Module 3

The macroeconomic approach
1 Introduction

This module uses country-level data to focus on the interconnection between trade openness and gender outcomes in terms of improving women’s economic, political, and social status. Because we use this level of aggregation in the data, we decided to title this module “macroeconomic approach”, but this does not necessarily imply that we will only use variables associated with macroeconomic theory such as inflation, unemployment, and growth.

The first macroeconomists in this area of research looked at the relationship between trade openness and macroeconomic outcomes by exploring the effects of trade openness on economic growth. It was only at a later stage that macroeconomists started to analyse the repercussions of trade on inequality, with some authors focusing on poverty among specific groups, such as women, and on gender inequality. It is well documented that opening an economy to international trade often produces significant changes that go beyond the changes associated with growth rates. For example, international trade often triggers structural transformation of the local economy, prompting shifts in employment with consequent feminization or de-feminization of the workforce (Tejani and Milberg, 2010). Moreover, access to new markets for exporting firms from low- and middle-income countries may generate higher income for workers in the exporting sectors. Local firms can also access higher-quality inputs and better technologies, which can help them close the productivity gap observed in most developing countries.

But international trade can also increase unemployment, poverty, and income inequality in the short and medium term due to stiff international competition, as well as create a socially, economically, and politically unsustainable situation in which the potential benefits of trade sometimes do not materialize. One reason for this could be rigidities in labour markets. For the gains from trade to occur, resources need to be reallocated from less productive activities to more productive ones, which may not happen in the presence of imperfect labour markets. This suggests that the relationship between international trade and labour market outcomes is complex and that there are important complementarities between trade and labour market policies. All the more, even when we observe aggregate benefits from increased trade, some groups, including women, may lose as a result. The overall effect of trade openness in a developing country may depend on complementary policies, institutions, and infrastructure – which is why public policies are important and policymakers need to consider the gender effects of trade.

Besides its direct employment effect, international trade connects countries in a way that such matters as standards, laws, cultural norms, and gender roles in a given country may have spillover effects in other countries, particularly in those linked by commercial and financial flows. Of particular interest to us is the effect of globalization, proxied by a measure of trade openness, on women’s economic, political, and social status. We will see below how econometric techniques can be used to assess this question.

Consequently, we need to ask ourselves whether gains from trade actually happen, and then for the purpose of this teaching material, whether they reduce or increase existing gender inequalities. It is also important to evaluate whether international trade empowers women, and what its effects are beyond income-generating opportunities. While some dimensions of the effect of trade on gender inequality (e.g. employment and wages, mostly linked to export expansion) are better documented than others (e.g. intra-household resources and time allocation), there remains great scope for more research on developing countries.

Section 2 of this module summarizes the macroeconomic literature on trade and gender. Section 3 provides the intuition behind the methodology used to link international trade to several gender outcomes using aggregate data. In particular, we review a collection of panel data techniques. For the hands-on application in Sections 4 and 5, we present two papers estimating the effects of globalization, captured by a variety of measures of trade openness, on women’s status. In this sense, we depart from typical economistic analyses that study the relationship between trade and labour market outcomes and instead present papers that take a broader view of globalization and women’s rights. The selected applications also allow us to see how similar data can be used with different estimation techniques. Section 6 draws some conclusions.

At the end of this module, students should be able to:

- Use the macroeconomic approach to analyse the link between trade and gender;
- Review and summarize the literature employing the macroeconomic approach to investigate the linkages between trade and gender;
- Understand how the macroeconomic ap-
proach differs from the microeconomic approach presented in the previous module;
- Have a basic understanding of econometric models, such as panel data (including dynamic panel data) with fixed and random effects;
- Compare the fixed-effects model with the random-effects model and identify which is more appropriate to use according to the research question of interest;
- Replicate, using Stata, the results of the paper by Richards and Gelleny (2007) titled "Women's Status and Economic Globalization";
- Replicate, using Stata, the results of the paper by Neumayer and de Soysa (2011) titled "Globalization and the Empowerment of Women: An Analysis of Spatial Dependence via Trade and Foreign Direct Investment".

2 Review of the literature

This section reviews a brief collection of macroeconomic studies on trade and gender. Its aim is to familiarize readers with a few well-known papers in the literature on trade and gender, rather than serve as an exhaustive literature review. The papers cited below may also prove useful when you are carrying out your own research.

The topic of trade and gender inequality is fairly recent. The policy prescription of trade liberalization was promoted in the 1970s and 1980s as a means to address (a) the efficiency distortions generated by the import substitution industrialization strategy, and (b) the disappointing economic performance of the inward-oriented Latin American countries in the 1960s and 1970s, which contrasted sharply with the success of the outward-oriented East Asian “Tigers”. Accordingly, the primary focus of economists in the empirical literature has been to establish the links between trade and growth and understand whether the latter could contribute to poverty alleviation and income equality, especially in developing countries, on the grounds that trade has greater potential as an engine of growth in countries with widespread poverty than in other countries. Economists have studied the empirical research on the relationship between trade liberalization and gender only at a later stage, and there is a need for more evidence, in particular for developing countries.

A number of papers have assessed cross-country evidence using a macroeconomic approach. The early work of Adrian Wood (1991) explores the changes in the gender composition of manufacturing employment for a set of developed and developing countries and investigates the extent to which these changes were caused by trade. His results suggest that the expansion of trade between developing and developed countries coincided with an increase in the intensity of female employment in the former but, contrary to prior evidence (Schumacher, 1984; Baldwin, 1984), did not result in a reduction in the demand for female workers in the latter. Wood (1991) provides several explanations for this asymmetry, including the possibility that it is easier for female workers in developed countries to relocate from one manufacturing sector to the other, (such as from textiles manufacturing to the manufacturing of food and beverages) since males are assumed to have more sector-specific skills. Kucera and Milberg (1999) update the work of Wood and focus on the employment effects of trade in terms of gender in the manufacturing sector of ten OECD countries. They find that in most cases trade with developing countries has adversely affected female manufacturing employment. Both the papers by Wood (1991) and Kucera and Milberg (1999) are part of a long-standing academic debate on the macroeconomic effects of trade on gender inequality. Another interesting study in this field is that of Bussmann (2009), who looks at 134 countries and discovers yet again that trade openness increases female labour force participation in developing countries, whereas the share of working women in OECD countries declines.

Also using cross-sectional data, Baliamoune-Lutz (2006) finds evidence that globalization and growth seem to have no effect on gender equality (measured as the difference between women’s and men’s illiteracy rates) in non-sub-Saharan African developing countries, but exacerbate gender inequality in sub-Saharan African countries. Wamboye and Seguino (2014) focus on 14 sub-Saharan African countries and claim that the employment effects of trade in terms of gender depend on the structure of a country’s economy rather than on its level of economic development. They find that trade liberalization plays a different role in women’s relative employment according to each country’s endowment of physical infrastructure (electricity, clean water, transport and communication infrastructure), which influences women’s care burdens and thus their labour supply. In a cross-country study on the effects of trade and FDI on the gender wage gap, Oostendorp (2009) finds evidence that increased trade and FDI contribute to narrowing the gender wage gap in developed countries but not in developing countries.

Other papers have explored indirect channels of interaction between trade and gender. For example, Black and Brainerd (2002) tested Becker’s (1959) hypothesis according to which there is
a negative correlation between employer discrimination and the degree of competition in the product market. Using data from United States manufacturing industries, the authors show that higher competition as a result of trade reduces the ability to discriminate against women in concentrated industries, and thus trade openness contributes to shrinking the gender wage gap. Berik et al. (2004) apply this framework to study the effect of trade on wage discrimination in Taiwan Province of China and the Republic of Korea. Contrary to Becker’s theory, the authors find that trade is linked to higher gender wage discrimination in more concentrated industries where women seem to be more affected by the cost-cutting strategy of their employers.

As explained in Volume 1 of this teaching material, the relationship between trade and gender is bi-directional. For this reason, among the macroeconomic literature on trade and gender you will also find studies that examine how gender affects trade. In particular, there is a wide range of studies that explore the linkages between gender inequalities and export performance. The basic idea of this strand of literature is that firms in labour-intensive, export-led sectors rely on cheap female labour to thrive in international markets.

In this context, gender norms and stereotypes also play an important role in the clustering of the female workforce in labour-intensive manufacturing (see Module 3 of Volume 1). For instance, Seguino (2000) studies a group of semi-industrialized, export-oriented countries and shows that gender inequality reflected in lower wages for women contributed to higher growth through its positive effect on exports. This paper opened a lively discussion with Schober and Winter-Ebmer (2011) who find that gender inequality is bad for economic growth and criticize Seguino (2000) for promoting gender inequality as a growth-enhancing strategy. Seguino (2011) replies by raising some empirical concerns about the approach of the paper by Schober and Winter-Ebmer. She concludes: “A finding that gender wage inequality is a stimulus to growth is not a vote or indeed justification for inequality. Rather, it is an evidence-based approach for assessing how things stand and what we need to do at the policy level to promote equity-led growth.” (Seguino, 2011: 1487).

Busse and Spielmann (2006) adopt a broader definition of gender inequality, including wages, labour market access, and education inequality. They argue that gender bias does not influence the amount of export flows but rather the type of products exported. In their view, gender inequality may favour the export of labour-intensive products but would disincentivize countries to switch to higher-value products and thus limit their growth potential.

These are just a few macroeconomic studies in the area of trade and gender in addition to the two studies reviewed in Sections 4 and 5 of this module. The papers reviewed here differ in their scope and theoretical approach, and use different definitions of gender inequality and trade. For example, they define gender inequality in terms of women’s status rather than measuring inequality in terms of labour market outcomes (e.g. gender wage gap). For a more detailed literature review you may read Çag˘atay (2001) and Fontana (2008). In conclusion, the aim of this literature review was to demonstrate how extensive the macroeconomic literature on trade and gender is, but also to make you realize that the debate on the interlinkages between trade and gender is still open. We encourage you to contribute to it through your own research.

3 Methodological approach: Panel data models

Panel data are repeated measures of a variable (i) over time (t). This variable may be related to individuals, households, firms, countries, etc. over a period of time. The main characteristic of a panel dataset is the two-dimensionality of the data. Most papers adopting the macroeconomic approach in the trade and gender literature use panel data where the main variable is defined in the country and the year dimension.

A micro-panel dataset is a panel for which the time dimension T is largely less important than the individual dimension N. A macro-panel dataset is a panel for which the time dimension T is similar to the individual dimension N. In panel data with N units and T periods, we could independently estimate N time series models or T cross-section models. However, there are several advantages of using panel data rather than independent regressions. One of them is that panel data allow us to control for unobserved heterogeneous characteristics. Panel data also allow us to aggregate information in some way, and the more information we have to run the estimation of a set of parameters, the more efficient such estimation is. However, panel data also have some disadvantages. Sometimes it is not possible to aggregate cross-sectional and temporal data. Panels, especially for micro data, are often expensive and difficult to assemble. There may be selection problems in panels, as some individuals may disappear, decide not to answer some specific questions, or be selected for the panel because...
they have particular characteristics of interest for the purpose of specific research. In a nutshell, selection problems usually occur when individuals are not selected randomly to be included in the sample.

The basic model in a panel data framework is:

$$ y_{it} = x'_{it} \beta + u_{it} $$  \hspace{1cm} (1) 

where $y$ is the dependent variable of interest (e.g. the gender wage gap); $x$ is a matrix of independent variables or covariates (e.g. GDP per capita, a measure of trade openness, etc.); $\beta$ are the coefficients that identify the statistical relationship between $y$ and $x$; and $u_{it} = \mu_i + \delta_t + \epsilon_{it}$  \hspace{1cm} (2)

is the error term. The latter includes three components that represent the three sources of unobserved variability. $\mu_i$ represents unobserved variability across individuals (some individual-specific characteristics that we are not able to capture); $\delta_t$ represents unobserved variability across periods of time (in a particular period, variables may be affected by something we cannot observe); and $\epsilon_{it}$ is pure unobservable variability specific to the individual and the time observation.

Assume that $\delta_t$ is zero and that $\epsilon_{it}$ satisfies all the classic assumptions. In the case that all individual-specific components $\mu_i$ are zero, we have $u_{it} = \epsilon_{it}$, the model becomes $y_{it} = x'_{it} \beta + \epsilon_{it}$ and the panel data structure does not add any useful information for the estimation of the parameters.

### 3.1 Fixed-effects model

In a nutshell, a fixed-effects model is an econometric specification of panel data model that allows us to "net out" from the estimation results the effects of unobserved time-invariant and individual-specific characteristics ($\mu_i$) that are probably correlated with the independent variables $x_{it}$. If we do not account for these fixed effects and they are related to the independent variables, we create an "omitted variable bias". Assume that the model now is:

$$ y_{it} = x'_{it} \beta + \mu_i + \epsilon_{it} $$  \hspace{1cm} (3)

Here we can see the advantage of using panel data, as parameters $\mu_i$ cannot be estimated with a cross-section but can be within a panel. If $\mu_i$ is correlated with $x_{it}$, the independent variables may be endogenous with respect to $\mu_i$ but not to $\epsilon_{it}$. This panel model can be seen as a linear model where each individual (or firm, country, etc.) has its own $y$-intercept. We can estimate this model using $N^{-1}$ dummy variables per individual in the sample. Having a panel allows us to control for individual omitted variables that do not vary over time.

### 3.2 Random-effects model

A random-effects model is a statistical model that is used when we assume that $\mu_i$ – the omitted or time-invariant component of the error term – are uncorrelated with $x_{it}$ – the independent variables. Take the same model as before:

$$ y_{it} = x'_{it} \beta + \mu_i + \epsilon_{it} $$  \hspace{1cm} (3)

but now instead of considering $\mu_i$ as constant for each individual, we assume that it is a random variable. In other words, the random-effects assumption refers to the uncorrelated individual-specific effects with the independent variables (the time-invariant characteristic $\mu_i$ is purely random and uncorrelated with $x_{it}$). Contrary to random effects, the fixed-effects assumption is that the individual-specific effects are indeed correlated with the independent variables. We can estimate a panel data model with either of the two models. Which one will be better (more efficient)? It depends on which one of the two assumptions is true in the data. The discussion of the tests to assess which model fits the data best is beyond the scope of this teaching material but it is worthwhile noting that in practice most papers use fixed-effects models (see Box 2).

<table>
<thead>
<tr>
<th>Fixed effects vs. random effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>In econometrics, fixed-effects models control for, or &quot;partial out&quot; the effects of omitted (unobserved) time-invariant variables that are correlated with one or more observed variables included in the model. This is true regardless of whether or not the time-invariant variables are explicitly measurable. By time-invariant variables, we mean variables whose value does not change over time; by time-invariant effects, we mean that the variables have the same effect on the dependent variable over time.</td>
</tr>
<tr>
<td>In a random-effects model, the omitted variables are assumed to be uncorrelated with (or, more strongly, statistically independent of) all the observed variables included in the model. This assumption will often not be valid, but a random-effects model may be still desirable under some circumstances.</td>
</tr>
</tbody>
</table>
Fixed effects vs. random effects

<table>
<thead>
<tr>
<th>Box 2</th>
<th>3.3 Dynamic panel data models</th>
</tr>
</thead>
<tbody>
<tr>
<td>There are three criteria you may wish to follow for choosing whether random or fixed effects best fit the model you need to estimate:</td>
<td></td>
</tr>
<tr>
<td><strong>(a) The nature of the variables that have been omitted from the model</strong></td>
<td></td>
</tr>
<tr>
<td>• If you think that you are not omitting any additional explanatory variables, or if you can justify that the omitted variables are uncorrelated with the explanatory variables included in the model, then a random-effects model is probably what you should use. It will produce unbiased estimates of the coefficients, use all the data available, and produce the smallest standard errors.</td>
<td></td>
</tr>
<tr>
<td>• However, if there are omitted variables, and these variables are correlated with the variables included in the model, then a fixed-effects model is the most appropriate for controlling for omitted variable bias. The idea is that whatever effects the omitted variables have on the dependent variable at a given time, they will also have the same effect at a later time; hence, their effects will be constant or “fixed”. Note that in order to apply the fixed-effects model, the omitted variables must satisfy the condition of being time-invariant values with time-invariant effects.</td>
<td></td>
</tr>
<tr>
<td><strong>(b) The amount of variability within the independent and dependent variables</strong></td>
<td></td>
</tr>
<tr>
<td>• If subjects – i.e. the key dependent variable and independent variable – change little or not at all over time, a fixed-effects model may not work very well. There needs to be within-dimension variability in the variables. If there is little variability, then the standard errors produced by the fixed-effects model may be too large, and it would be better to employ a random-effects model.</td>
<td></td>
</tr>
<tr>
<td>• A random-effects model will often produce smaller standard errors. However, there is a trade-off: the coefficients produced by applying random-effects are more likely to be biased if the assumption that there are no omitted variables is violated (which is most often the case).</td>
<td></td>
</tr>
<tr>
<td><strong>(c) Control vs. effect of time-invariant variables</strong></td>
<td></td>
</tr>
<tr>
<td>• A fixed-effects model does not estimate the effects of variables whose values do not change over time. Instead, it controls for them or “partials them out”.</td>
<td></td>
</tr>
<tr>
<td>• A random-effects model estimates the effects of time-invariant variables, but the estimates may be biased if you incorrectly assume that there are no omitted variables in the model. Source: Allison (2009).</td>
<td></td>
</tr>
</tbody>
</table>

We get a dynamic panel data model when we add to the independent variables of a panel data model the lagged value of its dependent variable. In other words, dynamic panel data models introduce the temporal dependency of the dependent variable into the equation. In equations, the latter can be represented as:

\[ y_t = \delta y_{t-1} + x_t' \beta + \mu_t + \epsilon_t \]  

(4)

where \( y_{t-1} \) is the lagged value of \( y_t \). In this model, we have two sources of persistence: \( y_{t-1} \) and \( \mu_t \). If we use an estimator like ordinary least squares or fixed effects, the estimations will be biased and inconsistent because by construction, both \( y_t \) and \( y_{t-1} \) depend on \( \mu_t \), and \( y_{t-1} \) is correlated with \( \mu_t + \epsilon_t \). We therefore need a different estimator that gets around this problem. Arellano and Bond (1991) provide an appropriate solution. Assuming for simplicity that \( \beta = 0 \), our model is now:

\[ y_t = \delta y_{t-1} + \mu_t + \epsilon_t \]  

(5)

If we subtract \( y_{t-1} \) from both sides we get:

\[ \Delta y_t = \delta \Delta y_{t-1} + \Delta \epsilon_t \]  

(6)

In this equation \( \mu_t \), which was creating problems, has disappeared. The first period for which we have this relationship is \( t = 3 \), where we have:

\[ \Delta y_3 = \delta \Delta y_2 + \Delta \epsilon_3 \]  

(7)

In this case, \( y_1 \) is a valid instrument as it is correlated with \( \Delta y_2 = y_2 - y_1 \), but is not correlated with \( \Delta \epsilon_3 \). In \( t = 4 \), the relationship is:

\[ \Delta y_4 = \delta \Delta y_3 + \Delta \epsilon_4 \]  

(8)

In this case, \( y_2 \) and \( y_3 \) are valid instruments. Using the same logic, the valid instruments for \( T \) are \( y_1 \), \( y_2 \), ... , \( y_{T-2} \). Arellano and Bond provide an estimator, the generalized method of moments (GMM), which optimally combines all these instruments.

In the following two sections, we will see how variants of these panel data models are used in the trade and gender literature.
4 Hands-on application I: “Women’s status and economic globalization” (Richards and Gelleny, 2007)

4.1 Context and overview

Richards and Gelleny (2007) study the relationship between economic globalization and the status of women by looking at arguments advanced both by proponents and sceptics of globalization. According to the authors, addressing this issue has value for two main reasons. The first is because economic globalization is state-induced ("globalization from above"): those typically most adversely affected by globalization have no voice in its implementation. Therefore, it is important to provide a clear understanding of its nature. Second, the authors want to bridge a theoretical disconnect that exists in the literature between papers applying macro-level analytical methods and those looking at the effects of globalization on particular vulnerable groups that often do not use theoretically oriented methodologies at the country-year or macro levels of analysis. The authors use a panel of 150 countries between 1982 and 2003 and check robustness using alternative measures of economic globalization and women’s status. Table 13 provides an overview of their paper.

Table 13

Overview of Richards and Gelleny (2007)

<table>
<thead>
<tr>
<th>Objective</th>
</tr>
</thead>
<tbody>
<tr>
<td>The objective of the paper is to analyse the relationship between economic globalization and the status of women.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Methodology</th>
</tr>
</thead>
<tbody>
<tr>
<td>• The authors use five different measures of women’s status as the dependent variable.</td>
</tr>
<tr>
<td>• The choice of estimation techniques depends on the nature of the dependent variable:</td>
</tr>
<tr>
<td>- For the United Nations indicators of women's status, the authors use a generalized estimation equation (GEE) technique with robust standard errors;</td>
</tr>
<tr>
<td>- For the Cingranelli-Richards (CIRI) indicators (ordinal variables) of women's status, the authors use the ordered logit estimation technique.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Sample description</th>
</tr>
</thead>
<tbody>
<tr>
<td>• 130 countries</td>
</tr>
<tr>
<td>• Period of analysis: 1982–2003</td>
</tr>
<tr>
<td>• Panel data</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Equation estimated</th>
</tr>
</thead>
<tbody>
<tr>
<td>( y_{it} = a + \beta_1 \text{Open}<em>{it} + \beta_2 \text{FDI}</em>{it} + \beta_3 \text{Portfolio}<em>{it} + \beta_4 \text{SAP}</em>{it} + \beta_5 \text{Development}<em>{it} + \beta_6 \text{Regime}</em>{it} + \varepsilon_{it} )</td>
</tr>
</tbody>
</table>

Note:
- In the CIRI indicators equations, the authors also control for the lagged dependent variable (\( y_{it-1} \)) to account for serial correlation;
- All variables are observed for country \( i \) and year \( t \).

<table>
<thead>
<tr>
<th>Dependent and independent variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>The dependent variable (( y )) are five different measures of women's status:</td>
</tr>
<tr>
<td>- Gender-Related Development Index (GDI) from the United Nations Human Development Report</td>
</tr>
<tr>
<td>- Gender Empowerment Measure (GEM) from the United Nations Human Development Report</td>
</tr>
<tr>
<td>- Women's economic status from the CIRI database</td>
</tr>
<tr>
<td>- Women's political status from the CIRI database</td>
</tr>
<tr>
<td>- Women's social status from the CIRI database</td>
</tr>
</tbody>
</table>

Six independent variables (\( x \)) are used to measure globalization:
- Trade openness: total value of a country’s imports and exports of goods and services as a percentage of GDP (Open)
- Foreign direct investment: net inflow of investment as a percentage of GDP (FDI)
- Portfolio investment: net amount of transactions in equity securities and debt securities, expressed as a percentage of a country's GDP (Portfolio)
- Structural Adjustment Programmes: a dummy variable to account for the effects of the IMF and World Bank Structural Adjustment Programmes (SAP)
- Development: log of per capita GDP as a proxy of the level of development of the country (Development)
- Democracy: ordinal regime-type indicator from the Polity IV to measure the level of democracy in the country (Democracy)

<table>
<thead>
<tr>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Women’s status in a given country is associated with that country’s involvement in the global economy.</td>
</tr>
<tr>
<td>• On average, economic globalization improves women’s status. 67% of the statistically significant globalization coefficients indicated an association with improved women’s status.</td>
</tr>
<tr>
<td>• However, the relationship between economic globalization and women’s status differs by type of globalization; type of status, and era.</td>
</tr>
<tr>
<td>• Trade openness has a generally positive influence on women’s status;</td>
</tr>
<tr>
<td>- Portfolio investment is associated with lower scores on the CIRI women’s economic and social rights indicators and the UN’s GEM measure;</td>
</tr>
<tr>
<td>- FDI does not show a statistically significant effect on women’s status;</td>
</tr>
<tr>
<td>• There is weak empirical support for the proposition that SAP implementation affects women’s status.</td>
</tr>
</tbody>
</table>

Source: Richards and Gelleny (2007)
4.2 Data sources

The dependent variables in the analysis are indicators that measure women’s status. The authors use five different indicators to control for the sensitivity of any finding to a particular indicator.

The first two indicators of women’s status are related to human rights and are drawn from the United Nations’ annual Human Development Report. This report includes two gender-specific indices covering the political, economic, and social dimensions of development: (a) the Gender-Related Development Index, and (b) the Gender Empowerment Measure. The GDI is a composite index that measures longevity (measured by life expectancy at birth), knowledge (measured by a combination of the adult literacy rate and the combined primary, secondary, and tertiary gross enrolment ratio), and standard of living (measured by GDP per capita in United States dollars in purchasing power parity terms). These features are combined in a manner so as to penalize gender inequality. The GEM is a composite index measuring gender inequality in three dimensions of empowerment: economic participation and decision-making power (measured as female shares of professional/technical positions and female shares of positions as legislators, senior officials, and managers); political participation and decision-making (measured as the female share of parliamentary seats); and power over economic resources (measured as women’s estimated earned income as compared to that of men). Both indexes, the GDI and the GEM, range from 0 to 1.0, with a higher score being more desirable than a lower score.

The authors also use three government indicators for women’s economic, political, and social rights from the CIRI Human Rights Dataset (Cingranelli and Richards, 2005). The CIRI economic rights indicator includes women’s rights to equal pay for equal work, free choice of employment, gainful employment without the need to obtain spousal consent, equality in hiring and promotion practices, job security, non-discrimination by employers, freedom from sexual harassment in the workplace, and the right to work at night, to work in dangerous occupations, and to work in the military and police force. The CIRI political rights indicator includes women’s rights to vote and/or run for political office, hold elected and appointed government positions, join political parties and petition government parties. The CIRI social rights indicator includes women’s rights to equal inheritance; enter into marriage on a basis of equality with men; travel abroad; obtain a passport; confer citizenship to children or a husband; initiate a divorce; own, acquire, manage, and retain property brought into marriage, participate in social, cultural, and community activities; obtain an education; freely choose a residence/domicile; to be free from female genital mutilation of children and adults without their consent; and to be free from forced sterilization. All three indicators are ordinal and range from 0 to 3, with a score of 3 representing the highest level of government respect for women’s rights, both in law and in practice.

The most important explanatory variables in Richards and Gelleny (2007) are those related to globalization. The authors use four indicators to account for a country’s level of economic globalization: FDI (net flows as a percentage of GDP), portfolio investment (net amount of transactions in equity securities and debt securities, expressed as a percentage of a country’s GDP), trade openness (total value of a country’s imports and exports of goods and services as a percentage of GDP), and structural adjustment policy implementation (dichotomous measure to account for the IMF and World Bank Structural Adjustment Programmes). The first three measures are from the World Bank’s 2005 World Development Indicators dataset. The last measure is from Abouharb and Cingranelli (2006).

Richards and Gelleny (2007) also control for the level of democracy in the country (using the Polity IV dataset) and its level of development (proxied by log of per capita GDP from the World Bank’s WDI, 2005). The expectations are that, on the one hand, democratic regimes are more likely to implement and enforce laws promoting women’s rights, and, on the other, countries with a higher level of economic development are more likely to provide all citizens with higher levels of income, thereby potentially giving women better prospects of social, political, and economic empowerment.

4.3 Empirical methodology

Richards and Gelleny (2007) use two different empirical methodologies according to the nature of the dependent variable.

Both the GEM and GDI data are interval-level, pooled cross-section, time-series data (with significantly more cross-section observations than temporal units). To deal with this type of data, the authors use the GEE estimation technique with robust standard errors. This approach extends generalized linear models to a regression setting with correlated observations within subjects, i.e. repeated observations on individuals over time.
and/or clustered observations. In these cases, the use of ordinary models to analyse data with correlated observations tends to produce incorrect standard errors and p-values for regression coefficients. Models that ignore clustering tend to underestimate standard errors of regression coefficients for covariates. However, with time-varying covariates, standard models may tend to overestimate standard errors. To solve this, we use GEE. This estimation technique can be used with a variety of models (linear, logistic, Poisson, etc.) and uses robust estimation of standard errors to allow for clustering. The robust standard errors are derived using the observed variability in the data rather than the variability predicted by an underlying probability model (which produces model standard errors).

The methodology applied in the estimations of the equations with the GDI and GEM indicators as dependent variables cannot be applied when the dependent variables come from the CIRI database, since the three CIRI indicators are ordinal (taking values 0, 1, 2, and 3). The authors therefore use the ordered logit estimation technique to estimate these models. A logit regression is a non-linear regression model that forces the output (predicted values) to be either 0 or 1 (estimating the probability of an outcome). When a dependent variable has more than two categories and the values of each category have a meaningful sequential order, where a value is indeed “higher” than the previous one, then you can use ordinal logit. This type of model is an extension of the logistic regression model that is applied to dichotomous dependent variables, allowing for more than two (ordered) response categories. The only difference is that the ordered logit model estimates the probability of each outcome as a subtraction of a cumulative probability. The authors incorporate a lagged dependent variable in this model to account for serial correlation, and also adjust standard errors to account for country-specific clustering. To account for the fact that the level of globalization was very different at the beginning and end of their sample period, the authors divide their sample into pre-globalization and globalization eras.

4.4 Step-by-step explanation of how to do the estimations in Stata

Together with this module, you are provided with the do-files that Richards and Gelleny created to run the estimations included in the paper. The authors created a do-file that only contains the commands for applying the GEE and the ordered logit model. Therefore, you need to open the statistical software first, set a memory level that is reasonable for the analysis (for instance, 100m), as we have explained in Module 1 of this volume, and then open the dataset (DR_RG_ISQ_07a.dta) manually. You can then open the do-file “STATA Richards”.

The structure of the do-file has eight command lines, two for each table. The first two lines estimate the GEE model, the results of which are shown in Table 1 in the Richards and Gelleny paper. One line corresponds to the GEM variable (gem) and the other to the GDI variable (gdi). Lines 3–8 estimate the ordered logit model for the other three variables: women’s economic rights (wecon) (see Table 2 in the paper), women’s political rights (wopol) (see Table 3 in the paper), and women’s social rights (wosoc) (see Table 4 in the paper). For each of the three variables, the data are divided into two sub-samples – pre- and post-1992 – because 1992 is the cut-off the authors choose to indicate the pre-globalization and globalization eras. Note that to do this, the authors created a dummy variable globz, taking a value of zero for data corresponding to years before 1992 and a value of one after 1992.

The Stata command to implement the GEE technique is xtgee (please refer to Stata help xtgee for a detailed explanation of the command). This command estimates longitudinal models and allows you to specify the within-group (within-subject) correlation structure. Using the command xtgee is equivalent to using the command xtreg, pa (the command for the estimation of the parameters of a linear panel data model using population averages).

Step 1: Run the GEE model for the GEM variable

For GEM as the dependent variable, the complete Stata command to estimate column 1 in Table 1 of the paper is:

```stata
xtgee gem tradeopenness_unlogged fdi_unlogged portgdp
gem sap_implementation gdppercap_logged democracy, i (country) t (time) robust
```

The command xtgee is followed by the dependent variable (gem), the four measures of globalization (tradeopenness_unlogged, fdi_unlogged, portgdp, and sap_implementation), the measure of economic development (gdppercap_logged), and the level of democracy (democracy). The dimensions i (country) and t (time) define the unit of analysis and the time dimension of the panel data. The option robust is included to obtain cluster-robust standard errors.
Step 2: Run the GEE model for the GDI variable

For the GDI variable (column 2 in Table 1), the command is the same, just replacing `gem` for `gdi`:

```stata
xtgee gdi tradeopenness_unlogged fdi_unlogged portgdp sap_implementation gdppercap_logged democracy, i (country) t (time) robust
```

Step 3: Run the ordered logit model for the women's economic rights variable

The Stata command to implement the ordered logit technique is `ologit` (see Stata help `ologit` for a detailed explanation of the command). This command fits ordered logit models of an ordinal dependent variable. The actual values taken on by the dependent variable are irrelevant, except that larger values are assumed to correspond to "higher" outcomes. The sign of the regressions parameters can be interpreted as determining whether the (latent) dependent variable increases with the regressor. If \( \beta \) is positive, then an increase in \( x \), reduces the probability of being in the lower category, and increases the probability of being in a higher category of \( y \).

For women's economic rights (\( wecon \)) as the dependent variable, the complete Stata command to estimate column 1 in Table 2 of the paper is:

```stata
ologit wecon wecon_lag1 tradeopenness_unlogged fdi_unlogged portgdp sap_implementation gdppercap_logged democracy, i (country) t (time) robust
```

For women's social rights (\( wosoc \)) the same command syntax (column 2 in Table 2) for the period of globalization (\( globz=1 \)):

```stata
ologit wosoc wosoc_lag1 tradeopenness_unlogged fdi_unlogged portgdp sap_implementation gdppercap_logged democracy if globz==1 & year>1981, cluster(polity) robust
```

Step 4: Run the ordered logit model for the women's political rights variable

The do-file then repeats the same estimation procedure replacing the women's economic rights (\( wecon \)) variable with the political (\( wopol \)) and social (\( wosoc \)) rights measures.

For Table 3, column 1 in the paper:

```stata
ologit wopol wopol_lag1 tradeopenness_unlogged fdi_unlogged portgdp sap_implementation gdppercap_logged democracy if globz==0 & year>1981, cluster(polity) robust
```

For Table 3, column 2 in the paper:

```stata
ologit wopol wopol_lag1 tradeopenness_unlogged fdi_unlogged portgdp sap_implementation gdppercap_logged democracy if globz==1 & year>1981, cluster(polity) robust
```

Step 5: Run the ordered logit model for the women's social rights variable

For Table 4, column 1 in the paper:

```stata
ologit wosoc wosoc_lag1 tradeopenness_unlogged fdi_unlogged portgdp sap_implementation gdppercap_logged democracy if globz==0 & year>1981, cluster(polity) robust
```

For Table 4, column 2 in the paper:

```stata
ologit wosoc wosoc_lag1 tradeopenness_unlogged fdi_unlogged portgdp sap_implementation gdppercap_logged democracy if globz==1 & year>1981, cluster(polity) robust
```
4.5 Discussion of findings and limitations of the analysis

The authors find that in most specifications, there is a relationship between the level of globalization of that country and the status of women. However, the relationship depends on the type of globalization we are considering, the type of status (economic, political, or social), and the period under consideration (before or after 1992). In most cases, globalization is associated with improvements in women’s status (a positive statistically significant coefficient), but there are negative coefficients for some variables (in particular the ones associated with the portfolio variable), and in some cases the coefficient is not statistically significantly different from zero.

These results show one of the difficulties of trying to establish relationships between aggregate macroeconomic variables using cross-section and panel regressions. The estimations of Richards and Gelleny show that, depending on the variables and time period we select for the analysis, the result could be different. There is also the possibility of omitted variables that may bias some of the results, which shows the difficulties the analyst faces when deciding on the set of relevant control variables that will be needed to account for the many dimensions in which the countries included in the sample differ. Another drawback with this type of analysis is the difficulties encountered when trying to establish causality between the variables. For instance, women’s status and the level of globalization could be caused by a common variable that was omitted in the analysis (e.g. the level of institutional development of the country).

Note that the authors assume somehow that what matters for women’s status is the level of globalization and not how this globalization happens (for instance, they do not ask if it matters with what countries an economy is trading). It could be argued that countries that trade with partners where women enjoy better status may benefit from spillover and demonstration effects. Something similar could be argued about FDI flows. In what follows, we will present a second paper that deals with the issues that were not addressed by Richards and Gelleny.

5 Hands-on application II: “Globalization and the empowerment of women: An analysis of spatial dependence via trade and foreign direct investment” (Neumayer and de Soysa, 2011)

5.1 Context and overview

Similar to Richards and Gelleny (2007), Neumayer and de Soysa (2011) also look at the effect of general openness to trade and FDI on women’s rights. However, their paper aims to identify a specific channel through which trade may affect the status of women, and it systematically addresses the question of whether trade and investment linkages can enable the empowerment of women. What matters in their analysis is not only if you trade but with whom you trade. However, the paper does not analyse the effects of certain policies often associated with globalization, such as capital account liberalization, trade liberalization, investment incentives, etc. The authors also do not analyse other important aspects of globalization, such as migration and the illegal trafficking of people.

The authors depart from previous studies in two important ways. First, they employ broader measures of women’s rights that include both economic and social rights (such as marriage and divorce rights, the right of movement, the right to property, the right to participate in social activities, the right to education, the right to inherit, etc.) as a better gauge of women’s empowerment than simple measures of the wage gap and employment ratios. Second, they examine whether it matters with whom one trades and from whom one receives FDI, whereas existing studies have only examined general openness to trade and FDI. For example, if a country mainly trades with and receives FDI from countries that violate rights, we would not expect domestic rights to be enhanced.

The paper is similar to the one by Richards and Gelleny both in terms of the questions being addressed and some of the data used. However, it is interesting to discuss these issues here to show how the same questions can be addressed from a different angle and using a different methodology. Table 14 provides an overview of the Neumayer and de Soysa paper.
The macroeconomic approach

Objective

The objective of the paper is to analyse whether the foreign country with which a country trades and from which it receives FDI matters for women’s economic and social rights in the home country. The main question is the following: If a country trades and receives FDI from countries where women’s status is high, would that lead to a higher status for women in the home economy?

Methodology

- The authors apply the “ordered logit” estimation method.
- However, ordered logit models do not allow to estimate country-fixed effects, alternatively, the authors use regional dummies.
- When the lagged dependent variable is added as an explanatory variable, Arellano and Bover’s system-GMM estimator is employed.

Sample description

- 152 countries
- Panel data

Equation estimated

\[
y_{it} = \alpha + \beta_1 y_{it-1} + \beta_2 GDP_{pcit} + \beta_3 democracy_{it} + \beta_4 trade_{it} + \beta_5 FDI_{it} + \beta_6 \sum_k w_{ikt-1} trade_{it} y_{kt-1} + \beta_7 \sum_k w_{ikt-1} FDI_{it} y_{kt-1} + \delta_t + \epsilon_{it}
\]

- Variables are observed for country \(i\), year \(t\), and partner country \(k\) (for trade or FDI).
- \(w\) are the weights estimated as the share foreign countries \((k)\) have in trade and FDI stock of partner country \(i\) under observation.

Dependent and independent variables

Two dependent variables \(y\), both from Cingranelli and Richards’ (2009) Human Rights Database:
- Measure of women’s economic rights
- Measure of women’s social rights

Two main explanatory variables (the spatial lag variables):
- Women’s rights in foreign countries weighted by the amount of trade of each country with its trading partners \((w_{trade_{ikt-1}})\)
- Women’s rights in foreign countries weighted by the amount of FDI received by each country from foreign countries \((w_{FDI_{ikt-1}})\)

Other control variables:
- \(GDP_{pc}: \log\) of per capita income in constant 2000 $ at market exchange rates (from the World Bank)
- \(democracy\): Polity II variable as a measure of democracy (from the Polity IV dataset)
- trade/GDP – trade openness measured as the ratio of the sum of exports and imports to GDP (from the World Bank)
- FDI/GDP – trade openness to FDI measured as the value of the total stock of inward FDI relative to GDP (from UNCTAD)
- \(\delta\) – time-fixed effects

Results

The paper finds that who you trade with matters for the status of women:
- Spillover effects on women’s economic and social rights:
  - The trade-weighted spatial lag effect is positive and significant in most specifications;
  - One exception: the sample including only low-income countries.
- FDI links seems to matter less for women’s rights:
  - Spillover effects on women’s economic and social rights are limited and weak;
  - The FDI-weighted spatial lag effect is positive and significant only for economic rights in middle-income countries.
In general terms, trade openness seems to be conducive to stronger women’s economic rights, whereas general FDI openness seems to not matter much.


5.2 Data sources

The measures of women’s economic and social rights, which represent the dependent variables in the analysis, are taken from the CIRI Human Rights Database. These data are also utilized by specialized agencies monitoring the progress of women in the economic and social spheres of their lives (UNIFEM, 2008).

Table 15 lists women’s economic and social rights covered in the database that are used for the estimations in Neumayer and de Soysa (2011). An older version of this dataset (Cingranelli and Richards, 2005) was used in the Richards and Gel-leny (2007) paper.
The main explanatory variables are the spatial lagged variables. They capture the dependent variable (i.e., women’s rights) in foreign countries, weighted by some link function connecting each country to its trading partners and the source countries of FDI, \( w^{\text{trade}} \) and \( w^{\text{FDI}} \), respectively.\(^76\)

Other control variables included in the analysis are trade openness, measured as the ratio of the sum of exports and imports to GDP, taken from the World Bank’s WDI (2009) \( (\text{trade}/\text{GDP}) \); openness to FDI, measured as the value of the total stock of inward FDI relative to GDP, taken from UNCTAD (2009) \( (\text{FDI}/\text{GDP}) \); the natural logarithm of per capita income in constant 2000 $ at market exchange rates, taken also from the World Bank’s WDI \( (\text{GDPpc}) \); and a measure of democracy from the Polity IV dataset \( (\text{democracy}) \).\(^77\)

### 5.3 Empirical methodology

The spatial patterns\(^78\) in women’s rights are often not caused by spatial dependence\(^79\) but by observable as well as unobservable phenomena – such as cultures and customs, preferences and perceptions, constitutions and institutions, etc. – that are typically spatially clustered. These unobservable variables might lead to spatial patterns in the dependent variable, even in the absence of spatial dependence. A popular method for mitigating the problem created by spatial clustering is the inclusion of country-fixed effects. Such models take out all of the “between” variation in the data and are estimated based on the “within” variation of the data in each observational unit only (each of the countries in the study). This reduces bias because any spatial clustering or unobserved spatial heterogeneity in the levels of women’s rights is fully captured by the fixed effects.

However, the authors cannot apply country-fixed effects here because of the nature of their dependent variable (women’s economic and social rights taken from Cingranelli and Richards, 2009). Women’s economic and social rights are measured as ordered categorical variables, which take on values 0, 1, 2, or 3. Thus, we need to use an ordered logit or probit model, and this type of econometric technique does not allow for using country-fixed effects. As a compromise, the authors include regional rather than country-fixed effects in ordered logit estimations, using dummy regional variables. They later consider a model that adds a lagged dependent variable and use Arellano and Bover’s (1995) system-GMM estimator to perform the analysis. This estimator is preferable to a standard fixed-effects estimator because it can treat both the lagged dependent variable and the spatial lagged variables as endogenous.

Another problem of spatial analysis in cross-sectional time series analysis is that of common shocks and common trends, such as a general increase in awareness of women’s rights over time. The authors control for this by including year-fixed effects representing separate intercepts for each year of the period under study, as well as the temporally lagged dependent variable.
5.4 Step-by-step explanation of how to do the estimations in Stata

The file “Article for World Development (women’s rights).do” contains the do-file to reproduce the tables in Neumayer and de Soysa (2011). The structure of the file is slightly more complicated than the previous one. We will therefore split the task into several steps.

**Step 1: Declare type of data**

Sometimes Stata does not recognize that the data have a time series dimension, so we need to indicate that using the command `tsset`. We can tell Stata we have a time series using `tsset plus the name of the variable measuring time`. If we have a panel, we use the same command followed by the variable recording the individual dimension (in this case the country) and the time dimension (e.g. year).

In this particular case, the command is:

```
.tsset countryid year
```

**Step 2: Fix the estimation sample and construct basic descriptive statistics**

We will create a table with sample statistics of the main variables (Table 2 in the Neumayer and de Soysa paper) and their correlation matrix (Table 3 in the paper). When we run and present multiple analyses for the same paper, we often want to keep the same sample across all our models and estimations. If we do not indicate this to Stata, different models can have different sample sizes because different variables have different patterns of missing data (e.g. unbalanced panels). We can avoid this by using the command `e(sample)` that creates a variable that records the estimation sample, i.e. the sample used in the most recent statistical command. For this reason, the authors first run the estimation of the ordered logit model they will later use in order to fix the sample for the analysis. They use the command `quietly` because they do not want to display the results of the estimation. Since the dependent variable is categorical, as in the Richards and Gelleny paper reviewed above, the estimation command is `xi: quietly ologit`. We use the command `xi` to tell Stata to create dummy variables for variables preceded by an `i.` prefix. For example, by adding `i.year` to the list of dependent variables, Stata will create year dummy variables. We regress the variable measuring women’s economic status using both FDI stocks (`l.wesocfdiinstockslrowst`) and bilateral trade flows (`l.wesoctradeflows`) as weights, and, finally, the region dummies (`i.year`) and the region dummies. Note that the authors could have listed the regional dummies one by one (`reg_eap reg_eca reg_lac reg_mena reg_na reg_sa reg_ssa reg_we`), but they preferred to use the suffix `_*`, which is a shortcut that tells Stata to use all the variables that have the same root (in this case “reg_*”).

We can summarize the variables of interest to obtain the number of observations, mean, standard deviation, and minimum and maximum values of each variable using the command `summarize`, here abbreviated as `su`. Note that we are asking Stata to use the observations that were included in the previous regression and defined as the sample we will work with throughout the entire paper.

```
x: su wecon lngdpconstpc polity2 trade fdiinstocktoxgd  
    l.wesocfdiinstockslrowst 
    l.wesoctradeflows i.year reg_*, robust cluster(country)
```

Similarly we ask Stata to produce the correlation matrix between the relevant variables using the Stata command `corr`. Note that we have also included here women’s social status and the trade-weighted spatial lag and FDI-weighted spatial lag variables, using the social status of women abroad.

```
x: corr wecon lngdpconstpc polity2 trade fdiinstocktoxgd 
    l.wesocfdiinstockslrowst 
    l.wesoctradeflows if e(sample)
```

We repeat the first quiet regression using women’s social status (`l.wosoc`) instead of economic status (`l.wecon`) as the dependent variable, and we summarize the variables related to women’s social status to include them in Table 2 of the paper.

```
x: quietly ologit l.wosoc lngdpconstpc polity2 trade fdiinstocktoxgd 
    l.wesocfdiinstockslrowst 
    l.wesoctradeflows l.wosoc i.year reg_*, robust cluster(country)
```

"The macroeconomic approach"
The macroeconomic approach

3

module

Table 4 in the paper shows estimates for all countries (columns 1–3) and developing countries only (columns 4–6). The estimator used is ordered logit in models 1–2 and 4–5 and system-GMM in models 3 and 6. Models 1–2 and 4–5 contain regional dummy variables, while models 3 and 6 contain country-fixed effects. Year-specific fixed effects are always included.

As before, we use the command ologit to estimate the ordered logit model. We ask Stata to create and include year dummy variables using xi and i.year. We regress women’s economic status (wecon) on the given independent variables and ask Stata to estimate robust standard errors using the country as the cluster by adding the option robust cluster(country).

We repeat the procedure including a lag of the dependent variable (l.wecon). Results in column 2 of Table 4 in the paper are found by running the following command:

xi: ologit wecon lngdpcnstpc polity2 trade fdiinstocktgdgp
  l.wconfdiinstockslrowst
  l.wecontradeslrowst i.year reg_*, robust cluster(country)

We only keep those countries that are not high-income OECD countries (inc_highoecd==0) using the command keep:

keep if inc_highoecd==0

We use the command xtabond2 to tell Stata that we will modify the data but that we want the programme to keep (preserve) the original dataset to eventually recover it (with the command restore):

preserve

However, when we include a lag of the dependent variable, our panel becomes dynamic. By construction, the unobserved country-level effects are correlated with the lagged dependent variable, making standard estimations like the one above inconsistent. Arellano and Bond (1991) and Arellano and Bover (1995) derived a consistent GMM estimator for the parameters of this type of model. The Stata command for this procedure is xtabond2. There are other closer command versions xtobond and xtdpd, but the explanation of the differences between them is beyond the scope of this material. Note that xtabond2 is not an official Stata command, but a free contribution to the research community (see Roodman, 2009). To install it, type ssc install xtabond2, replace in Stata. If you do not want to install xtabond2, you can use the command xtabond and get similar results. See Stata help for xtabond. An interesting feature of the xtabond2 is that it allows you to determine the variables you would like to include in the GMM estimation as instrumental variables (IV).

The results presented in Table 4 of the paper are those generated by the command xtabond2.

We can repeat the same procedure but considering a sub-sample of developing countries only.

We start by installing xtabond2 using the command:

ssc install xtabond2, replace

We can repeat the same estimation procedure we applied for columns 1–3 to get results in columns 4–6.
We recover the original dataset (both developing and OECD countries) by typing:

```
restore
```

**Step 4: Estimate results for women’s social**

To generate Table 5 in the paper, we repeat Step 3 replacing the economic rights variables (\textit{wecon}) by the social rights variable (\textit{wosoc}): 

** All countries**

```
**i: ologit wosoc lngdpconstpc polity2 trade fdiinstocktogo dp l.wosoctradeslrowst i.year reg_*, robust cluster(country)**
```

```
**i: ologit wosoc l.wosoc lngdpconstpc polity2 trade fdiinstocktogo dp l.wosoctradeslrowst, lag (2 8))**
```

**Step 5: Estimate the results for women’s economic and social rights in middle- and low-income countries**

We repeat the steps above for the sub-sample of low- and middle-income countries (Table 6 in the paper) using \textit{keep if inc\_low==1} and \textit{keep if inc\_middle==1}. Do not forget to use the commands \textit{preserve} and \textit{restore} to avoid modifying your original dataset. Note that all estimations in this step include the lagged dependent variable (\textit{l.wosoc}).

** Economic rights**

* Low-income countries only

```
**preserve
```

```
**keep if inc\_low==1
```

```
**i: ologit wecon l.wacon lngdpconstpc polity2 trade fdiinstocktogo dp l.wacontradeslrowst, lag (2 8))**
```

* Middle-income countries only

```
**preserve
```

```
**keep if inc\_middle==1
```

```
**i: ologit wecon l.wacon lngdpconstpc polity2 trade fdiinstocktogo dp l.wacontradeslrowst, lag (2 8))**
```
xi: xtabond2 wecon l.wecon lngdpconstpc polity2 trade fdiinstocktgdop  
1.weixinfidiinstokslrowst  
1.weixinfidiinstokslrowst i.year, robust  
iv(lngdpconstpc polity2 trade fdiinstocktgdopi.year) gmm(l.weixin  
1.weixinfidiinstokslrowst  
1.weixinfidiinstokslrowst, lag (2 8))
restore

** Social rights
* Low-income countries only

preserve
keep if inc_low==1

xi: ologit wosoc l.wosoc lngdpconstpc polity2 trade fdiinstocktgdop  
1.wosocfidiinstokslrowst  
1.wosoctradeslrowst i.year reg_*, robust cluster(country)

xi: xtabond2 wosoc l.wosoc lngdpconstpc polity2 trade fdiinstocktgdop  
1.wosocfidiinstokslrowst  
1.wosoctradeslrowst i.year, robust  
iv(lngdpconstpc polity2 trade fdiinstocktgdopi.year) gmm(l.wosoc  
1.wosocfidiinstokslrowst  
1.wosoctradeslrowst, lag (2 8))
restore

* Middle-income countries only

preserve
keep if inc_middle==1

xi: ologit wosoc l.wosoc lngdpconstpc polity2 trade fdiinstocktgdop  
1.wosocfidiinstokslrowst  
1.wosoctradeslrowst i.year reg_*, robust cluster(country)

xi: xtabond2 wosoc l.wosoc lngdpconstpc polity2 trade fdiinstocktgdop  
1.wosocfidiinstokslrowst  
1.wosoctradeslrowst i.year, robust  
iv(lngdpconstpc polity2 trade fdiinstocktgdopi.year) gmm(l.wosoc  
1.wosocfidiinstokslrowst

5.5 Discussion of findings and limitations of the analysis

The authors studied whether stronger women’s rights abroad translate into stronger economic and social rights in the home country via international trade and FDI linkages. On the one hand, the authors find evidence of spillover effects working via trade links for both women’s economic and social rights: \( w^{trade}_t \) is statistically significant across most of the estimated models. This result holds for all the sub-samples except the one restricted to low-income countries. On the other hand, the authors only find weak and limited evidence of spillover effects via FDI links for women’s economic or social rights: \( w^{FDI}_t \) is statistically significant only in a few cases. They also find that general trade openness (\( \text{tradeit}/\text{GDPit} \)) improves women’s economic and social rights in the home country whereas general FDI openness (\( \text{FDIit}/\text{GDPit} \)) contributes to the improvement of social rights, but not in developing countries.

Despite providing insightful evidence on the beneficial impact of trade openness on women’s rights, the paper has a few limitations. First, it cannot provide any conclusion on whether the improvement in women’s economic and social rights in absolute terms translates into greater gender equality in rights because the analysis does not consider any measure of men’s economic and social rights. Second, it does not provide any evidence supporting the assumption that improved rights for women leads to improved material outcomes for them.

From a technical point of view, most of the caveats we discussed for Richards and Gelleny (2007) – including the possibility of establishing causality, the problems of defining the variables, and of controlling for the many dimensions of heterogeneity, etc. – apply as well to Neumayer and de Soysa (2011).

6 Conclusions

This module discussed the macroeconomic approach that employs country-level data to study the relationship between trade and gender. Since the increased level of globalization starting in the 1990s and the liberalization policies carried out by many developing countries in the following decade, economists’ primary concern has been to study the relationship between trade, growth,
and poverty and income inequality. Subsequent ly, economists also started to be interested in establishing the links between trade liberalization and gender inequality. The basic idea is that trade has gender consequences because it brings structural transformations that have different repercussions on men and women depending on the role they play in the economy as a whole.

Although most studies have focused on the effects of trade on labour market outcomes (i.e. women’s share of employment in the manufacturing sector, the gender wage gap, etc.), some studies have analysed if and how trade, and more broadly globalization, can contribute to the empowerment of women. For example, the papers reviewed in this module represent a cross-country assessment on how trade openness in practice and trade orientation can improve women’s status in political, economic, and social terms. In terms of trade openness in practice, the papers analysed here seek to capture the level of liberalization of countries by measuring the amount of trade flows; in terms of trade orientation, the aim is to capture the spillover effect on women’s rights from one country to another by focusing on a country’s main trading partners rather than the volume of trade. The trade analysis can be extended to include other measures of trade openness, such as changes in tariffs that, however, do not necessarily imply adjustments in the volume of exports and imports. As regards the status of women, the most widely used sources of data are the United Nations Human Development Report, the World Bank’s WDI, and the CIRI dataset (Cingranelli and Richards, 2014). There are also more recent sources of information on gender-related outcomes collected at the macroeconomic level, such as the Global Gender Gap Report launched by the World Economic Forum in 2006 or the Demographic and Health Surveys Program. Each trade- and gender-related measure has its advantages and shortcomings and there is no universal rule as to which measure you should choose for your own research. One point you should be aware of, however, is that the most appropriate measure of trade and gender inequality to employ is highly dependent on the scope of your study.

For the purpose of this module, the method reviewed is based on panel data econometric techniques that are useful when dealing with country-level data. The main characteristic of panel data is that they contain observations for a number of variables over a specified timeframe, thereby allowing us to assess the effect of a potential explanatory or independent variable on the dependent variable of interest over time (e.g. the impact of trade liberalization on the female labour force participation rate). This module described and compared two estimation methods by means of which we can estimate panel data models: the fixed-effects and random-effects models. Additionally, the module introduced dynamic panel data models that are used when we want to include among our explanatory variables (at least) the first-time lagged values of the dependent variable, thereby allowing us to control whether the dependent variable at the time of analysis is influenced by its past value. When following these methods, the macroeconomic approach becomes an ex-post analysis whereby we can investigate the effect of trade and gender after changes in a country’s trade patterns have taken place.
REFERENCES


