ARTNeT- KRI Capacity Building Workshop on Trade Policy Analysis:
Evidence-based Policy Making and Gravity Modelling for Trade Analysis
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# Session 2 : Introduction to gravity models for trade analysis

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# Overview of the workshop

**Day 1 AM: Introduction to evidence-based policy making (EBPM) and tools**

**Day 1 PM: Introduction to gravity model for trade analysis**

- Its concepts, applications, weakness, and development

**Day 2 AM: Estimating the gravity models in STATA**

- Estimating intuitive gravity models
- Estimating trade potential using a gravity model
- Problems of intuitive gravity models

**Day 2 PM: Theoretical gravity models**

- Theoretical gravity models
- Econometric approaches to estimating theoretical gravity models

**Day 3: Advanced issues and consolidation**

- Recent development in gravity techniques
- Group exercises and presentation
- Workshop wrap-up

# Introduction

- Gravity model is a very popular econometric model in international trade
- Origins with Tinbergen (1962). Thousands of published articles and working papers since then.
  - "Some of the clearest and most robust findings in empirical economics." (Leamer & Levinsohn, 1995)
- The name came from its utilizing the gravitational force concept as an analogy to explain the volume of bilateral trade flows
- Initially, it was not based on theoretical model, but just intuition only
- Later on, a range of rigorous theoretical foundation has been given.

# Introduction

- Gravity's main comparative advantage lies in its ability to use real data to assess the sensitivity of trade flows with respect to policy factors we are interested in.
- Numerous applications looking at different types of factors affecting trade costs, and their impacts on trade flows:
  - Transport costs.
  - Tariffs and non-tariff barriers.
  - Regional integration agreements, currency unions, and the
  - GATT/WTO.
  - Time delays at export/import and trade facilitation.
  - Governance, corruption, and contract enforcement.

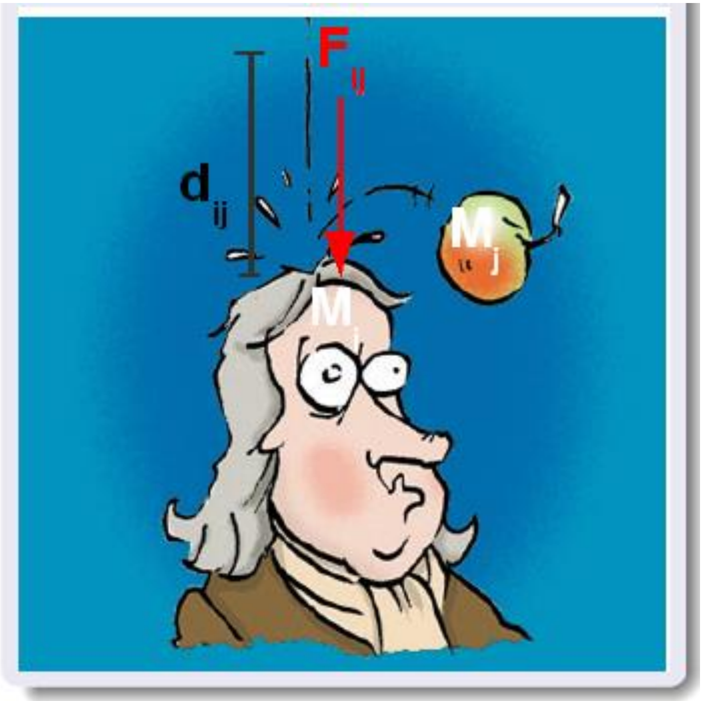
# Introduction

- In recent years, intuition is not enough.
- Gravity models have become a complex business: back to microfoundations!
  - Different microfoundations imply different estimation techniques.
  - Use of sectorally disaggregated data, and broad country samples, brings out new issues for theory and empirics.
- To do good applied/policy research, it is important to be on top of the latest developments in the literature.

# The traditional gravity model

- Concepts and stylized facts of the gravity approach
- Example of applications
- Identifying (“trade potentials”) using gravity approach

# Gravity force in Physics




$$F_{ij} = G\frac{M_i M_j}{d_{ij}^2}$$

The gravitational force between two objects (apple, head) is directly proportional to each of their masses, and inversely proportional to the square of the distance between them.

# Gravity Analogy

## Gravity force equation

$$F_{ij} = G\frac{M_i M_j}{D_{ij}^2}$$

Gravity force between two objects depends on their masses and inversely proportional to the square of distance between them.

## Intuitive gravity for trade

$$X_{ij} = C\frac{Y_i\, Y_j}{t_{ij}}$$

$X_{ij}$ = exports (or trade) from i to j,

$C$ = constant,

$Y$ = economic mass (≈ GDP),

$t$ = trade costs between two countries

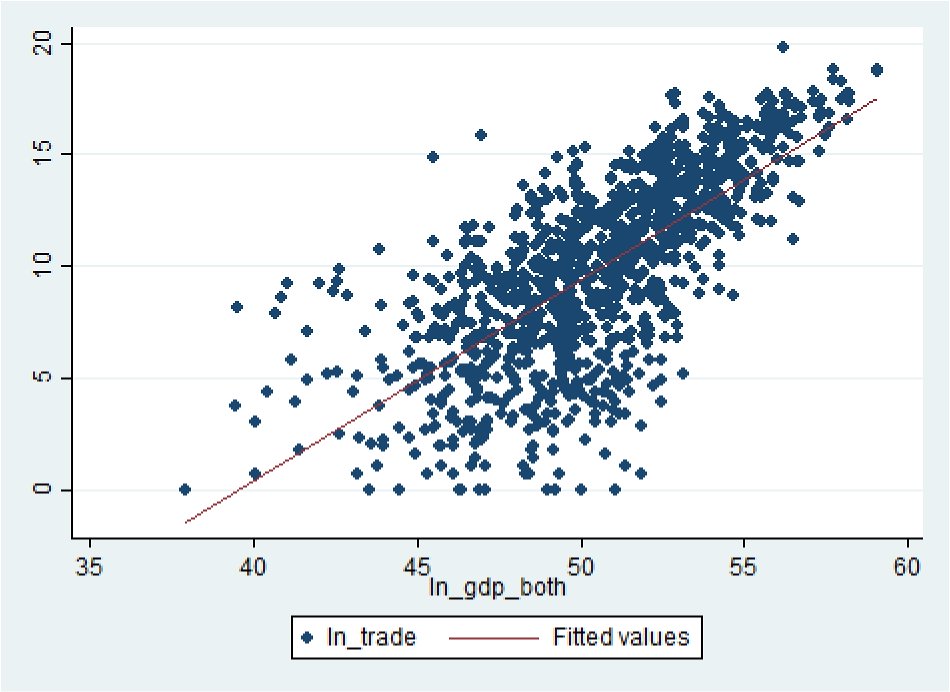
≈ distance, adjacency, .., "policy factors".

Export (or trade) between two countries depends on their economic masses and negatively related to trade costs between them.

# Trade and combined GDP

gen ln_gdp_both = ln(exp_gdp*imp_imp)

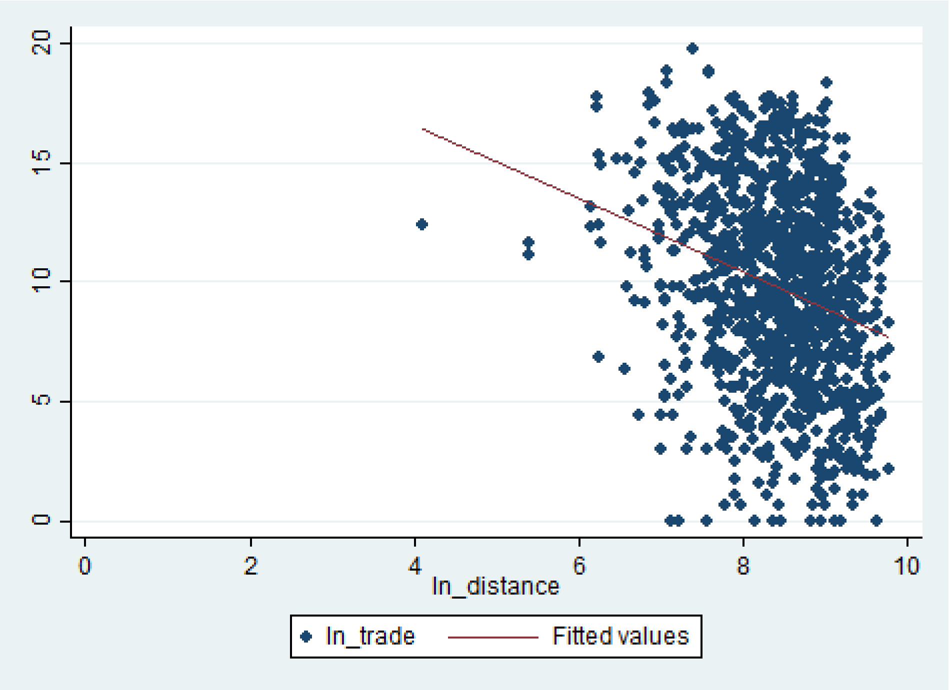
twoway (scatter ln_trade ln_gdp_both)  (lfit ln_trade ln_gdp_both)




Based on AP export data 2013 provided in WITS

# Trade and distance

twoway (scatter ln_trade ln_distance) (lfit ln_trade ln_distance)




Based on AP export data 2013 provided in WITS

# What is the gravity model?

- Gravity model is a very popular econometric model in international trade
- The name came from its utilizing the gravitational force concept as an analogy to explain the volume of bilateral trade flows
  - Proposed by Tinbergen (1962)
- Initially, it was not based on theoretical model, but just intuition only
- Later on, a range of rigorous theoretical foundation has been given.
  - The most well-known benchmark so far is Anderson and van Wincoop (2003).

# Intuitive gravity model of trade:

$$X_{ij} = C \frac{Y_i \; Y_j}{t_{ij}}$$

- Larger countries trade more than smaller ones
- Trade costs between two trade partners reduce trade between them.

Empirical equation for basic gravity model:

$$\ln X_{ij} = b_0 + b_1 \ln(Y_i) + b_2 \ln(Y_j) + b_3 \ln(t_{ij}) + e_{ij}$$

$$b_1, b_2 > 0; \quad b_3 < 0$$

A 1% change in $Y_i$ is associated with a $b_1$% chage in $X_{ij}$.

# Proxies for trade costs

- Distance
- Adjacency
- Common language
- Colonial links
- Common currency
- Island, landlocked
- Institutions, infrastructures, migration flows,..
- Bilateral tariff barriers

# Why is it so popular?

- Intuitively appealing
- Fits with some important stylized facts
- Easily to use real data to explain trade flows with respect to policy factors.
- Estimation using OLS

# Applications of gravity models

- Analysis of elasticities of trade volumes
  - Regional Trade Agreements (RTA), "natural regionalism" (Frankel & Wei, 1993, Baier & Bergstrand 2005)
  - WTO membership
  - Impact of NTBs on trade (Fontagné et al. 2005)
  - Cost of the border (Mac Callum, Anderson & van Wincoop 2003)
  - Impact of conflicts on trade
  - FDI & trade: complements or substitute (Eaton & Tamura, 1994; Fontagné, 2000)
  - Effect of single currency on trade (Rose, 2000)
  - Trade patterns: inter and intra-industry trade (Fontagné, Freudenberg & Péridy, 1998)
  - Diasporas (community of immigrants)
  - Internet

# Applications of gravity models

- Analyse predicted trade flows and observe differences between predicted and observed flows (analysis of residuals)
  - Trade potentials of economies in transition (out-of sample predictions)
  - Identify the natural markets and markets with an untapped trade potential
  - Predicted values are used in some cases as an input for CGE modeling (Kuiper and van Tongeren, 2006)
  - Use of confidence intervals in addition to predicted values, in order to take into account the residual variance

# Examples of Applications

- Effects of regional integration on trade

$$\text{Do RTAs boost trade between members?}$$

$$\ln X_{ij} = b_0 + b_1 \ln(Y_i) + b_2 \ln(Y_j) + b_3 \ln(t_{ij}) + b_4 (dummyRTA_{ij}) + e_{ij}$$

$$\text{Do RTAs reduce exports from non-members?}$$

$$\ln X_{ij} = b_0 + b_1 \ln(Y_i) + b_2 \ln(Y_j) + b_3 \ln(t_{ij}) + \ldots$$

$$+ b_4 (dummy\,BothInRTA_{ij}) + b_5 (dummy\,OneInRTA_{ij}) + e_{ij}$$

- By using dummy variables, gravity models provide a crude measure of RTA impact on trade but cannot distinguish the precise mechanisms.
- Both b4 > 0 and b5>0 implies trade creating RTA.
- Only b4> 0 while b5<0 implies trade diverting RTA

See, World Bank (2005) for survey.

- Two important limitations related to using gravity models for estimating the impact of a RTA:

1. RTAs may be endogenous variables (ie. the causal link between the formation of a RTA and trade flows). This endogeneity affects gravity-based estimates.
2. Recent literature is replete with models in which regional integration agreements are formed in the pursuit of other, non-trade goals (see, for instance, Limao, 2006) or in which they have “non-traditional” gains (see Ethier, 1998).
   – South–South agreements have been rather more successful in non-trade dimensions like the management of common resources than in the dimension of pure trade-liberalization.

- The analysis of RTAs should avoid limiting itself to measuring trade diversion and creation, although these are important issues for the welfare of member countries.

# Examples of Applications

- Effects of institutional weakness on trade

How does corruption affect trade?

$$\ln X_{ij} = b_0 + b_1 \ln(Y_i) + b_2 \ln(Y_j) + b_3 \ln(t_{ij}) + b_4 \ln(corruption_i) + e_{ij}$$

Anderson and Marcouiller use a 58-country gravity model and corruption data from the World Economic Forum to show that:

- Institutional weaknesses, generally corruption and lack of contract enforceability, have a significant negative impact on trade.
- If Latin America increased measured institutional quality to the same level as the EU, their trade would increase by about 30%: about the same as with a major tariff cut.

# Examples of Applications

- Effects of trade facilitation on trade

  How much can trade facilitation boost bilateral trade?

$$\ln X_{ij} = b_0 + b_1 \ln(Y_i) + b_2 \ln(Y_j) + b_3 \ln(d_{ij}) + b_4 \ln(time_i^X) + e_{ij}$$

- Djankov Freund & Pham (2010) use a gravity model with Doing Business data on border crossing times (98 countries) to show that:
  - Slower border crossing times can significantly reduce bilateral trade: One extra day reduces exports by 1%.
  - Time-critical agricultural and manufactured goods are particularly sensitive to border crossing times:
    - Agriculture: Fresh fruits and vegetables.
    - Manufactures: Electronic goods; parts and components.
- **Landlocked countries** are particularly sensitive to border crossing times: One extra day reduces exports by as much as 4%.

# Traditional gravity models in STATA

# Setting up the problem

- The long-linear (basic) gravity equation

$$\ln X_{ij} = b_0 + b_1 \ln(Y_i) + b_2 \ln(Y_j) + b_3 \ln(t_{ij}) + e_{ij}$$

$$\text{We expect :} \qquad b_1, b_2 > 0; \quad b_3 < 0$$

- Taking the model to the data: $Y_i \rightarrow \ GDP_i$, $Y_j \rightarrow \ GDP_j$, $t_{ij} \rightarrow \ distance_{ij}$
- Estimating the b parameters would let us know:
  - How well do distance and GDP explain bilateral trade flows?
  - Do the data support the expected coefficient signs?
  - How sensitive is bilateral trade to distance and GDP, controlling for the simultaneous influence of the other?

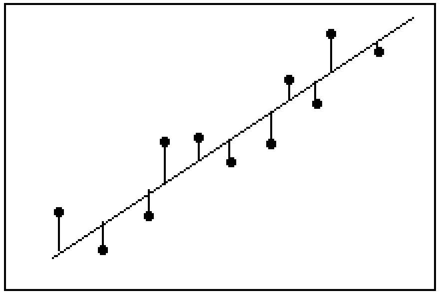
# Finding the method of estimation

$$\ln X_{ij} = b_0 + b_1 \ln(Y_i) + b_2 \ln(Y_j) + b_3 \ln(t_{ij}) + e_{ij}$$

$$b_1, b_2 > 0; \quad b_3 < 0$$

- We need a method for estimating the b parameters.
- One sensible candidate, and the usual place to start, is the ordinary least squares (OLS):
  - Choose $b_0$, $b_1$, $b_2$ and $b_3$ so as to minimize the sum of squared errors: $\sum_i \sum_j e_{ij}{}^2$

# OLS



- Linear regression calculates an equation that minimizes the distance between the fitted line and all of the data points.
- Technically, ordinary least squares (OLS) regression minimizes the sum of the squared residuals.

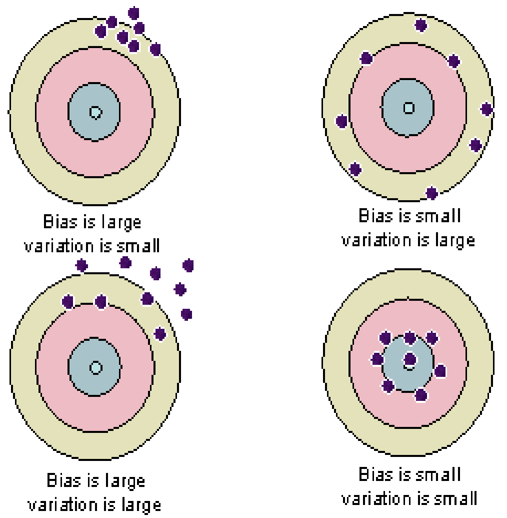
- The solution to the OLS minimization problem, $\widehat{\mathbf{B}}$ is not just a sensible set of slope coefficients, in the sense of satisfying an intuitive criterion.
- Under specific assumptions as to the properties of the random error term **E**, the OLS estimator also has some very useful statistical properties.
- We will make extensive use of these properties to:
  - Argue that our estimates are reasonable and reliable; and
  - To conduct formal tests of interesting economic hypotheses.

# OLS properties

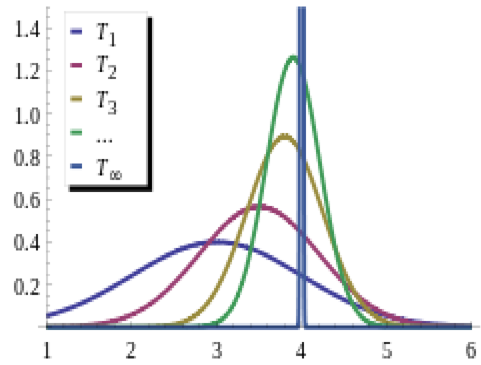
- Specifically, OLS is consistent, unbiased, and efficient as an estimator of **B** if the following conditions hold:
  - None of the dependent variables are perfectly correlated (multicollinearity).
  - **E** is an independently distributed normal error with mean zero, and with constant variance (homoskedasticity).
  - The underlying model relating the dependent and independent variables is linear.
  - **E** is uncorrelated with any of the independent variables.
- If these conditions hold, we can be confident that our estimates are reliable, and that hypothesis tests are informative. If they do not, we cannot!

# Reliability of an estimator

- Unbiased - The expected value (mean) of the estimate's sampling distribution is equal to the underlying population parameter.
- Consistency - Larger sample sizes tend to produce more accurate estimates; ie. the sample parameter converges on the population parameter.
- Efficiency – There is no other linear, unbiased estimator that produce smaller standard errors for the estimated coefficient.



Accuracy versus Quality of an Estimator Using Bias and Variation as Measurable Quantities Respectively




Consistent estimators are convergent and *asymptotically* unbiased (hence converge to the correct value): individual estimators in the sequence may be biased, but the overall sequence still consistent, if the bias converges to zero. Conversely, if the sequence does not converge to a value, then it is not consistent, regardless of whether the estimators in the sequence are biased or not.

- If the OLS assumptions hold, we can also use the model for hypothesis testing:
  - The estimated coefficients approximately normally distributed, with standard errors that can be easily calculated.
  - We can test hypotheses on a particular variable using its t-statistic.
  - We can test compound linear hypotheses (more than one variable) using the F-statistic.

# Violation of the OLS properties

- Not all violations of the OLS conditions are equal:
  - Perfect multicollinearity rarely arises in practice, although it can have some implications in panel data models with fixed effects.
  - Heteroskedasticity is usually relatively minor, and easily dealt with: always use a “robust” estimator for the variance-covariance matrix.
  - One type of correlation in the error terms can be fixed by using the “cluster ()” option, and specifying the highest level of data aggregation.
  - Violations of the last two conditions have serious consequences (bias and inconsistency), and are much harder to fix.

# Making the OLS talk

- Let’s use STATA to estimate a very simple gravity model by OLS, and then focus on interpreting the results (making it “talk”).
- We are interested in:
  - Giving economic interpretations to parameter estimates;
  - Testing simple (one parameter) hypotheses;
  - Testing compound (multiple parameter) hypotheses; and
  - Assessing how well the model fits the data.

# A simple OLS gravity model

regress ln_trade ln_gdp_exp ln_gdp_imp ln_distance contig comlang_off colony comcol, robust cluster(dist)

t-values test the hypothesis that each coefficient is different from 0. To reject this, the t-value has to be higher than 1.96 (for a 95% confidence). If this is the case then you can say that the variable has a significant influence on your dependent variable (y). The higher the t-value the higher the relevance of the variable.

Two-tail p-values test the hypothesis that each coefficient is different from 0. To reject this, the p-value has to be lower than 0.05 (95%, you could choose also an alpha of 0.10), if this is the case then you can say that the variable has a significant influence on your dependent variable (y)

**The model fitted 65% of the variation in the data**

**Note: we control for heteroskedasticity using robust option**

```
Linear                                   Number of obs =      1203
                                         F(  7,   802) =    313.17
                                         Prob > F      =    0.0000
                                         R-squared     =    0.6509
                                         Root MSE      =    2.4504

                          (Std. Err. adjusted for 803 clusters in distw)
```

| ln_trade | Coef. | Robust Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| ln_gdp_exp | 1.229322 | .033577 | 36.61 | 0.000 | 1.163413 | 1.295231 |
| ln_gdp_imp | .8111193 | .0271287 | 29.90 | 0.000 | .7578676 | .864371 |
| ln_distance | -1.621796 | .1313971 | -12.34 | 0.000 | -1.879719 | -1.363873 |
| contig | .393265 | .2999603 | 1.31 | 0.190 | -.195535 | .9820649 |
| comlang_off | 1.402018 | .2455724 | 5.71 | 0.000 | .9199773 | 1.884059 |
| colony | .4143014 | .6511902 | 0.64 | 0.525 | -.863937 | 1.69254 |
| comcol | .5482557 | .2425401 | 2.26 | 0.024 | .0721673 | 1.024344 |
| _cons | -28.74489 | 1.66054 | -17.31 | 0.000 | -32.00441 | -25.48537 |

```
. ereturn list r2 r2_a
scalar e(r2)        =  .6509149486732252
scalar e(r2_a)      =  .6488700990001813
```

# Interpretation

- Market-size effects

| ln_trade | Coef. | Robust Std. Err. | t | P>\|t\| |
|---|---|---|---|---|
| ln_gdp_exp | 1.229322 | .033577 | 36.61 | 0.000 |
| ln_gdp_imp | .8111193 | .0271287 | 29.90 | 0.000 |

- A 1% increase in exporter size is associated with about a 1.2 % increase in bilateral trade.
- A 1% increase in importer size is associated with about a 0.81% increase in bilateral trade.
- Both effects are statistically significant at the 1% level

# Interpretation

- Geography effects

| ln_trade | Coef. | Robust Std. Err. | t | P>\|t\| |
|---|---|---|---|---|
| ln_distance | -1.621796 | .1313971 | -12.34 | 0.000 |
| contig | .393265 | .2999603 | 1.31 | 0.190 |

- A 1% increase in distance between markets is associated with about a 1.62 % decrease in bilateral trade.
- Only distance is statistically significant.

# Interpretation

- History effects

| ln_trade | Coef. | Robust Std. Err. | t | P>\|t\| |
|---|---|---|---|---|
| comlang_off | 1.402018 | .2455724 | 5.71 | 0.000 |
| colony | .4143014 | .6511902 | 0.64 | 0.525 |
| comcol | .5482557 | .2425401 | 2.26 | 0.024 |

- A common official language is associated with an increase in bilateral trade of about a 300% (e^1.40-1≈3.055). The effect is statistically significant at the 1% level.

- A common colony is associated with an increase in bilateral trade of about a 73% (e^0.55-1≈0.73). The effect is statistically significant at the 5% level.

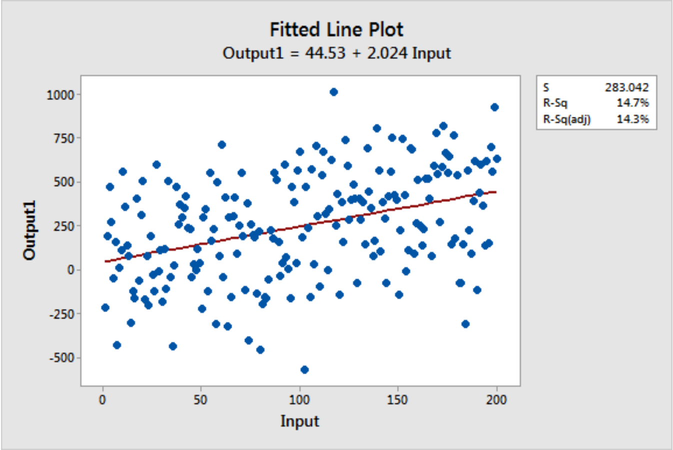
# How well the model "fits" the data

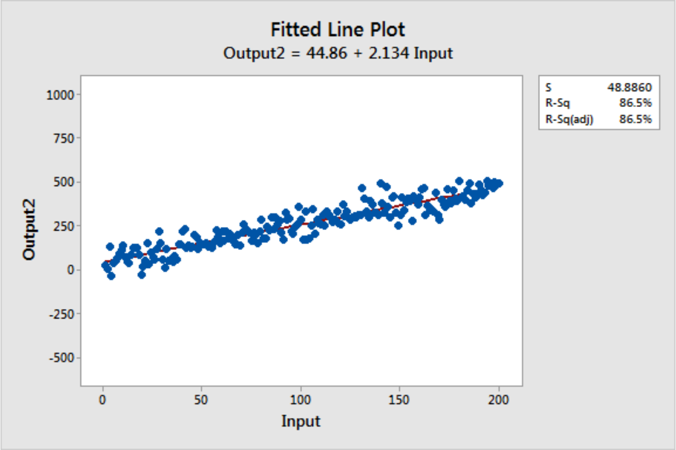
In general, a model fits the data well if the differences between the observed values and the model's predicted values are small and unbiased.

- R-squared is a statistical measure of how close the data are to the fitted regression line.

  R-squared = Explained variation / Total variation

  R-squared is always between 0 and 100%




**Be cautious when looking at R-square**

- Every time you add a predictor to a model, the R-squared increases, even if due to chance alone.
- The interpretation of coefficient and predicted value don't change between the low and high R2 models above

Output = 44 + 2 * Input

Input is significant with P < 0.001 for both models

# Adjusted R-Squared

The adjusted R-squared is a modified version of R-squared that has been adjusted for the number of predictors in the model.

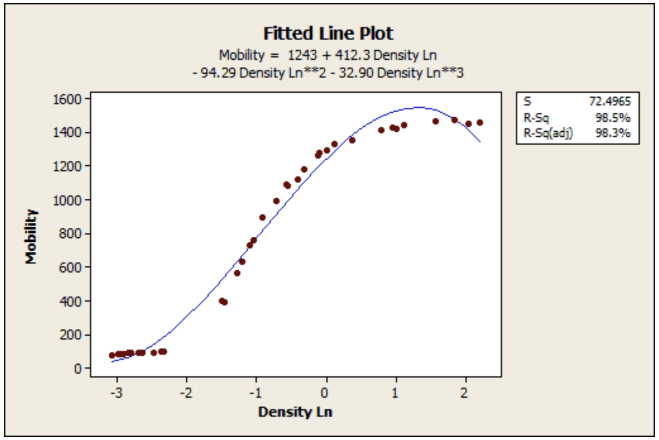
- The adjusted R-squared increases only if the new term improves the model more than would be expected by chance.
- It decreases when a predictor improves the model by less than expected by chance.
- The adjusted R-squared can be negative, but it’s usually not. It is always lower than the R-squared.

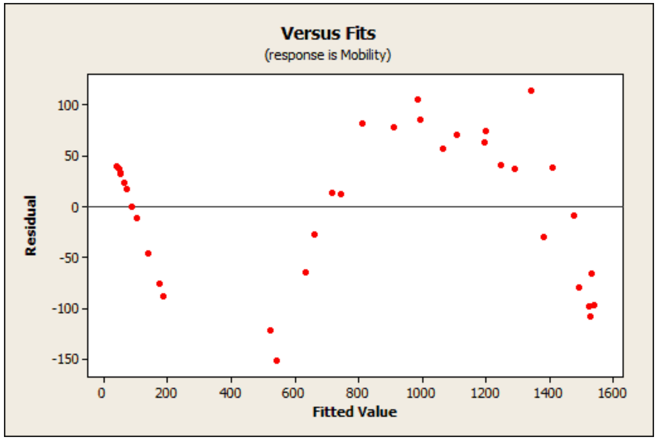
```
. ereturn list r2 r2_a
scalar e(r2)        =  .6509149486732252
scalar e(r2_a)      =  .6488700990001813
```

R-squared *cannot* determine whether the coefficient estimates and predictions are biased, which is why you must assess the residual plots.

# Are High R-squared Values Inherently Good?

- No! A high R-squared does not necessarily indicate that the model has a good fit




The regression line systematically over and under-predicts the data (bias) at different points along the curve: the residuals are not random. This indicates a bad fit:

- The model is wrongly specified (possible non-linearities)
- The coefficient estimates and predictions are biased.

# A test for model specification

- Ramsey's RESET test is a test for model specification (possible non-linearities) and omission of important variables:
  - Get fitted values from the gravity model, $\widehat{\mathbf{X}}$.
  - Calculate $\widehat{\mathbf{X}}^2$, $\widehat{\mathbf{X}}^3$, $\widehat{\mathbf{X}}^4$.
  - Include them as additional regressors, and check joint significance using an F-test.
  - H0: the model is correctly specified. A large test statistic indicates a problem.

- Although stata reports (through R2 and adj.R2) that the model accounts for about 65% of the observed variance in the log of bilateral trade, the Ramsey RESET test strongly rejects H0:

```
. estat ovtest

Ramsey RESET test using powers of the fitted values of ln_trade
       Ho:  model has no omitted variables
                F(3, 1192) =     20.61
                  Prob > F =      0.0000
```

  - Are there other variables that might be influencing bilateral trade, but are left out of our simple model?
  - Are there any non-linearities we need to worry about?

# An augmented gravity model

regress ln_trade tariff_exp_sim tariff_imp_sim ln_gdp_exp ln_gdp_imp ln_distance contig comlang_ off colony comcol, robust cluster(dist)

```
Linear regression                                      Number of obs =     858
                                                       F(  9,    519) =  181.17
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.6724
                                                       Root MSE      =   2.249

                                  (Std. Err. adjusted for 520 clusters in distw)
```

| ln_trade | Coef. | Robust Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| tariff_exp_sim | .0027192 | .017193 | 0.16 | 0.874 | -.0310573 | .0364957 |
| tariff_imp_sim | -.0325578 | .0136803 | -2.38 | 0.018 | -.0594335 | -.0056822 |
| ln_gdp_exp | 1.237804 | .0362567 | 34.14 | 0.000 | 1.166576 | 1.309032 |
| ln_gdp_imp | .8075699 | .0353095 | 22.87 | 0.000 | .7382027 | .8769371 |
| ln_distance | -1.685163 | .1443565 | -11.67 | 0.000 | -1.968757 | -1.401568 |
| contig | .2142709 | .3135988 | 0.68 | 0.495 | -.4018082 | .83035 |
| comlang_off | 1.484303 | .282989 | 5.25 | 0.000 | .9283582 | 2.040248 |
| colony | .3962441 | .8379968 | 0.47 | 0.637 | -1.250039 | 2.042527 |
| comcol | .5661145 | .2766012 | 2.05 | 0.041 | .022719 | 1.10951 |
| _cons | -28.00754 | 1.957916 | -14.30 | 0.000 | -31.85395 | -24.16112 |

- Adding explanatory variables to the basic gravity model increased $R^2$ increased from 0.65 to 0.67
- The Ramsey RESET test was improved but still rejects H0:

```
. ereturn list r2 r2_a
scalar e(r2)        =  .6724210499520176
scalar e(r2_a)      =  .6689443865670743

. estat ovtest

Ramsey RESET test using powers of the fitted values of ln_trade
       Ho:  model has no omitted variables
                 F(3, 845) =     12.65
                  Prob > F =      0.0000
```

# Interpretation

- Trade-policy effects

• The applied tariffs (simple average) are used (value in from 0 to 50 for exporters and importers).

• Only importer's tariffs are statistically significant at the 5% level

•A 1% increase in an importer's tariff level is associated with about a 3.3% decrease in bilateral trade. ($e^{0.0326}-1\approx0.033$).

# Estimating trade potential

# Identifying “trade potential”

- The OLS estimates give the prediction of “average” trade level.
- Actually, some countries trade “more” than average, while others trade “less” than average.
- Some of the literature uses the sign and size of the error term to examine trade potential.

# Identifying “trade potential”

- Estimating trade potential

$$\ln X_{ij} = b_0 + b_1 \ln(Y_i) + b_2 \ln(Y_j) + b_3 \ln(t_{ij}) + .... + e_{ij}$$

Fist step: estimate the model to get estimated coefficients

Second step: Use estimated coefficients give predicted Xij

$$\ln \hat{X}_{ij} = \hat{b}_0 + \hat{b}_1 \ln(Y_i) + \hat{b}_2 \ln(Y_j) + \hat{b}_3 \ln(t_{ij}) + ...$$

Third: Trade potential is the gap between predicted and actual Xij

```
qui regress  ln_trade  tariff_exp_sim tariff_imp_sim ln_gdp_exp ln_gdp_imp
ln_distance /// contig comlang_off colony comcol, robust cluster(dist)

predict ln_tradehat
gen tradehat=exp(ln_tradehat)   /***exp(ln_x)=x***/
gen tradeerror=trade-tradehat

list tradeerror exp_name imp_name if exp ==“MNG" & tradeerror <0
```

| | tradeer~r | exp_name | imp_name |
|---|---|---|---|
| 92. | -2726.591 | Malaysia | Armenia |
| 271. | -2102.08 | Malaysia | Azerbaijan |
| 453. | -3065.22 | Malaysia | Bhutan |
| 454. | -1638.758 | Malaysia | Bhutan |
| 587. | -32.74155 | Malaysia | Cook Islands |
| 1191. | -2396.02 | Malaysia | Kazakhstan |
| 1498. | -31510.43 | Malaysia | Lao PDR |
| 1499. | -15338.55 | Malaysia | Lao PDR |
| 2605. | -10124.81 | Malaysia | Korea DPR |
| 2606. | -7970.036 | Malaysia | Korea DPR |
| 2607. | -8111.941 | Malaysia | Korea DPR |
| 2807. | -2.58e+07 | Malaysia | Singapore |
| 3559. | -18.7494 | Malaysia | Cook Islands |

# Identifying “trade potential”

- Actual Trade- Predicted trade << 0 (Large negative errors:
  - A country could be trading more based on their economic and geographical fundamentals
  - Something is holding back trade.
- Positive errors: ??
- Keep in mind
  - The error term include also statistical noise and measurement error.
  - Do not overemphasized trade potential estimated by gravity model.
  - It may just give a first idea of what is going on with particular trade relationships. Things need to work in details of what is holding back trade.

# Major weaknesses of the basic gravity:

$$\ln X_{ij} = b_0 + b_1 \ln(Y_i) + b_2 \ln(Y_j) + b_3 \ln(t_{ij}) + e_{ij}$$

The basic gravity model cannot handle the facts that:

1. Trade costs of the third party can affect trade between the two partners.
2. Relative trade costs (relative prices, to be exact) matter, not absolute trade costs

A consequence:

- The OLS basic gravity models encounter the omitted variables bias

Ex. trade creation and trade diversion are not captured by the basic gravity model.