Master Thesis in Econometrics and Management Science

Specialization: Econometrics

Predicting the Achievement of SDG 8: Decent Work and Economic Growth Empirical Bayes Approach

Name student: Veronika Mihaldová

ID number: 502832

Supervisor: dr. Wendun Wang

Second assessor: dr. Yutao Sun

March 22, 2020

Abstract

This paper focuses on the prediction of achievement of one of the Sustainable Development Goals, Goal 8: Decent Work and Economic Growth, across the world. The panel data structure enables to use recently proposed empirical Bayes approach. It focuses on obtaining the individual-specific intercept parameters, instead of removing them from the model and treating them as a nuisance, as it is usually happening in most of the popular and widely used methods for linear dynamic panel data models. Application of the methodology on various data sets with different characteristics points out both the advantages and disadvantages of the method. It has been shown that in certain settings the proposed models may perform better than the chosen benchmark models. Consequently, modelling the individual intercept may lead to increase in the prediction accuracy. The method also works quite well with very short time series.

Key words: Panel Data, Forecasting, Empirical Bayes, Tweedie's Formula, Sustainable Development Goals, Economic Development

Contents

List of Abbreviations

AR Auto-regressive. 9

ARCH Auto-regressive Conditional Heteroskedasticity. 11

ATMs Automatic Teller Machines. 4, 27, 30, 33

BLUP Best Linear Unbiased Predictor. 9

GDP Gross Domestic Product. 11, 20, 22, 29, 31, 35

GLS Generalized Least Squares. 9

GMM Generalized Method of Moments. 9, 15

ILO International Labour Organization. 22, 23, 31

IV Instrumental Variable. 9, 15

LDCs Least Developed Countries. 4, 20–22, 27–29, 31, 32

MDGs Millennium Development Goals. 5, 6

MS Member States. 5

RMSE Root Mean Squared Error. 17, 18, 29, 31, 33–35

SDGs Sustainable Development Goals. 1, 5–8, 19, 22, 28, 34, 35

TAR Threshold Auto-regression. 11

UN United Nations. 5, 7, 19, 20, 25

UNDESA United Nations Department of Economic and Social Affairs. 5

VAR Vector Auto-regression. 11

List of Figures

List of Tables

1 Introduction

The change that our world is going through has been getting more and more attention for the past few years. The media supply us with terrifying predictions, awful pictures and videos that try to raise awareness about such problems such as climate change, global warming, terrorist attacks, fires, economic inequalities across the world, or the pollution of our environment daily. This change and its signs form a complex problem that can hardly be easily solved. For this reason, United Nations (UN) has arrived with the concept of Sustainable Development Goals (SDGs), that have been accepted by all UN Member States (MS) in 2015.

SDGs can be described as a collection of 17 calls for actions for all countries in the world in a global partnership to build a better world both for people and for the planet. They are to be reached by 2030. If all countries complied with the SDGs in reality, it would ensure the promotion of prosperity while the environment stays protected. Participating countries should understand that ending poverty goes closely together with actions to improve economic growth and a social needs and their wide range. The focus is on education, health, and equality. This is all happening while climate change is tackled, and the work is done so that oceans and forests are preserved.

The SDGs should not be considered only as a sudden idea from the UN that appeared out of nowhere. The goals are built on many years of systematic work conducted by participating countries and UN, especially by the United Nations Department of Economic and Social Affairs (UNDESA). The beginning of these ambitious plans dates to 1992, when the Agenda 21 was adopted by more than 178 countries. This document is the first well-written plan of actions towards sustainable development released by the UN. It contains 40 chapters that are grouped into 4 main areas of the focus: social and economic, management of development resources, role of leading groups, and ways of implementation. As such problems are occurring both across and within nations, the baseline is that no nation can successfully fight with these problems on its own, so the worldwide partnership for continuous development is required.

Following the main idea of Agenda 21, the most important move towards the global partnership in achieving the goal of improving standard of living for people and the environment was taken in 2000. The Millennium Development Goals (MDGs) were accepted by all UN MS. They consisted of 8 goals that altogether had an ambition of reducing poverty by the end of 2015. These goals became the main building block for the creation and establishment of the SDGs and a continuous sustainable development of the world, as they are considered as the most successful act against poverty in the history of the world (UN (2015)). This is supported by Sachs (2012), who states that the poverty rate has been reduced by half among developing countries in 2010, compared to the levels from 1990. Although there was a significant progress in reducing poverty, bringing up gender equality, and improving education and health, this progress has been uneven across the world leaving significant gaps. Therefore, to prevent MDGs to be just a momentum effect,

Figure 1: Sustainable Development Goals (United Nations, 2015)

the 2030 Agenda for Sustainable Development has been adopted in 2015 by 193 countries, and its core - 17 SDGs with 169 targets - has been introduced as a long-term plan for acting in favour of sustainable development. The 17 SDGs are displayed in Figure 1. The goals themselves are not directly measurable. Each goal is therefore broken down into multiple targets and each target has one or multiple indicators assigned. The indicator is a macroeconomic or climate variable which value can be measurable, e.g. GDP growth in %, etc.

The transition from MDGs to SDGs is summarized in Sachs (2012). Thanks to his professional experience as a Special Advisor on MDGs, his work brings additional insights into this topic and points out the need for global collaboration and the need to learn a lesson from the shortcomings of the MDGs. He indicates four areas to be learnt on which SDGs should built. Firstly, it should include some milestones during the 15-year interval that would ensure better feedback for the introduced policies. Secondly, to be able to measure the outcomes, there is an inevitable need for good quality data. This is still a huge problem, there are tons of missing data for the selected indicators, which makes them hardly accurately measurable and that consequently complicates the evaluation of the goals and their success. Thirdly, even though the goals might seem to be oriented solely to the public, it should not be forgotten that private sector, especially multinational companies, have enormous capacities and sources for research, and their actions have world-wide impact, so they might also serve as a leading example in actions toward success.

Fourthly, global cooperation and investments into sustainable development should be an obvious action without which the goals could hardly ever be reached.

UN is issuing a report on the progress in achieving the goals every year. According to the most recent paper, UN (2018) emphasize that urgent actions need to be taken immediately for the world to be at least theoretically able to achieve the goals. When there is progress in some area, other is getting worse. Even though the world might be on an upward trend in the economy and successfully reducing poverty, new problems arise especially with climate change and migration. Therefore, the most difficult part is to improve all areas without harming something. Again, the issue of non-quality data is discussed. When the SDGs have been launched to public, only 20% of indicators was being collected across the world, and about the same amount could have been created from the existing data. The rest needed to be collected. However, starting to collect data at the point in time when the new policies are introduced does not help in evaluating the impact of the policy, as there is nothing to be compared the new data. So, the main drawback of SDGs is their difficult measurability.

Probably the most relevant paper considering its content is written by Nikolai et al. (2015). They are fairly critical in their findings and conclude that none of the goals will be achieved by 2030. It seems that Goal 1, Goal 8, and Goal 15 are in the best position, but even in these the success will be only at a level of half of set target values. From the regional perspective, Sub-Saharan Africa have the most to catch up. On the other hand, Latin America, South Asia, and East Asia and the Pacific are likely to experience the most substantial progress. To ease the criticism, they praise the best performing countries with a comment that if all others were making such effort, we would be incomparably closer to the achievement of SDGs.

The main goal of this thesis is to present a methodology that can be used to predict the values of the individual indicators based on the available data using empirical Bayes approach. Due to the complexity of this problem of sustainable development, it is beyond the scope of this thesis to present whether all goals and their indicators will be achieved for all countries across the world until the deadline in 2030. Therefore, after introducing the general methodological approach, the predictions, results, and conclusions will be reported for one chosen Goal 8: Decent Work and Economic Growth. Achievement of this specific goal should ensure full employment and productivity, adequate work for everyone, and constant, inclusive, and continuous economic growth.

This goal has been chosen for the illustrative analysis not only because of my personal interest in the topic of economic development, but also because of its complexity, generality and interpretation. It consists of 12 different yet connected targets that have 17 different indicators assigned covering a wide range of topics within economic development. It is also expected that as it is composed mostly of macroeconomic indicators, the data should be freely available and complete for most of the countries, which could provide the complete picture about the possible achievement of the goal and about the economic state of the world in 2030.

I believe that Goal 8 is strongly linked to many other SDGs. It is tight to the economic situation in the country, and that serves as a basis to the standard of living for its inhabitants, such as employment and the job opportunities, poverty, or even human development (e.g. Piketty (2014) or Lüsted (2010)). Therefore, the direction of which the indicators of this Goal are likely to develop might indicate the possible achievement of e.g. Goal 1: No poverty, as it is much easier for families with informal or low paid jobs to be landed in poverty, especially in rural areas of the world where is not a lack of formal and decent job opportunities for the inhabitants. To put it in numbers, there were 700 billion workers living in moderate or extreme poverty (UNDP (2020)). Consequently, less poverty is expected to lead to the reduction of hunger (Goal 2) and an improvement in well-being and health (Goal 3). Goal 12 (to consume, create and manufacture responsibly) is also strongly linked to Goal 8, as one it targets is concerned with improving the resource efficiency, assuring that economic growth will not cause additional harm for the environment. This also links the chosen goal to any other climate-concerned goal. Targets that aim to achieve the full employment, decent work for everyone, as well as the protection of this work then touch the Goals 5, 10, and 16 that aim to assure gender equality, to reduce inequalities, and to protect justice and strong institutions, respectively. According to the UNDP (2020), 48 % of women participated in the labour force, in comparison to 75 % of men, and, moreover, 85 billion women were underutilized in the labour force, compared to 55 billion of men. Therefore, these strong ties to other SDGs, wide coverage of multiple topics, and availability of the data make Goal 8 a perfect candidate for the illustrative analysis.

Based on the obtained results, it can be stated that even though the Targets that form Goal 8 are unlikely to be achieved, certain progress especially in the developing countries is made that should be further supported, so that the effort made so far will not be wasted and will not stop in 2030 when the SDGs come to an end. From the methodological perspective, the prediction obtained from the proposed model combinations are often an improvement in comparison to traditional forecasting methods applied on dynamic panel data.

The rest of the paper is structured as follows: Section 2 describes the literature that relates both to the achievement of SDGs and to the prediction with the panel data. Section 3 explains the methodology and is followed by Section 4, that introduces and describes the empirical data. Next, Section 5 presents the results of an empirical analysis and Section 6 concludes.

2 Literature Review

This section describes the literature on the topic of dynamic panel data modelling as well as literature focused on forecasting the economic development. Unlike the static models, which calculate the system in the equilibrium and hence are time-invariant, dynamic models enable to account for time-dependent changes by containing lagged dependent variable as an explanatory variable. Probably the most compact review on dynamic panel data forecasting is the article written by Baltagi (2008). One of the first approaches has been to find the Best Linear Unbiased Predictor (BLUP) that originates back to Goldberger (1962) who shows how to predict a value using GLS model when the variance-covariance structure of the error terms is known.

Another widely used approach to forecasting with panel data is to consistently estimate the auto-regressive parameters in the Auto-regressive (AR) models. However, the usual asymptotic results from static panel data models - within and GLS estimator for fixed and random effects, respectively - are inconsistent in case of small time dimension. Moreover, the within estimator is biased due to the fact the transformed regressor and the residuals are correlated.

These challenges bring up the need for different approach when the explanatory variables include lagged dependent variable in the panel data setting. The first solution of Anderson and Hsiao (1981) is based on the first difference regression. As the explanatory variable is correlated with the error term, the estimator of the auto-regressive coefficient would be inconsistent under OLS. Therefore, they suggest to use an Instrumental Variable (IV) approach, i.e. to find an instrument for the explanatory variable that is correlated with it but not correlated with the error term. It is possible to find such instruments satisfying the condition. The resulting estimator is consistent, however, its efficiency goes down as it uses only the reduced number of time periods.

This issue was later tackled by Arellano and Bond (1991) by generalizing the orthogonality condition of Anderson and Hsiao (1981) The generalization causes the number of orthogonality conditions to rise which consequently increases the efficiency of an estimator. They propose to find a solution by minimizing a quadratic loss function with suitable weights (GMM approach) as single solution is not available, because number of restrictions is not equal to the number of parameters. This results in consistent and asymptotically normally distributed estimator.

Blundell and Bond (1998) showed that the instruments used in Arellano and Bond (1991) are weak when either the auto-regressive mechanism is strong or when the variance proportion of panel-level effect to idiosyncratic error is huge. Based on this argumentation they suggested to use an estimator in which the lagged differences are used as instruments for the level equation and not only in the first-difference equation. Recently, the efficiency of the estimator has been improved even more by using other weighting matrices in the GMM estimator that combines the moment conditions (e.g. Youssef and Abonazel (2015)).

When both the number of time periods and the number of individuals is large, Alvarez and Arellano (2003) suggest using the random effect maximum likelihood estimator, because it imposes heteroscedasticity in time dimension with unchanged number of moments of initial conditions. Such estimator is shown to be unbiased.

Apart from these methods that are built on a frequentist approach to a panel data analysis, fully Bayesian approach to the dynamic panel data modelling have also been developed.

Chamberlain and Hirano (1999) use a panel data on earnings and personal characteristics of multiple individuals and combine that information to present a conditional distribution for future earnings to each individual. They extend previous Bayesian models by allowing for the heterogeneity in volatility, which consequently enables the spread of a predictive distribution to be sensitive to the variability in past earnings. Hirano (2002) then develops a Bayesian method for inference in dynamic panel data models with individual effects and adapts a semi-parametric Bayesian methods to a random-effects auto-regressive model with non-parametric idiosyncratic shocks.

Models with fixed effects are tackled by Lancaster (2001) by finding an orthogonal reparametrization of the fixed effects and integrate such new effects from the likelihood with respect to suitable prior density. He shows that the marginal density of the homogeneous parameters have consistent modes and provides a consistent likelihood-based estimator for the first-order auto-regressive panel data models with heterogeneous intercept with likelihood conditional on the set of initial observations.

A different method has been recently suggested by Liu et al. (2016), built on an empirical Bayes approach. They aim at forecasting with short panels. The difference with the previous literature is that instead of considering the heterogeneous parameters to be nuisance and focusing on the estimation of homogeneous parameters, they see the evaluation of the individual-specific parameters as an important feature in delivering as accurate forecasts as possible.

The individual time series cannot provide enough information itself for the inference about the distribution of the individual-specific parameters in small time dimensions. To approximate these distributions, they use information from the cross-sectional dimension in the panel. This then provides a prior distribution for the heterogeneous coefficients and that allows to perform a posterior inference. The optimal forecast is then formulated as a total of the posterior mean and the values of explanatory variables.

Eventually, they perform both the simulation study and the analysis of the empirical dataset using their posterior mean predictor. In Monte Carlo simulations they use diverse implementations of the predictor. They conclude that their approach has higher accuracy than a predictor that does not make use of a prior distribution. Additionally, they conclude that the sampling variation is reduced because the common parameter estimates are shrunk toward a prior mean.

Forecasting and analysing economic development in panel data framework is widely covered in literature. There are attempts to explain the economic development with both static (e.g. Tiwari and Mutascu (2011), Trinajstic et al. (2018)) and dynamic panel data models (e.g. Sequeira and Maçäs (2008), Bilotkach (2015)). The Bayesian approach to the analysis of economic development with panel data is elaborated in the work of e.g. Moral-Benito (2012) or Błażejowski et al. (2016).

Various methods for economic forecasting are summarized in the paper written by Lehmann and Wohlrabe (2014). They evaluated the methodology used in the numerous academic papers on the topic of regional economic development over the past decade. For most of the time, economic forecasting is made with dynamic spatial panel data models, entropy-optimizing method, forecast combination, factor models, neural networks, and time series models.

For example, Kholodilin et al. (2008) work with dynamic spatial panel data models. They forecast the annual growth rates of real GDP for all 16 German states by the application of dynamic panel data models that account for the spatial dependence between GDP in individual states. According to their results, spatial effects substantially improve forecast accuracy, especially when making long-term forecasts. Another contribution has been made by Baltagi et al. (2013), who propose a dynamic spatial generalized method of moments estimator for the spatial auto-regressive error model and find a better ex post performance of their estimator compared to standard both spatial and non-spatial estimators.

Blien and Tassinopoulos (2001) use an entropy-optimizing method to forecast employment in western German district two years ahead. The bottom line of the forecast is to estimate a matrix from heterogeneous information using the entropy optimizing procedure based on finding the finding the probability distribution that best represent the actual state of knowledge under precisely stated prior data.

Forecast combination are often an improvement when compared to auto-regressive benchmark (e.g. Stock and Watson (2004), Constantini et al. (2010)). Factor models, that use large data sets of economic variables, have also been shown to outperform the benchmark auto-regressive model and lead to higher prediction accuracy as shown in Hindrayanto et al. (2016) or Lehmann and Wohlrabe (2013).

There is also a vast literature on the topic of economic forecasting using time series models in both uni-variate and multi-variate setting (Ghysels and Marcellino (2018), Frances et al. (2018)). The most common and popular models include various auto-regressive and moving average processes, Auto-regressive Conditional Heteroskedasticity (ARCH) models, Vector Auto-regression (VAR) models, Bayesian Vector Auto-regression (VAR) models, or Threshold Auto-regression (TAR), Markov switching, and state space models.

3 Methodology

3.1 Dynamic Panel Data Model

This section discusses the methodology based on Liu et al. (2016) that is followed throughout the thesis. Firstly, the general model is introduced. Secondly, the Tweedie's formula that is necessary to calculate the posterior mean is showed. Lastly, various estimation methods for both homogeneous and heterogeneous parameters are described.

3.2 Linear Dynamic Panel Data Model

Consider the following linear dynamic panel model with unobserved individual heterogeneity:

$$Y_{it} = \lambda_i' + \rho' Y_{it-1} + U_{it}, \tag{1}$$

where $i = 1,..,N$ is observation for an individual and $t = 1,...,T$ denotes the time period. Y is a matrix of observation for all individuals in all time periods, λ_i represents a heterogeneous intercept, and ρ is the common auto-regressive parameter. There are no exogeneous explanatory variables considered in this paper. U$_{it}$ is an unpredictable shock given by

$$U_{it} = \sigma_t V_{it}, \tag{2}$$

where V_{it} is an independent identically distributed variable with mean 0 and standard deviation 1. σ_t is assumed to be a function representing volatility dependent both on data and on some unknown parameter γ_t collected in parameter vector $\gamma = [\gamma_1', ..., \gamma_T']'$. This specification allows the error term to be conditionally heteroscedastic over both dimensions, the time and the cross-section, via γ_t and V_{it}, respectively. Also, the density of V_i will be denoted as $\varphi(v)$.

Altogether, three parameter vector need to be specified: homogeneous parameter vectors ρ and γ and heterogeneous parameter vector λ_i. Liu et al. (2016) specify the assumptions under which ρ, γ, correlated random effects distribution $\pi(\lambda_i/y_i)$, and the distribution of V_{it} are identified.

The likelihood function of the observed data may be combined with the conditional distribution of the heterogeneous parameters on the homogeneous parameters (assumption 2.1(iii) in Liu et al. (2016)). Moreover, under the assumption of cross-sectionally independent observations conditional on the predictors, joint density of the observed data and heterogeneous parameters can be obtained as a product of all observations across individuals:

$$p(y, \lambda|\rho, \gamma) \propto \prod_{i=1}^{N} \left(\left(\prod_{t=1}^{T} \frac{1}{\sigma_t(y_i, \gamma_t)} \varphi\left(\frac{y_{it} - \lambda_i' - \rho' y_{it-1}}{\sigma_t(y_i, \gamma_t)} \right) \right) \pi(\lambda_i|y_i) \right). \tag{3}$$

As the distribution of the individual-specific parameters and the values of common parameters are known, the individual-specific parameters may be substituted with the values of posterior mean. Let the homogeneous parameter vectors ρ and γ to be collected into one vector θ for the ease of notation: $\theta = [\rho', \gamma']'$. Then, the optimal forecast is obtained as

$$\hat{Y}_{iT+1}^{opt} = \mathbb{E}_{\theta, \mathcal{Y}_i}^{\lambda_i}[\lambda_i]' + \rho' Y_{iT}, \tag{4}$$

where $\mathbb{E}_{\theta, \mathcal{Y}_i}^{\lambda_i}[\lambda_i]'$ denotes the posterior mean of λ_i. The subscripts θ and $\mathcal{Y}_i$ indicate the conditional expectation on θ and the observed data, respectively. The superscript indicates that we are integrating over the unobserved heterogeneous parameters. (4) can be extended to forecast h periods ahead using the recursive formula:

$$\hat{Y}^{opt}_{iT+h} = \mathbb{E}^{\lambda_i}_{\theta,\mathcal{Y}_i}[\lambda_i]' \sum_{s=0}^{h-1} \rho^s + \rho^h Y_{iT}, \tag{5}$$

.

Two-step estimation procedure follows: Firstly, the auto-regressive common parameter ρ is estimated. Secondly, as the heterogeneous parameter is removed from the model in the first step, it is estimated conditional on the parameters from the first step.

3.3 Tweedie's Formula

In order to obtain a posterior mean, Liu et al. (2016) adjust the Tweedie's formula that was originally used to estimate a mean vector for Gaussian distribution by Robbins (1951) to fit the panel data framework. Tweedie's formula is the formula for posterior mean named after statistician Maurice Tweedie, which expresses the posterior mean as a function of cross sectional density of a sufficient statistics. That is obtained by the substitution of standard normal density for $\varphi(v)$ into (3) and the consecutive factorization of it.

Consequently, the posterior distribution of λ may be expressed as

$$p(\lambda|y,\rho,\gamma) = p(\lambda|\hat{\lambda},y,\rho,\gamma) = \frac{p(\hat{\lambda}|\lambda,y,\rho,\gamma)\pi(\lambda|y)}{p(\hat{\lambda}|y,\rho,\gamma)}, \tag{6}$$

where $\hat{\lambda}$ denotes the sufficient statistics and $p(\hat{\lambda}|\lambda,y,\rho,\gamma)$ is its likelihood function.

The likelihood function of a sufficient statistics is a proper density function, which means that it integrates to 1. It holds for a normal distribution that the posterior mean lies at the peak of the density function, and, therefore, the mean can be calculated by differentiating $\int p(\hat{\lambda}|\lambda,y,\theta)d\theta = 1$ with respect to $\hat{\lambda}$. Solving the first order condition gives the Tweedie's formula for the calculation of the posterior mean:

$$\mathbb{E}^{\lambda_i}_{\rho,\gamma,\mathcal{Y}_i}[\lambda_i] = \hat{\lambda}_i(\rho,\gamma) + \Sigma^{-1}(\rho,\gamma)^{-1} \frac{\partial}{\partial\hat{\lambda}_i(\rho,\gamma)} \ln p(\hat{\lambda}_i(\rho,\gamma), Y_i|\rho,\gamma), \tag{7}$$

i.e. the sum of a sufficient statistics to which is added a correction term reflecting the prior distribution of an individual-specific parameter. Hence, the optimal forecast is given by

$$\hat{Y}^{opt}_{iT+1}(\rho,\gamma) = \hat{\lambda}_i(\rho,\gamma) +' \Sigma^{-1}(\rho,\gamma)^{-1} \frac{\partial}{\partial\hat{\lambda}_i(\rho,\gamma)} \ln p(\hat{\lambda}_i(\rho,\gamma), Y_i|\rho,\gamma) + \rho' Y_{iT}. \tag{8}$$

Next subsections consider the two approaches to the estimation of the correction term, parametric and non-parametric.

3.4 Parametric Estimation of Tweedie's Correction Term

Under the assumption of a normally distributed random effects $\pi(\lambda|y_i)$, the marginal density of a sufficient statistics $p(\hat{\lambda}_i(\theta)|y_i, \theta)$ may be derived analytically. Let specify the Gaussian prior as

$$\lambda_i|(Y_i, \theta) \sim N(\Phi Y_i, \underline{\Omega}), \tag{9}$$

let the vector of hyperparameters denote as $\xi = (\text{vec}(\Psi), \text{vech}(\underline{\Omega}))$, and so the correlated random effects distribution can be written as $\pi(\lambda|h_i, \xi)$ in order to emphasize the dependence on the hyperparameter ξ. The marginal density of $\hat{\lambda}_i$ is then obtained by solving $\int p(\hat{\lambda}(\theta)|\lambda, y, \theta)\pi(\lambda|y, \xi)d\lambda$.

The vector of hyperparameters ξ conditional on the vector of parameters θ can be estimated by maximising the marginal likelihood and using the individual-specific distribution of the sufficient statistics:

$$\hat{\xi}(\theta) = \arg\max_{\xi} \prod_{i=1}^{N} p(\hat{\lambda}_i(\theta)|y_i, \theta, \xi). \tag{10}$$

These estimates are then filled into the marginal density, and so the density $p(\hat{\lambda}_i(\theta)|y_i, \theta, \hat{\xi}(\theta))$ can be used for the evaluation (7).

3.5 Non-parametric Estimation of Tweedie's Correction Term

A non-parametric estimation of Tweedie's correction term is done by kernel density estimation. That means that the density $p(\hat{\lambda}_i(\theta), y_i|\theta)$ as well as its derivative with respect to $\hat{\lambda}_i(\theta)$ are replaced with some kernel density estimate.

The kernel density estimator is a method suitable for estimating a density function of a random variable and may be described as a continuous form of the histogram. That means that instead of giving the same weight to the observation in the same bin when using an estimate based on a histogram density, the estimate based on a kernel density uses a kernel function, i.e. some other weighing function, to weigh the observations. With this type of estimation, one must choose a smoothing parameter, the bandwidth, denoted as B. This thesis uses an adaptive kernel density estimator of Botev et al. (2010), that is based on a linear diffusion process and plug-in bandwidth selection method.

3.6 Estimation of Homogeneous Parameters

This subsection elaborates on the estimation of the parameter vector θ. Firstly, the estimation under the assumption of a normally distributed disturbances will be discussed. Secondly, the discussion will continue with the estimation of the parameters when no distributional assumption about the error terms of the model is made.

3.6.1 Quasi-Maximum Likelihood Estimator of θ

Following Liu et al. (2016), when V_{it} from (2) has a standard normal distribution, $\hat{\lambda}_i(\theta)$ is a sufficient statistics of λ_i and $\pi_\lambda(\lambda_i|y_i,\xi)$ is a correlated random effect density. Then, integrating out λ under a parametric prior distribution $\pi_\lambda(\lambda|y,\xi)$, we obtain ($i$ subscripts are omitted): $p(y|\theta,\xi) = \int p(y|\theta,\lambda)\pi_\lambda(\lambda|y,\hat{\xi}(\theta))d\lambda$. Liu et al. (2016) shows that the density $p(\hat{\lambda}(\theta)|y,\theta,\xi)$ is identical to the objective function used for ξ in (10), and hence θ and ξ can be jointly estimated maximizing the integrated likelihood function

$$\left(\hat{\theta}_{QMLE}, \hat{\xi}_{QMLE}\right) = \arg_{\theta,\xi} \max \prod_{i=1}^{N} p(y|y_i,\theta,\xi). \tag{11}$$

This estimator is referred to as a quasi-maximum likelihood estimation because the correlated random effects distribution could be wrongly specified.

3.6.2 Generalized Method of Moments Estimation of θ

If no assumption about the error terms of a model, the parameter vector θ can be estimated using the sample analogues of the suitable moment conditions. Three alternatives will be considered and compared, Arellano-Bond, Arellano-Bover, and Blundell-Bond estimators.

Arellano and Bond (1991) generalise the moment conditions of Anderson and Hsiao (1981) for a dynamic panel data models' framework and introduce a GMM framework for an IV parameter estimation. The starting point is the first-difference model

$$\Delta Y_{it} = \rho \Delta Y_{it-1} + \Delta U_{it}. \tag{12}$$

Due to the correlation of explanatory variable with the error term, the estimator of ρ coefficient would be inconsistent under OLS. The baseline of the IV approach is to find an instrument for $\rho\Delta Y_{it-1}$ that is correlated with the explanatory variable but not correlated with the error term.

The generalized moment conditions of Arellano and Bond (1991) have the form of $\mathbb{E}[\Delta Y_{it} Y_{it-j} - \rho \Delta Y_{it-1} Y_{it-j}] = 0$, $t = 2, ..., T$, $j = 2, ..., t$. Valid instruments for Y_{it-1} are summarized in the following matrix

$$Z_{di} = \begin{pmatrix} Y_{i0} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & Y_{i0} & Y_{i1} & 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & Y_{i0} & Y_{i1} & Y_{i2} & 0 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & Y_{i0} & \dots & Y_{iT-2} \end{pmatrix}. \tag{13}$$

The number of legitimate instruments increases in time: the first row of a matrix in (13) contains instruments that are valid for $t = 2$, second row contains valid instruments for

$t = 3$, etc. Hence, the restrictions are as follows:

$$\mathbb{E}[Z'_{di}(\Delta Y_i - \rho \Delta Y_{i,-1}) - \alpha \Delta Z_{i,-1}] = 0, \tag{14}$$

with $\Delta Y_i = (\Delta Y_{i2}, \Delta Y_{i3}, \ldots, \Delta Y_{iT})'$, $\Delta Y_{i,-1} = (\Delta Y_{i1}, \Delta Y_{i2}, \ldots, \Delta Y_{iT-1})'$, and $\Delta Z_{i,-1} = (\Delta Z_{i1}, \Delta Z_{i2}, \ldots, \Delta Z_{iT-1})'$.

The parameters ρ and α are now to be found such that the sample analog of (14),

$$g(\rho, \alpha) = \frac{1}{N} \sum_{i=1}^{N} Z'_{di}(\Delta Y_i - \rho \Delta Y_{i,-1} - \alpha \Delta Z_{i,-1}), \tag{15}$$

is as close to zero as possible.

However, in this setting, there are more restrictions than parameters, so the exact solution is not possible. The estimates of the parameters are therefore obtained by making $g(\rho, \alpha)$ as small as possible, achieved by minimizing the quadratic function

$$\mathcal{Q}(\rho, \alpha) = g(\rho, \alpha)' \mathcal{W}_N g(\rho, \alpha), \tag{16}$$

with $\mathcal{W}_N$ being some positive semi-definite matrix of order m, where m is the number of restrictions. Thus, the estimator of ρ and α is such that

$$(\hat{\rho}, \hat{\alpha}) = \arg_{\rho,\alpha} \min g(\rho, \alpha) \mathcal{W}_N g(\rho, \alpha). \tag{17}$$

This estimator is consistent and asymptotically normal. The efficiency of an estimator depends on the choice of a weighting matrix $\mathcal{W}_N$. It is asymptotically efficient if the weighting matrix is chosen such that its limiting value is the inverse of the asymptotic matrix of covariances of $g(\rho, \alpha)$, i.e.

$$\mathcal{W}_N = \left(\lim_{N \to \infty} N \cdot \mathbb{E}[g(\rho, \alpha) g(\rho, \alpha)'] \right)^{-1}. \tag{18}$$

The approach of Arellano and Bover (1995) is slightly different in the estimation process. The Arellano-Bover estimator, in contrast to Arellano-Bond estimator, uses the moment conditions that are based on level values of the disturbances (and Arellano and Bond's (1991) moment conditions are based on the disturbances after first-differencing). Initially, the Forward Orthogonal Deviation transformation is performed on all variables. This means that each observation is adjusted by deducting the average of all future observations, and this is defined for every except the last observation in every panel (disregarding the gaps). Such transformation gives

$$Y^*_{it} = Y_{it} - \left(\sum_{s=t+1}^{T} Y_{is} W'_{is-1} \right) \left(\sum_{s=t+1}^{T} W_{is-1} W'_{is-1} \right)^{-1} W_{it-1}, \tag{19}$$

$t = 1, \ldots, T$ - 1. Y^*_{it-1} and Z^*_{it-1} are construed analogically. The moment conditions are then constructed as

$$\mathbb{E}\left[(Y^*_{it} - \rho' Y^*_{it-1} - \alpha' Z^*_{it-1})\begin{pmatrix} Y_i^{0:t-1} \\ Z_i^{0:T} \end{pmatrix}\right]. \tag{20}$$

The remaining part of the estimation procedure is analogical to the one with the Arellano-Bond estimator described above.

Blundell and Bond (1998) extend the work of Arellano and Bond (1991) and their estimator, as they notice that the instruments become weak under some circumstances, e.g. when the data generating process is random walk or when it is close to it. In order to overcome this issue, they suggest adding lagged differences of the dependent variable as instruments to be used in the level equation, which consequently extends the matrix of valid instruments to

$$Z_{SYS,i} = \begin{pmatrix} Z_{di} & 0 & 0 & \ldots & 0 \\ 0 & \Delta Y_{i2} & 0 & \ldots & 0 \\ 0 & 0 & \Delta Y_{i3} & \ldots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \ldots & \Delta Y_{iT-1} \end{pmatrix}. \tag{21}$$

Consequently, the moment conditions follow as

$$\mathbb{E}\left[Z'_{SYS,i}\begin{pmatrix} \Delta Y_i - \rho \Delta Y_{i,-1} - \alpha \Delta Z_{i,-1} \\ Y_i - \rho Y_{i,-1} - \alpha Z_{i,-1} \end{pmatrix}\right] = 0. \tag{22}$$

The estimation procedure then continues as with the Arellano-Bond estimator, with one additional initial condition for the instruments to be valid: $\mathbb{E}[\lambda_i \Delta Y_{i2}] = 0$, because the individual-specific effects are part of the original model.

3.7 Model Comparison

To evaluate the accuracy of the prediction and the comparison among different models, Root Mean Squared Error (RMSE) will be computed for six model combinations of interest and compared to the benchmark models. It is expected that models that estimate the heterogeneous parameter λ_i will have higher prediction accuracy (Liu et al. (2016)), i.e. their RMSE will be lower.

Eight model combinations are made of two approaches for the heterogeneous parameter estimation (parametric and non-parametric), and four variants of homogeneous parameter estimation (QMLE, Arellano-Bond, Arellano-Bover, and Blundell-Bond estimator). As the benchmark models are chosen the estimators that eliminate the individual heterogeneity during the estimation procedure, i.e. Arellano-Bond, Blundell-Bond, and Pooled OLS estimators applied to the dynamic panel.

In addition to the panel data benchmark models, the methodology as suggested by Liu et al. (2016) will be compared to one of the time series methods that have been extensively used in the literature on forecasting economic development, the state space models. The state-space representation allows to account for potential endogenous components in the variables to be predicted. Such representation consists of two equation – the observation and the state equation.

Kalman filter is used for the estimation of the values of the endogenous states. This algorithm calculates the mean and the variance of the states given the observed values. The states are filtered and updated with an addition of the new observation. Finally, the states will be smoothed to see any clear signals in the data. The smoothing step of the Kalman filter makes use of all data and computes the smoothed estimates by backward iteration.

The estimation of the unknown parameters is done by the Maximum Likelihood, i.e. by finding those values of the parameters giving the highest probability of observing the data. However, due to the dependence of consecutive observation, joint probability density function of all observations cannot be written as the product of individual probability density function. It is solved as follows: Firstly, the parameters are initialized. I will use the unconditional mean of the state which is zero, and the large variance of 10^6. The Kalman filter is run to get an estimate of the endogenous state, which is plugged into the log-likelihood to find a new estimate that yields bigger values of the log-likelihood function. These steps are iterated until such parameters' estimates are found for which the log-likelihood function is maximized. For more details and specific formulas refer to Hamilton (1994).

The parameters of the state space model will be estimated on each of the univariate series, and the averaged RMSE across all countries is reported.

4 Data

Following Section 1, the goal of my interest is the Goal 8: Decent Work and Economic Growth. This goal is composed of 12 targets and corresponding 17 indicators, displayed in Figure 2. This Section describes the data for indicators, i.e. dependent variables. No explanatory variables are included so no additional variables will be described.

Targets	Indicators
8.1 Sustained per capita economic growth – min. 7 % GDP growth per annum in least developed countries	8.1.1 Annual growth rate of real GDP/capita
8.2 Higher levels of economic productivity	8.2.1 Annual growth rate of real GDP/employed person
8.3 Development-oriented policies for formalized micro-, small- and medium-sized enterprises	8.3.1 Proportion of informal employment in non-agriculture employment (by sex)
8.4 Global resource efficiency in consumption and production and decoupling economic growth from environmental degradation	8.4.1 Material footprint (per capita and GDP) 8.4.2 Domestic material consumption (per capita and GDP)
8.5 Full and productive employment, decent work for all women and men, and equal pay for work of equal value	8.5.1 Average hourly earnings of female and male employees (by occupation, age and persons with disabilities) 8.5.2 Unemployment rate (by sex, age and persons with disabilities)
8.6 By 2020, proportion of youth not in employment, education or training substantially reduced	8.6.1 Proportion of youth not in education, employment or training
8.7 Forced labour, modern slavery, human trafficking and worst forms of child labour eradicated (by 2025 child labour in all its forms)	8.7.1 Proportion and number of children engaged in child labour (by sex and age)
8.8 Labour rights protected and safe and secure working environments for all workers	8.8.1 Frequency rates of occupational injuries (by sex and migrant status) 8.8.2 National compliance of labour rights (freedom of association and collective bargaining, by sex and migrant status)
8.9 Policies for sustainable tourism (job creation, promotion of local culture and products)	8.9.1 Tourism direct GDP (proportion of total GDP and growth rate) 8.9.2 Number of jobs in tourism industries (proportion of total jobs and growth rate, by sex)
8.10 Domestic financial institutions strengthened (enhanced access to banking, insurance and financial services)	8.10.1 Number of commercial bank branches and ATMs (per 100 000 adults) 8.10.2 Proportion of adults with an account at a bank or other financial institution or with a mobile-money-service provider
8.A Aid for Trade support for developing countries increased, in particular for least developed countries	8.A.1 Aid for Trade commitments and disbursements
8.B By 2020, a global strategy for youth employment and the Global Jobs Pact of ILO implemented	8.B.1 Total government spending in social protection and employment programmes (proportion of the national budgets and GDP)

Figure 2: Decomposition of Goal 8 into 12 Targets and 17 Indicators. Adapted from Stoian et al. (2019).

Data for four indicators are not yet publicly available: 8.8.2, 8.9.1, 8.9.2 and 8.b.1. This makes the further analysis and prediction of future values of Targets 8.9 about tourism and 8.b about youth employment impossible. Target 8.8 will be discussed below in Section 4.5.

The data is collected from various sources. The fundamental guide on where to find all necessary data is Statistics Division of the United Nations and its Metadata repository of the SDGs Indicators available online on the webpage of UN and from there it is possible to be directed to the corresponding institution that stores the searched data.

More detailed analysis of the goal broken down into targets and indicators follows in the next subsections. Unfortunately, not all the Targets can be quantitatively analysed due to the absence of decent and quality data sources.

In summary, based on the preliminary data analysis, even though some Targets are more likely to be met than others, the overall impression is that they are set to be either too high, too general, or hardly measurable.

4.1 Target 8.1

The first indicator, annual growth of GDP per capita, is one of the best in terms of monitoring and availability. The data coverage is from 1971 to 2017, which results in $T = 47$ for $N = 194$ states recognized by the UN[1]. The data constitutes an unbalanced panel, due to the later establishments or separations of the countries that have occurred.

The imputation of consequent missing data is not suitable and for this reason the time periods have been cut. The analysis will start in 1990, since when the clear majority of the data is available (therefore, $T = 28$). The reduces the sample size to 5,432 observations out of which 64 data points is missing, and these will be imputed with a multiple model-based imputation method (van Buuren and Groothuis-Oudshoorn (2011)). As the proportion of missing observations is around 1.2%, the imputation is not expected to have a large influence on the results. Following the simple rule of thumb (White et al. (2011)) saying that the number of imputations should be comparable to the proportion of incomplete observations, 2 imputations are used.

Target 8.1 is particularly interested in Least Developed Countries (LDCs). There are 47 such countries classified by the UN. Most of them are located in Africa, especially in Eastern, Western, and the Middle part of it. Africa is followed with Oceania, and then with Asia, mainly Southern and South-Eastern Asia. There is no such country in Europe, and the only LDC country in America is Haiti. This is summarized in Table 1.

On the regional level, the time series of GDP per capita growth is displayed in Figure 3. The average growth is displayed in yellow. The graph shows that less developed regions suffer from greater GDP per capita growth volatility and that there are huge differences between individual countries, whereas the GDP growth in more developed regions move more or less in the same direction for most of the time. Figure 4 interestingly shows, that especially in Africa and Oceania, it is not LDCs that account for most of the variation in recent years, but the non-LDC countries graphed in orange colour have had more volatile GDP growth. In Asia it is clearer to see the volatility of LDC countries is higher in recent years.

On the subregion level, according to the most recent data from 2017, the lowest GDP growth, -2.15 % has been in Middle Africa, and the highest in Northern Africa, more than 11 %. Out of the regions with the high percentage of LDCs, Eastern and Western Africa and Southern and South-Eastern Asia have been performing quite well and have experienced GDP per capita growth in the range from 1.78 to 4.07 %. Apart from Middle Africa, Southern Africa has also been experiencing a negative GDP per capita growth.

[1] In total, there are 195 countries recognized by the UN, but one state, Holy See, does not have data for this or any other analysed indicator.

Region	Subregion	No. of countries	No. of LDCs	% of LDCs
Africa	Eastern Africa	18	14	77.78 %
Africa	Middle Africa	9	5	55.56 %
Africa	Northern Africa	6	1	9.26 %
Africa	Southern Africa	5	1	20 %
Africa	Western Africa	16	12	75 %
Africa		54	33	61.11 %
Asia	Central Asia	5	0	0 %
Asia	Eastern Asia	5	0	0 %
Asia	South-Eastern Asia	11	4	36.36 %
Asia	Southern Asia	9	4	44.44 %
Asia	Western Asia	18	1	5.56 %
Asia		48	9	18.75 %
Europe	Eastern Europe	10	0	0 %
Europe	Northern Europe	10	0	0 %
Europe	Southern Europe	14	0	0 %
Europe	Western Europe	9	0	0 %
Europe		43	0	0 %
Latin America and the Caribbean	Caribbean	13	1	7.69 %
Latin America and the Caribbean	Central America	8	0	0 %
Latin America and the Caribbean	South America	12	0	0 %
Latin America and the Caribbean		33	1	3.03 %
Northern America	Northern America	2	0	0 %
Oceania	Australia and New Zealand	2	0	0 %
Oceania	Melanesia	4	2	50 %
Oceania	Micronesia	5	1	20 %
Oceania	Polynesia	3	1	33.33 %
Oceania		14	4	28.57 %
World		194	47	24.23 %

Table 1: Number of countries and LDCs in corresponding regions of the world

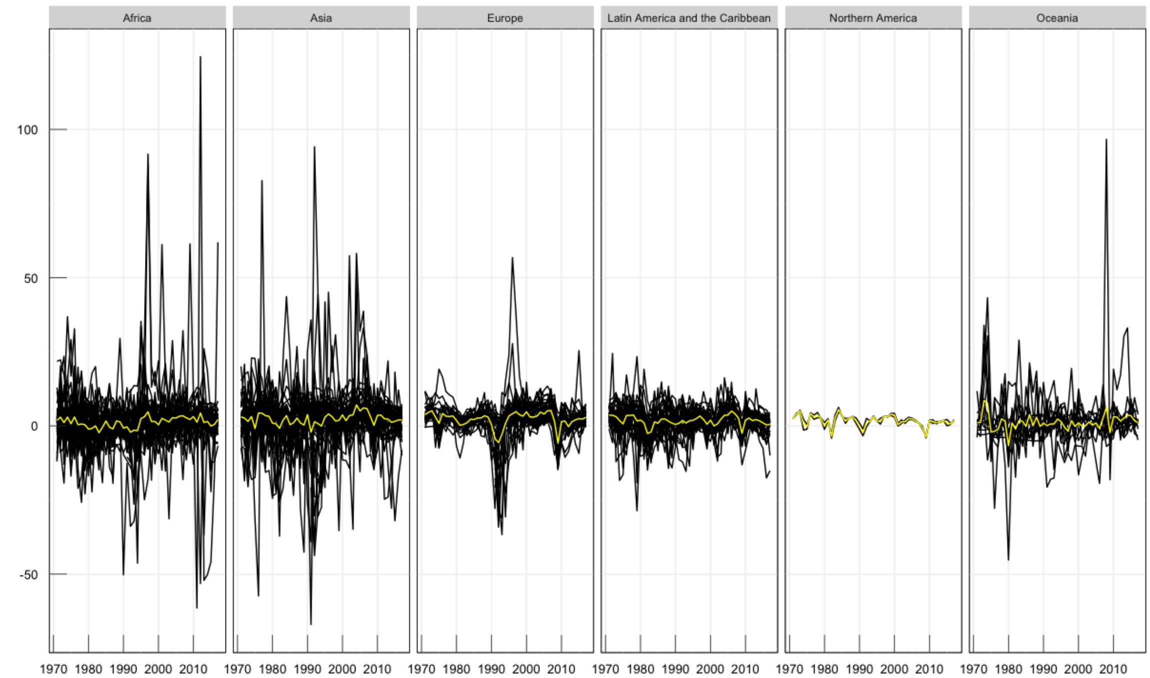


Figure 3: GDP growth per capita

On the country level, only one of the LDCs has had a growth rate higher than 7 %, Ethiopia. Nepal and Bangladesh are quite close with 6.3 and 6.2 %, respectively. On the other side of the ranking are Chad, Yemen, and Timor-Leste, all with negative growth that is more than 6 %. When taking the average growth over the 2015-2017 when the SDGs have become valid, only Ethiopia's average is equal to 7 %, all other LDCs are below the threshold. Hence, based on the available data, it is not very likely that many LDCs will actually reach the target of 7 % GDP growth per year. For not-listed countries, it is important to maintain the growth rate stable, i.e. to avoid any major periods of high volatility, which is quite questionable given the volatile orange curves in Figure 4.

4.2 Target 8.2

Second indicator that measures labour productivity is available from 2001 until 2022, where the values for the years 2020-2022 are estimated by ILO. It is measured as annual growth rate of real GDP per employed person. The data are available for 179 countries of the world, excluding the smallest countries: Antigua and Barbuda, Dominica, Grenada, Saint Kitts and Nevis (Caribbean), Kiribati, Marshall Islands, Micronesia, Nauru, Palau (all 5 countries of Micronesia), Liechtenstein, Monaco (Western Europe), San Marino (Southern Europe), Seychelles (Eastern Africa), and Tuvalu (Polynesia). From larger countries, only

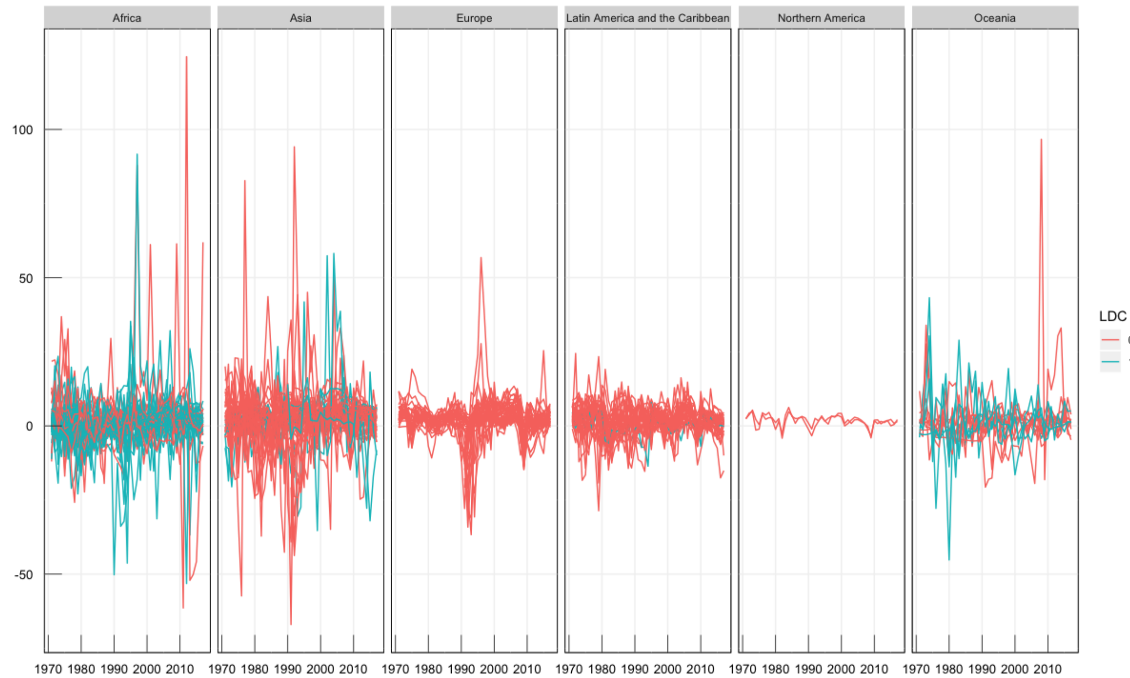


Figure 4: GDP growth per capita, LDC and non-LDC countries per region

the data for Angola (Middle Africa) is missing. As these countries belong to those that are less developed and may be assumed to have lower values in this Indicator, the numerical results might be slightly overstated and be ”more positive” than the true reality.

Following Liu et al. (2016) the presented method is expected to work better in this case because of shorter time horizon.

This target will be fulfilled if the values of the indicator in 2030 are higher than in 2015, ideally for all of the analysed countries. Its development averaged over regions and worldwide in time is shown in Figure 5. This shows that this target has a potential to be achieved, as, except Oceania and Northern America, other regions of the world have been experiencing more or less gradual increase in this indicator since 2015.

4.3 Target 8.3

The data for the third indicator 8.3.1 is also collected by ILO mainly through labour force surveys. As a result, the panel is unbalanced - for some countries, the data are obtained regularly, but some countries have only one input in time. The oldest data are from 2004, but only for 2 countries. In total, there are only 196 available data point for all countries in the world from 2004-2018, which makes the desired analysis unattainable and this indicator will not be further analysed.

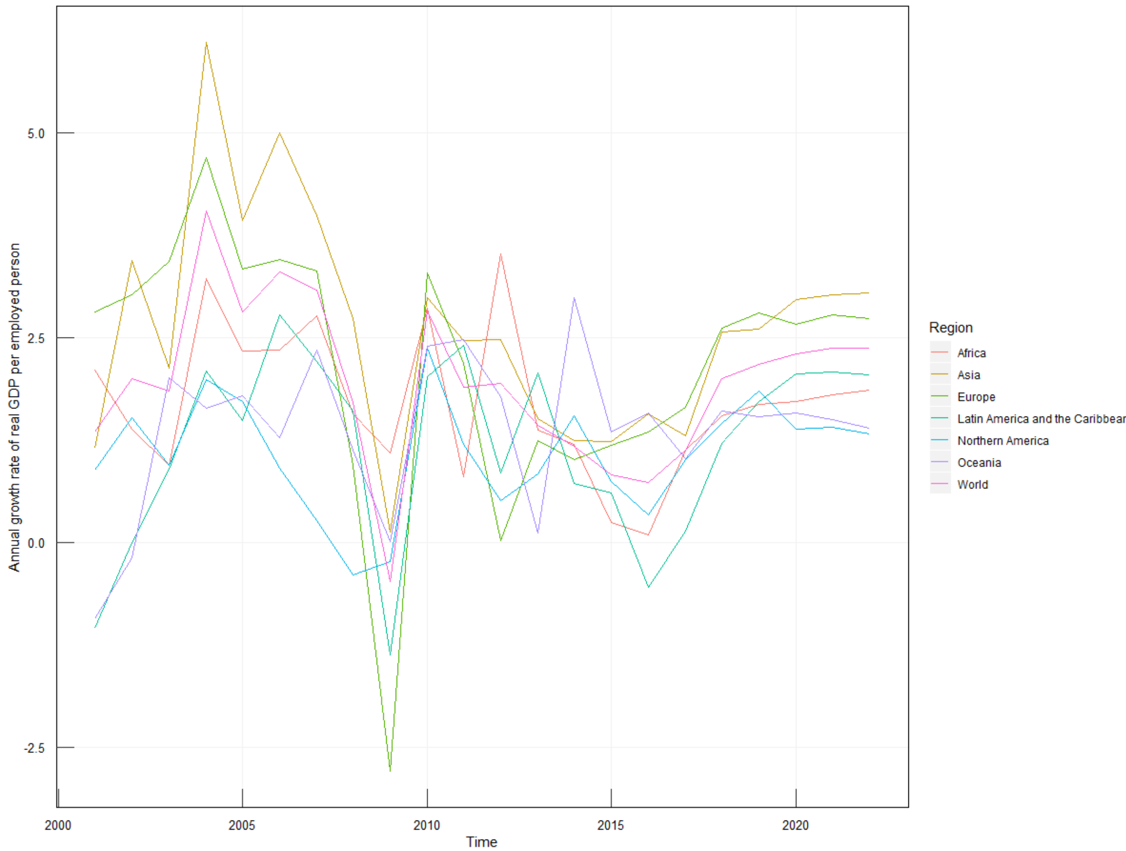


Figure 5: GDP growth per employed person per region

4.4 Target 8.4

Indicators for the fourth Target have time series available form 2000 up to 2016 (8.4.1) and 2017 (8.4.2). The material footprint is recorded per constant US dollars by type of a raw material; for further analysis the sum of all raw materials will be considered. Domestic consumption will be also tracked as a sum of a consumption of all raw materials in tonnes. It can be defined as a sum of a total material in an economy. These two indicators ought to be looked at together, as they deal with two opposite sides of the economy, production and consumption, where material footprint represents the implicit quantity of material that is needed in order to meet the ultimate demand of a country.

Out of 194 countries of the world, 27 countries have no data available for the first and 10 for the second indicator. In total, 27 countries will be dropped from the analysis of this Target, as those 10 that miss the second indicator miss also the first one. Most of them belongs to the smallest countries in the world and only Czechia is included in the list of 36 developed countries as stated by the UN and which are of major interest of this Target and should be delivering the best results. If it is assumed that the missing countries have high values in the observed indicators (they are mostly small and non-developed), the actual results might be even worse than reported here based on the available sample.

There are 14 missing out of 2,839 observations in the values of the Indicator 8.4.1, so the proportion of missing data is equal to 0.49 %. They will be imputed with a multiple model-based imputation method (van Buuren and Groothuis-Oudshoorn (2011)) with 2 imputations.

On average, according to the latest available data, developed countries has had a material footprint of 0.86 kilograms per constant USD, which is much lower than non-developed countries, 2.79 kilograms per constant USD. According to the latest data for the domestic consumption, for non-developed countries it has been 543 779 242 tonnes, and for the developed 442 409 837. In order for the Target to be met, it would be desirable to see a decrease in the values of material footprint and domestic consumption, as it would mean that we would be able to use our resources more efficiently in both consumption and production. The developed countries are already ahead non-developed countries.

4.5 Targets 8.5, 8.6, 8.7, and 8.8

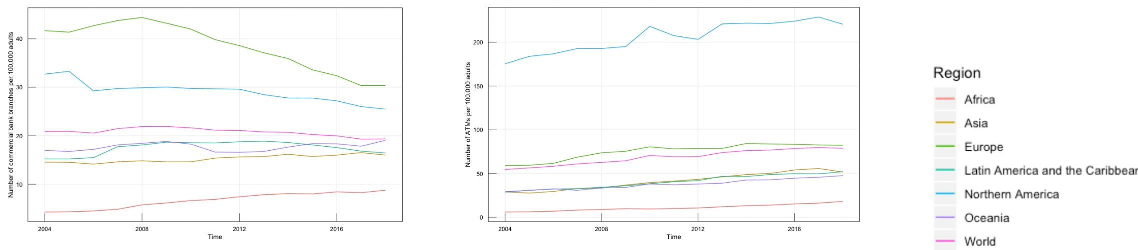
Indicator 8.5.1, hourly earnings, has been collected mainly through labour force or household surveys during 2010 - 2018. Maybe as a consequence the data is not available for all countries, does not have regular inputs in time, and is not available across all occupational categories or for persons with disabilities. For this reason, this indicator will not be further considered.

The second indicator has also limited availability. Although the data of general unemployment are quite easily available both by sex and by age, there is no data on this level for the unemployment of person and disabilities. Moreover, particularly African and Asian countries do not have unemployment data for all years, and it is hardly possible to obtain detailed data for the specified groups. Due to this incompleteness, this Target will not be further analysed.

Similar argumentation holds for Target 8.6, as it has been also collected mainly through surveys for 151 countries. Many countries have only 1-2 observations in 2000 - 2018. If every country from this sample had an input for each year, it would give 2,718 observations. However, only 1,254 are collected, which gives a proportion of missing data around 54 %, so this Target will also not be further analysed.

The availability of the data for the Indicator 8.7.1 is even worse, there are in total only 72 inputs for all countries since 2010, so deeper analysis of this Target is unattainable.

Data for Indicator 8.8.1 cover only 83 countries of the world, many again with a very few inputs in time, and no data for Indicator 8.8.2 are publicly available until now, so this Target will not be further considered.



(a) Number of bank branches per 100 thousand adults, averaged over regions and across the world.

(b) Number of ATMs per 100 thousand adults, averaged over regions and across the world.

Figure 6: Development of Indicator 8.10.1 in time.

4.6 Target 8.10

The data for Indicator 8.10.1 is available since 2004 until 2018 for 183 countries recognized by the UN. Countries with no data in this indicator are namely Andorra, Bahrain, Cuba, North Korea, Eritrea, Liechtenstein, Monaco, Nauru, Somalia, Turkmenistan, and Tuvalu, so, no predictions will be obtained for these countries.

For other countries, out of 2,745 observations is 171 missing for the a) part of the indicator, so the proportion of missing data is 6.91 %. For the b) part, 319 observations are missing, i.e. 11.62 %. These data will be imputed using multiple model-based imputation method (van Buuren and Groothuis-Oudshoorn (2011)) with 5 and 10 imputations, respectively.

Indicator 8.10.2 has a data collected every three years and three data points (2011, 2014, and 2017) are available for 155 countries, so the data should be interpreted with caution as there are no data for smaller or less developed countries. Due to this short time series, it will be interesting to see whether I will be able to obtain any reasonable prediction. However, Liu et al. (2016) claims that the method works especially well when the short time series are available. Out of 465 observations, 45 are missing and will again be imputed with model-based imputation method (van Buuren and Groothuis-Oudshoorn (2011)). As the proportion of missing data is 9.68 %, 10 imputations will be used.

For this target to be met, it is important that the values of the indicators will be increasing in time, i.e. more people will have access and will make use of financial services. Their development in time averaged over regions and also the world's average is displayed in Figure 6.

This figure shows an optimistic rise in the adjusted number of commercial bank branches over time, especially for the less developed regions, Africa, Oceania, and Asia. Interestingly, this number is decreasing in more developed parts of the world. Even though it would be desirable to see an increase in this Indicator over time, this graph might also be pointing out that the differences between the less developed and developed world areas are narrowing, which is definitely not a bad thing. Similar situation is happening with the adjusted number of ATMs, where the increase is noticeable across all regions. Only Northern America and Asia have experienced a slight drop in the latest available year, but the overall increasing trend is still visible.

The second indicator for this target looks also promising, despite the very few data points. Overall, the proportion of people above 15 that have a money account has been increasing everywhere, as it is displayed in Figure 7. The most developed regions, Europe and Northern America, are well above the world average along with Oceania. Almost 100 % of the adult population with an account here is however caused by the fact that for this region there are no other data available than for Australia and New Zealand.

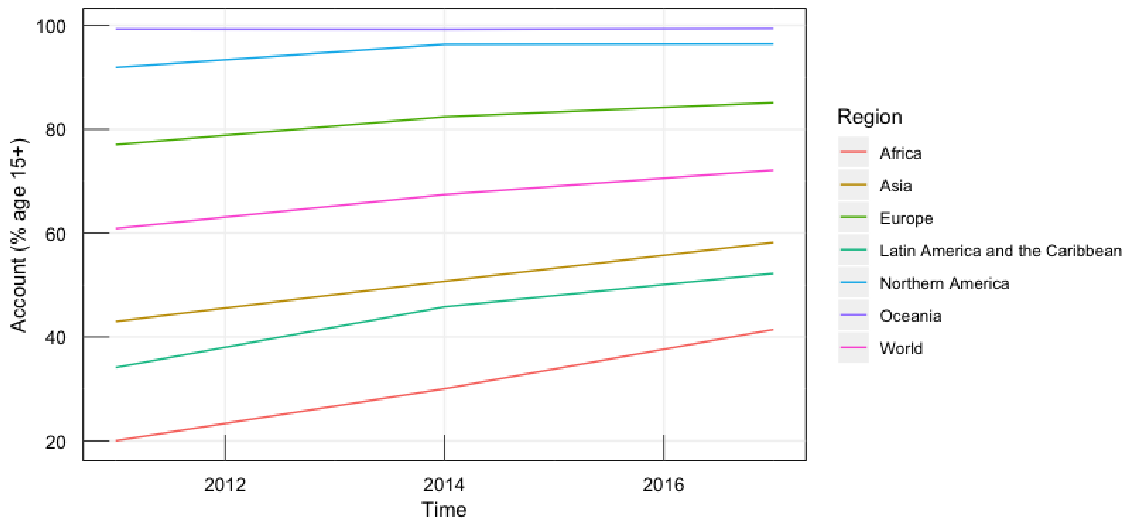


Figure 7: Proportion of adults with a money account, regional and world averages.

4.7 Target 8.a

This Target aims to help developing countries by increasing the financial aid that is coming to them from various sources measured by aid commitments to these countries in millions of constant US dollars. There are 144 developing countries in the list[2]: all 54 African countries, 37 Asian countries, 12 countries from Oceania (all except Australia and New Zealand), 32 countries from Latin America and the Caribbean (all except Bahamas) and 9 countries from Eastern and Southern Europe. The data are available since 2009 until 2017. The regional time series of this indicator are displayed in Figure 8. As Africa and Asia have the biggest numbers of developing countries, it is not surprising that the greatest

[2]Including 47 LDCs from Table 1.

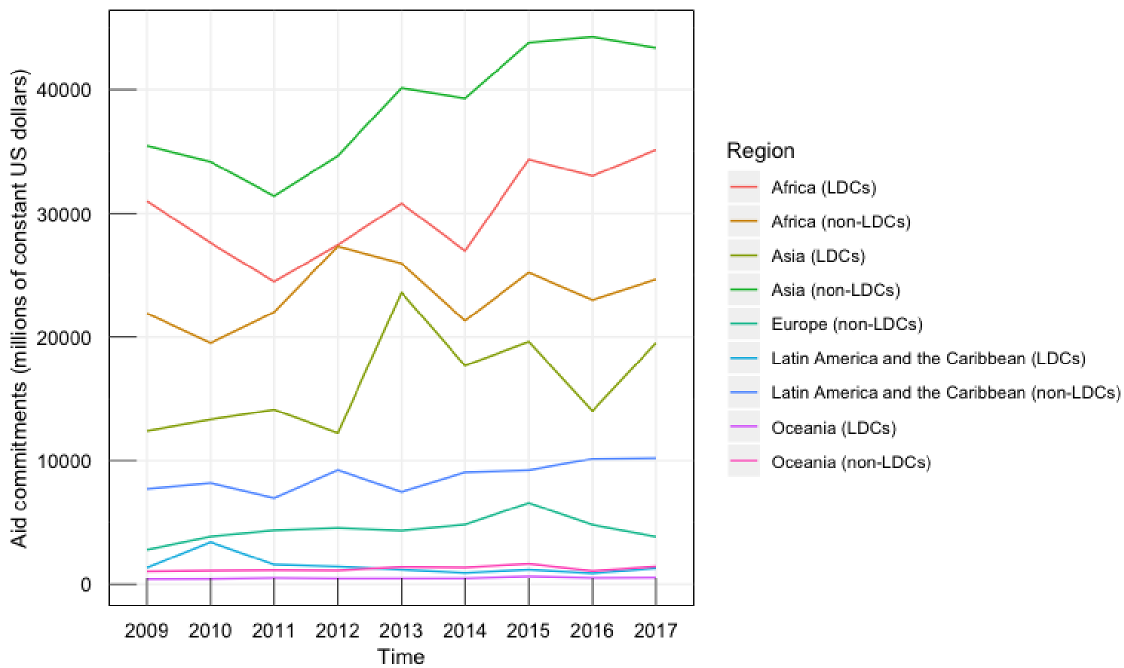


Figure 8: Aid commitments to developing countries in millions of constant 2017 US dollars.

amount of dollars go to these regions. Although there has been a noticeable increase in the amount since 2009, in recent years the amount is more or less the same and there is not that much of an increase in Aid for developing countries, including LDCs, as it would be desirable to see in order the Target to be met. European developing countries have experienced a remarkable decrease in the amount of financial aid.

5 Results

This section describes the results of the empirical application of the methodology described in Section 3 on the data described in Section 4. The model used for the estimation consists of a specific indicator as a dependent variable that is explained by the heterogeneous intercept and one lag of the dependent variable. As mentioned previously, no explanatory variables are considered.

Eight model combinations are evaluated for each indicator - four types of the estimation of homogeneous parameters and two types of the estimation of the heterogeneous parameters (Section 3). Consequently, the most accurate estimator with the lowest RMSE is chosen and the predictions for the year 2030 are discussed in line with the corresponding SDGs. Additionally, the performance of the models is compared also to the benchmark models: Arellano-Bond, Blundell-Bond (Section 3.6), Pooled OLS, that does not take the individual heterogeneity into account, and the state-space model.

Even though the model predicts future values of the indicators for every country in the dataset individually, I will present the averaged/aggregated results over the regions or other groups of countries that are of the interest for the particular indicator.

The results on average do not promise the achievement of any analysed Target, even though there is hope that the world is starting to move in the right direction. Especially developing and under-developed countries are showing much effort and deliver promising results, whereas the performance of developed countries is falling behind the expectations. More detailed discussion is presented in the few next subsections.

5.1 Target 8.1

For the first indicator, Annual growth rate of real GDP per capita, all models except the combinations made with Arellano-Bover estimator of homogeneous parameters performs comparably well and beat all benchmark models, yielding a slightly lower RMSE when combined with non-parametric estimation of the individual intercept. It might be caused by the fact that the random effects might not be perfectly normally distributed and, therefore, the non-parametric estimation yields better results as it does not make any distributional assumptions.

The lowest RMSE was achieved with the combination of QMLE estimation of auto-regressive parameter and non-parametric estimation of the heterogeneous intercept. The values of RMSE for all model combinations and the benchmark models are displayed in Table 2. The actual predictions of the most accurate model are presented in Table 3 together with the most recent value, averaged over regions and LDCs. The value of the auto-regressive parameter has been estimated to be 0.19, which suggest not very strong hence positive relation between the lagged value of GDP per capita growth and its current value.

The results indicate a move towards a higher growth of GDP per capita in the Least Developed Countries in Africa, Asia and Oceania, although the average results are still far from reaching the Target. Oceania is expected to experience a high increase in growth on average, as well as the non-LDCs in Latin America. The values of the indicator are expected to even decrease in time in other world areas.

On the sub-regional level (results not reported), the highest growth among LDCs is expected to be in Micronesia and Middle Africa (both more than 4 %, however, there is only 1 LDC country in Micronesia), followed by Melanesia, Northern Africa, Southern Asia, Eastern Africa (more than 2 %). Other LDCs are expecting a growth within the range from 1 to 2 % except for Caribbean (this is responsible for the negative growth as there is only one country in the sub-region as well as in the whole region).

However, when looking at the results for individual countries (not reported), there are 2 LDCs that are expected to achieve the Target because their GDP per capita growth is

Table 2: RMSE of the estimator for 8 model combinations and the benchmark models for the analysed Targets. The numbers of the Indicators represents the following: 8.1.1 Annual growth rate of real GDP per capita, 8.2.1 Annual growth rate of real GDP per employed person, 8.4.1 Material footprint per constant US dollars, 8.4.2 Domestic consumption in tonnes, 8.10.1a Number of commercial bank branches per 100,000 adults, 8.10.1b Number of ATMs per 100,000 adults, 8.10.2 Proportion of adults with an account at a bank or other financial institution or with a mobile-money-service provider.

	Indicator							
Model	8.1.1	8.2.1	8.4.1	8.4.2	8.10.1a	8.10.1b	8.10.2	8.a
$\hat{\theta}_{QMLE}$, par	6.9000	5.0284	0.6315	0.0896	11.4599	25.8661	0.0943	655.7536
$\hat{\theta}_{QMLE}$, kernel	6.8118	4.8027	23.1680	0.1016	95.4537	477.1117	0.4213	10,411.7053
$\hat{\theta}_{ABond}$, par	6.8907	5.0202	0.8034	0.2641	10.7811	38.0499	0.1103	940.6258
$\hat{\theta}_{ABond}$, kernel	6.8182	4.8064	14.2641	0.1166	298.9367	63.8262	0.2924	7,646.3966
$\hat{\theta}_{ABover}$, par	8.2322	6.7360	0.6694	0.1006	17.4503	35.0360	0.1010	1,247.1731
$\hat{\theta}_{ABover}$, kernel	17.8300	17.3492	0.6932	0.1432	25.0319	220.9221	0.2213	10,198.4899
$\hat{\theta}_{BBond}$, par	6.9362	5.1634	0.6932	1.6270	8.1831	21.6063	-	566.9118
$\hat{\theta}_{BBond}$, kernel	6.8546	4.8528	34.4913	0.1086	73.1760	26.9480	-	24,951.2379
Benchmark								
Pooled OLS	7.3308	6.6897	0.6420	0.1012	8.2887	21.4735	0.1625	574.0441
Arellano-Bond	9.4963	6.6561	0.6332	0.1201	8.5537	19.9165	0.1554	502.441
Blundell-Bond	12.0537	8.8374	1.0723	0.1854	13.9645	37.4286	-	1,024.1455
State-space	6,773.00	12,293.50	3.1508	0.0752	25.1024	8,801.53	0.0551	310,825,723

Table 3: Predictions of the GDP per capita in 2030 averaged over regions and LDCs from the best performing model.

Region		Value in 2017	Predicted value in 2030
Africa		2.51	2.16
	LDCs	1.01	2.24
	non-LDCs	4.00	2.08
Asia		1.90	1.75
	LDCs	1.74	1.94
	non-LDCs	2.06	1.55
Europe		2.89	1.88
Latin America and the Caribbean		0.25	0.15
	LDCs	-0.06	-1.83
	non-LDCs	0.56	2.13
Northern America		1.80	1.59
Oceania		1.44	2.22
	LDCs	2.29	2.66
	non-LDCs	0.53	1.78

expected to be higher than 7 % in 2030. These are Ethiopia (Eastern Africa) and Central African Republic (Middle Africa). Out of all 194 countries, 98 is expected to have higher value of this indicator in 2030. Therefore, even though the Target is not likely to be achieved on average, there is a certain progress likely to be made that should be appraised, especially in African and Asian LDCs.

5.2 Target 8.2

This target is measured by Indicator Annual growth rate of real GDP per employed person. Similarly, as with the previous Target, the non-parametric estimation of Tweedie correction combined with the QMLE estimation of homogeneous parameters yields the lowest RMSE, and the estimates are comparable with other models except the combinations of Arellano-Bover estimator (Table 2). As it is lower than all the benchmarks, it suggests the presence of individual effects in the data that subsequently lead to the more accurate prediction.

The data is provided by ILO until 2022, the estimated horizon is 8 years. The autoregressive coefficient has estimated value of 0.04, which indicates a very weak persistence in the value of the dependent variable. Estimated values in 2030 next to the most recent value from the data are shown in Table 4. Based on these results, it seems that unfortunately neither this Target have a great potential to be achieved. On average, the value of the measured indicator is expected to rise only in Oceania. In all other world regions, a drop in its value is expected to happen.

On the level of individual countries, the predicted values of the GDP growth per em-

Table 4: Predictions of the Annual growth rate of real GDP per employed person in 2030 averaged over regions and LDCs from the best performing model.

Region	Value in 2022	Predicted value in 2030
Africa	1.86	1.77
Asia	3.05	2.47
Europe	2.73	2.16
Latin America and the Caribbean	2.05	1.36
Northern America	1.32	1.23
Oceania	1.39	1.48

ployed person is expected to be higher in 59 countries, most of them located in Africa, Asia, and Latin America. Unfortunately, other countries in these regions are expected to suffer from the drop in this indicator which pulls the average value down. On average, it does not seem plausible that this Target will be met.

5.3 Target 8.4

The corresponding Indicators to this Target are Material footprint per constant US dollars and Domestic consumption in tonnes. The RMSE of the proposed model combinations are stated in Table 2. For the Indicator 8.4.1, the QMLE estimation of homogeneous parameters combined with the parametric estimation of the correction term gives the most precise results. Models that are based on the kernel estimation of the correction term perform notably worse. The estimated auto-regressive coefficient is equal to 0.54.

In case of the second indicator, the benchmark models are beaten by the proposed model that combines the Arellano-Bover estimation of homogeneous parameters with the parametric way of estimation of the heterogeneous parameters. The auto-regressive parameter is estimated to be 0.66, so the values of domestic consumption are quite persistent in time.

The values need to be estimated 14 and 13 years ahead for the first and the second indicator, respectively. The averaged estimated value of the material footprint is 2.81 kilograms per constant USD for non-developed countries, what is just slightly higher than the value of 2016, but still, not desirable. For the developed countries, the situation seems to be even worse as in those the material footprint increased since 2016 to the value of 1.25 (difference is 0.39 kilograms per constant USD). It is not in line with how the indicator should be developing in order to meet the target, especially for the developed countries, as we would like to see the opposite to happen, i.e. the material footprint should have a decreasing trend and the developed countries should be leading it.

The results for domestic material consumption confirms this. It is expected to see a large increase in its value. That would mean that the world needs more material to produce the same output, i.e. we are becoming less and less efficient when it comes to the use of our natural resources or other assets in production. Therefore, it seems that, as for other analysed indicators, we are not on a good way toward the achievement of this Target either.

5.4 Target 8.10

The best performing model for Indicator 8.10.1(a) - Number of commercial bank branches per 100,000 adults - as well as 8.10.1(b) - number of ATMs per 100,000 adults - out of 8 proposed model combinations are Blundell-Bond estimation of homogeneous parameters combined with parametric estimation of Tweedie's correction (Table 2). the auto-regressive parameters have the estimated values of 0.90 and 0.89, indicating strong persistence in the number of bank branches and ATMs, which is reasonable. However, for the (b) part of the indicator, the RMSE is higher than two benchmarks, Pooled OLS and Arellano-Bond, and so it indicates that the benefit of modelling the individual intercept is not very high.

Based on the predicted results, the number of bank branches is expected to drop in every world's region. Europe will still be leading in this Indicator, even though its value its expected to drop from 29.2 in 2018 to 20.2 number of bank branches per 100,00 adults in 2030. The situation will continue to be the worst in Africa, where the indicator is expected to drop to the value of 4.13 from the current 11.4. This number is scaled per 100 thousand individuals, which makes it comparable across countries.

This is also supported by the results of the (b) part of Indicator 8.10.1 - the number of ATMs per 100,00 results is expected to decrease across the world regions. In my opinion, this Target ovreall might not be perfect to measure the accessibility to financial services, especially in the developed countries. In recent years, there are new technologies or innovations coming - there are plenty of things that you can arrange or settle online or via phone, without the actual need of going to the bank. In addition, more people use cash-less ways of paying for goods and services, such as credit/debit cards or smartphones. I find it a bit natural that the need of a physical bank branch or the need of ATMs is losing its importance especially among younger generation. These arguments are, indeed, not true for many developing or under-developed countries in the world, therefore it would still be desirable to observe an increase in every Indicator in such countries, mainly in Africa, Asia, and Oceania.

For the Indicator 8.10.2 (Proportion of adults with an account at a bank or other financial institution or with a mobile-money-service provider), the Blundell-Bond estimation has not been performed. There are only 3 time periods, which leaves us with the only one valid instrument, Δy_{i1}, as in case of Arellano-Bond estimator. From the remaining options, the combinations of QMLE estimation of common parameters combined with the parametric estimation of Tweedie's correction produces the lowest RMSE (Table 2). Surprisingly, estimated ρ is negative in its sign.

It is remarkable how well the method seems to work with such a short time series, when the time dimension itself would be insufficient to perform any reasonable analysis and so the modelled individual effects have a large added value. With the proposed method, I have obtained prediction four time periods ahead for the years 2020, 2023, 2026, and 2029 (as the data has been collected every three years).

The obtained numerical results predict a slight drop in the percentage of an adult population that have a bank account. The decrease varies between 0.4% in Oceania and 5.6 % in Africa. Again, this is not a desirable result, but, on the contrary, it indicates that this Indicator will not help in achieving this Target.

5.5 Target 8.a

This Target is represented by the The lowest RMSE (Table 2) out of the proposed model combinations when analysing the panel of aid commitments to developing countries has been obtained by the combination of Blundell-Bond estimator of common parameters and parametric estimation of Tweedie correction. It is interesting to see that using Blundell-Bond estimator as a benchmark gives the highest RMSE, and hence it suggests the importance of modelling the individual effects in order to obtain as precise prediction as possible. However, neither in this case the winning model has been able to beat the best performing benchmark. The estimated ρ is equal to 0.74, indicating quite strong persistence in the amount of the financial aid.

According to the results averaged across the world's regions, the amount of financial aid is expected to fall for all of them. Again, it is therefore likely that this Target will be falling behind and will not be met. There are, however, many other effects that might influence this variable in the future. In an ideal case, lower financial amount coming to developing countries might indicate in the future that there are less countries who need it or that they need it in lower amounts. It would be interesting to do further deeper research on all of the above analysed indicators, as most of them are quite complex. Even though they on average indicate that we are not getting closer to achieve the SDGs, one should not forget how complex these targets and goals are and that the using these pure numerical results might not be the best way how to look at the state of the world that will be in 2030.

6 Conclusion

The main aim of this thesis has been an empirical analysis and prediction of the possible achievement of one of the SDGs, Goal 8, that is concerned mainly with the area of economic development. For doing so, recently developed methodology that is based on the empirical Bayes approach by Liu et al. (2016) has been applied and with the extension to multi-step forecasting, when the number of predicted time periods ahead ranges from 4 to 14. It constructs a prior distribution of the cross-sectional information in the panel which is then used to form a posterior mean for every individual in the dataset.

Altogether the thesis has examined 8 model combinations made of 4 estimation methods for the common parameters and 2 estimation method for the heterogeneous parameters.

The predictions made with these models have been evaluated in terms of RMSE for each dataset and subsequently compared to 4 benchmark models.

The application of the methodology on different datasets has shown both the advantages and the disadvantages of the method. For datasets with longer T, the benefits of modelling the posterior mean has been higher than for those with smaller T, which is in contrast with the argumentation of Liu et al. (2016). The models applied on data with more time periods available have been able to beat the benchmark models.

In case of very volatile data, in particular GDP per capita and GDP per employed person, the kernel estimation of Tweedie's correction has been preferred. In cases of less volatile data, the parametric approach have led to more precise results. No estimation method of homogeneous parameters has been constantly better than the others, so it should always be the case that more options are evaluated, and the best is chosen with respect to the empirical data on which it is applied.

It has been shown that when one is interested in modelling the panel for large N, the dynamic panel data methodology as developed by Liu et al. (2016) is preferred to the univariate state space model. Considering the cross-sectional information and modelling the heterogeneous intercept can increase the prediction accuracy in comparison to the state space models, that model each series separately and try to separate the signal and the noise in the data. The only time that the state space model performs better is in the case of $T = 3$. With this short time series, it suggests that the hidden signal in the time series is more important than the cross-sectional information. Additionally, it confirms the contradictory results of Liu et al. (2016) stated above that the benefits of the proposed method are higher for short time series.

Even though it is very likely that the Goal 8 of SDGs will not be achieved as set in the Indicators, it should not be forgotten to praise those, that are doing their best in improving the situation in their countries and are slowly moving towards better and sustainable future, at least in the economic aspects that has been analysed. However, the lack of (quality) data still remains to be a major problem. Also, it would be nice to have set some milestones during the period, which would make the analysis of the progress towards the Goal easier.

In conclusion, estimating and using a posterior mean in panel data forecasting can often increase the prediction accuracy when compared to the already existing models and give reasonable predictions when applied to short patterns when the short time period available would be insufficient to obtain enough information for predictions. Although reaching the SDGs sounds still more like an impossible dream, let's hope that everyone in the world will continue in making the best effort towards securing sustainable, healthy, and prosperous environment.

References

Alvarez, J. and Arellano, M. (2003). The time series and cross-section asymptotics of dynamic panel data estimators. *Econometrica*, 71(4):1121–1159.

Anderson, T. W. and Hsiao, C. (1981). Estimation of dynamic models with error components. *Journal of the American Statistical Association*, 76(375):598–606.

Arellano, M. and Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, 58(2):277–297.

Arellano, M. and Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, 68(1):29–51.

Baltagi, B. (2008). Forecasting with panel data. *Journal of Forecasting*, 27(2):153–173.

Baltagi, B. H., Fingleton, B., and Pirotte, A. (2013). Estimating and forecasting with a dynamic spatial panel data model. *Oxford Bulletin of Economics and Statistics*, 76(1):112 – 138.

Bilotkach, V. (2015). Are airports engines of economic development? A dynamic panel data approach. *Urban Studies*, 52(9).

Blien, U. and Tassinopoulos, A. (2001). Forecasting regional employment with the ENTROP method. *Regional Studies*, 35(2):113 – 124.

Blundell, R. and Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87(1):115–143.

Botev, Z. I., Grotowski, J. F., and Kroese, D. P. (2010). Kernel density estimation via diffusion. *The Annals of Statistics*, 38(5):2916 – 2957.

Błażejowski, M., Gazda, J., and Kwiatkowski, J. (2016). Bayesian model averaging in the studies on economic growth in the EU regions - application of the gretl BMA package. *Economics and Sociology*, 9(4):168 – 175.

Chamberlain, G. and Hirano, K. (1999). Predictive distributions based on longitudinal earnings data. *Annales d'économie et de statistique*, 55-56:211 – 242.

Constantini, M., Gunter, U., and Kunst, R. (2010). Forecast combination based on multiple encompassing tests in a macroeconomic DSGE system. *Institute for Advanced Studies, Economics Series.*

Frances, P. H., van Dijk, D., and Opschoor, A. (2018). *Time Series Models for Business and Economic Forecasting.* Cambridge University Press.

Ghysels, E. and Marcellino, M. (2018). *Applied Economic Forecasting using Time Series Methods*. Oxford University Press.

Goldberger, A. S. (1962). Best linear unbiased prediction in the generalized linear regression model. *Journal of American Statistical Association*, 57(298):369–375.

Hamilton, J. D. (1994). Chapter 50 State-space models. *Handbook of Econometrics*, 4:3039 – 3080.

Hindrayanto, I., Koopman, S. J., and de Winter, J. (2016). Forecasting and nowcasting economic growth in the euro area using factor models. *International Journal of Forecasting*, 32(4):1284 – 1305.

Hirano, K. (2002). Semiparametric Bayesian inference in autoregressive panel data models. *Econometrica*, 70:781 – 799.

Kholodilin, K., Siliverstovs, B., and Kooths, S. (2008). A dynamic panel data approach to the forecasting of the GDP of German Länder. *Spatial Economic Analysis*, 3(2):195 – 207.

Lancaster, T. (2001). Orthogonal parameters and panel data. *Review of Economic Studies*, 69:647 – 666.

Lehmann, R. and Wohlrabe, K. (2013). Forecasting GDP at the regional level with many predictors. *German Economic Review*, 16(2):226 – 254.

Lehmann, R. and Wohlrabe, K. (2014). Regional economic forecasting: state-of-art methodology and future challenges. *Economic and Business Letters*, 3(4):218 – 231.

Liu, L., Moon, H. R., and Schorfheide, F. (2016). Forecasting with dynamic panel data models. *PIER Working Paper No. 16022*.

Lüsted, M. A. (2010). *Poverty*. Edina, Minn. : ABDO Pub.

Moral-Benito, E. (2012). Determinants of economic growth: A Bayesian panel data approach. *Review of Economics and Statistics*, 94(2):566 – 579.

Nikolai, S., Hoy, C., Berliner, T., and Aedy, T. (2015). Projecting progress: Reaching the SDGs by 2030.

Piketty, T. (2014). *Capital in the twenty-first century*. Cambridge, MA: Belknap Press of Harvard University Press.

Robbins, H. (1951). Asymptotically subminimax solutions of compound decision problems. *Proceedings of the Second Berkeley Symposium on Mathematical Statistics and Probability*, I.

Sachs, J. D. (2012). From Millennium Development Goals to Sustainable Development Goals. *The Lancet*, 379:2206–2211.

Sequeira, T. N. and Maçäs, P. (2008). Does tourism influence economic growth? A dynamic panel data approach. *Applied Economics*, 40(18):2431 – 2441.

Stock, J. H. and Watson, M. W. (2004). Combination forecasts of output growth in a seven-country data set. *Journal of Forecasting*, 23:405 – 430.

Stoian, D., Monterroso, I., and Current, D. (2019). *SDG 8: Decent Work and Economic Growth – Potential Impacts on Forests and Forest-Dependent Livelihoods*, page 237–278. Cambridge University Press.

Tiwari, A. K. and Mutascu, M. (2011). Economic growth and FDI in Asia: A panel-data approach. *Economic Analysis and Policy*, 41(2):137 – 187.

Trinajstic, M., Baresa, S., and Bogdan, S. (2018). Regional economic growth and tourism: A panel data approach. *UTMS Journal of Economics*, 9(2):145 – 155.

UN (2015). The Millennium Development Goals report.

UN (2018). The Sustainable Development Goals report.

UNDP (2020). Goal 8: Decent work and economic growth.

van Buuren, S. and Groothuis-Oudshoorn, K. (2011). mice: Multivariate imputation by chained equations in R. *Journal of Statistical Software*, 45:1–67.

White, I. R., Royston, P., and Wood, A. M. (2011). Multiple imputation using chained equations: Issues and guidance for practice. *Statistics in Medicine*, 30(4):377–399.

Youssef, A. and Abonazel, M. R. (2015). Alternative GMM estimators for first-order autoregressive panel model: An improving efficiency approach. *Communications in Statistics-Simulation and Computation*, 46 (4):3112–3128.