for health and 1.2% for education with low levels of education and health capital, social development ranked very low as government priorities. However, the results show that the effect of social spending on GDP per capita equal on average 0.5% and an increase in primary education enrolment by 1% is associated with an increase in the growth of 0.8%, in contrast the health capital have negative and insignificant impacts.

The limited effects of social spending mentioned in the previous section appeared in the long run causality test; the causality runs from GDP per capita growth to social spending. Therefore, GDP per capita growth provides statistically significant information about future values of social spending in Sudan. The main challenge for the Sudanese policy makers is to rethinking into social spending as not only protective factor but also as productive factors enhance economic growth.

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[12] Granger causality is a technique for determining whether one time series is useful in forecasting another. Ordinarily, regressions reflect "mere" correlations. Granger (1969) defined causality as follows: A variable Y is causal for another variable X if knowledge of the past history of Y is useful for predicting the future state of X over and above knowledge of the past history of X itself. So if the prediction of X is improved by including Y as a predictor, then Y is said to be Granger causal for X. Granger Causality takes into account prediction rather than the name it suggests that is causation. This is because it creates the impression that while the past can cause or predict the future, the future cannot cause or predict the past. From what Granger deduced, 'X' causes 'Y' if the past values of 'X' can be used to predict 'Y' better than the past values of 'Y' itself.

[13] Dickey, A. and W.A. Fuller (1979), 'Distribution of the Estimators for Autoregressive Time Series with a Unit Root', American Statistical AssociationJournal, 74, Website: http://www.jstor.org/stable/2286348?seq=2

[14] VAR model describes the evolution of a set of k variables (called ***endogenous variables***) over the same sample period (t = 1, ...,T) as a linear function of only their past evolution. The variables are collected in a $k \times 1$ vector y_t, which has as the i[th] element $y_{i,t}$ the time t observation of variable y_i. For example, if the i^{th} variable is GDP, then $y_{i,t}$ is the value of GDP at t.A (reduced) p-th order VAR, denoted VAR(p), is $y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + e_t$,where c is a $k \times 1$ vector of constants (**intercept**), A_i is a $k \times k$ matrix (for every i = 1, ..., p) and e_t is a $k \times 1$ vector of error terms satisfying $\mathrm{E}(e_t) = 0$ every error term has mean zero, $\mathrm{E}(e_t e_t') = \Omega$ the contemporaneous covariance matrix of error terms is Ω (a $n \times n$ positive definite matrix), and $\mathrm{E}(e_t e_{t-k}') = 0$for any non-zero k there is no correlation across time; in particular, no serialcorrelation in individual error terms. The l-periods back observation y_{t-l} is called the l-th***lag*** of y. Thus, a pth-order VAR is also called a **VAR with *p* lags**.

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[17] Unfortunately, data for 2008 and 2009 are not available for most of variables used.

[18] Ibid

[19] Specification Tests in Over-identified Models An advantage of the GMM estimation in over- identified models is the ability to test the specification of the model. The J -statistic, introduced in Hansen (1982), refers to the value of the GMM objective function evaluated using an efficient GMM estimator: J = J(ˆδ (ˆS−1),ˆS−1) = ngn(ˆδ (ˆS−1))0ˆS−1gn(ˆδ (ˆS−1)) ˆδ (ˆS−1) = any efficient GMM estimator ˆS p→S Recall, If K = L, then J = 0; if K > L, then J > 0. Under regularity conditions (see Hayashi, 2000, Chap. 3) and if the moment conditions are valid, then as n → ∞ J d→ χ2(K − L) Remarks: 1. In a well-specified over-identified model with valid moment conditions the J-statistic behaves like a chi-square random variable with degrees of freedom equal to the number of over-identifying restrictions. 2. If the model is misspecified and/or some of the moment conditions do not hold (e.g., E[xitεt] = E[xit(yt − z0tδ0)] 6= 0 for some i), then the J –statistic will be large relative to a chi-square random variable with K – L degrees of freedom. 3. The J -statistic acts as an omnibus test statistic for model misspecification. A large J-statistic indicates a misspecified model. Unfortunately, the J –

statistic does not, by itself, give any information about how the model is misspecified

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