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IZA DP No. 10880

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ABSTRACT

The Relationship between Economic Growth and Democracy: Alternative Representations of Technological Change

This study investigates the relationship between economic growth and democracy by estimating a nation's production function specified as static and dynamic models using panel data. In estimating the production function, it applies a single time trend, multiple time trends and the general index formulations to the translog production function to capture time effects representing technological changes of unknown forms. In addition to the unknown forms, implementing the technology shifters model enabled this study to find possible known channels between economic growth and democracy. Empirical results based on a panel data of 144 countries observed for 1980–2014 show that democracy had a robust positive impact on economic growth. Credit guarantee is one of the most significant positive links between economic growth and democracy. The marginal effects of credit guarantee and foreign direct investment inflows are stronger in democratic countries than they are in non-democratic ones. In order to check the robustness of these results, a dynamic model constructed with a flexible adjustment speed and a target level of GDP is also tested. The results of this dynamic model also support the positive impacts of democracy on economic growth.

JEL Classification: D24, O43, O47, P16

Keywords: economic growth, democracy, production function, single time trend, multiple time trends, general index, technology shifters, flexible adjustment speed, target level of GDP

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1. Introduction

It is widely known that institutions matter to long-run economic growth. But how do they matter? Of late the belief that democracy has positive impacts on gross domestic product (GDP) growth has been gaining momentum through some empirical and theoretical studies. Acemoglu et al. (2014) suggest that democracy has a significant and robust positive effect on GDP. They add that democratization increases GDP per capita by about 20 per cent in the long run. Persson and Tabellini (2007) suggest that abandoning democracy can cause negative growth effects. On the other hand, according to the developmental state theory, the quality of an institution which leads to economic growth is not consistent with democratic quality.[1] In some East Asian countries, including South Korea and Taiwan, strategies for economic growth were aimed at controlling institutions efficiently in order to allocate capital and resources according to the government's objectives.[2] Democracy and human rights were mobilized in implementing these strategies with the goal of achieving economic growth. By persuading citizens to focus primarily on economic growth, developmental states created an atmosphere in which sacrificing personal freedom could be justified. Although their strategies did not guarantee democratic values and transparency in institutions, the countries experienced tremendous economic growth during the 1970s and 1980s.

Literature on the relationship between democracy and economic growth is growing. However, despite a number of empirical researches the nature of this relationship and its determinants are yet to be established. Therefore, one can ask the basic question: Is East Asia's experience an exception in the relationship between economic growth and democracy? We have to analyze a large sample of global economic data observed over a long period to clarify the direction and magnitude of the relationship between economic growth and democracy.

This study suggests some robust patterns between economic growth and democracy by estimating nations' production functions using panel data. It also generalizes the settings of the used production function for formulating static and dynamic models. As a variable of democracy, it used the dichotomous democracy dummy variable constructed by Acemoglu et al. (2014). Controlling time-specific effects is one of the most important issues in estimating a production function. Therefore, our study implemented the single time trend, multiple time trends and general index representations of technological changes. The single time trend used in this study is similar to the single time trend used by Solow (1957). The derivation in terms of this trend indicate the magnitude of unobservable technical changes. This single time trend can be generalized to multiple time trends and general index formulations. Baltagi and Griffin (1988) used year dummy variables to generalize the measure of unobservable technical changes, but it is still a function of time.

Moreover, by considering technology indices containing technology shifters, this study found some possible channels between economic growth and democracy. Technology shifters are a more generalized concept than the general index because technology shifters can measure technical changes in which the technology is specified in a known form. Heshmati and Kumbhakar (2013) applied this technology shifters model to the Organization for Economic Cooperation and Development (OECD) countries. Credit guarantee, trade openness, foreign direct investment (FDI) net inflows, electricity consumption, number of firms and

[1] For the developmental state theory, see Wade (1990) and Haggard (1990).

[2] For some additional information about East Asia, see Johnson (1982), Amsden (1989) and Woo (1991).

governmental consumption are included as technology shifters in this study.[3] The results of this study also suggest some differences in the effects of economic policies and economic shocks between democratic and non-democratic countries.

A generalization of the static model for formulating a dynamic model enables this study to reassure the positive and significant impacts of democracy on economic growth. The concepts of the optimal target level of GDP and adjustment speed are actively used to construct a flexible adjustment dynamic model. Empirical studies that have attempted to specify target levels and adjustment speeds have been severely tried by the capital structure theory. Modigliani and Miller (1958) suggested a fundamental model related to the capital structure theory. According to them, a firm's target debt ratio is determined based on the costs and benefits of debt and equity. Marsh (1982) suggests the famous empirical method to prove the capital structure theory by inserting the target debt ratio in a key regression analysis. Banerjee et al. (2000), Heshmati (2001), and Lööf (2004) have constructed systems of equations in their empirical studies which include an equation for the main regression model, an equation for the target level of the debt ratio and an equation for the adjustment speed of the debt ratio. Instead of a target level of debt ratio and adjustment speed of debt ratio, in the context of economic growth we implement the target level and flexible adjustment speed of GDP towards the target level. The functional forms for the target level and adjustment speed are also different from previous studies on the capital structure theory. Based on the likelihood ratio test, the proper functional form and flexible speed of adjustment is chosen for our analysis.

Regardless of the fact which model is used for estimating the production function, there are positive and significant impacts of democracy on economic growth. In this study credit guarantee (per cent of GDP of domestic credit to the private sector by banks) is the most significant positive possible channel among different observable technology shifters. FDI inflows is also a positive and significant possible channel but this technology shifter is significant only in two models among three technology shifters' models. In addition, the marginal effects of an increase in credit guarantee and FDI inflows are stronger in democratic countries. On the other hand, the marginal effects of an increase in trade openness, electricity consumption, the number of firms and in government consumption are stronger in non-democratic countries. Estimation results of the dynamic model also suggest that ceteris paribus democracy has positive and significant impacts on economic growth.

In the dynamic model, the adjustment speed is accelerated by an increase in trade openness and FDI inflows while the adjustment speed is delayed by an increase in government consumption and by improvements in infrastructure related to electricity.

The rest of this study is organized as follows. In Section 2, it shows the static model approach using the production function. After explaining econometric specifications, this section also gives the estimation results. Section 3 carries forward the discussion on the dynamic model approach. The concept of a dynamic model and methods for estimating a dynamic model are also detailed in this section. After interpreting the estimation results of the dynamic model the study gives a conclusion in Section 4 by synthesizing results from the static model and dynamic models.

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[3] Pellegrini and Gerlagh (2004) also considered investment and trade openness as linkages between corruption and economic growth.

2. A Static Model

2.1. Motivation

This study applies single time trend, multiple time trends, the general index and technology shifters' representations of technology to the translog production function. Several important facts have to be considered while choosing a proper econometric model for estimating the production function through panel data.

First, this research uses panel data arranged by each country and year to clarify the existence of institutional elements in the production function. Therefore, we have to capture the effects caused by time variation. Time effects can be captured by implementing single time trend, multiple time trends and general index models. These three approaches allow for a stepwise generalization of technology representation in the production function.

Second, for estimating the production function, deciding the specifications and deriving other information including technical changes and total factor productivity (TFP) are also important. In this respect, the translog production functional form is a very convenient and useful functional form. The translog production function has been widely used in empirical studies thanks to its general and simple characteristics. As the translog production function does not impose any priori restrictions on the return to scale and elasticities of substitution, it allows the flexible nature of production activities to be considered.[4] Moreover, the translog production function has richer specifications of the relationships between output and inputs than other linear specifications including the Cobb-Douglas approach (Evans et al., 2002).

After Bernt and Christensen (1972) and Christensen et al. (1973) suggested the standard form of the translog production function, many studies implemented the translog production function for productivity analyses and production function estimations. Through a flexible functional form for the production function, we can decompose technical change into a neutral part and a non-neutral part affecting production through inputs. The neutral part is affected only by time variation. The non-neutral part is the remaining part of the technical change. Overall TFP and its variations are influenced by two technical change components and the scale effect.

Third, if we can find possible important channels between economic growth and democracy, we can derive policy implications about the economy and society. The single time trend, multiple time trends and general index models are non-observable time trend and time dummy representations of technology. Technology shifters is an alternative representation of technology that is applied in this study to find the kind of observable possible channels discussed earlier.

2.2. Econometric Specifications

2.2.1. The single time trend (STT) model

As its name implies, a single time trend means that there is a unique time trend in the production function. In other words, the output in production increases or decreases linearly as time passes. We can assume that a single time trend is valid historically because we can observe that

[4] Kim (1992) and Lyu et al. (1984) give details of the strengths and weaknesses of estimating the translog production function.

humankind's production has increased consistently.[5] We can check this validity through the value of the neutral part of technical changes or coefficients related to the single time trend. After the single time trend method is implemented, the translog production function can be expressed as:

Model 1 (M1): The single time trend model:

(1)

$$GDP_{it} = \beta_0 + \sum_j \beta_j x_{jit} + \beta_d D_{it} + \beta_t t + \left(\frac{1}{2}\right)\left\{\sum_j \sum_k \beta_{jk} x_{jit} x_{kit} + \beta_u t^2\right\} + \sum_j \beta_{jt} x_{jit} t + C_i + \varepsilon_{it}$$

where x_{jit} is the log of inputs j (capital stock K_{it}, labor force L_{it}) for country i in time period t, D_{it} is the democracy dummy variable and GDP_{it} is the log of GDP level (more explanations about each variable are provided in the 'Data' section). C_i indicates the full set of country-specific fixed effects.

By the definition of the translog production function, inputs and time trend have squared and interacted terms. Through these squared and interacted terms, non-linearity between inputs and output and substitution/complementarity between inputs and input-biased technological changes can be captured. D_{it} is a dummy variable and as such is not squared or interacted because D_{it} is the controlled part from the error term ε_{it}. D_{it} is not interpreted as inputs in an analysis of this production function but rather as a shifter of the production function.

We can derive information from M1 including elasticities, returns to scale, rate of technical change and total factor productivity growth. The rate of technical change can be decomposed into neutral and non-neutral parts as:

E1: Input elasticities (E_j), technical chance (TC) and returns to scale (RTS) in a single time trend model:

(2) $$E_{jit}^{STT} = \frac{\partial GDP_{it}}{\partial x_{jit}} = \beta_j + \sum_{k=1} x_{kit} + \beta_{jt} t, \qquad RTS_{it}^{STT} = \sum_{j=1}^{J} E_{jit}^{STT}$$

As indicated in *E1*, elasticities can be derived easily by the first order derivative. Returns to scale are the sum of elasticities of inputs.

E2: The rate of technical change in a single time trend model:

(3) $$TC_{it}^{STT} = \frac{\partial GDP_{it}}{\partial t} = \beta_t + \beta_u t + \sum_j \beta_{jt} x_{jit}$$

Technical change, in fact, is the elasticity of the time trend in a mathematical sense. The first part, $\beta_t + \beta_u t$, is the neutral rate of technical change, which is only affected by the time effect. The second part, $\sum_j \beta_{jt} x_{jit}$, is the non-neutral technical change, which is not related to the time-specific effect but is related to changes in inputs affecting economies of scale.

E3: Total factor productivity (TFP) growth in a single time trend model:

(4) $$\mathrm{TFP}_{it} = (RTS_{it}^{STT}\text{-}1)(E_{K_{it}}^{STT} \Delta log K_{it} + E_{L_{it}}^{STT} \Delta log L_{it}) + TC_{it}^{STT}$$

---

[5] Solow (1957) also supposed a single time trend in his growth model.

Total factor productivity can be calculated as shown in *E3*. As the elasticities, returns to scale, technical changes and total factor productivity growth can be calculated for each observation an interesting analysis is possible by comparing sample means between specific groups. These input elasticities, rate of technical change, returns to scale and TFP components vary by observation. They provide detailed information on countries' response heterogeneity to changes in inputs. For example, we can generate the sample mean of this information according to country characteristics such as continent location and income group. Moreover, we can compare the sample mean between groups of democratic countries and groups of non-democratic countries.

2.2.2. The multiple time trends (MTT) model

The single time trend model has an important shortcoming related to controlling time variations. When there are some obvious global shocks that affect all identities in the panel data, assuming a unique time trend can be unconvincing. If these shocks are global and strong enough, it is expected that the slopes and intercepts of the time trend will change after encountering these shocks. The first oil shock, the second oil shock and the 2008 global economic crisis are typical examples of strong global shocks. In this case, when there are γ shocks, there are $\gamma + 1$ time trends. The econometric model for applying multiple time trends can be expressed as:

Model 2 (M2): The multiple time trends model:

(5)

$$GDP_{it} = \beta_0 + \sum_j \beta_j x_{jit} + \beta_d D_{it} + \sum_s \beta_s t_s + \left(\frac{1}{2}\right)\left\{\sum_j \sum_k \beta_{jk} x_{jit} x_{kit} + \sum_s \beta_{ss} {t_s}^2\right\} + \sum_j \beta_{jt} x_{jit} t_s + C_i + \varepsilon_{it}$$

Time trend t_s indicates multiple time trends by $t_s = d_s t$ where d_s is a time dummy representing the time interval *s* of unspecified length. Like M1, inputs and time trends are squared and interacted with each other. In this study, the threshold of multiple time trends is 2008; therefore we have two time trends. Extending a single time trend to a multiple one allows for heterogeneity in trend effects, namely changes in both the intercept and the slopes.

Elasticities, rate of technical change and returns to scale are derived by the same principle (described as *E1)*. Getting the technical change is different from *E2*:

E4: The rate of technical change in a multiple time trends model:

(6) $$TC_{it}^{MTT} = \sum_s (w_s \beta_s + \beta_{ss} t_s) + \sum_j \beta_{jt} x_{jit}$$

Here, w_s represents the weights of each time interval in aggregation of the time effect. Accordingly, the neutral technical change is $\sum_s (w_s \beta_s + \beta_{ss} t_s)$ and the non-neutral technical change is $\sum_j \beta_{jt} x_{jit}$ (Heshmati, 1996). Total factor productivity can also be obtained through a multiple time trends model using methods similar to *E3* through aggregation of the TFP components.

2.2.3. The general index (GI) model

A researcher determines the thresholds separating multiple time trends. If unspecified, the thresholds can be identified by switching regression models. Researchers can decide the borders of multiple time trends based on their intuition or based on scientific evidence. Regardless of their decision's accuracy, multiple time trends cannot be independent of a researcher's observations and perspectives. In order to include all possible potential shocks that are not observed by researchers, year dummies are widely used for estimating production and cost functions. This method was devised by Baltagi and Griffin (1988). In the translog production function case, time dummies are added for every year instead of time trend(s). Time dummies are not squared because they only have values of 0 and 1. The econometric model for the general index can be indicated as:

Model 3 (M3): The general index model:

(7)

$$GDP_{it} = \beta_0 + \sum\nolimits_j \beta_j x_{jit} + \beta_d D_{it} + A(t) + \left(\frac{1}{2}\right)\left\{\sum_j \sum\nolimits_k \beta_{jk} x_{jit} x_{kit}\right\} + \sum\nolimits_j \beta_{jt} x_{jit} A(t) + C_i + \varepsilon_{it}$$

where $A(t) = \sum_t z_t\, d_t$; d_t is time dummy for the year t and z_t is the corresponding coefficient. Since there are coefficients included in $A(t)$, M3 has interacted coefficients and is non-linear in parameters. This is a big difference compared to M1 or M2. M1 and M2 are log-linear models in terms of coefficients. There are interacted and squared terms of inputs and time trends allowing for non-linearity in explanatory variables, but there is no interaction between coefficients. Therefore, M1 and M2 can be estimated using the linear method. On the other hand, M3 is non-linear in terms of coefficients because of the interaction between them. We have to apply non-linear estimation methods to conduct a proper analysis of M3. M3 is regarded as an equation system.

Elasticities and returns to scale are derived through procedures indicated in *E1*. Technical change is derived through methods different from *E2* and *E4*. TFP can also be derived by a method similar to *E3*.

E5: The rate of technical change in a general index model:

- Neutral technical change: $A(t) - A(t-1)$
- Non-neutral technical change: $(A(t) - A(t-1))\ (\beta_{Kt} logK_{it} + \beta_{Lt} logL_{it})$
- TC_{it}^{GI} = Neutral technical change + non-neutral technical change

2.2.4. The technology shifters (TS) model

It is well known that in estimating the production function, a researcher's observations do not identify the level of technology very well. In order to enhance the estimation's accuracy, we can add some variables that capture the level of technology in the production function. Many variables can act as indicators of the technology level. For example, nations with advanced technologies are inclined to have higher average educational attainments, more foreign direct investment inflows and a more active movement of loans in the private sector. In addition, in order to have a more advanced level of technology, a nation should increase the availability of electricity and guarantee a proper-sized domestic market. These factors can capture a nation's technology level because they have a high correlation with its technology level.

By grouping these variables according to their functions and categories, we can build some indices consisting of several variables. Each variable, which constructs an index related to the level of technology of all the nations, is called a technology shifter. Consequently, the variables mentioned earlier, including the size of the domestic market, foreign direct investment inflows and electricity consumption are also classified as technology shifters. By inserting these indices constructed by technology shifters, we can implement the technology shifters model. First, let us assume a single time trend for this model:

Model 4 (M4): Technology shifters combined with a single time trend model:

(8)

$$\begin{aligned} GDP_{it} = {} & \beta_0 + \sum_j \beta_j x_{jit} + \beta_d D_{it} + \beta_t t + \sum_m \sum_p \delta_m T_m(Z_{it}^{mp}) \\ & + \left(\frac{1}{2}\right)\left\{\sum_j \sum_k \beta_{jk} x_{jit} x_{kit} + \beta_u t^2 + \sum_m \sum_p \delta_{mm} (T_m(Z_{it}^{mp}))^2\right\} \\ & + \sum_j \beta_{jt} x_{jit} t + \sum_m \sum_p \delta_{mt} T_m(Z_{it}^{mp}) t + \sum_j \sum_m \sum_p \gamma_{jm} x_{jit} T_m(Z_{it}^{mp}) \\ & + \sum_m \sum_p \theta_{tm} D_{it} T_m(Z_{it}^{mp}) + C_i + \varepsilon_{it} \end{aligned}$$

$T_m(Z_{it}^{mp})$ are technology indices and Z_{it}^{mp} are observable technology factors (technology shifters). In other words, $T_m(Z_{it}^{mp}) = \ln(\sum_{p=1}^{p_m} \gamma^{mp} Z_{it}^{mp})$; $\sum_{p=1}^{p_m} \gamma^{mp} = 1 \; \forall \, m$ (Heshmati and Kumbhakar, 2013). Inputs, time trend and indices are squared and interacted with each other. Here technology is specified by using a time trend to capture its unspecified long term and by using specific observable factors. Moreover, democracy dummy variables are interacted with technological indices to find a medium between economic growth and democracy. As in the general index Model M3, technology shifters Model M4 also has non-linearity in terms of coefficients. This is because M4 is a system of equations. Because of its non-linear relationship we have to apply the non-linear estimation method.

Technology shifters are not just highly related to the level of technology but are also deeply related to democracy. For example, in a developmental state, credit guarantee is mainly determined by government officers or politicians. Naturally, artificial adjustments in credit guarantee provoke inefficiencies in the economy. Improper and less productive funding cannot maximize its effect, and the total amount of credit guarantee in the economy is affected. On the other hand, democratization entails transparency in credit guarantee decisions both in the private and public sectors. Transparent decisions regarding credit guarantee result in capital being allocated to the best places to maximize its effects. This transparent and efficient cycle reproduces new capital and therefore the total amount of credit guarantee consistently increases if the other conditions are constant.

Many studies give positive relationships between democracy and trade or between democracy and foreign direct investment inflows. It has been empirically proven that there are some causal effects of openness on democratization.[6] Further, it is also widely known that there is a positive relationship between globalization and democracy in both directions.[7] Yu (2010) suggests that democracy fosters trade and Busse (2003) discusses how multinational firms invest more in

[6] For additional reading, see López-Córdova and Meissner (2005).

[7] See also Eichengreen and Leblang (2006).

democratic countries.

By concentrating on the interacted term, we can determine which technology shifters form significant possible channels between democracy and economic growth. If θ_{tm} and γ^{mp} are both significant, that technology shifter is acting as a link between democracy and economic growth.

Multiple time trends and the general index models can also be applied to a technology shifters model:

Model 5 (M5): Technology shifters combined with a multiple time trends model:

(9)

$$
\begin{aligned}
GDP_{it} = {} & \beta_0 + \sum_j \beta_j x_{jit} + \beta_d D_{it} + \sum_s \beta_s t_s + \sum_m \sum_p \delta_m T_m(Z_{it}^{mp}) \\
& + \left(\frac{1}{2}\right)\left\{\sum_j \sum_k \beta_{jk} x_{jit} x_{kit} + \sum_s \beta_{ss} {t_s}^2 + \sum_m \sum_p \delta_{mm} (T_m(Z_{it}^{mp}))^2\right\} \\
& + \sum_s \sum_j \beta_{jt} x_{jit} t_s + \sum_s \sum_m \sum_p \delta_{mt} T_m(Z_{it}^{mp}) t_s \\
& + \sum_j \sum_m \sum_p \gamma_{jm} x_{jit} T_m(Z_{it}^{mp}) + \sum_m \sum_p \theta_{tm} D_{it} T_m(Z_{it}^{mp}) + C_i + \varepsilon_{it}
\end{aligned}
$$

Model 6 (M6): Technology shifters combined with a general index model:

(10)

$$
\begin{aligned}
GDP_{it} = {} & \beta_0 + \sum_j \beta_j x_{jit} + \beta_d D_{it} + \mathrm{A(t)} + \sum_m \sum_p \delta_m T_m(Z_{it}^{mp}) \\
& + \left(\frac{1}{2}\right)\left\{\sum_j \sum_k \beta_{jk} x_{jit} x_{kit} + \sum_m \sum_p \delta_{mm} (T_m(Z_{it}^{mp}))^2\right\} \\
& + \sum_j \beta_{jt} x_{jit} \mathrm{A(t)} + \sum_m \sum_p \delta_{mt} T_m(Z_{it}^{mp}) \mathrm{A(t)} \\
& + \sum_j \sum_m \sum_p \gamma_{jm} x_{jit} T_m(Z_{it}^{mp}) + \sum_m \sum_p \theta_{tm} D_{it} T_m(Z_{it}^{mp}) + C_i + \varepsilon_{it}
\end{aligned}
$$

Elasticities, returns to scale, rate of technical change and total factor productivity and its decomposition can be derived through a simple use of *E1*, *E2*, *E3*, *E4* and *E5*.

2.3. Data

This study used panel data. To estimate a production function using panel data through pooling each nation's time series, we need access to output, inputs and other country characteristics and control variables. The data needs to include real GDP as a dependent variable (GDP_{it}), the number of employees and capital stock for inputs (x_{jit}), the democracy dummy variable for the key control variable (D_{it}) and technology shifters (Z_{it}^{mp}) for analyzing the effects of possible channels between economic growth and democracy. These shifters are used to represent technology or the sources of a shift in the production function over time. The vector of inputs includes the labor force variable as L_{it} and the capital stock variable as K_{it}. The coverage period for all the variables is from 1980 to 2014.

2.3.1. Variables' definitions

Real GDP is more appropriate than nominal GDP for our analysis because of differences in inflation rates across countries. If inputs and output are measured in terms of quantity, a transformation to fixed values is not required. Monetary values of output and inputs allow us to account for quality differences, which are reflected in prices, revenues and costs. Thus, nominal GDP as a monetary aggregate value includes information not only about output variations by inputs but also about output variations by economic cycles. Therefore, using nominal GDP is not consistent with our goal of concentrating on inputs and output by analyzing the production function. Data about population is widely used for the labor force variable. However, to be more precise in an analysis of the production function, we inserted data on the number of employees that was adjusted for the unemployment rate. For the capital variable, we used capital stock data accounting for new investments and depreciation of capital.

Data for these variables was obtained from the Penn World Table 9.0 (PWT).[8] Although PWT is a very long and wide panel data, it still has many missing unit observations, mainly in the beginning years for developing countries. Therefore, replacing missing observations with observations from other datasets is required to obtain a larger sample and a more robust estimation. Missing observations of real GDP and labor force in PWT were replaced by data from the World Bank's World Development Indicators (WDI).[9] The base year of real GDP in WDI and units of labor force in WDI were adjusted to be consistent with PWT. GDP_{it}, L_{it} and K_{it} are a log of real GDP, labor force and capital stock respectively. A logarithmic transformation of the variables in the simple Cobb Douglas production function allows for a direct interpretation of the relationship as a percentage of elasticities of output with respect to the percentage of changes in inputs.

The democracy dummy variable D_{it} is the key control variable in this production function estimation. We utilized the democracy dummy variable constructed in Acemoglu et al. (2014). The variable represents changes in democracy in each nation over time. The constructed democracy dummy variable had a value of 1 if the nation was democratic in a specific year or a value of 0 if the nation was not democratic in that specific year. This variable captures and clarifies the relationship between democracy and economic growth. A positive relationship is expected. In our study whether each observation has a value of 1 or 0 depends on the following criteria:

The first criterion is based on the Freedom House and Polity IV datasets. If a nation in a specific year has a 'free' or 'partially free' rating in the Freedom House dataset and has a positive Polity IV score, then the nation is regarded as democratic in that specific year and therefore has a value of 1. If a nation does not satisfy these requirements, then it is regarded as non-democratic and therefore has a value of 0.

Following this criterion, we can identify missing observations of the democracy dummy variable that are caused by the fact that the Freedom House dataset or the Polity IV dataset have missing observations for a specific year for that nation. In this case, we can replace that missing observation by using Cheibub et al. (2010) and Boix et al. (2012) datasets. The missing observation has a value of 1 if the nation in that specific year turned out to be democratic in

[8] Real GDP is indicated in PWT as 'Real GDP at constant 2011 national prices (in million US$).' Number of employees is indicated in PWT as 'Number of persons engaged (in millions).' Finally, capital stock is given in PWT as 'Capital stock at constant 2011 national prices (in million US$).'

[9] Real GDP is indicated in WDI as 'GDP (constant 2010 US$),' and labor force as 'Labor force, total.'

more than one dataset among these two datasets made by Cheibub et al. (2010) and Boix et al. (2012). If the observation turned out to be non-democratic in both Cheibub et al. (2010) and Boix et al. (2012) datasets, then the democracy dummy variable had a value of 0 in our dataset.

It is true that some shortcomings can result from the fact that the democracy dummy variable ignores the intensity of democracy by including only a value of 0 or 1. However, using a dummy variable also has many advantages. To be specific, by expressing the democratic situation using only 0 and 1, we can minimize the damage from measurement errors. Many people prefer expressing each nation's degree of democracy in several categories. However, we can find disadvantages in using categorical indices of democracy. Let us consider an index of democracy represented by 10 integers from 1 to 10. The differential between 2 and 3 and 7 and 8 is equal to 1. However, the differential between 2 and 3 and the differential between 7 and 8 cannot be equally interpreted in terms of effect even though their magnitudes are both 1. In other words, a categorical expression of democracy is not appropriate for a regression analysis due to an ambiguity in its quantitative interpretation. Moreover, coefficients derived from this categorical index of democracy are not convincing, yet they provide evidence of heterogeneity in effects. Even though a categorical index of democracy can be constructed by a scientific measure and objective criteria, we have to avoid its shortcomings because the meaning of differentials between categories is not globally consistent over all the categories. These shortcomings and trade-offs between the measurement effect and the homogeneity in effect can be more easily overcome using a dichotomous democracy dummy variable. The appendix gives two tables describing this dichotomous democracy dummy variable. Table A1 shows all cases of democracy transitions within a nation. The transitions occurred 128 times in 66 nations. Table A2 gives a list of countries with no transitions in democracy; 49 nations are always democratic in this dataset while 29 nations are always non-democratic in the dataset.

2.3.2. Observable technology shifters

The first thing to mention about data on technology shifters Z_{it}^{mp} are the variables chosen for the technology shifters. Briefly, technology shifters are variables that construct an index of the level of technology in the production function. This technology index is indicated as $T_m(Z_{it}^{mp})$ in our regression analysis. Technology is usually assumed to be exogenous and, in the absence of past information, is represented by a time trend representing the unknown state of technology that is progressing at the same speed and with the same effects across countries and over time. Unlike time dummies or time trends, technology shifters are observable and allow for heterogeneity in effects across countries and over time. Therefore, technology shifters should be deeply related to the level of technology in a nation.

In our study, each index of the level of technology contains three technology shifters. In addition, technology shifters can also have a potential relationship with democracy. In other words, technology shifters in our model not only capture the direct level effects of technology in each nation but they also act as an efficient indirect medium between economic growth and democracy. As our study deals with various countries, including developing ones, there are many missing observations in technology shifters. Consequently, constructing three indices was almost impossible because many technology shifters were required for the three indices and that generated a lot of missing unit observations. Hence, this model contains two indices of the level of technology in each nation. All the datasets for technology shifters were obtained from the World Bank WDI database.

The first index deals with the openness of each nation and its financial fundamentals.

Technology shifters in this index are credit guarantee, trade and FDI inflows. For credit guarantee, we used WDI's data on 'domestic credit to private sector by banks (defined as per cent of GDP).' WDI's 'trade openness (defined as import and export share of GDP)' data was used for our trade variable. WDI's 'foreign direct investment, net inflows (per cent of GDP)' was used for our FDI inflows variable. FDI is a source of transfer of finance, technology, management and skills.

The second index implies a nation's infrastructure and the magnitude of its domestic market. The technology shifters in this index are electricity consumption, governmental consumption expenditure and the number of firms. WDI's data on 'electric power consumption (KWh per capita)' was used for the electricity consumption variable. For governmental consumption expenditure, we used WDI's 'general government final consumption expenditure (defined as per cent of GDP).' Data on 'listed domestic companies, total' from WDI was used for the number of firms. Listed companies in general were large and were involved in innovation activities.

In our regression model, credit guarantee, trade and FDI inflows are indicated as Z_{it}^{11}, Z_{it}^{12} and Z_{it}^{13} respectively. Likewise, electricity consumption, the number of firms and governmental consumption expenditure are indicated as Z_{it}^{21}, Z_{it}^{22} and Z_{it}^{23} respectively.[10]

2.3.3. Managing the missing units' data

Applying proper methods for handling missing observations are important mainly because of the many missing observations in technology shifter Z_{it}^{mp}. First, if an observation had a missing value at GDP_{it} or D_{it}, that observation was deleted from our dataset because GDP_{it} is our dependent variable and D_{it} is our key control variable and as such no imputation should be applied. Even after inserting missing observations about the labor force using WDI, there were still some missing observations at L_{it}. In this case, the remaining missing observations were covered by each nation's sample mean by decade. There could still be some remaining missing observations because an entire decade may have no observations. In this case, the observations were dropped from the dataset. The variable capital stock K_{it} followed the same procedure for handling missing observations as L_{it}. This procedure helped us avoid dropping entire observations because of missing unit observations.

In the case of technology shifter Z_{it}^{mp}, we inserted each nation's sample mean by decade for the missing observations. The next step for handling missing observations varied according to each technology shifter. First, the remaining missing observations of credit guarantee Z_{it}^{11} were deleted (203 observations from 4,825 observations). In case of FDI inflows Z_{it}^{13}, the remaining missing observations were replaced by their minimum values of 0 (93 observations). This method can be used as a reasonable and rational remedy for missing observations in Z_{it}^{13}. Most of the missing observations in Z_{it}^{13} came from developing countries' datasets. Therefore, these missing observations will have significantly lower values than the sample mean. Inserting 0 does not mean an extreme case of a closed economy because Z_{it}^{13} was originally defined as a share of GDP.

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[10] Z_{it}^{11}, Z_{it}^{12}, and Z_{it}^{13} are expressed as CG_{it}, TO_{it} and FDI_{it} in the dynamic model. Z_{it}^{21}, Z_{it}^{22} and Z_{it}^{23} are expressed as EC_{it}, NL_{it} and GC_{it} in the dynamic model. In this static model we use Z_{it}^{mp} because this shortens the expression of our translog regression model.

The remaining missing observations of trade Z_{it}^{12} were replaced by a total sample mean of 79.9 (104 observations). Governmental consumption expenditure Z_{it}^{23} followed the same procedure as trade. A total sample mean of 15.8 was inserted for missing observations (159 observations).

Relative to these missing observations, electricity consumption Z_{it}^{21} and the number of firms, Z_{it}^{22} had many more missing observations even after inserting each nation's sample mean by decade. For two technology shifters we inserted their minimum values at those missing observations (Z_{it}^{21} – 884 observations and Z_{it}^{22} – 1,964 observations). This procedure was the same as that employed in the case of FDI inflows Z_{it}^{13}. Table 1 provides summary statistics of the data variables. It indicates the values of the variables before taking a logarithmic form. After handling missing observations, we had 4,622 observations for 144 nations observed unbalanced for the period 1980-2014.

Insert Table 1 about here

2.4. Estimation method

Before estimating the production model, we looked at the correlation between the variables. The correlation matrix (Table 2) provides correlation coefficients between different pairs of variables. With the exception of trade and FDI, the remaining variables were positively correlated with GDP suggesting explanatory variations in GDP. The capital and labor correlation was 0.57, suggesting no serious multi-collinearity and confounded effects. Democracy was positively correlated with GDP and capital but negatively with labor. Technology shifters, except for two cases, were positively correlated with each other.

Insert Table 2 about here

The 144 nations that constituted the data used in this study were not chosen randomly because the WDI dataset has many missing unit observations, especially in technology shifter variables in developing countries. Therefore, the 144 selected countries tended to be more developed than those countries which were omitted. As the results from the Hausman test indicate, the fixed effects model is preferred to the random effects model.

In M1 and M2, although the independent variables were interacted or squared, their coefficients remained linear. Consequently, M1 and M2 required the linear regression method. On the other hand, M3, M4, M5 and M6 were all regarded as systems of equations. The coefficients' interactions resulted in non-linearity, which we had to overcome. A full information maximum likelihood estimation enabled us to estimate non-linear systems of equations. In the SAS program, the 'proc model FIML' can be implemented with a little arrangement of parameters and variables.

2.5. Estimation Results

2.5.1. An analysis of coefficients

Results of the estimates for M1 to M6 are aggregated in Table 3. Table 4 gives the elasticities derived from M1, M2 and M3 while Table 5 gives the elasticities from M4, M5 and M6.[11] In

[11] The label N_America means North America and S_America means South America. The labels Income_L, Income_M, and Income_H mean the low income country group, middle income group and high income group.

Table 4 and Table 5, we can see that the elasticities of capital stock and labor force ($E_{K_{it}}$ and $E_{L_{it}}$) are always positive. Moreover, the share of capital and the share of labor are similar to the well-known share of inputs. This means this econometric specification of the translog production function is consistent with our intuition in terms of inputs.[12] Moreover, we can check that inserting technology indices $T_m(Z_{it}^{mp})$ successfully captured the level of technology because the elasticities of $T_m(Z_{it}^{mp})$ always had positive mean values (e_T_1 and e_T_2). In Table 3, the coefficients of the first time trend and the second time trend in Model 2 and Model 5 are all significant. Based on the fact that even squared terms of multiple time trends have significant coefficients, we can see that the specification of multiple time trends by choosing 2008 as the threshold was efficient.

Insert Table 3, 4 and 5 about here

The first order coefficient β_d was positive and significant in all the six models. Just based on Model 1, Model 2 and Model 3, we can say that democracy: has positive impacts on economic growth independent of the methods used to capture time effects. In Model 4, Model 5 and Model 6, as the sum of β_d and θ_{tm} is always positive and significant, we can say that democracy has positive impacts on economic growth. However, the existence and direction of institutional elements is not sufficient for us to evaluate democracy's contribution to economic growth in detail. Concentrating on the interacted term $\sum_m \sum_p \theta_{tm} D_{it} T_m(Z_{it}^{mp})$ is required in the technology shifters model to satisfy these goals.

In Model 4, Model 5 and Model 6, we can consider the elasticity of democracy (D_{it}), e_D_{it} as:

E6: Elasticity of D_{it} in the technology shifters model:

(11) e_D_{it} $=\beta_d + \sum_m \sum_p \theta_{tm} T_m(Z_{it}^{mp})$

As we divided technical change into a neutral part and a non-neutral part, we can also divide e_D_{it} into a neutral part (β_d) and a non-neutral part ($\sum_m \sum_p \theta_{tm} T_m(Z_{it}^{mp})$. There are two ways to interpret the coefficient θ_{tm} of the interaction term $\sum_m \sum_p \theta_{tm} D_{it} T_m(Z_{it}^{mp})$. First, θ_{tm} determines the direction and magnitude of the non-neutral part. That is, when democracy is interacted with technology shifters, it will impact GDP with an amount of θ_{tm}. In this interpretation, technology shifter Z_{it}^{mp} acts as a possible channel between democracy and economic growth. Second, note that θ_{tm} can be observed in the regression equations only when D_{it} has a value of 1. Therefore, we can interpret θ_{tm} as the differences in the effect of each technology shifter between democratic and non-democratic countries.

Let us concentrate on the first way to interpret θ_{tm}. The interacted terms $\sum_m \sum_p \theta_{tm} D_{it} T_m(Z_{it}^{mp})$always have significant coefficients. However, the direction of these coefficients varies depending on $T_m(Z_{it}^{mp})$. When $T_1(Z_{it}^{1p})$is interacted, the coefficients are positive. When $T_2(Z_{it}^{2p})$ is interacted, the coefficients are negative. Let us check each technology shifter to interpret specific implications. Note that the coefficients of the third technology shifter Z_{it}^{13} and Z_{it}^{23}, can be derived by subtracting the sum of another two shifters'

Income is defined as GDP divided by the labor force (GDP_{it}/L_{it}). Demo means democratic country groups and Non-demo means non-democratic country groups.

[12] Note that β_j is just one part of the impacts of inputs on GDP_{it}. Whole impacts which capital and labor have are made up of β_{jk}, β_{jt}, and γ_{jm}.

coefficients from 1. This is due to the constraints we have imposed $\sum_{p=1}^{p_m} \gamma^{mp} = 1 \; \forall \; m$.

Z_{it}^{11} stands for credit guarantee. Z_{it}^{11}'s coefficients are always positive and significant. As $D_{it}T_1(Z_{it}^{1p})$'s coefficients were also positive, we can suggest that credit guarantee acts as a positive linkage between democracy and economic growth. As Z_{it}^{12}'s coefficients were not significant in M6, we cannot determine the role of Z_{it}^{12} and Z_{it}^{13} in M6. However, when we look at M4 and M5, the technology shifters single time trend model and the technology shifters multiple time trends model, we can also clarify the roles of Z_{it}^{12} and Z_{it}^{13}. According to M4 and M5, trade openness can be interpreted as a negative medium between democracy and economic growth. On the other hand, FDI inflows turn out to be a positive medium between democracy and economic growth.

Because the coefficients of $D_{it}T_2(Z_{it}^{2p})$ are all significantly negative and because the coefficients of Z_{it}^{21} and Z_{it}^{22} are all significantly positive, we can draw some inferences from all technology shifters in $T_2(Z_{it}^{2p})$. When electricity consumption per capita and the number of listed firms are interacted with the democracy dummy variable, they have negative effects on production output. This means that these two variables can have negative linkages between democracy and economic growth. Moreover, as the sum of coefficients of Z_{it}^{21} and Z_{it}^{22} does not exceed 1 in all three models, governmental consumption can also be interpreted as a negative link between democracy and economic growth.

The roles of credit guarantee, FDI inflows and government consumption between democracy and economic growth are consistent with our expectation. More democratic countries guarantee transparency in credit guarantee decisions both in the private and public sectors. This transparency leads capital to be allocated to productive candidates. Therefore, the allocative efficiency of capital improves.[13] Transparency derived from democratization plays a key role in reducing capital distortions which exist in industry level and firm level allocations. In addition, as it is known that multinational firms invest more in democratic countries,[14] democratization attracts more FDI inflows. As productive foreign firms begin to compete with domestic firms, innovation activities of firms and spillover effects from already productive firms become more vibrant.[15]

Technological changes were the fundamental reason for economic growth in the 19th and 20th centuries. Because the contributions of both credit guarantee and FDI inflows to technological changes increase as the quality of democracy improves, it is natural for us to interpret them as positive linkages between economic growth and democracy.

We can also give reasons why trade openness and government consumption turned out to be negative linkages between economic growth and democracy by considering technological changes. As the quality of democracy improves, the government's consumption share of GDP can increase or decrease. However, it is relatively certain that the structure of government consumption will change as the quality of democracy improves. Tabellini and Alesina (1990) showed that most of the voters prefer a budget deficit; they also suggest that a balanced budget

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[13] The importance of allocative efficiency is presented in many studies including some seminal papers such as Olley and Pakes (1996) and Foster et al. (2001).

[14] For additional reading, see Busse (2003).

[15] Borensztein et al. (1998) and Alfaro et al.'s (2004) studies clarify the positive impacts of FDI on economic growth.

amendment is not durable under majority voting rule. Plumper and Martin (2003) added that in semi-democratic countries, as political participation increases, governments are inclined to over-invest in the provision of public goods. We have also seen many populist regimes and their governments' spending. When democratization takes place, elected governments provide policies or public goods in order to react to median voters' requests. It is natural for us to expect an increase in welfare policies and this will make the relative size of technological investments of governments, which lead to technological changes, to become smaller because the magnitude of the government's budget is limited. Based on the fact that technological changes are the main factor causing economic growth in a production function analysis, this changes in the structure of government consumption resulted from democratization will negatively affect economic growth. Alesina and Rodrik (1994) suggested that policies which maximize economic growth are optimal for a government that only cares about capitalists. It is evident that it is difficult for median voters to prefer such political parties.

As Yu's (2010) findings support, democracy fosters trade openness. In contrast to FDI inflows, however, this static model suggests that trade openness is a negative medium between economic growth and democracy. It is well known that trade's impact on economic growth has been significantly positive. Recent studies suggest that trade causes more innovation activities in domestic firms.[16] Therefore, it is difficult for us to describe trade openness' role as a negative linkage between economic growth and democracy based on existing literature. Yanikkaya (2003) provides one possible way to interpret the results of this static model by suggesting unconventional implications. Yanikkaya's study suggests that in developing countries, trade restrictions had strong positive impacts on economic growth under certain conditions. If this fact is generalized, we can imagine that a mechanism which lowered trade restrictions caused by democratization can lower economic growth.

The results of electricity consumption and number of listed firms are not identical to our general intuition. Why do electricity consumption and the number of firms act as negative linkages between democracy and economic growth? First, electricity consumption consists of household usage, public usage and industrial usage. GDP growth will be highly correlated to industrial usage. As our data about electricity consumption per capita includes information about household usage, the linkage's direction can be negative. It can be accepted that waste and inefficiencies in household consumption can be fostered in a free atmosphere. Therefore, when interacted with democracy, electricity consumption can be a negative link between economic growth and democracy. Second, for a number of listed firms global outsourcing can be the reason for this negative link. As an economy grows, the number of firms increases. However, as globalization is deepening, global outsourcing is also increasing as an economy grows. The firms whose production procedures are mainly centered in foreign countries will contribute less to GDP than those firms whose production procedures are mainly rooted in home countries. These effects of global outsourcing could change the direction of Z_{it}^{22}'s (number of listed firms) role in being a link between economic growth and democracy.

Let us now consider a second way of interpreting the meaning of θ_{tm}. Table 6 gives a list of technology shifters which have significant coefficients at the interacted term $\sum_m \sum_p \theta_{tm} D_{it} T_m(Z_{it}^{mp})$.

[16] Bloom et al. (2016) showed that imports from China increased European firms' innovation activities and productivity. Acharya and Keller (2009) suggested that goods trade is one of the main channels of technology transfer.

Insert Table 6 about here

Technology shifters that are underlined in Table 6 are significant in all the three models and their directions are consistent through the three models. Technology shifters with a (+) sign are positive links between democracy and economic growth as dealt with earlier. Likewise, technology shifters with a (-) sign are negative links between democracy and economic growth.

As θ_{tm} appears in the regression equations only when $D_{it} = 1$, technology shifters with a (+) sign have more marginal effects in democratic countries. On the other hand, technology shifters with a (-) sign have smaller marginal effects in democratic countries. This means that technology shifters with a (-) sign have bigger marginal effects in non-democratic countries. In other words, credit guarantee and FDI inflows have more marginal effects in democratic countries. Trade openness, electricity consumption, number of listed firms and government consumption have much higher marginal effects in the case of non-democratic countries.

2.5.2. An analysis of elasticities

In Table 4 and Table 5, elasticities derived from the six models are arranged according to criteria: continent, income level and the democracy dummy variable D_{it}. Income means GDP divided by the labor force. There are some tendencies in these tables. First, as income increases $E_{K_{it}}$ and RTS decrease. Second, democratic countries have lower $E_{K_{it}}$ as compared to non-democratic countries. Third, most of negative parts of the technical changes are derived from the non-neutral part whereas most of the positive parts of the technical change are derived from the neutral part. Finally, elasticities of democracy are sometimes negative in high income countries and high income continents. We can also find several other tendencies in these tables. But these four tendencies are the most remarkable ones that we could catch.[17]

3. A Dynamic Model

3.1. Motivation

The empirical production models are discussed in the previous section of this study with different generalizations related to representations of technology. Models M1-M6 are static models. Through these six models, we explain GDP output levels using the production function. To be specific, the GDP output level is explained by inputs (capital stock and labor force), technology indices constructed by technology shifters (six technology shifters) and a dichotomous democracy dummy variable. The functional forms of the production function are translog production function forms. This econometric specification turned out to be appropriate for our analysis. According to the estimation results of these static models, the role of inputs was consistent with the theoretical prediction. Moreover, the technology indices represented the level of technology successfully. The existence and direction of institutional elements in the production function were robustly consistent through all the six models. The implications derived by technology shifters were also consistent for three technology shifters (credit

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[17] The separate estimation of this static model is also implemented according to each income group (low, middle and high as in Table 4 and Table 5.). The direction and magnitude of coefficients for the democracy dummy variable vary according to income groups and models. As this study concentrates on the global impacts of democracy on economic growth, those results for each income group are excluded even though they require intense analysis. It is natural for us to make a detail analysis about democracy’s impacts in high income countries, middle income countries and low income countries.

guarantee, electricity consumption and number of listed firms) through all the technology shifters models.

In spite of these advantages of the static models' specifications, we have to consider alternative generalized empirical models for two main reasons. First, the GDP level cannot be explained enough by the production side of a nation's economy as a considerable part of the observed GDP output is explained by the demand side of a country's economy. Therefore, an omitted variable bias can be troublesome when we try to explain the GDP output level using production side variables only. Second, the static models assume that all changes and effects take place immediately. However, in practice changes take place gradually and are a part of a process which requires a dynamic adjustment process towards a target level of GDP.

By using a dynamic model, we can solve these two problems. Inserting a lagged GDP variable as an independent variable can help avoid the first problem caused by the fact that GDP also includes information about the demand side of an economy. Acemoglu et al. (2014) used a lagged GDP variable and the dichotomous democracy dummy variable as explanatory variables. The results of their analysis are similar to the results of this study's static model because both studies provide evidence that democracy has a significant and robust positive effect on GDP. In addition, a dynamic model's specifications provide information about the path of adjustment towards the target level of GDP and the speed of the adjustment process.

There are many ways to construct a dynamic model using lagged GDP as an independent variable. In choosing a specific form of a dynamic model, we have to consider the fact that we are concentrating on the role of institutions. Devising a dynamic model which reflects the institutional element successfully will be a key criterion when we evaluate whether this dynamic model is appropriate for our research question. By using the concept of the target GDP level and the concept of adjustment speed, we can make a dynamic model for exploring the relationship between democracy and GDP growth.

3.1.1. Target level of GDP and adjustment speed

Target level of GDP in a specific country in a specific year GDP_{it}^*, can also be interpreted as a predicted or an expected optimal level of GDP for each country and year. The public sector, the private sector or producers including government officers, politicians, researchers, reporters and businessmen have their expectations. The information set used for the prediction may not only contain all observable macroeconomic indices but also unobserved country specific characteristics or time specific characteristics as well as exogenous shocks. This target level of GDP is widely used when government officers or politicians make economic policies such as investments in infrastructure, education and developing technology. In addition, GDP_{it}^* can also act as criterion when we evaluate the results of an economic policy or when we analyze economic cycles. Accordingly, the target level of GDP, GDP_{it}^*, can also be considered as the GDP level in a steady state.

Adjustment parameter δ_{it} explains the differences between GDP_{it}^* and the realized GDP level GDP_{it}. The word 'adjustment' means the actual or observed GDP_{it}'s adjustment towards GDP_{it}^*. In other words, δ_{it} represents the magnitude of the expected proper adjustment between two subsequent years or the rate of convergence of GDP_{it} to GDP_{it}^*. Economic policies usually encounter unexpected impacts. Moreover, proper policies for attaining GDP_{it}^* may not be executed because there are many obstacles in the implementation of certain policies. Therefore, even though government officers do their best to attain the target level GDP_{it}^* every year, we observe that the realized GDP_{it} tends to be different from GDP_{it}^*. Some variables which form the differences between GDP_{it} and GDP_{it}^* construct the adjustment parameter δ_{it}. The parameter differs from 1 because it is costly and also because of limited resources. In other words, it is not feasible to adjust to the target level in one single period. Thus, the speed of adjustment which is constructed by the functions of some variables differs among countries and over time because every country has different levels of costs and resources which may change over time. For example, the economic situation of a small open economy is highly dependent on global economic trends. Therefore, the government's policy to attain GDP_{it}^* can be easily interfered with. When we embrace GDP_{it}^* and δ_{it}, we can consider a system of equations for a dynamic GDP model.

3.2. Econometric Specifications

3.2.1. Model

The main idea for this dynamic model is that the realized GDP level always tends to be different from the GDP target level. The difference between realized GDP and target GDP levels is explained by adjustment speed. Based on these facts, we can consider the equation: *E7:*

(12) $$GDP_{it} - GDP_{i\,t-1} = \delta_{it}(GDP_{it}^* - GDP_{i\,t-1})$$

As indicated in Eq. *AEI*, δ_{it} quantifies the difference between $GDP_{it} - GDP_{i\,t-1}$ and $GDP_{it}^* - GDP_{i\,t-1}$. If $\delta_{it} = 1$, it takes just one period for the entire adjustment to be completed. This means that the country in time t is at the nation's target level of GDP. $\delta_{it} < 1$ implies that the adjustment that occurred from year $t-1$ to t was smaller than the required magnitude of adjustment for GDP_{it}^*. We can check that $GDP_{it} \rightarrow GDP_{it}^*$ as $t \rightarrow \infty$ when $|\delta_{it}| < 1$. If $\delta_{it} > 1$, the nation's GDP is adjusted more than the required magnitude.

GDP_{it}^* is affected by some variables and we can consider a function $F(\cdot)$ which represents a detailed relationship between key variables differing in countries and time dimensions: *E8:*

(13) $$GDP_{it}^* = F(X_{it}, X_i, X_t)$$

X_{it} is a vector of variables affecting the target GDP level, GDP_{it}^*. (We discuss the variables included in X_{it} in the next section). X_i are country-specific variables but can also be represented by country dummy variables. X_t are a set of time-specific variables but can also be represented by time dummy variables or a time trend. As X_{it} can vary across countries and over time, it is also possible that GDP_{it}^* varies across countries and over time. This means a country's target level of GDP may change over time. Therefore, GDP's dynamic nature can be captured through these settings. The ratio between GDP's target level and realized GDP (GDP_{it}^* /GDP_{it}) can measure the degree of optimality of a specific nation's GDP in a specific year.

Likewise, δ_{it} is affected by several variables and we can express δ_{it} by a function $G(\cdot)$: *E9:*

(14) $$\delta_{it} = G(Z_{it}, Z_i, Z_t)$$

where Z_{it} is a vector of variables determining the adjustment speed δ_{it}. (Detailed information about the variables included in Z_{it} is given in the next section). Z_i and Z_t are country-specific and time-specific effects represented by country or time dummy variables (or time trend). By construction, we can also consider the dynamic nature of the adjustment speed, δ_{it}. This is attributed to the fact that countries' adjustment speeds may differ from each other and change over time.

One of the powerful advantages of this model is that although we acknowledge that countries may not have optimal target levels of GDP at any point in time, this model can show the optimal behavior of a country. This is possible because adjustment speed δ_{it} includes information about the adjustment costs that governments are required to pay to attain GDP^{*}_{it}. Realized GDP, GDP_{it} can be interpreted as a result of a government's decision that is always vulnerable to adjustment costs. If realized GDP is simply regressed on X_{it} or Z_{it} alone, then the inferred relationship suffers from specification errors. The aggregation of effects can be the reason for these specification errors. In addition, the absence of adjustment costs and the employment of non-dynamic adjustments can also contribute to these specification errors. Eq. *AE1* can be arranged again as *AE4* in order to avoid mis-specification errors:

Model 7 (M7): Dynamic model with adjustment speed and target level of GDP:

(15) $$GDP_{it} = (1-\delta_{it})GDP_{i\,t-1} + \delta_{it}GDP^{*}_{it} + \beta_d D_{it} + e_{it}$$

e_{it} is the statistical error term. This study assumes that e_{it} has mean 0 and constant variance. The exact form of functions $F(\cdot)$ and $G(\cdot)$ will be decided based on the results of the likelihood ratio functional form test. D_{it} is a dichotomous democracy dummy variable. D_{it} is also used in the static model in this study. By implementing this democracy dummy variable D_{it}, we can extract the impact of democracy on economic growth from the error term. The main focus of this dynamic model is checking the existence of democracy's positive impacts on economic growth which has already been proven by the static model. It should be noted that this functional form is non-linear for both parameters and explanatory variables.

3.2.2. Variables and Functional Forms for GDP^{*}_{it} and δ_{it}

As shown in the analysis of static models, the GDP output level is highly related to production inputs like capital stock and labor force. Economists have been trying to explain the production output of economic agents such as firms and nations using capital stock and labor force for a long time. Therefore, considering capital stock and labor force in expecting or estimating target GDP^{*}_{it} are essential. Although population is also a useful criterion for the size of the domestic market, we exclude the population variable because of a potential multi-collinearity problem with the labor force variable. In sum, for X_{it}, let us use capital stock (K_{it}), and labor force (L_{it}). Considering K_{it} and L_{it} for X_{it} is also consistent with the static model because those two variables are considered as inputs in the translog production function of the static models.

For Z_{it}, we consider six variables. First, if a nation's economy is largely dependent on global trends, adjustments to target level GDP will encounter many obstacles. To be specific, as the trade's share of GDP or foreign FDI inflows' share of GDP increases, the adjustment speed becomes more vulnerable to trade openness and FDI inflows. This is mainly due to the fact that the effect of the government's policies for attaining GDP^{*}_{it} will not have a significant impact on the realized GDP level without proper changes in trade or FDI inflows. Therefore, we have to include trade's share of GDP and FDI's share of GDP in Z_{it}. In addition, most of the government's policies for achieving GDP^{*}_{it} contain fiscal policy measures such as changes in government consumption. A larger share of the government's consumption as a part of GDP means that the impact of the policies made by government consumption becomes stronger. Consequently, the government consumption's share of GDP should be considered in order to capture adjustment speed effectively.

Another fact that we have to consider is that the impact of external shocks including the government's policies will vary according to private economic agents' abilities to actively react to the shocks. For example, economic agents' ability to react to government policies is determined mainly by their budget constraints. Large-scale domestic credit to the private sector by banks can guarantee flexible budget constraints for economic agents. This is attributed to the fact that most of the economic agents including households and firms supply their required capital by taking loans from banks when they have to execute important consumption or investment decisions such as buying a house or building a factory. Therefore, in Z_{it}, banks' domestic credit to the private sector (defined as per cent of GDP) is included in this study.

Another way in which firms finance their budgets is through financial markets. An active financial market guarantees firms more chances of getting funding for their costs. Therefore, the number of listed firms should be used for explaining adjustment speed by considering firms' financing processes. The quality of infrastructure of each nation should also be considered when we construct adjustment speed. Countries with poor infrastructure usually have a hard time maximizing the positive impacts of economic shocks. Electricity consumption per capita can effectively represent the level of infrastructure because electricity is a key input for industrial production. In sum, there are six variables: trade openness (TO_{it}), FDI inflows (FDI_{it}), government consumption (GC_{it}), credit guarantee (CG_{it}), number of listed firms (NL_{it}) and electricity consumption (EC_{it}) in Z_{it}.[18] All these six variables are in logarithmic form here.

Functions F and G that explain GDP^*_{it} and δ_{it} have country specific and time specific variables. First, for Z_i, which indicates country specific variables for δ_{it}, this study uses individual country dummy variables. Also, as time specific variables Z_t for δ_{it}, we use year dummy variables. Therefore, the heterogeneity in δ_{it} is controlled by two-way fixed effects. It is difficult for us to assume the existence of group characteristics or the existence of global time trends in adjustment speed δ_{it}. Consequently, controlling all individual effects can make better estimators.

For GDP^*_{it}, this study uses income level group fixed effects as country specific variables X_i. Income level means GDP_{it}/L_{it} which has already been used in the analysis of elasticities in the static model. We can also interpret it as the GDP level per labor force. All nations can be divided by five income level groups or ten income level groups. We tested this model by implementing both ten income level groups and five income level groups. We can also divide all countries just by the GDP level. However, dividing nations by income level groups is better than dividing them just by the GDP level because the heterogeneity between developed and developing countries cannot be properly considered when we divide countries just by the GDP level. The single time trend was implemented for X_t, time specific variables explaining GDP^*_{it}. As GDP^*_{it} is the target level of GDP explained by capital stock and labor force, using a single time trend for controlling time effects is a natural method.

In sum, this study specifies country specific variables and time specific variables differently for GDP^*_{it} and δ_{it}. One of the big reasons for this is that we have an interaction term made up of GDP^*_{it} and δ_{it} in our main estimation model. This study uses a dataset of 144 nations covering 35 years. If we control GDP^*_{it} also by two-way fixed effects, there are many dummy variables that are created in the interaction term $\delta_{it}GDP^*_{it}$. When we estimate the equation Model 7(M7) with both GDP^*_{it} and δ_{it} controlled by two-way fixed effects, MLE estimation

[18] These six variables are the same as the technology shifters variables' Z^{11}_{it}, Z^{12}_{it}, Z^{13}_{it} Z^{21}_{it}, Z^{22}_{it} and Z^{23}_{it} used in the static models. However, new notations CG_{it}, TO_{it}, FDI_{it}, EC_{it}, NL_{it} and GC_{it} are used in the dynamic model for convenience.

hardly converges. Sometimes, we can get some convergent results by implementing various starting points of the MLE estimation. But all the convergent results have unrealistic implications about capital share and labor share. Therefore, implementing income level group fixed effects and single time trend for GDP^*_{it} is the best way to improve the possibility of convergence and reduce specification errors.

Functions F and G are both linear functions in this dynamic setting. Of course, we can assume functions F and G as translog functions like the static model. However, in this dynamic model, the lagged variable of GDP_{it}, $GDP_{i\,t-1}$, is already included. Therefore, the demand of controlling by the translog function is lower than it is in the static model. Moreover, as there is an interaction term $\delta_{it}GDP^*_{it}$ in the estimation model, setting F and G as translog functions can create many parameters. This may make the interpretation more difficult and complex. Based on this discussion, functions F and G are: *E10:*

(16) $$GDP^*_{it} = F(X_{it}, X_i, X_t) = \beta_0 + \beta_K K_{it} + \beta_L L_{it} + \beta_t t + Income_g$$

and *E11:*

(17)

$$\delta_{it} = G(Z_{it}, Z_i, Z_t) = \propto_0 + \propto_{CG} CG_{it} + \propto_{TO} TO_{it} + \propto_{FDI} FDI_{it} + \propto_{EC} EC_{it} + \propto_{NL} NL_{it} + \propto_{GC} GC_{it} + Country_i + Year_t$$

$Income_g$ means the full set of income level fixed effects. We implemented both five income groups and ten income groups for robustness. $Country_i$ is the full set of country fixed effects. $Year_t$ indicates the full set of year fixed effects.

3.3. Data

All these variables have already been used in the static models. The dataset for this dynamic model is the same as that used for the static models. Penn World Table 9.0 (PWT) and the World Development Indicators (WDI) are the main sources of the variables. For GDP_{it} and $GDP_{i\,t-1}$, PWT's 'real GDP at constant 2011 national prices (in million US$)' is used. PWT gives capital stock as 'capital stock at constant 2011 national prices (in million US$).' The number of employees is appropriate for the labor force variable. The number of employees is indicated in PWT as 'number of persons engaged (in millions).'

For the number of listed firms (NL_{it}), WDI's 'listed domestic companies, total' is used. WDI's 'electric power consumption (KWh per capita)' is used for the electricity consumption variable (EC_{it}). For trade openness (TO_{it}), WDI data for 'trade openness (defined as import and export share of GDP)' is used. WDI's 'foreign direct investment, net inflows (per cent of GDP)' is used for the FDI inflows variable (FDI_{it}). For government consumption (GC_{it}) and credit guarantee (CG_{it}), WDI's 'general government final consumption expenditure (defined as per cent of GDP)' and 'domestic credit to private sector by banks (defined as per cent of GDP)' respectively are used. D_{it} is also the same as the democracy dummy variable used in the static models. After handling missing unit data, this study has 4,622 observations for 144 nations observed unbalanced for 1980-2014. The methods of handling the missing observations are also the same as those used in the static models. As this dynamic model requires a lagged GDP variable $GDP_{i\,t-1}$, the total number of observation becomes 4,478.

3.4. Estimation Method

The 144 nations that constitute the data in this study were not chosen randomly because the WDI dataset has many missing unit observations especially in the technology shifters' variables in developing countries. Therefore, the 144 selected countries tend to be more developed than those that were omitted. This means that the fixed effects model is preferred to the random effects model. At the function $G(Z_{it}, Z_i, Z_t)$ which is explaining the adjustment speed δ_{it}, individual country fixed effects and year fixed effects are implemented.

The coefficients' interaction at $\delta_{it} GDP_{it}^{*}$ results in non-linearity which has to be overcome. A full information maximum likelihood estimation enables us to estimate a non-linear system of equations made by actual GDP, target GDP and speed of adjustment. In the SAS program, 'proc model FIML' can be implemented with a little arrangement of parameters and variables. The correlation matrix (Table 2), indicates that the problems caused by multicollinearity are not expected.

3.5. Estimation Results

Table 7 shows the estimation results of M7. As there are two ways to specify $Income_g$, the third column of the table shows the results derived using five income groups for $Income_g$ and the fourth column uses ten income groups for $Income_g$. Table 8 is a summary of some statistics which is estimated through M7. Variables in Table 8 are classified according to continent, three income levels and democracy as in the analysis of static models. This analysis is possible because GDP_{it}^{*} and δ_{it} have different values for each identity and each year.

Insert Table 7 and 8 about here

According to Table 7, the two likelihood ratio made by the two methods of specifying $Income_g$ are almost the same. The direction of coefficients and their statistical significance are also very similar. Only the magnitude of these coefficients differs according to method by which $Income_g$ is specified. First, we can check that the determinants of GDP_{it}^{*}, K_{it} and L_{it} have positive and significant impacts on GDP_{it}^{*}. Moreover, the magnitude of coefficients of both K_{it} and L_{it} is very close to the traditional share of capital and labor. This shows that GDP_{it}^{*} successfully explains the target level of GDP of each nation.

Among the determinants of δ_{it}, there are two variables that are positively significant towards δ_{it}. In addition, there are two variables which are negatively significant towards δ_{it}. Two variables which are related to the openness of one nation, TO_{it} and FDI_{it}, have positive coefficients and those are statistically significant. TO_{it} has the bigger magnitude of positive impacts on δ_{it} than that of FDI_{it}. On the other hand, GC_{it} and EC_{it} have negative effects of δ_{it}. Credit guarantee (CG_{it}) and the number of listed firms (NL_{it}) have insignificant coefficients in Model 7(M7). One of the most important things that we have to consider is that the adjustment speed δ_{it} can have positive or negative values. The optimal GDP change, $GDP_{it}^{*} - GDP_{i\,t-1}$, and the realized GDP change ($GDP_{it} - GDP_{i\,t-1}$) which is adjusted by δ_{it} can also have both positive and negative values. We have to interpret the coefficients of determinants of δ_{it} based on these facts.

In literature on capital structure, it is natural to impose some restrictions about the adjustment speed and target level. The actual realized debt ratio finally depends on firms' decisions. Therefore, the possibilities of overshooting adjustment and negative adjustment are relatively low. However, imposing some restrictions on δ_{it} and GDP_{it}^{*} can be misleading because this study is about the nature of national GDP. This is mainly due to the fact that GDP_{it} which means the realized GDP level is impossible to be determined by each nation's government. Moreover, it is also difficult to have an expectation about GDP_{it}. There are always a lot of unexpected shocks and the exact mechanism determining GDP_{it} has not been clarified yet. Consequently, it is always possible that δ_{it} has an overshooting effect ($\delta_{it} > 1$) or that a negative adjustment occurs ($\delta_{it} < 0$).

Table 9 shows the actual distribution of adjustment speed δ_{it}, $GDP_{it} - GDP_{i\,t-1}$, and $GDP^*_{it} - GDP_{i\,t-1}$. Based on the first estimation results which use five income level groups for controlling GDP^*_{it}, 12.6 per cent of the adjustment speed δ_{it} among 4,478 observations have negative values. Just 0.3 per cent of δ_{it} are bigger than 1,[19] 14.5 per cent of $GDP_{it} - GDP_{i\,t-1}$ which means the realized GDP change are negative. On the other hand, just 1.9 per cent of $GDP^*_{it} - GDP_{i\,t-1}$ have negative values. Considering these facts about data distribution, we interpret the coefficients of determinants of adjustment speed δ_{it} after following two exclusion standards. As there are only a few observations that $\delta_{it} > 1$(0.3 per cent), this study excludes the cases which satisfy $\delta_{it} > 1$. In addition, there are only a few observations that $GDP^*_{it} - GDP_{i\,t-1}$ is negative (at the most 4 per cent). Therefore it is natural to make interpretation while assuming that $GDP^*_{it} - GDP_{i\,t-1}$ has positive values.

Insert Table 9 about here

First, we have to analyze the determinants of adjustment speed when $0 < \delta_{it} < 1$. As $GDP^*_{it} - GDP_{i\,t-1}$ is assumed to be positive, $GDP_{it} - GDP_{i\,t-1}$ is also positive in this case. This means that economic growth is occurring in this period between two period. As the trade's share of GDP and FDI inflows' share of GDP increase, the adjustment speed δ_{it} gets closer to 1. In other words, the realized GDP change $GDP_{it} - GDP_{i\,t-1}$ adjusts faster to an optimal GDP change $GDP^*_{it} - GDP_{i\,t-1}$ as trade openness and FDI inflows increase. Realized GDP becomes closer to the optimal target level of GDP GDP^*_{it}. On the other hand, as the government consumption's share of GDP increases, the adjustment speed δ_{it} gets closer to 0. Electricity consumption per capita (EC_{it}) has the same effects as government consumption. As the government consumption's share of GDP increases and as the quality of infrastructure related to electricity improves, it will take longer time for GDP_{it} to reach GDP^*_{it}.

Next, we can interpret these coefficients when $\delta_{it} < 0$. In this case, $GDP_{it} - GDP_{i\,t-1}$ becomes negative. This means that GDP declines between the two periods. Note that δ_{it} is not smaller than -1. First, as the proportion of trade openness and FDI among GDP increase, the adjustment speed gets closer to 0. This also means that the realized GDP change $GDP_{it} - GDP_{i\,t-1}$ adjusts to the optimal GDP change $GDP^*_{it} - GDP_{i\,t-1}$ faster if a nation's economy has a higher degree of openness including trade and FDI. When the government consumption's share of GDP and electricity consumption per capita increase, adjustment speed δ_{it} becomes closer to -1. Symmetrically to the above case, this means the GDP_{it}'s adjustment toward GDP^*_{it} becomes slower.

Whether the economy is growing or declining, TO_{it}, FDI_{it}, GC_{it} and EC_{it} have consistent impacts on adjustment speed δ_{it}. TO_{it} and FDI_{it} stimulate the adjustment of GDP_{it} towards GDP^*_{it}. However, GC_{it} and EC_{it} deter its adjustment. These findings about trade openness and FDI inflows were not expected. When this study constructed the function

[19] Similarly, based on the second estimation results which use ten income level groups for controlling GDP^*_{it}, just 0.3 per cent of δ_{it} are bigger than 1.

explaining δ_{it}, we expected that higher openness and bigger FDI inflows will delay the adjustment of GDP_{it}. Also, this study expected that as the government consumption's share of GDP increases, vulnerability towards external shocks derived by many factors including openness will decrease. This lowered vulnerability was expected to stimulate the adjustment speed. However, these expectations turned out to be incorrect according to M7's estimation. But one fact which is consistent with expectations is that the impact of trade and FDI inflows on adjustment speed can be offset by government consumption. As investments in infrastructure related to electricity are mainly made by the government, the coefficient of EC_{it} has the same direction as that of GC_{it}. Based on these facts, governments can control the adjustment process against the power of openness.

Surrounded by these findings derived by the dynamic model, the impact of democracy on GDP levels is positive and highly significant according to Table 7. The demand side of the economy and the dynamic aspects of economic growth were omitted in the static models (M1 – M6). On the other hand, M7 considered these omitted aspects. Both the static model and the dynamic model support that democracy can be regarded as one of the most important factors for analyzing economic growth. In addition, at least during 1980-2014, the impact of democracy on economic growth was positive.

4. Conclusion

This study obtained consistent yet variable and informative results from a panel data of 144 nations through the use of static and dynamic models' GDP specifications. This dataset covers the period 1980 to 2014. The GDP models M1, M2, M3, M4, M5 and M6 point out the existence of positive institutional elements in the production function. Models M4, M5 and M6 show various results related to technology shifters' specifications. In order to control for time-specific effects, a single time trend, multiple time trends and general index representations of technological changes are used. Dynamic settings constructed by optimal target level of GDP and flexible adjustment speed towards the target level are implemented in Model M7. Model M7 also shows democracy's positive and significant impacts on economic growth. Many interpretations about determinants of adjustment speed are also possible in Model M7.

The results of the static models study show that as Acemoglu et al. (2014) pointed out there is a robust and positive relationship between democracy and economic growth. Positive impacts of democracy on economic growth are seen by estimating the production function by different methods. However, we also found some interesting linkages between democracy and economic growth. Credit guarantee and FDI inflows turned out to be positive linkages between democracy and economic growth. And they had bigger marginal effects in democratic countries as compared to non-democratic countries. Trade, electricity infrastructure, number of listed firms and government consumption acted as negative mediums between democracy and economic growth. These four variables had bigger marginal effects in non-democratic countries than in democratic countries. Model M7, the dynamic model, also supported the positive impacts of democracy on GDP levels. Technology shifters' variables in the static models are used as determinants of adjustment speed in the dynamic model (M7). The effects to adjustment speed derived from trade openness and FDI inflows were opposite to the effects to adjustment speed caused by government consumption and electricity infrastructure.

Even though this study clarified robust impacts of democracy and identified some possible channels between democracy and economic growth, it would have been better if the dynamic model had also found and tested possible channels between democracy and economic growth.

When we implement the dichotomous democracy dummy variable as the explain variable for the target level of GDP, we can analyze some possible channels between economic growth and democracy. However, it was impossible to discover meaningful mediums between the two concepts using the dynamic model. This is due to the fact that the role of democracy in the target level of GDP was not consistent with the findings of the static models. If one can find significant possible channels between democracy and economic growth which are also consistent with the nature of the optimal target level of GDP and adjustment speed, it will be a great contribution to this field.

References

Acharya, R.C. and W. Keller (2009). Transfer through Imports. *The Canadian Journal of Economics*, 42(4), 1411-1448.

Acemoglu, D., S. Naidu, P. Restrepo, and J.A. Robinson (2014). Democracy does cause growth. *NBER Working Paper Series*, NBER Working Paper No. 20004.

Alesina, A. and D. Rodrik (1994). Distributive Politics and Economic Growth. *Quarterly Journal of Economics*. 109(2), 465-490.

Alfaro, L., A. Chanda, S.K. Ozcan, and S. Sayek (2004). FDI and Economic Growth: The Role of Locan Financial Markets. *Journal of International Economics*, 64(1), 89-112.

Amsden, A.H. (1989). Asia's Next Giant: South Korea and Late Industrialization. New York: Oxford University Press.

Baltagi, B. and J. Griffin (1988). A General Index of Technical Change. *Journal of Political Economy*, 96(1), 20-41.

Banerjee, S., A. Heshmati and C. Wihlborg (2000). The Dynamics of Capital Structure. *SSE/EFI Working Paper Series*, No. 333.

Berndt E. and Christensen L.R. (1972). The Translog Production Function and the Substitution of Equipment, Structures, and Labour in US Manufacturing. *Journal of Econometrics*, 1, 81-114.

Bloom, N., M. Draca, and J.V Reenen (2016). Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity. *Review of Economic Studies*, 83, 87-117.

Boix, C. and M. Miller and S. Rosato (2012). A Complete Data Set of Political Regimes, 1800–2007. *Comparative Political Studies*, 46(12), 1523-1554.

Borensztein, E., J.D. Gregorio, and J.W. Lee (1998). How Does Foreign Direct Investment Affect Economic Growth? *Journal of International Economics*, 45(1), 115-135.

Busse, B. (2003). Democracy and FDI. H*WWA Discussion Paper*, HWWA Discussion Paper 220.

Chalmers, J. (1982). MITI and the Japanese Miracle: The Growth of Industrial Policy, 1925-1975. Stanford: Stanford University Press

Cheibub J.A., J. Gandhi, and J.R. Vreeland (2010). Democracy and Dictatorship Revisited. *Public Choice*, 143(1-2), 67–101.

Christensen, L.R., D.W. Jorgenson, and L.J. Lau (1973). Transcendental Logarithmic

Production Frontiers. *The Review of Economics and Statistics*, 55(1), 28-45.

Eichengreen, B. and D. Leblang (2006). Democracy and Globalization. NBER *Working Paper Series*, NBER Working Paper No. 12450.

Evans, A.D, C.J. Green, and V. Murinde (2002). Human Capital and Financial Development in Economic Growth: New Evidence Using the Translog Production Function. *International Journal of Finance and Economics*, 7, 123-140.

Foster, L., J.C. Haltiwanger, and C.J. Krizan (2001). Aggregate Productivity Growth, Lessons from Microeconomic Evidence, *'New Developments in Productivity Analysis'*, NBER, 303-372.

Haggard, S. (1990). Pathways from the Periphery: The Politics of Growth in the Newly Industrializing Countries. Ithaca: Cornell University Press.

Heshmati, A. (1996). On the Single and Multiple Time Trends Representation of Technical Change. *Applied Economics Letters,* 3, 495–499.

Heshmati, A. (2001). The Dynamics of Capital Structure: Evidence from Swedish Micro and Small Firms. *Research in Banking and Finance*, 2, 199-241.

Heshmati, A and S.C. Kumbhakar (2013). A General Model of Technical Change with an Application to the OECD Countries. *Economics of Innovation and New Technology,* 23, 25-48.

Kim, H. Youn (1992). The Translog Production Function and Variable Returns to Scale. *The Review of Economics and Statistics*, 74(3), 546-552.

Lööf, H. (2004). Dynamic Optimal Capital Structure and Technical Change. *Structural Change and Economic Dynamics,* 15, 449-468.

López-Córdova, E.J. and C.M. Meissner (2005). The Globalization of Trade and Democracy, 1870-2000. NBER *Working Paper Series*, NBER Working Paper No. 11117.

Lyu, S.L, F.C. White, and Y. Lu. (1984). Estimating Effects of Agricultural Research and Extension Expenditures on Productivity: A Translog Production Function Approach. *Southern Journal of Agricultural Economics*, 16(2), 1-8.

Marsh, P. (1982). The Choice between Equity and Debt: An Empirical Study. *Journal of Finance*, 37(1), 121-144.

Modigliani, F. and M.H. Miller (1958). The Cost of Capital, Corporation Finance and the Theory of Investment. *The American Economic Review*, 48(3), 261-297.ey

Olley, G.S. and A. Pakes (1996). The Dynamics of Productivity in the Telecommunication Equipment Industry. *Econometrica*, 64(6), 1263-1297.

Pellegrini, L. and R. Gerlagh (2004). Corruption's Effect on Growth and its Transmission Channels. *Kykos International Review of Social Sciences*, 57(3), 429-456

Persson, P. and G. Tabellini (2007). The Growth Effect of Democracy: Is it Heterogeneous and How Can it be Estimated? NBER *Working Paper Series,* NBER Working Paper No. 13150.

Plumper, T. and C.W. Martin (2003). Democracy, Government Spending, and Economic Growth: A Political-Economic Explanation of the Barro-Effect. *Public Choice*, 117, 27-50.

Solow, R.M. (1957). Technical Change and the Aggregate Production Function. *The Review of Economics and Statistics*, 39(3), 312-320.

Tabellini, G. and A. Alesina (1990). Voting on the Budget Deficit. *American Economic Review*, 80(1), 37-49.

Wade, R. (1990). Governing the Market: Economic Theory and the Role of Government in East Asian Industrialization. Princeton: Princeton University Press.

Woo, J.E. (1991). Race to the Swift: State and Finance in Korean Industrialization. New York: Columbia University Press.

Yanikkaya, H. (2003). Trade Openness and Economic Growth: A Cross-Country Empirical Investigation. *Journal of Development Economics*, 72, 57-89.

Yu, M. (2010). Trade, Democracy, and the Gravity Equation. *Journal of Development Economics*, 91(2), 289–300.

Table 1: Summary statistics of the data, N=4,622					
Variable	Mean	Median	Std Dev	Minimum	Maximum
GDP	437005.40	56982.26	1358618.00	336.10	17150538.00
Capital	1458643.00	184047.30	4459800.00	475.42	67590072.00
Labor	17.48	3.44	69.31	0.05	798.36
Democracy	0.59	1.00	0.49	0.00	1.00
Credit guarantee	39.22	26.98	35.88	0.15	253.44
Trade	79.73	69.52	49.96	6.32	531.73
FDI	3.73	1.69	8.17	0.00	255.42
Electricity	2831.04	1000.17	4176.37	12.49	25590.69
No of Firms	252.19	20.00	755.37	0.00	8090.00
Gov. Consumption	15.84	15.68	6.33	0.00	84.51

Table 2: The correlation matrix , N=4622										
	GDP	Capital	Labor	Demo	Credit	Trade	FDI	Elec	No Firm	Gov. Cons
GDP	1.00									
Capital	0.98	1.00								
Labor	0.60	0.57	1.00							
Demo	0.11	0.13	-0.02	1.00						
Credit	0.26	0.29	0.16	0.30	1.00					
Trade	-0.19	-0.18	-0.17	-0.06	0.19	1.00				
FDI	-0.06	-0.05	-0.04	0.01	0.10	0.41	1.00			
Elec	0.24	0.25	-0.02	0.21	0.49	0.17	0.06	1.00		
NoFirm	0.75	0.73	0.44	0.20	0.31	-0.17	-0.05	0.28	1.00	
GovCons	0.00	0.02	-0.08	0.06	0.17	0.18	0.04	0.26	0.00	1.00

Table 3: Estimation results for M1, M2, M3, M4, M5 and M6						
	M1_STT		M2_MTT		M3_GI	
	coeff	std err	coeff	std err	coeff	std err
K_{it}	0.85***	0.03	0.81***	0.03	0.82***	0.03
L_{it}	-0.47***	0.07	-0.15***	0.06	-0.37***	0.06
D_{it}	0.02***	0.007	0.03***	0.01	0.02***	0.007
t	0.009***	0.002	-	-	-	-
t_1	-	-	-0.01***	0.00	-	-
t_2	-	-	0.08***	0.01	-	-
$K_{it}K_{it}$	-0.03***	0.007	-0.01**	0.01	-0.03***	0.006
$L_{it}L_{it}$	0.05***	0.01	0.05***	0.01	0.04***	0.01
tt	0.0005***	0.00	-	-	-	-
t_1t_1	-	-	0.001***	0.00	-	-
t_2t_2	-	-	-0.01***	0.00	-	-
	M4_TS_STT		M5_TS_MTT		M6_TS_GI	
	coeff	std err	coeff	std err	coeff	std err
K_{it}	0.98***	0.05	0.90***	0.05	0.91***	0.05
L_{it}	-0.38***	0.08	-0.17**	0.07	-0.26***	0.07
D_{it}	0.07***	0.02	0.06**	0.02	0.11***	0.02
t	0.005*	0.003	-	-	-	-
t_1	-	-	-0.01***	0.00	-	-
t_2	-	-	0.09***	0.01	-	-
$K_{it}K_{it}$	-0.02***	0.009	-0.01	0.01	-0.01	0.01
$L_{it}L_{it}$	0.05***	0.01	0.06***	0.01	0.06***	0.01
tt	0.0005***	0	-	-	-	-
t_1t_1	-	-	0.001***	0.00	-	-
t_2t_2	-	-	-0.008***	0.00	-	-
$T_1(Z_{it}^{1p})$	-0.004	0.02	0.04	0.03	-0.03	0.02
$T_2(Z_{it}^{2p})$	-0.11**	0.05	-0.06	0.05	-0.09*	0.05
Z_{it}^{11}	0.10***	0.02	0.20***	0.03	0.01***	0.00
Z_{it}^{12}	-0.001**	0	-0.002**	0.00	-0.0001	0.00
Z_{it}^{21}	0.17***	0.04	0.17***	0.05	0.16***	0.04
Z_{it}^{22}	0.11***	0.04	0.19***	0.07	0.12**	0.05
$D_{it}T_1(Z_{it}^{1p})$	0.04***	0.006	0.04***	0.01	0.02***	0.00
$D_{it}T_2(Z_{it}^{2p})$	-0.02***	0.005	-0.02***	0.01	-0.02***	0.01

Note: *** : p-value <0.01; ** : p-value<0.05; * : p-value <0.10 ; 4622 observations

Table 4: Elasticities calculated based on estimation results from M1, M2 and M3							
A. Elasticities, Technical change, RTS, TFP _ M1 _ Single time trend (Mean)							
	$E_{K_{it}}$	$E_{L_{it}}$	TC	neutral	n_neutral	RTS	TFP
Asia	0.583	0.295	0.008	0.019	-0.011	0.878	0.004
Africa	0.645	0.179	0.009	0.019	-0.010	0.823	0.004
N_America	0.520	0.476	0.005	0.018	-0.013	0.995	0.005
S_America	0.595	0.232	0.009	0.019	-0.010	0.826	0.005
Europe	0.553	0.278	0.010	0.020	-0.010	0.831	0.007
Income_L	0.651	0.224	0.008	0.019	-0.011	0.875	0.005
Income_M	0.595	0.232	0.010	0.019	-0.010	0.827	0.004
Income_H	0.544	0.278	0.009	0.019	-0.009	0.823	0.005
Demo	0.582	0.264	0.010	0.020	-0.010	0.847	0.006
Nondemo	0.619	0.215	0.008	0.018	-0.010	0.834	0.003
Mean	0.597	0.245	0.009	0.019	-0.010	0.842	0.005
B. Elasticities, Technical change, RTS, TFP _ M2 _ Multiple time trends (Mean)							
	$E_{K_{it}}$	$E_{L_{it}}$	TC	neutral	n_neutral	RTS	TFP
Asia	0.613	0.322	-0.022	0.011	-0.033	0.935	-0.024
Africa	0.651	0.260	-0.018	0.012	-0.030	0.910	-0.021
N_America	0.566	0.434	-0.026	0.015	-0.040	0.999	-0.026
S_America	0.626	0.276	-0.018	0.011	-0.029	0.902	-0.021
Europe	0.605	0.293	-0.019	0.011	-0.029	0.898	-0.02
Income_L	0.646	0.299	-0.022	0.012	-0.034	0.946	-0.023
Income_M	0.626	0.277	-0.019	0.011	-0.030	0.904	-0.022
Income_H	0.602	0.288	-0.017	0.011	-0.028	0.890	-0.020
Demo	0.617	0.297	-0.021	0.010	-0.031	0.914	-0.023
Nondemo	0.637	0.275	-0.017	0.013	-0.030	0.912	-0.020
Mean	0.625	0.288	-0.019	0.011	-0.031	0.913	-0.022
C. Elasticities, Technical change, RTS, TFP _ M3 _ General index (Mean)							
	$E_{K_{it}}$	$E_{L_{it}}$	TC	neutral	n_neutral	RTS	TFP
Asia	0.588	0.274	0.006	0.015	-0.009	0.861	0.002
Africa	0.642	0.174	0.007	0.014	-0.007	0.816	0.002
N_America	0.534	0.423	0.004	0.014	-0.010	0.957	0.003
S_America	0.597	0.222	0.007	0.014	-0.008	0.819	0.002
Europe	0.559	0.265	0.007	0.016	-0.009	0.824	0.005
Income_L	0.649	0.209	0.007	0.015	-0.008	0.858	0.003
Income_M	0.597	0.223	0.007	0.015	-0.008	0.820	0.002
Income_H	0.551	0.266	0.007	0.015	-0.008	0.817	0.002
Demo	0.586	0.251	0.007	0.016	-0.009	0.836	0.004
Nondemo	0.620	0.206	0.006	0.013	-0.007	0.825	0.001
Mean	0.599	0.232	0.007	0.015	-0.008	0.832	0.002

Table 5: Elasticities calculated based on estimation results from M4, M5 and M6										
A. Elasticities, Technical change, RTS, TFP _ M4 _ Technology shifters _ Single time trend (Mean)										
	$E_{K_{it}}$	$E_{L_{it}}$	e_D_{it}	TC	neutral	non_ neutral	RTS	TFP	e_T_1	e_T_2
Asia	0.454	0.294	0.009	0.009	0.016	-0.008	0.747	0.001	0.022	0.158
Africa	0.584	0.162	0.040	0.009	0.016	-0.007	0.746	0.002	0.016	0.045
N_America	0.327	0.457	-0.020	0.006	0.015	-0.010	0.784	0.002	0.048	0.233
S_America	0.492	0.232	0.018	0.008	0.016	-0.008	0.724	0.002	0.043	0.107
Europe	0.397	0.309	0.000	0.010	0.017	-0.007	0.706	0.006	0.042	0.208
Income_L	0.577	0.200	0.036	0.009	0.016	-0.007	0.777	0.003	0.017	0.057
Income_M	0.491	0.233	0.023	0.009	0.017	-0.007	0.724	0.002	0.029	0.117
Income_H	0.393	0.305	-0.000	0.008	0.016	-0.008	0.698	0.003	0.039	0.204
Demo	0.454	0.275	0.013	0.010	0.017	-0.008	0.729	0.004	0.044	0.147
Nondemo	0.537	0.204	0.025	0.008	0.015	-0.007	0.740	0.000	0.006	0.094
Mean	0.487	0.246	0.018	0.009	0.016	-0.008	0.733	0.003	0.029	0.126
B. Elasticities, Technical change, RTS, TFP _ M5 _ Technology shifters _ Multiple time trends(Mean)										
	$E_{K_{it}}$	$E_{L_{it}}$	e_D_{it}	TC	neutral	non_ neutral	RTS	TFP	e_T_1	e_T_2
Asia	0.507	0.321	0.017	-0.02	0.014	-0.042	0.828	-0.030	0.023	0.145
Africa	0.607	0.235	0.044	-0.02	0.015	-0.040	0.842	-0.030	0.016	0.042
N_America	0.405	0.444	-0.010	-0.03	0.017	-0.048	0.850	-0.030	0.054	0.203
S_America	0.542	0.268	0.026	-0.02	0.014	-0.042	0.810	-0.030	0.048	0.099
Europe	0.475	0.308	0.012	-0.02	0.014	-0.042	0.783	-0.030	0.049	0.190
Income_L	0.594	0.277	0.039	-0.02	0.015	-0.039	0.871	-0.020	0.016	0.050
Income_M	0.541	0.270	0.030	-0.02	0.014	-0.042	0.811	-0.030	0.034	0.109
Income_H	0.473	0.301	0.009	-0.02	0.014	-0.043	0.774	-0.030	0.046	0.188
Demo	0.513	0.298	0.023	-0.02	0.014	-0.042	0.811	-0.030	0.048	0.134
Nondemo	0.571	0.259	0.031	-0.02	0.015	-0.040	0.830	-0.030	0.008	0.087
Mean	0.536	0.282	0.026	-0.02	0.015	-0.041	0.819	-0.030	0.032	0.115
C. Elasticities, Technical change, RTS, TFP _ M6 _ Technology shifters _ General index (Mean)										
	$E_{K_{it}}$	$E_{L_{it}}$	e_D_{it}	TC	neutral	non_ neutral	RTS	TFP	e_T_1	e_T_2
Asia	0.476	0.877	0.004	0.007	0.013	-0.006	1.353	0.025	0.016	0.159
Africa	0.588	0.846	0.045	0.007	0.012	-0.005	1.433	0.027	0.007	0.046
N_America	0.371	0.877	-0.020	0.005	0.012	-0.007	1.249	0.012	0.023	0.233
S_America	0.513	0.876	0.018	0.007	0.012	-0.006	1.389	0.022	0.017	0.110
Europe	0.430	0.916	-0.010	0.008	0.014	-0.006	1.346	0.013	0.018	0.213
Income_L	0.578	0.836	0.042	0.007	0.013	-0.005	1.414	0.025	0.012	0.055
Income_M	0.511	0.876	0.021	0.007	0.013	-0.006	1.387	0.023	0.010	0.119
Income_H	0.429	0.917	-0.010	0.007	0.013	-0.006	1.346	0.018	0.020	0.210
Demo	0.477	0.887	0.008	0.008	0.014	-0.006	1.364	0.020	0.022	0.151
Nondemo	0.549	0.860	0.028	0.006	0.011	-0.005	1.409	0.026	0.002	0.094
Mean	0.506	0.876	0.016	0.007	0.013	-0.006	1.382	0.022	0.014	0.128

Table 6: Technology shifters and their directions which have significant coefficients in the interacted term $\sum_m \sum_p \theta_{tm} D_{it} T_m (Z_{it}^{mp})$
Model 4: Credit guarantee, Z_{it}^{11}(+) / Trade, Z_{it}^{12}(-) / FDI, Z_{it}^{13}(+) / Electricity consumption, Z_{it}^{21}(-) / Number of firms, Z_{it}^{22}(-) / Government consumption, Z_{it}^{23}(-)
Model 5: Credit guarantee, Z_{it}^{11}(+) / Trade, Z_{it}^{12}(-) / FDI, Z_{it}^{13}(+) / Electricity consumption, Z_{it}^{21}(-) / Number of firms, Z_{it}^{22}(-) / Government consumption, Z_{it}^{23}(-)
Model 6: Credit guarantee, Z_{it}^{11}(+) / Electricity consumption, Z_{it}^{21}(-) / Number of firms, Z_{it}^{22}(-) / Government consumption, Z_{it}^{23}(-)

Table 7: Estimation results for M7			
	Target level of GDP(GDP_{it}^{*}) : Single time trend & Income level groups Adjustment speed(δ_{it}) : Two way fixed effects(By nations and years)		
		5 Income Level Groups	10 Income Level Groups
	L Likelihood	6588	6587
	D_{it}	0.01267***	0.014189***
GDP_{it}^{*}	K_{it}	0.663267***	0.582054***
	L_{it}	0.325295***	0.374526***
δ_{it}	GC_{it}	-0.01757***	-0.03143***
	FDI_{it}	0.002652***	0.004489***
	TO_{it}	0.011469***	0.025836***
	CG_{it}	-0.00136	-0.00253
	EC_{it}	-0.01178***	-0.01981***
	NL_{it}	0.001272	0.001079

Table 8: Statistics calculated based on estimation results from dynamic models						
A. Model 7. Five income level groups for fixed effects of GDP_{it}^{*} (Mean)						
	GDP_{it}^{*}	GDP_{it}	δ_{it}	$GDP_{it} - GDP_{i\,t-1}$	$GDP_{it}^{*} - GDP_{i\,t-1}$	$\delta_{it}(GDP_{it}^{*} - GDP_{i\,t-1})$
Asia	12.895	11.946	0.088	0.045	0.994	0.040
Africa	10.672	9.553	0.042	0.037	1.155	0.033
N_America	15.312	14.752	0.024	0.025	0.585	0.012
S_America	12.524	10.998	0.019	0.029	1.555	0.018
Europe	13.210	12.170	0.012	0.021	1.061	0.009
Income_L	10.874	9.844	0.040	0.037	1.067	0.032
Income_M	12.730	11.088	0.028	0.035	1.676	0.027
Income_H	13.041	12.390	0.058	0.028	0.679	0.019
Demo	12.717	11.535	0.023	0.032	1.214	0.019
Nondemo	11.452	10.451	0.071	0.035	1.036	0.036
Mean	12.211	11.102	0.042	0.033	1.142	0.026
B. Model 7. Ten income level groups for fixed effects of GDP_{it}^{*} (Mean)						
	GDP_{it}^{*}	GDP_{it}	δ_{it}	$GDP_{it} - GDP_{i\,t-1}$	$GDP_{it}^{*} - GDP_{i\,t-1}$	$\delta_{it}(GDP_{it}^{*} - GDP_{i\,t-1})$
Asia	12.413	11.946	0.131	0.045	0.512	0.039
Africa	10.204	9.553	0.058	0.037	0.687	0.031
N_America	15.084	14.752	0.033	0.025	0.356	0.011
S_America	11.823	10.998	0.030	0.029	0.854	0.017
Europe	12.813	12.170	0.013	0.021	0.663	0.008
Income_L	10.338	9.844	0.084	0.037	0.531	0.030
Income_M	12.024	11.088	0.032	0.035	0.971	0.026
Income_H	12.833	12.390	0.064	0.028	0.471	0.018
Demo	12.204	11.535	0.032	0.032	0.700	0.018
Nondemo	11.011	10.451	0.102	0.035	0.595	0.035
Mean	11.727	11.102	0.060	0.033	0.658	0.025

Table 9: Minimum, maximum and number of negative observations					
A. Model 7. Five income level groups for fixed effects of GDP_{it}^{*}					
	Mean	Std Dev	Minimum	Maximum	Number of Negative observations (%)
δ_{it}	0.042	0.086	-0.107	1.122	565(12.6%)
$GDP_{it} - GDP_{i\,t-1}$	0.033	0.063	-0.714	0.724	697(15.5%)
$GDP_{it}^{*} - GDP_{i\,t-1}$	1.142	0.721	-0.451	3.288	89(1.9%)
B. Model 7. Ten income level groups for fixed effects of GDP_{it}^{*}					
	Mean	Std Dev	Minimum	Maximum	Number of Negative observations (%)
δ_{it}	0.060	0.113	-0.249	1.126	694(15.4%)
$GDP_{it} - GDP_{i\,t-1}$	0.033	0.063	-0.714	0.724	697(15.5%)
$GDP_{it}^{*} - GDP_{i\,t-1}$	0.658	0.429	-0.466	2.620	183(4%)

Appendix

Table A1: Cases of transitions in democracy within a nation (128 times in 66 nations.)		
Country	Transition Year	Transition
Albania	1990-1991	From Nondemocratic to Democratic
	1995-1996	From Democratic to Nondemocratic
	1996-1997	From Nondemocratic to Democratic
Azerbaijan	1991-1992	From Nondemocratic to Democratic
	1992-1993	From Democratic to Nondemocratic
Argentina	1982-1983	From Nondemocratic to Democratic
Bangladesh	1990-1991	From Nondemocratic to Democratic
	2006-2007	From Democratic to Nondemocratic
	2008-2009	From Nondemocratic to Democratic
Armenia	1995-1996	From Democratic to Nondemocratic
	1997-1998	From Nondemocratic to Democratic
Bhutan	2007-2008	From Nondemocratic to Democratic
Bolivia	1981-1982	From Nondemocratic to Democratic
Brazil	1984-1985	From Nondemocratic to Democratic
Burundi	2004-2005	From Nondemocratic to Democratic
	2013-2014	From Democratic to Nondemocratic
Belarus	1994-1995	From Democratic to Nondemocratic
Cambodia	1992-1993	From Nondemocratic to Democratic
	1994-1995	From Democratic to Nondemocratic
Cabo Verde	1990-1991	From Nondemocratic to Democratic
Central African Republic	1992-1993	From Nondemocratic to Democratic
	2002-2003	From Democratic to Nondemocratic
Chile	1988-1989	From Nondemocratic to Democratic
Comoros	1989-1990	From Nondemocratic to Democratic
	1994-1995	From Democratic to Nondemocratic
	1995-1996	From Nondemocratic to Democratic
	1998-1999	From Democratic to Nondemocratic
	2001-2002	From Nondemocratic to Democratic
Congo	1991-1992	From Nondemocratic to Democratic
	1996-1997	From Democratic to Nondemocratic
Croatia	1999-2000	From Nondemocratic to Democratic
Benin	1990-1991	From Nondemocratic to Democratic
El Salvador	1983-1984	From Nondemocratic to Democratic
Ethiopia	1994-1995	From Nondemocratic to Democratic
	2004-2005	From Democratic to Nondemocratic
Fiji	1986-1987	From Democratic to Nondemocratic
	1989-1990	From Nondemocratic to Democratic
	1999-2000	From Democratic to Nondemocratic
	2000-2001	From Nondemocratic to Democratic
	2005-2006	From Democratic to Nondemocratic
	2013-2014	From Nondemocratic to Democratic
Djibouti	1998-1999	From Nondemocratic to Democratic
	2009-2010	From Democratic to Nondemocratic
Georgia	1991-1992	From Nondemocratic to Democratic
Gambia	1993-1994	From Democratic to Nondemocratic
Ghana	1995-1996	From Nondemocratic to Democratic
Guatemala	1985-1986	From Nondemocratic to Democratic
Guinea	2009-2010	From Nondemocratic to Democratic

Haiti	1990-1991	From Democratic to Nondemocratic
	1993-1994	From Nondemocratic to Democratic
	1998-1999	From Democratic to Nondemocratic
	2005-2006	From Nondemocratic to Democratic
	2009-2010	From Democratic to Nondemocratic
Honduras	1981-1982	From Nondemocratic to Democratic
Indonesia	1998-1999	From Nondemocratic to Democratic
Kenya	2001-2002	From Nondemocratic to Democratic
Korea, Republic of	1987-1988	From Nondemocratic to Democratic
Kyrgyzstan	2004-2005	From Nondemocratic to Democratic
	2008-2009	From Democratic to Nondemocratic
	2010-2011	From Nondemocratic to Democratic
Lebanon	2004-2005	From Nondemocratic to Democratic
Lesotho	1992-1993	From Nondemocratic to Democratic
	1997-1998	From Democratic to Nondemocratic
	2001-2002	From Nondemocratic to Democratic
Liberia	2005-2006	From Nondemocratic to Democratic
Madagascar	1991-1992	From Nondemocratic to Democratic
	2008-2009	From Democratic to Nondemocratic
	2010-2011	From Nondemocratic to Democratic
Malawi	1993-1994	From Nondemocratic to Democratic
Mali	1991-1992	From Nondemocratic to Democratic
	2011-2012	From Democratic to Nondemocratic
	2012-2013	From Nondemocratic to Democratic
Mauritania	2006-2007	From Nondemocratic to Democratic
	2007-2008	From Democratic to Nondemocratic
Mexico	1993-1994	From Nondemocratic to Democratic
Mozambique	1993-1994	From Nondemocratic to Democratic
Nepal	1989-1990	From Nondemocratic to Democratic
	2001-2002	From Democratic to Nondemocratic
	2005-2006	From Nondemocratic to Democratic
Nicaragua	1989-1990	From Nondemocratic to Democratic
Niger	1991-1992	From Nondemocratic to Democratic
	1995-1996	From Democratic to Nondemocratic
	1998-1999	From Nondemocratic to Democratic
	2008-2009	From Democratic to Nondemocratic
	2009-2010	From Nondemocratic to Democratic
Nigeria	1983-1984	From Democratic to Nondemocratic
	1998-1999	From Nondemocratic to Democratic
Pakistan	1987-1988	From Nondemocratic to Democratic
	1998-1999	From Democratic to Nondemocratic
	2007-2008	From Nondemocratic to Democratic
Panama	1989-1990	From Nondemocratic to Democratic
Paraguay	1988-1989	From Nondemocratic to Democratic
Peru	1991-1992	From Democratic to Nondemocratic
	1992-1993	From Nondemocratic to Democratic
	1999-2000	From Democratic to Nondemocratic
	2000-2001	From Nondemocratic to Democratic
Philippines	1986-1987	From Nondemocratic to Democratic
Guinea-Bissau	1993-1994	From Nondemocratic to Democratic
	1997-1998	From Democratic to Nondemocratic

	1999-2000	From Nondemocratic to Democratic
	2002-2003	From Democratic to Nondemocratic
	2004-2005	From Nondemocratic to Democratic
	2011-2012	From Democratic to Nondemocratic
	2013-2014	From Nondemocratic to Democratic
Romania	1990-1991	From Nondemocratic to Democratic
Russian Federation	2003-2004	From Democratic to Nondemocratic
Senegal	1999-2000	From Nondemocratic to Democratic
Sierra Leone	1995-1996	From Nondemocratic to Democratic
	1996-1997	From Democratic to Nondemocratic
	2001-2002	From Nondemocratic to Democratic
South Africa	1980-1981	From Democratic to Nondemocratic
	1982-1983	From Nondemocratic to Democratic
	1991-1992	From Democratic to Nondemocratic
	1993-1994	From Nondemocratic to Democratic
Zimbabwe	1986-1987	From Democratic to Nondemocratic
Suriname	1989-1990	From Nondemocratic to Democratic
Thailand	1990-1991	From Democratic to Nondemocratic
	1991-1992	From Nondemocratic to Democratic
	2005-2006	From Democratic to Nondemocratic
	2007-2008	From Nondemocratic to Democratic
	2013-2014	From Democratic to Nondemocratic
Tunisia	2013-2014	From Nondemocratic to Democratic
Turkey	1982-1983	From Nondemocratic to Democratic
Uganda	1984-1985	From Democratic to Nondemocratic
Uruguay	1984-1985	From Nondemocratic to Democratic
Venezuela	2008-2009	From Democratic to Nondemocratic
	2012-2013	From Nondemocratic to Democratic
Zambia	1990-1991	From Nondemocratic to Democratic

Table A2: Countries with no transitions
Nations that are always democratic (49 nations)
Australia, Austria, Belgium, Botswana, Bulgaria, Canada, Sri Lanka, Colombia, Costa Rica, Cyprus, Czech, Denmark, Dominican Republic, Ecuador, Estonia, Finland, France, Germany, Greece, Hungary, India, Ireland, Israel, Italy, Jamaica, Japan, Latvia, Lithuania, Luxembourg, Malaysia, Mauritius, Mongolia, Montenegro, Namibia, Netherlands, New Zealand, Norway, Poland, Portugal, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Trinidad and Tobago, Ukraine, United Kingdom of Great Britain and Northern Ireland, United States of America
Nations that are always nondemocratic (29 nations)
Algeria, Angola, Bahrain, Cameroon, Chad, China, Congo, Equatorial Guinea, Gabon, Iran, Iraq, Kazakhstan, Jordan, Kuwait, Lao People's Democratic Republic, Morocco, Oman, Qatar, Rwanda, Saudi Arabia, Singapore, Viet Nam, Swaziland, Tajikistan, Togo, United Arab Emirates, Egypt, Burkina Faso, Yemen