ILO EMPLOYMENT TRENDS UNIT

Trends Econometric Models:

A Review of the Methodology

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Table of Contents

List of Figures

List of Tables

Acknowledgments

The Trends Econometric Models, and in particular, the Global Employment Trends (GET) model presented in this paper have been developed and revised over the past 10 years, by the ILO Employment Trends Team, under the direction of Lawrence Jeff Johnson. The foundation of the methodology consists of the work of Wes Schaible, Lawrence Jeff Johnson, Maria Jeria Caceres, and Gustavo Crespi. The methodology benefited significantly from revisions undertaken by Jean Michel Pasteels, Steven Kapsos and Souleima El Achkar. Further technical contributions to the model were made by Theo Sparreboom, Yves Perardel, Ina Pietschmann and Francisco Guerreiro. A special acknowledgement is due to Sara Elder, Isabelle Guillet, Alan Wittrup and Philippe Blet for preparing the input data required for the models. The work presented here would not have been possible without the continued collaboration of the ILO Department of Statistics.

Trends Econometric Models: A Review of the Methodology

1. Introduction

The need to monitor progress toward the Millennium Development Goals (MDGs) at the country, regional and global levels, has refocused attention on the importance of developing adequate indicators and expanding data coverage. The collection, production and dissemination of comparable international statistics continue to be a major challenge for all international agencies. The first step is setting standard concepts and definitions that can be applied, and are relevant, to all countries. The second is building the capacity of government departments to collect, disseminate and analyze labour market data that conform to these standards. The final step involves making the best use of the data available to conduct research and analysis and to provide a basis for effective and informed policymaking. A particular challenge in this regard lies in producing regional and global aggregates for MDG indicators in the presence of inconsistent data across countries, and of missing data for some countries. Solid methodologies are necessary to address these issues in the short-term, while working towards the longer-term ideal of complete, comparable and regularly collected data from all countries.

During the past decade, the Employment Trends Unit of the International Labour Organization's (ILO) Economic and Labour Market Analysis Department, in collaboration with other departments, has made intensive efforts to compile and analyze country-level labour market information, and to produce a complete dataset of comparable cross-country statistics. The results of these efforts are compiled in the Key Indicators of the Labour Market (KILM) database.[1] The KILM is a significant collection and review of labour market indicators, allowing in-depth analysis of labour market conditions at both the country and regional levels. To complement available data and expand data coverage, the Trends Unit has developed a number of econometric models to produce estimates of labour market indicators, including labour force participation rates, unemployment rates, the share of workers in different sectors and by status in employment, and the share of the working poor in total employment, among others. A crucial element of the Trends Econometric Models is the methodology used to address the 'missing data problem'.

1.1 Measuring progress towards the MDGs

Several inter-agency and expert meetings on MDG indicators highlighted the difficulties and challenges in preparing regional and global figures for the MDG indicators. In response to these concerns, the ILO commissioned a report to identify key methodological issues and best practices.[2] The report, which was considered at the second meeting of the Committee for the Co-ordination of Statistical Activities (CCSA) held in Geneva in September 2003, identified a diversity of practice for measuring progress towards the MDGs at the regional and global levels by the UN agencies.[3] The report found that UN agencies often use different methodologies, generally involving some imputation technique, to address the missing data problem and to produce regional aggregates, but few agencies provide a detailed description of the methods they use. Although a standard methodology is not necessary, and indeed may not be desirable as the MDG indicators themselves vary considerably in terms of both statistical

[1] http://kilm.ilo.org/KILMnetBeta/default2.asp

[2] Holt, T. "Aggregation of National Data to Regional and Global Estimates" Report prepared for the Committee for the Coordination of Statistical Activities, Geneva, September 2003

[3] UNSD (2003) Inter-agency and Expert Meeting on Millennium Development Goals Indicators, held in Geneva, 10-13 November 2003 – Report of the meeting" E SA/STAT/AC.92/6, December 19, 2003

properties and data availability across countries and over time, “differences of practice ought to be based on rational statistical criteria” (Holt, 2003).

1.2 Development and evolution of the Trends Econometric Models and methodologies

Because statistics are fundamental to its work and mission, the ILO has made considerable efforts to expand data collection and improve its methods of producing statistics. In 1999, the ILO’s Employment Strategy Department commissioned a study of various methods of producing regional and global estimates of key labour market indicators. The resulting paper[4] published in 2000, presented and assessed two approaches: 1. Imputation methods for estimation in the presence of missing data, and 2. Indirect or small area estimation. These approaches are described in section 2. The paper concluded that the best approach to generating regional and global estimates consisted in treating the problem as a missing data problem. The recommended methodology was used in a follow-up report[5] published in 2002, to produce regional and global estimates for four key labour market indicators: the labour force participation rate, the employment-to-population ratio, the unemployment rate and the youth unemployment rate.

The methodologies and approaches used in the Trends Econometric Models have been updated, reviewed and revised over the years, and documented in several publications, including Crespi (2004) and Kapsos (2007). In addition, these methodologies have been evaluated internally within the ILO, and externally in the context of evaluation studies commissioned by the ILO of its statistical activities and procedures. A list of studies is provided by Bilsborrow and Mayer (2007).

1.3 Purpose and structure of the report

The aim of this report is to describe the current state of the methodologies and procedures used in the Trends Econometric Models, to assess these methodologies in light of existing best practices, and to identify strengths and areas for improvement.

This report is divided as follows: The next section describes the main approaches considered by the ILO Trends Unit to deal with the problem of generating regional and global aggregates in the presence of missing data, namely small area estimation techniques, and treating the problem as a ‘missing data problem’. The third section provides a brief literature review on ways to address the missing data problem. Section 4 presents a key Trends econometric model, the Global Employment Trends (GET) model. It describes the model’s evolution, emphasizing the approaches used to deal with missing values. This section also describes modifications and extensions of the GET model since the onset of the 2008-2009 economic crisis to increase the model’s flexibility and capacity to reflect the rapidly evolving labour market situation. The section also describes the methodology developed to forecast unemployment rates over the short- to medium run, during the post-crisis recovery period, and to provide insights about the potential duration of the labour market impact of the crisis at the regional and global levels. Section 5 assesses the methodologies presented in the previous section based on common criteria and compliance with best practices; and the final section concludes with a proposal for the way forward.

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[4] Schaible, W. (2000) “Methods for Producing Estimates for Selected Key Indicators of the Labour Market”, *Employment Paper 2000/6*, International Labour Office, Geneva.

[5] Schaible, W. and Mahadevan-Vijaya, R. (2002) “World and Regional Estimates for Selected Key Indicators of the Labour Market”, *Employment Paper 2002/36*, International Labour Office, Geneva.

2. Generating regional and global aggregates

Two approaches have been considered within the ILO to address the problem of generating regional and global estimates in the presence of missing (non-reported) data for many countries: The first approach is treating the problem as a missing data problem, and the second, as a small area estimation problem (Schaible, 2000).

2.1 Small area estimation or missing data problem?

Small area estimation is a technique used by when the sample size of a geographic area, or of another sub-national 'domain' (e.g. demographic group) is too small for a direct estimator to produce reliable estimates. Alternative estimators are used that "increase the effective sample size and decrease the variance using data from other domains and/or time periods through models that assume similarities across domains and/or time periods" (Schaible 2000, p.4). These *indirect* estimators are commonly referred to as 'small area estimators', because the domains of interest are often geographic areas, although this need not be the case. The term 'small' refers to the sample size of the domain, rather than to the size of the domain's population. Small area estimators are also referred to as 'local area', 'small domain', 'sub domain' estimators, among other terms.

While direct estimators use values of the variables of interest from the time period of interest only, and from units within the domain only, indirect estimators use values of the variable of interest from another domain and/or time period. This is often done through a regression model using auxiliary variables that are known for the domain and time period of interest. Examples of indirect estimators include the mean of an entire sample of the universe as an estimator for the mean of a specific domain (a 'domain indirect' estimator), or the mean of a domain sample in a previous period as an estimator for the mean of the domain in the current period (a 'time indirect' estimator). For the estimators in these two examples to be unbiased, the variable of interest must have the same expected value for the specific domain as for the population as a whole (for the domain indirect estimator), or the same expected value across time periods (time indirect estimator).

Commonly used small area estimators include the *synthetic estimator*, which uses the sample mean of observed values in post strata across all domains to impute for the unobserved values in the domain.[6] Post strata are created by subdividing the sample using a variable that is correlated with the variable of interest. Note that a synthetic estimator can be a domain indirect estimator, a time indirect estimator, or both a time and domain indirect estimator. *Indirect regression estimators* use auxiliary variables, but differ from direct estimators in that they use data from other domains or time periods in the regressions. Composite estimators (combining the synthetic and regression approaches) have also been developed (Schaible, 2000).

Schaible (2000) presents characteristics of indirect estimators, and some problems associated with their use. For small area estimation methods to be used to generate regional and global KILM estimates, the sample of reporting countries must constitute a representative, random sample of the overall population of countries, which is not the case (see Section 4.1.3).

One way of framing the problem is to consider each region as consisting of two 'strata': one consisting of reporting countries, and one of non-reporting countries. Standard methods for estimation in

[6] The synthetic estimator is similar to a post stratified estimator (see Section 3.1.2). However, while the post stratified estimator would use the sample mean of observed values in the post strata and the domain of interest only, the synthetic estimator uses the sample mean of observed values across all domains.

the presence of missing data such as weighting or imputation can then be tested and used to generate missing values for the non-reporting countries.

2.2 The missing data problem

Missing data problems can take a number of forms, such as when the sample to be used in estimation is incomplete, or when only a subset of the sample data is available for estimation. In the survey analysis and social sciences fields, the missing data problem is often due to 'non-response'. Missing data or non-response arises when the required data are not available for a unit of observation (*unit non-response*), for some elements or a sub-set of the data for a unit of observation (*item non-response*), or – in the case of a longitudinal dataset – when data are not available for a unit of observation during a wave of the survey, or for some years (*wave non-response*).

Different methods are used to deal with the different types of non-response. In general, methods of dealing with unit non-response involve using sampling weights to adjust the sample to account for non-response. Item non-response methods depend on the variable of interest, and often involve imputing values into the data record. Regression methods, and most of the methods presented in Section 3, are generally considered to be item non-response methods. The difference in approach is largely due to practical considerations however, as developing an adjustment method for each variable (when the dataset consists of a large number of variables) would require significant resources. For this reason, when the dataset includes a limited set of variables, the distinction is less meaningful and both types of methods should be considered (Schaible, 2000).

2.2.1 Missing data structure and mechanisms

Different types of missing data structures or mechanisms necessitate different treatments. On the one end, there are data *missing completely at random (MCAR)*, which means that the probability of response (or reporting probability) depends neither on the variable subject to non-response (the variable for which data are missing) nor on any other variable. MCAR is a very strong assumption, and usually does not hold. A less restrictive assumption is that of data *missing at random (MAR)*, which holds when the probability of response does not depend on the variable subject to non-response, but depends on other variables (observable characteristics), such that when we condition on these variables, the dependency no longer holds, and the response probability can be considered random. A common procedure to correct for sample selection bias when data are MAR involves using weights that are set as the inverse probability of selection or inverse propensity score (Kapsos, 2007).

MCAR and MAR missing data mechanisms can be considered 'ignorable', because under these assumptions, the incomplete sample can be considered representative of the population, and the usual estimation methods can be used. If the missing data are *not missing at random (NMAR)*, meaning that the probability that data would be missing is related to the nature of the variable itself (and neither MCAR nor MAR hold) then the missing data mechanism is 'non-ignorable', and standard estimation methods cannot be applied. When data are NMAR, it may be possible to identify covariates that impact on the response probability, such that the MAR assumption is plausible. In other words, although the MAR assumption may not hold, it is often possible to have a 'workable approximation' of this assumption. Unlike MCAR, which is testable using the observed data, the MAR assumption usually cannot be tested. Nevertheless, the impact on the imputed estimators of a departure from the MAR assumption may be small, in which case MAR-based procedures may still be usable (Durrant, 2005).

2.3 Considerations in addressing the missing data problem

2.3.1 Whether or not to impute

While the need to generate regional and global aggregates to measure progress towards the MDG indicators has been established, a lack of consensus remains with regards to the best approaches to use, given the problem of missing data for some countries. In particular, there has been an ongoing debate around whether, as a matter of principle, imputation should be done at all (Holt, 2003). In generating regional averages for MDG indicators, some agencies use only data from reporting countries. With this approach however, users are likely to interpret the measures as summarizing the situation for all countries in the region, including non-reporters. For this reason, it may be argued that although no *explicit* imputation has been undertaken, in reality, when regional and global aggregates are produced, an *implicit* imputation has taken place. In other words, "implicitly countries with missing data have a (collective) imputed value equal to the regional or global mean" (Holt 2003, p.6). When data are missing for a large country, such as China for example, which would have a major influence on the regional average, it may make sense to produce a summary measure that excludes this country, and to clearly inform users not to implicitly interpret the regional measure as including the country in question. This approach has the disadvantage of producing aggregate measures that are less representative due to the exclusion of a highly influential country.

If we accept that some form of imputation (implicit or explicit) always takes place when regional and global aggregates are produced, then the question becomes not whether or not to impute, but rather what form of imputation should be used. Imputation has many benefits, including the possibility of recreating balanced datasets and using the corresponding estimation procedures, and efficiency gains from larger sample sizes (Durrant, 2005). That being said, it is important to be aware and transparent about the limitations of the imputation process, and to avoid treating imputed values as 'real' or observed values.

2.3.2 Implicit and explicit imputation

In the context of the work of international organizations, an important issue to consider is whether or not to report the values that are imputed for individual countries, and what to set as a threshold (in terms of share of reported data) to publish the regional estimates (Holt, 2003). When the values imputed for countries are published as such, with an explanatory note about the methodology employed to produce them, the process is referred to as explicit imputation. In this case, the imputed values that are then used to generate regional and global averages are 'transparent', and countries for which data are imputed can have some oversight on the imputation process and outcome. Furthermore, the summary measures can be replicated by the users, other forms of aggregation can be applied, and the data can be used for analysis with other country-level statistics.

In the case of implicit imputation, country-level imputed values are used in regional and global averages, but the imputed values themselves, and the methodology used to obtain them are not published. This often occurs when the imputed data have 'political importance', such that individual countries may refuse to have imputed data published in lieu of the actual values. It may also be the case that imputed values are not accurate enough to be published as country-level values, yet they are adequate for use in constructing regional and global estimates.

In the context of ILO Trends Econometric Models, imputed data that are more politically sensitive, such as the unemployment rates produced by the GET model, are not published at the country level, but are used to construct regional and global aggregates. Some other imputed data are published, such as labour force participation rates produced by the Labour Force Model. Whether or not country-level imputed data are published, the ILO Trends Unit approach is transparent in that the methodology used for imputation and an explanation of the underlying assumptions and empirical basis are made available to users in easily accessible publications.

3. Addressing the missing data problem: A literature review

The missing data problem has been the subject of an extensive literature, primarily in the fields of survey analysis, market studies and social science research. The choice of methods for dealing with the problem is often a function of the data available and the purpose of the analysis (Durrant, 2005). This section presents the common methods, and discusses the pros and cons of the different approaches.

3.1 Common Methods

One way of dealing with missing data is to ignore it, and conduct the analysis using only the available data. In dealing with item-non response, a commonly used method is *case deletion* or *listwise deletion*, which involves discarding observations with incomplete information (item non-response), and conducting the analysis on the complete data only. This is a default approach used in many statistical programs. Case deletion and *available case analysis*, another method that uses only observed units in the analysis have a number of drawbacks. Using complete observations only, decreases the sample size, and therefore the statistical power of any estimation or analyses conducted. Missing data are also a cause for concern because the incomplete sample could be 'unrepresentative' or 'unbalanced' as the units for which data are available could have different characteristic from those for which data are unavailable. As a result, the sample estimates of the variable of interest are likely to be biased (Schaible, 2000).

3.1.1 Simple imputation methods

A basic form of imputation, deductive methods, involves using logical relationships between variables to derive a value for the missing item (Durrant, 2005). For instance, *ratios* can be used to preserve a relationship between variables. For instance in the GET model, the ratios of female and male unemployment rates to the total unemployment rate are used in imputing data for unemployment rate sub-components for years when only the total rates are reported (see Section 4.2.1).

A common form of deductive methods is *mean substitution*, which involves using the sample mean of the observed values of a variable to impute a missing value. The underlying assumption behind this method is that the expected value of the variable of interest for the non-responding units (non-reporting countries) is equal to that of responding units (reporting countries). This is a strong assumption that is rarely verifiable. Mean substitution occurs *implicitly* when regional averages are generated using reporting countries only, but are interpreted as representing all countries in the region, including non-reporters. In such a case, the missing values are assumed to be equal to the sample mean of the observed values, although this is not explicitly stated.

A variation of this approach is to impute the 'class mean' for missing values, where classes are defined based on explanatory variables (Durrant, 2005). Mean methods distort the distribution of the data. Although the mean is preserved, the variance and other aspects of the data distribution are affected (Durrant 2005, Hu, 1998, Schafer and Graham, 2002). Specifically, a 'spike' is created in the data at the mean of the observed values, and the variance is underestimated (Engel 2003, Buhi et al, 2008). This affects the correlations and other relationships between the variable for which data was imputed and other variables (Schafer and Graham, 2002; Buhi et al, 2008).

3.1.2 Post stratification: correcting for non-response bias

Post stratification from the complete sample to the population, a commonly used technique to reduce the variance of estimators, involves dividing the sample into ‘cells’ or ‘post strata’ by using a variable or variables that are correlated with the variable of interest, constructing weights within each post strata to adjust the sample, and using the weighted sample values to estimate the population value. This technique can be adapted to correct for non-response bias.

In post stratification from the incomplete to the complete sample, the cells or post strata are referred to as ‘weighting cells’ or ‘adjustment cells’. A “non-response adjustment factor” weight is constructed within each adjustment cell. For example, the weight can be obtained by dividing the number of complete sample units by the number of incomplete sample units (Schaible, 2000). The non-response adjustment weight is then multiplied by the inverse of the probability of selection to generate the final sample weight. The population total is then estimated as the sum of the weighted values over the incomplete sample. This method amounts to imputing the missing values by using the (weighted) sample mean within each adjustment cell or post strata. For this *post stratified estimator* to be unbiased, the expected value of the variable for which data is missing should be a constant within each post stratum (j):

$$E\left[Y_{ij}\right] = \mu_j \quad \forall\, i\, \in j$$

If the variable used to create the adjustment cells is related to the variable of interest, then this assumption is more likely to hold, and is less restrictive than the assumption required for the unweighted sample mean described in section 3.1.1. to be an unbiased estimator (i.e. that the expected value of the variable of interest for reporting and non-reporting countries).

3.1.3 Regression imputation

Regression imputation, like post stratification, involves the use of one or many auxiliary variables that are correlated with the variable of interest and available for all units in the sample. Instead of using the auxiliary variables to create cells and impute the cell mean for missing values, however, the auxiliary variables are used as independent variables in regressions (Schaible, 2000). Specifically, the parameters of the model are estimated using the incomplete sample data (dependent and independent (auxiliary) variables for all units). The estimated parameters are then used with the auxiliary variables to predict the missing values.

Regression imputation is a parametric approach, and may therefore be sensitive to the misspecification of the regression model (Durrant, 2005). Indeed, if the auxiliary variables are not appropriately selected, the model could have weak predictive power. Because the values imputed using regression methods are predicted values, rather than actual, observed values as with some other methods (e.g. hot deck methods described below), there is a risk that these predicted values would be problematic or unlikely to be observed in reality. Regression imputation also affects the data distribution, because imputed values lie on the regression line, causing a “shrinkage to the mean” phenomenon, and therefore underestimates the variance (Hu, 1998). Furthermore, because imputed variables are predicted as a function auxiliary variables only, the statistical relationship between them could be artificially inflated (Durrant, 2005)

3.1.3 Hot deck, cold deck and nearest neighbor imputation

Hot deck imputation methods assign value from a record with an observed item (the ‘donor’) to a record with a missing item (‘the recipient’) from the same source. Various hot deck methods differ from one another based on the selection of the 'donor'. In the simplest case, the donor is randomly selected from the overall sample. Alternatively, the donor is selected at random within 'imputation classes' defined using observed auxiliary variables (e.g. geographic proximity, demographic group). Thus, missing data for a recipient is substituted with data from a donor that has similar characteristics. The fact that the imputed data are always "actually occurring values" is an advantage of this approach, particularly when dealing with data that are skewed in some way, or truncated (Durrant, 2005). These methods are generally non-parametric, or semi-parametric, do not require distributional assumptions. Hot deck imputation may require a large sample size however, to ensure that the number of times the same 'donor' is used is limited, such that the data distribution is not unaffected and the variance is not underestimated. *Cold deck* methods are similar to hot deck methods, except that the donors are selected from another source, such as an earlier survey or historical data (Schaible, 2000).

A similar method to the hot deck/cold deck approach, where the donor is selected such as to minimize a specific 'distance' which is a function of auxiliary variables, is the *nearest neighbor imputation* method or *distance function matching* (Lalton, 1983; Lessler and Kalsbeek, 1992; Rancourt, 1999; Chen and Shao, 2000 and 2001, and Durrant, 2005).

A special case of nearest neighbor imputation, where the distance is defined based on the predicted values from a regression imputation model, is *predictive mean-matching imputation* (Little, 1988; Heitjan and Little, 1991; Heitjan and Landis, 1994; Durrant and Skinner (2005); Durrant 2005). One form of predictive mean-matching is when hot deck imputation within classes is used, but "classes are defined based on the range of predicted values from the imputation model" (Durrant, 2005). Predictive mean-matching is a composite method that combines elements of several approaches (regression, nearest neighbor and hot deck imputation). It is "a semi-parametric method, which makes use of the imputation model but does not fully rely on it", and is therefore assumed to be less sensitive to model misspecification than regression imputation (Schenker and Taylor, 1996; Durrant 2005).

3.1.4 Multiple and fractional imputation

The methods listed above generated one imputed value for each missing value. With multiple imputation and fractional imputation, a random imputation method generates several values for each missing item. With *fractional imputation*, missing values are imputed through repeating the same random imputation method several times. This approach allows reducing "the random component of the variance of the estimator arising from imputation" (Durrant 2005).

With *multiple imputation (MI)*, several missing values are also imputed through repeated imputations that are independent realizations of the distribution of the missing values conditional on the observed values (referred to as 'proper multiple imputations') (Rubin, 1987). The aim of this approach is to account for the uncertainty regarding the true, but unobserved missing values. MI allows generating several complete datasets to be used with standard data analysis techniques, and that can then be combined or averaged to obtain a single overall inference or point estimate (Durrant, 2005). Differences between the results obtained based on the different imputations can be used as a measure of the uncertainty due to the missing data. An advantage of MI is that it is possible and relatively easy to obtain "an approximately unbiased estimator of the variance" using this approach (Durrant, 2005).[7]

[7] Specifically, according to Rubin's formulae (1987, pp. 76-81, presented in Durrant, 2005) if a point estimate of the parameter θ is written as:

$$\hat{\theta} = \frac{1}{M}\sum_{m=1}^{M} \hat{\theta}_m \qquad for\ m = 1, \ldots, M$$

Obtaining such a variance estimator is significant, because standard variance estimation techniques are known to be inadequate in the presence of imputation. In particular, non-MI methods tend to underestimate the variance of estimators by failing to account for the higher variability due to non-response and imputation. Durrant (2005) argues that if adequate adjustments are made to the standard variance estimators to reflect the additional variability, then it is also possible to correctly estimate the variance of an imputed estimator under single value and fractional imputation.

3.2 Practical applications: Approaches of other international agencies

While the literature deals largely with non-response in surveys, where the individual non-respondents are usually not identifiable, MDG indicators data are missing for countries and years. Few UN agencies provide a detailed description of the methods they use to address the missing data problem, or to construct regional and global aggregates. However, datasets held on the United Nations Statistics Division (UNSD) website[8] have all "been subject to different amounts of imputation before being deposited" (Holt, 2003).

To address the challenges posed by estimating child mortality (MDG 4) when data availability is limited, the Inter-agency Group for Child Mortality Estimation was formed in 2004. The Group, which consists of experts from the United Nations Children's Fund (UNICEF), The World bank, the World Health Organization (WHO), and the United Nations Population Division (UNPD), was tasked to produce country, regional and global estimates of levels and trends in childhood mortality and enhance the capacity of countries to produce timely and reliable child mortality estimates.[9] While several methods have been investigated and compared (see Silverwood and Cousens, 2008), the Inter-agency Group favors 'a spline-based approach' to estimating child mortality for each country, which involves the following steps: 1. Assigning a weight to each observation of infant or under-five mortality rate. The weight assigned depends on a several factors such as the source of the data point, the number of data points from each source, and the age-group of the sample, and reflects the level of accuracy associated with the data, and the representativeness of the sample on which it is based. 2. The rate of change in infant or under-five mortality is allowed to shift over time. For each of the two variables, moments when such shifts occur (referred to as 'knots') are defined using the assigned weights (every time the sum of weights for successive observations reaches a multiple of 5, indicating that there are sufficient data points to justify a different slope). 3. A model allowing for the shift in slope is estimated by weighted least squares for each of the two variables.[10] Current values are therefore obtained as a result of trend extrapolation. 4. The

where M is the number of imputations undertaken, and $\hat{G}_m$ is the variance associated with each of the $\hat{\theta}_m$ estimators, then, the *within-imputation variance* can be computed as:

$$\bar{G} = \frac{1}{M}\sum_{m=1}^{M}\hat{G}_m$$

The *between-imputation variance* can be computed as:

$$\bar{B} = \frac{1}{M-1}\sum_{m=1}^{M}(\hat{\theta}_m - \hat{\theta})^2$$

The *overall variance estimate* can be computed as:

$$\hat{T} = \bar{G} + \left(1 + \frac{1}{M}\right)\bar{B}$$

where (1+1/M) is an adjustment factor. Note that this formula may not be appropriate depending on the estimator in question, and on the multiple imputation process (Fay, 1996, Kim and Fuller, 2004; Neilsen, 2003; Allison, 2000; Durrant, 2005).

[8] http://mdgs.un.org/unsd/mdg/Default.aspx

[9] http://www.childinfo.org/mortality_igme.html

[10] The model is as follows:

resulting datasets are examined to identify anomalies, and the weights adjusted accordingly. 5. The model is re-run using the revised weights for each of the two variables. The two resulting sets of estimates are compared, and the more consistent of the two is kept. The corresponding values of the second indicator are then derived using a 'model life table' (see Inter-agency Group for Child Mortality Estimation, 2007). This methodology results in country-level estimates that are different from countries' official statistics, but also that are not directly comparable with the previous years' estimates (since estimates are updates annually, incorporating newly available data which can affect past trends and extrapolated values). Changes in "estimates from one year to the next may reflect increased knowledge of the situation rather than actual changes in mortality rates, which tend to change little from one year to the next" (Inter-agency Group for Child Mortality Estimation, 2007, p. 35). The resulting child mortality database includes detailed information on the data sources and methodology used for producing estimates for the specific countries, which are indicative of the level of uncertainty associated with the estimates. For the 2008 estimates, a methodology was developed to adjust the mortality estimates for countries severely affected by HIV/AIDS.[11] Regional and global estimates of child mortality are produced and disseminated only if data are available "for at least 50% of the region or the total population of the countries considered."[12]

The WHO-UNICEF Joint Reporting Forum (JRF) use simple methods to impute missing values for countries that reported data for some years only during the time period of interest to generate regional trends in vaccine financing indicators. Specifically, for the first indicator, which measures whether countries (WHO members) have a line for purchasing vaccines used in routine immunizations – a binary (yes/no) indicator – the trends are extrapolated based on a simple assumption, that once the country has the budget line in question, it will likely continue to have it in the future (such that if the last observed value was "yes", missing values for subsequent years would be imputed as "yes".[13] For the second indicator (percentage of all expenditures on routine vaccines financed using government funds), the dataset was cross-checked and completed using comments provided by countries, while some missing data were imputed using a similar method than what was used for the first indicator (for instance, if a country reported 0% or 100% for most years, then these same values were entered for the years with missing values).

The World Bank uses five methods of aggregation for producing World Development Indicators (WDI), ranging from no imputation for missing values (taking sums of available data only) to simple imputation methods of group mean or median substitution, and composite methods involving deductive elements (using ratios and relationships) and auxiliary (proxy) variables.[14] Specifically, (1) missing values are not imputed, and aggregates are simply the sum of available data. (2) Aggregates of ratios are generally calculated as weighted averages of the available data (including available data that may not be presented in the relevant table), using the denominator variable (e.g. size of the population when the ratio is a share of the population) or another indicator variable as a weight. These aggregates are only calculated if the missing data account for less than a third of the value of the weights in the benchmark year. Aggregates of ratios are in a few cases calculated as the ratio of group totals, where group totals may have been imputed using another method. (3) Aggregates of growth rates are also generally computed as weighted averages, with a few exceptions where they are calculated from time series of

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$\ln(y) = \beta_0 + \beta_1 x + \sum_{k=1}^{K} b_k (x - k_k)_+ + \varepsilon$ where $(x - k_k)_+ = \begin{Bmatrix} x - k_k & if\ x \geq k_k \\ 0 & if\ x < k_k \end{Bmatrix}$

where y is the childhood mortality rate, x is the year, $k_1, \dots, k_k$ are the K knot moments (see Silverwood and Cousens, 2008; Inter-agency Group for Child Mortality Estimation, 2007).

[11] http://www.childinfo.org/files/Detailed_Information_on_Methodology_2008.pdf (Accessed Oct 22, 2009).

[12] http://www.childinfo.org/mortality_methodology.html (Accessed Oct 22, 2009).

[13] http://www.who.int/immunization_monitoring/routine/immunization_financing_2004.pdf (Accessed Oct 22, 2009).

[14] The World Bank, permanent URL site for aggregation rules: http://go.worldbank.org/AGKBM7SPO0

group totals. Note that when means of available data or groups are used for aggregates, the missing values are assumed to have the same average as the available data. (4) The median values of available data, or of sub-sets of the available data, are sometimes used to represent aggregates. (5) Another method involves using a proxy variable for which data are available for the benchmark year (2000) to impute for missing values for that year, and using the relationship between the sum of available data and the total in the year of the previous estimate to impute missing values forward and backward from 2000. Proxy or auxiliary variables used to compute the WDI aggregates include the total population, and the Gross National Income (GNI), exports and imports of goods and services, and sectors value added (in U.S. dollars).

In general, the simpler the methodologies used to impute for missing data, the stricter the data requirements in terms of coverage. The World Bank imputation methods vary in their level of simplicity, and accordingly have a defined threshold of missing data beyond which aggregates are generally not calculated. In particular, aggregates are not computed if missing data account for more than: a third of the potential observations in a given year (for method 1); a third of the potential observations in the benchmark year (method 5); a third of the value of weights in the benchmark year (method 2); half of the observations in a period (method 3). For the fourth method, aggregates are generally not calculated if data are missing for more than half of the large countries (with a population of more than 1 million). There are exceptions, however, when aggregates are calculated even though these thresholds are not met, for instance when missing values are deemed to be small or not to have a significant impact.

4. The Global Employment Trends (GET) Model

The Global Employment Trends (GET) model was developed to provide estimates – disaggregated by age and sex – of unemployment, employment, status in employment, and employment by sector. The model output is a complete dataset of data for 178 countries. The country-level data are then aggregated to produce regional and global estimates of key labour market indicators, including the unemployment rate, the employment-to-population rate, sectoral employment shares, status in employment shares and the share of workers in vulnerable employment.

This section details the methodology used in the GET model to produce unemployment estimates, emphasizing the missing data imputation process. The methodologies used to impute missing data and provide regional and global aggregates of the other indicators are not presented here, but are based on the same principles.

A key theoretical underpinning of the GET model is Okun's law, according to which there is a negative relationship between movements of the unemployment rate and changes in real GDP. This empirical relationship is established in macro-economic theory, and constitutes "a major part of every traditional macro-model as the aggregate supply-curve is derived by combining Okun's law with the Phillips curve" (Stögner and Stiassny, 2000). The relationship between changes in the unemployment rate and in GDP growth is used in the context of the GET model to impute missing unemployment rates (section 4.2.2), and to forecast unemployment rates over the short- to medium-run (section 4.3).

4.1 Considerations in developing the GET model

While a large number of countries report unemployment rates for a limited number of years only (wave non-response), and a few countries do not report unemployment figures at all (unit non-response), there are additional issues pertaining to the reported unemployment rates that need to be accounted for. First, some countries do not report information with the required level of detail (item non-response). For example, while unemployment rates are required for the two sexes and the two age categories (youth and adult workers), some countries only report the total unemployment rate. Second, even if information was reported with the appropriate level of detail, significant differences remain among reporting countries, not only in terms of their labour market conditions, but also in terms of their data collection and processing mechanisms (Crespi, 2004).

4.1.1 Initial data selection

The first consideration with respect to the GET model, as for all Trends Econometric Models, pertains to the selection of the data to be used in the model. In order to ensure that the data contained in the original dataset are comparable, and therefore can be used to construct regional and global aggregates, analysts from the Employment Trends Unit examine the initial dataset, to identify breaks in the series. Kapsos (2007) lists four causes of data 'non-comparability' in the context of the Trends Labour Force model: Survey type, age-group coverage, geographic coverage and other causes, such as the inclusion or non-inclusion of military conscripts in the labour force, differences in the survey reference period, variations of national definitions of the key concepts, etc. These same causes are examined in the context of the GET model, and the following selection criteria for the inclusion of unemployment rates were established accordingly:

1. *Data Source*: When data are available from various sources, the data selected for inclusion in the GET model are preferably taken from a Labour Force Survey (LFS) or a Household Survey (HS). If LFS data are not available, alternative sources, such as Population Census data, are considered for inclusion, if the data conform to ILO standards and guidelines, and if they are consistent with the existing series.

2. *Age group coverage*: For the purpose of the model, the youth labour force consists of the economically active population aged from 15 to 24 years, and the adult labour force consists of the economically active population aged 25 and above. The age groups covered by the reported data must be sufficiently comparable across countries.

3. *Geographic coverage*: Only national (not geographically limited) labour market data are included in the GET model.[15] There are typically large differences between urban and rural labour markets, such that data corresponding to only urban or only rural areas are not representative of the overall labour market situation of a country. Data with limited geographic coverage are not comparable across countries, and are inconsistent with data from benchmark files such as GDP.

4.1.2 GET model benchmarks

In addition to country-reported labour market information, four key datasets are used as benchmarks for the GET model: 1. Population data are taken from the United Nations World Population Prospects (UNWPP) Revision Database; 2. Labour force estimates are taken from the ILO's Economically Active Population Estimates and Projections (EAPEP) Database,[16] and are the result of

[15] In some cases, observations on limited geographic areas are included if the coverage is sufficiently comparable to national data. For instance, for some years, data for Argentina pertaining to 28 or 31 urban agglomerations are included, because some 90 per cent of Argentina's population lives in urban areas. Trends Unit analysts preferred including these data over allowing the model to generate data for Argentina, given the size of the country and its influence on regional aggregates.

[16] See Kapsos (2007) for a description of the Trends Labour Force Model and methodologies used to estimate regional and global trends in labour force participation, including the method used to correct for potential sample selection bias.

collaborative work between the ILO's Bureau of Statistics and the Employment Trends Unit; 3. Economic growth estimates and projections from the International Monetary Fund (IMF) World Economic Outlook database; and 4. Per capita GDP adjusted for purchasing power parity (PPP) data are taken from the World Bank's World Development indicators (WDI) database.

Benchmark data are used at various stages in the GET model. For instance, GDP growth and per capita GDP are variables used in regressions to obtain unemployment rate estimates. Labour force estimates are multiplied by the unemployment rate estimates generated by the model to obtain nominal unemployment figures, which are then used to compute regional and global aggregates. For this reason, it is essential to use reliable and frequently updated benchmark data. The estimates generated by the model can only be as reliable as the benchmarks on which they are based.

4.1.3 Analyzing the missing data structure

A key consideration is the 'missingness' pattern or mechanism of the data. If non-reporting countries (countries with missing values) are statistically different from reporting ones, then the sample of reporting countries cannot be considered a random, representative sample of the total population (all countries). In the context of the GET model, missing data (unemployment rates) cannot be said to be missing completely at random (MCAR). Whether or not a country regularly compiles and releases unemployment rate and other labour market data depends to a large extent on the capacity of its statistical agency and/or labour department, both in terms of expertise and of resources available to conduct labour force surveys. In other words, the probability that a country will have complete and consistent unemployment rate series depends on its institutional capacity and on its financial and human resources, which in turn depend on its level of economic and institutional development, social stability, etc.

Therefore, the probability that data would be missing for a country (or conversely, the country's reporting probability) is likely to depend on observable country-specific characteristics (variables for which data are available for both reporters and non-reporters), such that, if we account for these variables, missing data can be considered missing at random (MAR). For instance, depending on its level of economic development, or its institutional characteristics, one country may be more likely than another to report unemployment rates. However, within a group of 'similar countries' (countries at the same level of economic development or with the same type of institutional characteristics), it is quite possible that missing data are MAR. In other words, countries can be assigned to imputation groups, based on a variable or set of variables, such that within these imputation groups, the data can be considered MAR, and MAR-based techniques can be used.

To develop the Trends Econometric Models, several auxiliary variables were evaluated, including geography as represented by sub-regions; population size; and the Human Development Index (HDI), which is a composite index based on GDP per capita, educational attainment, and life expectancy and GDP per capita adjusted for purchasing power parity.[17] Auxiliary variables were used in determining appropriate imputation groups, and also as independent variables in regressions. The relationships between auxiliary variables and the variable of interest can be verified through correlations, simple plots and other diagnostics.

4.2 Addressing missing data in the GET model

To deal with the issues mentioned above, the GET methodology involves two stages. First, country-specific imputation techniques are used to deal with the missing sub-components, when total

[17] Geography and the HDI as auxiliary variables were evaluated in an unpublished ILO Report, "Regional and World Aggregate Estimates", by Maria Jeria Caceres (1998)

unemployment and sub-components data are available for some years (wave non-response), or when total unemployment data are available but sub-component data are not available for some years (item non-response). These techniques preserve the richness provided by the heterogeneity of the data and ensure consistency of the imputed values with the existing country-level statistics.

Second, weighted regressions are used for imputation when observations (total and sub-component rates) are missing for some countries and some years (unit and wave non-response). To control for the heterogeneity underlying the data, panel data estimation techniques are used. The two stages are described in detail below.

Although some of the imputation approaches described here for unemployment rates are used for other variables[18] in the GET model, for simplicity, this section will focus on the imputation of unemployment rates.

4.2.1 Stage 1. Country-level imputations

A key consideration throughout the model is keeping consistency between total unemployment and its different sub-components. To ensure this consistency, a *bottom-up* strategy is used, whereby the primary unit of analysis is the lowest possible disaggregated sub-component (youth male unemployment, adult male unemployment, youth female unemployment, adult female unemployment).

Stage 1a. Imputing missing unemployment sub-components, when total unemployment is reported (item non-response)

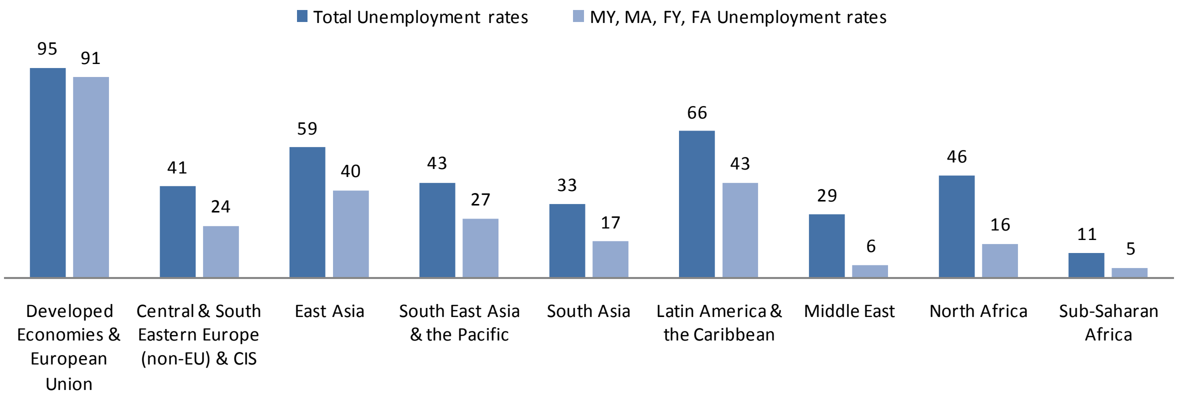
Many countries report total unemployment rates, but do not provide the data disaggregated by sex and by age group. Figure 1 shows the average response rates for total unemployment rates and for unemployment rate sub-components by region in the initial (pre-imputation) dataset over the 1991-2008 period.[19] For instance, response rates for the total unemployment rates are almost 5 times as high as subcomponent response rates in the Middle East, almost 3 times as high in North Africa, and approximately twice as high in South Asia and Sub-Saharan Africa.

The first phase of the imputation process involves imputing data for the missing unemployment sub-components, when total unemployment rates are reported. Simple imputation methods are used at this stage, which essentially consist of using the relationship between the total unemployment rate and the unemployment rates for the sub-components from years with complete observations (observations on both unemployment rates and sub-components) to fill the gaps for years when sub-components are not reported.

[18] Specifically, missing per capita GDP data is imputed for each country using GDP growth and population growth. In the absence of either variable, missing per capita GDP values are replaced by the sub-regional average of the per capita GDP.

[19] It is important to note that while the percentage of real observations is rather low, 150 out of 178 countries have at least one reported unemployment rate in at least one year between 1991 and 2008 (see Appendix 1). Thus, some information on unemployment rates is known for the vast majority of countries in the dataset.

Figure 1 Total unemployment rate and unemployment rate sub-components average response rates before imputation (1991-2008)



The specific procedure for this stage has evolved over the years. The approach first used (when the GET model was initially developed) consisted of the following (Crespi, 2004): For countries that have reported unemployment sub-components for some years, the relationship between the total unemployment and the sub-components from these years is used to fill the gaps for years when sub-components are not reported, but total unemployment rates are reported. Specifically, for years with 'complete observations', the ratio of sub-components to the total are computed. The median value from these computed ratios is then used to impute the sub-components for the years in which they are missing.[20] When information on sub-components is missing for all years for a country, a similar procedure is applied, but with the ratios and the adjustment factor computed at the sub-regional level.

The approach currently used at this stage of the GET model involves computing the following ratios of the sub-components to total unemployment: [21]

$$R_{it} = {}^{Y_{itk}}\!/_{Y_{it}}$$

[20] The unemployment rate, the dependent variable under analysis is censored at the interval [0,1]. As a consequence, simple linear interpolations can result in out-of-range imputed values. To prevent this, the unemployment rate is logistically transformed before the imputations are undertaken. Accordingly, the adjustment factors (the ratios of sub-component to total unemployment) are defined as differences. The transformed dependent variable (unemployment rate sub-component) is defined as:

$$Y_{itk}^{T} = \ln\left(\frac{y_{itk}}{1 - y_{itk}}\right)$$

where y_{itk} is the observed unemployment rate for sub-component *k*, in country *i* and period *t*. The transformed independent variable (total unemployment rate) is defined as:

$$Y_{it}^{T} = \ln\left(\frac{y_{it}}{1 - y_{it}}\right)$$

where y_{it} is the observed total unemployment rate in country *i* and period *t*. An adjustment factor is then defined as:

$$AF_i = Med(Y_{itk}^{T} - Y_{it}^{T})$$

When the total unemployment rate is observed (available), this adjustment factor is used to recover the missing unemployment rate for sub-component *k*, as follows:

$$\tilde{Y}_{itk}^{T} = AF_i + Y_{it}^{T} \qquad \forall\, Y_{itk}^{T} = missing$$

[21] This procedure and other procedures currently used in the GET model were last revised in 2009 by Jean-Michel Pasteels, ILO Consultant.

where y_{itk} is the observed unemployment rate for sub-component *k*, in country *i* and period *t*. This ratio is first calculated for the male unemployment sub-component (k = male unemployment rate). Three measures based on this ratio are then computed: the mean of the ratio over the entire time period for which data are available ($\bar{R}_i$), and the mean of the ratio over three periods: the more distant period pre-1996 ($\bar{R}_{i1}$), an intermediate period from 1996-2001($\bar{R}_{i2}$), and the recent post-2001 period ($\bar{R}_{i3}$). A final ratio is finally constructed as a weighted average of the mean over the entire time period and the mean during most recent period for which it can be calculated:

$$\tilde{R}_i = 0.33 \times \bar{R}_i + 0.67 \times \bar{R}_{i3} \quad if\ \bar{R}_{i3} \neq missing$$
$$\tilde{R}_i = 0.33 \times \bar{R}_i + 0.67 \times \bar{R}_{i2} \quad if\ \bar{R}_{i3} = missing\ and\ \bar{R}_{i2} \neq missing$$
$$\tilde{R}_i = 0.33 \times \bar{R}_i + 0.67 \times \bar{R}_{i1} \quad if\ \bar{R}_{i3},\ \bar{R}_{i2} = missing\ and\ \bar{R}_{i1} \neq missing$$

The final ratio is then used to recover the missing sub-component *k*, in this case, the male unemployment (M) rate:

$$\tilde{Y}_{itM} = \tilde{R}_i \times Y_{it}$$

Thereafter, the nominal male unemployment figure is computed using the imputed rate and the labour force as:

$$U_M = \tilde{Y}_{itM} \times LF_M$$

The nominal female unemployment rate is calculated from total and male nominal unemployment:

$$U_F = U_T - U_M$$

The missing female unemployment sub-component is then recovered using this residual unemployment and the female labour force:

$$\tilde{Y}_{itF} = {}^{U_F}/_{LF_F}$$

This procedure results in an increase in the average response rates[22] for the male and female unemployment sub-components of 4 percentage points for North Africa and for South East Asia and the Pacific, 3 percentage points for East Asia and for Central and South Eastern Europe and the Commonwealth of Independent States (CIS) and 1 percentage point for Latin America and the Caribbean (see Figure 4.)

The same procedure is repeated to impute the male adult and female adult unemployment sub-components when only the adult unemployment rate is available, and the male youth and female youth unemployment sub-component when only the youth unemployment sub-component is available. This procedure concerns a limited number of observations, and results in an increase in the average response rates for the male youth, male adult, female youth and female adult unemployment sub-components of 2 percentage points for North Africa only (for this reason, in Figure 3, changes in response rates are lumped together with changes that occur at stage 1b).

Compared with the initial approach, the new procedure has the following advantages: adult and youth unemployment rates, when available, are used instead of the total unemployment rates to impute the four missing sub-components. Using the lowest possible disaggregation level (in this case, youth and adult unemployment) results in efficiency gains, as more information is utilized, and a stronger

[22] An increase in the percentage of non-missing data is referred to as an increase in response rates throughout this paper.

relationship can be expected to hold between disaggregation levels that are closer together. Furthermore, calculating female unemployment as a residual, ensures consistency between total unemployment and its sub-components. The new procedure also gives more weight to recent observations of the relationship between unemployment sub-components and total unemployment, thus accounting for a potential trend in this relationship over time.

Stage 1b. Imputing missing national and sub-component unemployment rates when these are available for some years only (wave non-response, missing values across the time dimension)

While the previous part dealt with imputing sub-components data for the years when total unemployment rates were reported, this part addresses the problem of missing national (total) unemployment rates and sub-component unemployment rates when these are available for some years only (wave non-response).

This part involves filling in missing data along the time dimension. It requires examining the evolution of the unemployment rate over time, which depends on structural factors (e.g. sectoral composition of employment) as well as cyclical factors (e.g. economic growth). Therefore, a procedure that accounts for the effects of both these factors is used. Two imputed values are obtained, each accounting for one of the two components. The final imputed value is then produced as a weighted average of these two values.

Part 1: Structural component

Structural factors can cause a shift in the unemployment rate over time, which is not attributable to the economic cycle. This part of this procedure, which takes into account the structural aspect, involves using a moving average method to impute missing values between data points that are one or two years apart. For each of the total unemployment rate and unemployment rate sub-components, missing values are imputed as follows:

$$\tilde{Y}_{it}^{S} = \frac{(Y_{it-1} + Y_{it+1})}{2} \quad if \;\; Y_{it-1} and \; Y_{it+1} \neq missing$$

or,

$$\tilde{Y}_{it}^{S} = \frac{(Y_{it-2} + Y_{it+1})}{2} \quad if \;\; Y_{it-1} = missing, but \; Y_{it+1} \; and \; Y_{it-2} \neq missing$$

or,

$$\tilde{Y}_{it}^{S} = \frac{(Y_{it-1} + Y_{it+2})}{2} \quad if \;\; Y_{it+1} = missing, but \; Y_{it-1} \; and \; Y_{it+2} \neq missing$$

As a result of this procedure, missing values for each sub-component are filled in across the time dimension, as: 1. The simple average of the value for the year immediately preceding and that of the year immediately following the year with the missing observation, 2. The simple average of the value two years before and the value one year after the year with the missing observation, and 3. The simple average of the value one year before and the value two years after the year with the missing observation. The underlying assumption is that structural factors lead to shifts in unemployment rates at certain points in time. A moving average method allows the linear trend in the movement of unemployment rates (the slope of the trend line) to vary over time, reflecting these structural changes.

Part 2: Cyclical component

The second part of the procedure, which accounts for the cyclical component of changes in unemployment, uses a country unemployment-elasticity approach to impute missing total unemployment rates. For each country *with more than six years of reported unemployment rates,* the following regression is run:

$$\dot{Y}_t = \alpha + \beta \dot{G}_t + \epsilon$$

where $\dot{Y}_t$ is the annual *change in unemployment rate,* and $\dot{G}_t$ is the annual *change in GDP growth.* A country-elasticity is then obtained as:

$$\xi_i \equiv \beta = \frac{\partial \dot{Y}_t}{\partial \dot{G}_t}$$

A regional elasticity is defined as the median of the country-elasticities within each region *R*:

$$\xi_R = Med(\xi_i) \quad \forall\, i \in R$$

Missing values are then generated as:

$$\tilde{Y}_{it}^{C} = Y_{it-1} \times \left[1 + (\xi_R \times \frac{\dot{G}_{it}}{100})\right]$$

Note: if the values generated through the elasticities approach are below the lowest observed value in the dataset, then these values are replaced by that minimum value.

Alternative methods that do not impose a parameter (elasticity) have been tested, such as simple interpolations of the unemployment rates. However, these methods were found to have drawbacks, and were not used. In particular, interpolations gave some out of bound results when there were few reported unemployment rates.

Part 3: Combining structural and cyclical components

Finally, the structural and cyclical components are combined to produce the imputed value that will replace the missing data across time. For countries where the growth-employment linkages are weaker, such as oil or mineral export-dependent countries, a large discrepancy can be expected between the structural and cyclical component. In such a case, the cyclical component is not accounted for in the final imputed value. The deviation between structural and cyclical components is measured as:

$$\delta_{it} = \frac{abs\left|\tilde{Y}_{it}^{S} - \tilde{Y}_{it}^{C}\right|}{\tilde{Y}_{it}^{S}}$$

The imputed value is generated as:

$$\tilde{Y}_{it} = \theta_i \tilde{Y}_{it}^{S} + (1-\theta_i)\, \tilde{Y}_{it}^{C} \qquad \text{where } \theta_i = \left\{ \begin{matrix} 1 & if\ max\ (\delta_{it}) > 0.15 \\ 0.5 & otherwise \end{matrix} \quad for\ each\ country\ i \right\}$$

Thus, for countries where a large discrepancy exists between structural and cyclical components, the imputed value relies entirely on the structural components (moving average approach, no use of auxiliary variables). For countries where the discrepancy is small, the imputed value is a simple average of the two components.

This procedure results in an increase in the average response rates for *total unemployment rates* by 4 percentage points for North Africa and for Sub-Saharan Africa, 3 percentage points for Latin America and the Caribbean, South East Asia and the Pacific, and the Middle East, and 2 percentage points for East Asia and South Asia (see Figure 2). Response rates for male and female unemployment rates increase by 4 percentage points for North Africa, 3 percentage points for South East Asia and the Pacific, Latin America and the Caribbean, the Middle East and Sub-Saharan Africa, and 2 percentage points for East Asia and South Asia (see Figure 4). For adults and youth unemployment rates, and for the lowest level of disaggregated components (male youth, male adult, female youth and female adult), response rates increase by 7 percentage points for Latin America and the Caribbean and North Africa, 6 percentage points for South Asia, 3 percentage points for East Asia and for Central and South Eastern Europe and the CIS, 2 percentage points for South East Asia and the Pacific and for Sub-Saharan Africa, and 1 percentage point for the Middle East and for the Developed Economies and the European Union (EU) (see Figure 3).

Stage 1c. Filling in missing sub-components data, when total unemployment rates are now available for more years (item non-response)

The previous phase allowed filling in missing values across the time dimension for total unemployment and unemployment sub-components, when these were available for some years. Because more data are now available on total rates and on sub-component rates, a ratio method, similar to the procedure used in Stage 1.a., can now again be used to produce additional missing sub-component values. A square root transformation is applied to the unemployment rate data.[23] The transformed sub-component and total unemployment rates are defined respectively as:

$$Y_{itk}^{T} = \sqrt{y_{itk}} \quad \text{and} \quad Y_{it}^{T} = \sqrt{y_{it}}$$

where y_{itk} is the observed unemployment rate for sub-component *k*, in country *i* and period *t*, and y_{it} is the observed total unemployment rate in country *i* and period *t*.

A ratio is then defined as:

$$R_{itk} = {Y_{itk}^{T}}/{Y_{it}^{T}}$$

[23] A square root transformation, just like a logistic transformation, prevents the imputation model from generating out of bound (negative) unemployment rates.

Figure 2 Total unemployment response rates at various stages of the imputation process

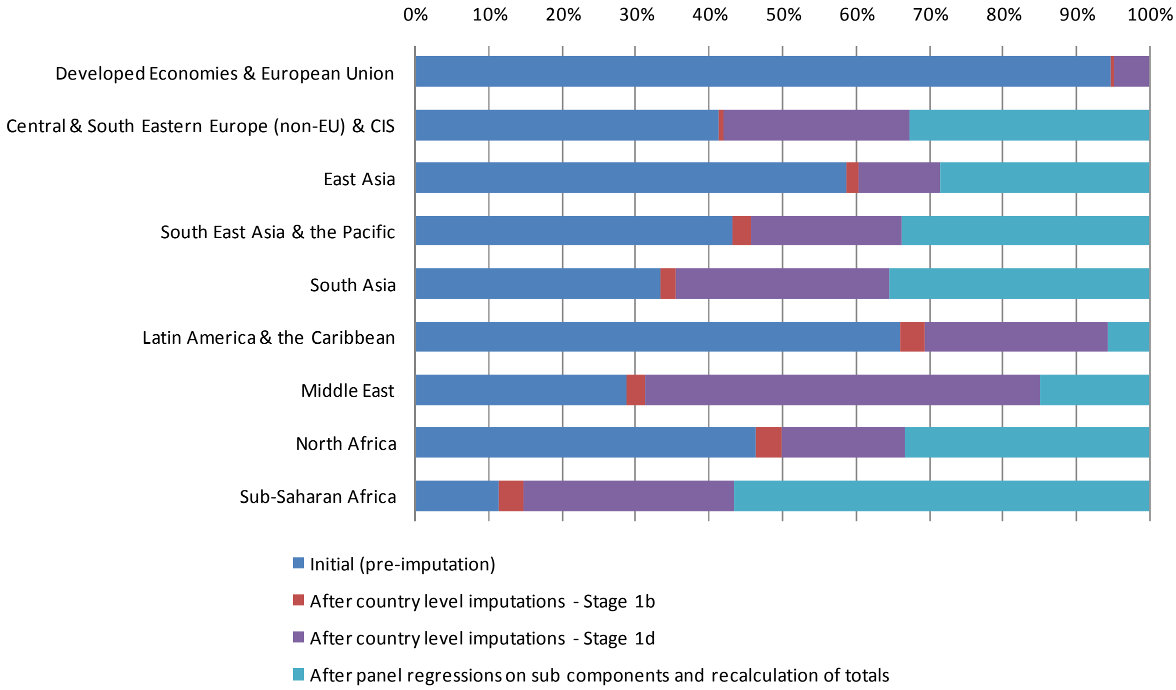


Figure 3 Sub-component (YM, YF, AM, AF) response rates at various stages of the imputation process

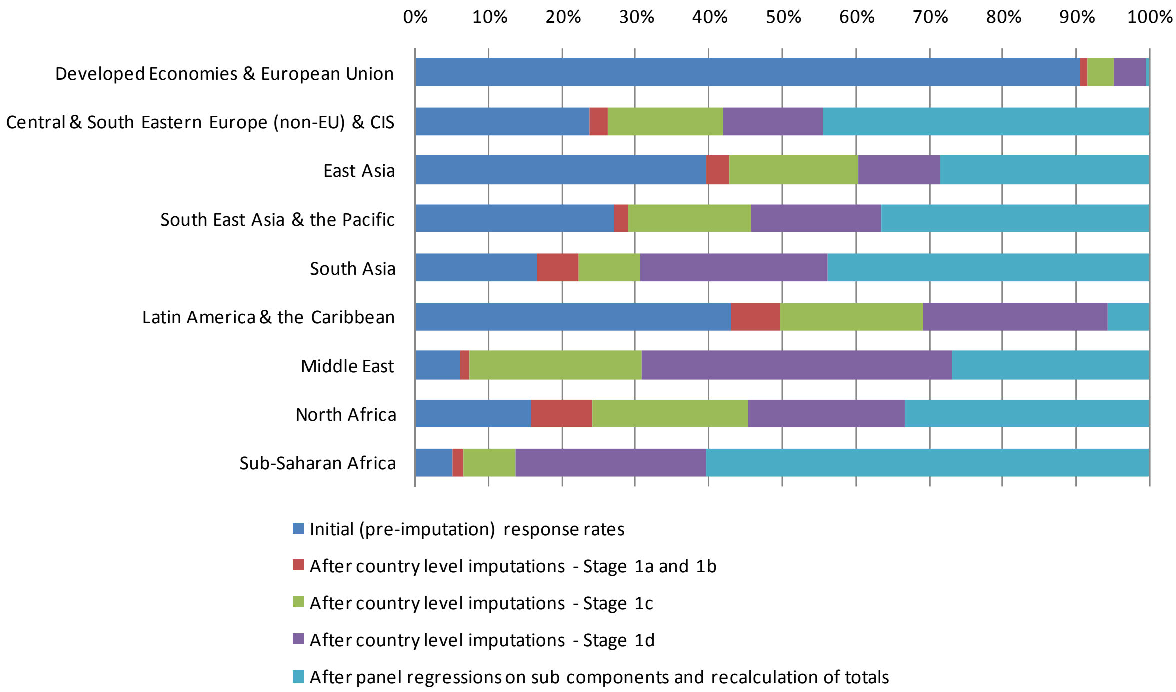


Figure 4 Male and Female unemployment rates - response rates at stages of the imputation process

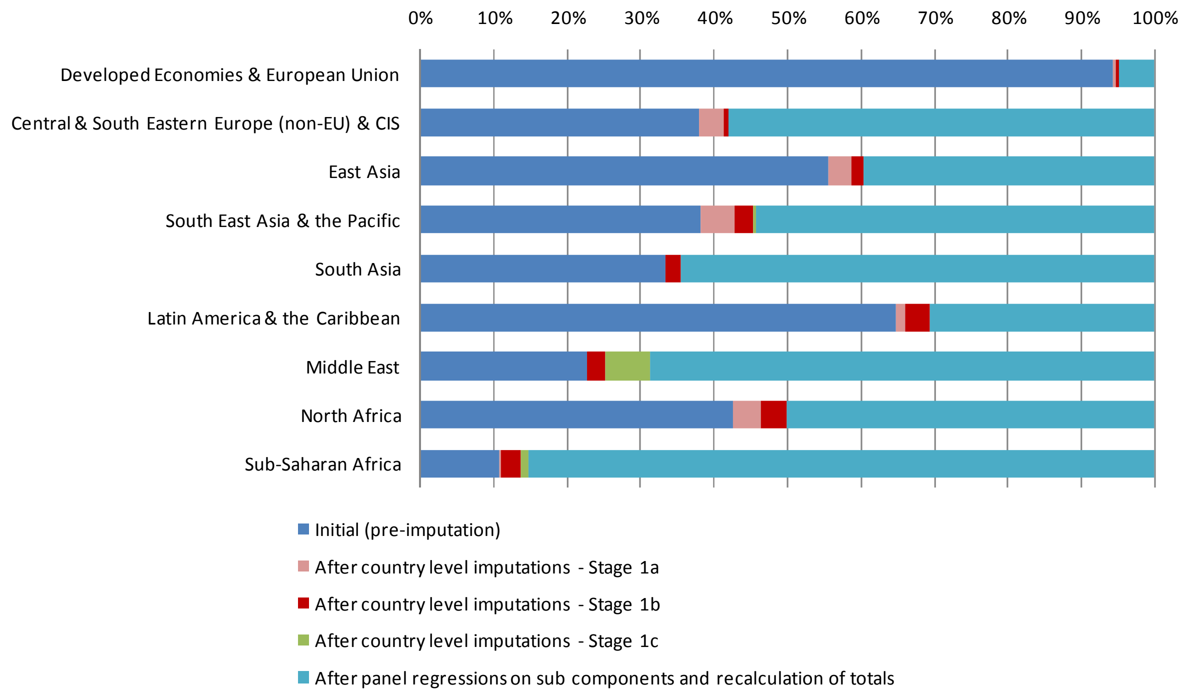
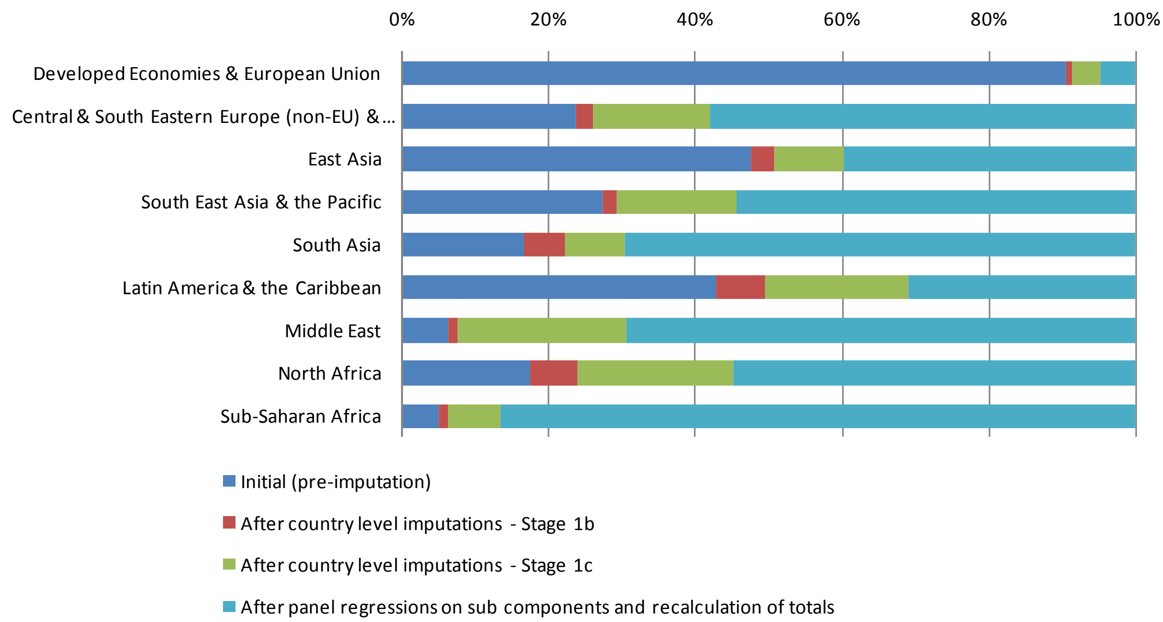


Figure 5 Adult and Youth unemployment rates - response rates at stages of the imputation process



Two measures based on this ratio are then computed: the median of the ratio over the entire time period for which data are available ($\bar{R}_{ik}$), and the median of the ratio over the recent post-2001 period ($\bar{R}_{ik3}$). A final ratio is finally constructed as follows:

$$\tilde{R}_{ik} = \begin{cases} 0.3 \times \bar{R}_{ik} + 0.7 \times \bar{R}_{ik3} & for\ years \geq 2001, if \geq 3\ data\ points\ available\ for\ this\ period \\ \bar{R}_{ik} & for\ years < 2001, and\ years \geq 2001\ if\ < 3\ data\ points\ available \end{cases}$$

The final ratio is then used to recover the missing sub-component *k*:

$$\tilde{Y}_{itk} = \tilde{R}_{ik} \times Y_{it}$$

These ratios are first calculated at the country level, when sufficient data are available. Otherwise, they are calculated at the sub-regional level, and in the case of insufficient data at the sub-regional level, they are calculated at the regional level.

This part results in an increase in the average response rates for the lowest level of disaggregated components (male youth, male adult, female youth and female adult): by 24 percentage points the Middle East, 21 percentage points for North Africa, 19 percentage points for Latin America and the Caribbean, 16 percentage points South East Asia and the Pacific, 15 percentage points for Central and South Eastern Europe and the CIS, and for East Asia, 8 percentage points for South Asia, 7 percentage points for Sub-Saharan Africa, and 3 percentage points for the Developed Economies and the EU (see Figure 3). Response rates for *male and female unemployment rates*: by 6 percentage points for the Middle East and 1 percentage point for Sub-Saharan Africa (see Figure 4). Finally, for adults and youth unemployment rates response rates increase by 23 percentage points the Middle East, 21 percentage points for North Africa, 19 percentage points for Latin America and the Caribbean, 15 percentage points for Central and South Eastern Europe and the CIS and for South East Asia and the Pacific, 8 percentage points for South Asia, 7 percentage points for East Asia and Sub-Saharan Africa, and 3 percentage points for the Developed Economies and the EU (see Figure 5).

Stage 1d. Filling in missing data through interpolations (wave non-response, missing values across the time dimension)

The last phase of the country-level techniques involves filling in missing values along the time dimension once again, to obtain as complete as possible a dataset before regression analysis is performed. The unemployment rate data are logistically transformed and then interpolated in four steps. Note that interpolations at this stage do not result in out-of-bound results, because of the logistic transformation of the unemployment rates, but also because more data points are now available (due to the imputations from the previous stages). The transformed sub-component and total unemployment rates are defined respectively as:

$$Y_{itk}^{T} = \ln\left(\frac{y_{itk}}{1-y_{itk}}\right) \text{ and } Y_{it}^{T} = \ln\left(\frac{y_{it}}{1-y_{it}}\right)$$

where y_{itk} is the observed unemployment rate for sub-component *k*, in country *i* and period *t*, and y_{it} is the observed total unemployment rate in country *i* and period *t*. The following four-step procedure is then applied:

1. The total unemployment rate is interpolated using the following equation *for each country*, with the annual change in GDP growth ($\dot{G}_t$) as the independent variable (therefore, auxiliary variable):

$$Y_t^T = \frac{Y_b^T - Y_a^T}{\dot{G}_b - \dot{G}_a} \times \left(\dot{G}_t - \dot{G}_a\right) + Y_a^T$$

where $a < t$ and $b > t$ represent the closest points to t, for which unemployment rates are observed.

2. The four sub-component unemployment rates are in-turn interpolated *for each country*, with the total unemployment rate used as the independent variable:

$$Y_{tk}^T = \frac{Y_{bk}^T - Y_{ak}^T}{Y_b^T - Y_a^T} \times (Y_t^T - Y_a^T) + Y_{ak}^T$$

3. The total unemployment rate is interpolated based on a linear time trend:

$$Y_t^T = \frac{Y_b^T - Y_a^T}{t_b - t_a} \times (t_t - t_a) + Y_a^T$$

4. The four sub-component unemployment rates are in-turn interpolated based on a linear trend:

$$Y_{tk}^T = \frac{Y_{bk}^T - Y_{ak}^T}{t_b - t_a} \times (t_t - t_a) + Y_{ak}^T$$

This part results in an increase in the average response rates for *total unemployment rates* by 54 percentage points in the Middle East, 29 percentage points for Sub-Saharan Africa and for South Asia, 25 percentage points for Central and South Eastern Europe and the CIS and for Latin America and the Caribbean, 21 percentage points for South East Asia and the Pacific, 17 percentage points for North Africa, 11 for East Asia, and 5 for the Developed Economies and the EU (see Figure 2). This procedure also increased response rates for the *four sub-component unemployment rates*: by 42 percentage points the Middle East, 26 percentage points for Sub-Saharan Africa and for South Asia, 25 percentage points for Latin America and the Caribbean, 21 for North Africa, 18 for South East Asia and the Pacific, 14 for Central and South Eastern Europe and the CIS, 11 for East Asia, and 4 for the Developed Economies and the EU (see Figure 3).

4.2.2 Stage 2. Regression Imputation

This section addresses missing unemployment data along both the country and time dimension (unit and wave non-response) for all sub-components. The most significant issue that arises in this context is that of the 'missingness' structure of the data. As previously explained, if non-reporting countries are statistically different from reporting ones, then the sample of reporting countries cannot be considered a random, representative sample of the total population. If this is the case, weights can be used in panel regressions to diminish the influence of countries that are less similar to non-reporting countries (based on a set of covariates), and to increase the influence of countries that are more similar. As a result, the weighted sample resembles more closely the theoretical population than the unweighted sample did.

As explained in section 4.1.3, missing data in the context of the GET model cannot be considered MCAR. Within each sub-regional group, however, missing data can be considered MAR and the corresponding imputation methods (e.g. weighted regressions) can be used. Weighted panel regressions are therefore used for all sub-regions with the possible exception of Europe and Major non-Europe, for which there are no missing observations.[24] For the latter two sub-groups, unweighted panel regressions are run for each of the four unemployment sub-components, as follows:

$$Y_{itk}^{T} = \alpha_i + \beta \dot{G_{it}} + \epsilon \qquad where\ i \in SR\ , and\ 1991 \leq t \leq max\ year$$

where Y_{itk}^{T} is the logistically transformed unemployment rate sub-component, α_i is the country fixed-effect, $\dot{G_{it}}$ is the annual rate of GDP growth for country *i*, SR is the sub-region (in this case Developed economies in Europe, and Developed economies non-Europe), and $max\ year$ is the latest year for which data are available. Note that the GET model is a 'live' model; the time dimension of the panel dataset expands to include additional data as these data become available. The 2009 runs of the model included data for years starting in 1991 through 2008.

For all other sub-regions, weights to be used in regressions are constructed as the ratio between the proportion of non-missing observations in the sample, and the reporting probability attached to each country in each year. The reporting probabilities are estimated using a logistic regression, conditioned on a set of covariates or country-specific characteristics. Specifically, following Horowitz and Manski (1998), each observation in the dataset is characterized by a vector $(y_{it}, x_{it}, w_{it}, r_{it})$, where y is the outcome of interest (the unemployment rate), *x* is a set of covariates that determines the value of the outcome, and *w* is a set of covariates that affects the probability of the outcome being observed. Finally, *r* is a binary variable indicating a missing response as follows:

$$r_{it} = \begin{cases} 1 & if\ i\ reports \\ 0 & if\ i\ is\ missing \end{cases}$$

The essence of the problem is estimating conditional expectations of the unemployment rates of the form $E[g(y_{it})|x_{it} \in A]$ where *g(.)* is a specified real-valued function of outcome and *A* is a specified set of values of the covariates x_{it}. Thus, $r_{it} = 1$ indicates that the set (y_{it}, x_{it}) is fully observed, and $r_{it} = 0$ indicates that data on y_{it} are missing. The vector of covariates, which is always observed, is used to compute weights in order to balance the observed sample of countries. The covariates used in the GET model include the following country-specific variables: economic growth, population size, per capita GDP and membership in the Heavily Indebted Poor Countries Initiative (HIPC).[25] On average, reporting countries tend to have higher per capita GDP and larger populations than non-reporting countries.

An index value that determines whether or not a country reports data is defined as a linear function of the covariates *w*, as follows:

$$r_{it}^{*} = w'_{it}\delta + \varepsilon_{it}$$

where each country reports if this index value is positive:

$$r_{it} = \begin{cases} 1 & if\ r_{it}^{*} > 0 \\ 0 & otherwise \end{cases}$$

A country's probability of reporting unemployment can be written as follows:

$$P_i = P(r_{it} = 1) = P(\varepsilon_{it} > -w'_{it}\delta) = 1 - F(-w'_{it}\delta)$$

---

[24] For these two sub-regions no observations are missing since 2000, and very few observations are missing in previous years. Observations missing in previous years are filled in earlier imputation stages (See Appendix 2).

[25] HIPC membership is included because one of the implications of the initiative is that national statistics offices in HIPC countries are required to collect fuller information and to strengthen their data capabilities.

where F is the cumulative distribution function of ε_{it} , which is assumed to be symmetric. Therefore, a country's probability of reporting unemployment can be written as:

$$P_i = F(w'_{it}\delta)$$

The functional form of F depends on the assumption on the distribution of the error term ε_{it}. In the GET model, the error term is assumed to have a logistic distribution:

$$F(w'_{it}\delta) = \frac{\exp{(w'_{it}\delta)}}{1+\exp{(w'_{it}\delta)}}$$

A logit model is therefore estimated. The likelihood function can be written as:

$$L = \prod_{r_i=1} P_i \prod_{r_i=0} (1-P_i)$$

Predicted response probabilities for each country are then computed, and used to construct weights defined as:

$$S_{it}(w) = \frac{P(r_{it}=1)}{P(r_{it}=1|w'_{it},\hat{\delta})}$$

These weights are therefore computed as the ratio of the proportion of non-missing observations in the sample, over the reporting probability attached to each country in each year. Thus, the higher its reporting probability relative to the sample, the lower the weight assigned to a country. For this reason, the weights serve to diminish the influence of countries that are less similar to non-reporting countries (based on the set of covariates), and increase the influence of countries that are more similar. As a result, the weighted sample resembles more closely to the theoretical population than the unweighted sample did. Table 1 provides the results from the logit regressions to estimate the response probabilities. For most sub-regions, per capita GDP and population size are found to be highly significant in determining response probabilities.

Table 1 Determinants of response probabilities

	Eastern Europe & Baltic	CIS	South East Asia	Central America	South America	Subsahara Africa	North Africa & Middle East
Per capita GDP	++	++	++	+	++	++	
GDP Growth		-		+			
HIPC		++		+	++		
Population	+	++	++		++	++	++
Constant	--	--	--	-	--	--	
Observations	300	240	280	323	228	840	380
Pseudo R-squared	0.7069	0.2253	0.3476	0.8921	0.2534	0.0738	0.1202
LR Chi-square	174.3	74.9	128.8	143.3	36.7	79.4	52.7

Coefficient signs are given. Double signs indicated significance at 1%. Single signs indicate significance at 10%.

Once the weights are computed, the conditional expectations of the unemployment rates, $E[g(y_{it})|x_{it} \epsilon A]$, can be estimated by the weighted average $\sum_{i \epsilon N_1} s(w_{it})g(y_{it})$ where N_1 is the set of reporting countries.

In order to preserve the unobserved heterogeneity of the various countries, panel data techniques are used. Specifically, a fixed-effects equation is specified as:

$$Y_{itk}^{T} = \alpha_i + x'_{it}\beta + \varepsilon_{it} \qquad where\ i \in SR\ , and\ 1991 \le t \le \max year$$

where Y_{itk}^{T} is the logistically transformed unemployment rate sub-component, α_i is a country fixed-effect, and x'_{it} is a set of covariates including GDP growth rate and, for regions where there is clear evidence of structural break, some time dummies,[26] SR is the sub-region, and $max\ year$ is the latest year for which data are available.

This model can also be written as:

$$Y^T = X\beta + \alpha_1 d_1 + \alpha_2 d_2 + \ldots + \alpha_{N1} d_{N1} + \varepsilon$$

where $d_1 \ \ldots d_{N1}$ are country dummy variables for the set of reporting countries.

The fixed-effects model controls for all the country-specific factors that influence the unemployment rate. The panel regressions are run at the sub-regional level (imputation classes consist of sub-regional country groupings) for all sub-regions except for the two developed economies sub-groups (EU and non-EU), using the weights constructed in the previous step. Before being used in the regressions, the weights are normalized as follows[27]:

$$s(w_{it})^* = \frac{s(w_{it})}{\sum s(w_{it})} N_1$$

Once the models are estimated, they are used for imputation and prediction, and generate a 'complete dataset', which can then be used to create Sub-regional and regional aggregates.[28] The complete regression results are provided in Appendix 3.

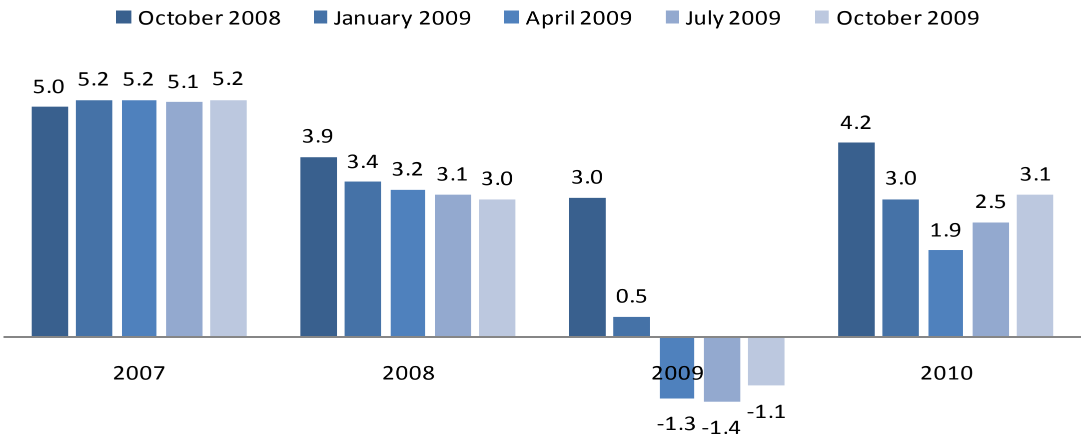
This stage results in increased response rates for the *four sub-component unemployment rates* by 60 percentage points for Sub-Saharan Africa, 44 percentage points for Central and South Eastern Europe and the CIS, and for South Asia, 37 percentage points for South East Asia and the Pacific, 33 for North Africa, 29 for East Asia, 27 for the Middle East, and 6 percentage points for Latin America and the Caribbean (see Figure 3). The male and female rates and the total unemployment rates are then obtained by aggregating the sub-components, resulting in a complete dataset. This stage resulted in an increase in the average response rates for *total unemployment rates* by 54 percentage points for Sub-Saharan Africa, 33-35 percentage points for South Asia, South East Asia and the Pacific Central and South Eastern Europe and the CIS, and North Africa, 29 percentage points for East Asia, 15 percentage points for the Middle East, and 6 for Latin America and the Caribbean (see Figure 2).

[26] For Eastern Europe, and the Commonwealth of Independent States, two subregions that include many Transition Economies, observations prior to 1995 are treated differently, to take into account the economic transition period.
[27] This is done automatically in Stata, by using the analytic weights regression option.
[28] The standard errors are also computed. However, these are underestimated because they do not account for the uncertainty associated with the estimation of the fixed effects.

4.3 Economic Crisis and Unemployment

The impact of the economic crisis that began in 2008 on labour markets worldwide has been widespread and severe. To monitor the rapidly deteriorating conditions and reflect the increased level of uncertainty, the GET model, which was initially developed to provide annual estimates of unemployment rates had be extended, made more flexible, and has been run more frequently. This section describes the modifications made to the model to enable it to capture the adverse break in the historical trends of unemployment rates caused by the crisis, and to process the most recently available information on labour market developments.

Figure 6 Revisions of Real GDP Growth Estimates and Projections (October 2008 - October 2009)



Source: IMF World Economic Outlook (WEO) Database

Figure 6 illustrates the frequent revisions made by the International Monetary Fund (IMF) of GDP growth estimates and projections, published in their World Economic Outlook (WEO) publications and updates. The forecast for world growth in 2009 which was 3 per cent in October 2008, fell to 0.5 per cent in January 2009, was revised down to negative 1.3 per cent in April, and to negative 1.4 per cent in July. In the most recent WEO update, released in October 2009, the IMF estimated negative growth of 1.1 per cent for 2009. The significant volatility in growth projections reflects a high level of uncertainty regarding the economic outlook, and implies uncertainty surrounding estimates based on these projections, such as the GET unemployment estimates.

Because the IMF growth data constitute a key benchmark for the GET model, the model was run using the new data when they became available. The GET model was run four times since the end of 2008 (for the January 2009 GET, the March 2009 Women's GET, the May 2009 GET Update, and finally in July for the KILM 6th edition, published in September 2009). Additionally, the model will be run in November for the January 2010 GET.

4.3.1 Unemployment Scenarios

During the first half of 2009, when limited labour market information (monthly and quarterly unemployment rates) were available, and considerable uncertainty remained as to the extent and duration of the crisis, the ILO Trends Team estimated the unemployment rate for 2009 using three different projection models (scenarios). At the time, a point estimate was not produced, partly because of the large degree of uncertainty surrounding the economic growth forecasts that constitute a basis for the unemployment rate projections.

Scenario 1

The first scenario simply uses the historical relationship between economic growth and unemployment at the country level between 1991 and 2008, and applies this relationship to the latest IMF GDP growth projections for 2009. The values for 2009 are generated by the fixed effects panel regressions used to impute missing values from the GET model (see section 4.2.2).

Scenario 2

The second scenario is generated on the basis of the relationship between economic growth and unemployment during the worst observed economic downturn in each country. Specifically, for each country, a ratio corresponding to the 'unemployment rate elasticity during the worst economic downturn', for each of the two sexes (s), is computed as:

$$\xi_i^s = \frac{\Delta Y_{ij}^s}{\Delta G_{i0}} \qquad and\ j \in \{-1, 0, 1, 2\}\ ;\ s \in \{Male, Female\}$$

where ΔG_{i0} is the largest annual drop in GDP growth during the 1991 and 2007 period (the corresponding year is identified as t_{i0}) and ΔY_{ij}^s is the largest increase in unemployment rate that occurred within one year before the crisis to two years after the crisis (between $t_{i(-1)}$ and $t_{i(+2)}$) for men and women respectively. Note that positive elasticities are replaced by 0.[29] The elasticity is then used, with the projected change in GDP growth in 2009 (ΔG_{i08-09}) to obtain the projected change in male and female unemployment rates in 2009, as follows:

$$\Delta \hat{Y}_{i08-09}^s = \xi_i^s \times \Delta G_{i08-09}$$

The male and female unemployment rates in 2009 can then be obtained as:

$$\hat{Y}_{i09}^s = Y_{i08}^s + \Delta \hat{Y}_{i08-09}^s$$

Note that positive GDP growth rates in 2009 are set to 0, such that the projected male and female unemployment rates in 2009 for countries projected to have positive economic growth that year are equal to their unemployment rates in 2008. In other words, in scenario 2, by construction, male and female unemployment rates in 2009 will be at least as high as their unemployment rates in 2008.

The male and female youth unemployment sub-components are then obtained using the relationship between the male or female youth unemployment and the male or female total unemployment rate, adjusted by a multiplier that captures this relationship during the worst downturn period experienced by each country. Specifically, a multiplier for each of the two sexes is constructed as follows:

$$\tilde{R}_i^s = \frac{R_{i0}^s}{R_{i(-1)}^s} = \frac{Y_{i0}^{y,s} / Y_{i0}^s}{Y_{i(-1)}^{y,s} / Y_{i(-1)}^s}$$

[29] Cases where unemployment has decreased in times of economic crisis (where the 'crisis unemployment rate elasticity' is positive) are considered exceptions, rather than representing a solid relationship between the two variables (unemployment and growth).

This multiplier is used to adjust the ratio of male or female youth unemployment and the male or female total unemployment rate in 2008, and used to estimate the youth unemployment sub-components in 2009 as follows:

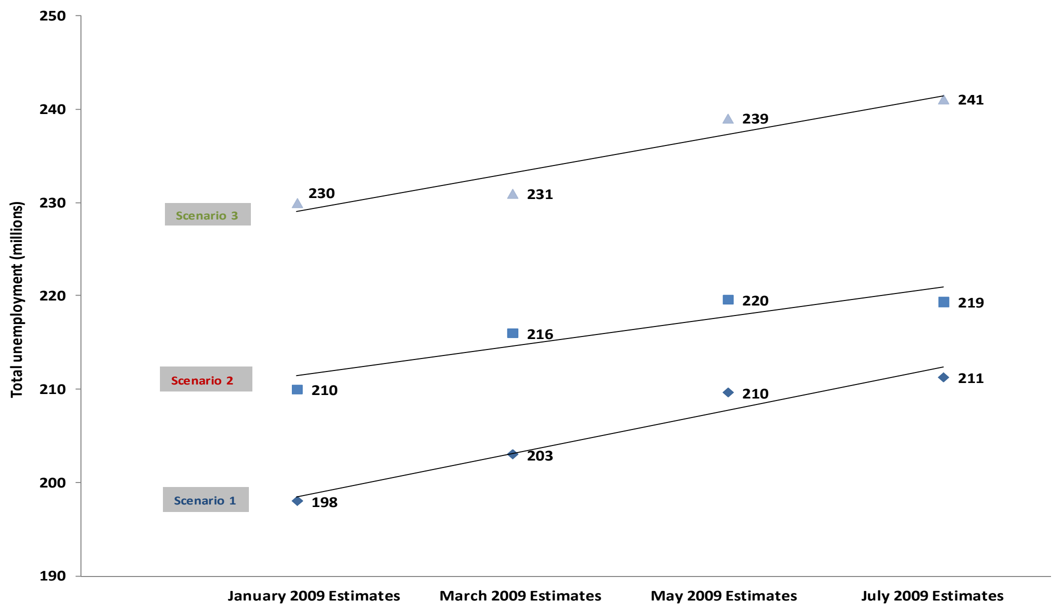
$$\hat{Y}_{i09}^{y,s} = \left(\tilde{R}_i^s \times R_{i08}^s\right) \times \hat{Y}_{i09}^s$$

The nominal male and female unemployment figures are then calculated using the labour force figures; the male and female adult unemployment figures are obtained as a residual, and the corresponding rates calculated using the labour force figures.

Scenario 3

Scenario 3 is generated by taking the worst observed year-over-year increase in each country's male and female unemployment rates and assumes that a slightly higher increase (by a multiple of 1.1) would happen simultaneously in all developed countries, and that half of the largest observed increase would occur for developing economies in 2009. The rationale for a different multiplier for developing countries is that the impact of the crisis on developing economies in terms of unemployment is likely to be less severe and to lag the crisis impact on developed economies. Finally, the youth and adult sub-components are computed using the same method as for scenario 2.

Figure 7 Evolution of unemployment scenarios for 2009



Source: Trends Econometric Models (January, March, May and July 2009).

The three unemployment scenarios: Results

The three unemployment scenarios were constructed on very different assumptions, and were not meant to provide a range for unemployment rate projections, in the sense of a confidence interval around a point estimate. At the country level, while scenario 1 generally produced the lowest bound (the crisis impact on labour markets has been unprecedented over the observed period for these countries, such that the historical trend likely underestimates the projected unemployment rates for 2009), the highest bound was provided by scenario 3 for most countries and scenario 2 for others. At the global level however, scenario 3 always produced the highest projected unemployment. Figure 7 presents the evolution of the global unemployment scenarios during the first half of 2009. All three scenarios were shifted upwards as new information became available.

4.3.2 Incorporating the latest monthly and quarterly data

To monitor the rapidly deteriorating conditions, timely Labour Market Information (LMI) is needed. This information is not always available however, and the time required for data collection, processing and dissemination varies across countries. Among the 178 countries included in the GET model, 67 countries produce monthly or quarterly unemployment rates. Some of these countries, such as the United States, Canada and the Republic of Korea, publish monthly unemployment rates within a week following the end of each month. The majority of EU member states release their monthly unemployment rates 31 days after the end of each month. For some other countries, such as Sri Lanka and the Republic of Macedonia, there is an average three months lag between the collection and dissemination of unemployment rates.

By the last quarter of 2009, as economic growth forecasts were less volatile, and more LMI became available (up to 9 monthly or 3 quarterly unemployment rates), a new approach was developed to provide a point estimate for the 2009 unemployment rate based on the most recently available data. For countries that do not produce monthly or quarterly unemployment rates, or for which these rates were not yet available for 2009, a point estimate was generated by the Global Employment Trends (GET) model, using the historical relationship between unemployment and economic growth at the country level.

Developing the new approach required examining the relationship between countries' monthly/quarterly unemployment rates and their reported annual rates. While most national statistical offices generate annual unemployment rates as averages of the quarterly unemployment rates, weighted by the quarterly population levels,[30] or as a simple average of monthly unemployment rates, some statistical offices present the rate of a specific 'sample' month or quarter as the annual rate.[31] Therefore, for most countries, obtaining a point estimate for the 2009 annual unemployment rate when unemployment rates are available for some but not all the months/quarters of the year, requires estimating the missing (remaining) monthly or quarterly rates, and averaging over the 12 months or the four quarters (observed and estimated rates). For countries that present a sample month or quarter rate as the annual unemployment rate, this rate is taken as the point estimate for 2009 if it is available.[32] If the sample month or quarter unemployment rate is not available, but unemployment rates for previous months or quarters are, then the country's unemployment rates are estimated for the missing months/quarters, and the point estimate is produced as an average of all monthly/quarterly figures for 2009 (using the new approach).

Estimating the unemployment rate for the remaining months or quarters of 2009 (months or quarters for which unemployment rates have not yet been reported) is done as follows:

[30] This approach is used for the annual unemployment rates in the Eurostat database. Specifically, annual unemployment rates for EU countries are generated as averages of unemployment rates from the quarterly EU Labour Force Survey (LFS), weighted by the quarterly population levels.

[31] For instance, Chile uses the November monthly rate (a moving average rate), Colombia uses the July rate,Thailand uses the Quarter 3 rate, Ecuador and Jamaica use the Quarter 4 rate, and Indonesia uses the August (semi-annual) rate.

[32] In October 2009, at the time of writing, the sample month unemployment rate was available and used as the point estimate for two countries only (specifically the July unemployment rate for Colombia, and the Q2 unemployment rate for Singapore).

1. Monthly/quarterly rates are projected forward using a linear trend over the period since the beginning of the global economic crisis (from September 2008 or 2008 Q3 to the most recent month/quarter). Because the labour market impact of the economic crisis has been unprecedented for most countries, the trend is calculated over the post-crisis period, rather than over a longer-term, historical period. This is due to the fact that the evolution of unemployment rates in the months following the onset of the current crisis has followed a pattern that is significantly different than that of previous years, as is illustrated in Figure 8 for the United States and Mexico.

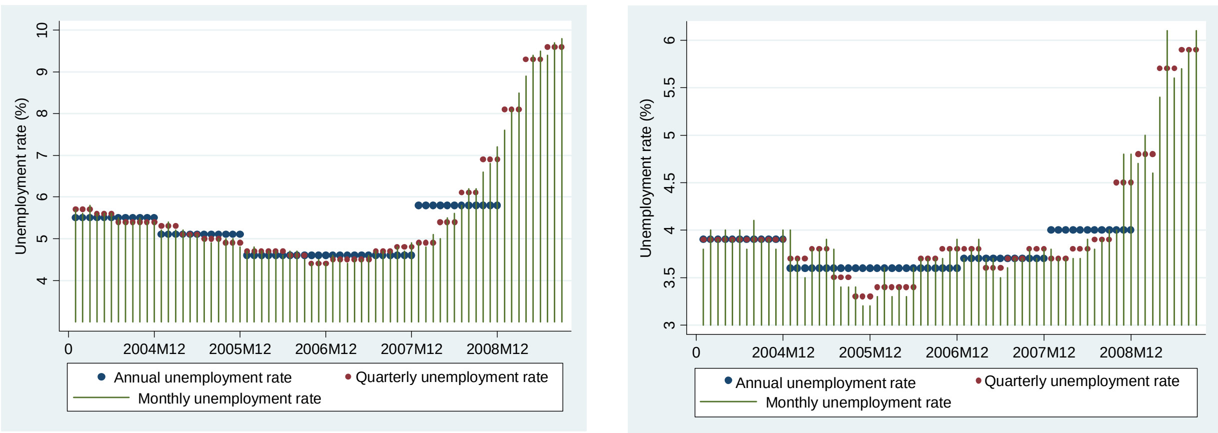
2. Monthly/quarterly rates are projected forward using a linear trend over a short-run period (the last three months or the last two quarters for which data are available).

Two annual unemployment rate estimates are then obtained as simple averages of all the monthly/quarterly rates for 2009 (each annual estimate is an average of the observed rates and of the rates estimated in 1. or 2. above). Thereafter, the two annual estimates are averaged to produce a final annual estimate. The underlying assumption is that for all countries, the likelihood of either the short-term or long-term trend persisting for the remaining months of 2009 is equal. The two annual estimates are used to construct the lower and upper bound of a confidence interval around the 2009 point estimate.

When monthly/quarterly data are available for all unemployment sub-components, the missing rates are estimated for male unemployment, female unemployment, male youth unemployment and female youth unemployment. Male adult and female adult unemployment rates are then generated as a residual. When monthly/quarterly total or youth unemployment data disaggregated by sex are not available, the total or youth total unemployment rates are estimated instead.

Figure 8 Monthly, quarterly and annual unemployment rates (2004-2009)

United States **Mexico**



Sources: U.S. Bureau of Labour Statistics, Mexico Instituto Nacional de Estadística y Geografía (INEGI), and OECD.Stat

For the rest of the countries, for which monthly or quarterly unemployment data are not available, the estimate provided by scenario 2, based on the country's employment elasticity during a crisis period (as described in section 4.3.1) is used as the point estimate for 2009 for most countries, with the exception of a few countries for which scenario 1 (based on the historical trend) is used. The rationale here is that, for most countries affected by the crisis, a clear break in the historical unemployment rate series is expected to occur in 2009, such that scenario 2 is expected to provide a more accurate estimate of the 2009 unemployment rate than the estimate based on the historical trend alone. For these countries, the lower and upper bounds of the confidence interval around the 2009 point estimate are constructed as follows: The country-level standard deviation of the unemployment rate over the 1998-2008 period is calculated, along with the ratio of this standard deviation to the 2009 predicted unemployment rate. The ratio is used to determine the significance level for the confidence interval around the 2009 point estimate. Countries for which we have limited real data tend to have very low ratios (caused by stable estimated unemployment rates). The lowest significance level (20%) is ascribed to these countries (those with ratios less than 0.06) in order to widen the confidence interval around the estimates and acknowledge higher uncertainty associated with labour market conditions in these countries. For most (approximately 80 per cent) of the countries in the sample, with ratios between 0.06 and 0.20, inclusively, a significance level of 50% is applied. For countries with the highest ratios (historical standard deviation greater than 20% of the 2009 unemployment rate), a 80% significance level is ascribed, resulting in a narrower adjusted confidence interval.

4.4 Forecasting unemployment over the short-term – an extension of the GET model

In the context of the recent economic crisis, the ILO's Employment Trends team was asked to develop a methodology to forecast unemployment in the short- to medium-term. Following previous economic crises (mainly crises that occurred in Developed economies) there has been a lag of several years between the resumption of economic growth (economic recovery) and the recovery of labour market conditions, a phenomenon often referred to as 'unemployment rate stickiness'. The methodology developed and presented in this section allows for labour market recovery to follow a different pattern and occur at a different pace across countries and regions. The unemployment rate forecast for 2010 was obtained using the historical relationship between unemployment rates and GDP growth during the worst crisis/downturn period for each country between 1991 and 2005, and during the corresponding recovery period. [33] This was done through the inclusion of interaction terms of crisis and recovery dummy variables with GDP growth in fixed-effects panel regressions. Specifically, the logistically transformed unemployment rate was regressed on a set of covariates including the lagged unemployment rate, the GDP growth rate, the lagged GDP growth rate, (the log of) per capita GDP, and a set of covariates consisting of the interaction of the crisis dummy, and of the interaction of the recovery-year dummy with each of the other variables.

4.4.1 Defining crisis and recovery

The worst crisis/downturn is defined as the largest drop in GDP growth experienced by a country during this period. The crisis period is comprised of the span between the 'crisis year' (year t_{i0}) and the year when growth reaches its lowest level following the crisis 'turning point year' (year t_{i1}), before starting to climb back to its pre-crisis level. The recovery period is comprised of the years between the 'turning point year' and the year when growth returns to its pre-crisis level, (year t_{i2}).[34] Appendix 4 lists the crisis year, turning point year, and recovery year for each country.

A crisis dummy variable and a recovery dummy variable were constructed as:

$$c_{it} = \begin{cases} 1 \;\; for \;\; t_{i0} \leq t_i \leq t_{i1} \\ 0 \;\; otherwise \end{cases}$$

[33] The period during which the crisis could have occurred was limited to 1991-2005, to ensure observations over at least 3 'recovery years'

[34] Specifically, a GDP index is constructed which takes on the value 100 the year before the sharpest economic downturn experienced by a country, defined as a crisis year. The crisis year dummy takes on the value "1" for the crisis year and the following years until the GDP index reaches its lowest point (minimum or "turning point") before returning to its pre-crisis level. The recovery dummy takes on the value "1" for the years between the "turning point" year and the year when the GDP index returns to its pre-crisis level.

$$r_{it} = \begin{cases} 1 & for\ t_{i1} < t_i \leq t_{i2} \\ 0 & otherwise \end{cases}$$

In order to project unemployment during the 'current' recovery period, the crisis-year and recovery-year dummies were adjusted based on the following definition: A country was considered "currently in crisis" if the drop in GDP growth after 2007 was larger than 75 per cent of the absolute value of the standard deviation of GDP growth over the 1991-2008 period and/or larger than 3 percentage points.

4.4.2 The regression model

As in the GET model, preserving the heterogeneity of country data is key, panel data techniques were used. The regression model was specified as follows:

$$Y_{itk}^{T} = \alpha_i + x'_{it}\beta_1 + c_{it}\_x'_{it}\beta_2 + r_{it}\_x'_{it}\beta_3 + \varepsilon_{it} \qquad where\ i \epsilon\ Group\ , and\ 1991 \leq t \leq 2005$$

where Y_{itk}^{T} is the logistically transformed unemployment rate; α_i is a country fixed-effect; x'_{it} is a set of covariates including the lagged unemployment rate, the GDP growth rate, the lagged GDP growth rate, (the log of) per capita GDP; $c_{it}\_x'_{it}$ is a set of covariates consisting of the interaction of the crisis dummy with each of the covariates in x'_{it} and $r_{it}\_x'_{it}$ is a set of covariates consisting of the interaction of the recovery-year dummy with each of the covariates in x'_{it}.

Using the above regression equation, separate panel regressions were run across three different groupings of countries, based on: 1. Geographic proximity and economic/institutional similarities, 2. Income levels[35], and 3. Level of export dependence (measured as exports as a percentage of GDP).[36] Results from these regressions are provided in Appendix 5.

The rationale behind these groupings is the following: Countries within the same geographic area or with similar economic/institutional characteristics are likely to be similarly affected by the crisis, and have similar mechanisms to attenuate the crisis impact on their labour markets. Furthermore, because countries within geographic areas often have strong trade and financial linkages, the crisis is likely to spill-over from one economy to its neighbour (e.g. Canada's economy and labour market developments are intricately linked to developments in the United States). Countries of similar income levels are also likely to have more similar labour market institutions (e.g. social protection measures) and similar capacities to implement fiscal stimulus and other policies to counter the crisis impact. Finally, as the decline in exports was being the primary crisis transmission channel from developed to developing economies, countries were grouped according to their level of exposure to this channel, as measured by their exports as a percentage of their GDP. The impact of the crisis on labour markets through the export channel also depends on the type of exports (the affected sectors of the economy), the share of domestic value added in exports, and the relative importance of domestic consumption (for instance, countries like India or Indonesia with a large domestic market were less vulnerable than countries like Thailand and Singapore). These characteristics are controlled for by using fixed-effects in the regressions.

[35] The income groups correspond to the World Bank income group classification of four income categories, based on their 2008 GNI per capita (calculated using the Atlas method): low income countries (LIC), \$975 or less, lower middle income countries (LMIC), \$976 - \$3,855, upper middle income countries (UMIC), \$3,856 - \$11,905; and high income countries (HIC), \$11,906 or more.

[36] The export dependence-based groups are the following: highest exports (exports ≥70% of GDP), high exports (exports <70% but ≥50% of GDP), medium exports (exports <50% but ≥20% GDP) and low exports (exports <20% of GDP).

To minimize the impact of imputed data from the GET model on the forecasts, separate regressions were run on a sub-sample of countries with 14 or more real data points (out of a maximum of 18 possible observations) to obtain coefficients for these countries. For the other countries, regressions were run on the entire sample.

In addition to the panel regressions, country-level regressions were run for countries with sufficient data. The OLS country-level regressions included the same variables as the panel regressions, with the exception of per capita GDP. The final projection was generated as a simple average of the estimates obtained from the three group panel regressions and, for countries with sufficient data, the country-level regressions as well.

A confidence interval around the 2010 projection is constructed in the same way as for the 2009 point estimate for countries for which no monthly or quarterly unemployment rates are available (see section 4.3.2). Specifically, countries are divided in three groups based on the ratio of the standard deviation of their unemployment rate during the 1998-2008 period to their 2009 unemployment rate estimate. A lower significance level (and therefore a wider confidence interval) is ascribed to countries with lower ratios to reflect the higher uncertainty associated with labour market conditions in these countries. This methodology can be adapted to provide medium-term (up to 5 years) projections. The confidence intervals would increase to reflect a higher uncertainty with respect to labour market conditions in all countries in the longer run.

5. Methodology assessment and evaluation

The ILO commissioned a report to identify key methodological issues and best practices in preparing regional and global figures for the MDG indicators.[37] The report, which was considered at the second meeting of the Committee for the Co-ordination of Statistical Activities (CCSA) held in Geneva in September 2003, included specific recommendations. Appendix 6 lists these recommendations and assesses the extent to which ILO Trends methodologies are consistent with them.

A key point is that the methodology for generating regional and global aggregates should be based on appropriate imputation methods, which take into account the data characteristics (missing data patterns, statistical properties, economic significance). Criteria for choosing imputation methods include robustness under model misspecification, the efficiency and minimum bias of the estimator (Durrant, 2005).

5.1 Data consistency and outlier detection mechanisms

The GET methodology involves checks and assessments of the validity of the data (both reported and imputed) at various stages. At an initial stage, analysts from the Trends Unit examine all data input files, to identify any inconsistencies due to breaks in data series, changes in sources or data entry errors. When problematic data are identified, the corresponding observations are removed from the dataset before any imputation is undertaken.

At various stages in the data imputation process, an outlier detection mechanism has been integrated in the GET model, to identify imputed data that may be out of bound, and in some cases, adjust or remove the data identified as such. One such outlier detection mechanism identifies two cases: 1. The total unemployment rate is positively correlated with real GDP growth, and 2. The difference between

[37] Holt, T. "Aggregation of National Data to Regional and Global Estimates" Report prepared for the Committee for the Coordination of Statistical Activities, Geneva, September 2003

total unemployment and unemployment sub-components is highly volatile over time. The first case may occur if there is a structural break in the time series for a country, or problems in the data for some years, or it can reflect a weak relationship between economic growth and employment/unemployment, or a relationship that involves a time lag. For instance, the relationship between growth in resource (particularly) oil exporting countries and employment is likely to be weak or even ambiguous. Because there is a subjective element to whether the data series identified through this procedure should be treated as outliers, the data identified through this routine are not adjusted nor removed, but flagged as requiring further attention from the analyst, who can then decide on the best course to follow.

Other examples of routine checks on the model include identifying the minimum and maximum of the imputed values and compared with the minimum and maximum observed values to ensure that no out of bound values have been generated by the imputation process. For instance, at one stage of the imputation process, imputed values that are larger than regional or global maximum are dropped.

5.2 Assessing imputation and estimation techniques

In developing the Trends econometric models, analysts conducted sensitivity analysis and tested various model specifications. The models are based on carefully and clearly defined assumptions. Trends econometric models integrate a variety of imputation and estimation techniques, allowing the empirical investigation of alternative models. Different imputation techniques are tested at various stages of the GET model. Criteria used to select the most appropriate method include the simplicity of the method, consistency of the assumptions with economic principles, and minimum bias (that the technique produces closest approximation of the real (observed) values, and does not produce outlying values).

The regression weights used conform to best practices for imputation with MAR data. Country weights for aggregation are based on logical relationships (e.g. labour force size as weight for unemployment aggregates) Auxiliary variables used are selected are empirically tested.

When estimating trends based on data resulting from repeated imputations (e.g. forecasting short-to - medium term unemployment rates), care is taken to separate countries with a large number of imputed values from other countries, to prevent the imputed data from driving the results that would be obtained from observed data. The impact of large countries are analyzed and accounted for in the models (e.g. China is not included in the construction of regression weights for East Asia).

The uncertainty associated with the estimates generated by the models – attributable to the imputation process, and to uncertainty surrounding benchmark data – is always acknowledged in the analysis based on these estimates. A point estimate is not provided when the level of uncertainty associated with it is very high. Whenever possible, a confidence interval (e.g. for the short-to-medium term unemployment projections) that accounts for the impact of imputations is constructed and presented as a measure of uncertainty.

6. Conclusion and way forward

In the context of monitoring progress towards the achievement of the MDGs, the Coordination Committee on Statistical Activities (CCSA) stated that “imputations for missing data were an essential and unavoidable part of making regional estimates”.[38] The CCSA recommended that international agencies document imputation methods used in manuals and guidelines, that can be used by national agencies. Imputed country level data are not to be published by international agencies, unless the countries were themselves involved in producing them.

The ILO Trends econometric models produce complete datasets of key labour market indicators that can be used to generate regional and global averages. As this paper has demonstrated, the methodologies used to impute missing country data correspond to existing best practices. These methodologies are continuously being refined, are documented and readily accessible to the practitioners and the public at large. GET model estimates, initially revised semi-annually, have been revised on a more regular basis since January 2009. The ILO has provided clear explanations of data and or/methodological changes underpinning the revisions.

There is no doubt that intensive data collection efforts to further expand data coverage and increase the frequency of data collection is necessary. The ILO has a crucial role to play in supporting countries to collect, analyze and disseminate timely labour market information.

In the short run, the ILO will continue to refine and enhance the Trends econometric models. Future work in this regard must include additional sensitivity analysis and testing. Specifically, new equations and model specifications need to be developed and evaluated. For instance, variables representing structural factors that may affect the relationship between growth and employment (e.g. natural resource exports dependence) can be explicitly controlled for in the regressions.

Additional work is also required to further improve the models’ flexibility and responsiveness to economic and social shocks resulting in breaks in data series. This could involve the inclusion of variables that capture countries’ vulnerability to external shocks, for instance, macroeconomic stability, financial sector development and integration into the global system, dependence on exports (exports as a share of GDP, or exports relative to domestic consumption), dependence on remittances, dependence on foreign aid, among others.

[38] Report of the Inter-agency and Expert Meeting on MDG Indicators, held in Geneva, 10-13 November 2003. Available at http://www.unece.org/stats/documents/2003.11.mdg.htm

Appendix 1 – Initial dataset

Percentage of countries with at least 1, at least 2 and at least 3 data points in the initial dataset:

Total unemployment rate

	Total Countries	Percent of countries		
		≥ 1	≥ 2	≥ 3
Developed Economies & European Union	36	100	100	100
Central & South Eastern Europe (non-EU) & CIS	18	78	67	61
East Asia	7	71	71	57
South East Asia & the Pacific	14	79	64	57
South Asia	8	100	63	50
Latin America & the Caribbean	31	100	94	94
Middle East	13	92	85	54
North Africa	6	67	67	67
Sub-Saharan Africa	45	64	42	24

Male and Female unemployment rates

	Total Countries	Percent of countries		
		≥ 1	≥ 2	≥ 3
Developed Economies & European Union	36	100	100	100
Central & South Eastern Europe (non-EU) & CIS	18	78	67	61
East Asia	7	71	71	57
South East Asia & the Pacific	14	71	64	57
South Asia	8	100	63	50
Latin America & the Caribbean	31	100	94	90
Middle East	13	77	69	46
North Africa	6	67	67	67
Sub-Saharan Africa	45	60	40	20

Adults and Youth unemployment rates

	Total Countries	Percent of countries		
		≥ 1	≥ 2	≥ 3
Developed Economies & European Union	36	100	100	100
Central & South Eastern Europe (non-EU) & CIS	18	78	61	44
East Asia	7	71	71	57
South East Asia & the Pacific	14	71	43	43
South Asia	8	88	50	38
Latin America & the Caribbean	31	94	84	77
Middle East	13	54	38	8
North Africa	6	67	67	50
Sub-Saharan Africa	45	38	27	11

Male Adults, Female Adults, Male Youth and Female Youth unemployment rates

	Total Countries	Percent of countries		
		≥ 1	≥ 2	≥ 3
Developed Economies & European Union	36	100	100	100
Central & South Eastern Europe (non-EU) & CIS	18	78	61	44
East Asia	7	57	57	43
South East Asia & the Pacific	14	64	43	43
South Asia	8	88	50	38
Latin America & the Caribbean	31	94	84	77
Middle East	13	46	38	8
North Africa	6	67	50	33
Sub-Saharan Africa	45	38	24	11

Appendix 2 – Imputation stages and response rates

Total unemployment rate - Regional response rates

Initial (pre-imputation) response rates

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	Average
Developed Economies & European Union	75	81	86	92	92	94	94	94	97	100	100	100	100	100	100	100	100	100	**95**
Central & South Eastern Europe (non-EU) & CIS	11	11	11	17	28	33	39	44	50	50	56	56	61	61	61	67	61	28	**41**
East Asia	57	57	57	57	57	57	57	57	57	71	57	57	71	57	57	57	57	57	**59**
South East Asia & the Pacific	36	43	36	29	43	50	43	50	43	57	50	43	43	57	43	43	36	36	**43**
South Asia	38	25	25	38	25	50	25	25	25	50	38	25	38	38	63	38	25	13	**33**
Latin America & the Caribbean	45	55	58	52	71	71	71	71	77	68	84	77	77	74	68	81	58	32	**66**
Middle East	23	0	23	23	31	23	31	15	38	38	54	46	38	46	23	15	23	23	**29**
North Africa	33	33	33	33	33	17	50	17	50	67	67	67	67	67	67	50	50	33	**46**
Sub-Saharan Africa	9	7	4	13	13	13	18	13	13	13	9	7	11	20	13	13	9	4	**11**

After country level imputations part 1b

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	Average
Developed Economies & European Union	75	86	89	92	92	94	94	94	97	100	100	100	100	100	100	100	100	100	**95**
Central & South Eastern Europe (non-EU) & CIS	11	11	11	17	28	33	39	44	50	50	61	56	61	61	61	67	61	33	**42**
East Asia	57	57	57	57	57	57	57	57	57	71	71	71	71	57	57	57	57	57	**60**
South East Asia & the Pacific	36	43	36	36	43	50	43	50	50	57	50	50	50	57	57	43	36	36	**46**
South Asia	38	25	25	38	25	50	25	25	25	50	50	38	38	50	63	38	25	13	**35**
Latin America & the Caribbean	45	55	61	58	71	74	71	71	81	81	87	84	81	77	77	81	61	32	**69**
Middle East	23	8	23	31	31	31	31	23	38	38	54	46	46	46	23	23	23	23	**31**
North Africa	33	33	33	33	33	33	50	50	67	67	67	67	67	67	67	50	50	33	**50**
Sub-Saharan Africa	9	11	9	18	20	22	24	20	22	13	11	9	11	24	13	13	9	4	**15**

After country level imputations part 2

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	Average
Developed Economies & European Union	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
Central & South Eastern Europe (non-EU) & CIS	67	67	67	67	67	67	67	67	67	67	78	67	67	67	67	67	67	67	**67**
East Asia	71	71	71	71	71	71	71	71	71	71	71	71	71	71	71	71	71	71	**71**
South East Asia & the Pacific	71	71	71	71	64	64	64	64	64	71	64	64	64	64	64	64	64	64	**66**
South Asia	63	63	63	63	63	63	63	63	63	63	63	63	63	63	88	75	63	63	**65**
Latin America & the Caribbean	94	94	97	94	94	94	97	97	97	94	94	94	94	94	94	94	94	94	**94**
Middle East	85	85	85	85	85	85	85	85	85	85	92	85	85	85	85	85	85	85	**85**
North Africa	67	67	67	67	67	67	67	67	67	67	67	67	67	67	67	67	67	67	**67**
Sub-Saharan Africa	42	42	44	44	44	42	42	42	44	42	42	42	44	49	42	44	44	42	**43**

After panel regressions on sub components and recalculation of totals

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	Average
Developed Economies & European Union	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
Central & South Eastern Europe (non-EU) & CIS	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
East Asia	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
South East Asia & the Pacific	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
South Asia	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
Latin America & the Caribbean	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
Middle East	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
North Africa	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
Sub-Saharan Africa	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**

Male Adults, Female Adults, Male Youth and Female Youth unemployment rates - Regional response rates

Initial (pre-imputation) response rates

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	Average
Developed Economies & European Union	72	78	78	81	81	86	92	92	92	97	100	100	100	100	100	100	100	83	**91**
Central & South Eastern Europe (non-EU) & CIS	11	11	6	6	11	11	6	22	22	17	22	44	39	50	44	44	50	11	**24**
East Asia	29	43	43	43	43	43	43	43	14	57	43	43	57	43	43	43	43	0	**40**
South East Asia & the Pacific	7	21	14	21	21	43	29	43	29	43	36	29	36	29	21	29	36	0	**27**
South Asia	13	13	13	25	13	25	13	13	0	38	0	13	13	25	25	38	25	0	**17**
Latin America & the Caribbean	35	42	42	35	55	48	45	52	58	48	39	55	48	45	39	45	42	0	**43**
Middle East	8	0	0	8	8	0	0	0	0	0	15	15	8	8	15	8	15	0	**6**
North Africa	0	0	0	0	0	0	17	17	33	0	33	33	17	33	50	33	17	0	**16**
Sub-Saharan Africa	0	4	2	4	4	4	9	4	11	11	0	4	4	7	7	4	7	0	**5**

After country level imputations part 1a (in blue) and 1b (in red)

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	Average
Developed Economies & European Union	72	83	81	83	83	86	92	92	92	100	100	100	100	100	100	100	100	83	**92**
Central & South Eastern Europe (non-EU) & CIS	11	11	11	11	11	11	11	22	22	22	33	44	44	50	44	50	50	11	**26**
East Asia	29	43	43	43	43	43	43	43	43	57	57	57	57	43	43	43	43	0	**43**
South East Asia & the Pacific	7	21	14	21	29	43	29	43	36	43	36	36	36	36	29	29	36	0	**29**
South Asia	13	13	13	25	13	38	13	13	13	38	25	25	25	38	38	38	25	0	**22**
Latin America & the Caribbean	35	48	48	48	55	55	52	52	61	61	65	61	52	55	55	48	42	0	**50**
Middle East	8	0	0	8	8	0	0	0	0	0	15	15	15	8	23	15	15	0	**7**
North Africa	0	0	0	0	0	0	17	17	33	33	50	50	50	50	67	50	17	0	**24**
Sub-Saharan Africa	0	4	2	4	9	9	11	11	16	11	4	4	4	9	7	4	7	0	**7**

After country level imputations part 1c

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	Average
Developed Economies & European Union	75	86	89	92	92	94	94	94	97	100	100	100	100	100	100	100	100	100	**95**
Central & South Eastern Europe (non-EU) & CIS	11	11	11	17	28	33	39	44	50	50	61	56	61	61	61	67	61	33	**42**
East Asia	57	57	57	57	57	57	57	57	57	71	71	71	71	57	57	57	57	57	**60**
South East Asia & the Pacific	36	43	36	36	43	50	43	50	50	57	50	50	50	57	57	43	36	36	**46**
South Asia	25	13	13	25	13	38	13	25	25	50	50	38	38	50	63	38	25	13	**31**
Latin America & the Caribbean	45	55	61	58	71	74	71	68	81	81	87	84	81	77	77	81	61	32	**69**
Middle East	23	8	23	31	31	31	31	23	38	38	54	46	38	46	23	23	23	23	**31**
North Africa	33	33	33	33	17	17	50	33	50	50	67	67	67	67	67	50	50	33	**45**
Sub-Saharan Africa	9	11	9	18	20	20	22	18	20	11	9	9	9	20	13	13	9	4	**14**

After country level imputations part 2

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	Average
Developed Economies & European Union	94	97	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
Central & South Eastern Europe (non-EU) & CIS	39	39	39	44	50	50	50	56	61	61	72	61	61	61	61	67	67	61	**56**
East Asia	71	71	71	71	71	71	71	71	71	71	71	71	71	71	71	71	71	71	**71**
South East Asia & the Pacific	64	64	64	64	64	64	64	64	64	71	64	64	64	64	64	57	57	57	**63**
South Asia	50	50	50	50	50	63	63	63	63	63	63	50	50	50	75	63	50	50	**56**
Latin America & the Caribbean	94	94	97	94	94	94	97	97	97	94	94	94	94	94	94	94	94	94	**94**
Middle East	46	62	69	77	77	77	77	77	77	77	85	77	77	85	69	69	69	69	**73**
North Africa	67	67	67	67	67	67	67	67	67	67	67	67	67	67	67	67	67	67	**67**
Sub-Saharan Africa	29	29	36	36	42	42	42	42	44	42	42	40	42	44	40	42	42	36	**40**

After panel regressions on sub components and recalculation of totals

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	Average
Developed Economies & European Union	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
Central & South Eastern Europe (non-EU) & CIS	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
East Asia	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
South East Asia & the Pacific	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
South Asia	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
Latin America & the Caribbean	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
Middle East	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
North Africa	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
Sub-Saharan Africa	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**

Male and Female unemployment rates - Regional response rates

Initial (pre-imputation) response rates

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	Average
Developed Economies & European Union	75	81	86	89	89	94	94	94	97	100	100	100	100	100	100	100	100	97	**94**
Central & South Eastern Europe (non-EU) & CIS	11	11	11	11	22	28	33	39	44	44	56	56	61	61	56	61	56	22	**38**
East Asia	57	57	57	57	57	57	57	57	57	71	57	57	71	43	43	43	43	57	**56**
South East Asia & the Pacific	21	29	21	21	36	50	36	50	43	50	50	43	43	57	43	36	36	21	**38**
South Asia	38	25	25	38	25	50	25	25	25	50	38	25	38	38	63	38	25	13	**33**
Latin America & the Caribbean	45	55	58	52	71	71	71	71	77	68	81	74	74	74	68	77	58	23	**65**
Middle East	23	0	15	15	23	15	15	8	31	31	46	38	31	31	23	15	23	23	**23**
North Africa	33	33	17	17	33	17	50	17	50	67	67	50	67	67	67	33	50	33	**43**
Sub-Saharan Africa	9	4	4	13	11	13	18	11	11	13	7	7	11	20	13	13	9	4	**11**

After country level imputations part 1a

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	Average
Developed Economies & European Union	75	81	86	92	92	94	94	94	97	100	100	100	100	100	100	100	100	100	**95**
Central & South Eastern Europe (non-EU) & CIS	11	11	11	17	28	33	39	44	50	50	56	56	61	61	61	67	61	28	**41**
East Asia	57	57	57	57	57	57	57	57	57	71	57	57	71	57	57	57	57	57	**59**
South East Asia & the Pacific	36	43	36	29	43	50	43	50	43	50	50	43	43	57	43	43	36	36	**43**
South Asia	38	25	25	38	25	50	25	25	25	50	38	25	38	38	63	38	25	13	**33**
Latin America & the Caribbean	45	55	58	52	71	71	71	71	77	68	84	77	77	74	68	81	58	32	**66**
Middle East	23	0	15	15	23	15	15	8	31	31	46	38	31	31	23	15	23	23	**23**
North Africa	33	33	33	33	33	17	50	17	50	67	67	67	67	67	67	50	50	33	**46**
Sub-Saharan Africa	9	4	4	13	11	13	18	11	11	13	9	7	11	20	13	13	9	4	**11**

After country level imputations part 1b

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	Average
Developed Economies & European Union	75	86	89	92	92	94	94	94	97	100	100	100	100	100	100	100	100	100	**95**
Central & South Eastern Europe (non-EU) & CIS	11	11	11	17	28	33	39	44	50	50	61	56	61	61	61	67	61	33	**42**
East Asia	57	57	57	57	57	57	57	57	57	71	71	71	71	57	57	57	57	57	**60**
South East Asia & the Pacific	36	43	36	36	43	50	43	50	50	50	50	50	50	57	57	43	36	36	**45**
South Asia	38	25	25	38	25	50	25	25	25	50	50	38	38	50	63	38	25	13	**35**
Latin America & the Caribbean	45	55	61	58	71	74	71	71	81	81	87	84	81	77	77	81	61	32	**69**
Middle East	23	8	15	23	23	23	15	15	31	31	46	38	38	31	23	23	23	23	**25**
North Africa	33	33	33	33	33	33	50	50	67	67	67	67	67	67	67	50	50	33	**50**
Sub-Saharan Africa	9	9	7	16	18	20	22	18	20	13	11	9	11	24	13	13	9	4	**14**

After country level imputations part 1c

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	Average
Developed Economies & European Union	75	86	89	92	92	94	94	94	97	100	100	100	100	100	100	100	100	100	**95**
Central & South Eastern Europe (non-EU) & CIS	11	11	11	17	28	33	39	44	50	50	61	56	61	61	61	67	61	33	**42**
East Asia	57	57	57	57	57	57	57	57	57	71	71	71	71	57	57	57	57	57	**60**
South East Asia & the Pacific	36	43	36	36	43	50	43	50	50	57	50	50	50	57	57	43	36	36	**46**
South Asia	38	25	25	38	25	50	25	25	25	50	50	38	38	50	63	38	25	13	**35**
Latin America & the Caribbean	45	55	61	58	71	74	71	71	81	81	87	84	81	77	77	81	61	32	**69**
Middle East	23	8	23	31	31	31	31	23	38	38	54	46	46	46	23	23	23	23	**31**
North Africa	33	33	33	33	33	33	50	50	67	67	67	67	67	67	67	50	50	33	**50**
Sub-Saharan Africa	9	11	9	18	20	22	24	20	22	13	11	9	11	24	13	13	9	4	**15**

After panel regressions on sub components and recalculation of totals

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	Average
Developed Economies & European Union	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
Central & South Eastern Europe (non-EU) & CIS	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
East Asia	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
South East Asia & the Pacific	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
South Asia	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
Latin America & the Caribbean	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
Middle East	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
North Africa	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
Sub-Saharan Africa	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**

Adults and Youth unemployment rates - Regional response rates

Initial (pre-imputation) response rates

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	Average
Developed Economies & European Union	72	78	78	81	81	86	92	92	92	97	100	100	100	100	100	100	100	83	**91**
Central & South Eastern Europe (non-EU) & CIS	11	11	6	6	11	11	6	22	22	17	22	44	39	50	44	44	50	11	**24**
East Asia	29	43	43	43	43	43	43	57	29	71	57	57	71	57	57	57	57	0	**48**
South East Asia & the Pacific	7	21	14	21	21	43	29	43	29	50	36	29	36	29	21	29	36	0	**27**
South Asia	13	13	13	25	13	25	13	13	0	38	0	13	13	25	25	38	25	0	**17**
Latin America & the Caribbean	35	42	42	35	55	48	45	52	58	48	39	55	48	45	39	45	42	0	**43**
Middle East	8	0	0	8	8	0	0	0	0	0	15	15	8	15	15	8	15	0	**6**
North Africa	0	0	0	0	0	0	17	17	33	0	50	33	17	33	50	50	17	0	**18**
Sub-Saharan Africa	0	4	2	4	4	4	9	4	11	11	2	4	4	7	7	4	7	0	**5**

After country level imputations part 1b

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	Average
Developed Economies & European Union	72	83	81	83	83	86	92	92	92	100	100	100	100	100	100	100	100	83	**92**
Central & South Eastern Europe (non-EU) & CIS	11	11	11	11	11	11	11	22	22	22	33	44	44	50	44	50	50	11	**26**
East Asia	29	43	43	43	43	43	43	57	57	71	71	71	71	57	57	57	57	0	**51**
South East Asia & the Pacific	7	21	14	21	29	43	29	43	36	50	36	36	36	36	29	29	36	0	**29**
South Asia	13	13	13	25	13	38	13	13	13	38	25	25	25	38	38	38	25	0	**22**
Latin America & the Caribbean	35	48	48	48	55	55	52	52	61	61	65	61	52	55	55	48	42	0	**50**
Middle East	8	0	0	8	8	0	0	0	0	0	15	15	15	15	23	15	15	0	**8**
North Africa	0	0	0	0	0	0	17	17	33	33	50	50	50	50	67	50	17	0	**24**
Sub-Saharan Africa	0	4	2	4	9	9	11	11	16	11	4	4	4	9	7	4	7	0	**7**

After country level imputations part 1c

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	Average
Developed Economies & European Union	75	86	89	92	92	94	94	94	97	100	100	100	100	100	100	100	100	100	**95**
Central & South Eastern Europe (non-EU) & CIS	11	11	11	17	28	33	39	44	50	50	61	56	61	61	61	67	61	33	**42**
East Asia	57	57	57	57	57	57	57	57	57	71	71	71	71	57	57	57	57	57	**60**
South East Asia & the Pacific	36	43	36	36	43	50	43	50	50	57	50	50	50	57	57	43	36	36	**46**
South Asia	25	13	13	25	13	38	13	25	25	50	50	38	38	50	63	38	25	13	**31**
Latin America & the Caribbean	45	55	61	58	71	74	71	68	81	81	87	84	81	77	77	81	61	32	**69**
Middle East	23	8	23	31	31	31	31	23	38	38	54	46	38	46	23	23	23	23	**31**
North Africa	33	33	33	33	17	17	50	33	50	50	67	67	67	67	67	50	50	33	**45**
Sub-Saharan Africa	9	11	9	18	20	20	22	18	20	11	9	9	9	20	13	13	9	4	**14**

After panel regressions on sub components and recalculation of totals

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	Average
Developed Economies & European Union	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
Central & South Eastern Europe (non-EU) & CIS	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
East Asia	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
South East Asia & the Pacific	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
South Asia	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
Latin America & the Caribbean	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
Middle East	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
North Africa	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**
Sub-Saharan Africa	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	**100**

Appendix 3 – Regression results

Male Youth Unemployment	Europe	Major Non Europe	Eastern Europe & Baltic	CIS	Eastern Asia	South Central Asia	South East Asia	Central America	South America	Subsahara Africa	North Africa & Middle East	South Africa	East Asia incl China
GDP Growth	-0.03	-0.03	-0.01	-0.01	-0.02	-0.00	0.00	-0.04	-0.02	-0.00	0.00	-0.07	-0.03
	(-5.38)**	(-2.23)*	(-1.57)	(-3.20)**	(-2.37)*	(-0.19)	(0.31)	(-6.31)**	(-5.26)**	(-0.02)	(0.38)	(-3.00)**	(-3.25)**
Growth x Period 2			0.01	0.01	-0.02								
			(-1.65)	(2.68)**	(-1.01)								
Period 2			-0.02	0.13	-0.43								
			(-0.29)	(2.08)*	(-4.55)**								
Constant	-2.16	-2.41	-1.06	-1.31	-1.81	-2.03	-2.32	-1.56	-1.65	-2.2	-1.58	-0.54	-1.92
	(-29.65)**	(-40.05)**	(-27.91)**	(-38.54)**	(-35.08)**	(-28.52)**	(-79.63)**	(-65.75)**	(-88.04)**	(-134.92)**	(-73.78)**	(-4.88)**	(-35.20)**
Observations	414	99	257	117	100	88	175	301	206	285	280	57	100
R-squared	0.7345	0.5207	0.7355	0.6010	0.7514	0.8529	0.7930	0.9184	0.8405	0.9798	0.9502	0.1404	0.5742
Adj R-squared	0.7202	0.4949	0.7167	0.5634	0.7325	0.8537	0.7791	0.9132	0.8315	0.9779	0.9469	0.1247	0.5516

*** Significant at 1%, * Significant at 5%*

Male Adult Unemployment	Europe	Major Non Europe	Eastern Europe & Baltic	CIS	Eastern Asia	South Central Asia	South East Asia	Central America	South America	Subsahara Africa	North Africa & Middle East	South Africa	East Asia incl China
GDP Growth	-0.01	-0.03	-0.01	-0.01	-0.02	0.04	-0.00	-0.04	-0.02	0	0.00	-0.14	-0.03
	(-2.39)*	(-1.75)	(-0.96)	(-2.84)**	(-2.16)*	(2.18)*	(-0.26)	(-6.83)**	(-5.70)**	(0.16)	(0.49)	(-2.73)**	(-3.22)**
Growth x Period 2			0.01	0.01	-0.02								
			(-1.49)	(2.46)*	(-1.28)								
Period 2			-0.01	0.08	-0.46								
			(-0.19)	(-1.34)	(-4.28)**								
Constant	-2.46	-3.32	-2.27	-2.33	-2.79	-3.88	-3.84	-2.66	-2.9	-3.03	-2.94	-1.55	-2.91
	(-31.93)**	(-40.8)**	(-71.24)	(-70.96)**	(-48.22)**	(-39.54)**	(-121.34)**	(-109.26)**	(-139.92)**	(-161.45)**	(-144.76)**	(-6.75)**	(-47.56)**
Observations	414	99	257	117	100	88	175	301	206	285	280	57	100
R-squared	0.6836	0.3817	0.7630	0.5956	0.8491	0.6867	0.7784	0.8892	0.7329	0.955	0.9622	0.1195	0.743
Adj R-squared	0.6667	0.3484	0.7461	0.5574	0.8377	0.655	0.7635	0.8821	0.7177	0.9507	0.9598	0.1035	0.7293

*** Significant at 1%, * Significant at 5%*

Female Youth Unemployment	Europe	Major Non Europe	Eastern Europe & Baltic	CIS	Eastern Asia	South Central Asia	South East Asia	Central America	South America	Subsahara Africa	North Africa & Middle East	South Africa	East Asia incl China
GDP Growth	-0.01	-0.02	-0.02	-0.01	-0.03	-0.01	0.00	-0.03	-0.02	0.00	0.00	-0.05	-0.03
	(-1.92)	(-1.49)	(-2.45)**	(-1.19)	(-3.98)**	(-0.48)	(0.47)	(-4.79)**	(-3.46)**	(0.19)	(0.84)	(-2.28)*	(-3.62)**
Growth x Period 2			0.01	0									
			(-1.10)	(0.33)									
Period 2			-0.033	0.35									
			(-3.11)**	(3.40)**									
Constant	-2.33	-2.60	1.06	-1.53	-2.7	-0.68	-2.00	-0.48	-0.41	-0.40	-0.2	-0.05	-2.29
	(-30.24)**	(-54.77)**	(8.34)**	(-12.94)**	(-32.94)**	(-2.18)**	(-270.51)**	(-6.14)**	(-46.09)**	(-40.19)**	(-2.45)**	(-0.43)	(-49.37)**
Observations	414	99	257	117	100	88	175	301	206	285	280	57	100
R-squared	0.8047	0.6191	0.8266	0.7404	0.798	0.8733	0.8470	0.9017	0.785	0.988	0.945	0.0864	0.798
Adj R-squared	0.7943	0.5986										0.0698	0.7873

*** Significant at 1%, * Significant at 5%*

Female Adult Unemployment	Europe	Major Non Europe	Eastern Europe & Baltic	CIS	Eastern Asia	South Central Asia	South East Asia	Central America	South America	Subsahara Africa	North Africa & Middle East	South Africa	East Asia incl China
GDP Growth	0.00	-0.03	-0.01	-0.01	-0.03	0.04	-0.00	-0.03	-0.02	0.00	0.01	-0.07	-0.03
	(-0.47)	(-1.90)	(-1.78)	(-0.97)	(-3.54)**	(2.20)*	(-0.45)	(-4.06)**	(-3.52)**	(0.47)	(1.67)	(-2.09)**	(-3.42)**
Growth x Period 2			0.01	-0.00									
			(0.63)	(-0.07)									
Period 2			-0.25	0.37									
			(-2.52)*	(4.59)**									
Constant	-2.31	-3.37	-0.50	-2.44	-3.37	-2.13	-3.46	-1.82	-1.99	-2.16	-1.58	-1.01	-3.24
	(-31.4)**	(-54.04)**	(-4.58)**	(-22.52)**	(-36.56)**	(-6.13)**	(-395.27)**	(-31.64)**	(-33.23)**	(-233.26)**	(-23.86)**	(-6.42)**	(-54.55)**
Observations	414	99	257	117	100	88	175	301	206	285	280	57	100
R-squared	0.7325	0.4881	0.8395	0.8213	0.8086	0.8051	0.8349	0.9128	0.7688	0.9825	0.9467	0.0739	0.8086
Adj R-squared	0.7182	0.4606										0.057	0.7985

*** Significant at 1%, * Significant at 5%*

Appendix 4 – Historical Crisis and Recovery Years

	Crisis Year	Turning Point	Recovery Year	Largest drop in GDP growth
Developed Economies & European Union				
Australia	1991	1991	1992	-2.9
Austria	2001	2001	2002	-3.1
Belgium	1996	1996	1997	-3.4
Bulgaria	1996	1997	2001	-6.4
Canada	2001	2001	2002	-3.4
Cyprus	1996	1996	1997	-6.3
Czech Republic	1991	1992	2000	-10.3
Denmark	2001	2001	2002	-2.8
Estonia	1992	1994	2000	-13.7
Finland	1991	1993	1997	-6.3
France	2001	2001	2002	-2.3
Germany	1993	1993	1994	-3.1
Greece	1992	1993	1994	-2.4
Hungary	1991	1993	1998	-8.4
Iceland	2002	2002	2003	-3.8
Ireland	1991	1991	1992	-6.1
Israel	2001	2002	2003	-9.2
Italy	2001	2001	2002	-1.9
Japan	1998	1999	2000	-3.6
Latvia	1992	1993	2004	-19.5
Lithuania	1992	1994	2004	-15.6
Luxembourg	1992	1992	1993	-6.8
Malta	2000	2001	2004	-4.8
Netherlands	2001	2001	2002	-2.0
New Zealand	1998	1998	1999	-2.2
Norway	1998	1998	1999	-2.7
Poland	2001	2001	2002	-3.0
Portugal	1991	1991	1992	-4.5
Romania	1997	1999	2002	-10.0
Slovakia	1991	1993	2001	-15.5
Slovenia	2001	2001	2002	-1.5
Spain	1993	1993	1994	-2.2
Sweden	2001	2001	2002	-3.3
Switzerland	1991	1993	1994	-4.6
United Kingdom	1991	1991	1993	-2.2
United States	2001	2001	2002	-2.9

	Crisis Year	Turning Point	Recovery Year	Largest drop in GDP growth
Central & South Eastern Europe (non-EU) & CIS				
Albania	1997	1997	1998	-19.3
Armenia	1992	1993	2005	-40.2
Azerbaijan	1992	1995	2005	-22.0
Belarus	1992	1995	2003	-8.4
Bosnia and Herzegovina	1997	1997	1998	-32.6
Croatia	1991	1993	2003	-9.5
Georgia	1992	1994	2014	-23.8
Kazakhstan	1991	1995	2004	-8.7
Kyrgyzstan	1998	1998	1999	-7.8
Republic of Moldova	1991			-31.8
Russian Federation	1992	1998	2006	-9.5
Serbia and Montenegro	1999	1999	2002	-11.9
Tajikistan	1992	1996	2010	-21.8
The former Yugoslav Republ	2001	2001	2004	-9.1
Turkey	1994	1994	1995	-13.5
Turkmenistan	1994	1997	2001	-7.3
Ukraine	2005	2005	2006	-9.4
Uzbekistan	1992	1995	2001	-10.5

	Crisis Year	Turning Point	Recovery Year	Largest drop in GDP growth
East Asia				
China	1995	1995	1996	-2.2
Hong Kong, China	1998	1998	2000	-11.1
Korea, Republic of	1998	1998	1999	-11.5
Mongolia	1991	1993	2000	-6.7
Taiwan, China	2001	2001	2002	-7.9
South East Asia & the Pacific				
Brunei Darussalam	1993	1993	1994	-4.5
Cambodia	2000	2000	2001	-3.1
Fiji	1996	1996	1997	-27.5
Indonesia	1998	1998	2003	-17.8
Lao People's Democratic Republic	1998	1998	1999	-2.9
Malaysia	1998	1998	2000	-14.7
Myanmar	1993	1993	1994	-3.7
Papua New Guinea	1997	1997	2004	-12.9
Philippines	1998	1998	1999	-5.8
Singapore	2001	2001	2002	-12.4
Solomon Islands	2000	2002	2007	-13.8
Thailand	1998	1998	2001	-9.1
Viet Nam	1998	1998	1999	-2.4
South Asia				
Afghanistan	2004	2004	2005	-6.3
Bangladesh	2001	2001	2002	-0.8
Bhutan	1991	1991	1992	-11.1
India	1991	1991	1992	-3.9
Maldives	2005	2005	2006	-14.1
Nepal	2002	2002	2003	-5.5
Pakistan	1993	1993	1994	-6.6
Sri Lanka	2001	2001	2002	-7.6

	Crisis Year	Turning Point	Recovery Year	Largest drop in GDP growth
Latin America & the Caribbean				
Argentina	1995	1995	1996	-8.7
Bahamas	2003	2004	2005	-3.5
Barbados	2001	2001	2003	-4.8
Belize	2001	2001	2002	-8.1
Bolivia	1999	1999	2000	-4.6
Brazil	1998	1998	1999	-3.3
Chile	1993	1993	1994	-5.3
Colombia	1999	1999	2001	-4.8
Costa Rica	2000	2000	2001	-6.4
Dominican Republic	2003	2003	2004	-6.0
Ecuador	1999	1999	2001	-8.4
El Salvador	1996	1996	1997	-4.7
Guatemala	1996	1996	1997	-1.6
Guyana	1998	1998	1999	-7.9
Haiti	1994	1994	1996	-6.7
Honduras	1994	1994	1995	-7.5
Jamaica	1991	1991	1992	-3.9
Mexico	1995	1995	1997	-10.6
Nicaragua	2000	2000	2001	-2.9
Panama	1999	1999	2000	-3.4
Paraguay	1996	1996	1997	-5.1
Peru	1998	1998	1999	-7.5
Suriname	1993	1993	1997	-7.1
Trinidad and Tobago	2004	2004	2005	-6.7
Uruguay	1995	1995	1996	-8.7
Venezuela	2002	2003	2005	-12.2

	Crisis Year	Turning Point	Recovery Year	Largest drop in GDP growth
Sub-Saharan Africa				
Angola	1993	1993	1996	-18.1
Benin	1991	1991	1992	-4.8
Botswana	1992	1993	1994	-7.8
Burkina Faso	1992	1992	1993	-8.8
Burundi	1993	1996	2009	-7.3
Cameroon	2005	2005	2006	-1.4
Cape Verde	2000	2000	2001	-4.6
Central African Rep	1996	1996	1998	-13.0
Chad	2005	2005	2006	-25.7
Comoros	1991	1991	1992	-10.5
Congo	1999	1999	2000	-6.3
Congo, Democratic	1997	2001	2005	-4.3
Côte d'Ivoire	2000	2003	2008	-6.5
Equatorial Guinea	1998	1998	1999	-126.2
Eritrea	1995	1995	1996	-18.6
Ethiopia	1994	1994	1995	-9.9
Gabon	1999	2000	2007	-12.4
Gambia	2002	2002	2003	-9.0
Ghana	1994	1994	1995	-1.6
Guinea	2003	2003	2004	-3.0
Guinea-Bissau	1998	1998	2012	-33.7
Kenya	2002	2002	2003	-4.4
Lesotho	2005	2005	2006	-3.9
Madagascar	2002	2002	2004	-18.4
Malawi	1994	1994	1995	-20.0
Mali	1992	1992	1993	-12.3
Mauritania	1997	1997	1999	-9.9
Mauritius	1994	1994	1995	-5.4
Mozambique	1992	1992	1993	-11.8
Namibia	1993	1993	1994	-10.9
Niger	1999	2000	2001	-11.7
Nigeria	1991	1991	1993	-13.4
Rwanda	1994	1994	1998	-38.2
Senegal	2002	2002	2003	-3.9
Sierra Leone	2003	2003	2004	-18.0
South Africa	1998	1998	1999	-2.1
Swaziland	1991	1991	1992	-8.0
Tanzania	1991	1991	1992	-5.0
Togo	1993	1993	1995	-13.1
Uganda	1991	1991	1992	-4.7
Zambia	1994	1995	2001	-13.2
Zimbabwe	1992	1992	1996	-15.5

	Crisis Year	Turning Point	Recovery Year	Largest drop in GDP growth
Middle East				
Bahrain	1994	1994	1995	-13.1
Iran	1992	1992	1993	-8.3
Jordan	1993	1993	1994	-9.9
Kuwait	1994	1994	1995	-25.1
Lebanon	1992	1992	1993	-33.7
Oman	2002	2002	2003	-4.9
Qatar	1998	1998	1999	-19.4
Saudi Arabia	1993	1993	1994	-4.6
Syrian Arab Republic	1999	1999	2001	-8.7
United Arab Emirates	1991	1991	1992	-21.7
Yemen	1991	1991	1992	-13.0
North Africa				
Algeria	1993	1994	1995	-3.7
Egypt	2001	2001	2002	-1.9
Libyan Arab Jamahiriya	1992	2002	2005	-18.7
Morocco	1995	1995	1996	-16.9
Sudan	1992	1992	1993	-11.0
Tunisia	1993	1993	1994	-5.6

Appendix 5 – Regression results for short- to medium- term forecasting

Results by Geographic group

	Europe	Major Non Europe	Eastern Europe & Baltic	CIS[a]	Eastern Asia	South Central Asia	South East Asia[a]	Central America	South America	Subsahara Africa[a]	North Africa & Middle East[a]	South Africa	East Asia including China[a]
UR_{t-1}	0.78	0.87	0.83	0.75	0.80	0.80	0.69	0.71	0.57	0.86	0.65	0.82	0.80
	(25.06)**	(28.56)**	(18.98)**	(11.86)**	(15.54)**	(13.23)**	(14.26)**	(15.17)**	(10.03)**	(37.06)**	(12.40)**	(10.34)**	(19.46)**
GDP $Growth_t$	-0.03	-0.03	-0.01	-0.01	-0.03	0.01	-0.00	-0.02	-0.02	0.00	0.00	-0.01	-0.03
	(-6.48)**	(-4.39)**	(-3.28)**	(-1.38)	(-3.76)**	(1.91)	(-0.08)	(-4.30)**	(-5.72)**	(0.37)	(0.08)	(-0.75)	(-3.91)**
GDP $Growth_{t-1}$	-0.01	-0.02	0.002	0.002	-0.004	-0.01	0.00	-0.003	-0.00	0.00	-0.00	0.02	0.00
	(-3.22)**	(-4.13)**	(0.88)	(0.52)	(-0.47)	(-1.59)	(0.13)	(-0.58)	(-0.03)	(0.08)	(-0.26)	(2.23)**	(0.10)
LN (pc $GDP)_t$	-0.33	-0.3	-0.14	-0.09	-0.01	0.01	0.05	-0.24	-0.01	0.02	-0.07	-0.2	0.01
	(-4.89)**	(-3.56)**	(-3.03)**	(-2.19)*	(-0.01)	(0.15)	(0.74)	(-2.64)**	(-0.12)	(0.90)	(-1.29)	(-1.26)	(0.14)
Crisis x UR_{t-1}	-0.05	-0.002	-0.14	-0.11	-1.36	0.13	-0.26	-0.08	-0.14	-0.01	0.11		-1.01
	(-1.02)	(-0.02)	(-2.81)**	(-1.76)	(-3.42)**	(1.11)	(-4.36)**	(-1.49)	(1.48)	(-0.55)	(1.69)		(-3.18)**
Crisis x GDP $Growth_t$	0.01	0.01	0.01	0.01	0.03	0.01	-0.03	-0.01	0.001	-0.00	0.00	-0.21	-0.01
	(0.76)	(0.29)	(1.69)	(1.36)	(1.03)	(0.59)	(-2.99)**	(-0.75)	(0.08)	(-0.24)	(0.53)	(-1.49)	(-0.33)
Crisis x GDP $Growth_{t-1}$	-0.02	0.01	-0.001	-0.002	-0.07	-0.01	0.003	-0.01	0.01	-0.00	-0.00	0.09	-0.04
	(-1.77)	(1.14)	(-0.40)	(-0.71)	(-1.77)	(-0.81)	(0.45)	(-0.47)	(0.53)	(-0.30)	(-0.52)	(1.10)	(-1.37)
Crisis x LN (pc $GDP)_t$	-0.01	0.002	-0.03	-0.03	-0.42	0.05	-0.11	-0.02	0.03	-0.00	0.03	-0.01	-0.31
	(-0.87)	(0.07)	(-2.30)*	(-1.60)	(-3.54)**	(1.14)	(-4.30)**	(-0.89)	(1.1)	(-0.40)	(1.83)	(-0.19)	(-3.32)**
Recovery x UR_{t-1}	0.07	-0.01	0.01	-0.05	-0.22	0.03	0.09	-0.04	-0.07	-0.03	-0.06		-0.16
	(1.46)	(-0.15)	(0.19)	(-0.99)	(-1.29)	(0.24)	(1.34)	(-0.64)	(-0.86)	(-1.80)	(-1.15)		(-1.79)
Recovery x GDP $Growth_t$	-0.02	-0.05	-0.004	-0.002	-0.01	-0.003	-0.01	-0.002	0.03	-0.00	0.02	-0.08	-0.01
	(-1.02)	(-1.98)	(-0.70)	(-0.34)	(-0.33)	(-0.21)	(-0.49)	(-0.10)	(3.30)**	(-0.52)	(1.90)	(-2.73)**	(-0.84)
Recovery x GDP $Growth_{t-1}$	0.004	0.03	-0.002	0.002	-0.01	-0.02	-0.001	0.02	0.001	-0.00	0.01	0.01	-0.01
	(0.32)	(1.22)	(-0.50)	(0.34)	(-0.43)	(-1.05)	(-0.71)	(1.97)	(0.13)	(-0.48)	(1.79)	(0.21)	(-1.20)
Recovery x LN (pc $GDP)_t$	0.02	0.01	0.02	-0.02	-0.05	0.01	0.05	-0.01	-0.03	-0.01	-0.03	0.03	-0.02
	(1.20)	(0.51)	(1.39)	(-1.09)	(-0.96)	(0.24)	(1.81)*	(-0.70)	(-1.35)	(-1.29)	(-1.88)	(1.35)	(-0.99)
Constant	3.14	2.83	0.88	0.71	-0.37	-0.79	-1.46	1.01	-0.75	-0.81	0.16	1.37	-0.61
	(4.52)**	(3.48)**	(1.92)	(2.11)*	(-0.26)	(-1.27)	(-1.93)	(1.72)	(-0.98)	(-3.92)**	(0.33)	(0.95)	(-0.90)
Observations	357	85	248	204	68	126	221	238	204	660	306	51	85
R-squared	0.9426	0.9835	0.9570	0.9516	0.9817	0.9502	0.9107	0.9536	0.8881	0.9806	0.9655	0.9732	0.9799
Adj R-squared	0.9369	0.9797	0.9519	0.9454	0.9765	0.9411	0.8998	0.9481	0.8738	0.9760	0.9619	0.9648	0.9751

** Significant at 1%, * Significant at 5%

[a] Regions for which regressions two different regressions were run, as a subset of countries had less than 14 out of 18 real observations. Results presented in this table are for regressions that included all countries in the region.

Results by Income group

	Low Income Countries (LIC)		Lower Middle Income Countries (LMIC)		Upper Middle Income Countries (UMIC)		High Income Countries (HIC)	
	> 13/18 real observations	all countries	> 13/18 real observations	all countries	> 13/18 real observations	all countries	> 13/18 real observations	all countries
	0.81	0.82	0.66	0.66	0.75	0.75	0.81	0.82
UR_{t-1}	(27.50)**	(34.45)**	(21.29)**	(22.88)**	(21.56)**	(22.17)**	(43.04)**	(43.57)**
	-0.00	-0.00	-0.01	-0.01	-0.01	-0.01	-0.01	-0.00
GDP $Growth_t$	(-0.82)	(-0.75)	(-2.52)*	(-2.48)*	(-4.20)**	(-4.29)**	(-4.93)**	(-2.41)*
	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	-0.00
GDP $Growth_{t-1}$	(0.74)	(0.76)	(0.81)	(0.65)	(0.76)	(0.14)	(-4.13)**	(-3.42)**
	0.08	0.04	-0.08	-0.05	-0.21	-0.11	-0.22	-0.11
LN (pc $GDP)_t$	(1.33)	(1.19)	(-2.31)*	(-1.87)	(-3.95)**	(-2.66)**	(-5.47)**	(-4.14)**
	0.03	0.01	-0.01	-0.01	-0.09	-0.06	-0.08	-0.07
Crisis x UR_{t-1}	(0.69)	(0.37)	(-3.58)**	(-3.48)**	(-1.93)	(-1.46)	(-2.25)*	(-2.08)*
	-0.00	-0.00	0.00	0.00	0.02	0.02	-0.02	-0.03
Crisis x GDP $Growth_t$	(-0.67)	(-0.38)	(0.92)	(0.94)	(3.79)**	(3.71)**	(-2.28)*	(-4.71)**
	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.00	0.01
Crisis x GDP $Growth_{t-1}$	(-0.39)	(-0.53)	(-0.94)	(-0.97)	(-1.23)	(-1.08)	(0.89)	(3.30)**
	0.01	0.00	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
Crisis x LN (pc $GDP)_t$	(0.59)	(0.20)	(-2.61)**	(-2.53)*	(-1.45)	(-1.08)	(-2.07)*	(-1.59)
	-0.06	-0.04	-0.09	-0.07	-0.01	0.00	0.06	0.05
Recovery x UR_{t-1}	(-2.06)*	(-2.07)*	(-3.33)**	(-3.12)**	(-0.17)	(0.01)	(1.76)	(1.42)
	-0.00	-0.00	0.00	-0.00	0.00	0.00	-0.01	-0.01
Recovery x GDP $Growth_t$	(-0.63)	(-0.38)	(0.69)	(-0.32)	(0.19)	(0.22)	(-1.46)	(-0.89)
	-0.00	-0.00	0.00	0.00	-0.00	-0.00	-0.01	-0.01
Recovery x GDP $Growth_{t-1}$	(-0.88)	(-0.64)	(0.89)	(1.06)	(-0.51)	(-0.49)	(-1.64)	(-1.24)
	-0.02	-0.02	-0.02	-0.01	0.00	0.001	0.02	0.02
Recovery x LN (pc $GDP)_t$	(-1.96)*	(-1.97)*	(-2.44)*	(-2.05)*	(0.26)	(0.57)	(2.38)*	(2.17)*
	-1.49	-1.21	0.25	0.03	1.01	0.66	1.97	0.45
Constant	(-3.25)**	(-4.25)**	(0.86)	(0.12)	(2.34)*	(1.68)	(4.59)**	(1.57)
Observations	497	750	646	748	469	503	748	782
R-squared	0.964	0.9665	0.9675	0.9691	0.9344	0.9326	0.9525	0.9483
Adj R-squared	0.9608	0.9638	0.9648	0.9666	0.9284	0.9266	0.9488	0.9443

**** Significant at 1%, * Significant at 5%**

Results by Export group

	Exports <20%GDP		20% ≤ Exports/GDP <50%		50% ≤ Exports/GDP <70%		Exports/GDP ≥ 70%	
	> 13/18 real observations	all countries	> 13/18 real observations	all countries	> 13/18 real observations	all countries	> 13/18 real observations	all countries
UR_{t-1}	0.69	0.69	0.79	0.79	0.78	0.78	0.81	0.80
	(17.32)**	(21.04)**	(40.44)**	(43.09)**	(25.53)**	(27.65)**	(29.91)**	(30.30)**
GDP $Growth_t$	-0.01	-0.00	-0.01	-0.01	-0.00	-0.00	-0.01	-0.00
	(-1.82)	(-1.49)	(-3.71)**	(-3.79)**	(-1.83)	(-1.64)	(-2.47)*	(-0.39)
GDP $Growth_{t-1}$	-0.00	-0.00	0.00	0.00	-0.00	-0.00	-0.01	-0.00
	(-0.48)	(-0.34)	(0.94)	(0.76)	(-0.43)	(-0.42)	(-2.31)*	(-1.73)
LN (pc $GDP)_t$	0.01	0.01	-0.1	-0.07	-0.15	-0.13	-0.07	-0.03
	(0.08)	(0.20)	(-3.23)**	(-2.70)**	(-3.09)**	(-3.03)**	(-1.37)	(-1.00)
Crisis x UR_{t-1}	0.06	0.06	-0.02	-0.01	0.00	0.00	-0.22	-0.24
	(1.15)	(1.89)	(-0.92)	(-0.38)	(0.06)	(0.01)	(-5.31)**	(-6.17)**
Crisis x GDP $Growth_t$	0.00	-0.00	0.01	0.01	0.01	0.00	-0.01	-0.01
	(0.56)	(-0.18)	(2.60)**	(2.86)**	(1.36)	(1.19)	(1.23)	(-1.20)
Crisis x GDP $Growth_{t-1}$	-0.01	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.00
	(-0.96)	(-0.54)	(-1.24)	(-1.17)	(-1.23)	(-1.06)	(-0.07)	(0.83)
Crisis x LN (pc $GDP)_t$	0.03	0.03	0.00	0.00	0.00	0.00	-0.07	-0.07
	(1.79)	(2.28)*	(0.08)	(0.63)	(0.22)	(0.13)	(-5.59)**	(-5.63)**
Recovery x UR_{t-1}	-0.06	-0.05	-0.02	-0.01	0.05	0.05	0.05	0.03
	(-2.15)*	(-2.17)*	(-0.96)	(-0.61)	(1.54)	(1.69)	(1.73)	(1.09)
Recovery x GDP $Growth_t$	-0.01	-0.01	0.00	0.00	-0.01	-0.01	0.00	-0.00
	(-1.47)	(-1.83)	(0.71)	(1.00)	(-1.10)	(-2.08)*	(0.05)	(-0.59)
Recovery x GDP $Growth_{t-1}$	-0.00	-0.00	0.00	-0.00	-0.00	0.00	-0.00	-0.00
	(-0.07)	(-0.13)	(0.02)	(-0.04)	(-0.34)	(0.78)	(-0.70)	(-0.59)
Recovery x LN (pc $GDP)_t$	-0.01	-0.01	-0.00	-0.00	0.02	0.02	0.02	0.02
	(-0.07)	(-0.72)	(-0.53)	(-0.24)	(1.83)	(1.97)*	(2.02)*	(2.00)*
Constant	-0.82	-0.99	0.59	0.30	0.68	0.42	-0.08	-0.33
	(-1.55)	(-1.93)	(2.19)*	(1.38)	(1.39)	(1.00)	(-0.23)	(-1.01)
Observations	294	428	1200	1370	492	560	374	425
R-squared	0.9777	0.9781	0.9515	0.9532	0.9677	0.9675	0.9659	0.9615
Adj R-squared	0.9752	0.9761	0.9479	0.9498	0.9648	0.9647	0.9626	0.958

**** Significant at 1%, * Significant at 5%**

Appendix 6 – Suggestions regarding the aggregation of national data to regional and global estimates

Suggestion/ CCSA comment	ILO and other agencies actions
1. For each indicator, the lead agencies review the available documentation on the methods employed to generate country level indicator values, including methods of imputation or modelling for missing figures and subsequent production of regional and global estimates and that a brief, clear description be provided to UNSD for publication on the millennium indicator data-base citing further references as appropriate. *CCSA comment: Supported*	ILO reviews and documents methodology employed (Crespi, 2004; Kapsos 2007, this paper among others). Clear description provided to UNSD. Other agencies provide brief description to UNSD, but few methodology papers are made publically available.
2. As far as possible, and subject to protecting the confidentiality of the original respondents, surveys should be funded and conducted with the intention that the micro-data should become available for legitimate use as soon as possible after each survey is completed. *Not discussed by CCSA*	
3. All presentations of regional and global estimates should clearly identify the year or period to which they apply. *CCSA comment: Supported*	Applied by ILO, and most agencies
4. All agencies present regional estimates to the same agreed regional classification System. *CCSA comment: Supported by all agencies. However, IPU recommended that Nordic countries be treated as separate group for the purpose of MDG 12 - Women in National Parliaments.*	Applied by ILO, and most agencies
5. If deliberate imputation is applied the choice of countries to form an imputation group requires judgment. Wherever possible it should be explored through data analysis (see later suggestions). *No comment by CCSA*	ILO explored choice of countries for imputation groups
6. Agencies should seek to establish explicit imputation methods where thorough empirical analyses can demonstrate that these are robust and methodologically sound. *CCSA comment: Imputation of missing country data deemed 'essential and unavoidable part of making regional estimates'. Methods used and number of countries for which data is imputed should be clearly documented. Imputed country data on MDG Indicators should not be published by international agencies, unless the countries were themselves involved in producing them. Manuals, guidelines and best practices for imputation and estimation should be published by international agencies and made available for use by national agencies.*	Imputed values through the GET model are used to construct regional and global aggregates, but are not published at the individual country level. Nevertheless, empirical analysis that provide a basis for the methodologies used are made available in working papers and other documents. Little information is available regarding explicit imputation methods used by other agencies.
7. Whenever possible changes to standards or questionnaires over time should be allowed for so as to present consistent time series of indicator values. *No comment by CCSA*	ILO checks input data for consistency of series. Changes in questionnaires (including change of data sources) are accepted, if data are consistent.
8. Whenever imputation is used to address non-response, the method adopted should be based on as thorough an evaluation of alternatives as the available data will allow. *No comment by CCSA*	ILO has undertaken thorough evaluations of alternative imputation methods.

Suggestion/ CCSA comment	ILO and other agencies application
9. If linear regression on *t* is used for imputing missing values then as long and complete a time series as is available should be used (subject to ensuring that too long a series does not invalidate the assumption of linearity on *t)*. Diagnostic checks should be made on the model fit and the variance of the imputed value calculated. *CCSA comment: see suggestion 6*	ILO ensures linear regressions on time are based on an appropriate length of time (as long and complete a time series, for a period over which the linearity assumption is valid)
10. A wide range of imputation models may be embedded within a single coherent framework using multi-level models. This would allow the robustness of alternative models to be investigated empirically. *CCSA comment: see suggestion 6*	Trends econometric models integrate a variety of imputation and estimation techniques, allowing the empirical investigation of alternative models.
11. If no time series is available then a search for auxiliary variables that are highly correlated with the desired value and are likely to be available when the indicator value is not is needed. As far as possible an empirical investigation of the robustness of the imputation method should be undertaken. *CCSA comment: see suggestion 6*	Auxiliary variables used in the Trends econometric models are selected based on their correlation with the desired value, and on their availability. Their validity is empirically tested.
12. Considerable care should be taken when estimating change or trend based on time series in which repeated imputation for different years has taken place. *No comment by CCSA*	When estimating trends based on data resulting from repeated imputations (e.g. forecasting short- to - medium term unemployment rates), care is taken to separate countries with a large number of imputed values from other countries, to prevent the imputed data from driving the results that would be obtain from observed data
13. Agencies should review the choice of weights for regional and global estimation. *No comment by CCSA*	The regression weights used in the Trends econometric models conform to best practices for imputation with MAR data. Country weights for aggregation are based on logical relationships (e.g. labour force size as weight for unemployment aggregates)
14. Global estimates should be based on the regional estimates with regional weights reflecting all countries in the region (both responding and non-responding countries). *No comment by CCSA*	Trends econometric models estimates based on weights reflecting both responding and non-responding countries. This is made possible through imputation.
15. Given that UNSD is responsible for compiling the annual reports it could prepare recommendations on how to present change after consulting with other agencies. *CCSA comment: see suggestion 6*	
16. Estimates of trend or change should be based on consistent sets of countries (perhaps involving imputed values for missing values). *CCSA comment: This suggestion should be made more flexible, and take into account constraints on international data availability over time.*	Trends econometric models estimates based on same set of countries. This is made possible through imputation (note: see suggestion 12).
17. Consideration should be given to […] using constant weights as a measure of change. *No comment by CCSA*	

Suggestion/ CCSA comment	ILO and other agencies application
18. Given that successive estimates of level and of change (or trend) may be arithmetically inconsistent, appropriate estimates of change (or trend) should be estimated (rather than simply using the default of the time series of estimates of level) and consideration should be given to the most effective form of presentation for change or trend. *No comment by CCSA*	
19. Revisions to country indicator values and to regional and global estimates should be considered when new data becomes available. The presentation of revised estimates of level or change will need careful consideration. *No comment by CCSA*	GET model estimates, initially revised annually, have been revised on a more regular basis since January 2009, as new data became available. ILO has provided clear explanations of data and or/methodological changes underpinning revisions
20. Diagnostic measures of the impact of large countries and the effect of compositional change should be regularly produced. *No comment by CCSA*	Impact of large countries (e.g. China) are analyzed and accounted for in the Trends econometric methodologies.
21. Consideration be given to summarizing the distribution of country values of level and change. *No comment by CCSA*	
22. Sensitivity analyses should be used to explore the robustness of regional and global estimates to imputation. *No comment by CCSA*	Sensitivity analysis is conducted in the context of the Trends econometric models
23. Wherever possible a measure of uncertainty (e.g. a confidence interval) should be calculated and presented in association with each regional or global estimate. When appreciable use of imputation is made then the impact of this on the measure of uncertainty should be assessed. *No comment by CCSA*	Confidence interval constructed for Trends short-to-medium term unemployment projections. Uncertainty measure accounts for the impact of imputations.
24. All agencies to consider the future pattern and content of survey data collection to identify inadequate data sources for future estimates of change or trend in particular. Additionally, consideration be given to the possibility that even greater co-ordination of data collection would permit the coverage of the regional and global estimates to be improved for more MDG indicators. *No comment by CCSA*	

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