The results suggest that oil price movements impact bank variables in a significant way – (i) the ratio of non-performing loans increases following the drop in the oil price growth, and (ii) the growth rates of bank credit and deposits also drops following slumps in oil price growth. In addition, non-performing loans seem to lower bank credit and deposit growth. Finally, equity price developments play a role in amplifying the effect of adverse oil price shocks on the banking system.

Khandelwal et al. (2016) opts for the panel VAR of order 2, which is in view of the short time series dimension of their panel sample, i.e. 2000-2014. The model is estimated using the GMM estimator where the individual fixed effect is filtered using the Helmert transformation. From the estimated Panel VAR models, they simulate impulse-response functions using the Cholesky decomposition with the following ordering: real oil price growth, NPL ratio, real credit growth, real deposit growth and real equity price growth.

Example III	Love, I., Turk-Ariss, R., 2014. Macro-financial linkages in Egypt: A panel analysis of economic shocks and loan portfolio quality. Journal of International Financial Markets, Institutions and Money 28, 158-181.

Love and Turk-Ariss (2014) examine macro-financial linkages using a panel sample of 41 Egyptian banks covering the period 1993-2010. They employ the panel VAR modelling in addition to the standard dynamic panel modelling. In their baseline specification, three macroeconomic variables and three bank-level variables are included: capital inflows, GDP growth rate, aggregate lending rate, bank loan growth, loan loss reserves, and return on average equity. The results from their analysis suggest substantial interactions among the variables included in the model. Most importantly, they hint on improvement in bank performance (i.e. stronger loan growth, better loan quality and higher profitability) following positive shocks in capital inflows and GDP growth. By contrast, higher lending rate tends to lower bank profitability and worsen loan quality (higher loan loss reserves).

The panel VAR used in Love and Turk-Ariss (2014) is of order 1. As is standard in the panel VAR modelling, the Helmert transformation is used to filter out the individual specific effects and the Cholesky factorization to simulate the impulse-response functions. The baseline ordering of the variables is capital inflows, GDP growth rate, aggregate lending rate, bank loan growth, loan loss reserves, and return on average equity. For robustness, they also experiment with alternative orderings of the variables. Finally, unlike the two examples above, they do test for the stationarity of the variables using the Fisher ADF and PP Panel unit root tests.

4.4 PANEL VAR IN STATA

As an illustration of the panel VAR, the *Risk-Capital.xlsx* file will be used to evaluate dynamic interactions between bank capital (equity-to-asset ratio) and bank credit risk (non-performing loans to gross loans). Theoretically, the relations between them can go both ways. Higher credit risk may lead banks to be more prudent by building up capital and higher capital may lead banks to be more conservative since there is more at risk. It is also conceivable that the better capitalized banks will undertake more risk or have more risk appetite. The Panel VAR of order 1 is specified as:

$$npl_{it} = \alpha_1 npl_{it-1} + \alpha_2 eta_{it-1} + u_{1i} + \varepsilon_{1it} \tag{5}$$

$$eta_{it} = \beta_1 npl_{it-1} + \beta_2 eta_{it-1} + u_{2i} + \varepsilon_{2it} \tag{6}$$

where *npl* is the non-performing loans as a ratio of total loans and *eta* is the equity-to-asset ratio.

Taking that all data are already placed in STATA, the data structure setting is specified using *tsset code year* and the variable *eta* is generated using *gen eta = (equity/ta)*100* (note: *npl* can be directly used from the file), this section demonstrates the implementation of panel VAR. It benefits greatly from Abrigo and Love (2016), which should be referred to for details.

4.4.1 STATA Code

The STATA codes for estimating the panel VAR are provided by Inessa Love of the University of Hawaii, which can be retrieved from:

https://sites.google.com/a/hawaii.edu/inessalove/home/pvar.

There are 13 files for panel estimation and its subroutines. These files are:

Files	Commands
• pvar.ado • pvar.sthlp	Estimating panel VAR
• pvarsoc.ado • pvarsoc.sthlp	Implementing model and moment selection criteria (MMSC)
• pvarstable.ado • pvarstable.sthlp	Examining panel VAR stability
• pvargranger.ado • pvargranger.sthlp	Performing Granger causality
• pvarirf.ado • pvarirf.sthlp • pvarirf_dm.ado	Simulating impulse-response functions and dynamic multipliers
• pvarfevd.ado • pvarfevd.sthlp	Generating variance decompositions

These files need to be copied into a sub-folder of the *ado* file folder in STATA, i.e. folder *p* (since all files begin with *p*) in either *base* or *updates* sub-folders of the *ado* folder. Alternatively, these files can be placed in a folder (name it PVAR and place it on the Desktop for easy reference). In the latter case, a reference to this folder must be made before the execution of all commands through **Change Working Directory**. This can be done by clicking **File/Change Working Directory** and then specifying the folder to PVAR.

4.4.2 Panel VAR Lag Order

The subroutine **pvarsoc** selects the optimal lag order and moment conditions. It reports the model overall coefficient of determination (CD), Hansen's (1982) J statistic for over-identifying restrictions and its p-value and the optimal moment and model selection criteria (MMSC) developed by Andrews and Lu (2001).

<u>**Syntax:**</u>

pvarsoc *depvarlist, options*

where *depvarlist* is the list of dependent variables and the *options* are *maxlag(#)*, *pinstlag(numlist)*, *pvaropts(options)*.

- *maxlag*(#): the maximum lag number for which the statistics are obtained
- *pinstlag*(numlist): specifies the numlist*th* lag from the highest lag order of the depvarlist specified in the panel VAR model implemented using **pvar** be used. It cannot be used with *pvaropts*(instlag(numlist))
- *pvaropts*(options) passes arguments to **pvar**. All arguments specified in options are passed to and used by **pvar** in the estimation.

<u>**Illustrations and notes:**</u>

1. **pvarsoc** npl eta, maxlag(4)

The command runs Panel VAR lag order selection up to maximum lag 4 (*maxlag(4)*).

```
. pvarsoc npl eta, maxlag(4)
Running panel VAR lag order selection on estimation sample
....

 Selection order criteria
 Sample:  1999 - 2014                              No. of obs       =       261
                                                    No. of panels    =        23
                                                    Ave. no. of T    =    11.348

  +--------------------------------------------------------------------------
-+
  |  lag |   CD          J       J pvalue     MBIC       MAIC       MQIC     |
  |------+-------------------------------------------------------------------
-|
  |    1 |  .8637762          .          .          .          .          .
|
  |    2 |  .8671861          .          .          .          .          .
|
  |    3 |  .8688508          .          .          .          .          .
|
  |    4 |   .762128          .          .          .          .          .
|
  +--------------------------------------------------------------------------
-+
```

Note that, except CD, the statistics are not reported. By default, the estimation specifies the number of moments to be equal to the number of endogenous variables and, hence, the J statistics for over-identifying restrictions are not available. Since Andrews and Lu's (2001) MMSC statistics are based on the J statistics, they cannot be computed.

To have those statistics, the number of moment conditions must be more than the number of endogenous variables in the model. In the present case, it means that the instrument lags must be more than the Panel VAR lag orders. This is demonstrated below.

2. **pvarsoc** npl eta, maxlag(4) pvaropts(instl(1/4))

The above command specifies the instrument lags from 1 to 4 [i.e. pvaropts(instl(1/4))]. With this, the statistics can be computed for PVAR(1), PVAR(2), PVAR(3), but not PVAR(4) as given below:

```
. pvarsoc npl eta, maxlag(4) pvaropts(instl(1/4))
Running panel VAR lag order selection on estimation sample
....

 Selection order criteria
 Sample:  1999 - 2014                                 No. of obs      =       261
                                                       No. of panels   =        23
                                                       Ave. no. of T   =    11.348

  +-------------------------------------------------------------------------
-+
  |   lag |    CD          J       J pvalue     MBIC        MAIC        MQIC    |
  |-------+-----------------------------------------------------------------
-|
  |     1 |  .8509051   18.07783   .1133477  -48.69642   -5.92217  -23.11603
|
  |     2 |  .8558977   13.48089   .0963403  -31.03528  -2.519114  -13.98169
|
  |     3 |  .8676171   3.832726    .429117  -18.42536  -4.167274   -9.89856
|
  |     4 |   .762128          .          .          .          .          .
|
  +-------------------------------------------------------------------------
-+
```

The result indicates that PVAR(1) is optimal: MBIC, MAIC and MQIC are all at minimum at lag 1 and the J statistic indicates non-rejection of the over-identifying restrictions. It is suggested that, if the over-identifying restrictions are rejected, experiments with various instrument lags be made to arrive at the optimal model and moment selection. Never choose the PVAR order that the J-statistic rejects the validity of the instruments.

4.4.3 Panel VAR Estimation

This subroutine estimates the panel VAR model.

Syntax:
pvar *depvarlist, options*

(Some options are discussed below. Please refer to Abrigo and Love (2016) for details)

Illustrations and Notes:

1. **pvar** npl eta, instl(1/4) overid

From the previous **pvarsoc,** the PVAR(1) with the instrument lags from 1 to 4 is chosen. To estimate this, we write ("overid" generates the J-stat for over-identifying restriction test. It should be the same as the one reported under *pvarsoc* above):

```
. pvar npl eta, instl(1/4) overid
Panel vector autoregresssion
GMM Estimation

Final GMM Criterion Q(b) =     .0693
Initial weight matrix: Identity
GMM weight matrix:     Robust
                                                    No. of obs      =       261
                                                    No. of panels   =        23
                                                    Ave. no. of T   =    11.348

----------------------------------------------------------------------------
--
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+--------------------------------------------------------------
--
npl          |
         npl |
         L1. |   .9636098   .0588383    16.38   0.000     .8482889    1.078931
             |
         eta |
         L1. |   .0406749   .0217987     1.87   0.062    -.0020497    .0833995
-------------+--------------------------------------------------------------
--
eta          |
         npl |
         L1. |  -.2076167   .0705458    -2.94   0.003    -.3458839   -.0693494
             |
         eta |
         L1. |   .2233015   .0939337     2.38   0.017     .0391949     .407408
----------------------------------------------------------------------------
--
Instruments : l(1/4).(npl eta)

Test of overidentifying restriction:
  Hansen's J chi2(12) = 18.07783 (p = 0.113)
```

The default settings of the above are (i) PVAR lag order 1, (ii) forward orthogonal deviation (Helmert transformation) to remove unit specific effects, (iii) no time specific effects in the model specification, and (iv) 95% confidence interval.

2. **pvar** npl eta, lags(2) instl(1/4)

The option *lags(2)* specifies the panel VAR of order 2.

```
pvar npl eta, lags(2) instl(1/4)

Panel vector autoregresssion
GMM Estimation

Final GMM Criterion Q(b) =     .0517
Initial weight matrix: Identity
GMM weight matrix:     Robust
                                                    No. of obs      =       261
                                                    No. of panels   =        23
```

```
                                                    Ave. no. of T   =    11.348
------------------------------------------------------------------------------
--
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
--
npl          |
         npl |
         L1. |   .9407431   .0931496    10.10   0.000     .7581732    1.123313
         L2. |     .01027   .0793976     0.13   0.897    -.1453464    .1658864
             |
         eta |
         L1. |    .033927   .0202931     1.67   0.095    -.0058467    .0737007
         L2. |   .0166621    .009243     1.80   0.071    -.0014539    .0347781
-------------+----------------------------------------------------------------
--
eta          |
         npl |
         L1. |  -.0615879   .1126881    -0.55   0.585    -.2824526    .1592767
         L2. |  -.1907078    .117138    -1.63   0.104    -.4202941    .0388785
             |
         eta |
         L1. |    .137635   .0838201     1.64   0.101    -.0266493    .3019193
         L2. |    .032239   .0363196     0.89   0.375    -.0389462    .1034242
------------------------------------------------------------------------------
--
Instruments : l(1/4).(npl eta)
```

3. **pvar** npl eta, fd instl(1/4) overid

The option fd applies first differencing to filter out individual specific effects.

```
. pvar npl eta, fd instl(1/4) overid

Panel vector autoregresssion

GMM Estimation

Final GMM Criterion Q(b) =      .0677
Initial weight matrix: Identity
GMM weight matrix:      Robust
                                                    No. of obs      =       284
                                                    No. of panels   =        23
                                                    Ave. no. of T   =    12.348


------------------------------------------------------------------------------
--
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
--
npl          |
         npl |
         L1. |   .3243332     .19571     1.66   0.097    -.0592514    .7079178
             |
         eta |
         L1. |   .0057972    .005831     0.99   0.320    -.0056313    .0172257
-------------+----------------------------------------------------------------
--
eta          |
         npl |
         L1. |   .2651632   .1942333     1.37   0.172     -.115527    .6458534
             |
         eta |
         L1. |  -.0262305   .1082377    -0.24   0.809    -.2383725    .1859115
------------------------------------------------------------------------------
--
Instruments : l(1/4).(npl eta)

Test of overidentifying restriction:
  Hansen's J chi2(12) = 19.229036 (p = 0.083)
```

4. **pvar** npl eta, instl(1/4) gmmstyle overid

The option *gmmstyle* applies the GMM-style instruments as proposed by Holtz-Eakin et al. (2001). To use this, the instrument lags must be specified. For each instrument based on lags of *depvarlist*, missing values are substituted with zero. Observations with no valid instruments are dropped.

```
. pvar npl eta, instl(1/4) gmmstyle overid

Panel vector autoregresssion


GMM Estimation

Final GMM Criterion Q(b) =     .0557
Initial weight matrix: Identity
GMM weight matrix:     Robust
                                                   No. of obs      =       330
                                                   No. of panels   =        23
                                                   Ave. no. of T   =    14.348


----------------------------------------------------------------------------
--
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+--------------------------------------------------------------
--
npl          |
         npl |
         L1. |   .9719418   .0619965    15.68   0.000     .8504308    1.093453
             |
         eta |
         L1. |    .040445   .0132148     3.06   0.002     .0145444    .0663456
-------------+--------------------------------------------------------------
--
eta          |
         npl |
         L1. |  -.2633101   .0834177    -3.16   0.002    -.4268058   -.0998143
             |
         eta |
         L1. |   .1427755   .0810473     1.76   0.078    -.0160744    .3016254
----------------------------------------------------------------------------
--
Instruments : l(1/4).(npl eta)


Test of overidentifying restriction:
  Hansen's J chi2(12) = 18.370101 (p = 0.105)
```

5. **pvar** npl eta, instl(1/4) exo(gdp)

In running the panel VAR, exogenous variables can also be included. The option *exo(gdp)* includes GDP growth as an exogenous variable.

```
. pvar npl eta, instl(1/4) exo(gdp)
Panel vector autoregresssion

GMM Estimation

Final GMM Criterion Q(b) =     .0614
Initial weight matrix: Identity
GMM weight matrix:     Robust
                                                   No. of obs      =       261
                                                   No. of panels   =        23
                                                   Ave. no. of T   =    11.348
----------------------------------------------------------------------------
--
```

```
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
--
npl          |
         npl |
         L1. |   .9508633   .0597345    15.92   0.000     .8337859    1.067941
             |
         eta |
         L1. |   .0459751   .0269407     1.71   0.088    -.0068278    .0987779
             |
         gdp |   .0006628   .0630623     0.01   0.992    -.1229371    .1242627
-------------+----------------------------------------------------------------
--
eta          |
         npl |
         L1. |  -.2048529   .0688443    -2.98   0.003    -.3397853   -.0699205
             |
         eta |
         L1. |   .2912966   .1211717     2.40   0.016     .0538045    .5287887
             |
         gdp |   .1319521   .1379454     0.96   0.339    -.1384159    .4023202
------------------------------------------------------------------------------
--
Instruments : l(1/4).(npl eta) gdp
```

4.4.4 Panel VAR Stability

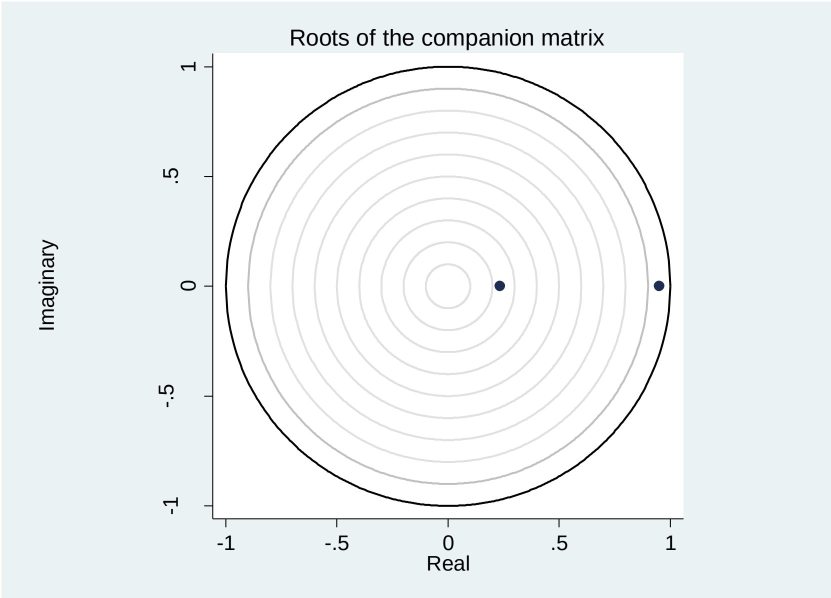
The stability of the PVAR is essential since it implies that the model is invertible and has an infinite-order vector moving average (VMA) representation for the simulation of impulse-response functions and variance decompositions. The **pvarstable** is the post-estimation command that provides the modulus of each eigenvalue of the fitted model. The model is stable if all moduli are within the unit circle.

Syntax:

pvarstable, *graph*

This will give (after implementing **pvar** npl eta, instl(1/4)):

```
. pvarstable, graph

   Eigenvalue stability condition

  +----------------------------------+
  |       Eigenvalue        |        |
  |    Real       Imaginary |  Modulus |
  |-----------------------+----------|
  |  .9520212           0 |  .9520212 |
  |    .23489           0 |    .23489 |
  +----------------------------------+

   All the eigenvalues lie inside the unit circle.
   pVAR satisfies stability condition.
```



4.4.5 Panel VAR Granger Causality

Let say, the following model is estimated

- **pvar** npl eta, instl(1/4)

The results are as given under PVAR ESTIMATION. Note that the estimated coefficients of VAR/Panel VAR are hard to interpret due to the dynamic nature of the specification.

One way to interpret the model is to assess "Granger" causality between the variables as indication of significance of a variable in predicting/anticipating variations in another variable. In our example, by virtue of lag order 1 being selected, we can infer the causality directly from the significance the estimated coeffients, namely, of one-lagged *eta* coefficient in *npl* equation and one-lagged *npl* coefficient in the *eta* equation. Equivalently, this can be done by using **pvargranger,** the command that implements Granger causality tests among the variables with the PVAR model with any lag order.

After the estimation is done, type **pvargranger** to obtain:

```
. pvargranger

  panel VAR-Granger causality Wald test
    Ho: Excluded variable does not Granger-cause Equation variable
    Ha: Excluded variable Granger-causes Equation variable

  +------------------------------------------------------+
  |  Equation \ Excluded |    chi2     df    Prob > chi2  |
  |----------------------+-------------------------------|
  |npl                   |                               |
  |                  eta |    3.482     1        0.062  |
  |                  ALL |    3.482     1        0.062  |
  |----------------------+-------------------------------|
  |eta                   |                               |
  |                  npl |    8.661     1        0.003  |
  |                  ALL |    8.661     1        0.003  |
  +------------------------------------------------------+
```

The results thus suggest bi-directional causality between *npl* and *eqa*.

4.4.6 Impulse-Response Functions

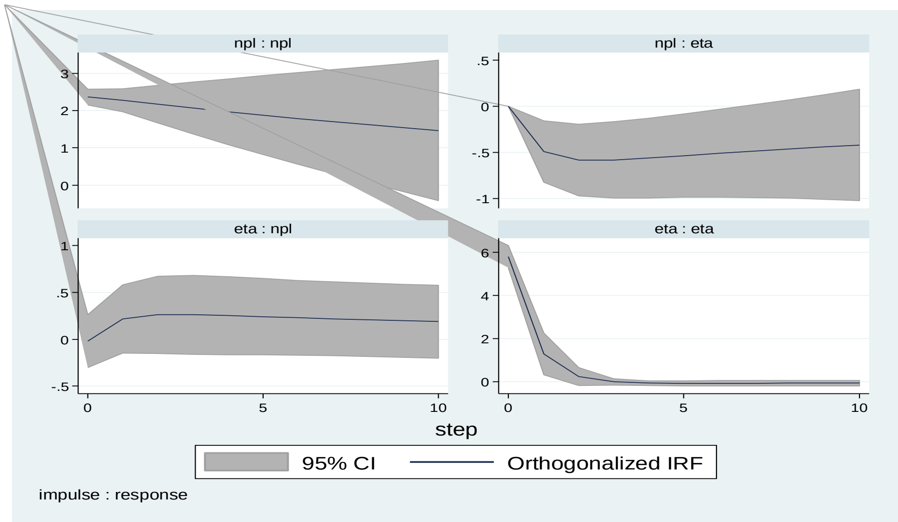
The **pvarirf** command generates the impulse-response functions for the estimated panel VAR model.

Syntax:
pvarirf, *step(#) impulse(impulsevars) response(responsevars) oirf porder(varlist) dm mc(#) level(#) byoption(by_option)*

Where,

(i) *step(#)* specifies the forecast horizon. If it is omitted, the horizon is set at 10;
(ii) *impulse(impulsevars)* lists the impulse variables. If it is not specified, impulses of all endogenous variables are introduced;
(iii) *response(responsevars)* computes the responses of the variables listed. If it is not specified, the responses will be generated for all endogenous variables;
(iv) *oirf* applies orthogonalized impulse-response functions (Choleski decomposition). If it is not specified, the simple IRFs are generated;
(v) *porder(varlist)* orders the variables in the generation of orthogonalized IRFs. If it is not specified, the order will be according to the order entered in the estimation of panel VAR;
(vi) *dm* computes the dynamic multiplier of the exogenous variables (if included)
(vii) *mc(#)* requests that Monte Carlo draws be used to compute confidence intervals for the impulse-response functions and # is the number of draws. The default is not to estimate the confidence interval;
(viii) *level(#)* specifies the confidence level. The default is 95% or level (95)
(ix) *byoption(by_option)* affects how subgraphs are combined, labelled etc.

The command: **. pvarirf,** mc(200) oirf byoption(yrescale) porder(eta npl) yields:



From the above impulse-response functions, we may note that following the shock (or impulse in npl), banks' equity-to-asset ratio (eta) drops (see second graph in row 1). As the 95% confidence band does not contain 0 up till 7-year horizons, the drop is significantly different from 0. However, following the positive in eta, the response of npl is not significant. In other words, the exogenous increase in eta does not lead to future changes in npl. In a nutshell, the above impulse-response functions depict the significant impact of npl on eta but not vice versa.

4.4.7 Variance Decompositions

The subroutine **pvarfevd** generates variance decompositions.

<u>**Syntax:**</u>

pvarfevd, *step(#) impulse(impulsevars) response(responsevars) porder(varlist) mc(#)*

This command computes the variance decompositions using the Choleski decomposition. The mc(#) option requests Monte-Carlo draws be used to estimate the standard errors and the percentile-based 90% confidence intervals of the FEVDs. Other options are as explained above under **pvarirf**.

The command: **. pvarfevd, porder(eta npl)** yields:

```
. pvarfevd, porder(eta npl)

Forecast-error variance decomposition

------------------------------
Response   |
variable   |
and        |
Forecast   |  Impulse variable
horizon    |      eta        npl
-----------+------------------
eta        |
         0 |        0          0
         1 |        1          0
         2 | .9932228   .0067772
         3 | .9838569   .0161432
         4 |  .974682    .025318
```

```
         5 | .9663287  .0336713
         6 | .9588417  .0411583
         7 | .9521483  .0478517
         8 | .9461614  .0538385
         9 | .9408007  .0591993
        10 | .9359949  .0640051
----------+------------------
npl       |
         0 |        0         0
         1 | .0000761  .9999239
         2 | .0043478  .9956522
         3 | .0073701  .9926298
         4 | .0091806  .9908195
         5 |  .010314   .989686
         6 | .0110721  .9889279
         7 |  .011609   .988391
         8 | .0120067  .9879933
         9 | .0123116  .9876885
        10 | .0125517  .9874483
-----------------------------
```

The above results suggest that, roughly 6.4% (i.e. 0.064) the variations in eta 10-year ahead is accounted by shocks in npl. However, only 1.2% of the variations in npl 10-year ahead is explained by shocks in eta.

4.5 CONLUSION

The endogeneity issue is normally encountered in econometric modelling, which may be due the feedback effect or reverse causality between variables. While the GMM estimators elaborated in the preceding chapter allows us the address the issue, it is a one-equation model that pre-specifies the dependent variable and independent variables and hence does not allows empirical verification whether such a feedback effect exists. In many cases, we may be interested in establishing the causal relations between the variables. The panel VAR enable us a set of variables in the model to be potentially endogenous while specifying another to be exogenous. Accordingly, inferences on causal interactions can be made.

In panel VAR modelling, it is a good econometric practice to proceed step by step as illustrated in this chapter. The lag order and instruments must be set first using the moment and model selection criteria (MMSC) by Andrews and Lu (2001). Then, after the estimation of the PVAR model as guided by the MMSC using the GMM estimator, the stability of the PVAR must be assessed. Once the PVAR stability is established, the Granger causality test, impulse-response functions and variance decompositions can be conducted and simulated for making inferences.

MODELS WITH INTERACTIONS

A survey of the top three political science journals from 1998 to 2002 suggests that the execution of these models is often flawed and inferential errors are common. We believe that considerable progress in our understanding of the political world can occur if scholars follow the simple checklist of dos and don'ts for using multiplicative interaction models presented in this article. Only 10% of the articles in our survey followed the checklist.

(Brambor et al., 2006)

5.1 INTRODUCTION

An interaction term, which refers to the multiplication of two or more variables, has featured prominently in empirical research including in Islamic banking and finance research. Some examples from the Islamic banking and finance literature are:

- Beck, T., Demirguc-Kunt, A., Merrouche, O., 2013. Islamic vs. conventional banking: Business model, efficiency and stability. Journal of Banking & Finance 37, 433-447.
- Cihak, M., Hesse, H., 2010. Islamic banks and financial stability. Journal of Financial Services Research 38, 95-113.
- Ibrahim, M. H., Rizvi, S.A.R., 2017. Do we need bigger Islamic banks? An assessment of bank stability. Journal of Multinational Financial Management 40, 77-91.
- Mollah, S., Hassan, M.K., Al-Farooque, O., Mobarek, A., 2017. The governance, risk-taking and performance of Islamic banks. Journal of Financial Services Research 51(2), 195-219.
- Mollah, S., Zaman, M., 2015. Shari'ah supervision, corporate governance and performance: Conventional vs. Islamic banks. Journal of Banking & Finance 58, 418-435.

The use of the interaction term is to address a hypothesis that the effect of a focal/key independent variable on the dependent variable of interest depends on a certain condition (for example, cost efficiency depends on whether banks are Islamic or conventional as in Beck et al. (2013)) or on a certain modifying variable (for example, the risk – size relation depends on banking regulation as in Ibrahim and Rizvi, 2017).

While the appeal of incorporating the interaction term to capture conditionality is its simplicity, its implementation and interpretation are often flawed. To avoid potential pitfalls in handling and interpreting the interaction term, Brambor et al. (2006) suggest the following:

- Include all constitutive terms
- Do not interpret constitutive terms as unconditional marginal effects
- Do not forget to calculate substantively meaningful marginal effects and standard errors.

It is suggested that, when the interaction term involves two quantitative variables, a plot of marginal effects be computed as a basis for interpretation. This chapter provides guidelines for proper implementation of models with interaction terms, which include plotting the marginal effects.

5.2 SPECIFICATION AND INTERPRETATION

As noted by Brambor et al. (2006), the proper specification of a model involving an interaction term must include all constitutive terms independently in the model. The failure to include all constitutive terms, as Brambor et al. demonstrate, results in biased estimates. The specification of models with an interaction term together with interpretation and examples are detailed below.

5.2.1 Interaction with a Dummy Variable

Interaction with a dummy variable is to address whether the relation between the dependent variable of interest and a key independent variable depends on a specific qualitative attribute or a categorical variable, e.g. (i) Islamic or conventional banks, (ii) crisis or normal periods, and (iii) privately-owned or public-owned banks.

In Islamic banking and finance literature, a predominant focus is on comparative analysis of Islamic and conventional banks. A typical specification is:

$$y_{it} = \theta_1 IB_i + \theta_2 x_{it} + \theta_3 (IB_i \times x_{it}) + \beta z_{it} + f_i + u_{it} \qquad (1)$$

where y_{it} is the dependent variable, IB_i is the Islamic bank dummy, x_{it} is the key variable whose relation with the dependent variable depends on IB, z_{it} is a vector of controlled variables, f_i is the unit-specific effect, and u_{it} is the standard error term. $IB_i \times x_{it}$ is normally referred as the interactive dummy or slope dummy by the fact that a dummy variable is interacted with a quantitative variable to allow the effect of x_{it} on y_{it} to depend on whether the bank is Islamic or conventional.

Note that, in the above specification, both IB_i and x_{it} are included independently in the model, fulfilling a condition that all constitutive terms must be included. In other words, the following specifications are considered mis-specified:

$$y_{it} = \theta_1 IB_i + \theta_3 (IB_i \times x_{it}) + \beta z_{it} + f_i + u_{it} \qquad (2)$$

$$y_{it} = \theta_2 x_{it} + \theta_3 (IB_i \times x_{it}) + \beta z_{it} + f_i + u_{it} \qquad (3)$$

where x_{it} is missing in specification (2) and IB_i in specification (3).

From (1), the relation between y_{it} and x_{it} is:

$$\frac{\partial y_{it}}{\partial x_{it}} = \theta_2 + \theta_3 IB_i \qquad (4)$$

It is clear from (4) that θ_2 captures the impact of x_{it} on y_{it} for conventional banks while $\theta_2 + \theta_3$ the impact of x_{it} on y_{it} for Islamic banks. This means that θ_3 represents the difference in the impact that x_{it} exerts on y_{it} between Islamic and conventional banks. If θ_3 is significantly different from 0, a conclusion can be made that the relation between y_{it} and x_{it} is different for Islamic bank and conventional bank. There are 4 different cases (taking both θ_2 and θ_3 to be significantly different from 0):

(i) $\theta_2 >$ and $\theta_3 > 0$: the positive impact of x_{it} on y_{it} is stronger for Islamic banks, all else equal.
(ii) $\theta_2 >$ and $\theta_3 < 0$: the (positive) impact of x_{it} on y_{it} is less for Islamic banks, all else equal.
(iii) $\theta_2 <$ and $\theta_3 > 0$: the (negative) impact of x_{it} on y_{it} is less for Islamic banks, all else equal.
(iv) $\theta_2 <$ and $\theta_3 < 0$: the negative impact of x_{it} on y_{it} is stronger for Islamic banks, all else equal.

Take note that, for cases (ii) and (iii), caution must be exercised in making inferences on the relation between y_{it} and x_{it} for Islamic banks whether it is positive or negative and whether it is significant. θ_3 only indicates the difference in marginal effect between Islamic and conventional banks and not on the relation between y_{it} and x_{it} for Islamic banks. As noted above, $\theta_2 + \theta_3$ represents the relation between y_{it} and x_{it} for Islamic banks. The mistake commonly made is the absence of testing whether $\theta_2 + \theta_3$ is significantly different from 0. In cases (ii) and (iii), it can be insignificant and hence interpreting the value of $\theta_2 + \theta_3$ other than there is no relation between y_{it} and x_{it} for Islamic banks would be flawed.

Example I	Cihak, M., Hesse, H., 2010. Islamic banks and financial stability. Journal of Financial Services Research 38, 95-113.

Cihak and Hesse (2010) is one of the early works that performs empirically comparative analysis of Islamic and conventional banks. An example of results they obtain is (Table 4, page 108):

$$zscore_{it} = -1.737IB_i - 4.786div_{it-1} + 1.815(IB_i \times div_{it-1}) + \cdots$$
p-values (0.324) (0.002) (0.552)

where *zscore* is Z-score capturing bank stability, *IB* is Islamic bank dummy, and *div* is income diversification. The significant and negative coefficient of *div* means that, for conventional banks, income diversification exerts a negative effect on bank stability. The insignificance of the interaction term coefficient means that there is no difference in the impact of diversification on bank stability between Islamic and conventional banks. In other words, the stability of Islamic banks is also adversely affected by income diversification.

Note that, if the coefficient of the interaction term is statistically significant, then hypothesis testing must be conducted whether the sum of *div* coefficient and interaction term coefficient is statistically significant.

- If it is not statistically significant, the conclusion is income diversification has no bearing on the stability of Islamic banks.
- Conversely, if it is statistically significant, the conclusion is the adverse effect of income diversification on bank stability is less for Islamic banks.

There may be a case that the positive coefficient of the interaction term is larger than the absolute value of the *div* coefficient and hence $\theta_2 + \theta_3 > 0$. In this case, if $\theta_2 + \theta_3$ is statistically significant, then income diversification would bring more stability to Islamic banks.

Example II	Zins, A., Weill, L., 2017. Islamic banking and risk: The impact of Basel II. Economic Modelling 64, 626-637.

Zin and Weill (2017) assess the risk implication of Basel II on Islamic banks vis-à-vis conventional banks. They employ various risk measures - Z-score, loan loss reserves, loan loss provisions and impaired loans. In their case, Basel II is a dummy variable, which is equal 1 if Basel II is implemented in the year under consideration and 0 otherwise. To address the research objective, they interact the Islamic bank dummy and Basel II dummy. Some results are (Table 3, page 631):

$$\begin{aligned} Zscore = {} & 10.29^{*} Islamic + 6.594^{**} BaselII \\ & - 17.27^{***}(Islamic \times BaselII) + \cdots \end{aligned}$$

$$\begin{aligned} LLR = {} & -1.955 Islamic + 0.898^{*} BaselII \\ & + 4.709^{***}(Islamic \times BaselII) + \cdots \end{aligned}$$

$$\begin{aligned} LLP = {} & 0.141 Islamic - 0.155 BaselII \\ & + 0.483(Islamic \times BaselII) + \cdots \end{aligned}$$

$$\begin{aligned} Impaired = {} & 0.237 Islamic + 2.175^{**} BaselII \\ & + 0.178(Islamic \times BaselII) + \cdots \end{aligned}$$

where *Zscore* is the Z score, *LLR* is the loan loss reserves, *LLP* is the loan loss provisions, *Impaired* is the impaired loans, *Islamic* is Islamic bank dummy and *BaselII* is Basel II dummy. *, ** and *** indicate significance at 10%, 5% and 1% respectively.

Based on the above results, what are the effects of Basel II implementation on Islamic bank stability and risk? Are the effects different from those on conventional banks? These questions are left for readers to answer.

5.2.3 Interaction with a Quantitative Variable

In some applications, two quantitative variables are interacted to address conditionality or policy complementarity in the effect of a variable in the interaction on the dependent variable of interest. The specification normally takes the following form:

$$y_{it} = \theta_1 x1_{iti} + \theta_2 x2_{it} + \theta_3(x1_{it} \times x2_{it}) + \beta z_{it} + f_i + u_{it} \qquad (5)$$

where $x1_{it}$ is the focal independent, $x2_{it}$ is a variable hypothesized to condition or modify the relations between y_{it} and $x1_{it}$, and other variables/notations are as above. Equation (5) includes both constitutive terms separately and hence is not mis-specified.

In the absence of the interaction term, the coefficient of *x1* (i.e. θ_1) measures the marginal effect of *x1* on *y*, holding other variables constant. In the presence of the interaction term, θ_1 cannot be interpreted as such since the effect of *x1* on *y* is made dependent on a modifying variable, i.e. *x2*:

$$\frac{\partial y_{it}}{\partial x1_{it}} = \theta_1 + \theta_3 x2_{it} \qquad (6)$$

This means that, in order to infer on the effect of *x1* on *y*, the hypothesis $\theta_1 + \theta_3 x2_{it} = 0$ must be tested at various possible values of *x2*. Thus, Brambor et al. (2006) suggest to calculate substantively the marginal effects, i.e. $\theta_1 + \theta_3 x2_{it}$, and their standard errors given by:

$$\sqrt{var(\theta_1) + x2_{it}^2 \times var(\theta_3) + 2 \times x2_{it} \times cov(\theta_1, \theta_3)} \qquad (7)$$

where *var*(.) and *cov*(.) are variance and covariance respectively.

It needs mentioning that θ_1 does carry meaning if $x2_{it} = 0$ is meaningful. If y_{it} is GDP growth, $x1_{it}$ is investment ratio, and $x2_{it}$ is financial sector size, it does not make sense to say that θ_1 represents the effects of investment on economic growth when financial size is zero. However, if $x2_{it}$ is the corruption control index from the World Bank's Worldwide Governance Indicators, which is measured in units of a standard normal distribution and hence $x2_{it} = 0$ means the average level of corruption control, then θ_1 represents the effects of investment on economic growth when the corruption is at the mean level. Note that, even in this case, "holding other variables constant" does not hold. In other words, interpreting θ_1 as the marginal effect of *x1* on *y*, holding other variables constant, is flawed. Example V below shows how researchers can specify the model such that θ_1 in itself has meaning even if $x2_{it} = 0$ is not meaningful.

Example III	Chang, R., Kaltani, L., Loayza, N.V., 2009. Openness can be good for growth: The role of policy complementarities. Journal of Development Economics. 90, 33-49.

Chang et al. (2009) examine how policy reforms shape the effect of trade openness on economic growth using a panel dataset of 82 countries. The regression equation with an interaction term they use is (Equation 3.2, page 38):

$$y_{it} - y_{it-1} = \beta_0 y_{it-1} + \boldsymbol{\beta_1 CV_{it}} + \beta_2 OP_{it} + \beta_3 (cv_{it} \times OP_{it}) + \mu_t + \theta_i + \varepsilon_{it} \qquad (8)$$

where y is the log of GDP per capita, CV is a vector of control variable, cv is one of the control variables, OP is a measure of trade openness. In their analysis, they consider the following policy variables: Educational Enrolment, Financial Depth, Inflation, Telecommunications Infrastructure, Governance, Labor Market Flexibility, Firm Entry Flexibility, and Firm Exit Flexibility.

The results they obtain are in Table 1 (page 40) and Table 2 (page 41) of their paper and are represented by the following plots of marginal effects:

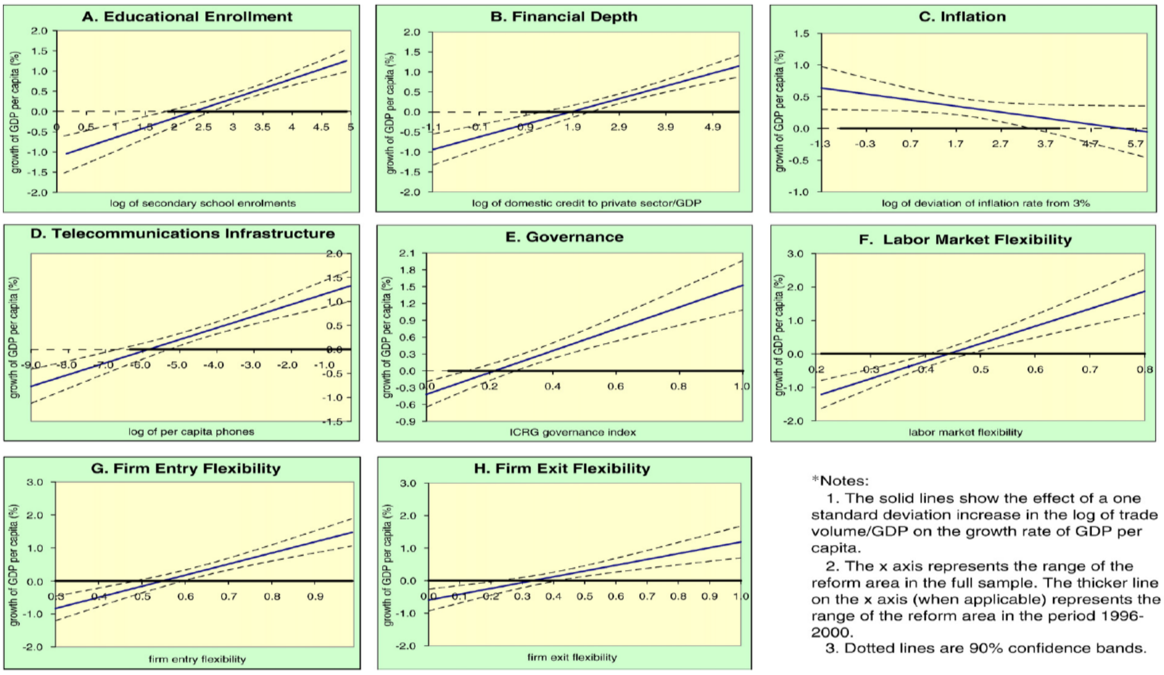


Fig. 2. Growth effect of trade openness as a function of complementary reforms.

Source: Chang et al. (2009), page 42.

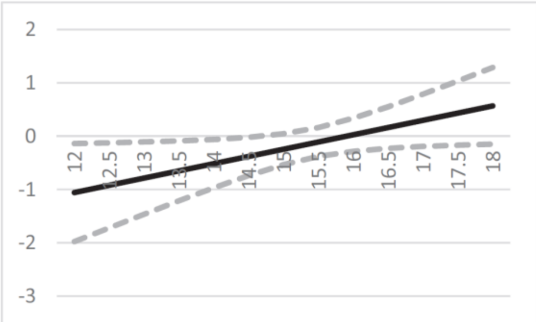
Example IV	Ibrahim, M.H., Rizvi, S.A.R., 2017. Do we need bigger Islamic banks? An assessment of bank stability. Journal of Multinational Financial Management 40, 77-91.

Ibrahim and Rizvi (2017) assess the stability – size relations using a panel sample of Islamic banks. They further assess whether regulations play any role in shaping the stability – size relations by interacting bank size with banking regulation (activity restrictions, supervisory power, private monitoring and capital stringency):

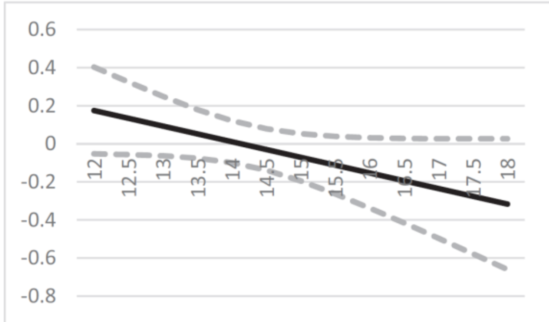
$$NZ_{it} = \beta_0 + \beta_1 NZ_{it-1} + \beta_{21} Size_{it-1} + \beta_2 Size_{it-1}^2 + \beta_3 (Size_{it-1} \times Reg_{it}) + \theta X_{it} + \mu_i + \varepsilon_{it} \quad (9)$$

where *NZ* is normalized Z-sore, *Size* is bank size represented by natural log of total asset, *Reg* is a regulation variable, and *X* is a vector of controlled variables.

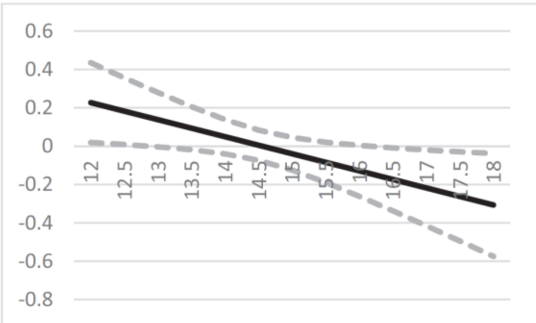
From the model estimation results (Table 4, page 84), they plot both the marginal effects of bank size on bank stability and the marginal effect of regulation on bank stability. The latter is given below:



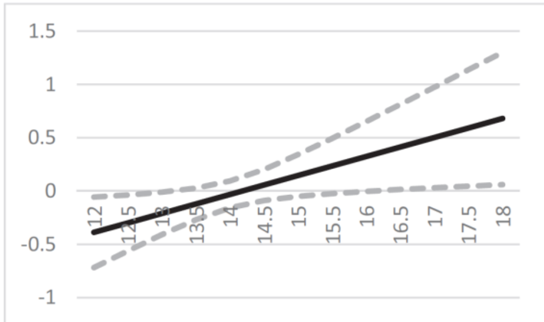
(a) Activity Restrictions



(b) Private Monitoring



(c) Supervisory Power



(d) Capital Stringency

Source: Ibrahim and Rizvi (Figure 2, page 86)

Example V	Deli, Y.D., Hasan, I., 2017. Real effects of bank capital regulations: Global evidence. Journal of Banking and Finance 82, 217-228.

Deli and Hasan (2017) examine the effect of capital stringency on loan growth using a bank-level from as many as 125 countries. They interact capital stringency with either bank capital or bank liquidity to see whether bank capital and bank liquidity can offset potential negative effects of capital stringency on loan growth. Unlike Change et al. (2009) and Ibrahim and Rizvi (2017), they mean-center the variables involved in the interaction terms. This, as they correctly point out, allows direct interpretation of "the estimates on the main term as the effect of e.g. *capital stringency* for the bank with an average level of *bank capital*."

As an illustration, let the model be written as:

$$\begin{aligned} \Delta L_{it} = \beta_0 + \beta_1 \Delta L_{it-1} + \beta_2 CS_{t-1} + \beta_3 Cap_{it-1} \\ + \beta_4 (CS_{it-1} - \bar{S})(Cap_{it-1} - \overline{Cap}) + \cdots \end{aligned} \quad (10)$$

where ΔL is loan growth, CS is capital stringency, Cap is bank capital, and $\overline{CS}$ and $\overline{Cap}$ are respective the mean capital stringency and mean capital. In (1), β_2 captures the effect of capital stringency for the bank holding capital at $\overline{Cap}$ (i.e. the mean level of capital).

5.3 PLOTTING MARGINAL EFFECTS

This section demonstrates the use of STATA code, which is adapted from Professor Matt Golder's code (http://mattgolder.com/interactions#code), to plot the marginal effects. The required data are from *IslamicBank.xlsx* and the code is in the *interaction.do* file.

5.3.1 Model Specification

The following model is specified to address a question whether the effect of capital stringency requirement on Islamic bank stability depends on Islamic bank size:

$$lnz_{it} = \rho lnz_{it-1} + \theta_1 cr_t + \theta_2 lnta_{it-1} + \theta_3 (cr_t \times lnta_{it-1}) + \vartheta BS_{it-1} + \varphi M_{it} + f_i + u_{it} \quad (11)$$

where lnz_{it} is the natural logarithm of the *Z* score (Islamic bank stability), cr_t is capital stringency requirement, $lnta_{it}$ is the natural logarithm of total asset (Islamic bank size), BS_{it-1} is a vector of other bank-specific, $M_{it-1}$is a vector of macroeconomic variables, f_i is the unit-specific effect, and u_{it} is the standard error term. The bank-specific variables considered are equity-to-asset ratio (*eqa*) and liquid asset-to-asset ratio (*liqta*) while the macroeconomic variables are GDP growth and inflation rate.

From (11), the marginal effect of capital stringency requirement is:

$$\frac{\partial lnz_{it}}{\partial cr_t} = \theta_1 + \theta_3 lnta_{it} \quad (12)$$

Thus, the effect of capital stringency requirement on Islamic bank stability depends on Islamic bank size.

5.3.2 Model Estimation

With the data from *IslamicBank.xlsx* already placed/copied to STATA, the following commands tell STATA the data structure and generate variables needed for the estimation of (11)

```
tsset code year
gen lnz = ln(zscore + 3)
gen lnta = ln(ta)
gen crlaglnta = cr*l.lnta
gen liqta = liquid/ta*100
```

The first command indicates that the data structure is panel, where *code* identifies the cross-section unit and *year* identifies the time unit. The remaining commands generate the variables used in the model, i.e. *lnz*, *lnta*, $cr \times lnta_{-1}$, and *liqta*. Note that the *Z* score as given in the data file is added 3 first to avoid taking natural logarithm of a negative number, given that the minimum *Z* score is -2.289. Other variables in the model can be directly used from the data file.

For illustrative purpose (without dwelling into an appropriate estimation method), the model is estimated using the panel fixed-effect estimator with robust standard errors:

```
. xtreg lnz l.lnz cr l.lnta crlaglnta l.eqa l.liqta gdpg inf, fe vce(robust)

Fixed-effects (within) regression               Number of obs      =       460
Group variable: code                            Number of groups   =        45

R-sq:  within  = 0.3419                         Obs per group: min =         6
       between = 0.6631                                        avg =      10.2
       overall = 0.4348                                        max =        12

                                                 F(8,44)            =     31.88
corr(u_i, Xb)  = 0.0846                         Prob > F           =    0.0000

                                   (Std. Err. adjusted for 45 clusters in code)
----------------------------------------------------------------------------
--
             |               Robust
         lnz |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+--------------------------------------------------------------
--
         lnz |
         L1. |   .5118474   .0409166    12.51   0.000     .4293855    .5943094
             |
          cr |  -.7775599   .2662843    -2.92   0.006    -1.314221   -.2408992
             |
        lnta |
         L1. |  -.1047176   .1046019    -1.00   0.322    -.3155288    .1060937
             |
   crlaglnta |   .0535818   .0180673     2.97   0.005     .0171695    .0899942
             |
         eqa |
         L1. |  -.0126219   .0067099    -1.88   0.067    -.0261448     .000901
             |
       liqta |
         L1. |  -.0064116    .003045    -2.11   0.041    -.0125484   -.0002748
             |
        gdpg |   .0438741   .0124112     3.54   0.001      .018861    .0688873
         inf |  -.0089131   .0073073    -1.22   0.229    -.0236399    .0058137
       _cons |   3.312766   1.513043     2.19   0.034     .2634286    6.362104
-------------+--------------------------------------------------------------
--
     sigma_u |  .39704315
     sigma_e |  .72568542
         rho |  .23038416   (fraction of variance due to u_i)
----------------------------------------------------------------------------
--
```

The followings will be useful later:

```
. summarize lnta
    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
        lnta |       603    14.67686     1.37349   11.05596   18.22292


. lincom cr + crlaglnta*11
 (1)  cr + 11*crlaglnta = 0
```

```
------------------------------------------------------------------------------
--
         lnz |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
--
         (1) |  -.1881596   .0708812    -2.65   0.011    -.3310113   -.0453078
------------------------------------------------------------------------------
--

. lincom cr + crlaglnta*18
 ( 1)  cr + 18*crlaglnta = 0
------------------------------------------------------------------------------
--
         lnz |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
--
         (1) |   .1869134   .0650272     2.87   0.006     .0558598     .317967
------------------------------------------------------------------------------
--
```

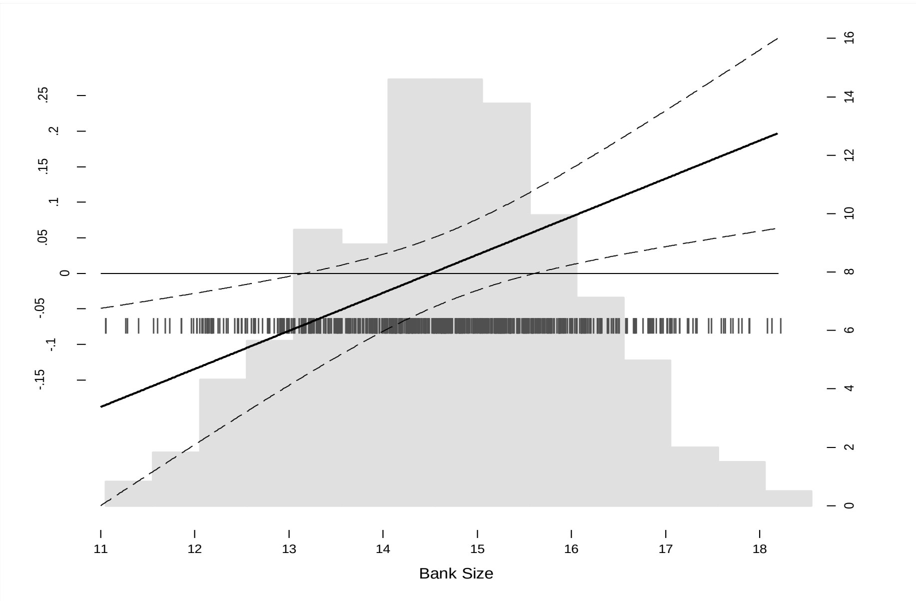
These commands provide respectively the minimum and maximum values of the modifying variable, i.e. *lnta*, and the marginal effects of capital stringency requirement on Islamic bank stability at those two values. They indicate that the impact of capital stringency requirement on Islamic bank stability does depend on bank size. For a small bank, i.e. *lnta* = 11, the stability effect of capital stringency requirement is negative and significant at 5% significance level. For a big bank, i.e. *lnta* = 18, it turns positive. In other words, capital stringency requirement tends to favor large Islamic banks.

The *interaction.do* file contains STATA commands/instructions to plot the marginal effects at various bank size:

```
#delimit ;
set more off;

set obs 10000;

matrix b=e(b);
matrix V=e(V);
scalar b1=b[1,2];
scalar b3=b[1,4];
scalar varb1=V[2,2];
scalar varb3=V[4,4];
scalar covb1b3=V[2,4];
scalar list b1 b3 varb1 varb3 covb1b3;

generate MVZ=((_n+1099)/100);
replace  MVZ=. if _n>721;
gen conbx=b1+b3*MVZ if _n<721;
gen consx=sqrt(varb1+varb3*(MVZ^2)+2*covb1b3*MVZ) if _n<721;
gen ax=1.96*consx;
gen upperx=conbx+ax;
gen lowerx=conbx-ax;

gen where=-0.045;
gen pipe = "|";
egen tag_lnta = tag(lnta);

gen yline=0;
```

```
graph twoway hist lnta, width(0.5) percent color(gs14) yaxis(2)
      ||   scatter where lnta if tag_lnta, plotr(m(b 4)) ms(none)
mlabcolor(gs5) mlabel(pipe) mlabpos(6) legend(off)
      ||   line conbx   MVZ, clpattern(solid) clwidth(medium)
clcolor(black) yaxis(1)
      ||   line upperx  MVZ, clpattern(dash) clwidth(thin)
clcolor(black)
      ||   line lowerx  MVZ, clpattern(dash) clwidth(thin)
clcolor(black)
      ||   line yline  MVZ,  clwidth(thin) clcolor(black)
clpattern(solid)
      ||   ,
           xlabel(11 12 13 14 15 16 17 18, nogrid labsize(2))
           ylabel(-0.15 -0.10 -0.05 0 .05 .1 .15 .2 .25, axis(1)
nogrid labsize(2))
           ylabel(0 2 4 6 8 10 12 14 16, axis(2) nogrid labsize(2))
           yscale(noline alt)
           yscale(noline alt axis(2))
           xscale(noline)
           legend(off)
           xtitle("Bank Size" , size(2.5)  )
           ytitle("Marginal Effect" , axis(1) size(2.5))
           ytitle("Percentage of Observations" ,
orientation(rvertical) margin(small) axis(2) size(2.5))

           xsca(titlegap(2))
           ysca(titlegap(2))
            scheme(s2mono) graphregion(fcolor(white) ilcolor(white)
lcolor(white));

drop MVZ conbx consx ax upperx lowerx where pipe tag_lnta yline;
```

To execute the file, click **File/Do**. Locate and double click the file to have:



The plot provides complete description of how the effects of capital stringency requirement depend on bank size.

5.4 STATA CODES – DO FILES

The commands in the interaction.do file fit model (9) for the plot of marginal effects. In other words, the commands need to be modified accordingly to the specifics of a model estimated. Apart from explaining the commands, this section indicates the parts that need to be modified, which are written in **bold**. Throughout, *lnta* is referred as the modifying variable. Again, this section benefits tremendously from the explanation given by Matt Golder in his webpage.

```
#delimit;
```

This command tells STATA that all command lines end with a semi-colon.

```
set more off;
```

This command tells STATA not to pause when executing the do-file.

```
set obs 10000;
```

This command sets the number of observations to 10000. It is needed if the number of marginal effect computed is more than the number of observations. In other words, it can be omitted if the number of observations is more than the number of marginal effect, i.e. the marginal effect at various values of the modifying variable (in our case, *lnta*) (see below).

```
matrix b=e(b);
matrix V=e(V);
scalar b1=b[1,2];
scalar b3=b[1,4];
scalar varb1=V[2,2];
scalar varb3=V[4,4];
scalar covb1b3=V[2,4];
scalar list b1 b3 varb1 varb3 covb1b3;
```

This set of commands retrieve relevant coefficients, variances, and co-variance and list them (it is good to check against the reported results whether the right figures are retrieved).

Scalar b1=b[1,**2**]; refer to the second coefficient of the model. Note that b is a row vector of the estimated coefficients. Thus, in our context, b[1,1]=ρ, b[1,2]= θ_1, and so on. Thus, scalar b3=b[1,**4**];= θ_3. It needs to be noted that b1 represents the coefficient of a variable whose marginal effect to be computed and b3 is the coefficient of the interaction between the variable and the modifying variable. Accordingly, the **number in bold** must be changed accordingly to tally with a model estimated.

The following three lines are respectively the variance of *cr* coefficient, the variance of the interaction term coefficient, and their covariance. The numbers in squared brackets thus must tally with the coefficients used to calculate the marginal effect. For example, since b1=b[1,**2**]= θ_1, its variance would be V[**2,2**], which is named varb1. The same can be said for the other two lines/commands.

The command scalar list b1 b3 varb1 varb3 covb1b3; is to make sure that the right parameters to be used are retrieved.

```
generate MVZ=((_n+1099)/100);
```

This command is important. It generates a variable named MVZ that takes all values (from minimum with a specified increment) of the modifying variable (in our case, *lnta*). In STATA, _n = 1. Thus, in the above command, the minimum value of the conditioning variable is (_n+1099)/100 = 11.00 and the increment is 1/100 = 0.01. This means that the marginal effect will be computed for the following values of the modifying variable: 11.00 11.01 11.02 11.03 11.04 11.05 11.06 and so on.

To write this command, it is important to obtain the minimum value of the modifying variable. Note also that, the smaller the increment, and hence the more values of marginal effect to be computed, the smoother the marginal effect line would be. In the present example, the minimum of *lnta* is roughly 11. If the minimum value of the conditioning variable starts at 0 and the marginal effect is to be computed for each increment of 0.1, then the command would be: generate MVZ=((**_n-1)/10**);

```
replace  MVZ=. if _n>721;
```

This command determines the last value of the modifying variable at which the marginal effect is computed. This requires its maximum value. In the present case, the maximum value of *lnta* is 18.2. If the modifying variable starts with 11 and is incremented by 0.01 till it reaches 18.2, there will be 721 values. Essentially, this command designates MVZ to have missing values for the observations after 721.

```
gen conbx=b1+b3*MVZ if _n<721;
```

This command generates the marginal effect at various values of the modifying variable as set in the preceding two commands, i.e. $\frac{\partial lnz}{\partial cr} = \theta_1 + \theta_3 lnta$. The number 721 must tally with the preceding command.

```
gen consx=sqrt(varb1+varb3*(MVZ^2)+2*covb1b3*MVZ) if _n<721;
```

This command generates the standard errors of the marginal effect at various values of the modifying variable as set in the preceding two commands.

```
gen ax=1.96*consx;
gen upperx=conbx+ax;
gen lowerx=conbx-ax;
```

This set of commands generates the 95% confidence interval around the marginal effect.

```
gen where=-0.045;
gen pipe = "|";
egen tag_lnta = tag(lnta);
```

This set of commands create a rug plot in the marginal effect plot. It can be deleted if the rug plot is not needed. *lnta* is the modifying variable in the present example.

```
gen yline=0;
```

This command creates a horizontal line at 0 on the vertical axis.

The next command is a long command to plot the marginal effect:

```
graph twoway hist lnta, width(0.5) percent color(gs14) yaxis(2)
```

The line overlays the histogram of *lnta* on the marginal effect plot. The histogram represents the percentage of observations, which is associated with the second vertical axis.

```
||  scatter where lnta if tag_lnta, plotr(m(b 4)) ms(none) mlabcolor(gs5)
mlabel(pipe) mlabpos(6) legend(off)
```

This overlays the rug plot.

```
xlabel(11 12 13 14 15 16 17 18, nogrid labsize(2))
```

This sets the label for the X-axis. Note that the label ranges from the minimum of *lnta* to maximum of *lnta*, the modifying variable.

```
ylabel(-0.15 -0.10 -0.05 0 .05 .1 .15 .2 .25, axis(1) nogrid labsize(2))
```

This sets the label for the first y-axis. To get some idea of the values to be set, run the following command: **lincom cr + crlaglnta*11** and **lincom cr + crlaglnta*18** after model estimation (see above). These give the marginal effect at respectively the minimum and maximum values of the xlabel.

```
ylabel(0 2 4 6 8 10 12 14 16, axis(2) nogrid labsize(2))
```

This sets the label for second y-axis

```
xtitle("Bank Size" , size(2.5)  )
```

This writes the title of the X-axis, i.e. Bank Size as represented by the natural log of total assets

```
ytitle("Marginal Effect" , axis(1) size(2.5))
```

This writes the title of the first Y-axis.

```
ytitle("Percentage of Observations" , orientation(rvertical) margin(small)
axis(2) size(2.5))
```

This writes the title of the second Y-axis

drop MVZ conbx consx ax upperx lowerx where pipe tag_**lnta** yline;

Finally, this command drops/deletes all variables generated by the do-file so that it can be executed without the need to delete them later.

Note again: the **bold figures/words** are the ones that need changes to tally with models estimated.

5.5 CONLUSION

Models with interaction terms are commonly employed to assess conditionalities in the relations between the dependent variable and focal explanatory variables. Many early empirical Islamic banking and finance studies assess whether the relations between variables of interest for Islamic banks are different from those of conventional banks. In these studies, the interaction between the independent variable of interest and Islamic bank dummy is included as an additional regressor in the model. Some studies also evaluate whether the relations between variables under focus are contingent on a quantitative variable and hence adopt models with interactions.

As we have quoted in the beginning of the chapter, many studies that use models with interaction terms tend to commit specification and inferential errors. This chapter provides guides such that the execution and interpretation of the models are not flawed and incomplete by overstating and understating the significance of the association between the variables. In the interpretation of the coefficients of the variable constituting the interaction term, it is advisable to plot the marginal effects such that we can have a complete description of the results.

CONCLUSION: R.I.C.E IN ISLAMIC BANKING & FINANCE RESEARCH

The rapid development of the Islamic banking and finance in many Muslim countries especially in Malaysia and the Middle East and its increasing acceptance in non-Muslim world has captivated much interest in recent years. Its alleged resiliency during the recent global financial crisis has prompted some to offer the Islamic banking model as a solution to the malaise of the present interest rate–based financial system, normally dubbed as the conventional financial system.

A pre-dominant view among Muslim professionals and policymakers holds Islamic finance to be more equitable and more stable, aspects well-noted to be critical for societal well beings. This view is principally based on the belief in the Islamic finance business model as prescribed by Islamic laws or the Shari'ah. Islamic finance is free from interest rate and gharar, which are the root of injustice, speculation and uncertainty. Engagements in activities with negative externalities that bring harms to society such as production of alcoholic beverages, gambling and prostitutions are prohibited. Adding to the stabilizing role of Islamic finance, the profit-and-loss sharing principle enables the society to equitably share the benefits and shoulder the burdens of riding through business cycles rendering the financial and economic systems to be stable.

Despite the conviction that Muslim professionals and scholars have on Islamic finance, more is needed to demonstrate that the Islamic financial system is not merely a viable alternative system but it is the financial system for mankind.

While the number of studies attempting to demonstrate the viability and relative stability of the Islamic financial system is increasing, the empirical evidence uncovered so far remains inadequate due not only to the pre-dominant confinement of the analyses to comparative performance of Islamic finance and conventional finance but also to contradictory findings. At the same time, in practice, Islamic finance seems to be trapped within the "mimicking" realm, offering Shari'ah compliant versions of existing conventional financial products, to the extent that some view Islamic finance to be no different from conventional finance.

Thus, moving forwards, there is a need to intensify research efforts and go beyond merely Islamic – conventional finance comparative analyses. The scope of the Islamic finance research must be widened. In parallel to the importance of continuously engineering Islamic financial products that are not only based on Shari'ah principles and are distinct, the demonstration of the socio-economic effects of Islamic finance is a must. As examples, these questions deserve attention: Is Islamic finance pro-growth and, at the same time, facilitating more equal income distribution? Is Islamic banking subject to financial accelerator mechanisms? Is it able to dampen cyclical fluctuations? How does Islamic banking fit into the existing monetary framework? Does it help smoothing the conduct of monetary policy? Does it shield the systems from adverse shocks? And more.

The demonstration of the Islamic finance and its impacts must be founded on a concrete foundation. In any empirical research, four basic principles must be adhered to in order to make the cases for Islamic finance convincing. These are Identification, Clarity, Robustness and Ethical.

Identification **:** A key issue in any empirical research is whether the proposed model or method is able to produce results that clearly addresses the research objective. The results from the proposed model should not be open to alternative interpretation or, at least, the alternative interpretation is less likely. For instance, to demonstrate that Islamic banking financing decision is less pro-cyclical and, as such, its financing exhibits less fluctuations over business cycle phases, partition of Islamic financing movements due to supply and demand forces must be made since it is only the former that is pertinent to the issue at hand. Likewise, for understanding the role of Islamic banks in monetary transmission mechanisms, isolation of the variations in Islamic financing due to banks' financing supply decisions from financing demand must be made. Theoretically, changes in monetary policy may have shifted both the demand and supply for financing and, again, the financing supply is all relevant for understanding the role of Islamic banks in transmitting monetary impulses to the real economy.

Several empirical studies have appeared in recent years demonstrating the relative stability of the banking sector and the documented relative stability is attributed to the Islamic finance principles based on the Shari'ah or Islamic laws. The question is: Is the relatively stability of Islamic banks really due to its Shari'ah-based operations or is it simply due to it being less exposed to external shocks? It may be that by operating on the basis of the Shari'ah, Islamic banks become less exposed. For instance, Riba or interest rate, which is viewed to be speculative in nature, is absent in all Islamic bank transactions. Moreover, financial products of Islamic banks are also tightly linked to the real sector. However, while these fundamental and other features of Islamic banks may have shielded them relatively well from external fluctuations, Islamic banks in practice are small in size and scope of operations and are less integrated to the international markets. Accordingly, the finding that they are immune from for example the recent global financial crisis may be due to their balance sheet composition (e.g. less foreign assets or liabilities) and not the characteristics of their assets and liabilities (i.e. being Sharia'h compliant). To resolve this, again, proper identification must be made.

It needs emphasis that Islamic banking and finance research should focus on issues and ways or methods to address the issues and not on demonstration of various methods or techniques. Do not dilute the Islamic banking research to merely exercises of numbers.

Clarity : This refers to clarity in the theoretical foundations and empirical implementation. Research objectives must be based on clear theoretical foundations and arguments. At present, empirical research is Islamic banking and finance invariably relies on prevailing mainstream theories but with the added phrase that "Islamic banking and finance is different" and Islamic banking and finance is supposed to be different. Yes, Islamic finance different. But, why do the distinct features of Islamic finance make it, for example, more stable? Why is Islamic finance pro-growth? Why is Islamic finance welfare enhancing?

The theoretical arguments and explanation for these illustrative potential research questions must go beyond merely stating that Islamic finance is different.

The steps taken in any empirical implementation must also be in such a way that it is easily replicable by any average researcher. Replicability is a major concern in empirical research, mainly due to obscurity in the explanation of the steps taken. Empirically, to increase confidence in the results, they must be substantiated and reaffirmed in repeated studies and in wide ranges of settings. Being clear in the empirical implementation is thus a necessity.

Ethical : the evidence should not be tempered with unethical practices. One may have heard the remark: "There are three kinds of lies: lies, damn lies and statistics." One may also have a quotable quote of Ronald H. Coase: "If you torture the data long enough, it will confess" to anything. This means that statistical methods employed in empirical works can be manipulated to reach any conclusion. Edward E. Leamer also suggested in 1983 to take the con out of econometrics.

Being ethical means that findings should not be directed and driven by the pre-conceived ideas of researchers. Driven by religiosity reasons, it is very easy for researchers to be tempted to try as hard as possible to arrive at the desired conclusion. Manipulation of samples to be used in the analysis is made so that the desired results can be uncovered. Alternative model specifications and estimation techniques may be experimented with the hope of stumbling to the results that are wished to be seen. Try myriads of approaches, samples, and regressions and report only those that support the conclusion wished to be made. These are unethical.

It needs to be remembered that there is nothing wrong to find conclusions contradicting established theoretical predictions. As such, there is nothing wrong to conclude that Islamic banking and finance has not contributed to, for example, more economic stability or to economic growth. Any finding would surely provide lessons as long as we search and contemplate for the lessons. Thus, there should be no hiding of findings not wanted to be seen. Report all that have been done. Be objective and be transparent.

Robustness : the conclusion must stand alternative empirical settings. Robust, robust and robust is key to empirical research. One has to be convinced of the findings before attempting to convince others. And being rigorous and being robust in the empirical analyses would make one to be more convinced of the results, whatever they might be. Moreover, being rigorous and being robust is a mechanism to curb the temptation to report only those findings consistent with the pre-conceived views of a researcher.

There are many different ways to perform robustness analysis, according to standard practices in the literature. In attempting to identify whether Islamic banks are relatively more stable as compared to conventional banks, for example, a starting point would be to construct an estimable empirical model of bank stability using an acceptable proxy of bank stability or bank risk such as the Zscore, non-performing loans ratio or market-based measures of bank stability. Obviously, in the specification, the Islamic bank dummy would be a focal variable whose coefficient brings implications of whether Islamic banks are more or less stable. The suggestion would be to first estimate the baseline model, which includes the focal variable and core variables the omissions of which may render the estimation bias. Then, for robustness, sets of other explanatory variables may be added to see whether the findings from the baseline regression remains robust. Starting from this commonly adopted robustness check, one may proceed to evaluating the main findings using different measures of bank risk or stability, using different estimation methods, or using alternative sample splitting. Such approaches as Extreme Bound or Sensitivity Analysis, Jackknife Regressions, and Model Uncertainty may also be adopted. The point is to try to exhaust all possibilities in the modelling and to address potential queries as much as possible.

Obviously, the development of Islamic banking needs to be founded on research. At the present stage, more research is needed and it must be implemented well. We need more R.I.C.E. in Islamic banking research. This refers to Robustness, Identification, Clarity and Ethics of the research. This book is our humble effort to contribute to empirical Islamic banking and finance research with more R.I.C.E.

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PRACTICAL PANEL MODELLING

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