QUANTITATIVE METHODS - Data Analysis

Presented by: Alex Oguso
June 3-6, 2019
Kenya School of Monetary Studies (KSMS)
OUTLINE

- Overview of Time series data analysis
- Overview of Cross-sectional data analysis
- Panel Data analysis:
  - Important tests & Models
  - Establishing Causation
  - Pseudo (Quasi) Panel Estimation Models:
    1. Experimental method – Randomized evaluation
    2. Quasi –experimental methods – DID, Regression discontinuity, Instrumental variable estimation etc
Time Series Analysis

- A collection of observations made sequentially in time. A time series is a collection of data $y_t$ ($t=1,2,...,T$), with the interval between $y_t$ and $y_{t+1}$ being fixed and constant.

- We can think of time series as being generated by a stochastic process, or a data generating process (DGP).
Time Series Analysis – Properties

1. Time series data have autoregressive (AR), moving average (MA), and seasonal dynamic processes. Because time series data are ordered in time, past values influence future values – problem of serial correlation.

2. Time series data often have time-dependent moments (e.g. mean, variance, skewness, kurtosis). The mean or variance of many time series increases over time – problem of nonstationarity (spurious relationship).

3. The sequential nature of time series data allows for forecasting of future events.

4. Events in a time series can cause structural breaks in the data series.

5. Many time series are in an equilibrium relationship over time (cointegration). We can model this relationship with error correction models (ECM).

6. Many time series data are endogenously related, which we can model with multi-equation time series approaches, such as vector autoregression (VAR).

7. The effect of independent variables on a dependent variable can vary over time; we can estimate these dynamic effects with time varying parameter models.
Time Series Analysis – Important Tests

- **Trend analysis**
  - If the trend variable is deterministic (not stochastic), then include a time trend variable, t, as one of the regressors to avoid spurious correlation.
  - A trend stationary series has a data generation process of:
    \[ y_t = a_0 + a_1t + \varepsilon_t \]

- **Test for structural breaks** - We can check for structural breaks in our data set using Chow (or other) tests.

- **Autocorrelation** - measures the dependence between the current value of a time series variable and the past value of the same variable.

- **Heteroskedasticity Test** - It tests whether the variance of the errors from a regression is dependent on the values of the independent variables (Breusch-Pagan & White heteroscedasticity tests). The tests assume that the error terms are normally distributed (homoscedasticity)
Time Series Analysis – Important Tests...

Stationarity Test (Unit Root Test)

- Assumption of stationarity - the mean and variance of the process generating the data do not change over time
- In general, a time series must be differenced \( d \) times to become stationary; it is integrated of order \( d \) or \( I(d) \).
- A stationary series is \( I(0) \). A random walk series is \( I(1) \).
- Tests for Unit Roots: Dickey-Fuller test, Augmented Dickey-Fuller test, Phillips-Perron test
Cointegration Test

- Two time series are cointegrated if: they are integrated of the same order, I(d); and there exists a linear combination of the two variables that is stationary (I(0)).

Tests:
- Engle-Granger & Johansen tests for testing cointegration in a model with I(1) series
- Autoregressive Distributed Lag (ARDL) cointegration technique testing a cointegration in a model with I(0) and I(1) series
- If there is cointegration, then estimate an Error Correction Model (ECM) estimated using the lagged residuals from long run model (et-1) as instruments for the long run equilibrium term.
Time Series Models

- **Autoregressive (AR) Models**
- **Moving Average Models**
- **ARMA Models** – Combined AR and MA model
- **ARIMA (Autoregressive Integrated Moving Average)/Box-Jenkins models** - ARIMA (p,d,q) modeling - determine the appropriate values of p, d, & q using the autocorrelation function, and unit root tests (p is the AR order, d is the integration order, q is the MA order).
- **Vector Autoregressive (VAR) models** - allows all variables to be endogenous. If you have 3 variables, you have 3 equations, with each variable containing a certain number of lags in each equation. You estimate the system of equations and you can then examine how variables respond when another variable is shocked above its mean.
**Time Series Models...**

- **Autoregressive Conditional Heteroskedasticity (ARCH) models** - are useful if you have non-constant variance, especially if that high variance occurs in only certain periods in the dataset (conditional heteroskedasticity). Generalize ARCH (GARCH) allows for AR and MA processes in the residuals; TGARCH allows for threshold/regime changes; EGARCH allows for negative coefficients in the ARMA process.
Cross-sectional Data Analysis
Cross-sectional Data Analysis

- **Cross-sectional study** - is a research tool used to capture information based on data gathered for a specific point in time. The data gathered is from a pool of participants with varied characteristics and demographics (age, gender, income, education, geographical locations, and ethnicity).

- **Cross-sectional data** - information about different individuals (or aggregates such as work teams, sales territories, stores, etc.) at the same point of time or during the same time period.

- A cross-sectional study is an observational study - often described as a “snapshot” of a population in a certain point in time.
Cross-sectional Study - Advantages

- Used to prove and/or disprove assumptions
- Not costly to perform and does not require a lot of time
- Captures a specific point in time
- Contains multiple variables at the time of the data snapshot
- The data can be used for various types of research
- Many findings and outcomes can be analyzed to create new theories/studies or in-depth research
Cross-sectional Study - Disadvantages

• Cannot be used to analyze behavior over a period to time
• Does not help determine cause and effect
• The timing of the snapshot is not guaranteed to be representative
• Findings can be flawed or skewed if there is a conflict of interest with the funding source
• May face some challenges putting together the sampling pool based on the variables of the population being studied
Cross-sectional Data Analysis - Models

- Models of this type are sometimes called qualitative response models, because the dependent variables are discrete, rather than continuous.

The qualitative response models are determined by:

- **Qualitative dichotomy** (e.g., vote/not vote type variables)- We equate "no" with zero and "yes" with 1. However, these are qualitative choices and the coding of 0-1 is arbitrary. We could equally well code "no" as 1 and "yes" as zero.

- **Qualitative multichotomy** (e.g., occupational choice by an individual)- Let 0 be a clerk, 1 an engineer, 2 an attorney, 3 a politician, 4 a college professor, and 5 other. Here the codings are mere categories and the numbers have no real meaning.

- **Rankings** (e.g., opinions about a politician's job performance)- Strongly approve (5), approve (4), don't know (3), disapprove (2), strongly disapprove (1). The values that are chosen are not quantitative, but merely an ordering of preferences or opinions. The difference between outcomes is not necessarily the same from 5 to 4 as it is from 2 to 1.

- **Count outcomes**
Cross-sectional Data Analysis – Models...

• **Linear Probability Models:**
  - *using weighted least squares*
  
  In practice, there are many situations where the probability of a yes outcome follows a non-linear distribution, rather than the linear distribution alleged by the linear probability model.

• **Non-Linear Probability Models:**
  • The cumulative standard normal distribution *(probit)* model
  • The cumulative logistic distribution *(logit)* model - The cumulative logistic function for logit is grounded in the concept of an odds ratio.
  • Choosing Between Logit/Probit- In the dichotomous case, there is no basis in statistical theory for preferring one over the other. In most applications it makes no difference which one uses.
Panel Data Analysis
Panel Data Analysis

- In a panel dataset the same cross section units (e.g. individuals, households) are followed over time – **Longitudinal study**
- A **longitudinal study** is an observational study that involves repeated observations (measurements) of the same variable(s) over long periods of time (sometimes years or even decades).
- In the case of repeated cross-section, the best one can do is to construct a pseudo-panel which is a panel of cohorts of cross section units formed from the repeated cross sections

**Benefits of panel data:**
- More observations, controls omitted variable bias, less multicollinearity, better analysis of dynamics

**Limitations of panel data:**
- Attrition bias, non-randomness of sample, more observations means more opportunities for measurement, inability to forecast, complicated asymptotic analysis
Panel Data Analysis

- By definition, panel data has a cross section dimension (which refers to the cross section units themselves) and a time dimension (which refers to the time periods over which the cross section units are observed).

  N: No cross section units
  T: No. time periods

**Balanced panel vs unbalanced panel:**

- A balanced panel has no missing observations i.e. Balanced panel: No. obs. = NT
- An unbalanced panel has missing observations i.e. Unbalanced panel: No. obs < NT
Panel Data Analysis – Important Tests

Hausman Test (Testing for Fixed vs Random Effects)

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Fixed effects (within) estimator</th>
<th>Random effects estimator</th>
</tr>
</thead>
<tbody>
<tr>
<td>Null hypothesis</td>
<td>Consistent but inefficient</td>
<td>Consistent and efficient</td>
</tr>
<tr>
<td>Alternative hypothesis</td>
<td>Consistent and efficient</td>
<td>Inconsistent</td>
</tr>
</tbody>
</table>

- Under the null hypothesis, both random effects and fixed effects estimators are consistent implying that one could use either random effects or fixed effects.
- Under the alternative hypothesis: the random effects estimator is inconsistent implying that the fixed effects estimator is better.
- Failure to reject the null hypothesis means that either random effects or fixed effects estimator should be used; rejection of the null hypothesis implies that the fixed effects estimator should be used.
Panel Data Analysis – Important Tests

F-Test (Testing For Fixed Effects Vs. Classical Pooling)

- Null hypothesis: No fixed effects (No individual heterogeneity; common intercepts; classical pooling appropriate)
- Alternative hypothesis: Fixed effects exist (Different intercepts; classical pooling inappropriate)
- The null hypothesis of absence of fixed effects is rejected if the computed F-statistic exceeds the critical value.
- Some econometrics textbooks commonly refer to this F-test as the Chow test owing to some similarities between this test and the Chow test for structural change
Panel Data Analysis – Important Tests

Breusch-pagan Lm Test (Testing For Random Effects Vs. Classical Pooling )

- Null hypothesis: variance of individual effects equals zero; pooled model is same as random effects model
- Alternative hypothesis: variance of individual effects greater than zero; random effects exist
- LM tests are useful when it is not difficult to estimate the model under the null hypothesis, which turns out to be the pooled model) and more complicated under the alternative model, which turns out to be the random effects model.
Panel Data Analysis – Other Important Tests

- Test for autocorrelation - using Wooldridge LM test
- Test for cross-section dependence – using Breusch-Pagan test, Pesaran test, Friedman test
- Testing for heteroscedasticity (because of the existence of the cross-section dimension). Could test for heteroscedasticity within groups or heteroscedasticity between groups.
- Panel unit roots and panel cointegration – for Panel structures with long time dimensions (the macro panels)
- Test for Endogeneity - endogeneity is a problem of the correlation between the independent variable(s) and the error term. As a result of the correlation between the independent variable(s) and the error term, the resulting regression estimates may be biased
Panel Data Analysis – Models

1. The pooled model:
   - The pooled model ignores the panel structure of the data
   - Estimation of the pooled model is by OLS
   - The pooled model can be tested against the fixed effects model (using the standard F test) and against the random effects model using the Breusch-Pagan Lagrange multiplier test

2. The fixed effects model:
   - The fixed effects model assumes fixed intercepts
   - Estimation of the fixed effects model is by a variety of methods including the first difference estimator, Least Squares Dummy Variables (LSDV), the within-estimator and the between estimator
   - The fixed effects model can be tested against the pooled model (using the standard F test) and against the random effects model using Hausman’s test.
Panel Data Analysis – Models

3. The random effects model:
   - The random effects model assumes random intercepts
   - Estimation of the random effects model is by a variety of methods including Generalized Least Squares (GLS) and Maximum Likelihood (ML).
   - The random effects model can be tested against the pooled model (using the Breusch Pagan Lagrange Multiplier test) and against the fixed effects model using Hausman’s test

4. Dynamic panel model:
   - Dynamic panel models have lagged dependent variables
   - The goal of dynamic models is to capture the existence of contracts, habit persistence, etc.
   - OLS cannot be applied to dynamic models owing to bias problems
   - The appropriate estimation techniques for dynamic models include instrumental variables (IV) and Generalized Method of Moments (GMM).
Panel Data Analysis – Models

5. The Pseudo Panel (or Quasi Panel) models:

- As the name suggests, a pseudo panel looks like a typical panel dataset, yet it does not have all the features of a full-fledged panel dataset.
- A pseudo-panel has some (but not all) the characteristics of a true panel data set
- Commonly referred to as quasi-panel or repeated cross section
- In repeated cross section surveys for which the same cross section units are not followed over time pseudo panels may be created by constructing panels of cohorts of individuals (individuals with similar characteristics e.g males aged 30 – 35 years)
- The panel dataset would then comprise of average values for the different cohorts observed over time. To ensure that the averages are meaningful, the cohorts should meet stipulated guidelines with respect to the minimum cohort size.
Establishing Causation

Establishing Causation (Impact Evaluation)

- An assessment of the causal effect of a project/program or policy on beneficiary outcomes
- Estimates the change in outcomes attributable to the intervention
- Aims to answer what works and what does not work

Causal inference:

“Estimate the causal effect (Impact) of intervention (P) on outcome (Y)”

(P) = Treatment (Program/policy/intervention)
(Y) = Outcome, Measure of success

Correlation is not causation: Systematic empirical associations between two variables can exist, but this does not in any way imply that one is causing the other
Establishing Causation...

Criteria for relationship to be considered causal

1. There should be an association between the variables
2. An appropriate time order/directionality problem
   - Refers to the fact that X and Y will be statistically related if X causes Y..or if Y causes X
3. Elimination of alternative explanations - endogeneity
   - Two variables that are associated and have the correct time order still do not satisfy a causal relation
   - The relationship may be spurious (existence or a 3rd variable Z that affects both X and Y) i.e as age (Z) changes, it simultaneously affects height (X) and math score (Y)
   - Estimate what would have happened to Y in the absence of P (the treatment) – the counterfactual
Pseudo (Quasi) Panel Estimation Methods

1. Experimental Method – Randomized Evaluation

2. Quasi-experimental methods
   - Instrumental variables
   - Regression discontinuity (RDD),
   - Difference-in-differences (DiD)
   - Propensity score matching (PMS)
Experimental Method – Terminologies

- **Treatment Group**: in an experimental design, a randomly assigned group from the same population that receives the intervention.

- **Comparison/Control Group**: a randomly assigned group from the same population that does not receive the intervention, but is the subject of evaluation. Participants in the comparison group are used as a standard for comparison against the treated subjects in order to validate the results of the intervention.

- **Baseline**: data describing the characteristics of participants measured across both treatment and comparison groups prior to implementation of intervention.

- **Endline**: data describing the characteristics of participants measured across both treatment and comparison groups after implementation of intervention.

- **Counterfactual**: what would have happened to the participants in a program had they not received the intervention. The counterfactual cannot be observed from the treatment group; it can only be inferred from the comparison group.
Experimental Method – Terminologies...

- **Level of randomization**: the level of observation (e.g., individual, household, school, village) at which treatment and comparison groups are randomly assigned.

- **Attrition**: the process of individuals dropping out of either the treatment or comparison group over the course of the study.

- **Partial Compliance**: individuals do not “comply” with their assignment (to treatment or comparison). Also termed "diffusion" or "contamination."

- **Intention to Treat**: the measured impact of a program comparing study (treatment versus control) groups, regardless of whether they actually received the treatment.

- **Externality**: an indirect cost or benefit incurred by individuals who did not directly receive the treatment. Also termed "spillover."

- **Cluster**: The unit of observation at which a sample size is randomized (e.g. school), each of which typically contains several units of observation that are measured (e.g. students). Generally, observations that are highly correlated with each other should be clustered and the estimated sample size required should be measured with an adjustment for clustering.
Experimental Method – Randomized Evaluation

- Experimental method for measuring a causal relationship between two variables
- **Comparison group:** Participants are randomly assigned to the control groups.
- **Assumption:** Randomization “worked.” That is, the two groups are statistically identical (on observed and unobserved factors).
- **Data Required:** Outcome data for control and experimental groups. Control variables can help absorb variance and improve “power”.
Randomized Assignment

- Using a lottery or another randomized process to decide who among the eligible population receives the program and who doesn’t - gives each eligible unit equal probability to receive the program, has clear selection rules
- Treatment and comparison groups will be similar not only in their observed characteristics but also in their unobserved characteristics
- Test the assumption that the treatment and comparison groups are equivalent with respect to observed characteristics before the program starts
- After introduction of the program, observed differences in outcomes between the treatment and comparison groups will be explained only by the program
  - External validity - Random sampling
  - Internal validity - Random assignment
Experimental Method – Randomized Evaluation

Randomization

1. Simple Randomization

- Using a list of taxpayers, we can assign them to treatment or control based on a coin flip (heads = treatment and tails = control).
- We can do this by randomly generating the value of 0 or 1 using the RANDBETWEEN function, and choosing 0 and 1 as the range. We could then assign all schools with 0 to the control group, and all schools with 1 to the treatment group (or vice versa).
- Equivalently, we could produce a continuous random number for each observation and assign those with (say) random number greater than or equal to 0.5 to treatment and smaller than 0.5 to control.
- The function \textit{RAND()} is Excel’s basic random number generator.
Experimental Method – Randomized Evaluation

Randomization

2. Stratified Randomization

- Stratification is the process of dividing a sample into groups, and then randomly assigning individuals within each group to the treatment and control.
- This ensures that subgroups are balanced, making it easier to perform certain subgroup analyses.
Experimental Method – Randomized Evaluation

Units of Randomization

- Level at which we will randomize units to the treatment and comparison
- The unit of randomization is determined by where and how the program is being implemented. Units can be: individual/Household, town, region etc
- As a rule of thumb, randomize at the smallest viable unit of implementation.
- As the level of randomized assignment gets lower, the chances of spill overs and contamination increase
- Level of randomization also affects attrition and program staff and participant compliance - operational and survey costs
- Clustering reduces effective sample size
**Impact of Intervention (P) on Outcome (Y)**

\[ \alpha = (Y \mid P=1) - (Y \mid P=0) \]

**OBSERVE**  
(Y | P=1)  
Outcome with treatment

**ESTIMATE**  
(Y | P=0)  
The Counterfactual

**IMPACT**  
Outcome with treatment  - counterfactual

- Intention to Treat (ITT) – *Those to whom we wanted to give treatment*
- Treatment on the Treated (TOT) – *Those actually receiving treatment*
- Use **comparison** or **control** group
### Experimental Method – Randomized Evaluation

|                           | Treatment Group (Randomized to treatment) | Counterfactual (Randomized to Comparison) | Impact $(Y | P=1) - (Y | P=0)$ |
|---------------------------|-------------------------------------------|------------------------------------------|-------------------------------|
| **Baseline (T=0)** Consumption $(Y)$ | 233.47                                     | 233.40                                   | 0.07                          |
| **Follow-up (T=1)** Consumption $(Y)$   | 268.75                                     | 239.5                                    | 29.25**                      |
Where Random Assignment is not Feasible

It’s not always possible to assign pure control and treatment groups in:

- National programs where everyone is eligible
- Programs where participation is voluntary
- Programs where you can’t exclude anyone

> Employ Quasi-experimental methods
Quasi – Experimental Methods

1. Pre-Post
   - Measure how program participants improved (or changed) over time.
   - **Comparison group:** program participants themselves—before participating in the program.
   - **Assumption:** program was the only factor influencing any changes in the measured outcome over time.
   - **Data Required:** Before and after data for program participants.
Quasi – Experimental Methods...

2. Simple Difference of Means

- Measure difference between program participants and non-participants after the program is completed.
- **Comparison group:** Individuals who didn’t participate in the program (for any reason), but for whom data were collected after the program.
- **Assumption:** Non-participants are identical to participants except for program participation, and were equally likely to enter program before it started.
- **Data Required:** After data for program participants and non-participants.
3. Differences in Differences

- Measure improvement (change) over time of program participants relative to the improvement (change) of non-participants
- **Comparison group:** Individuals who didn’t participate in the program (for any reason), but for whom data were collected both before and after the program.
- **Assumption:** If the program didn’t exist, the two groups would have had identical trajectories over this period
- **Data Required:** Before and after data for both participants and non-participants
3. Differences in Differences (contd..)

- Difference-in-difference (or “diff-in-diff” or “DID” or “DD”) impact evaluations combine the pre vs.post and enrolled vs.not enrolled approaches.
- The basic idea is to observe the treatment group and a comparison group (for example, the not enrolled) before and after the program.
- The diff-in-diff estimator removes the selection bias, time trend:
- The diff-in-diff estimator is:

\[
DD = \bar{Y}_{\text{treatment post}} - \bar{Y}_{\text{treatment pre}} - (\bar{Y}_{\text{comparison post}} - \bar{Y}_{\text{comparison pre}})
\]
Quasi – Experimental Methods...

3. Differences in Differences (contd..)
### 3. Differences in Differences (contd..)

**Table 1:** Differences in Differences

<table>
<thead>
<tr>
<th></th>
<th>After</th>
<th>Before</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment/enrolled</td>
<td>B</td>
<td>A</td>
<td>B – A</td>
</tr>
<tr>
<td>Comparison/nonenrolled</td>
<td>D</td>
<td>C</td>
<td>D – C</td>
</tr>
<tr>
<td>Difference</td>
<td>B – D</td>
<td>A – C</td>
<td>DD = (B – A) – (D – C)</td>
</tr>
</tbody>
</table>

**Table 2:** Example Differences in Differences

<table>
<thead>
<tr>
<th></th>
<th>After</th>
<th>Before</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment enrolled</td>
<td>0.74</td>
<td>0.60</td>
<td>0.14</td>
</tr>
<tr>
<td>Comparison/nonenrolled</td>
<td>0.81</td>
<td>0.78</td>
<td>0.03</td>
</tr>
<tr>
<td>Difference</td>
<td>−0.07</td>
<td>−0.18</td>
<td>DD = 0.14 − 0.03 = 0.11</td>
</tr>
</tbody>
</table>
4. Regression Discontinuity Design

- Individuals are ranked based on specific, measureable criteria. There is some cut-off that determines whether an individual is eligible to participate. Participants are then compared to non-participants and the eligibility criterion is controlled for.

- **Comparison group:** Individuals who are close to the cut-off, but fall on the “wrong” side of that cut-off, and therefore do not get the program.

- **Assumption:** After controlling for the criteria (and other measures of choice), the remaining differences between individuals directly below and directly above the cut-off score are not statistically significant and will not bias the results. A necessary but sufficient requirement for this to hold is that the cut-off criteria are strictly adhered to.

- **Data Required:** Outcomes as well as measures on criteria (and any other controls).
Quasi – Experimental Methods...

4. Regression Discontinuity Design (contd.)

When to use Regression Discontinuity:

- The beneficiaries/non-beneficiaries can be ordered along a quantifiable dimension.
- This dimension can be used to compute a well-defined index or parameter.
- The index/parameter has a cut-off point for eligibility:
  - Households with a score $\leq$ cutoff are eligible.
  - Households with a score $>cutoff$ are not eligible.
- The index value is what drives the assignment of a potential beneficiary to the treatment (or to non-treatment.)

Gives a good comparison – since the potential beneficiaries (units) just above the cut-off point are very similar to the potential beneficiaries just below the cut-off. We compare outcomes for units just above and below the cut-off point.
4. Regression Discontinuity Design (contd.)

Example: Effect of cash transfer on consumption - Targeted transfer to poorest households

- Construct poverty index from 1 to 100 with pre-intervention characteristics
  - Households with a score ≤ 50 are poor
  - Households with a score >50 are non-poor

- Intervention - Cash transfer to poor households

- Evaluation: Measure outcomes (i.e. consumption, school attendance rates) before and after transfer, comparing households just above and below the cut-off point.
Quasi – Experimental Methods...

4. Regression Discontinuity Design (contd.)

Figure 1: Baseline
Quasi – Experimental Methods...

4. Regression Discontinuity Design (contd.)

Figure 2: Post Intervention
5. Statistical Matching

- Individuals in control group are compared to similar individuals in experimental group.

- **Comparison group:**
  - **Exact matching:** For each participant, at least one non-participant who is identical on selected characteristics.
  - **Propensity score matching:** non-participants who have a mix of characteristics which predict that they would be as likely to participate as participants.

- **Assumption:** The factors that were excluded (because they are unobservable and/or have been not been measured) do not bias results because they are either uncorrelated with the outcome or do not differ between participants and non-participants.

- **Data Required:** Outcomes as well as “variables for matching” for both participants and non-participants.
6. **Instrumental Variables**

- Participation can be predicted by an incidental (almost random) factor, or “instrumental” variable, that is uncorrelated with the outcome, other than the fact that it predicts participation (and participation affects the outcome).

- **Comparison group**: Individuals who, because of this close to random factor, are predicted not to participate and (possibly as a result) did not participate.

- **Assumption**: If it weren’t for the instrumental variable’s ability to predict participation, this “instrument” would otherwise have no effect on or be uncorrelated with the outcome.

- **Data Required**: Outcomes, the “instrument,” and other control variables.
Q & A Session
Breakaway Session Activity

- Group discussion of an exemplary case study
References

References...

- Applied impact evaluation massive open online course (MOOC) https://edge.edx.org/courses/BerkeleyX/CEGA101AIE/2015_2016/about
- Presentations from Impact Evaluation Methodologies Training, held On 27th July 2018 in Nairobi, KCA University (Main Campus). Facilitated by Dr. Anthony Mveyenga (A Research Economist, Sustainable Development Team, World Bank) and Samuel Muhula (Monitoring, Evaluation and Research Manager, Amref Health Africa in Kenya).