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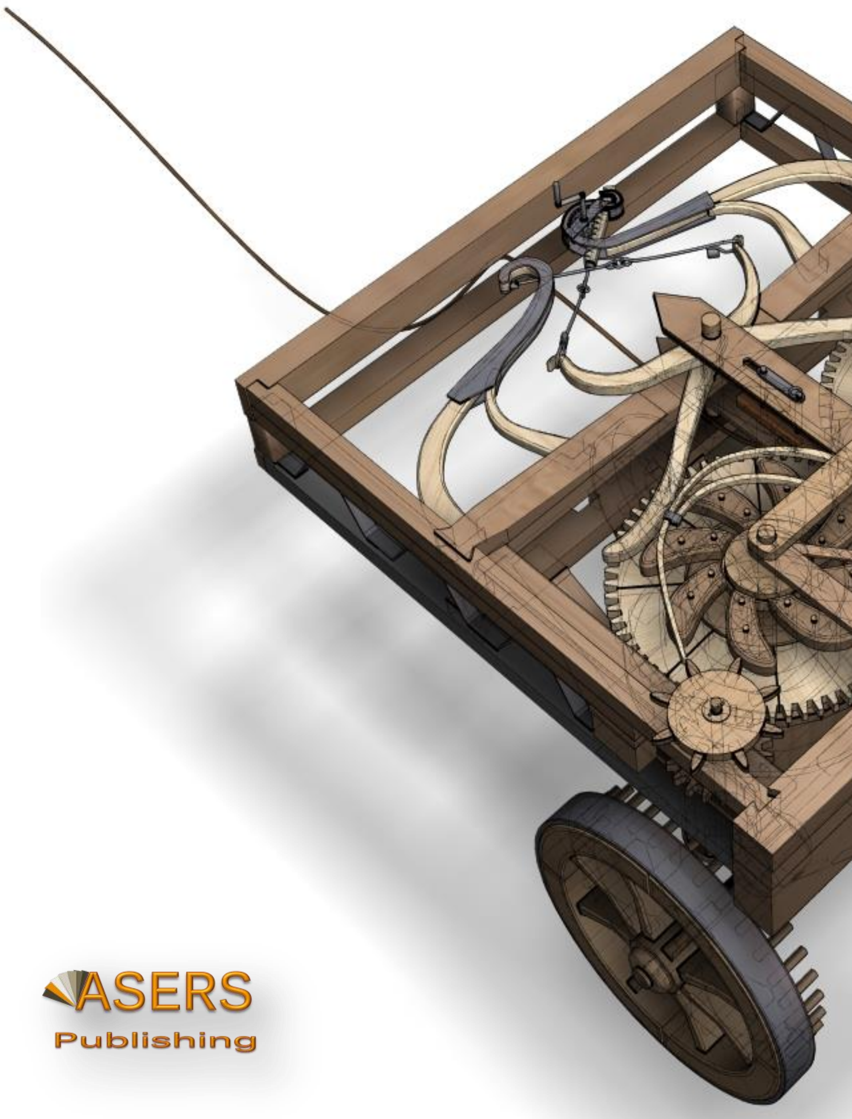

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ANALYZING THE DYNAMICS OF GROSS DOMESTIC PRODUCT GROWTH. A MIXED FREQUENCY MODEL APPROACH

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Abstract:

Frequency mismatch has been a problem in time series econometrics. Many monthly economic and financial indicators are normally aggregated to match quarterly macroeconomic series such as Gross Domestic Product when performing econometric analysis. However, temporal aggregation, although widely accepted, is prone to information loss. To address this issue, mixed frequency modelling is employed by using state space models with time-varying parameters. Quarter-on-quarter growth rate of GDP estimates are treated as monthly series with missing observation. Using Kalman filter algorithm, state space models are estimated with eleven monthly economic indicators as explanatory variables. A one-step-ahead forecast for GDP growth rates is generated and as more indicators are included in the model, the predicted values became closer to the actual data. Further evaluation revealed that among the group competing models, using Consumer Price Index (CPI), growth rates of Philippine Stock Exchange Index (PSEi), Exchange Rate, Real Money Supply, Wholesale Price Index (WPI) and Merchandise Exports are the more important determinants of GDP growth and generated the most desirable forecasts (lower forecast errors).

Keywords: Multi-frequency models, state space model, Kalman filter, GDP forecast.

JEL Classification: C5, C53, E3, E37

1. Introduction

Time series econometric models usually operate in a uniform time frequency (e.g. weekly, monthly, or quarterly data) even though most macroeconomic variables are observed or collected at different regularity. For instance, gross domestic product (GDP) of a country is normally reported quarterly while leading economic indicators, such as, value of net exports is collected monthly. Financial data relevant to the economy, such as the local composite stock price index, for instance, is even observed at a higher frequency, daily data. As a result, econometricians are faced with a dilemma of constructing a model with variables sampled at different frequencies. One has to aggregate the data with higher frequency to match variables with lower frequency to proceed with model building and estimation.

Temporal aggregation has been the predominant technique among practitioners to address the problem of having multi-frequency series. Albeit practical and widely acceptable, aggregation of higher frequency data to match that of lower frequencies may result in information loss. The dynamics between two series certainly cannot be assessed if say, both series are not measured at the same time period.

For example, on one hand, the stock exchange index – a usual barometer of capital investment in the country and one of the leading economic indicators (LEI) – can be observed intraday. On the other hand, GDP, which measures the overall economic activity is reported quarterly. Any dynamics between the two variables is normally assessed by aligning the variables to the same frequency and in this case, quarterly. The daily or monthly fluctuations in the stock exchange index, therefore, are not taken into account since it had to be aggregated or trimmed down to represent the value of the index at each quarter's end.

Same goes with GDP and exports. Since the economy is affected by exports of goods to other countries, it is important to see how a drop or rise in export would affect the overall economic growth. However, GDP estimates are not available in a monthly format unlike the value of exports. Dynamics within each quarter between the two series then cannot be analyzed if models are operated in a quarterly format.

The mismatch of frequencies in most macroeconomic data potentially leads to information loss when econometric models resort to temporal aggregation motivated this study. Thus, this paper primarily aims to provide an alternative in the form of a multi-frequency model.

Multi-frequency models, such as Mixed Data Sampling (MIDAS) regression models of Ghysels, et. al (2004) and Varied Data Samling (VARDAS) model of Qian (2010), have shown to carry desirable results in empirical studies when compared to the usual models with time aggregated data. Retaining the original frequency of the data in an econometric model, intra-month or intra-quarter dynamics can be analyzed.

Using multi-frequency approach can also be used to forecast end-quarter or end-day values using monthly or intraday data, respectively – or *nowcast* as Gotz and Hecq (2013) coined the procedure.

This study employed a multi-frequency procedure in forecasting instead of resorting to temporal aggregation. Specifically, quarterly GDP estimates are treated as a monthly data with missing observations and relevant macroeconomic indicators, such as total merchandise exports, imports, terms of trade index, consumer price index, wholesale price index, electricity (Meralco) sales, the peso-dollar exchange rate, money supply (M1), number of new businesses from Securities and Exchange Commission (SEC), stock price index and tourist arrivals were used as explanatory variables – all of which are available at a monthly basis. The ability of the state space model in handling missing observation was utilized to predict GDP using monthly series.

2. Mixed-frequency models

Even before the problem of mismatched frequencies of data, econometricians have already been challenged with the peculiarities of macroeconomic data. Practitioners have hundreds of series at their disposal, although most of them are not desirably long enough (e.g. 20 to 40 years of quarterly data). Dynamic factor models (DFM) which can produce models for datasets that has more number of series than the number of time observations. Stock and Watson (2010) discussed in detail the DFM and enumerated several related studies.

The DFM, which was based on the theory that there are latent dynamic factors that affect the co-movement of a collection time-series variables, was first used by Geweke in 1977 to apply a factor model designed for cross-sectional data in a time-series analysis. Sargent and Sims in the same year showed that two latent factors were able to explain a large portion of variability of different macroeconomic variables in the United States. The technique, however, has now been used in different applications such as in two-stage regression as instruments and in forecasting (Stock and Watson, 2010).

Giannone, Reichlin and Small (2008), for instance, developed a procedure that updates current-quarter GDP forecast every time a monthly data within that quarter are released using DFM. With a large collection of monthly data with varying release dates factors were computed using principal component and then Kalaman Smoothing. The marginal impact of each data released was able to be analyzed since the model was updated every time a monthly observation was released. Their results showed that current-quarter GDP forecast's precision increases as new monthly data comes in. Moreover, empirical evaluation of their proposed model showed fare performance compared to benchmarks they used.

Arouba, Deibold and Scotti (2008) also used dynamic factor model to measure economic activity at high frequency. They used a DFM to extract latent factors from a variety of stock and flow data sampled at different frequencies as a measure of the macroeconomic state. They further suggested using higher frequency data in empirical macroeconomic studies instead of the usual monthly or quarterly data. One of the empirical examples shown in their study revealed that incorporating weekly initial jobless claims to GDP and unemployment model was better compared to GDP and unemployment model only.

Similarly, Camacho and Perez-Quiros (2008) proposed an approach in forecasting euro area quarterly GDP in real-time using dynamic factor model. They also looked at the impact of each release of new data to their forecasts. Their work primarily dealt with problems such as asynchronous macroeconomic data release and using euro area aggregated data with short time spans.

Aside from DFM, another popular approach in dealing with multi-frequency model Mixed Data Sampling (MIDAS) regression models. Ghysels, Santa-Clara and Valkanov (2004) introduced MIDAS to deal with models with varied frequencies of dependent and explanatory variables. These models use distributed lags of regressors which are sampled at a higher frequency compared to dependent variables which is sampled at a lower frequency. One of their example models involved stock market volatility. The quadratic variation over a long future horizon which was sampled at low frequency was modelled using intra-day market information.

Another example in their 2004 paper involved GDP and other macroeconomic variable sampled at higher frequency such as inflation. They suggested that instead of aggregating monthly inflation data to match the quarterly GDP estimates, one can implement a MIDAS regression to combine the two series. One of their key findings was they were able to show a more efficient estimation using MIDAS regression compared to the usual regression with time-aggregated data.

Armesto, Engemann and Owyang (2010) surveyed different procedures aside from MIDAS modeling to circumvent the dilemma of mixed frequency data. Their problem was most of the macroeconomic variables are sampled monthly or quarterly whereas financial data which were found to be related to the macroeconomy are sampled at higher frequencies. Their paper showed that in some cases, aggregating the higher frequency data (e.g. averaging) did not have any disadvantage, although in some cases, the MIDAS technique introduced by Ghysels, Santa-Clara and Valkanov showed to be more beneficial especially in intra-period analysis.

Faced with the similar problem, Clements and Galvão (2008) used monthly and weekly data to generate short-term forecasts of US output growth. Since GDP is sampled at quarterly basis, an AR process was a reasonable candidate model. Thus, they extended the distributed lag MIDAS specification of Ghysels, et. al., and introduced an AR component, resulting to a MIDAS-AR specification which was shown to have better short term forecast compared to a benchmark AR model or and AR distributed lag model.

Similarly, Tay (2006) compared an AR(1) GDP growth model following a MIDAS framework and a usual quarterly AR(1) model of GDP growth with the most recent stock price index for each quarter as an additional explanatory variable. The result of his paper showed that particularly in recent years, stock returns were useful in predicting GDP growth. His results also showed that his MIDAS model was superior to his benchmark model. Furthermore, his study suggests that mixing frequencies can lead to better forecasts.

MIDAS was also used in Asimakopoulos, Paredes and Warmedinger's (2013) study of forecasting fiscal time series of different euro area countries. Using mixed frequency fiscal variables, MIDAS was employed to analyze annual or year-end fiscal variables. Their empirical work was able to show that as quarterly information within the year was able to improve the year-end forecast.

Aside from MIDAS, another approach in multi-frequency modelling is Mixed-Frequency VAR (MF-VAR) models. Basically, MF-VARs are VAR models containing component variables with different frequency. Götz and Hecq (2013) showed that a low frequency (aggregated) data (e.g. A quarter), as a function of its lagged value and distributed lagged values of the independent variable with higher frequency (disaggregated data, e.g. monthly data within the same quarter). Disaggregated data, meanwhile, is a function of the aggregated data and its lagged values. In the same study, they introduced *nowcasting* causality for mixed-frequency VAR models.

Nowcasting was predicting the value of a certain variable observed at lower frequency using variables observed at higher frequency and available in the current period. Nowcasting causality, meanwhile, is analogous to Granger causality, but is restricted to a certain time period, say, months within each quarter. Both nowcasting and Granger causality was then tested among selected US economic data.

As an example, they showed that the weekly growth rate of the stock of money (M2) in the US does not Granger causes the monthly growth rate of industrial production index but nowcasting causality was detected between the two series. They also showed that weekly growth of M2 does not Granger causes nor nowcasting causes monthly variation in the civilian unemployment rate.

A variation of MF-VAR but in a Bayesian context was used by Qian (2010) called Varied Data Sampling (VARDAS). A key feature of the procedure was that it only requires users to provide the data and the aggregation structure of each series while the estimation of VAR is similar to the ordinary VAR model. As an example, a previous study involving demand and supply component of GNP and unemployment (both quarterly series) was replicated using monthly unemployment data. The results showed, using impulse-response function, that the dynamics between unemployment and GNP components was more evident.

Still in the context of mixed-frequency VAR, Mittnik and Zadrozny (2004) used Kalman filtering method to forecast monthly German real GDP. They argued that when quarterly GDP is regressed to monthly indicators, it may not address reverse causality. Instead, they proposed a quarterly and monthly VAR(2) models of quarterly GDP, monthly industrial production, and monthly current business condition. Their empirical work showed that the monthly VAR model produced better short-term (1 to 3 months) GDP forecast while their quarterly model produced a better long-term forecast (1 up to 24 months ahead).

A paper by Kuzin, Marcellino and Schumacher (2009) compared the performance of the two popular approaches, MIDAS and MF-VAR, in terms of forecasting and now-casting of GDP growth of euro area using 20 monthly indicators as explanatory variables. Their results showed that two competing models tend to complement each other. MF-VAR was found to perform better for longer horizons while the other approach performs better for shorter horizons.

Aside from using the MIDAS approach, some papers treated low frequency data as high-frequency data with missing observations. Those missing observations are then forecasted to proceed with model building at a high sampling frequency. Fernández (1981) suggested interpolation by estimating missing data points using relevant series. This can be applied to stock data such as demand deposits which are usually available at year end to produce quarterly or monthly series.

Aside from Macroeconomics, mixed-frequency models were also used in signal processing. The Kalman Filter algorithm was also used by Fulton, Bitmead and Williamson (2001) to reproduce missing elements in an array processing. Using a state space model, a signal model was used to reconstruct missing data streams. Kalman smoothing was implemented and showed fare performance compared to an existing process to reconstruct missing data streams.

From those literatures noted above, this study was driven in treating deseasonalized (quarter-on-quarter) GDP growth rates as a monthly series with missing observations. A one-step-ahead predicted GDP growth rates was then generated from state space models with monthly leading economic indicators as independent variables. Forecasting capabilities of competing models were then evaluated using different criteria.

3. Proposed model and methodology

The study treats the quarter-on-quarter growth rate of the seasonally-adjusted GDP estimates as a monthly series to match the higher frequency of different macroeconomic variables used in the study. The quarterly observations were placed on months corresponding to end of quarters (e.g. March, June, September and December) and the rest of the months were treated as missing observations. A monthly GDP growth rate series is generated by estimating the state space model with actual GDP growth rate as the left hand side of the signal equation and leading economic indicators (e.g. Stock price index (PSEi), Peso-Dollar exchange rate, consumer price index, money supply - M1, wholesale price index, total merchandise exports, total merchandise imports, terms of trade index for merchandise goods, Meralco sales, registered stock corporations and partnership, and tourist/visitor arrivals) as exogenous variables with time-varying parameters.

With the exception of exports, these are the same set of variables used as leading economic indicators of GDP by the Philippine Statistics Authority (PSA). Since they are available on a monthly series and are used in official economic planning, the study adopted the same set of indicators and opted to add merchandise exports as well. The hotel occupancy rate was also in the list of variables considered, however, a monthly series with length suitable for the study was not available.

The indicators were entered in the model one at a time depending on the usual order of their release or frequency resulting to eleven competing state space models. To evaluate the accuracy of the monthly GDP growth rates, 3-month averages corresponding to each quarter of the year were compared to the actual data. Root mean squared error and mean percentage errors were also computed to compare the state space models.

3.1. Data definition and source of data

The study used data sampled at different frequencies, specifically, quarterly and monthly economic time series variables. Quarterly GDP data was the low frequency series while all other indicators were collected on a higher frequency, i.e. monthly basis. When seasonality was present, the data were seasonally adjusted using Census X12[1] program which was a built-in package in Eviews7.

Real GDP level from 2000 to 2013 was downloaded from the NSCB website and was seasonally adjusted. Quarter-on-quarter growth rates were then computed by taking the first difference of logarithms of the seasonally adjusted series. The resulting series was then converted to a monthly series by placing the quarterly observations on months corresponding to quarter ends. This now served as the dependent variable or the left hand side of the signal series in the state space models.

The explanatory variables used, meanwhile, were growth rates of eleven different economic variables mentioned earlier. Their growth rates were computed by taking the first difference of logarithm of

[1] Census X12 is a seasonal adjustment program developed by U.S. Census Bureau and is the improved version of X-11 Variant of Census II seasonal adjustment program originally written by Shiskin, Young and Musgrave in 1967. The program is based on the premise that economic time series can be decomposed to seasonal component, trend-cycle component, trading-day component and irregular component.

their levels as well, i.e. month-on-month growth rate. The indicators and their variable names are listed in Table 1. The time series data are from January 2000 to December 2013 except for the Meralco sales which was only up to May 2013 and number of new business incorporations which was up to December 2012 only. The definition and sources of each indicator are briefly discussed in the succeeding paragraphs.

Table 1. List of economic indicators used

Indicator
Stock price index *(psei)*
Peso-Dollar exchange rate *(fx)*
Consumer price index *(cpi)*
Real Money supply - M1 *(rm1)*
Wholesale price index *(wpi)*
Total merchandise exports *(exports)*
Total merchandise imports *(imports)*
Terms of trade index for Merchandise Goods *(trade_indx)*
Tourist/visitor arrivals *(visitors)*
Meralco sales *(meralco)*
Registered stock corporations and partnership *(new_buss)*
() - variable name

Stock price index or PSEi is the main composite index of the local stock market. It primarily serves as a measure of fluctuations in average price of equities being traded in Philippine Stock Exchange (PSE) and is available by end of each business day on the PSE website (http://www.pse.com.ph). For this study, the month-end value of PSEi was used for each month from January 2000 to December 2012. The historical data were downloaded from Bangko Sentral ng Pilipinas (BSP) website (http://www.bsp.gov.ph/), Yahoo!Finance website (http://finance.yahoo.com/) and Bloomberg website (http://www.bloomberg.com/).

The Peso-Dollar exchange rate (fx) is the official guiding rate of exchange of one US dollar to the local currency. It is the weighted average of all foreign exchange trades done through the Philippine Dealing System. It is reported daily and is available for download from the BSP website. The monthly exchange rate used in the study was the monthly average exchange rate which was also downloaded from the central bank's website.

Consumer price index (CPI) is a composite index that serves as an indicator of average monthly changes in retail prices of a basket of commodities purchased by households and is based on 2006 prices. The monthly series was downloaded from the PSA - National Statistics Office website http://census.gov.ph/.

Real money supply is the ratio of money supply (M1) over CPI multiplied by 100. Money supply (M1), also called narrow money, is currency in circulation or outside depository corporations and transferable deposits. It is available as a monthly series and was downloaded from the central bank's website.

Similar to CPI, wholesale price index is also a composite index of prices, wholesale prices in particular, of certain commodities. It has a base year of 1998 and has a monthly series available for download from NSO website.

Total merchandise imports and exports are the free on board (FOB) value of goods coming in and out (respectively) of the country through a seaport or airport and are properly cleared by the Bureau of Customs. Observations in the time series are in thousands of US dollars and correspond to cumulative value for the month only. Trade data were downloaded from the NSO website as well.

A monthly series was not readily available for the terms of trade index, thus, it was computed by following the LEI technical notes posted on the NSCB website[2]. The formula below was applied to the monthly series to come up with a monthly series for terms of trade index with 2000 as the base year.

$$Terms\ of\ Trade\ index = \frac{Merchandise\ export\ price\ index}{Merchandise\ import\ price\ index} \times 100$$

$$Merchandise\ export\ price\ index = \frac{FOB\ value\ of\ export\ current\ price}{\frac{\sum_{\forall\ months\ of\ 2000} export\ value}{12}} \times 100$$

$$Merchandise\ import\ price\ index = \frac{FOB\ value\ of\ import\ current\ price}{\frac{\sum_{\forall\ months\ of\ 2000} import\ value}{12}} \times 100$$

Data on tourist arrival pertains to the number of visitors in the country. A visitor, as defined by NSCB Resolution No. 11 Series of 2003, is anyone travelling to a place outside his/her usual environment and staying there for less than a year. The data is compiled by the Department of Tourism and can be downloaded from their website (http://www.tourism.gov.ph/). Monthly Meralco sales (in million kilowatt per hour) and registered stock corporations and partnership from the Securities and Exchange Commission were proxy variables for electric energy consumption and number of new businesses, respectively.

3.2. State space model and Kalman filter

The study's main feature is its use of state space models to fit a model consisting of variables with different frequencies. A state space model is usually employed to deal with dynamic relationship of time series data with unobserved components. A wide range of literature have used such model to estimate underlying components such as rational expectations, trend and cycle and missing observations to name a few. Many time series models, such as simple linear regression and ARIMA models, can also be represented using state space models.

State space modelling has two primary benefits first of which is it can integrate unobserved components called state variables with observable series in a single system. The second advantage of the technique is it uses a recursive algorithm called Kalman filter to recursively update the state variables.

To illustrate, consider a univariate time series y_t represented as:

$$y_t = \mu_t + e_t \ , \ e_t \sim N(0, \sigma_e^2) \quad (1)$$

$$\mu_{t+1} = \mu_t + \eta_t \ , \ \eta_t \sim N(0, \sigma_\eta^2) \quad (2)$$

where {e_t} and {η_t} are independent Guassian white noise series and $t = 1,2,\ldots,T$.

[2] http://nscb.gov.ph/lei/2014/1st_Qtr/TechnicalNotes.asp

For the moment, let the initial value μ_1 be equal to zero. In this example, y_t is the observed series with an underlying or unobserved component μ_t. In state space modelling, the first equation is called the signal equation while the second, which follows a drift-less random walk and is not directly observable, is called the state equation. The signal equation incorporates the state variable with the observed series accounting for measurement error e_t while the state equation represents the time evolution of the state variable with innovation η_t. The purpose of the analysis is to recover or estimate the unobserved state μ_t from the observable data $\{y_t|t=1, \ldots, T\}$. To do this, there are three common approaches or inferences that can be employed. These are, filtering, prediction and smoothing.

The three approaches differ on how they recover the state variable using the information available. To illustrate, let $F_t = \{y_1, \ldots, y_t\}$ be the information available at time t (inclusive). Filtering uses the information F_t, i.e. removing measurement errors from the data. Prediction, meanwhile, uses a one-step ahead forecast of μ_t or y_t and smoothing estimates μ_t using F_T (where $T>t$, i.e. using all information).

Furthermore, these approaches can be done using the Kalman filter algorithm. Its main purpose is to recursively update the state variables when new information becomes available. Consider the basic filter approach where estimation of the state variable uses information up to time t. The algorithm consists of two major parts, namely, predicting and updating. In the first part, a one-step ahead prediction of y_t is estimated utilizing information from $t=1$ up to $t-1$, i.e. $y_{t|t-1}$. When y_t is realized at time t, the prediction error or innovation can be computed as $\eta_{t|t-1} = y_t - y_{t|t-1}$. This innovation, η_t, now contains information about the state variable μ_t which was not captured in $\mu_{t|t-1}$ and is incorporated in estimating μ_t with $\mu_{t|t} = \mu_{t|t-1} + K_t\eta_{t|t-1}$, where K_t is called the Kalman gain or the weight assigned to the innovation.

3.3. Generating monthly Gross Domestic Product estimates

One of the methodologies adopted in this paper came from Fulton, Bitmead and Williamson (2001) study on signal processing which was discussed earlier. This paper departs from theirs mainly by using economic data, specifically, quarter-on-quarter growth rates of deseasonalized GDP entered at a monthly frequency with observations placed at each month corresponding to quarter ends (e.g. March, June, September and December) and the rest of the sample were treated as missing observation. To illustrate the series, let $t = 1, 2, \ldots, 165$ corresponding to 165 months from January 2000 to December 2013. The second quarter of 2000 GDP growth rate was denoted as $GDPGR_6 = 0.13$ at June 2000 – corresponding to the last month of Q2 2000. Third quarter 2000 GDP growth rate is denoted as $GDPGR_9 = 2.11$ and entered at September 2000 and so on. The observations in between quarter ends were treated as missing observations.

The study then took advantage of the state space models' ability to handle missing observations. Thus, state space models were fitted to the monthly GDP data and the Kalman Filter algorithm was used to generate monthly GDP growth rate series. Following the discussion of state space models in the previous section, let y_t or the signal equation be the monthly GDP data with missing observations and μ_t is the state equation or unobserved component. We then supposed that $\{ y_t \}_{t=l+1}^{l+h}$ were missing, where $h\geq 1$ and $1\leq l\leq T$. For $t \in \{l+1,\ldots, l+h\}$, μ_t is expressed as a linear combination of μ_{l+1} and $\{\eta_j\}_{j=l+1}^{t-1}$. Thus, for $t \in \{l+1,\ldots, l+h\}$,

$$E(\mu_t|F_{t-1}) = E(\mu_t|F_t) = \mu_{l+1|l} \tag{3}$$

$$Var(\mu_t|F_{t-1}) = Var(\mu_t|F_t) = \Sigma_{l+1|l} + (t-l-1)\sigma_\eta^2. \tag{4}$$

Consequently, $\mu_{t|t-1} = \mu_{t-1|t-2,}$ for t = *l+1,…, l+h*. In other words, the Kalman filter algorithm can still be used even with missing observations by equating the Kalman gain and prediction error (η_t, used in updating state estimates) to zero.

Similarly, the study made use of this procedure, but instead of having a signal equation stated above, a set of exogenous variables with time-varying parameters were fitted. The time-varying parameters were considered as state variables and the corresponding state equations followed a drift-less random walk process. Thus, on periods with no actual GDP growth rate is available, a one-step-ahead forecast is generated factoring in the indicators in the signal equation.

Each indicator is entered one after the other, depending on their time of release, starting with the growth rate of PSEi in the first model. The change in Peso-Dollar exchange rate is then added to that to form the second state space model and so on until all indicators were included resulting to a group of eleven different models.

The signal equation was composed of the GDP growth rate on the left hand side and growth rate of the economic indicators with time-varying parameters on the right hand side. Generally, the signal and state equations are described below.

$$dlog(GDP_t) = C(1) + \begin{pmatrix} SV_{1,t} \\ \vdots \\ SV_{11,t} \end{pmatrix} (PSEi_t \quad \dots \quad new\_buss_t) + e_t \tag{5}$$

$$\begin{pmatrix} SV_{1,t} \\ \vdots \\ SV_{11,t} \end{pmatrix} = \begin{pmatrix} SV_{1,t-1} + \eta_{1,t-1} \\ \vdots \\ SV_{11,t-1} + \eta_{11,t-1} \end{pmatrix} \tag{6}$$

To have another set of competing models, the same set of indicators were used and entered with the same manner but the error term in each signal equation is treated as a state variable and follows has an AR(1) state equation.

The initial one-step-ahead predicted value for the states and variance matrix was set to zero and 1 million, respectively. After a state space models were specified, signal series was generated using one-step-ahead forecast to represent the monthly estimates of GDP growth rates.

3.4. Evaluating the monthly estimates of Gross Domestic Product growth rate

To assess the performance of the proposed method, the monthly growth rates were aggregated by quarter using simple arithmetic mean and were compared to the actual data. Root mean squared error (RMSE) and mean absolute error (MAE) are also calculated to further check the models' performance.

4. Results and discussion

4.1. Preliminary analysis

The study used macroeconomic variables sampled at different frequencies to illustrate a multi-frequency model. Specifically, a state space model consisting of growth rates of GDP and of leading economic indicators was generated. The GDP series was treated as a monthly series with missing observations, then a one-step-ahead predicted series was generated using a Kalman filter algorithm.

Gross domestic product from the National Income Accounts (NIA) report of the PSA, is released quarterly, specifically, a month after each quarter end. The quarterly GDP levels at constant 2000 prices were seasonally adjusted using Census X12 in Eviews7 then the quarter-on-quarter growth rate was calculated by taking the difference of logarithms of two succeeding quarters (i.e. *log(GDPt) – log(GDPt-1)*). After which, it was treated as a monthly series and the observations were placed on months corresponding to quarter ends. This new series is then used as the left-hand side of the signal equation.

Figure 1 and 2 below illustrates the original and seasonally adjusted quarterly series of GDP levels and quarter-on-quarter growth rates, respectively. Figure 3, meanwhile, shows the growth rate series in monthly frequency.

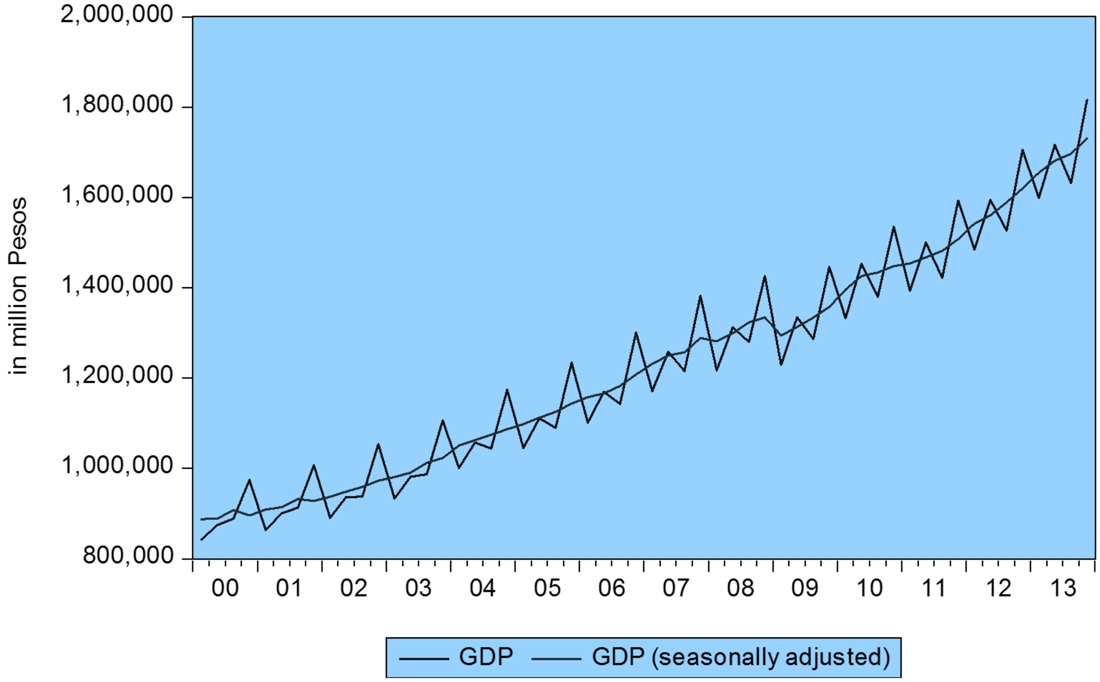


Figure 1. Quarterly GDP levels at constant 2000 prices, original and seasonally adjusted series, 2000 -2013

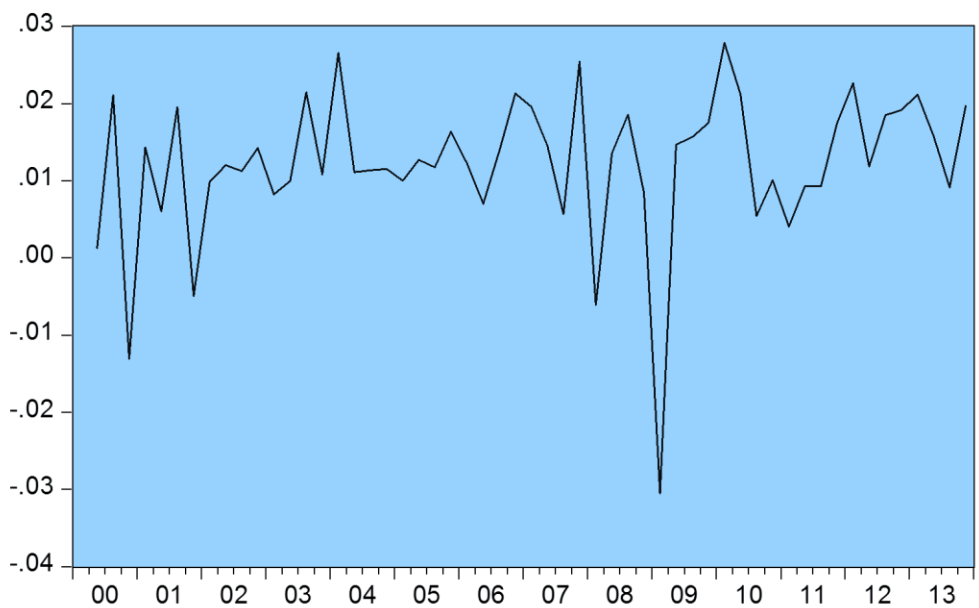


Figure 2 - Quarter-on-quarter GDP (seasonally adjusted) growth rate, 2000-2013

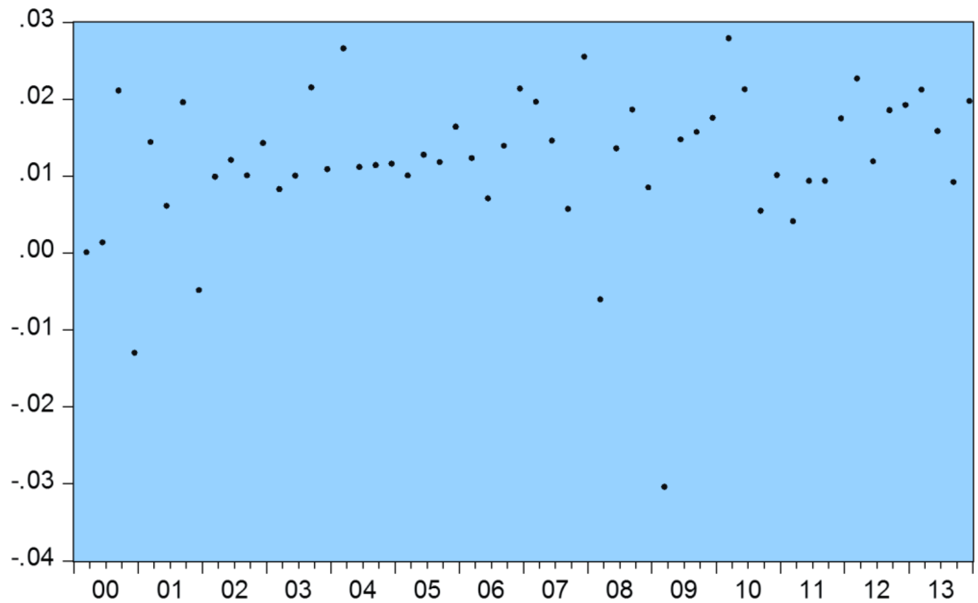


Figure 3. Monthly series of GDP (seasonally adjusted) growth rate, 2000-2013

Since Figure 3 is the monthly equivalent of the original quarterly growth rate series, the graph only shows the quarterly observations placed at months corresponding to quarter ends. The rest of the series is treated as missing observations. Both graphs, however, illustrate the same movement or pattern of growth. A noticeable drop in growth can be seen in both graphs during 2008 which clearly reflects the global financial crisis during the period.

Meanwhile, the leading economic indicators together with merchandise exports were also seasonally adjusted when seasonality was present and its growth rates were used as exogenous variables with time-varying coefficient in the signal equations.

After using Census X12 to seasonally adjust the series (except for PSEi where no seasonality was detected), presence of a unit root on their growth rates – computed as first difference of the logarithm of each variables – were tested. Results of Augmented Dickey-Fuller unit root test (see Appendix) revealed that growth rates of the indicators were all stationary.

Figure 4 and 5 illustrates the levels and growth rates of the economic indicators used in the study. Similar to the graphs of GDP, most of the graphs of monthly economic indicators reflect the 2008 financial crisis. It is apparent, especially in the PSEi, foreign exchange, exports, imports, and registered stock corporations and partnerships.

4.2. Estimation of state space models

State space models were estimated using EViews 7 statistical package. Models were fitted by entering the indicators one by one depending on its date of release or availability (e.g. PSEi is available by end of day, thus, it was the first indicator used followed by exchange rate, and so on). Another set of competing models were estimated by replacing the error term in signal equations, which was previously set to a normalized error, with a state variable that follows an AR(1) process. Table 2 summarizes the signal equation of the eleven state space models estimated.

Table 2 – State space models and corresponding signal equation

Model	Signal equation
SS01	@signal dl_gdp_sa = c(1) + sv1*dlog(psei) + [var=1]
SS02	@signal dl_gdp_sa = c(1) + sv1*dlog(psei) + sv2*dlog(fx_sa) + [var=1]
SS03	@signal dl_gdp_sa = c(1) + sv1*dlog(psei) + sv2*dlog(fx_sa) + sv3*dlog(cpi_sa) + [var=1]
SS04	@signal dl_gdp_sa = c(1) + sv1*dlog(psei) + sv2*dlog(fx_sa) + sv3*dlog(cpi_sa) + sv4*dlog(rm1_sa) + [var=1]
SS05	@signal dl_gdp_sa = c(1) + sv1*dlog(psei) + sv2*dlog(fx_sa) + sv3*dlog(cpi_sa) + sv4*dlog(rm1_sa) + sv5*dlog(wpi_sa) + [var=1]
SS06	@signal dl_gdp_sa = c(1) + sv1*dlog(psei) + sv2*dlog(fx_sa) + sv3*dlog(cpi_sa) + sv4*dlog(rm1_sa) + sv5*dlog(wpi_sa) + sv6*dlog(exports_sa) + [var=1]
SS07	@signal dl_gdp_sa = c(1) + sv1*dlog(psei) + sv2*dlog(fx_sa) + sv3*dlog(cpi_sa) + sv4*dlog(rm1_sa) + sv5*dlog(wpi_sa) + sv6*dlog(exports_sa) + sv7*dlog(imports_sa) + [var=1]
SS08	@signal dl_gdp_sa = c(1) + sv1*dlog(psei) + sv2*dlog(fx_sa) + sv3*dlog(cpi_sa) + sv4*dlog(rm1_sa) + sv5*dlog(wpi_sa) + sv6*dlog(exports_sa) + sv7*dlog(imports_sa) + sv8*dlog(trade_indx_sa) + [var=1]
SS09	@signal dl_gdp_sa = c(1) + sv1*dlog(psei) + sv2*dlog(fx_sa) + sv3*dlog(cpi_sa) + sv4*dlog(rm1_sa) + sv5*dlog(wpi_sa) + sv6*dlog(exports_sa) + sv7*dlog(imports_sa) + sv8*dlog(trade_indx_sa) + sv9*dlog(visitor_sa) + [var=1]
SS10	@signal dl_gdp_sa = c(1) + sv1*dlog(psei) + sv2*dlog(fx_sa) + sv3*dlog(cpi_sa) + sv4*dlog(rm1_sa) + sv5*dlog(wpi_sa) + sv6*dlog(exports_sa) + sv7*dlog(imports_sa) + sv8*dlog(trade_indx_sa) + sv9*dlog(visitor_sa) + sv10*dlog(meralco_sa) + [var=1]
SS11	@signal dl_gdp_sa = c(1) + sv1*dlog(psei) + sv2*dlog(fx_sa) + sv3*dlog(cpi_sa) + sv4*dlog(rm1_sa) + sv5*dlog(wpi_sa) + sv6*dlog(exports_sa) + sv7*dlog(imports_sa) + sv8*dlog(trade_indx_sa) + sv9*dlog(visitor_sa) + sv10*dlog(meralco_sa) + sv11*dlog(new_buss_sa) + [var=1]

Figure 4. Monthly economic indicators used as exogenous variables, levels and seasonally adjusted (SA)

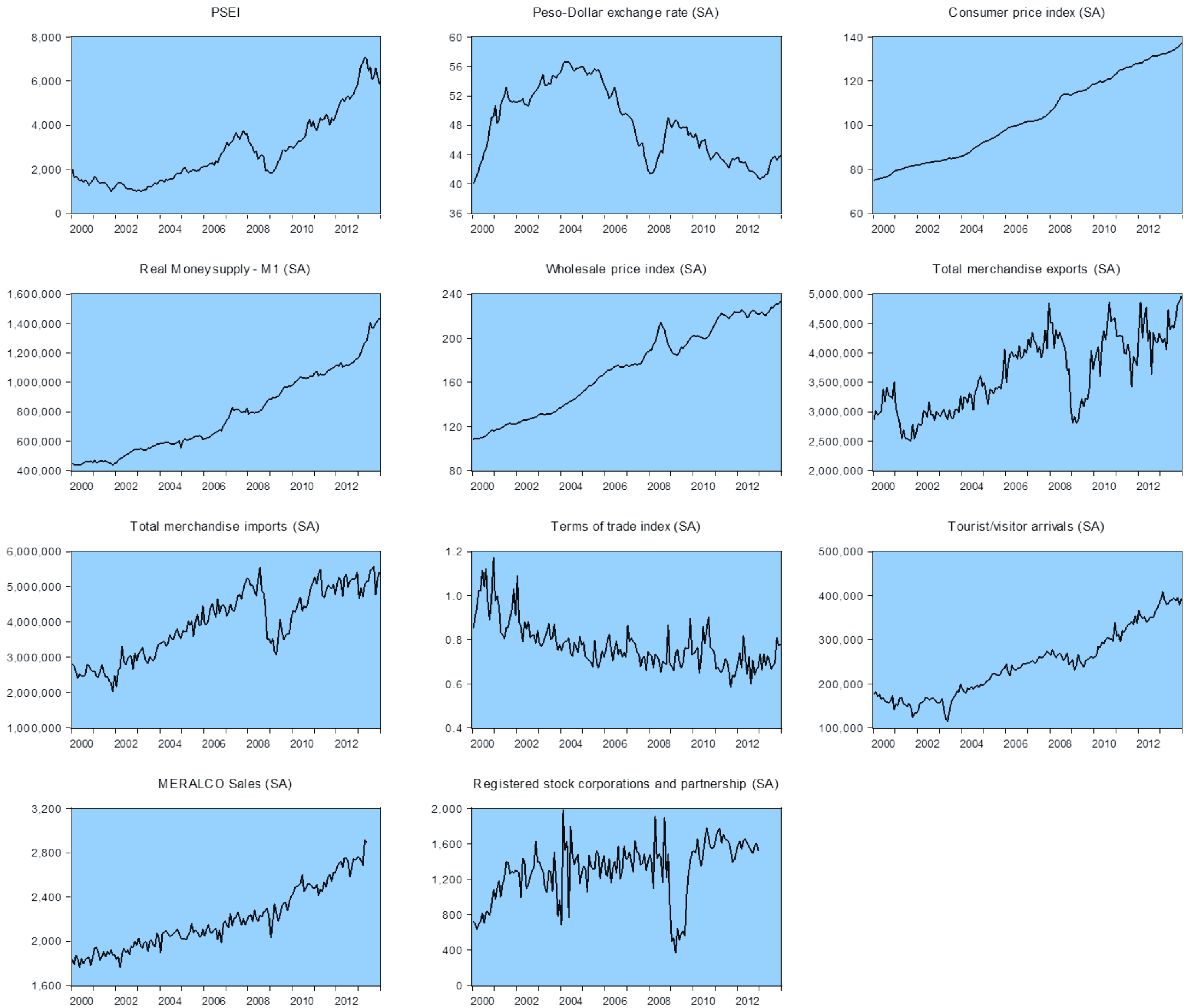
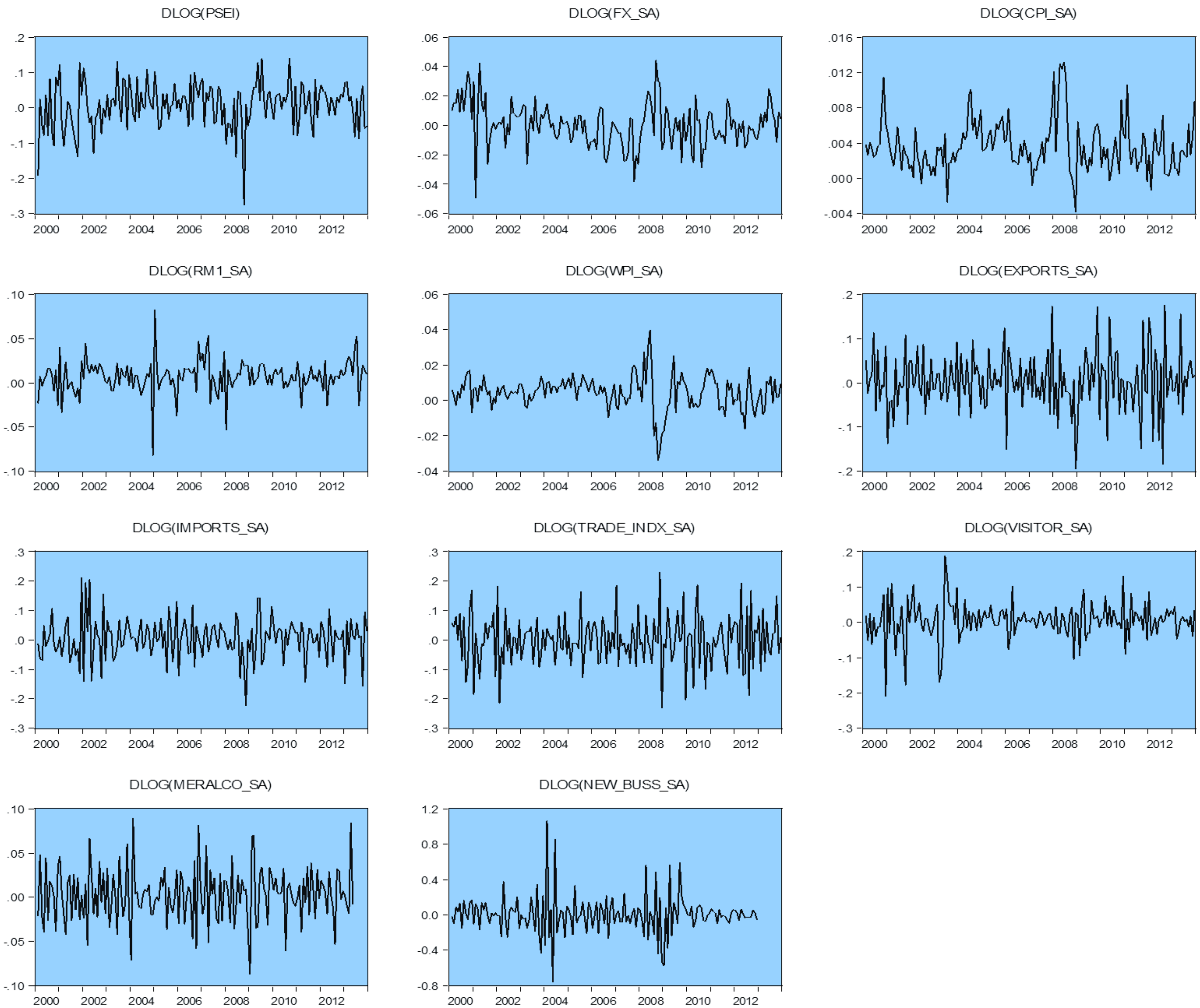


Figure 5. Monthly economic indicators used as exogenous variables, growth rates



A second set of competing models were estimated wherein the error term in each signal series (*[var=1]*) is replaced by a state variable which follows an AR(1) process.

Table 3. Eviews 7 state model estimation, SS06

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.0181	33.1971	0.0005	0.9996
	Final State	Root MSE	z-Statistic	Prob.
SV1	-0.0827	6.2976	-0.0131	0.9895
SV2	-0.2258	14.3358	-0.0158	0.9874
SV3	-1.3077	45.2049	-0.0289	0.9769
SV4	0.0800	10.0241	0.0080	0.9936
SV5	0.0855	19.1895	0.0045	0.9964
SV6	0.0266	5.0834	0.0052	0.9958
Log likelihood	-84.4252	Akaike info criterion		3.0509
Parameters	1.0000	Schwarz criterion		3.0871
Diffuse priors	0.0000	Hannan-Quinn criter.		3.0649

After running the specification codes in Eviews 7, the one-step-ahead predicted signals for each state space model were generated. Table 3 summarizes a sample EViews7's estimation output of the state space model for the model with six indicators in the signal equation and normalized error. Figure 6 illustrates the corresponding one-step-ahead predicted signals from the same state space model shown in Table 3. Likewise, Table 4 and Figure 7 correspond to generated state space model with all eleven indicators in the signal equation with normalized error. The predicted signals of the other state space models are illustrated in Figure 8.

Table 3. Eviews 7 state model estimation, SS06

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.0181	42.1628	0.0004	0.9997
	Final State	Root MSE	z-Statistic	Prob.
SV1	-0.0419	7.3599	-0.0057	0.9955
SV2	-0.3625	19.3121	-0.0188	0.9850
SV3	-1.3848	56.8430	-0.0244	0.9806
SV4	0.0913	12.4696	0.0073	0.9942
SV5	0.1880	25.0936	0.0075	0.9940
SV6	0.0918	8.9788	0.0102	0.9918
SV7	-0.1123	10.7053	-0.0105	0.9916
SV8	-0.0883	9.5361	-0.0093	0.9926
SV9	0.0152	7.6970	0.0020	0.9984
SV10	-0.0560	10.5959	-0.0053	0.9958
SV11	0.0123	6.6167	0.0019	0.9985
Log likelihood	-117.0225	Akaike info criterion		4.5393
Parameters	1.0000	Schwarz criterion		4.5769
Diffuse priors	0.0000	Hannan-Quinn criter.		4.5537

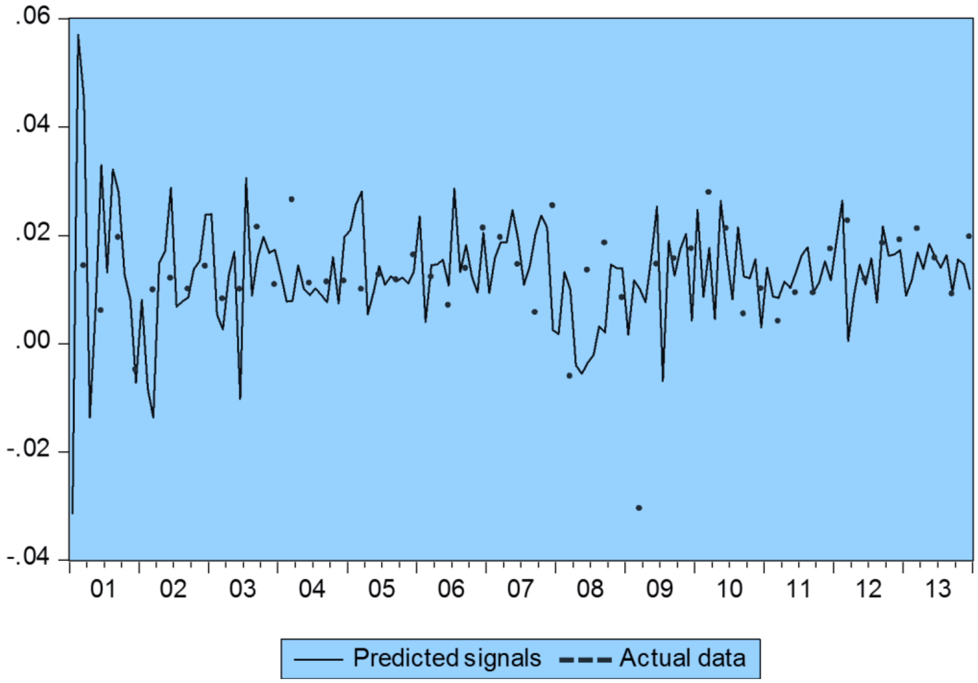


Figure 6. Monthly actual GDP growth and 1-step-ahead predicted signals from SS06

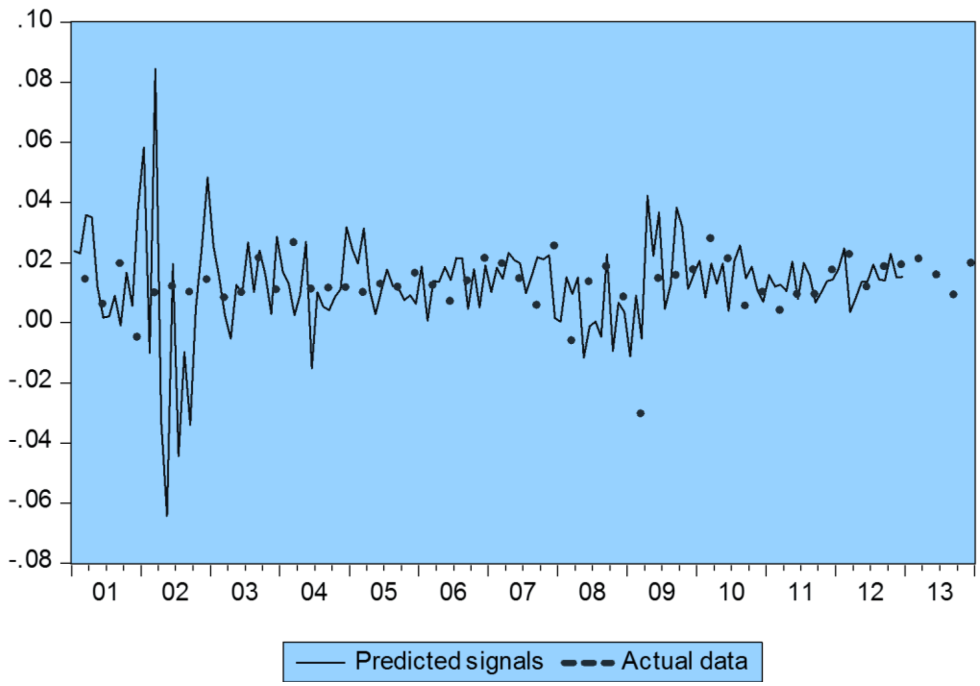


Figure 7. Monthly actual GDP growth and 1-step-ahead predicted signals from SS11

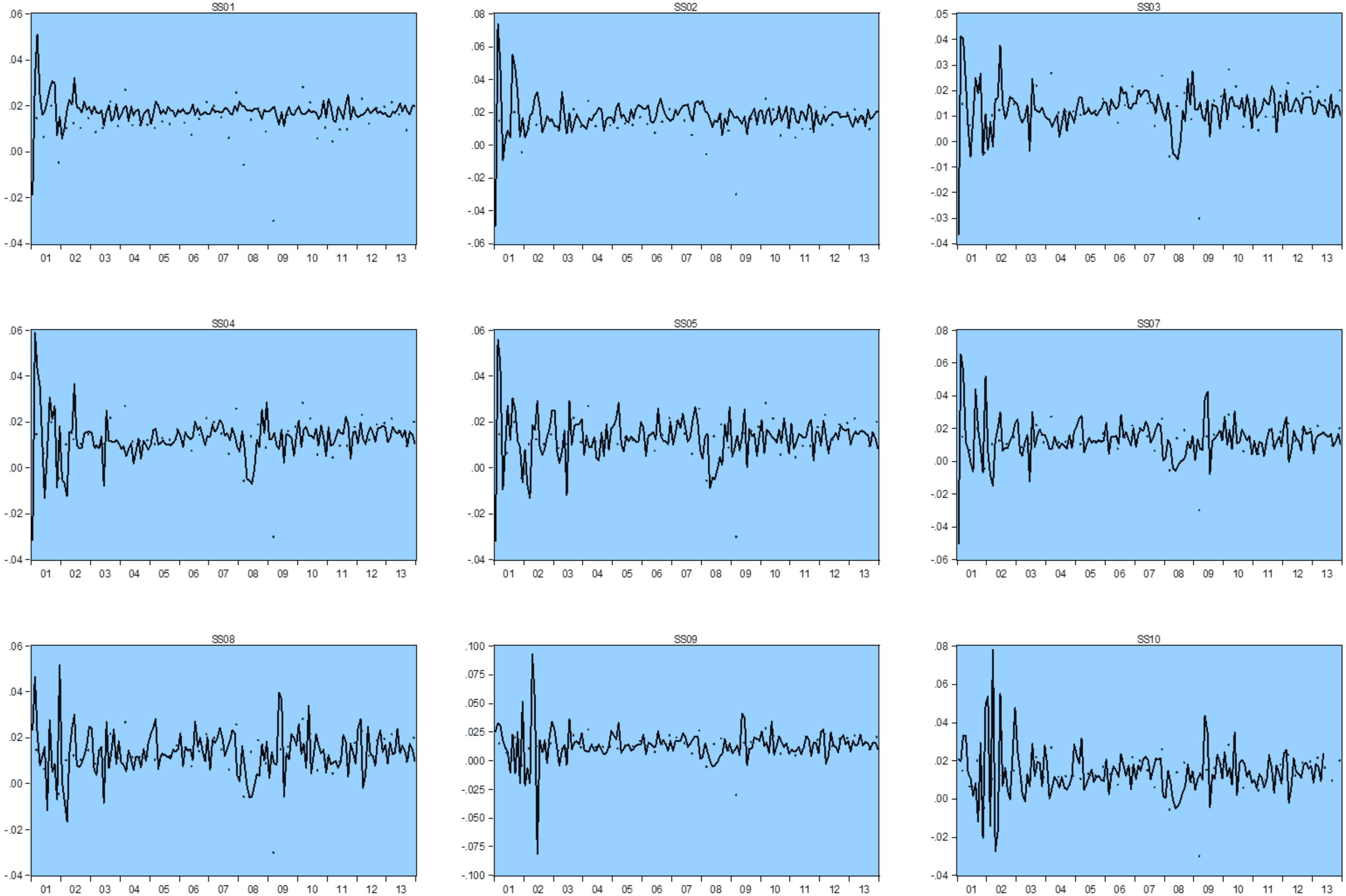


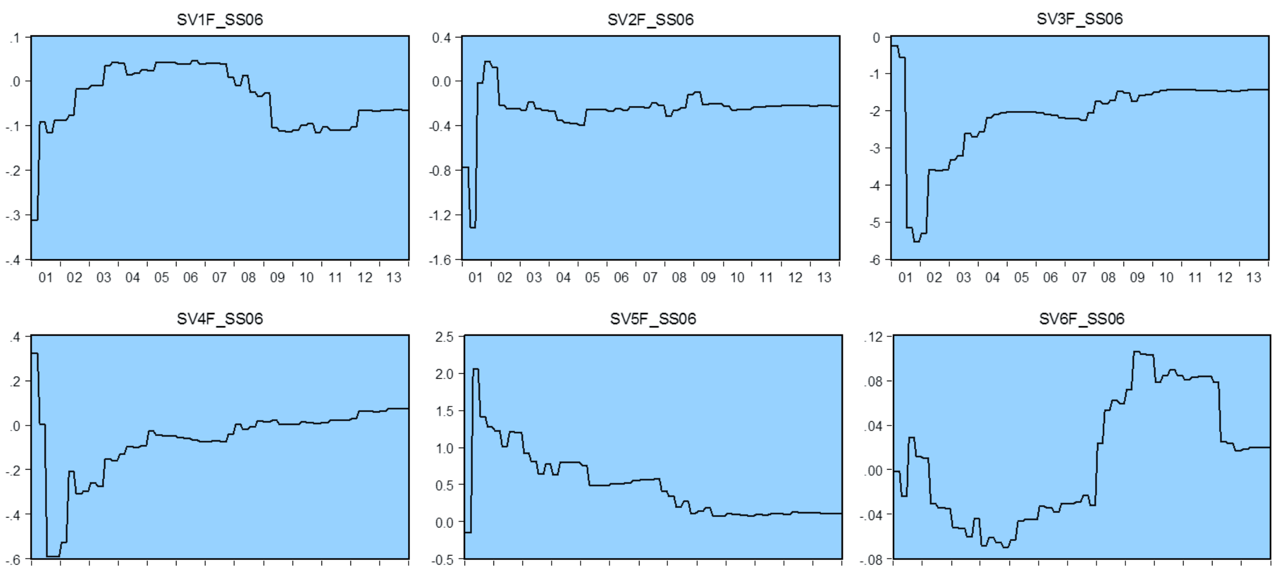
Figure 8. Monthly actual GDP growth (red) and 1-step-ahead predicted signals (blue) of state space models

The estimated state space model which included registered stock corporations and partnerships was only up to 2012 since the series was only up to that point. Same goes with SS10 which included Meralco sales that extended up to May 2013 only. Although the state space model has the ability to handle missing data, variables in the signal equation should have at least the same time horizon.

It can be noted that the generated one-step-ahead predicted signals from the first two state space models (SS01 & SS02) were not relatively far from the plotted actual data but does not exhibit much fluctuations unlike on other models. The first model's (SS01) signal equation is composed of the growth rate of PSEi as exogenous variable while the second model (SS02) has PSEi and exchange rates as explanatory variables. The models with these two indicators, apparently, were not sufficient to predict the GDP growth based on the graphs alone.

As expected, by adding more variables in the signal equation the predicted signal series came closer to the actual data. Moreover, the large dip in GDP growth during 2008 was only reflected starting from SS03. It can be noted that most indicators used exhibited dramatic changes during 2008 reflecting the economic turmoil in that period.

To illustrate how each indicator contributes to the fluctuation of the monthly GDP growth, i.e. the 1-step-ahead predicted signals, the predicted state variables were also plotted and are shown in Figure 9. Most parameters exhibited a notable change in regime during 2001 and 2008 when there were global economic turmoil.



**SV1F – psei, SV2F – fx, SV3F – cpi, SV4F – rm1, SV5F – wpi, SV6F - exports*

Figure 9. Predicted state variables from SS06

4.3. Evaluating the forecasting capabilities

To further evaluate the forecasting ability of the state space models, the predicted monthly signal series of GDP growth rates were aggregated by simple averaging to form a quarterly series and then compared to the actual data.

Figure 10a and 10b illustrates the aggregated one-step-ahead predicted signal series of each state space model. Similar to the non-aggregated data, the generated signal series from the first two models were relatively far from the actual data compared to the rest of the models. When CPI was added, though, it came closer to the actual data as shown in the third graph in Figure 10b (*SS03*) and as more indicators were added, the aggregated predicted values came closer to the actual data.

The aggregated signal series clearly follows the actual data although the huge dip in 2008 was not captured in any of the generated models. Moreover, there are more noticeable fluctuations in SS11 compared to SS11. Difference between the actual and aggregated predicted signals is summarized in Table 8 in the Appendix. Other aggregated signals from the rest of the models are shown in Figure 10b.

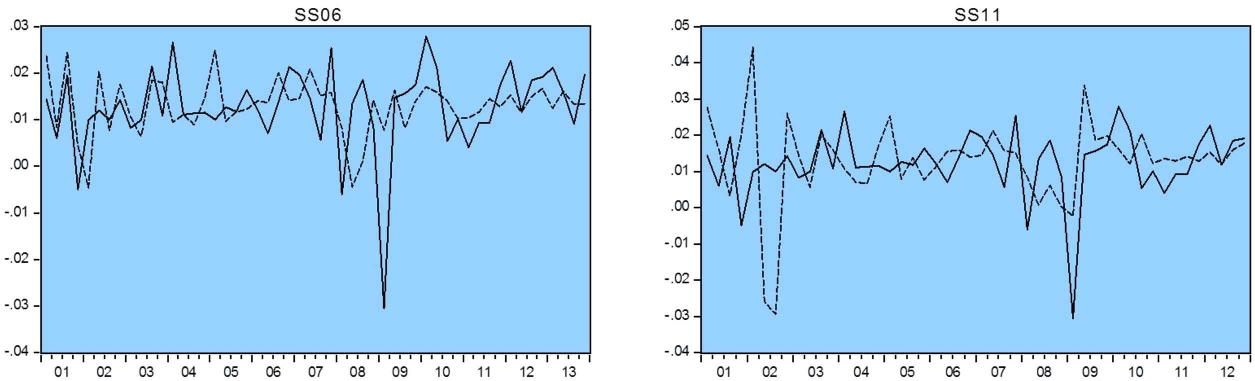


Figure 10a. Quarterly actual GDP growth (solid line) and aggregated 1-step-ahead predicted signals (blue) of state space models

To have another set of competing models, the state space models were re-estimated but included a signal equation with an error term represented as a state variable following an AR(1) process, i.e. *[var=1]* in each signal equation was replaced with another state variable. After re-estimation of the state space models, 1-step ahead predicted signals were also generated and then aggregated into a quarterly series. Model specifications and aggregated series resulting from these re-estimated models are posted in the Appendix. To compare the predicting capabilities of the competing models, root mean squared error (RMSE) and mean absolute error (MAE) were computed for each model to evaluate which among them had the most desirable result. Formula for RMSE and MAE are summarized below.

$$RMSE = \sqrt{\sum_{t=1}^{n}(\widehat{y}_t - y_t)^2/n} \qquad MAE = \sum_{t=1}^{n}|\widehat{y}_t - y_t|/n$$

Root mean squared error and mean absolute error were calculated for each aggregated series and the results are summarized in Table 5.

Table 5 – RMSE and MAE of estimated models

with normalized error in signal equation					with AR(1) error in signal equation				
Model	RMSE	Rank	MAE	Rank	Model	RMSE	Rank	MAE	Rank
SS01	0.0108	7	0.0074	6	SS01	0.0161	10	0.0146	10
SS02	0.0114	9	0.0080	9	SS02	0.0167	11	0.0150	11
SS03	0.0098	3	0.0069	2	SS03	0.0129	8	0.0104	8
SS04	0.0102	5	0.0072	5	SS04	0.0111	1	0.0084	3
SS05	0.0097	2	0.0072	3	SS05	0.0111	2	0.0083	1
SS06	0.0092	1	0.0067	1	SS06	0.0117	6	0.0088	6
SS07	0.0099	4	0.0072	4	SS07	0.0112	3	0.0083	2
SS08	0.0104	6	0.0077	7	SS08	0.0113	4	0.0085	4
SS09	0.0109	8	0.0080	8	SS09	0.0115	5	0.0086	5
SS10	0.0115	10	0.0085	10	SS10	0.0119	7	0.0090	7
SS11	0.0137	11	0.0102	11	SS11	0.0135	9	0.0105	9

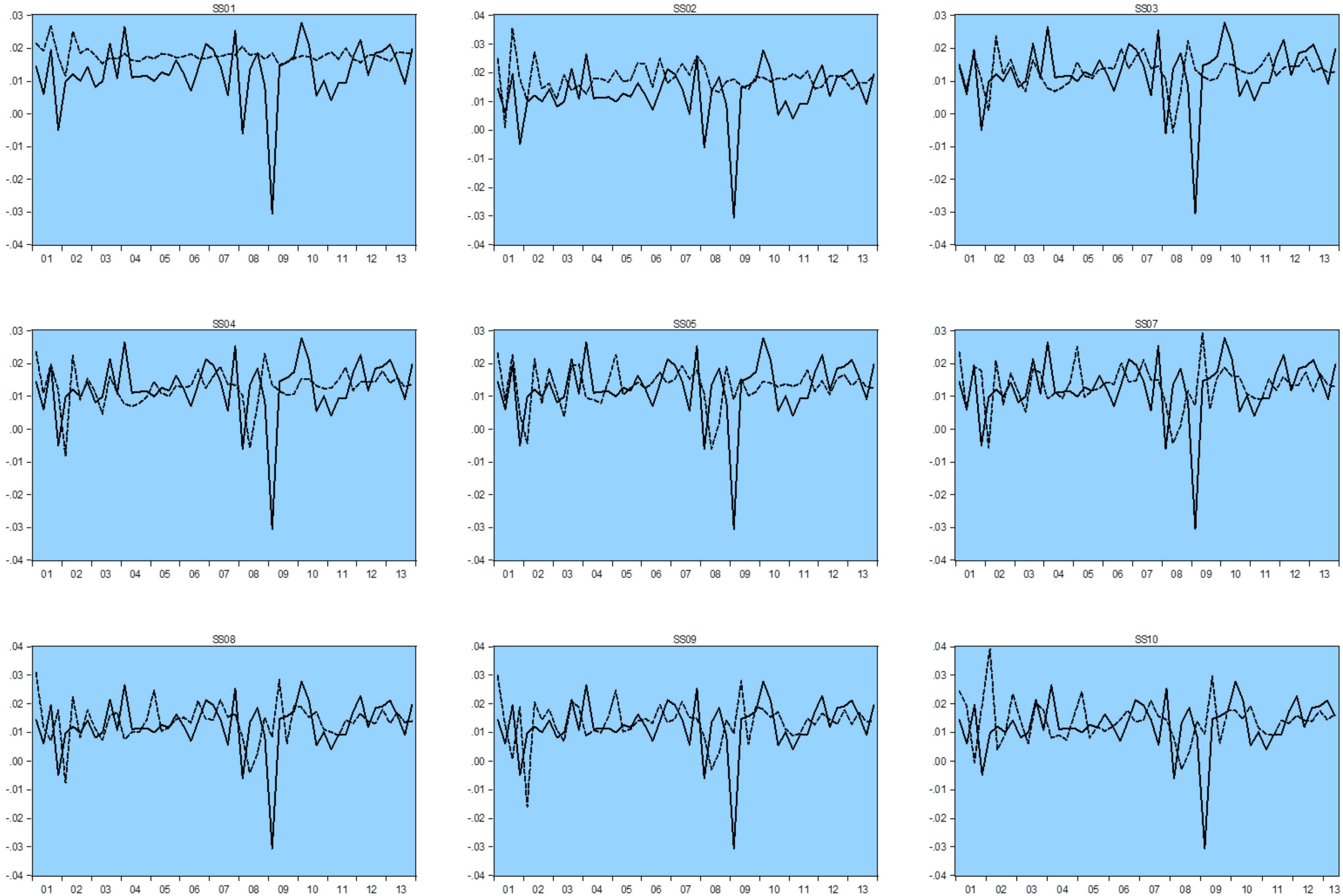


Figure 10b. Quarterly actual GDP growth (solid line) and aggregated1-step-ahead predicted signals (blue) of state space models

Among the first set of models, *SS06* had the lowest RMSE and MAE. *SS06* signal equation is composed of growth rates of PSEi, exchange rate, CPI, real money supply, WPI and exports. *SS05* was the next model with lowest RMSE and also had the 3rd least MAE. Including all indicators in the signal equation, i.e. SS11, resulted with the least desirable RMSE and MAE. When an error term following an AR(1) process was introduced in the signal equation, *SS04* and *SS05* had the least RMSE and MAE, respectively. *SS06*, meanwhile, ranked 6th in both criteria.

Conclusion and recommendation

Mismatch in frequency of most macroeconomic variables has been a problem of econometricians for quite some time. Surveyed economic indicators such as price indices and foreign trade data, for example, are usually reported on a monthly basis while macroeconomic variables, such as GDP, are usually reported quarterly. And to accommodate variables with different frequencies in an econometric model, researchers usually resort to temporal aggregation to match the lowest frequency in the dataset. However, based on different literature, temporal aggregation may result in information loss. To address this issue, mixed frequency models can be employed instead of resorting to temporal aggregation.

Since this field of study is relatively new, the collection of literature is fairly limited, but it has been applied in different areas of research, such as macroeconomic forecasting, financial modelling and engineering, to name a few. This study aims to contribute to the literature of mixed-frequency modelling by using state space models with time-varying parameters in generating higher frequency macroeconomic variable.

The study used quarter-on-quarter growth rate of deaseasonalized GDP estimates and treated it as a monthly series with missing observation. Using a state space model, specifically a time-varying parameter model with random walk coefficients, the quarterly GDP growth rates converted to a monthly series was fitted with eleven monthly economic indicators. A one-step-ahead predicted value for GDP growth rates was generated and as more indicators were included in the equation, the predicted values came closer to the actual data. Further evaluation revealed that among the group of models, using the PSEi, exchange rate, CPI, real money supply, WPI and exports generated the most desirable forecasts based on RMSE and MAE.

The state space models used in this study followed time-varying parameters. In future studies, a different specification of the state variable can be explored. Further research can also entail different combinations of exogenous variables in the signal equation instead of entering the indicators one by one. Lastly, other relevant variables can also be included in the model.

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APPENDIX - Test for unit root of eleven economic indicators

Table 6a. Summary of results of test for presence of unit root

Variable	Augmented Dickey-Fuller test	P-value	Remark
LOG(PSEI)	-3.2259	0.0830	I(1)
LOG(FX_SA)	-3.6835	0.0262	I(0)+Trend
LOG(CPI_SA)	-2.1043	0.5392	I(1)
LOG(RM1_SA)	-2.7859	0.2046	I(1)
LOG(WPI_SA)	-2.3651	0.3964	I(1)
LOG(EXPORTS_SA)	-3.7409	0.0224	I(0)+Trend
LOG(IMPORTS_SA)	-2.9799	0.1411	I(1)
LOG(TRADE_INDX_SA)	-4.5117	0.0020	I(0)+Trend
LOG(VISITOR_SA)	-4.3014	0.0040	I(0)+Trend
LOG(MERALCO_SA)	-2.3575	0.4003	I(1)
LOG(NEW_BUSS_SA)	-3.4681	0.0465	I(0)
using 5% level of significance			

Table 6a. Summary of results of test for presence of unit root of growts rates

Variable	Augmented Dickey-Fuller test statistic	P-value
DLOG(PSEI)	-12.3358	0.0000
DLOG(FX_SA)	-9.3592	0.0000
DLOG(CPI_SA)	-7.0059	0.0000
DLOG(RM1_SA)	-15.1681	0.0000
DLOG(WPI_SA)	-7.1152	0.0000
DLOG(EXPORTS_SA)	-18.7891	0.0000
DLOG(IMPORTS_SA)	-16.1547	0.0000
DLOG(TRADE_INDX_SA)	-19.4828	0.0000
DLOG(VISITOR_SA)	-14.6424	0.0000
DLOG(MERALCO_SA)	-11.9915	0.0000
DLOG(NEW_BUSS_SA)	-19.5476	0.0000
using 5% level of significance		

Table 7. Summary table of actual GDP growth rate data and predicted (aggregated) data, SS06 & SS11

Year/ Quarter	Actual	Predicted		Year/ Quarter	Actual	Predicted	
		SS06	SS11			SS06	SS11
2000Q1	0.0000	0.0181	0.0181	2007Q1	0.0196	0.0146	0.0144
2000Q2	0.0013	0.0374	0.0234	2007Q2	0.0145	0.0209	0.0213
2000Q3	0.0211	0.0207	0.0257	2007Q3	0.0057	0.0151	0.0158
2000Q4	-0.0131	0.0014	0.0093	2007Q4	0.0254	0.0158	0.0151
2001Q1	0.0143	0.0236	0.0276	2008Q1	-0.0061	0.0083	0.0084
2001Q2	0.0061	0.0084	0.0163	2008Q2	0.0135	-0.0044	0.0008
2001Q3	0.0196	0.0244	0.0034	2008Q3	0.0186	0.0010	0.0062
2001Q4	-0.0049	0.0046	0.0200	2008Q4	0.0084	0.0142	0.0003
2002Q1	0.0099	-0.0046	0.0443	2009Q1	-0.0305	0.0078	-0.0024
2002Q2	0.0120	0.0203	-0.0258	2009Q2	0.0147	0.0163	0.0338
2002Q3	0.0100	0.0077	-0.0294	2009Q3	0.0157	0.0082	0.0186
2002Q4	0.0142	0.0176	0.0260	2009Q4	0.0175	0.0140	0.0198
2003Q1	0.0082	0.0106	0.0145	2010Q1	0.0279	0.0170	0.0162
2003Q2	0.0100	0.0064	0.0057	2010Q2	0.0212	0.0158	0.0122
2003Q3	0.0214	0.0184	0.0203	2010Q3	0.0054	0.0140	0.0204
2003Q4	0.0108	0.0180	0.0159	2010Q4	0.0101	0.0102	0.0122
2004Q1	0.0265	0.0095	0.0109	2011Q1	0.0041	0.0104	0.0136
2004Q2	0.0111	0.0111	0.0071	2011Q2	0.0093	0.0116	0.0129
2004Q3	0.0114	0.0089	0.0066	2011Q3	0.0093	0.0145	0.0141
2004Q4	0.0115	0.0144	0.0172	2011Q4	0.0174	0.0127	0.0128
2005Q1	0.0100	0.0249	0.0252	2012Q1	0.0226	0.0153	0.0154
2005Q2	0.0127	0.0097	0.0080	2012Q2	0.0118	0.0115	0.0119
2005Q3	0.0117	0.0116	0.0138	2012Q3	0.0185	0.0150	0.0159
2005Q4	0.0163	0.0122	0.0077	2012Q4	0.0191	0.0167	0.0178
2006Q1	0.0123	0.0140	0.0112	2013Q1	0.0212	0.0125	
2006Q2	0.0070	0.0136	0.0155	2013Q2	0.0158	0.0161	
2006Q3	0.0139	0.0200	0.0159	2013Q3	0.0091	0.0133	
2006Q4	0.0213	0.0141	0.0140	2013Q4	0.0197	0.0134	

Table 8. Summary table of difference of actual and predicted (aggregated) data from SS06 & SS11

Year/ Quarter	Difference from actual		Year/ Quarter	Difference from actual	
	SS06	SS11		SS06	SS11
2000Q1	0.0181	0.0181	2007Q1	-0.0049	-0.0052
2000Q2	0.0361	0.0221	2007Q2	0.0063	0.0068
2000Q3	-0.0004	0.0047	2007Q3	0.0095	0.0101
2000Q4	0.0144	0.0224	2007Q4	-0.0096	-0.0104
2001Q1	0.0093	0.0132	2008Q1	0.0144	0.0144
2001Q2	0.0023	0.0102	2008Q2	-0.0179	-0.0128
2001Q3	0.0049	-0.0161	2008Q3	-0.0175	-0.0123
2001Q4	0.0095	0.0250	2008Q4	0.0057	-0.0081
2002Q1	-0.0145	0.0344	2009Q1	0.0383	0.0281
2002Q2	0.0082	-0.0378	2009Q2	0.0016	0.0191
2002Q3	-0.0023	-0.0394	2009Q3	-0.0074	0.0030
2002Q4	0.0034	0.0117	2009Q4	-0.0035	0.0024
2003Q1	0.0024	0.0063	2010Q1	-0.0108	-0.0116
2003Q2	-0.0035	-0.0042	2010Q2	-0.0054	-0.0090
2003Q3	-0.0030	-0.0011	2010Q3	0.0086	0.0150
2003Q4	0.0071	0.0050	2010Q4	0.0001	0.0021
2004Q1	-0.0170	-0.0157	2011Q1	0.0064	0.0095
2004Q2	0.0000	-0.0040	2011Q2	0.0023	0.0036
2004Q3	-0.0024	-0.0048	2011Q3	0.0052	0.0048
2004Q4	0.0029	0.0057	2011Q4	-0.0047	-0.0046
2005Q1	0.0149	0.0152	2012Q1	-0.0073	-0.0072
2005Q2	-0.0030	-0.0047	2012Q2	-0.0004	0.0001
2005Q3	-0.0002	0.0020	2012Q3	-0.0036	-0.0026
2005Q4	-0.0041	-0.0087	2012Q4	-0.0025	-0.0014
2006Q1	0.0018	-0.0011	2013Q1	-0.0086	
2006Q2	0.0066	0.0084	2013Q2	0.0003	
2006Q3	0.0062	0.0020	2013Q3	0.0042	
2006Q4	-0.0072	-0.0073	2013Q4	-0.0063	

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ESTIMATES OF INCOME INEQUALITY ARE BIASED OR MISINTERPRETED

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Article's Histor

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Abstract:

We consider definitions and measuring procedures of personal income used by three U.S. agencies as well as the evolution of household size distribution and reveal major quantitative inconsistencies in the reported figures of personal and household inequality. The problem with the inequality estimates reported by the Internal Revenue Service consists in the changing proportion of people with lower incomes. The increasing proportion of low-income population is misinterpreted as the growth in income inequality. The Census Bureau provides personal income distributions scaled from a small subset of households to the whole population. Surprisingly, the Gini coefficient estimated from the Census Bureau data for people with income does not depend on the dramatic change in income definition in 1977, when the share of working age population with (likely low) incomes increased by 10%. When corrected to the population without income, the Gini coefficient demonstrates a significant decrease in 1978. The changing composition of households in the U.S. is the effect explaining the reported increase in Gini coefficient for households since 1967. When corrected for actual decrease in the average household size the relevant Gini coefficient returns to that of personal incomes. According to the Census Bureau, the latter coefficient has been hovering in a very narrow range between 0.50 and 0.51 since 1974. Evaluating the evolution of labour and capital shares of the U.S. personal income reported by the Bureau of Economic Analysis we found that the increasing share of income of the top 1% households does not affect the labour share income. The growth in the income share of richest families is related to the increasing share of the consumption of fixed capital which is converted into private money though the reduction in taxes on production and imports.

Keywords: income inequality, Gini coefficient, households

JEL Classification: D3

1. Introduction

There are three major agencies reporting various measures of personal income in the USA. The Census Bureau (CB) measures personal incomes in household surveys (CPS ASEC) at an annual rate (CB, 2006). This measure is called Money Income (MI) and includes a variety of personal income sources. The CB provides these estimates to the Bureau of Labor Statistics, also in form of personal/household/family distributions. The Bureau of Economic Analysis (BEA) carries out annual estimates of (gross) personal income (GPI) as based on administrative records, censuses, and similar surveys, but it does not provide fine structured income distributions (BEA, 2012). The BEA reports aggregate income figures and does not allow inferring the evolution of personal or household income distribution in time. The most important similarities and differences of the CB and BEA measures are discussed in depth in (CB, 2012). The Internal Revenue Service (IRS) also measures and reports personal incomes filed for tax purposes. Since 1996, the IRS has been publishing electronic tables of personal incomes distribution (IRS, 2012). This is similar but somewhat different from the CB's reports. Due to intrinsic inconsistencies in definition and methodology of measurements, the measures of income inequality provided by these three agencies are subject to bias. In this paper, we demonstrate a few examples of bias and even misinterpretation of income inequality measurements.

2. Bias in income inequality measures. Census Bureau and Internal Revenue Services

From the point of view of scientific methodology, different purposes and measuring procedures used by three agencies reporting personal incomes make it difficult to follow up the actual evolution of income distribution and income inequality in the U.S. in quantitative terms. As a result, there is no comprehensive definition or measure of personal/household/family income and its distribution. Moreover, there is no way to merge all data in one consistent table, to estimate the distribution of income over age/race/sex, and to calculate quantitative measures of inequality like the Gini coefficient. It is possible to illustrate the level of difficulties associated with the introduction of a unified personal income distribution in two simple plots. Figure 1a shows the portion of personal incomes in the U.S. nominal GDP as reported by three agencies. Currently, the BEA reports as the (Gross) Personal Income (GPI) around 85% of the estimated nominal GDP. The GPI covers almost all incomes included in the definition of national income. The IRS reports the total portion of personal incomes in the GDP fluctuating between 55% and 64% (i.e. ~10%) since 1996. The CB also demonstrates a decrease from 63% in 2000 to 57% in 2008 in the portion of personal income in the GDP, while having large differences from the IRS in income sources. It is worth noting that the IRS portion of the GDP is subject to strong variations, apparently, related to the rate of economic growth. The total personal income reported by the CB reveals no link to economic conditions but rather to the introduction of new definitions of income and measuring procedures in 2003.

The BEA provides no population estimates as related to its measures of personal incomes and Figure 1b shows two curves representing the proportions of population with income as defined by the CB and IRS. The IRS population was 45% in 2004 and 48% in 2008 with the respective total personal income of 57% and 62%. The CB reports that the proportion of population with income has been falling from 71% in 2000 to 69% in 2010 together with a proportional fall in the CB's total personal income. The difference of 30% in population share between two agencies is a dramatic one. The IRS does not count as personal (at least) those incomes which 30% of the total population defines as money income. The incomes ignored by the IRS seem to be generally small as producing negligible differences in the estimates of total personal income, but these incomes are extremely important for measures of income inequality. By excluding 30% of population when calculating the Gini coefficient one obtains a severely biased inequality estimate. On the contrary, the overall consistency of the household set and controlled changes in measurement methodology may provide less biased estimates of income inequality.

In practical and theoretical terms, the measured differences in the proportions of population and income definition are crucial. To measure personal/household incomes in the U.S., the Census Bureau conducts annual surveys (the March Current Population Surveys) covering a set of households carefully selected from the whole population. This scientifically designed set has to provide consistent measurements of incomes over time and one can carry out reliable quantitative analysis of principal characteristics of income inequality and their evolution. The IRS measures incomes of a randomly changing portion of the whole population driven by changing rules of taxation and by unpredictable times of economic crisis.

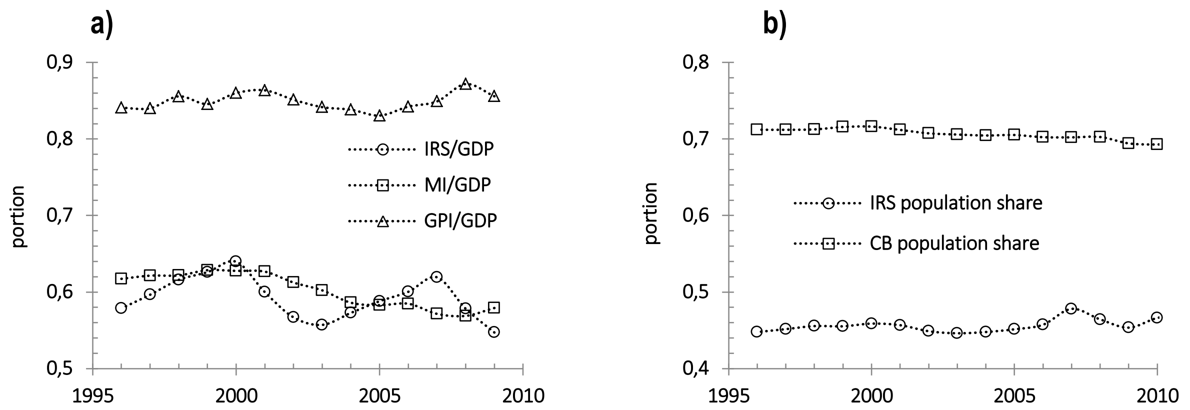

Figure 1. a) Portion of personal income in GDP: Internal Revenue Service (IRS), Money Income (MI) measured by the Census Bureau, and (Gross) Personal Income (GPI) measured by the Bureau of Economic Analysis. b) The proportion of people in total population counted as having personal income by the IRS and CB.

In the CPS, there exists a well-know problem with "top-coded" incomes - if the individual interviewed has earnings higher than $999,999, those earnings are recorded simply as $999,999. However, this artificial limit does not affect the accuracy of estimates of income in the richest group and the related measures of income inequality. In the estimates of Gini coefficient, the CB considers the highest personal incomes as distributed according to the Pareto (power) law. One can accurately approximate the actual, biased by "top-coding", measurements by a theoretical curve. Figure 2 depicts two Pareto distributions (straight lines in the log-log axes) for the CPS and IRS personal income data. The IRS data set contains actual values of incomes "top-coded" in the CPS, which do not demonstrate statistically significant deviation from the Pareto law in the highest income range (R2 = 0.996). As a matter of fact, we do not need to measure any personal income in the high-income group. It is just enough to estimate the number of persons with income above some given (high enough) threshold, with the total income in this group playing the role of quantitative constraint. Then, one can use a simple power function for accurate estimates of population density at any income level and also total income above any threshold. Since 2003, the CB has been using the Pareto law interpolation of high-income data for the calculations of Gini coefficient.

The effect of changing population basis is also observed in the CPS income data (Census Bureau, 2006). The proportion of people with income changes over time (see Figure 3a). It was increasing in the 1950s through 1970s due to strong growth in the women's rate of participation in labour force. It has been falling since 1990, however. The CB reports the estimates of Gini coefficient since 1993 as related to the introduction of new income definitions and questionnaire. We have estimated the Gini coefficient for population with income since 1947 using the CPS data published by the Census Bureau (Kitov, 2009). Solid line presents the estimates published by the Census Bureau which are obtained for people with income. Both curves are depicted in Figure 3b and demonstrate an insignificant difference (less than 0.01) likely associated with some intrinsic differences in calculation methods. The Gini coefficient for people with income reveals a large degree of stability since the 1960s, which implies that the Lorentz curve, i.e. the underlying dimensionless distribution of personal income, does not depend on the proportion of population with income. Surprisingly, the personal income distribution repeats itself for any proportion of population with income.

When more than 30,000,000 people with zero income are added one should expect a dramatic increase in Gini coefficient. Essentially, thirteen per cent of working population has zero income what shifts the Lorentz curve further from the bisecting line. Figure 3b shows that, when people without income are included in calculations of income inequality, the Gini coefficient (for personal incomes) actually has been intensively falling since 1947 due to strong growth of the proportion of people with income. In 1993, the Gini coefficient for the whole working age population started to grow again in accordance with the increasing proportion of people without income. Currently, the personal income inequality in the U.S. is likely higher than the Census Bureau reports: the Gini coefficient is rather 0.58. This estimate is justified by the broader consideration of measurements adopted in hard sciences. In terms of physics, it is a mistake to neglect a substantial part of the full ensemble (closed system) when calculating aggregate variables. All aggregates based on portions of the full ensemble are intrinsically biased and cannot characterize the system and its behaviour. Hence, one must include people without income in inequality estimates. Otherwise, all inequality measures are biased by fluctuating shares of total income and population.

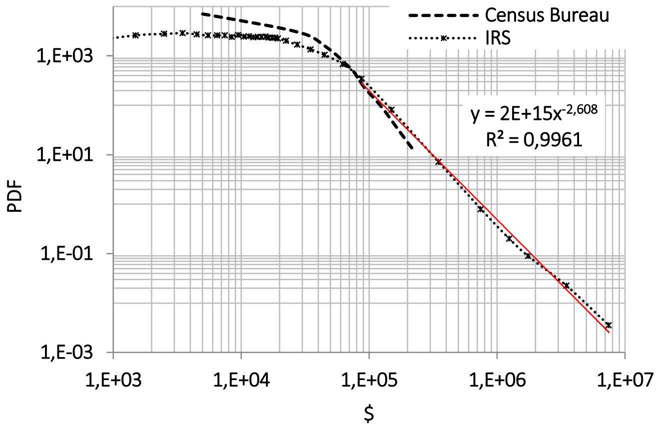

Figure 2. Population density functions (PDF) [number of people per $1 as a function of income for the estimated obtained by the IRS and CB in 2001.

Notice log-log scale. The Pareto law for higher incomes is an accurate approximation. Linear regression gives R^2=0.996 for incomes between $70,000 and $10,000,000. The regression line is shown by red.

Now we focus on some problems with the IRS measures of income which may result in biased estimates of inequality. The main problem of the IRS income definition consists in the floating low-end income threshold. The population used for inequality calculation fluctuates randomly or according to some predetermined relationship (*e.g.*, tax code). So, one can suggest that the driving force behind the increasing personal income inequality, as reported by the IRS, likely consist in biased measurements and inconsistent definitions. Original (tax) income distributions are tabulated by the IRS (2012) in constant income bins and these tables provide a basis for estimates of economic inequality in the USA.

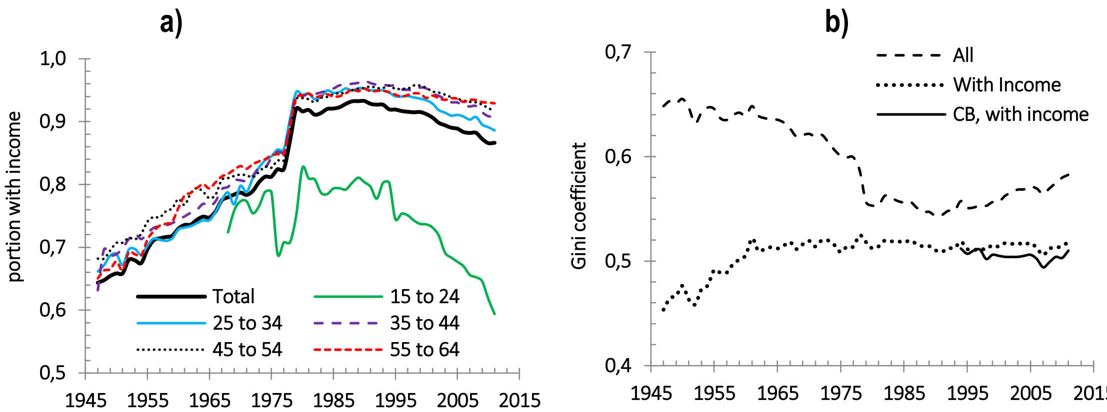

Figure 3. a) The overall and age-dependent proportions of working age population with income in the CPS.

Notice the 0.07 step between 1977 and 1978 caused by new income definition and steeper fall after 2003 – the year when new counting methodology was introduced. b) Three estimates of Gini obtained from the CPS data: “All” – for total population of working age including people without income, “With income” – for working age population reporting incomes in the CPS,”CB, with income” – the estimate reported by the Census Bureau.

Figure 4 compares income distributions for 1990 and 2011 as they are reported by the IRS. Since the income bins presented in the IRS tables are of increasing width one can observed some fluctuations in the distributions. These fluctuations are, obviously, related to those income bins, which are wider than their lower income neighbours. For example, the bin between $25,000 and $30,000 (width $5,000) is followed by the bin between $30,000 and $40,000 (width $10,000). Therefore, one can expect a larger number of people in the latter bin than in the former one. This effect is clearly observed in Figure 4, where the enumerated populations are assigned to the centres of corresponding income bins. We prefer to use the *log-log* scale in order to present highly changing population (and density) distributions in a very wide range of income, spanning seven orders of magnitude. The lowest income bin, corresponding to zero and negative (loss) reported incomes, is assigned to $1 income. The bin with incomes above $10,000,000 is not shown because of the absence of mean income estimate. One can easily derive an obvious conclusion from Figure 4 - there are more people with lower and high incomes in 2011 than in 1990. This is a mechanical result of increasing population – more and more people get income as the working age population is growing.

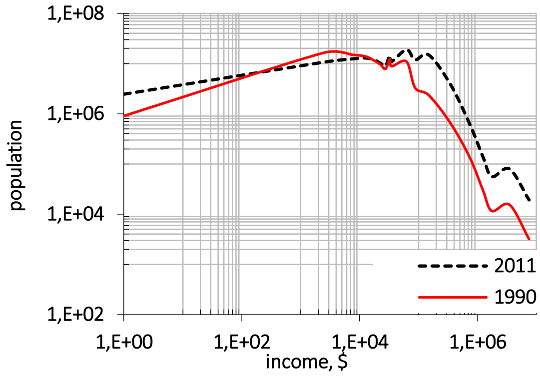

Figure 4. Comparison of (taxable) income distribution in 1990 and 2011, as reported by the IRS.

Note: Income bins increase in width. Enumerated populations are assigned to the centres of corresponding bins. Notice the *log-log* scale. The lowest income bin corresponds to zero and negative (loss) reported incomes, *i.e*. people without income. The bin with incomes above $10,000,000 is not shown because of the absence of mean income estimate in this bin.

One should normalize the curves to the total population (with the IRS reported income) in given years in order to obtain population independent results. In addition to this normalization one can use population density instead of original population estimates in width-changing bins. When the measured populations are normalized to the corresponding income bin widths one obtains density of population as a function of income, i.e. the number of people per $1 bin (for given year). As before, we assign the obtained population densities to the centres of corresponding bins. Figure 5a depicts two population density curves obtained after the normalization of the curves in Figure 4 to the total population with (IRS reported) income, which includes people without income and those with incomes above $10,000,000, and to the respective widths of income bins. Both curves accurately follow the Pareto law at higher incomes.

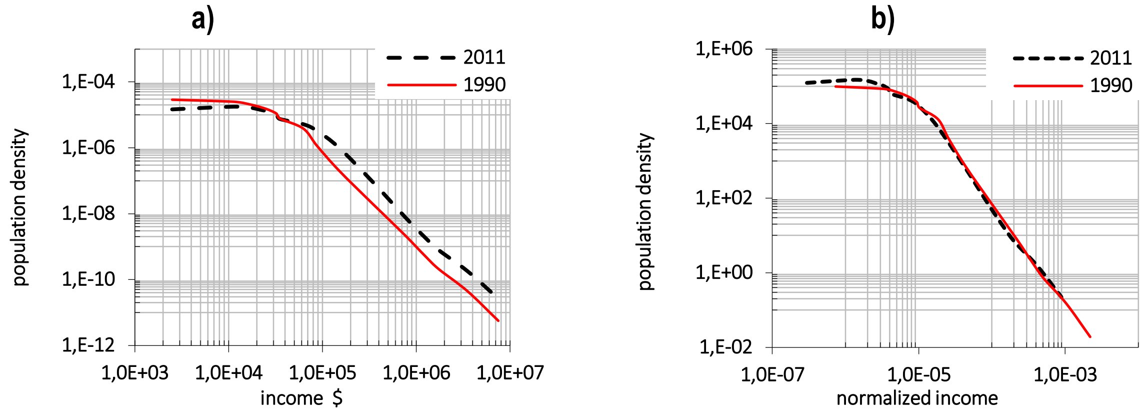

Figure 5. a) The curves in Figure 4 are normalized to the total population with income reported to the IRS and to the widths of corresponding income bins.

Note: Resulting population density distributions, *i.e.* the portion of people per $1-wide bin, are plotted as a function of income (central point of corresponding income bin). First (zero width) and the last (open-ended) income bins are not presented. b) The income scale in Figure 5a is normalized to the IRS total incomes, i.e. to $8.37+12 in 2011 and $3.41E+12 in 1990.

The total IRS personal income increased from $3.41E+12 in 1990 to $8.37+12 in 2011. The larger total income is a possible reason for the increased number of people with higher incomes. Two curves in Figure 5b represent those in Figure 4, which are normalized to the total personal income reported by the IRS. Income scales in 1990 and 2011 are also normalized to these total incomes and represent dimensionless portions of the total income. As a result, the width of a given income bin (say, between $5,000 and $10,000) in 1990 and 2011 becomes different since the relevant income scales are compressed by different factors. Also, the centres of the original income bins which were the same in 1990 and 2011 (see Figure 5a) are now shifted relative to each other by the factor equal the total incomes ratio. Figure 5b shows that the level of population density at lower incomes is higher in 2011, with the distributions in the Pareto range coinciding to the observed limit ($4,000,000 in 2011). There are several explanations of this observation. First, this is the results of some real (objective) processes of income redistribution between rich, middle class and poor people in the USA. This is a common opinion in economic literature. Because of the changes in the measured personal income distributions one needs some driving force explaining the process. Second reason for the changing distribution is not related to increasing income inequality but is associated with lower (and varying) accuracy of income measurements at lower incomes. The low-end of income distribution is open for uncontrolled variations which introduce a significant bias in inequality estimates.

The IRS covers smaller proportion of population and total personal income than the Census Bureau. Basically, the IRS reports some subset of income gainers relative to the Census Bureau. Therefore, the observed difference between economic inequality estimates based on IRS and Census Bureau data is likely results from lower reliability of the IRS estimate. Income reports for tax purposes cannot provide a consistent measure of personal income.

3. The household income inequality reported by the Census Bureau

When discussing the increase in income inequality, economists often forget those people who have no income at all. According to the Census Bureau, there are tens of millions reporting no income every year and this number has been really growing since 1990 as Figure 6a shows. As mentioned above, the dramatic fall in 1978 was caused by a larger revision to income definition. More than 15,000,000 were added to income gainers in a few seconds. The total population has been growing by approximately 1% per year. Figure 6b depicts the ratio of the number of people without income and the total working age population (15 years of age and over). This ratio has been growing since 1990 as well and there was no specific acceleration after 2007. It is not clear why these people are excluded by the

Census Bureau from the reported measure of income inequality in the U.S. Fortunately, they are included in the household-related inequality estimates.

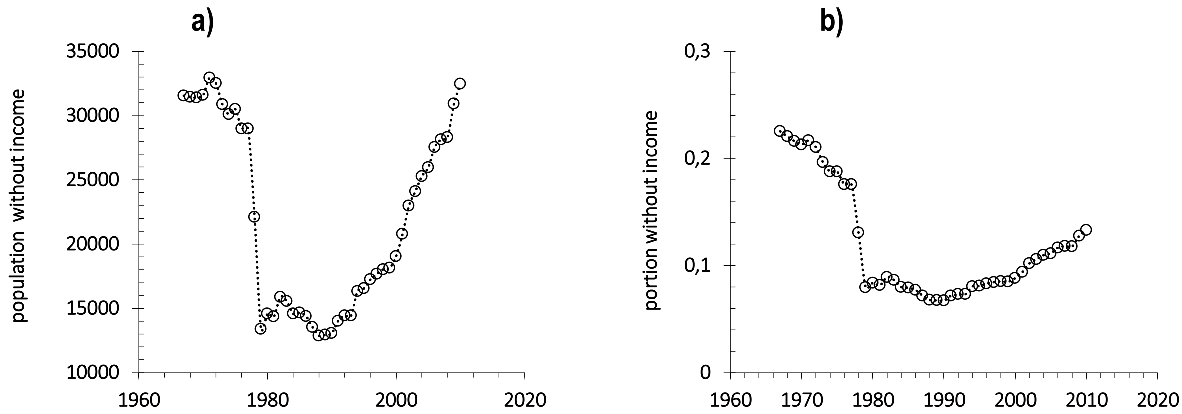

Figure 6. The number (a) and the portion (b) of people without income according to the Census Bureau's definition.

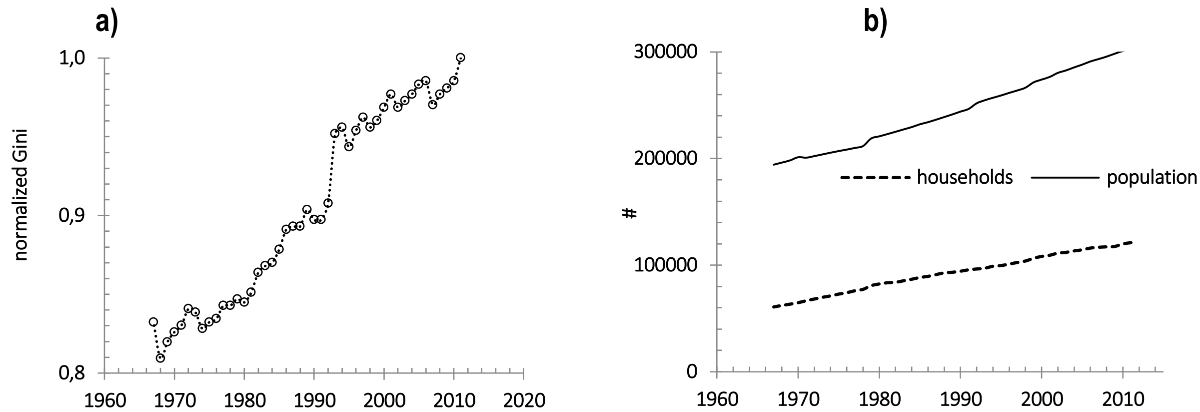

Figure 7. a) The evolution of normalized Gini coefficient for households. b)The evolution of total household population and the number of households (both in thousands)

In Figure 7a, we present the Gini coefficient for households. We intentionally normalized the ratio to its maximum value (0.477 in 2011) in order to show that this inequality measure has risen by 20% since 1967. This dramatic increase is interpreted as a big problem for the US but contradicts the observation of constant Gini coefficient for individuals. Unlike personal incomes, the household data are collected for entities which can evolve in size. Figure 7b presents the total household population and the number of households reported by the CB. From figure 7b one can obtain the evolution of the average household size, which is depicted in Figure 8a. Actually, the fall in the average size is quite spectacular: from 3.2 in 1967 to 2.49 in 2011. The simplest effect leading to the observed size decrease is household split - instead of one big household two smaller households appear. Obviously, the Gini coefficient depends on the distribution of household sizes. For fixed total income, the increasing number of households (split), which share the same amount of money, should result in a higher Gini coefficient. When all households are split to the smallest pieces (one person households) we have the personal income distribution with a larger Gini.

The observed fall in the average size indicates that one gets smaller households over time and the Gini coefficient should increase accordingly. The link between the average size and the Gini coefficient is not necessary a linear one. However, the simplest assumption of a linear relationship between the average size and Gini coefficient may give a conservative estimate of Gini coefficient for the observed fall in the average household size. Figure 8b shows the product of the Gini curve for households (Figure 7a) and the curve in Figure 8a. Now we see the time history of Gini coefficient corrected for the household size. This corrected Gini coefficient might be not fully compensated for the changes in household sizes and income distribution but tells a different story: the Gini for households fell from 0.82 in 1967 to 0.72 in 1980, and then has not been changing. The step in 1993 is induced by the revision to income definition, i.e. this step is fully artificial. We consider the Gini coefficient for households as constant since 1980. This observation is consistent with constant Gini for personal incomes.

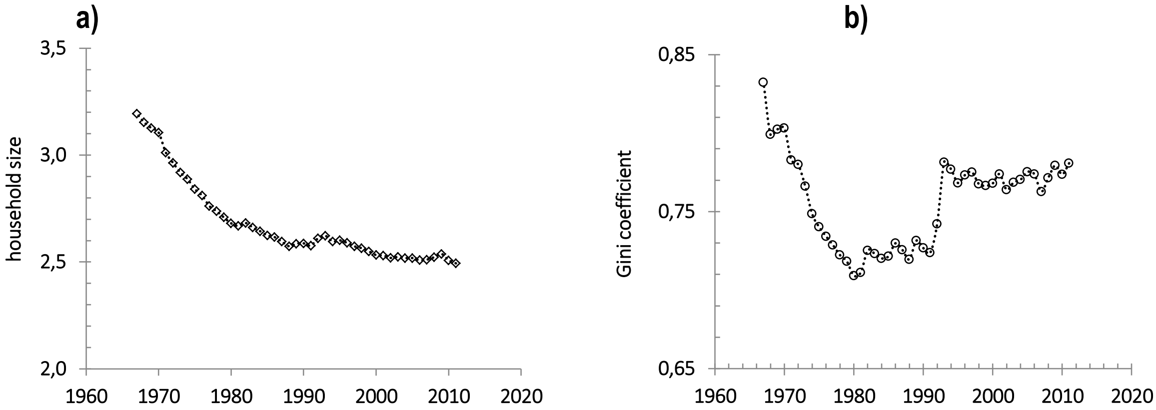

Figure 8. a) The evolution of an average household size. b) The household Gini coefficient corrected for the size of average household.

Overall, the Gini coefficient for households has not been changing as the CB estimate says because these estimates do not take into account the change in the household size distribution. This is a methodological error. The same logic must be applied to family income distribution – the CB's estimate is also biased. The mean and median income estimates are also affected by this mistaken procedure. Since the size of household has been decreasing the number of households has been growing faster than the total household population. The mean household income must also be corrected for the changing size. Figure 9a shows the actual evolution of the mean income (the evolution of median income is harder to recover).

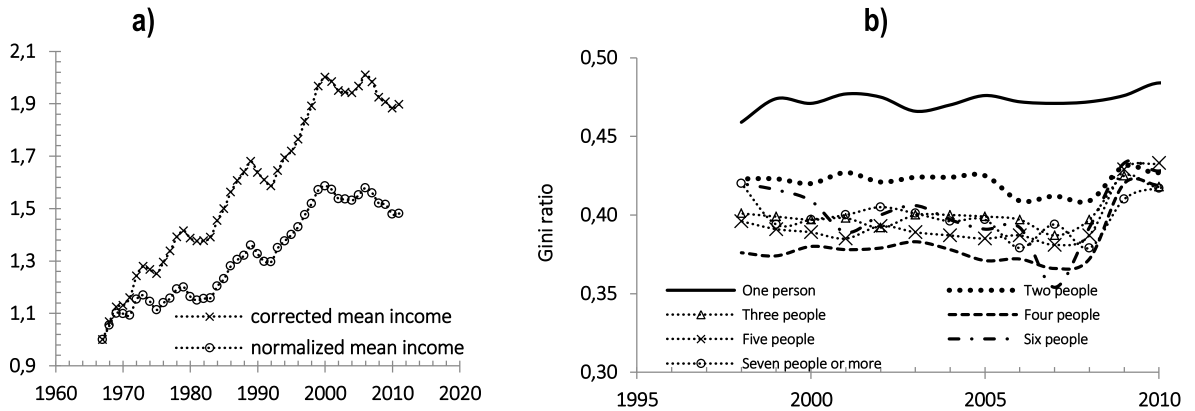

Figure 9. a) The growth of normalized (household) mean income and that corrected for the fall in the household average size. b) Gini coefficient for households of different sizes as reported by the Census Bureau.

The necessity of the household size correction is supported by the Census Bureau, which reports the Gini coefficient for households of fixed size. Figure 9b depicts these estimates, which demonstrate no change at all since 1993, except the one in 2009. (This step is induced by the introduction of new bins in the highest income end.) It is obvious that the change in the distribution of income among all households (e.g. the growth in the overall Gini coefficient) must be proportionally mapped into the growing Gini coefficient for all household sizes. Otherwise, the richest households should not have some prevailing size. Therefore, the absence of Gini growth in the households of given size proves the absence of the overall Gini coefficient change since 1993 (at least).

4. The Bureau of Economic Analysis

Thomas Piketty's book "*Capital in the Twenty-First Century*" (2014) attracts common attention and discusses the distribution of income between labour and capital. The deepest concern is related to the increasing share of capital income, which is also expressed in the growing portion of total income in the top 1% of families. Here we are showing that capital does not eat from the part of labour income but rather converts corporate income into the personal income. The source of increasing income inequality is in the tax law. At the end of the day, U.S. politicians are responsible for the increase in the portion of personal income for the richest families. There are no economic forces behind the change, which would be much more difficult to overcome.

The proportion of personal (money) income in the Gross Domestic Product has not been changing much since 1947. This is the year when the Bureau of Labor Statistics started to measure personal incomes. The source of some virtual increase in income inequality – private companies redistribute their income in favor of personal income of their owners. The question is – how do they get extra money to redistribute to their private owners? The U.S. tax system started to reduce the level of tax for private companies. Primarily, it was made by increase in the rate of depreciation which enterprises are officially permitted to charge for tax purposes (usually fixed by law).

We start with a graph showing the growth in GDP, gross personal income (GPI) measured by the BEA, and compensation of employees (paid) since 1929. Figure 10a demonstrates that the level of GPI has been rising faster than that of the GDP (and the compensation) since 1979. The share of GPI in the GDP has been rising since 1979 - the difference between the GPI and GDP curves depicted in Figure 10b has a striking kink around 1979. And this is the start of the rally in the rich families' personal income. In other words, a new political (taxation) era started in 1979. We would like to stress again that the proportion of the compensation of employees in the GDP has not been changing since 1929, with a small positive deviation in the end of 1990s and a negative deviation since 2009. This observation supports our previous finding that the proportion of personal (money) income in the GDP has not been changing.

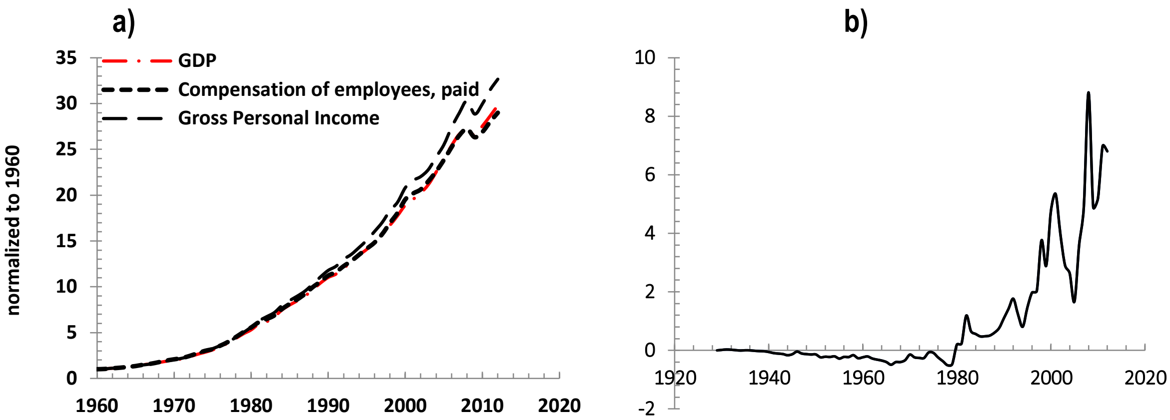

Figure 10. a) GDP, GPI, and compensation of employees normalized to their respective levels in 1960. b) The difference between the GPI and GDP curves.

Where the extra money is from? If the portion of personal income has been actually increasing in the GDP it should be a looser, which lost its share in the GDP. Figure 11a shows two major components of the GPI and the consumption of fixed capital. The net operating surplus (private) has been changing at the same rate as the GDP since 1929, while the proportion of taxes on production and imports has been growing at a lower rate since 1979. Finally, we have allocated the source of income for rich families. They take money from the decreasing taxes. But what is the mechanism of money appropriation? Figure 11a demonstrates that the decrease in taxes goes directly into the increasing share of consumption of fixed capital. This is the force behind the increasing income inequality. The increasing share of the consumption of fixed capital is successfully converted in private money, not in direct investments.

Piketty projects some further growth in the portion of capital income. Here we present an extremely simple observation which bans any further growth in the capital's share of income. Figure 11b displays the evolution of national income (NI), *i.e.* the sum of labour and capital income, and personal income (PI), both reported by the Bureau of Economic Analysis. In the 1940s, the difference between NI and PI was 15% and then stared to decrease. This is the period which Piketty highlights as the era of capital income, i.e. all increase in the share of personal income was appropriated by capital. However, no extrapolation of this tendency in the future is possible. Since 2011, there is no room for further growth in the share of capital income – the whole national income is distributed as personal income. There is no other source of income, except may be some decrease in the consumption of fixed capital (CFC). There is nothing to share any more.

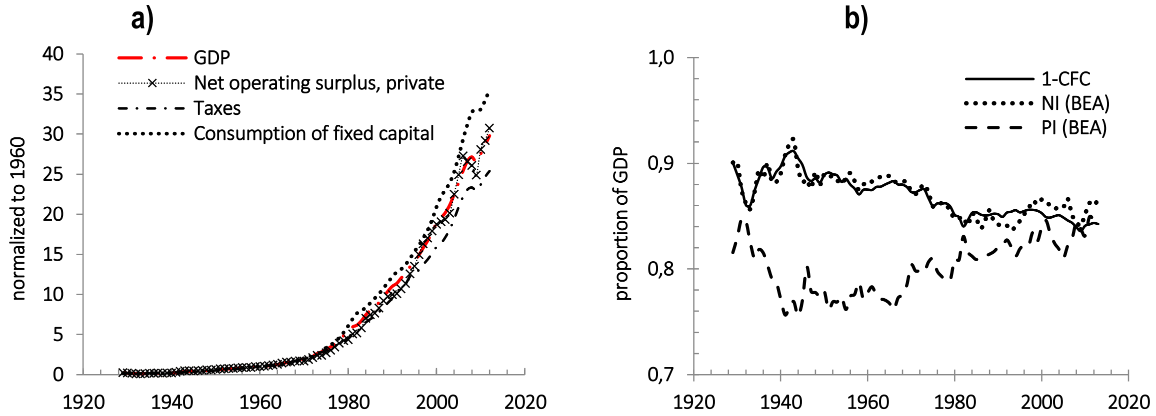

Figure 11. a) GDP, net operation surplus (private), and taxes (on production and imports), and consumption of fixed capital normalized to their respective levels in 1960. b) Evolution of national income (NI) and personal income (PI) both normalized to Gross Domestic Product. Currently, they are almost identical.

Conclusion

We conclude that the way three major U.S. agencies consider and resolve the problem of personal/household/family income and income inequality is counterproductive and confusing for quantitative analysis. The speculations about income inequality involve different and varying without control portions of the total income and population. Thus, these speculations are based on wrong qualitative assumptions because no of the involved quantities are compatible in definitions, measuring procedures, and over time (*e.g.*, CB, 2006). There is a specific aspect of inequality, which is full of intentionally biased numbers, however. The increasing inequality in incomes of household and families is directly misinterpreted.

The current estimates of income inequality based on data reported by the IRS are not reliable. The principal problem of the estimates is highly volatile incomes of people in the low-end of income distribution. This volatility is likely related to measurement errors, changes in definitions or improper reporting. At the same time, the IRS income estimates at high and the highest incomes are robust and follow the Pareto law. When normalized to total population with income and total (gross) personal income personal income distributions for 1990 and 2011 practically coincide. Hence, the inequality estimates based on the IRS data are distorted by readings in the low-income range.

The portions of labour and capital income in the total personal income reported by the BEA demonstrate secular changes. The portion of labour income in the GDP has not been changing much while the capital share increased significantly since the 1950s. The increasing share of income of the top 1% households does not affect the labour share income. The growth in the income share of richest families should be effectively stopped when the total personal income reaches the level of national income. This happened in 2011.

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DIFFERENTIAL EFFECTS OF TARGET PRICE RELEASES ON STOCK PRICES: PSYCHOLOGICAL ASPECTS

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Abstract:

In the present study, we attempt to shed light on potential factors affecting how investors react to target price announcements made by security analysts. More specifically, the study focuses on cross-sectional differences between the magnitude of reactions for stocks whose prices have increased and reactions for stocks whose prices decreased immediately prior to such announcements. Employing a sample of target price announcements classified as "buy" (positive) recommendations for Israeli stocks, we document their significantly positive effect on stock prices both on the day of the announcement and during a short period following the announcement. The effect of target price releases is also found to be significantly stronger for smaller stocks. Moreover, we document that those stocks that have experienced positive cumulative abnormal returns prior to target price releases yield significantly higher abnormal returns on average, both on the event day and during a short subsequent period. We explain this finding by the effect of the availability heuristic on investors' perceptions and decisions. Namely, we suggest that investors may expect target price releases to have a stronger effect on stock prices if these releases are preceded by stock returns of the same sign as the recommendation itself (making the recommendation more available, or in other words, subjectively more informative).

Keywords: analyst recommendations, availability heuristic, economic psychology, event study, stock market efficiency, target prices.

JEL Classifications: C12, G02, G14, G17, G19.

1. Introduction

In recent years and especially in the wake of the 2008 world financial crisis, low interest rates on all developed markets caused people to look for new ways of maintaining the real value of their money and gaining returns on their assets. One of these ways is to invest money in the capital market. Many investors chose to invest their money independently, without employing the services of an investment advisor or portfolio manager to make investment decisions for them. Yet in many cases, these individual investors lack professional knowledge in the field of investments in general and concerning capital markets in particular. Therefore, many of them rely heavily on recommendations issued by security analysts, who are assumed to possess much more profound knowledge than individual investors as well as professional skills in processing and analyzing data.

Security analysts play an important role in the capital market. Two of the most commonly used vehicles for conveying information from equity analysts are analyst earnings estimates and analyst recommendations. Over the years, many studies devoted to these two channels have focused either on documenting market response to these analyst forecasts or on cross-sectional differences in the performance of analysts or brokerages (e.g., Stickel, 1995; Womack, 1996; Barber *et al.*, 2001; Jagadeesh *et al.*, 2004; Bae *et al.*, 2008; Loh and Stulz, 2011).

Yet, a third metric issued by analysts, known as target price, has received relatively little attention in academic literature. Target prices convey sell-side analysts' assessment of the future value of underlying stocks and are presumably the culmination of analysts' research efforts. In recent years, analysts have increasingly issued target prices alongside earnings forecasts and stock recommendations in their equity research reports. An emerging body of literature has examined the information content of target prices (e.g., Bonini *et al.*, 2010; Da and Schaumburg, 2011; Bradshaw *et al.*, 2013). Yet despite the substantial increase in disclosure of target prices in analyst reports and the incremental role of release of these target prices in the price discovery process, the claim made by Brav and Lehavy (2003) that "their role in conveying information to market participants and their contribution to the formation of equity prices have remained largely unexplored" is still probably still true today.

In the present study, we attempt to shed light on the mechanism governing the effect of target price releases on stock prices by examining the impact of stock returns registered *before* target price announcements on stock price reactions to the announcements. We suggest that the availability heuristic[3] has an impact on investors' decisions, so that stock price reactions to target price announcements should be stronger if these announcements were preceded by stock returns of the same sign as the announcement itself, thus making the announcement more available, or in other words, subjectively more informative. Employing a sample of recent target price announcements (released after the global financial crisis) classified as "buy" (positive) recommendations (the target price is substantially higher than the current price)[4] for stocks traded on the Tel Aviv Stock Exchange, we document that target prices have a significant effect on the respective stock prices both on the day of the announcement itself and during the two weeks following the announcement. The effect of target price releases is also found to be significantly stronger for smaller stocks. Moreover, in line with our research hypothesis, we detect that the price of a stock shows a significantly stronger reaction to a positive target price announcement if the stock yielded positive excess returns over a short period preceding the announcement day.

The rest of the paper is structured as follows. In Section 2, we briefly review the literature on target prices and their informational value, as well as the literature dealing with the availability heuristic and its economic applications. Section 3 defines our research hypothesis. In Section 4, we describe the database and the basic methodology. Section 5 provides the empirical tests and the results. Section 6 concludes and provides a brief discussion.

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[3] According to the availability heuristic (Tversky and Kahneman, 1973), people tend to determine the likelihood of uncertain events according to the ease of recalling similar instances.

[4] The majority of target prices released by Israeli analysts fall into this category, consistent with the worldwide phenomenon of an optimistic bias in target prices relative to current trading prices (Asquith *et al.*, 2005; Brav and Lehavy, 2003; Bradshaw *et al.*, 2013). We have not included target prices classified as "hold" recommendations, as they, in fact, imply that the current stock price is approximately "correct" so that no action concerning the stock has to be taken, while we are interested in target prices, which may be regarded as "news" and have the potential to affect stock prices. We also have not included target prices classified as "sell" recommendations, since in general there are very few such recommendations and in almost all cases may be suspected of being biased (are not properly announced in the mass media, refer to small or highly distressed stocks, etc.).

2. Literature review

2.1. Analysts' estimates and forecasts; target prices

As information intermediaries, security analysts provide three main quantitative outputs for investors: earnings forecasts, stock recommendations and target prices.

An extensive body of literature has examined the role of security analysts on capital markets and has documented the informative value of various components of analyst research, with the focus mainly on earnings forecasts and stock recommendations. The evidence in support of the value of analysts' work is substantial.[5] A number of studies have demonstrated immediate and delayed responses to analyst earnings forecast revisions (Stickel, 1991; Elgers *et al.*, 2001; Gleason *et al.*, 2003). Francis and Soffer (1997) find that stock recommendation revisions contain information incremental to the information in earnings forecast revisions, and that investors assign significantly greater weight to earnings forecast revisions accompanied by buy recommendations than by those accompanied by sell or hold recommendations. Ivkovic and Jegadeesh (2004) show that analysts' upward stock recommendations and earnings forecast revisions issued shortly before earnings announcements contain more new information than forecast revisions issued shortly after earnings announcements. Asquith *et al.* (2005) find that the combination of earnings forecast revisions, stock recommendations, target price revisions and the strength of analysts' (positive or negative) arguments in support of stock recommendations explain a quarter of the return variation around the release of analysts' research reports. Boni and Womack (2006) show that analyst recommendation changes lead to more profitable trading strategies within industries than across industries, suggesting that analysts are more capable of distinguishing performance within an industry. Green (2006) finds that early access to analyst recommendation changes facilitates profitable trades for brokerage firm clients. According to Barber *et al.* (2010), abnormal returns to analysts' recommendations stem both from assigned rating levels and from changes in those ratings. A number of studies have documented return drifts subsequent to analyst recommendations (e.g., Barber *et al.*, 2001). Another matter of interest is how market responses to analyst forecast revisions or stock recommendation revisions vary in the cross-section or across event time with various firm or analyst characteristics (e.g., Gleason *et al.* 2003; Jegadeesh and Kim, 2010). Overall, this line of research suggests that analyst earnings forecast revisions and recommendation revisions convey significant information to the capital market, yet the capital market does not immediately incorporate such information in full.

Much less attention, however, has been paid to market responses to target price revisions. In recent years, analysts have been including these revisions more and more in their reports, alongside earnings forecasts and stock recommendations. These target prices explicitly convey analysts' assessments of the expected value of underlying stocks, usually over the next twelve months from the date of issuance. Based on a sample of 114 Canadian firms, Bandyopadhyay *et al.* (1995) find that analysts derive their price forecasts from their earnings forecasts. Bradshaw (2002) examines analysts' use of target prices to justify their stock recommendations. Using a database of analysts' target prices for the period 1997-1999, Brav and Lehavy (2003) find a significant market reaction to the information contained in analysts' target prices, even after controlling for contemporaneously issued stock recommendations and earnings forecasts. Asquith *et al.* (2005) find that target prices and the strength of arguments in analysts' research reports have stronger impacts on prices than do earnings forecast revisions and stock recommendations alone. Bianchini *et al.* (2008) find that investment strategies based on target prices deliver positive abnormal returns. Huang *et al.* (2009) find that portfolios based on changes both in consensus recommendations and in target prices are more profitable than those based merely on changes in recommendations or on target prices. Da and Schaumburg (2011) document that the relative within-industry valuations that are implicit in analyst target prices provide

[5] For excellent reviews, see Schipper (1991), Brown (1993) and Ramnath *et al.* (2008), which focus on analysts' earnings forecasts and/or on stock recommendations only.

investors with valuable information, although the implied absolute valuations themselves are much less informative.

While the above literature review indicates that target prices are informative, the value of target prices is somewhat in doubt (e.g., Lyssimachou *et al.*, 2009; Demirakos *et al.*, 2010). According to Bradshaw *et al.* (2013), analysts seem unable to provide consistent target prices and indeed lack incentive to do so. Similarly, Bonini *et al.* (2010) find that target prices lack accuracy. Prior research has also demonstrated a significant optimistic bias in target prices relative to current trading prices. Studies by Asquith *et al.* (2005) and Brav and Lehavy (2003) both document an implied average return of 32.9% from analyst target prices for the period from 1997 to 1999, while Bradshaw *et al.* (2013) document an implied return of 24.0% from analyst target prices for the period from 2000 to 2009. In contrast, Mehra (2003) finds that from 1802 to 1998, the real annual U.S. equity return was only 7.0% and that the equity returns in other developed countries were even lower.

2.2. Availability heuristic: Psychological aspects and economic applications

The availability heuristic (Tversky and Kahneman, 1973) refers to the phenomenon of determining the likelihood of an event according to the ease of recalling similar instances. In other words, the availability heuristic may be described as a rule of thumb people use to estimate the probability of an outcome based on how easy that outcome is to imagine. As such, possibilities that are vividly described and emotionally charged will be perceived as being more likely than those that are harder to picture or difficult to understand. Tversky and Kahneman (1974) provide examples of ways in which availability may provide practical clues for assessing frequencies and probabilities. They argue that "recent occurrences are likely to be relatively more available than earlier experiences" (p. 1127), and thus conclude that people assess probabilities by overweighting current information as opposed to processing all relevant information.

A number of studies have discussed the influence of the availability heuristic on market investors. Shiller (1998) argues that investors' attention to investment categories (e.g., stocks versus bonds or real estate) may be affected by alternating waves of public attention or inattention. Similarly, Barber and Odean (2008) find that when choosing which stock to buy, investors tend to consider only those stocks that have recently caught their attention (stocks in the news, stocks experiencing high abnormal trading volume, stocks with extreme one-day returns). Daniel *et al.* (2002) conclude that investors and analysts are on average too credulous. That is, when examining an informative event or a value indicator, they do not adequately take into account the incentives of others to manipulate this signal. Credulity may be explained by limited attention and by the fact that the availability of a stimulus causes it to be weighed more heavily. Frieder (2003) finds that stock traders seek to buy following large positive earnings surprises and to sell following large negative earnings surprises. He explains this tendency by the availability heuristic, assuming that the salience of an earnings surprise increases its magnitude. Ganzach (2001) offers support for a model in which analysts base their judgments of risk and return for unfamiliar stocks upon a global attitude. If stocks are perceived as good, they are judged to have high return and low risk, whereas if they are perceived as bad, they are judged to be low in return and high in risk. Lee *et al.* (2007) discuss the "recency bias," or people's tendency to make judgments about the likelihood of events based on their recent experience. They find that analysts' forecasts of firms' long-term growth in earnings per share tend to be relatively optimistic when the economy is expanding and relatively pessimistic when the economy is contracting. This finding is consistent with the availability heuristic, indicating that forecasters overweigh the current state of the economy in making long-term growth predictions. Kliger and Kudryavtsev (2010) find that positive stock price reactions to analyst recommendation upgrades are stronger when accompanied by positive stock market index returns, and negative stock price reactions to analyst recommendation downgrades are stronger when accompanied by negative stock market index returns. They designate this finding as the "outcome availability effect" and explain it by the higher availability of positive (negative) outcomes on days of market index rises (declines). Moreover, Kliger and Kudryavtsev (2010) document weaker (stronger) reactions to recommendation upgrades (downgrades) on days of substantial stock market moves. They designate this finding as the "risk availability effect" and explain it by the greater availability of risky outcomes on such "highly volatile" days.

3. Research hypothesis

As shown in the previous section, recent studies dealing with target prices concentrate mainly on the accuracy of the target prices or on their information value, that is, on the effects they have on the prices of the respective stocks. In the present study, we shed light on the mechanism governing the effect of target price releases on stock prices. Namely, we focus on the effect of stock returns registered *before* target price announcements on stock price reactions to the announcements.

As explained in the next section, in our analysis we employ target price announcements classified as "buy" recommendations, that is, target prices that are substantially higher than the current stock price at the time of the announcement. These announcements may be regarded as "good news." We hypothesize that because of the effects of the availability heuristic, investors may expect positive stock recommendations ("good news") to have greater potential to lead to positive stock returns if the stock being recommended experienced positive abnormal returns during a short period immediately preceding the release of the recommendation. In other words, we expect that if a stock's price increased before the stock was positively recommended by an analyst, it may be easier for investors to think about a scenario in which the stock's price will continue to increase as a result of the recommendation (i.e., such a scenario becomes more available or more subjectively probable). Such a perception of positive recommendations may make the respective stocks more attractive and increase the positive stock price reactions to the recommendations. This hypothesis is in line with the findings of Lee *et al.* (2007) and Kliger and Kudryavtsev (2010) with respect to people's tendency to make judgments about the likelihood of events based on their recent experience or on the similarity of the events to current states.

Thus, our study's main hypothesis may be formulated as:

Hypothesis: *A positive stock price reaction to a stock's target price release classified as a "buy" recommendation should be stronger if the stock's abnormal returns prior to the day of the release were positive.*

In the next section, we explain how the abnormal stock returns are calculated, and in Section 5, we test the hypothesis empirically.

4. Data description and methodology

For the purposes of this study, we employed all target prices for the stocks listed on Tel Aviv Stock Exchange (TASE) released by sell-side analysts during the period from August 2011 to March 2013. To minimize the effect of potential biases in target prices and other potential side effects, we applied a number of sample filters and included only the following target price announcements in our analysis:

- Announcements classified as "buy" recommendations, that is, target prices that are substantially higher than the current stock price at the time of the announcement.[6] The majority of target prices released by Israeli analysts fall into this category, consistent with the worldwide phenomenon of an optimistic bias in target prices relative to current trading prices (Asquith *et al.*, 2005; Brav and Lehavy, 2003; Bradshaw *et al.*, 2013). A possible reason for this bias may be that analysts strive to optimally "serve their clients," who are in general considered to be more interested in identifying "stocks to buy" than "stocks to sell." We have not included target prices classified as "hold" recommendations, as these in fact imply that the current stock price is approximately "correct" so that no action concerning the stock has to be taken. In contrast, we are interested in target prices that may be regarded as "news" and have

[6] All target price announcements for Israeli stocks are explicitly attributed to a specific "recommendation category" according to the relation of the target price to the current stock price.

the potential to affect stock prices. We also have not included target prices classified as "sell" recommendations, since there are generally very few such recommendations and almost all the cases may be suspected of being biased (not properly announced in the mass media, refer to small or highly distressed stocks, etc.).

- Announcements for the stocks included in TA-25 or TA-75 stock market indexes.[7] We have not included target price releases for small stocks, which are usually highly volatile and quite difficult to predict (even for security analysts).
- Announcements for the stocks listed on TASE only. We have excluded the target prices for dually listed stocks, since their prices on foreign stock exchanges may be virtually unaffected by local analysts' opinions.
- Announcements that appeared on at least three major Israeli financial websites.[8] All these websites are free and represent well-known and widely accepted channels of financial information in Israel. In this way we ensure that the announcements we examine have the highest exposure rate among the available recommendations.
- "Stand alone" announcements, meaning that there were no other analyst recommendations related to a given stock during the period ranging from 7 days before to 14 days after the announcement. This condition allows us to "isolate" stock price reaction to the announcement, ensuring that it was not driven by any other report released by the same or another security analyst.
- Announcements for stocks that were included in the TA-100 index[9] for at least one year prior to the release of the target price. This condition allows us to calculate the Market Model parameters of the stock, describing its "normal" performance conditional to contemporaneous stock market performance.

Our filtered working sample consists of 65 target price releases for 43 different stocks, including 26 releases for 17 different stocks included in the TA-25 Index and 39 releases for 26 different stocks included in the TA-75 Index. The average ratio of the target price to the current stock price is 1.228 (implied expected return of 22.8%), with a maximum of 1.457 and a minimum of 1.124.

To estimate the effect of target price releases on stock prices, we calculate abnormal (excess) stock returns around the announcement day. We employ the well-known event study methodology (Campbell *et al.*, 1997). Based on the Market Model for each stock that experienced an event (target price announcement), we first calculate its "normal" performance conditional upon contemporaneous market returns. That is, using daily data over an "estimation window" of roughly one year prior the event (Days -250 to -8 relative to the event[10]), we run the following regression:

$$SR_{it} = \alpha_i + \beta_i MR_t + \varepsilon_{it} \qquad (1)$$

where SR_{it} is the stock's return on day *t* within the "estimation window" preceding event *i*, and MR_t is the general stock market (TA-100 Index) return on day *t* within the "estimation window."

Thus for each stock we calculate its Market Model parameter estimates, $\widehat{\alpha}_i$ and $\widehat{\beta}_i$, relative to event *i*, and subsequently, for each day within the "event window" (Days -7 to 14 relative to event), we calculate the stock's abnormal returns as follows:

$$AR_{it} = SR_{it} - [\widehat{\alpha}_i + \widehat{\beta}_i MR_t] \qquad (2)$$

[7] TA-25 Index tracks the share prices of the 25 companies with the highest market capitalization on the TASE. TA-75 Index tracks the 75 companies with the highest market capitalization that are not included in the TA-25 Index.

[8] There are four major financial websites in Israel: Globes (http://www.globes.co.il); TheMarker (http://www.themarker.co.il); Bizportal (http://www.bizportal.co.il); Calcalist (http://www.calcalist.co.il).

[9] TA-100 Index tracks the share prices of the 100 companies with the highest market capitalization on the TASE. It includes the TA-25 and TA-75 Indexes, and represents a widely recognized proxy for the "market portfolio" of the TASE.

[10] The event day (the day of the target price announcement) is defined as Day 0.

where AR_{it} is the stock's abnormal return on day *t* within the "event window" surrounding event *i*, SR_{it} is the stock's return on day *t* within the "event window" surrounding event *i*, and MR_t is the general stock market (TA-100 Index) return on day *t* within the "event window."

Finally, in order to estimate stock price reactions over a number of days within the "event window," we calculate each stock's cumulative abnormal returns for the respective time interval:

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{it} \qquad (3)$$

where $CAR_i(t_1, t_2)$ is the stock's cumulative abnormal return between day *t1* and *t2* within the "event window" surrounding event *i*.

The ratios of the cross-sectional means of ARs and CARs to their respective standard deviations serve as t-statistic values for estimating the statistical significance of the results.

5. Results description

5.1. Effect of target price releases on stock prices: General sample

Table 1 shows the means and the standard deviation of the abnormal returns for all the days within the "event window" and of the cumulative abnormal returns for a number of time intervals within this period. It also shows the respective t-statistic values and their statistical significance. The table demonstrates that positive target price announcements are a valuable source of information and have a significant effect on stock prices. The Day-0 effect amounts to 0.65% on average and is statistically significant. Moreover, the reaction continues, though not homogeneously, until Day 14. The mean cumulative abnormal returns for Days 1 to 4 and Days 1 to 14 are 1.831% and 2.487% respectively and are highly significant. These findings contradict the semi-strong form of stock market efficiency, indicating that a significant profit potential still exists from the point of view of the investors who buy positively recommended stocks after the recommendations have been released. Another point worth mentioning is the significantly positive (1.593%) mean cumulative abnormal return for Days -7 to -1. This finding has two possible explanations. First, it may be a result of dissemination of private (insider) information prior to the announcement of the analyst report. If this is the case, it seems to contradict the strong form of stock market efficiency, indicating that a company's insiders are able to gain abnormal returns. Alternatively, the price increase itself may, at least in some cases, drive security analysts to provide positive recommendations due to the expectation that the price momentum may continue.

Table 1: Abnormal and cumulative abnormal returns within the "event window": General sample

Days relative to event	Mean, %	Standard Deviation, %	t-statistic
Abnormal Returns:			
-7	0.623	0.392	1.589
-6	0.694	0.428	1.623
-5	0.132	0.312	0.423
-4	0.236	0.348	0.680
-3	-0.175	0.359	-0.487
-2	-0.001	0.343	-0.002
-1	0.082	0.342	0.241
0	0.650	0.323	**2.014
1	0.614	0.399	1.541
2	0.065	0.276	0.235
3	0.710	0.399	*1.781
4	0.441	0.325	1.358
5	-0.028	0.337	-0.084
6	0.144	0.258	0.560
7	-0.319	0.333	-0.956

Days relative to event	Mean, %	Standard Deviation, %	t-statistic
8	-0.293	0.349	-0.841
9	0.047	0.302	0.156
10	0.112	0.283	0.397
11	-0.048	0.277	-0.172
12	0.215	0.311	0.692
13	0.270	0.293	0.921
14	0.555	0.335	1.658
Cumulative Abnormal Returns:			
Days -7 to -1	1.593	0.787	**2.025
Days 0 to 4	2.481	0.891	***2.784
Days 1 to 4	1.831	0.762	***2.401
Days 0 to 14	3.137	1.260	***2.489
Days 1 to 14	2.487	1.235	**2.013

Asterisks denote two-tailed p-values: *p<0.1, **p<0.05, ***p<0.01.

5.2. Cross-sectional differences in the effect of target price releases: Large versus small stocks

Having established the effect of target price announcements on stock prices, we proceed to analyze the cross-sectional differences in the magnitude of the effect. First of all, we distinguish between large and (relatively) small stocks. Table 2 compares the mean abnormal and cumulative abnormal returns between the stocks included in the TA-25 and TA-75 indexes by presenting the respective return differences and their statistical significance. The results show that the effect of target price announcements is substantially stronger for smaller stocks. The difference between the mean abnormal returns for stocks on the TA-75 and the TA-25 for Day 0 (immediate reaction to the event) amounts to 0.966% and is statistically significant. The differences between the mean cumulative abnormal returns for Days 1 to 4 and Days 1 to 14 (stock price drifts following the event) are 1.850% and 1.387% respectively and are also significant. Figure 1 visualizes the mean cumulative abnormal returns for stocks on both indexes starting with Day 0[11] and once again demonstrates that smaller stocks are much more affected by target price releases, in line with the well-documented phenomenon of a generally stronger reaction among small stocks to different kinds of company-specific news.

Table 2: Cross-sectional differences in abnormal and cumulative abnormal returns: Large versus small stocks

Days relative to event	Mean, %		
	TA-75 (Small stocks)	TA-25 (Large stocks)	Difference
Abnormal Returns:			
-7	0.429	1.136	-0.707
-6	0.642	0.619	0.023
-5	0.491	-0.046	0.537
-4	0.422	-0.014	0.435
-3	-0.123	-0.154	0.031
-2	0.251	-0.478	0.729
-1	-0.147	0.397	-0.544
0	0 .974	0.007	**0.966
1	0.731	0.580	0.151
2	0.328	-0.374	*0.702
3	0.697	0.666	0.031
4	0.957	-0.010	*0.966
5	-0.033	-0.001	-0.032
6	-0.050	0.507	-0.556
7	-0.304	-0.348	0.044
8	-0.222	-0.524	0.302
9	-0.166	0.337	-0.503
10	0.115	-0.086	0.201

[11] That is, CAR (0, *t*) for each day *t* within the "event window".

Days relative to event	Mean, %		
	TA-75 (Small stocks)	TA-25 (Large stocks)	Difference
11	-0.268	-0.019	-0.249
12	0.381	0.041	0.341
13	0.274	0.265	0.009
14	0.547	0.565	-0.018
Cumulative Abnormal Returns:			
Days -7 to -1	1.964	1.460	0.505
Days 0 to 4	3.687	0.870	***2.816
Days 1 to 4	2.713	0.863	**1.850
Days 0 to 14	3.960	1.606	***2.354
Days 1 to 14	2.986	1.599	**1.387

Asterisks denote two-tailed p-values: *p<0.1, **p<0.05, ***p<0.01.

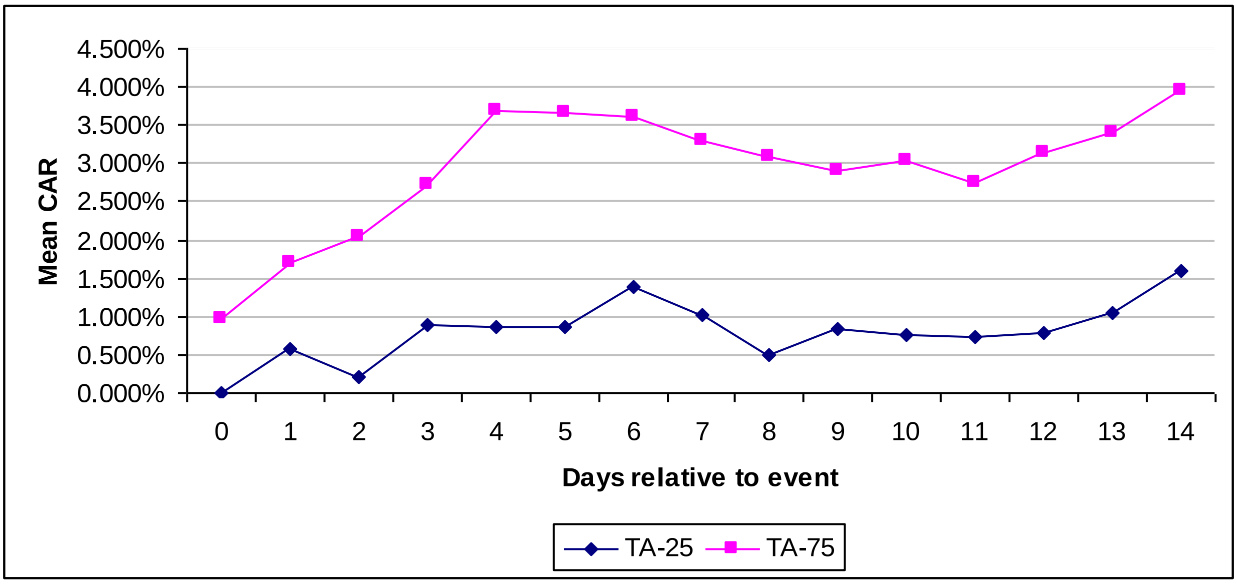

Figure 1. Mean cumulative abnormal returns starting from Day 0 for stocks in TA-25 and TA-75

5.3. Cross-sectional differences in the effect of target price releases: Stocks with positive versus negative abnormal returns before the event day

At this stage, we continue the cross-sectional analysis of the effect of target price announcements and proceed to explicit testing of our main research hypothesis that positive stock price reactions to positive target price releases should be stronger if the abnormal returns of the respective stocks before the day of the release were positive. For each of the sample stocks, we employ the sign of its cumulative abnormal return over Days -7 to -1 as a proxy for the direction of change in stock price before the event.[12] Table 3 compares the mean abnormal and cumulative abnormal returns between the stocks that registered positive and negative CARs (-7, -1) and presents the respective return differences and their statistical significance.

[12] Alternatively, we employed a number of other proxies, including the sign of CAR (-5, -1), CAR (-3, -1), and CAR (-2, -1). The results of the AR and CAR differences analysis as presented in Table 3 remained qualitatively similar.

Table 3: Cross-sectional differences in abnormal and cumulative abnormal returns: Stocks with positive CAR (-7, -1) versus stocks with negative CAR (-7, -1)

Days relative to event	Mean, %		
	Stocks with positive CAR (-7, -1)	Stocks with negative CAR (-7, -1)	Difference
Abnormal Returns:			
0	0.992	0.137	**0.854
1	0.762	0.393	0.369
2	0.564	-0.683	**1.247
3	0.717	0.700	0.017
4	0.845	-0.164	**1.009
5	-0.022	-0.038	0.015
6	0.076	0.247	-0.171
7	-0.459	-0.109	-0.350
8	-0.307	-0.272	-0.036
9	-0.306	0.577	-0.883
10	0.163	0.037	0.125
11	-0.076	-0.005	-0.071
12	0.276	0.124	0.152
13	0.241	0.313	-0.072
14	0.671	0.382	0.288
Cumulative Abnormal Returns:			
Days 0 to 4	3.879	0.383	***3.497
Days 1 to 4	2.888	0.245	***2.642
Days 0 to 14	4.134	1.640	***2.494
Days 1 to 14	3.143	1.503	**1.640

Note: Asterisks denote two-tailed p-values: *p<0.1, **p<0.05, ***p<0.01.

The results strongly corroborate our hypothesis. The stocks that experienced positive cumulative abnormal returns before target price releases yield on Day 0 impressively higher (by 0.854%) mean abnormal returns than the stocks that experienced negative cumulative abnormal returns before target price releases. Subsequent stock price drifts are also substantially affected, showing highly significant mean cumulative abnormal differences in returns of 2.644% and 1.640% for Days 1 to 4 and 1 to 14, respectively. Figure 2 graphically visualizes the mean cumulative abnormal returns for both groups of stocks, starting with Day 0.

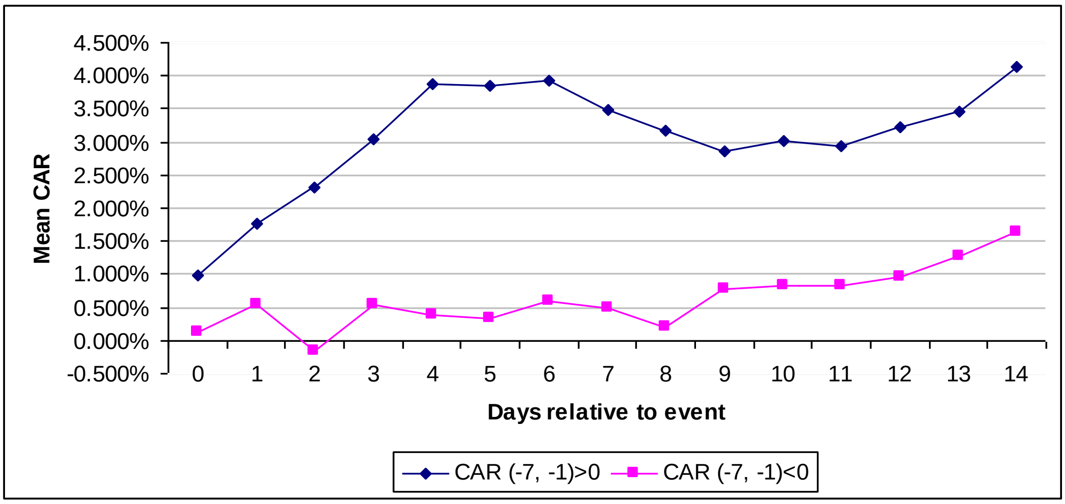

Figure 2. Mean cumulative abnormal returns starting from Day 0 for stocks with positive and negative CAR (-7, -1)

Thus, in line with our research hypothesis, we document that investors react more strongly to positive target price announcements in cases when there are positive stock price moves prior to the announcements. Following these moves, stock price increases in general become more psychologically available. As a result, the subjective probability of positive stock price reactions to the announcements increases, strengthening the reactions themselves.

Conclusion

In the present study, we shed light on potential factors affecting investors' reactions to target price announcements by security analysts. We focus on cross-sectional differences in the magnitude of the reaction between stocks whose prices increased immediately prior to the announcements and those whose prices decreased. We suggest that investors' perceptions and decisions may be affected by the availability heuristic, leading them to expect target price releases to have a stronger effect on stock prices if preceded by stock returns of the same sign as the recommendation itself.

Employing a sample of target price announcements classified as "buy" (positive) recommendations for Israeli stocks, we document their significantly positive effect on stock prices both on the day of the announcement (in line with the findings of Brav and Lehavy (2003), and Da and Schaumburg (2011)) and during a short period following the announcement. This finding regarding the period following the announcement is consistent with the conclusions of Bianchini *et al.* (2008), suggesting that investment strategies based on target prices may deliver positive abnormal returns even for investors who do not manage to react to news immediately. Interestingly, we document that positive target price announcements are on average preceded by short periods of positive abnormal stock returns. Potential explanations for this finding include dissemination of private (insider) information prior to the announcement of analyst reports and an explicit effect of stock price momentum on the contents of the reports themselves.

Furthermore, we detect that the effect of target price announcements on stock prices is significantly stronger for smaller stocks, in line with the well-documented phenomenon of a generally stronger reaction of small stocks to different kinds of company-specific news. Finally, we find supportive evidence for our main research hypothesis. We document that the stocks that experienced positive cumulative abnormal returns prior to target price releases yield significantly higher mean abnormal returns, both on the event day and during a short subsequent period, than do the stocks that experienced negative cumulative abnormal returns prior to target price releases. These findings continue the line of research of economic psychology (Lee *et al.*, 2007; Kliger and Kudryavtsev, 2010), which considers people's tendency to make judgments about the likelihood of events based on recent experience or on the similarity of the events to current states. This demonstrates that if a stock's price has increased before the stock has been positively recommended by an analyst, it may be easier for investors to consider a scenario in which the stock's price increase continues as a result of the recommendation.

To summarize, our study demonstrates that target price releases contain valuable information for stock market investors, and that stock price reactions to these releases systematically differ in the cross-section. These results may prove to be valuable both for financial theoreticians in their eternal discussion about stock market efficiency and for practitioners in search of potentially profitable investment strategies. Potential directions for further research may include expanding the analysis to other stock exchanges and to target price announcements classified as "sell" recommendations.

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STUDY ON PRE-ASSESSMENT AND EVALUATION SYSTEM. INDICATORS FOR ENERGO - MINING COMPLEX IN BASIN OF OLTENIA

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Abstract

General behavior of the company's mining and energy is superstate, pursuit function entity, independent of multiple relationships with the external environment. For a superstate behavior, mining company, energy internal control circuit acts that manages to attract, to resolve the problems that arise in the functioning of the internal capabilities of resourcefulness and initiative.

Statement by offsetting adjustment takes place by opening the internal control circuit to apply the means of establishing equilibrium. In our assessment, the company mining / energy has double adjustment possibilities, but is really effective only when they occur in the system superstate. Intervention-compensation adjustment is necessary in some periods, precisely because of the place it has mining company / energy in general economic system. The Company has analyzed the precise functions and features specific means, but was only able to take over certain disturbances.

Key words: evaluation system, indicators, energy and mining sector.

JEL Clasiffication: D3

1. Introduction

The system concept enables highlighting the many factors that contribute to the assessment decision area. Decision making energy-mining without reference to a specific mining energy-econometric system will be hazardous. Restructuring of the mining sector management in connection with the energy can not prove reliable conceptual if not taken into account in making the decision econometric perspective.

Reporting the results of any action economic structures econometric energy-mining system that competed in the result of the subsequent results would increase the chances of adopting some decisions based on variables that contribute to their success. The systemic perspective to explain the production processes and maximum complexity and dynamic econometric, mining and thermal power system, the essence of which can hardly be highlighted by other means of investigation.

Basin Oltenia Using econometric system concept through this process is trying real economic analysis of the phenomenon productive as he is, as a set of interacting elements. The system concept is the expression of a way of thinking econometric management.

It provides a framework that allows to highlight the internal and external factors of technological lines of pits and burning of lignite power plants as an integral whole. The concept of econometric energy-mining system is used to explain the mechanism of expression of hurt economic phenomena-productive area of Oltenia, or operational means to optimize economic activity by building models based on system behavior in the field. Econometric system in this case is a conceptual tool which delimit the field within which investigates the energy-mining target, ie objective basis, structural, temporal and spatial two areas.

The system provides a new light means used to improve the career civil process lines and systems of power plants burning lignite, management and prognosis, and other aspects, such as self-organization and self-specific processes, aspects of creative expression the individual in the group, explaining the behavior of subjects responsibility as a social phenomenon in the area.

2. State the decision econometric energy-mining complexes

Econometric modellers situation in the area, according to our research, is characterized by the meeting of 3 elements, namely:

- The set of independent parameters or stimuli (denoted S) defining the objectives and uncontrollable variables form;
- The set of rational alternatives or possible reactions (denoted R), which is able to respond to each objective conditions that make up the controllable variables;
- The set of outcome indicators that can be reasonably considered in the choice of decision criterion.

Stimuli. This includes elements of the environment that can not be changed in the decision (eg geo-mining conditions natural energy-mining basin Oltenia). There uncontrollable parameters, common form of political and economic restrictions of the country, the behavior of machines, innovation, phenomena related to employment. Uncontrollable parameters may be continuous or discrete categories of state.

Reactions. This set consists of all the possibilities that are available to decision makers and lignite power plants careers for solving decision problems. Reactions are generally understood in the sense of ,, value "(quantity, size, type, number, etc). The crowd crowd reactions generated by stimuli from a state of nature.

Indicators. In the state of nature, for each rational variant applicable results are obtained, which can be characterized by indicators. Deciding means choosing an econometric versions of several possible action, and is subordinate to the requirement of optimality in the energy-mining research. It is estimated that the optimization is carried out with respect to all criteria. An alternative is better than another only to the extent that it satisfies more than one criterion than another.

The decision criteria for the study are:

- *simple decision criterion:* we consider a single output indicator (tons of lignite, KWh electricity), the other being neglected or kept at a constant level (optimum yield relatively).
- *complex decision criterion*. This is a subset of the set {I} outcome indicators, to be taken into account when solving a decision problem Basin Oltenia. If complex decision criteria differ more options:
  - you can choose limiting values for all indicators derived from the subset of {I}, less than one, depending on which optimizes max. or min. (Via mathematical programming);
  - determine the functional relationship between two or more indicators and combine into one.
  - it shall result in the transformation of indicators deviations from the optimal.

It establishes a matrix containing rows indicator value of each option, and the columns, the value of all indicators for a variant.

Table 1 – The value of all indicators for a variant.

I/V	V_1	V_2	V_3	…	V_N
I_1	a_{11}	a_{12}	a_{13}	…	a_{1n}
I_2	a_{21}	a_{22}	a_{23}	…	a_{2n}
I_3	a_{31}	a_{32}	A_{31}	…	a_{3n}
…	…	…	…	a_{ij}	…
I_M	a_{m1}	a_{m2}	a_{m3}	…	a_{mn}

The result indicators matrix elements of a matrix C is calculated transformed.

Table 2 - Deviations from the optimal value of the result indicator.

I/V	V_1	V_2	V_3	…	V_N
I_1	c_{11}	c_{12}	c_{13}	…	c_{1n}
I_2	c_{21}	c_{22}	c_{23}	…	c_{2n}
I_3	c_{31}	c_{32}	c_{31}	…	c_{3n}
…	…	…	…	c_{ij}	…
I_m	c_{m1}	c_{m2}	c_{m3}	…	c_{mn}
Σc_{ij}					

Elements c_{ij} are obtained using the relation:

$$c_{ij} = \xi \frac{a_{ix} - a_{ij}}{a_{ix}} \tag{1}$$

unde: $\xi = \begin{cases} +1 \text{ for max. (when it comes to the max.)} \\ +1 \text{ for min. (when it comes to min.)} \end{cases}$

a_{ik} = the optimal value of an indicator

The optimal variant is that which has the minimal deviations c_{ij}:

The optimal variant = variant min [Σc_{ij}] (2)

with a_{ij} = elements of the matrix A.

3. Decision-making in energy-mining complexes

Deciding the researched area is based on: the selection criteria decision; alternative choice of action (decision itself).Decision criterion is a measure that compares each action options to choose the best alternative.Simple decision criteria apply when the objective can be characterized by a single indicator of outcome (all other results are ignored, considered insignificant for the ultimate goal). The objective of energy-mining complexes composed of the maximum amount of energy production variant would ensure maximum yield criterion would be the best option, quantity of products. Typically, the maximum similarity in criterion coincides with the minimum cost, minimum investment, etc. We conclude from our analysis that rarely Basin Oltenia decision shall be taken by a simple criterion. Most often resorting to a complex criterion, since it reflects more results indicators:

$$D = S \cup R \cup I \tag{3}$$

in which: D = decision*;*

I = set of outcome indicators (variables that reflect the results that would be obtained by taking a lot of reactions R, defined objectives in terms of stimuli S).

Simultaneously,

$$I = \{I_K\} \tag{4}$$

$$I = F^k(X,Y,Z)$$

These outcome variables (response) according to R and S are taken. It concludes that the results reasonably possible to consider the energy-mining production system in Oltenia are: the amount of energy, works, services; production costs, investment; consumption of materials; benefit; delivery or the putting into use; security; the degree of compliance of technical safety at work; the social effects etc.

Ways to use a criterion energy-mining complex entities, are mainly the following:

a) Identify a mathematical relationship between several indicators result.

Example: cost price / unit is a complex criterion c;

$$c = f(Q,C_e,C,) \tag{5}$$

in which: Q = production of lignite / energy; C_e = operating expenses (in careers lignite power plants); C_i = investment expenditure.

Similarly, the benefit b is:

$$b = f(Q, C, p_v) \tag{6}$$

in which: Q = output; C = cost price; Pv = cash price.

For K = considered equivalent expenditure, the relationship is:

$$K = C_{ie} + C_e \tag{7}$$

in which: C_{ie} = investment costs for achieving; e = coefficient (rate) of efficiency of investments (as a percentage of investment returns / returns as accumulation); C_e = operating expenses.

b) Limit values they can take some of the indicators for results and maximize (minimize) after another indicator considered of prime importance (constrained optimization). This we believe that is the most widely used in energy-mining complexes decisions Basin Oltenia (which appeals to operational research). The decision is constrained optimization:

$$\begin{cases} Q \geq Q_p \\ C_i \leq C_{iN} \\ \min \{C_e\} \end{cases} \tag{8}$$

in which: Q_p = planned production quantity (tonnes lignite kWh); C_{iN} = rated investment.

The best solution (conventionally favorable) is required which ensures production volume Qp, which refers to the assignment of an investment fund available CIN, and leads to minimal operating costs what.

Table 3 - The weighting results in degrees of importance or utility

I/V	V_1	V_2	V_3	…	V_N
I_1	c_{11}	c_{12}	c_{13}	…	c_{1n}
I_2	c_{21}	c_{22}	c_{23}	…	c_{2n}
I_3	c_{31}	c_{32}	c_{31}	…	c_{3n}
…	…	…	…	c_{ij}	…
I_m	c_{m1}	c_{m2}	c_{m3}	…	c_{mn}

From the set {I} indicators extract a subset containing only indicators of utility grade> 0 and 0. Looking for a procedure to transform the results into a common unit of measurement in order to proceed with their summation. At its heart is the concept of „nullity".

4. Model the pre-evaluation indicators energy-mining complexes in Oltenia

Energy is considered essential to catalyze actions vector for inducing general welfare in society in human communities. Functional perspectives and maintain/increase the role of energy in the context of overall development are set taking into account some basic relations and relations of physical force, transformative, effective energy production systems in the same area with the consumer (Figure 2).

In classical economics evaluation using indicators known to the current economic productive applications. Due to the complexity of production in the new economy it is found that exclusive estimate using strong indicators outline is insufficient. The consequence of such observations lead to the need for pre-assessment, using complementary indicators or to express the same indicators in an early evaluation segment, projected under probabilistic incidence.

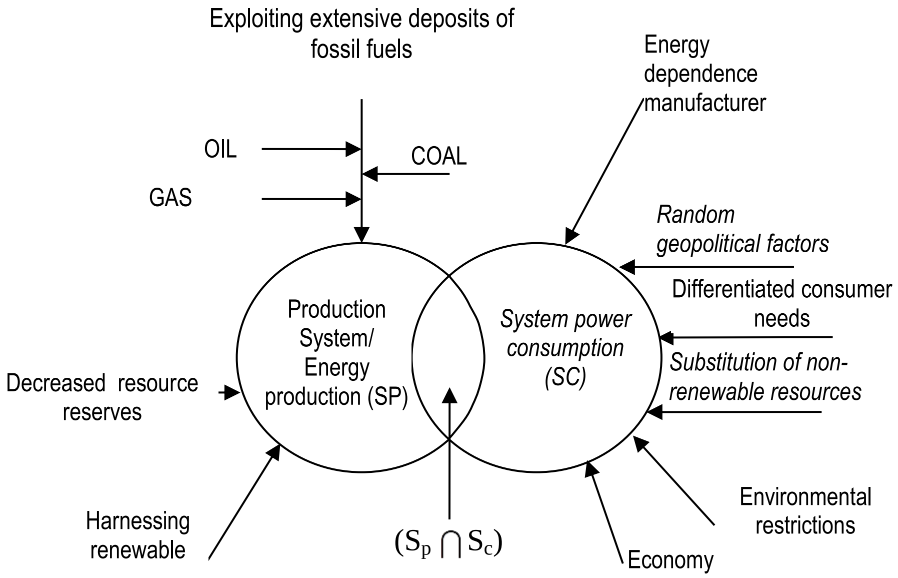

Figure 2. The resulting system functional perspectives (Sp Sc) production a Energy consumption

It is observed that always between energy production systems {SP} i and consumer {SC} i found an intersection (Sp Sc), which generates a surface relational / satisfactory dynamic economic advance in society. In this context, if:

$$\{S_P\}_i * \{S_C\}_i \rightarrow \max (S_p \cap S_c) \qquad (9)$$

then get extensive image-economic productive environment considered a complex unit (country, region, region). This case study is for the energy-mining basin Oltenia.

In such a condition occurs an accelerated dynamics of production / economic reproduction. As such, it appears relatively normal conventional functional state of quasi-linear energy-mining economy in the area.

$$\{S_P\}_i * \{S_C\}_i \rightarrow \min (S_p \cap S_c) \qquad (10)$$

There is restriction of production, energy-mining economic reproduction caused mainly by the following restrictive alternative:

- country, region, area, etc. does not have sufficient resources for setting up a powerful system of energy production;
- economic system locale (country, region, area, etc.) is not appropriate for functional valences of "absorb" amounts of energy consumption (reduced demand occurs), which demonstrates the inconstancy of development / progress.

The types and quantities of energy (produced and/or consumed) causes a lot quasi-finite influences the economic environment studied entity (country, region, area etc.) The appreciation of the relationships between the surfaces visible result from the intersection of production systems/energy and influences the type and amount of energy in the economic environment leads to the conclusion that between economic growth and energy consumption is manifested direct link, direct.

The investigations carried out for this doctoral dissertation that is necessary to explain motivations underlying the alignment of managerial decision on the establishment / setting type energy-mining entities. Data influences the type and quantity of energy produced from mining and energy production determines, in fact, developments in the national economy and changes in the public state budget to the extent that the latter was involved in the last 20 years in Romania to participation subsidies in the energy-mining.

The problem of determining and / or measurement proves nedeterminativă influences prevailed in connection with the operation of tangible assets. In such a situation, contributory recourse for the first time in the field, the allocation of pre-evaluation indicators index (IPI) mentioned influences. It starts from the intersection configuration of the system matrix of indicators of influence, and appreciated feature of synthesis of two indicators: GDP (i1) and investment.

As such, the general symbolic model of the pre-assessment indicators is:

$$\{P\} * \{VF\} * \{M\} \rightarrow \{I\} \subset PIB \qquad (11)$$

restrictions:

$$\begin{cases} \{i_1; i_4; i_7; i_8; i_{11}\} \rightarrow \max \\ \{i_3; i_5; i_9; i_{10}; i_{13}\} \rightarrow \{\min/\max\} / \{\max/\min\} \\ \{i_2; i_{12}\} \rightarrow \min \end{cases} \qquad (12)$$

The {(3); (4)}, set the first time in the literature, is subject to specific data parameterization of energy-mining complexes Rovinari, Turceni and Craiova-Işalniţa give information for economic decision-dominated productive efficiency/more reliable/conceptual feasibility systemic .

Formalizing, contextual, a set of sizes/conventional units of measurement/assessment influences} {SMI is possible to conduct comparisons on data influences of changes in technical, economic and organizational returned essentially the establishment and operation of energy-mining complexes.

The set {S} conventional units of measurement include:

$$\begin{cases} \Phi_0 = \text{influence economic technical and managerial null;} \\ \Phi_{1;2;3} = \text{economic technical and managerial influence reduced;} \\ A_0 = \text{harmonization null; A1; 2; 3 = reduced harmonization or medium, large;} \\ D_0 = \text{zero fault; D1, 2, 3 = low fault or medium, large.} \end{cases} \qquad (13)$$

On a statistical basis, using multiple systematization of a set of assessments, scores symbolic form of influence concerned.For each energy-mining complex in the present study is the first developed an array/matrix table, the intersections between political, financial vectors respectively and investment environment in connection with the GDP, provides images of influence (Tables 1, 2 and 3).

Table 1. Table matrix of technical-economic and managerial influences in energy-mining complex Rovinari

Specifications		**Policies $\{P\}_R$**				**Financial values $\{VF\}_R$**				**Medium $\{M\}_R$**		
		i_3	i_5	i_{11}	i_{13}	i_2	i_9	i_{10}	i_{12}	i_4	i_6	i_8
Investment $\{I\}_R$	i_7	Φ_1	Φ_2	Φ_3	Φ_2	Φ_3	Φ_0	Φ_0	Φ_3	Φ_3	Φ_3	Φ_2
		A_2	A_1	A_1	A_1	A_2	A_3	A_3	A_0	A_1	A_0	A_1
		D_1	D_0	D_0	D_0	D_1	D_0	D_0	D_2	D_2	D_1	D_2
$(PIB)_R$	i_1	Φ_1	Φ_3	Φ_2	Φ_3	Φ_0	Φ_0	Φ_0	Φ_1	Φ_1	Φ_0	Φ_1
		A_2	A_3	A_2	A_3	A_0	A_0	A_0	A_1	A_1	A_1	A_1
		D_1	D_3	D_2	D_3	D_1	D_0	D_0	D_0	D_2	D_0	D_1

Table 2. Table matrix of technical-economic and managerial influences in energy-mining complex Turceni

Specifications		**Policies $\{P\}_T$**				**Financial values $\{VF\}_T$**				**Medium $\{M\}_T$**		
		i_3	i_5	i_{11}	i_{13}	i_2	i_9	i_{10}	i_{12}	i_4	i_6	i_8
Investment $\{I\}_T$	i_7	Φ_1	Φ_2	Φ_3	Φ_2	Φ_3	Φ_0	Φ_0	Φ_3	Φ_3	Φ_3	Φ_2
		A_2	A_1	A_1	A_1	A_2	A_3	A_3	A_0	A_0	A_0	A_1
		D_1	D_0	D_0	D_0	D_1	D_0	D_0	D_2	D_2	D_1	D_2
$(PIB)_T$	i_1	Φ_1	Φ_3	Φ_2	Φ_3	Φ_0	Φ_0	Φ_0	Φ_1	Φ_1	Φ_0	Φ_1
		A_2	A_3	A_2	A_3	A_0	A_0	A_0	A_1	A_1	A_1	A_1
		D_1	D_3	D_2	D_3	D_1	D_0	D_0	D_0	D_2	D_0	D_1

Table 3. Table matrix of technical-economic and managerial influences in the complex energy-mining Craiova-Işalniţa

Specifications		Policies {P}c				Financial values {VF}c				Medium {M}c		
		i_3	i_5	i_{11}	i_{13}	i_2	i_9	i_{10}	i_{12}	i_4	i_6	i_8
Investment {I}c	i_7	Φ_1	Φ_3	Φ_3	Φ_2	Φ_3	Φ_0	Φ_0	Φ_3	Φ_3	Φ_3	Φ_2
		A_2	A_2	A_2	A_1	A_2	A_3	A_3	A_0	A_1	A_0	A_0
		D_1	D_1	D_0	D_0	D_1	D_0	D_0	D_2	D_2	D_2	D_3
(PIB)c	i_1	Φ_1	Φ_3	Φ_2	Φ_3	Φ_0	Φ_0	Φ_0	Φ_1	Φ_1	Φ_0	Φ_1
		A_2	A_3	A_2	A_3	A_0	A_0	A_0	A_1	A_1	A_1	A_1
		D_1	D_3	D_2	D_3	D_1	D_0	D_0	D_0	D_2	D_0	D_1

Pre-evaluation indicators of the 3 energy-mining complexes is statistically formalized step which systematizes and worked correlative findings indicators based on observations and their analysis.

Observations taken in the coal basin of Oltenia and thermal power production network in the area were concentrated by statistical cores appreciative destination for characterization data influences the types of energy (electricity and heat) and quantities output from the Integrated system for power plants using fuel burning lignite coal caustobiolitici category. Finally, it retained a number of useful feedback alignments decisions in the transformation of technical, economic and managerial energy-mining infrastructure, as follows:

- characterization matrix of the set of conventional size influences unit turns out to be normally distributed (see Table 4).

Table 4 - Normal distribution of the number of units, conventional to measure the influences transformative technical, economic and managerial energy-mining complexe in Oltenia

Specifications	{Φ}	{A}	{D}	TOTAL conventional
0	12	11	18	41
1	10	17	12	39
2	8	8	10	26
3	14	8	4	26
TOTAL conventional	44	44	44	

- It follows that approximate levels {0, ..., 3} for each unit have one relative maximum;
- Technical-economic and managerial influences are found significantly null (in context meta-physical) index content "fault";
- In other words, between "influence" and "harmonization" fault manifestation is observed that the maximum tends to zero, ie practically the lowest fault, or the fault essentially non-happening;
- The actual content of pre-evaluation indicators indicators shows that technical-economic and managerial influences {Φ} have maximum on the maximum step (3) specifications (max / max) (94%);
- Harmonization {A} record (max/max) (89%) in step (1) a set of units and faults {D} is the zero step (max/min) (- 59%);
- The graph manifestation trends show that the set of units is marked by arranging histogram values decreasing time influences {(0,1,2,3)} min (see Figure 4).

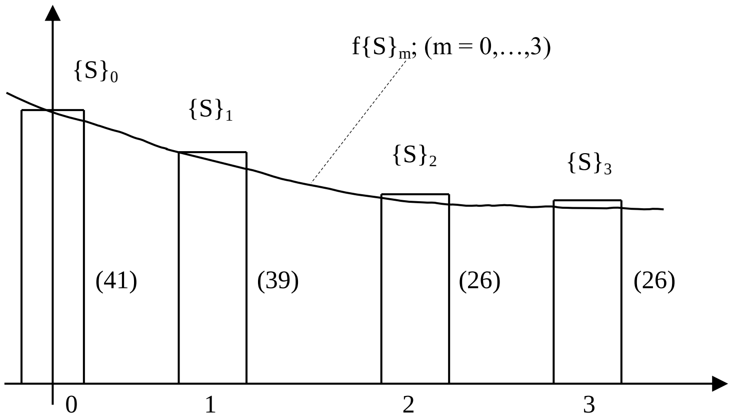

Figure 4. Growth curve determined values histogram of assessments for pre-evaluation indicators energy-mining complexes

In this context, we obtain:

▪ Preliminary conclusion no. 1:

$$\begin{cases} \{\Phi\} \text{ is the maximum (3);} \\ \{A\} \text{ is the maximum (1);} \\ \{D\} \text{ is the maximum (0).} \end{cases} \qquad (15)$$

▪ Preliminary conclusionnr no. 2:

$$\begin{cases} \text{„0” \} is the maximum \{D\};} \\ \quad \text{„2” \} is the maximum \{D\};} \\ \text{„1” \} is the maximum \{A\};} \\ \text{„3” \} is the maximum } \{\Phi\}. \end{cases} \qquad (16)$$

▪ Preliminary conclusionnr no. 3:

$$\begin{cases} \text{„0” is the most significant indicator "not edit";} \\ \text{„1 is 2}^{\text{nd}}\text{”;} \\ \text{„2” is 3}^{\text{rd}}\text{;} \\ \text{„3” is 3}^{\text{rd}}\text{.} \end{cases} \qquad (17)$$

Among the three types of comparisons can be made preliminary conclusions, cases in which a conclusion is given priority / chosen and used in the restructuring decision.

Conclusions

In the chapter is considered the first pre-assessment and evaluation indicators system energy-mining complex in Oltenia using the concept of econometrics / econometric energy-minier.Procedând behavior analysis result from the intersection of the relationships between areas of production systems / energy and influences the type and amount of energy in the economic environment, it is concluded that between economic growth and energy consumption is manifested direct link, direct.

Does the research that is necessary to explain motivations underlying the alignment of managerial decision on the establishment/setting type energy-mining entities. The problem of determining and/or measurement proves nedeterminativă influences prevailed in connection with the operation of tangible assets. In such a situation, contributory recourse for the first time in the field, the allocation of pre-evaluation indices indicators mentioned influences. It starts from the intersection configuration of the system matrix of indicators of influence and, in context, the chapter has formalized a general symbolic model of the pre-evaluation indicators.

Model, set the first time in the literature, was set up with concrete data mining complexes energy-Rovinari, Turceni and Craiova-Işalniţa give information for decision-dominant economic productive efficiency/more reliable/systemic conceptual feasibility. Formalizing, contextual, a set of sizes/conventional units of measurement/assessment of influences is possible to obtain data comparisons influences on changes in technical, economic and organizational returning the establishment and operation of complete energy-miniere.Apelând the systematization of a set of multiple assessments on a statistical basis is formed for symbolic influences in question.

For each energy-mining complex is developed for the first time an array/matrix table, the intersections between political, financial vectors respectively and investment environment in connection with the GDP of providing images of influence. Pre-evaluation indicators of the 3 energy-mining complexes is statistically formalized step which systematizes and worked correlative findings indicators based on observations and their analysis.

Observations between 2010-2014 in the coal basin of Oltenia and thermal power production network in the area were concentrated by statistical cores appreciative destination for characterization data influences the types of energy (electricity and heat) and energy quantities obtained from the output of integrated system for power plants using fuel burning lignite coal caustobiolitici category.

To qualify a number of alignments of assessment, decision-useful in the transformation of technical, economic and managerial energy-mining infrastructure, as follows:

- the characterization of the set matrix size of conventional units influences turns out to be normally distributed;
- It follows that approximate levels were appreciative for each unit one relative maximum.

Technical-economic and managerial influences are found in significant void in the content index "dranjament". Between "influences" and "harmonization" fault manifestation is observed that the maximum tends to zero, ie practically the lowest fault, or essentially non-deranjamentul.În happens actual content of pre-evaluation indicators indicators it is found that technical and economic influences and managerial maximum specifications on maximum gear (max/max) (94%).

Harmonization records (max/max) (89%) on the first stage of a set of units and faults are on stage zero (max/min) (- 59%). The graph manifestation trends show that the set of units is marked by the histogram values arranging decreasing time influences.

The article is plotted normal distribution of the number of conventional units of measurement transformative influences of technical, economic and managerial energy-mining complexes in Oltenia area. It is also shown by the growth curve determined values histogram of assessments for pre-assessment indicators energy-mining complexes.

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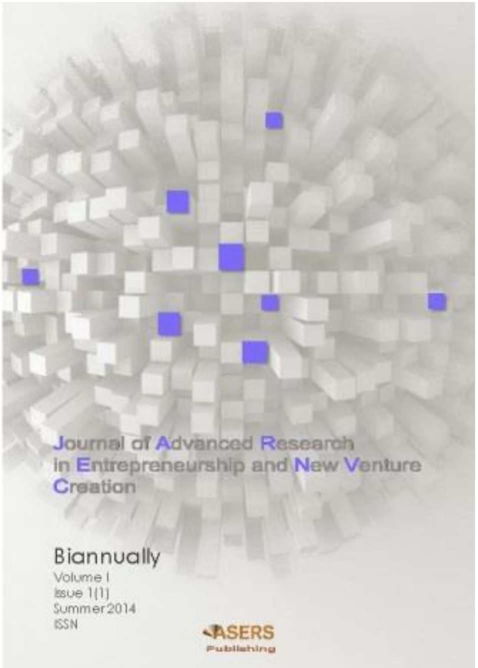

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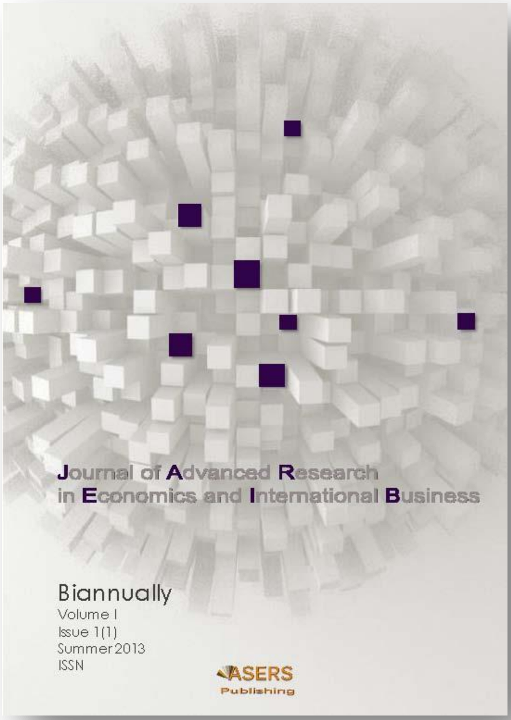

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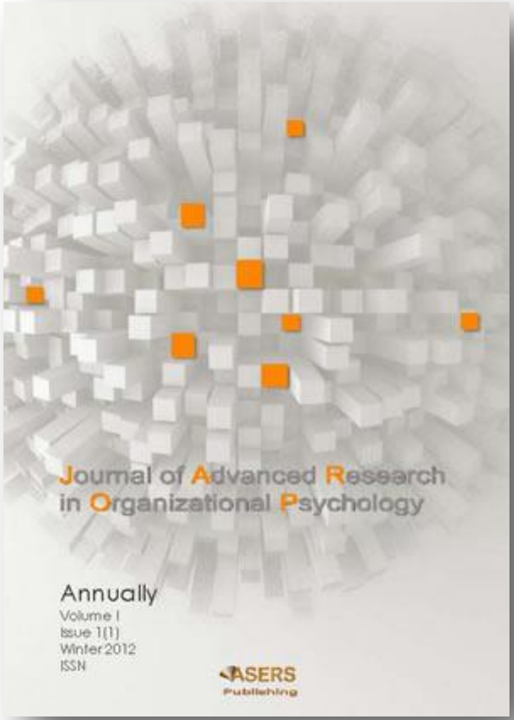

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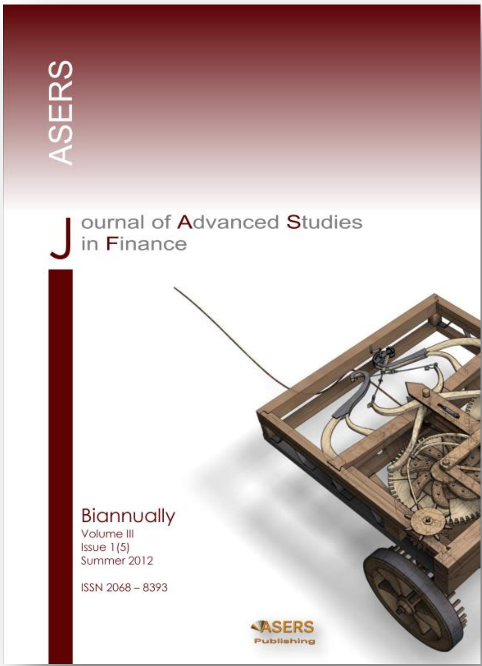

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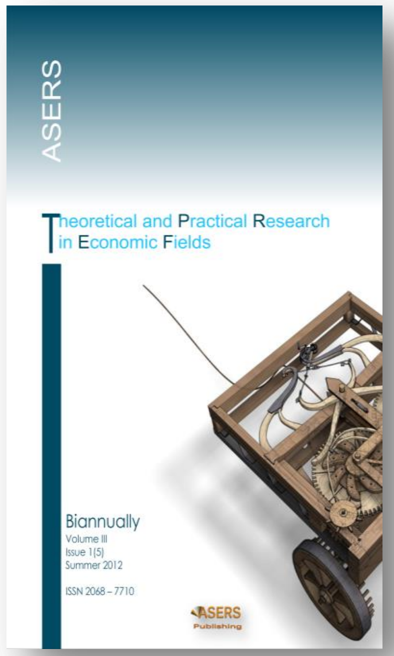

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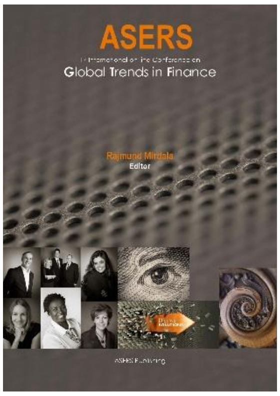

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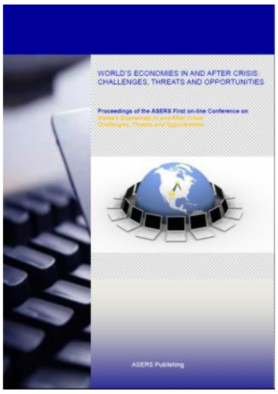

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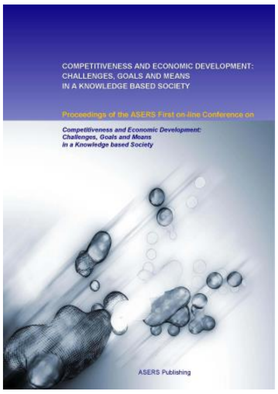

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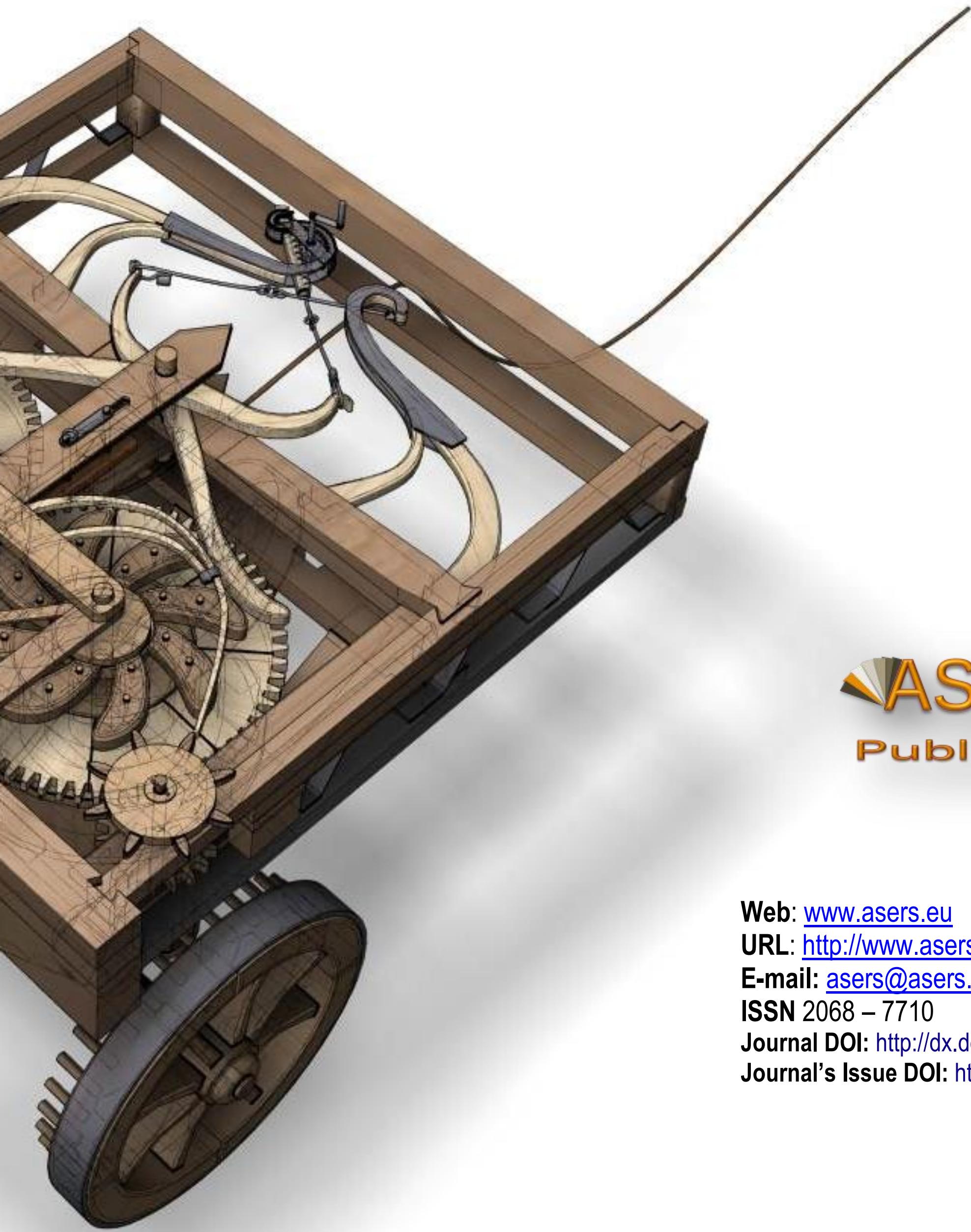

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