Soft Modelling of Military Expenditures, Inequality and Profits
(Falling Profits and Military Expenditures: An Empirical Analysis)

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Abstract

This paper investigates the nexus of military expenditures and inequality and profits. To the best of our knowledge, this is the first systematic quantitative study about the relationships between these three variables as a whole. The effects of military expenditures on economic growth are examined in many studies. Dunne and Uye (2010) review hundreds of such papers. Some other works focus on the relationship between military expenditures and profits (Elveren and Hsu 2015). There are also studies explaining the relationship between military expenditures and income inequality (Ali 2007; Töngür and Elveren 2016).

This Threevariate setting of MIP is quite important since it provides a better picture of the internal relationships of the dependent variables together with their respective explanatory blocks of variables. We treat military expenditures, inequality and profit as three latent variables in an inner model and employ their corresponding blocks of factors as manifest variables in an outer model. The approach, we follow in this paper is the non-parametric technique of Partial Least Squares Path Modelling (PLS-PM) which is formulated first by Wold (1975). It is a soft modelling technique, which is particularly useful when the theoretical foundation of the problem, such as in the Threevariate setting, is scarce, measurements are not well-defined and the empirical distributions of the dependent variables are not clear. The study finds out the variables, which are statistically important in the modelling. The findings of the general pooled analysis, based on 21 countries for the period of 1988-2008 suggest that while military expenditures have a negative effect on income (inequality), and income (inequality) has a negative impact on profit rates, military expenditures have (relatively small) positive effect on profit rates. However, these results remarkably change once unobserved heterogeneity is considered. Accordingly, based on four segments, although the negative effect of income (inequality) on profits remains the same for each segment, for some segments the effect of military expenditures on income (inequality) and on profit rates become positive.

Keywords: Military expenditures, inequality, profits, soft modelling, non-parametric estimation, PLS-PM.

JEL Codes: C14, C38, C51, D31, E11, E12, E13, H56

Introduction

The relationships in the Threevariate of military expenditures (milex), inequality and profits (MIP) are very important. Until now, these problems had been studied in either univariate or bivariate settings, such as milex, growth, inequality or, milex-inequality or, milex-growth, or milex-profits. This paper is the first attempt to study these vital issues in such a whole context since these are being the most substantial parts of the capitalist system. Military expenditures are connected to the growth, income distribution and the profits in the society. It is affecting not only the current state of the capitalist societies, but also, their future developments. Theoretically, each topic in the Threevariate is analyzed using different types of approaches, like neo classical, Keynesian or Marxist. Although the latter is being the most fruitful in practice, there is still no consensus over the approaches. Furthermore, the theoretical differences call different types of conceptualizations and measurements of the main variables in the Threevariate. For example, military expenditures are measured as per capita military spending differently in the COW and SIPRI data sets. In some other studies, military expenditures are expressed in terms of armed forces per 1000 people (Ali 2007). Inequalities are expressed either as industrial pay inequality Theil, per capita income or Gini coefficients as the income distribution of a nation's residents. Inequalities in Piketty's setting or class based Marxist setting are still lacking. Profits are measured mainly in the classical and neoclassical settings or seldomly in Marxist settings (Elveren and Hsu 2015). Different measurements of the variables as a result of the different conceptualizations of the theoretical approaches cause, thus incorrect types of empirical distribution functions of the Threevariate. There are thus no consistent empirical distribution specifications of military expenditures, inequalities and profits. As consequences of different types of measurements and specifications of the dependent variables, the statistical modelling in these analyses is an ad-hoc character. These analyses use the dependent variables without discussing their distribution functions. Studies using cross-sectional, time-series or longitudinal data sets are based on different estimation methods and find inconclusive evidences. Statistical models are bridges between deterministic theoretical models and stochastic real world based data sets. One can thus find both systematic and non-systematic parts in the statistical models. The specification of the theoretical models of the Threevariate problem set does not exist in the literature. In such cases, where the problems explored complex and theoretical knowledge is scarce and no detailed assumptions about the statistical distributions of the dependent variables could be made, the non-parametric soft-modelling approach of PLS-PM by Wold (1975) is a good choice. Because of the scarcity of theoretical knowledge of the Threevariate, distributional properties of the observables are not available, PLS modelling instead uses Least-Squares oriented but distribution-free methods.

In this paper, military expenditures, inequalities and profits are treated as three latent variables in an inner (structural) model and their corresponding blocks of factors as manifest variables in an outer (measurement) model. Using a Principal Component Analysis at the bottom and applying an iterative process by weighting first the outer model manifest variables with the inner model latent variables and successively repeating it, one finds out factor loadings of outer model and path coefficients of the inner model. Obtaining bootstrapped estimates and controlling the unobserved heterogeneity, one can predict the values of three latent variables as scores. Comparisons of predicted values of the three latent variables with their model specific measurements give new insights. The findings of the study showed, which variables depending on their theoretical model specific measurements are statistically important in the modelling.

The plan of this paper is as follows. Section 2 reviews different theoretical modelling of Threevariate of latent variables: Military expenditures, inequality and profits and reports different measurements used by these approaches. Section 3 reports descriptive statistical analysis of the data and variables used in the study. PLS-PM technique with its corresponding latent and manifest variables is explained in Section 4. Section 5 displays results of the study. The last section concludes the paper.

2. Theoretical Models of the Nexus of Milex, Inequality and Profits

2.1 Single or bivariate settings

2.1.1 Milex

Neoclassical Models:

According to the basic neoclassical model, defense is a public good, provided by the state in the context of the production possibility frontier where there is a trade-off between civil and military spending. The state, a rational agent, aims to maximize the national interest with respect to opportunity costs and benefits of milex. There are several models within the neoclassical tradition that examine the effect of milex on the economy. Among them one of the earliest models is the Feder-Ram model (Feder 1982, Ram 1986, Biswas and Ram 1986). In the Feder-Ram model the military sector is treated as one sector of the economy in a single-equation model.

In an another criticized exogenous growth model, the military expenditures simply incorporated into Cobb-Douglas production function (Dunne et al. 2005). In the same context, Dunne et al (2005), based on Mankiw et al. (1992), suggest an augmented Solow-Swann growth model to examine the effect of military expenditures. This is superior to the Feder-Ram model since it allows proper interpretation of the coefficients with testable hypotheses in a consistent specification (Dunne et al. 2005).

Military expenditures are also explained in the endogenous growth models based on Barro (1990). The endogenous growth models consider the varying growth rates and income levels and assume a constant or increasing return to capital (Dunne 2010).

Game theoretic approaches try to explain interstate behavior, particularly in the context of conflict and arms race (Coulomb 2004).

Overall, the neoclassical approach to military expenditures are being criticized in several strands (Dunne 2000). It is ahistoric, ignores the internal role of the military and military interests, and has unrealistic presumptions that the rational actors have extensive knowledge and computational ability in the decision making process.

Keynesian Models:

Keynesian models have a demand side perspective. In this approach milex is a part of general government expenditures. The main argument of Keynesian models is that increase in milex boost aggregate demand via multiplier effect. Also, it is argued that in case of spare capacity, higher milex increases the utilization of resources. On the other hand, how milex is financed is of importance because “cuts in other public expenditures”, “increased taxes”, “borrowing” or “expansion of money supply” will have different effects on the extent of crowding-out.

Military Keynesianism is the policy of using military expenditures as countercyclical and economic tools. However, there is no specific theory of military Keynesianism. Keynesian models have been criticized for their failure to consider supply side issues. So, some scholars incorporated an explicit production function in their Keynesian models (Deger and Smith, 1983, Deger 1986).

Some Keynesian scholars tried to explain the role of interest groups in the economy. The military-industrial complex (MIC), has a sound institutional perspective to explain military power and conflict (Dunne, 2011). The MIC is defined as unified groups of vested interests within the state that result in decisions favorable to those in power and not necessarily favorable to the requirements of national security. This is an important explanation of high military expenditures during the Cold War. As a matter of fact, the MIC creates internal pressure to justify increasing military expenditures even when there is no actual threat (Fine 1993, Dunne and Sköns, 2010).

The MIC theory argues for the negative effects of military expenditures on the economy. The theory argues that defense spending does not result in economic growth, but rather channels resources away from civilian industries that are more productive (Melman, 1965). Within the MIC, the Defense Department de facto acts like a ‘planning ministry’ (Melman, 1970), transforming the economy into a military-based ‘state capitalism’ (Melman, 1974). However, Melman also maintains that military expenditures may have Keynesian economic effects, boosting the economic activities. Overall, there is no clear theoretical model to explain the military expenditures in Keynesian approach.

Marxist Models:

There is no “the” Marxist model to explain the role of military expenditures in the economy. Rather, the Marxist thought regarding the effect of military expenditures on the economy presents diverse linkages based on different crisis theories with different underlying assumptions (Smith, 1977; 1983, Georgiou 1983, Kollias and Mantias 2003, Coulomb 2004, Dunne et al 2013, Elveren and Hsu 2016).

The role of military expenditures in capitalist economy in the Marxist tradition can be categorized into four general approaches (Georgiou 1983, Elveren and Hsu 2016): i) Marx and Engels, ii) Rosa Luxemburg, iii) the underconsumptionists, particularly Baran and Sweezy, and (iv) critiques of underconsumptionists.

Marx and Engels have no systematic analysis of militarism. For them it was a result of the socio-political structure, which is in turn dependent on the economic structure. Luxemburg argued that in addition to ideological benefits, military spending enables economies to expand to external markets (Luxemburg 1913). She argued that the militarism is the key means for the realization of the surplus value. Luxemburg's theory was interpreted in two different ways. While some view it as an 'underconsumptionist theory,' in which military expenditures allocate surplus without increasing productive capacity, some others interpret it as stating that military expenditures boost capital accumulation by encouraging technological development and lessening/overcoming the internal contradictions of capitalist expansion (Rowthorn 1980, cited in Coulomb 2004).

A major theory of under-consumption is suggested by Baran and Sweezy (1966). Baran and Sweezy stated that military spending can take in the economic surplus created by capitalism in the monopolistic stage. They argued that military expenditures are an integral part of the monopolistic nature of the postwar capitalist system as they encourage aggregate demand, and absorb surplus without raising wages or capital, thereby preventing realization crises. Research and development in the defense sector encourage the development of new products and technologies in non-defense sectors and stimulates the competitiveness and profit margins of those firms. However, on the other hand, it is noted that as military expenditures require higher expenditures in research and development, engineering, control and maintenance, through time they require fewer employees with more skills, creating fewer jobs than they used to.

Later on Baran and Sweezy's analysis was revisited by some other scholars, including Finkelhor and Reich (1970), Kidron (1970), Magdoff (1970), Reich (1972), Cypher (1974), and Mandel (1978).

One major restatement made by Kidron, the theory of 'the permanent arms economy,' in which militarism stabilizes the capitalist system (Kidron 1970). Accordingly, first, imperialist policies in neo-colonies expanding the boundaries of the market slow down the fall in the profit rate. Second, military expenditure stimulates aggregate demand, which helps to prevent the realization of a surplus resulting from under-consumption. Finally, military research and development benefits the civil sector, namely technological spin-off effect, which has been raised further by Mandel (1978).

Mandel argued that expenditures on armaments are economically unproductive as armaments are neither production nor consumption goods. Also, the prices and profit margins are set up through a direct negotiation between the state and the industry, making it possible for firms in the defense sector to obtain a rate of profit much higher than that corresponding to similar activities of a firm situated in competitive markets. It is also noted that military expenditures are neither dependent on peoples' purchasing power nor on economic fluctuations (Mandel 1978). The validity of the permanent arms economy theory has been challenged both theoretically and empirically (Purdy 1973, Kaldor 1977, Szymanski 1973 and Smith 1977). Moreover, Gottheil (1986) argued that Baran and Sweezy (1966) disregard the question of who ultimately pays for military production (the taxpayer), thereby also failing to account for the impact of military spending on the after-tax profit rate.

2.1.2 Inequality and Profit

The labor share (wage share) can be defined as compensation of employees as a share of value added or GDP, and the residual is the profit share (capital share).

Neoclassical Models:

The neoclassical distribution of income is a generalized form of Ricardo's decreasing marginal productivity principle. The distribution of national income is determined by factor prices, which are determined by supply and demand. Each factor will be paid according to its contribution to the production process. In equilibrium, the marginal product of labor is equal to the real wage rate and the marginal product of capital is equal to the rate of interest.

Hence, there is an inverse relationship between the profit rate and amount of capital utilized, and between the wage rate and the quantity of labor employed.

Hence, the exploitation of workers does not exist as each agent receives the amount of income corresponding to his contribution to total output, the marginal productivity theory "presumably" fair. Skill-biased technological change and globalization are two main causes of the declining labor share according to Neoclassical economists.

Keynesian Models:

For (monetary) Keynesians, the profit rate is provided by the interest rate. In Keynes's work income distribution is constant. According to Kalecki, distribution depends on the pricing behavior of firms in monopolistic markets, not in a perfect competition framework. The profitability is strongly associated with the relative power of labor unions. Hence, at the aggregate level income distribution is determined by the average markup and the ratio of raw material prices to unit labor costs, and by the sectoral composition of the economy.

Kaldor (1955), the profit share is determined by the ratio of investment to output given the workers' and capitalists' propensities to save. In the case of when spend what they earn (i.e. no saving) then profits are determined by the capitalists' propensity to invest and consume, hence, in contrast to classical economics, wages become a residual, not the profits (Kaldor,1955, p. 96). Departing from Kaldor (1955), Pasinetti (1962) showed that even workers save total profits are still determined by the capitalists spending. In the Neo-Kaleckian approach income distribution is a function of capacity utilization, which is determined by investment and saving.

Marxist Models:

The extraction of surplus value is the core of the Marxist approach to the theory of income distribution. According to Marx, wages are determined with respect to a subsistence level and the relative bargaining power. The industrial reserve army pushes the wages down. So, labor market bargaining conditions are the main determinants of income distribution.

2.1.3 The Milex-Growth Nexus

The literature on military expenditure and economic growth is led by the seminal work of Benoit (1973). Since then different growth models, namely the Feder-Ram (Biswas and Ram 1986), the Deger type model (Deger and Smith 1983, Deger 1986), the model of Barro (1990), the augmented Solow growth model (Mankiw et al. 1992), and the new macroeconomic model of Romer (2000) and Taylor (2000), have been adopted to explain the impact of military spending on economic growth. Also, an immense number of studies attempt to investigate this relationship by utilizing causality tests.

Some early studies (Ram, 1995; Dunne, 1996; Smith, 2000) as well as recent ones (Dunne and Uye, 2010; Alptekin and Levin, 2012; Awaworyi and Yew, 2014) review this extensive literature on military expenditures and economic growth nexus. A part of this literature contends that military expenditures have a negative effect on economic growth due to misallocation of resources. The second strand argues for the positive impact as military expenditures lead to fiscal expansion and higher aggregate demand, and therefore increases employment and output. Finally, the third group suggests no causal relationship between military spending and economic growth.

Although empirical works provide inconclusive evidence in general, three major tendencies can be stated. Accordingly, i) both negative and ambiguous effects of military expenditures on economic growth are more commonly found than positive effect, ii) recent studies with advanced methods are likely to find negative effect, iii) positive effect is more pronounced in the case of developed countries.

2.1.4 The Milex-Inequality Nexus

There are very few studies that address the milex-inequality nexus. The interaction between milex and income inequality can be explained from four different perspectives (Dixon and Moon 1986; Lin and Ali 2009, p.673). First, the conventional Keynesian theory argues that higher milex boosts aggregate demand and increases employment in the economy. Since this expansion in the economy benefits the poor relatively more it reduces income inequality. Second, according to microeconomic theory, since labor in military-related industries is better paid than other sectors, pay inequality between sector rises as milex increases (Ali 2007, p. 520). Third, since military spending includes both payments for less-skilled labor and for skilled R&D personnel, their relative shares may have different impacts on the wage discrepancy (Lin and Ali 2009, p. 674). Finally, there is welfare-defense tradeoff. Those that have higher milex have fewer funds for social expenditures such as education, health, and social transfers. However, there are no consistent results in the literature on the welfare-defense trade-off (Dunne 2000; Yildirim and Sezgin 2002).

The first study that attempts to examine the possible relationship between the variables in question is Ali (2007). Using the Theil pay inequality and Estimated Household Income Inequality data sets both provided by the University of Texas Inequality Project as basic indicators of income inequality and global panel data for the 1987-1997 period in a two-stage least squares setting, Ali (2007) states that increase in military expenditures leads to higher income inequality after controlling for some major macroeconomic issues such as the size of armed forces, internal and external threats, arms import, economic growth, and per capita income. Similarly, Ali (2012) finds that military expenditures have significant negative impact on income distribution in MENA countries over the period 1987–2005. Lin and Ali (2009), on the other hand, covering 58 countries for the 1987-1999 period, utilized the panel non-Granger causality test to find no causal relationship between military expenditures and pay and income inequality. Moreover Kentor et al. (2012) utilizes a generalized least square method covering 82 countries for the period of 1970-2000. They found that higher milex leads to higher inequality.

Later on, some scholars further examine the effect of military expenditures on pay and income inequality with respect to the welfare regimes (Töngür and Elveren 2015), the political regimes (Töngür et al. 2015), and in the context of an augmented Solow growth model (Töngür and Elveren 2016).

2.1.5 The Milex-Profit Nexus

Kollias and Mantias (2003) notes that depending on the assumptions (i.e. full employment, structure of military expenditures in terms of R&D or personnel expenditures, etc.) and short term-long term distinction, military expenditures may have a positive or negative effect on the profit rate (cited in Elveren and Hsu 2016). Accordingly, "positive effects include increasing demand, avoiding the rise in te organic composition of capital and an accompanying fall in the profit rate, increasing labor productivity, increasing the rate of surplus value, and bringing about international trade dominance. Negative impacts include crowding out of investment, reducing productivity through the purchase of "unreproductive" goods, increasing the organic composition of capital by expanding a capital-intensive sector, and taxing capital income" (Elveren and Hsu 2016: 562).

There are very few studies that deal with the milex-profit nexus. While Georgiou (1992) is in the U.S., the U.K., and West Germany, Kollias and Maniatis (2003) on Greece, and Dunne et al (2013) on the US, Elveren and Hsu (2016) is the only panel data analysis on the issue. Elveren and Hsu (2016), in a Marxist framework like previous studies, cover 24 OECD countries for the period of 1963-2008 by employing a panel autoregressive distributed lag model to find that while for the whole period there is positive linkage between military expenditures and profit rates, in the post-1980 era the impact of military expenditures is negative. The study also finds weak evidence that while for arms-exporting countries, there is positive linkage between military expenditures and profit rates, the linkage is negative for non-arms-exporter countries.

2.1.6 The Profit-Inequality Nexus

The paradox of thrift suggests that if wage income is redistributed from low- to high-saving classes this leads to lower aggregate demand because leakage increases. However, in the case of low-saving classes are able to accumulate debt due to a greater availability of finance and because of rising asset prices the negative effect of the increase in inequality cannot be realized at least in the short term. However, this consumption promoted by debt is not long lasting because low income households will be forced to save more when they face with the interest obligations, likely to lead to a debt burdened recession (Palley 1994, 2002).

Vasudevan (2015) discusses the effect of inequality on profitability. She, along with others such as Palley 2002, Dutt 2006, Carvalho and Rezai 2016, argue that high aggregate demand was maintained by "debt-fueled consumption" despite stagnant wage and rising inequality. Vasudevan (2015) shows that increase in inequality as a result of rising managerial power reduces accumulation in a regime where consumer borrowing is exogenous.

Wolf (2015) states that there is a strong econometric evidence on the relationship between the overall capital share and the concentration of household income find strong support for a positive association in general. In his work for the United States covering the period of 1947–2012, he finds that "the inequality measures are more strongly correlated with the overall profit rate than the overall profit share", which makes sense, he states, since the compensation of top executives "are generally tied to the profit rate of a company (that is, its return on equity), not to its profit share" (p. 757). The study also finds that the correlation between "the income shares of the top one, 0.1, and 0.01% with the profitability measures are stronger than those between either the overall Gini coefficient or the share of the top 5% and profitability." Also, in contrast to the findings of Adler and Schmid (2013) and Schlenker and Schmid (2014), the study argues that it is income shares of the top 1%, the top 0.1%, and the top 0.01% that are positively and significantly related to profitability in regression analyses, not overall family income inequality measured by the Gini coefficient.

2.2 Threevariate setting

To the best of our knowledge there is not any work that has the Threevariate setting of military expenditures, profit, and inequality. While Ali (2007, 2012), Töngür and Elveren (2015) and Töngür et al. (2015) consider both inequality and growth as a determinant of military expenditures, Töngür and Elveren (2016) incorporate inequality into an augmented Solow model to better explain milex. Elveren and Hsu (2016), on the other hand, consider both economic growth and milex as determinant of profit.

3. Data sets with missing values and descriptive statistical analysis

The data used for this paper are collected from different sources. The table 1 below presents the sources

Table 1: Data set

Data Set	Web Source
World Income Distribution	http://www.gc.cuny.edu/Page-Elements/Academics-Research-Centers-Initiatives/Centers-and-Institutes/Luxembourg-Income-Study-Center/Branko-Milanovic,-Senior-Scholar/Datasets
COW	http://www.correlatesofwar.org/data-sets
Nordhaus et al. (2012)	William Nordhaus, John R. Oneal and Bruce Russett (2012). The Effects of the International Security Environment on National Military Expenditures: A Multicountry Study. International Organization, 66, pp 491513 doi:10.1017/ S0020818312000173
size of informal economy	http://www.econ.boun.edu.tr/public_html/RePEc/pdf/201205.pdf
size of informal economy	http://www.gfintegrity.org/storage/gfip/documents/reports/world_bank_shadow_economies_all_over_the_world.pdf
Marxian profit rate	https://sites.google.com/a/newschool.edu/duncan-foley-homepage/home/EPWT
UTIP-UNIDO manufacturing Theil pay inequality index	http://utip.lbj.utexas.edu/data.html
UTIP-EHII inequality index	http://utip.lbj.utexas.edu/data.html
SIPRI	http://www.sipri.org/research/armaments/milex/milex_database
World Development	http://data.worldbank.org/data-catalog/world-development-

Indicators	indicators
US Department of State's Bureau of Verification and Compliance	http://www.state.gov/t/avc/rls/rpt/wmeat/
Center for Systemic Peace, Major Episodes of Political Violence, 1946-2014 (War List)	http://www.systemicpeace.org/inscrdata.html
Uppsala Conflict Data Program	www.prio.no/cscw
Penn World Tables	http://www.rug.nl/research/ggdc/data/pwt/pwt-8.1

3.1 Missing values and multiple imputation

There are missing values of the series used in the analysis. Missing observation on a latent variable causes different problems compared to a manifest variable. The latter type of missingness is more important since the latent variables need to be predicted, their completeness is not so necessary.

In the literature, three types of missingness are reported.

- Missing completely at random (MCAR)
- Missing at random (MAR) and
- Not missing at random (NMAR).

Data observations are missing completely at random (MCAR) where the missing values of a variable are not related to both that variable and any other variable in the data set. In this case, non-missing observations form a random sub-sample of the population. The only unfavorable side of MCAR is the loss of information and thus the inefficiency of the estimates.

If a variable's missingness is not related to itself, but related to other variables in the data set, then missingness is called missing at random (MAR). The other variables which will explain the missingness of the variable in question must be included in the analysis to obtain unbiased parameter estimates.

Although including all possible variables in the model, the missingness of the variable in question is still related to it, then it means that there is a case of missingnes, which is not missing at random (NMAR). Observations having NMAR characteristics yield biased results.

Generally, missing observations are addressed by one of two methods. First, missing observations are deleted either listwise or pairwise. In listwise deletion, variables with observations with any missing values are deleted in the data set before the analysis. Removing observations with all variables make estimates less precise, i.e., their standard errors increase thus their confidence intervals widen. If missing is not MAR then listwise deletion methods produce bias parameter estimates.

In pairwise deletion, the loss that occurs in listwise deletion is tried to be minimized. It works, for instance, in a correlation analysis, by measuring the strength of the relationship between two variables with complete observations. Again, it causes underestimated variability.

The second method replaces the missing value with another reasonable value and is called imputation. There are several ways of imputation. It can be done replacing missing values by the mean, median of the series, or matched observation values (hot-, cold-deck) or predicted values of a regression.

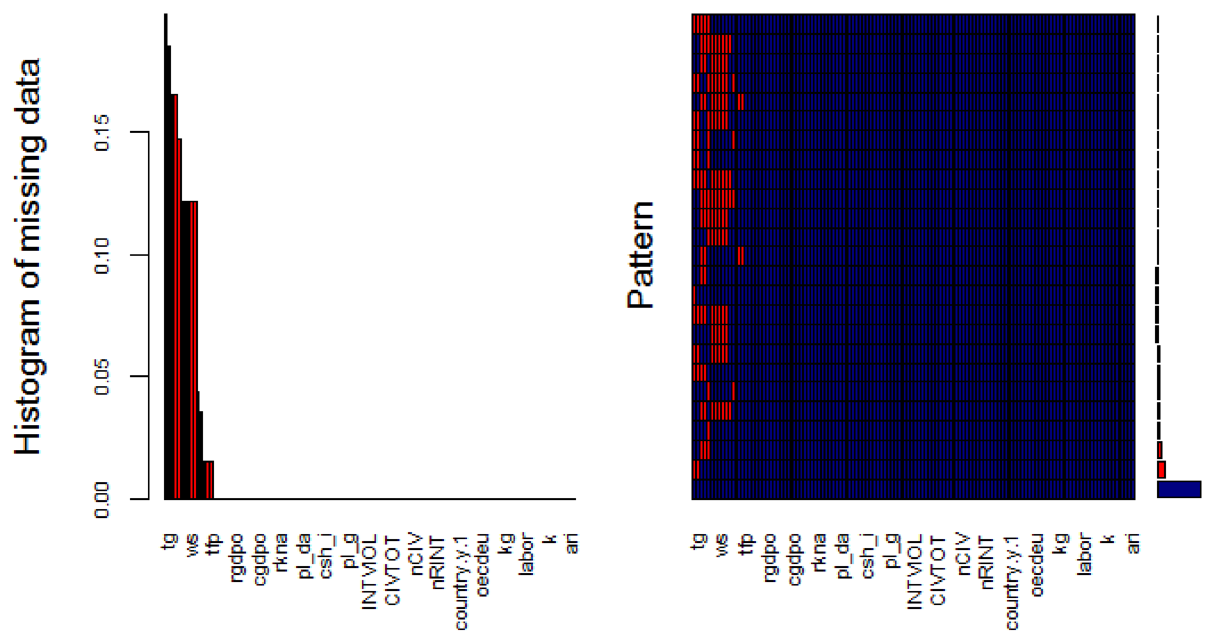
There are two essential ways to impute missing values. These are Maximum Likelihood Method and Multiple Imputation Procedures. In the Maximum Likelihood Imputation Method, one procedure uses an iterative two-step Expectation-Maximization(EM) algorithm, assuming a joint multivariate normal distribution for all variables. The expectation step uses linear regressions to impute missing values and the maximization step computes the basic parameters of the variables, which are then re-used to estimate linear regressions in the first step. The other Maximum Likelihood procedure uses a Full Information Maximum Likelihood (FIML) technique, where the likelihood function for the specified model is directly maximized. Both approaches require a joint multivariate distribution for all variables, which may not be the case very often in practice.

In this paper, we use another imputation procedure, which is called: the Multiple Imputation by Chained Equations (MICE). It assumes that some joint probability distribution exists for a mixed set of variables, but it employs only conditional distribution of the variable being imputed. The underlying joint distribution is not specified, while it is expected that the iterative imputation procedure based on conditional distributions will converge the underlying joint distribution. At the end of this procedure, instead of imputing a single value for a missing observation, we impute multiple m data sets. Later, these data sets are used in the estimation steps.

There are total 423 observations and 143 variables in our major data set. 18 variables that had missing values more than 20% are deleted from the major data set. After deletion, in the major data set there are 423 observations and 125 variables. Data set covers 21 countries for the years from 1988 to 2008.

The figure below shows the pattern of missing.

Figure 1: The pattern of missing values



We had imputed of the variables that had missing values less than 20% using the Multiple Imputation by Chained Equations (MICE). In the model estimation, we use only one of the five imputed series since the last model choice is based on the Bootstrap estimation, which it is a replication technique itself.

4. Partial Least Squares Path Modeling of the Threevariate

To find out the determinants of the Threevariate, we first try to predict the series of Milex-Inequality-Profit using a technique which is called Partial Least Squares Path Modeling by

Herman Wold, (1975). His paper from 1980, has the title: “Model Construction and Evaluation When Theoretical Knowledge is Scarce”. He writes:

“Unfortunately, there are few topics in economics where these assumptions are tenable, at least in full. There are two areas of knowledge deficiency. First, in many topics in economics our theories are merely prescriptions of a likely list of causal variables for some specified set of effect variables. Second, our knowledge of the statistical distributional properties of the relevant variables is even less complete. A related empirical difficulty is that usually the variables of direct interest cannot be observed and one must rely on the indicator (marker) variables which are assumed to have some degree of association with the variables of theoretical interest. Under such circumstances to proceed along conventional lines with numerous heroic assumptions is inferentially hazardous. Another less ambitious but less knowledge sensitive approach is needed. Two items are required: a less knowledge intensive formulation of theory and a robust statistical procedure for drawing inferences when one is ignorant about the relevant statistical distributions. The former requirement can be met by the development of what has come to be known in the sociological literature as "path models." The latter requirement is met by the use of partial least squares.” (page 48).

PLS Path Modeling is mainly a statistical data analysis methodology that exists at the intersection of Regression Models, Structural Equation Models, and Multiple Table Analysis methods. It quantities the relationships by considering the network as a system of multiple interconnected linear regressions. We will use it to rank countries after their scores of the Threevariate.

4.1 Factors of the Threevariate

One of the most common applications of PLS Path Modeling is the calculation of indices to quantify some key concept or notion of importance.

4.1.1 Latent Variables

The issue with the concepts of Military Expenditures, Income Inequalities and Profits is that they are not things can be measured directly in the economic literature. These concepts receive the special name of latent variables, but they are also known as constructs or composites. The relationship between these variables can be explained as

$$Profits = f(Military\ Expenditures,\ Income\ Inequalities) \qquad (1)$$

or as linear equation

$$Profits = f(b_1*Military\ Expenditures + b_2*\ Income\ Inequalities) \quad (2)$$

In addition to expressing our model in text and mathematical format, we can also display our model in a graphical format using what is called a path diagram -this is why is called PLS path modeling-. These diagrams help us to represent in a visual way the relationships stated in our models.

4.1.2 Manifest Variables

Latent variables cannot be directly measured, but they can be indirectly measured by means of variables which can be perfectly observed-measured. These types of variables are called manifest variables (MVs), also known as indicators or items.

Formative and Reflective Indicators

Once we have assumed that latent variables can only be observed and measured indirectly through the use of manifest variables, we need to consider the ways in which latent variables are indirectly measured. Latent variables can be measured in two ways:
-through their consequences or effects reflected in their indicators
-through different indicators that are assumed to cause the latent variables

In the first case, called reflective way, manifest variables are considered as being caused by the latent variables. The second case is known as a formative way because the latent construct is supposed to be formed by its indicators. The main difference between the reflective and formative ways has to do with the causal-effect relationships between the indicators and the constructs.

Reflective Indicators of Military Expenditures

- nhc: negative of human capital index
- emp: employment
- pop: population

The other variables are eliminated, such as

- rgdpo: Output-side real GDP at chained PPPs (in mil. 2005US$)

- Total imports of GDP

Reflective Indicators of Income Inequalities

- Milex/GNP, whole period

- wage_share: wage income/GDP

- rgdpl, rgdpch: real GDP per capita based on Laspeyres and chain method

- negative of informal: Elgin and Oztunali (2012) informal sector data set

- negative of tg: Negative of the Theil and Gini variable, provided by UTIP

The other variables are eliminated, such as

- avh: Average annual hours worked by persons engaged

Formativetive Indicators of Profits (The rate of profit, the gross profit rate)

- negative of x: negative of labor productivity expressed in real GDP in 2000 purchasing power parity per worker in 2005 purchasing power parity

- negative of k: negative of capital-labor ratio in 2005 purchasing power parity

- somuru: Marginal product of labor/wage share (i.e. Pigouvian exploitation)

A full path model is comprised by two sub-models: the structural model, also known as inner model and the measurement model, also known as outer model. The inner model is the part of the model that has to do with the relationships between latent variables. The outer model is the part of the model that has to do with the relationships between each latent variable and its block of indicators.

4.2 SEM versus PLS-PM

PLS methods are analytical tools with algorithmic origins aiming at solving models in a very practical way. PLS-PM treats the data "just" as a dataset. Although there can be a data-generating process in principle, it plays no direct role in PLS-PM. The proposed models are not considered to be ground truth, but only an approximation with useful predicts. In other words, PLS-PM assumes no model by which the data were generated. The ultimate goal in PLS-PM is to provide a practical summary of how the set of dependent variables is systematically explained by their sets of predictors. The text of PLS-PM is almost fully taken from (Sanchez 2013).

4.2.1 Notation

Let's assume that we have *p* variables measured on *n* observations of countries, and that the variables can be divided in *J* blocks.

X is the data set containing the *n* observations and *p* variables.

X can be thought as a matrix of dimension *n*x*p*

X can be divided in *J* (mutually exclusive) blocks X_1, X_2, …X_J

Each block X_j has *K* variables: X_{j1}, …X_{jK} Each block X_j is assumed to be associated with a latent variable LV_j. The estimation of a latent variable, also known as score, is denoted by $LV_j = Y_j$

4.2.2 The Structural Model

There are three things which we consider about the specifications of the structural part in a PLS Path Model.

Linear Relationships The first aspect of an inner model is that we treat all the structural relationships as linear relationships. The structural relations can be expressed as:

$$LV_J = \beta_0 + \sum_{i \to j} \beta_{ji} LV_i + error_j \qquad (3)$$

The subscript *i* of LV_i refers to all the latent variables that are supposed to predict LV_j. The coefficients β_{ji} are the path coefficients and they represent the “strength and direction” of the relations between the response LV_j and the predictors LV_i. β_0 is just the intercept term, and the $error_j$ term accounts for the residuals (Sanchez 2013).

Recursive Models The second thing we need is that the system of equations must be a recursive system. What this means is that the paths formed by the arrows of the inner model cannot form a loop.

Regression Specification The third aspect about the inner relationships is something called predictor specification which expresses a linear regression idea. It can be written as:

$$E(LV_j|LV_i) = \beta_{oi} + \sum_{i \to j} \beta_{ji} LV_i \qquad (4)$$

The conditional expected values of the response LV_j determined by its predictors LV_i: The only extra assumption is:

$$cov(LV_i, error_j) = 0 \tag{5}$$

which means that a latent variable LV_i is uncorrelated with the residual $error_j$. Notice that nothing is assumed about the distributions of the variables and error terms (Sanchez 2013).

4.2.3 The Measurement Model

This part has to do with the relationships between a latent variable and its block of manifest variables.

Reflective Way The most common type of measurement is the reflective mode. In this case the latent variable is considered as the cause of the manifest variables. That's why it's called reflective because the manifest variables are “reflecting” the latent variable (Sanchez 2013).

Formative Way The other type of measurement is the formative mode. In this case, the manifest variables are considered to be the cause of the latent variable. That's why it is called formative because the manifest variables are “forming” the latent variable (Sanchez 2013).

Linear Relationships Just like in the inner model, the outer model relationships are also considered to be linear. In statistical notation, we have that:

$$X_{jk} = \lambda_{0jk} + \lambda_{jk}LV_j + error_{jk} \qquad \text{Reflective} \tag{6}$$

$$LV_j = \lambda_{0j} + \lambda_{jk}X_{jk} + error_j \qquad \text{Formative} \tag{7}$$

The coefficients λ_{jk} are called loadings; λ_0 is just the intercept term, and the error terms account for the residuals.

Regression Specification In addition, we also have the concept of predictor specification or regression specification: the linear relationships are conceived from a standard regression perspective:

$$E(X_{jk}|LV) = \lambda_{0jk} + \lambda_{jk}LV_j \qquad \text{Reflective} \qquad (8)$$

$$E(LV_j|X_{jk}) = \lambda_{0j}+\lambda_{jk}X_{jk} \qquad \text{Formative} \qquad (9)$$

It expresses the conditional expected values of the response variables (either manifest or latent) in terms of the predicted ones (Sanchez 2013).

4.2.4 The Weight Relations

In PLS-PM, latent variables are estimated as a linear combination of their manifest variables. Moreover, an estimated LV_j is called a score, which we will denote as Y_j:

$$Y_j = \sum_k \omega_{jk} X_{jk} \qquad (10)$$

In fact, this is the very reason why PLS-PM is referred to as a component-based approach because latent variables are calculated as a weighted sum of their indicators, something similar to what is done in principal component analysis. It does not matter if a latent variable is measured in a reflective or a formative way; a latent variable is calculated as a linear combination of its block of indicators (Sanchez 2013).

5. Results

5.1 Unidimensionality of indicators

When we have a block of reflective indicators it is supposed that those indicators will reflect, to some extent, the latent variable that they are associated with. Actually, it is assumed that the latent variable is the cause of its indicators. This means that if a construct changes (increases or decreases), then the indicators associated with it will also change in the same direction. Thus, it is logical to suppose that the indicators are closely related in such a way that they are in one dimensional space. In PLS-PM we have three main indices to check unidimensionality:

. Calculate the Cronbach's alpha

. Calculate the Dillon-Goldstein's rho

. Check the first eigenvalue of the indicators' correlation matrix

These metrics are provided in the following table.

Table 1: Blocks Unidimensionality when the whole data set is treated as pooled cross-sections and after deleting reflective indicators with low communalities.

	Type	Indicators	Cronbach α	Dillon-Goldstein ρ	Eigen 1st	Eigen 2nd
Military expenditures	Reflective	3	0.820	0.898	2.25	0.728
Income Inequality	Reflective	3	0.838	0.892	2.70	0.642
Profits	Formative	3	0.000	0.000	2.33	0.585

Cronbach's alpha The Cronbach's alpha is a coefficient that is intended to evaluate how well a block of indicators measure their corresponding latent construct. If a block of manifest variables is unidimensional, they have to be highly correlated, and consequently we expect them to have a high average inter-variable correlation. The computation of the Cronbach's alpha requires the observed variables to be standardized and positively correlated. In our example, Military Expenditures and Income Inequality blocks have alpha values of 0.82 nd 0.83 respectively. As a rule of thumb, a Cronbach's alpha greater than 0.7 is considered acceptable.

Dillon-Goldstein's rho Another metric used to assess the unidimensionality of a reflective block is the Dillon- Goldstein's rho, which focuses on the variance of the sum of variables in the block of interest. It has a value of 0.90 for Military Expenditures and Income Inequality blocks. As a rule of thumb, a block is considered as unidimensional when Dillon-Goldstein's rho is larger than 0.7. This index is considered to be a better indicator than the Cronbach's alpha because it takes into account to which extent the latent variable explains the block of indicators.

First and second eigenvalues The third metric involves an eigen-analysis of the correlation matrix of indicators and it is based on the importance of the first eigenvalue. If a block is unidimensional, then the first eigenvalue should be “much more” larger than 1 whereas the second eigenvalue should be smaller than 1. This is the case for all three latent variables.

5.1.2 Loadings and Communalities

The next thing to examine are the loadings and the communalities. The loadings are correlations between a latent variable and its indicators. In turn, Communalities are squared correlations. With model estimates, we get a list with as many elements as latent variables. Loadings greater than 0.7 are acceptable. Communalities are just squared loadings. They represent the amount of variability explained by a latent variable.

Communality Communality is calculated with the purpose to check that indicators in a block are well explained by its latent variable. Communalities are simply squared loadings and they measure the part of the variance between a latent variable and its indicator that is common to both. To see why, we need to assume that each indicator represents an error measurement of its construct. The relation:

$$mv_{jk} = loading_{jk} * LV_j + error_{jk} \qquad (11)$$

implies that the latent variable LV_j explains its indicator mv_{jk}, so we have to evaluate how well the indicators are explained by its latent variable. To do this, we examine the loadings which indicate the amount of variance shared between the construct and its indicators. The communality for the *jk-th* manifest variable of the *j-th* block is calculated as:

$$Com(LV_j, mv_{jk}) = cor^2(LV_j, mv_{jk}) = loading_{jk}^2 \qquad (12)$$

Looking at the previous formula, communality measures how much of a given manifest variable's variance is reproducible from the latent variable. In other words, the part of variance between a construct and its indicators that is common to both. One expects to have more shared variance between an LV and its error variance, that is:

$$loading_{jk}^2 = var(error_{jk}) \qquad (13)$$

Indicators with low communality are those for which the model is “not working” and the researcher may use this information to drop such variables from the analysis. One can delete the variables, which are not important from the indicator list.

Cross-loadings Besides checking the loadings of the indicators with their own latent variables, we must also check the so-called cross-loadings. That is, the loadings of an indicator with the rest of latent variables. The reason for doing so is that we need to be sure that we don't have traitor indicators. With the cross-loadings we evaluate the extent to which a given construct differentiates from the others. The whole idea is to verify that the shared variance between a construct and its indicators is larger than the shared variance with other constructs. In other words, no indicator should load higher on another construct than it does on the construct it intends to measure. Otherwise, it is a traitor indicator. If an indicator loads higher with other constructs than the one it is intended to measure, we might consider its appropriateness because it is not clear which construct or constructs it is actually reflecting (Sanchez 2013).

5.2 Measurement Model Assessment: Formative Indicators

Unlike reflective indicators, formative indicators are considered as causing (i.e. forming) a latent variable. The truth is that all blocks of indicators could always be taken in a reflective way. However, there may be theoretical or conceptual reasons to consider a block as formative. Formative indicators do not necessarily measure the same underlying construct. In this case, any change experienced by a construct does not imply a change in all its indicators; that is, formative indicators are not supposed to be correlated. For this reason, formative measures cannot be evaluated in the same way of reflective measures; and all the assessment criteria based on the loadings are discarded in the formative measures.

We compare the outer weights of each indicator in order to determine which indicators contribute most effectively to the construct. Attention must be paid in order to avoid misinterpreting relative small absolute values of weights as poor contributions. If we are considering the elimination of some indicator, this should be done based on multicollinearity: the elimination is recommended if high multicollinearity occurs (Sanchez 2013).

5.3 Structural Model Assessment

After assessing the quality of the measurement model, the next stage is to assess the structural part. The quality of the structural model is evaluated by examining three indices or quality metrics:

. the R2 determination coefficients

. the redundancy index

. the Goodness-of-Fit (GoF)

5.3.1 Coefficients of determination R^2

The R^2 are the coefficients of determination of the endogenous latent variables. For each regression in the structural model we have an R2 that is interpreted similarly as in any multiple regression analysis. R2 indicates the amount of variance in the endogenous latent variable explained by its independent latent variables. In fact, values for the R-squared can be classified in three categories:

1. Low: $R < 0 : 30$ (although some authors consider $R < 0 : 20$)
2. Moderate: $0 : 30 < R < 0 : 60$ (you can also find $0 : 20 < R < 0 : 50$)
3. High: $R > 0 : 60$ (alternatively there is also $R > 0 : 50$)

5.3.2 Redundancy

Redundancy measures the percent of the variance of indicators in an endogenous block that is predicted from the independent latent variables associated to the endogenous LV. The redundancy index for the *j-th* manifest variable associated to the *k-th* block is:

$$Rd(LV_k, mv_{jk}) = loading_{jk}^2 * R_k^2 \tag{14}$$

High redundancy means high ability to predict. In particular, the researcher may be interested in how well the independent latent variables predict values of the indicators' endogenous construct. Analogous to the communality index, one can calculate the mean redundancy, that is, the average of the redundancy indices of the endogenous blocks (Sanchez 2013).

5.3.3 Goodness of Fit

A remarkable aspect is that no single criterion exists to measure the overall quality of a model, so we cannot perform inferential statistical tests for goodness of fit. As an alternative, non-parametrical tests can be applied for the assessment of the structural model. The Goodness of fit index is a pseudo Goodness of fit measure that accounts for the model quality at both the measurement and the structural models. Goodness of fit is calculated as the geometric mean of the average communality and the average R^2 value. Since it takes in to account communality, this index is more applicable to reflective indicators than to formative indicators. However, we can also use the Goodness of Fit index in presence of formative blocks, in which case more importance will be given to the average R^2.

5.4 Validation

Since PLS-PM does not rest on any distributional assumptions, significance levels for the parameter estimates (based on normal theory) are not suitable. Instead, resampling procedures such as blindfolding, jackknifing, and bootstrapping are used to obtain information about the variability of the parameter estimates.

5.4.1 Bootstrapping

Bootstrapping is a non-parametric approach for estimating the precision of the PLS parameter estimates. The bootstrap procedure is the following: *B* samples are created in order to obtain *B* estimates for each parameter in the PLS model. Each sample is obtained by sampling with replacement from the original data set, with sample size equal to the number of cases in the original data set. This statistics will be reported after eliminating the variables which have very low communalities (Sanchez 2013).

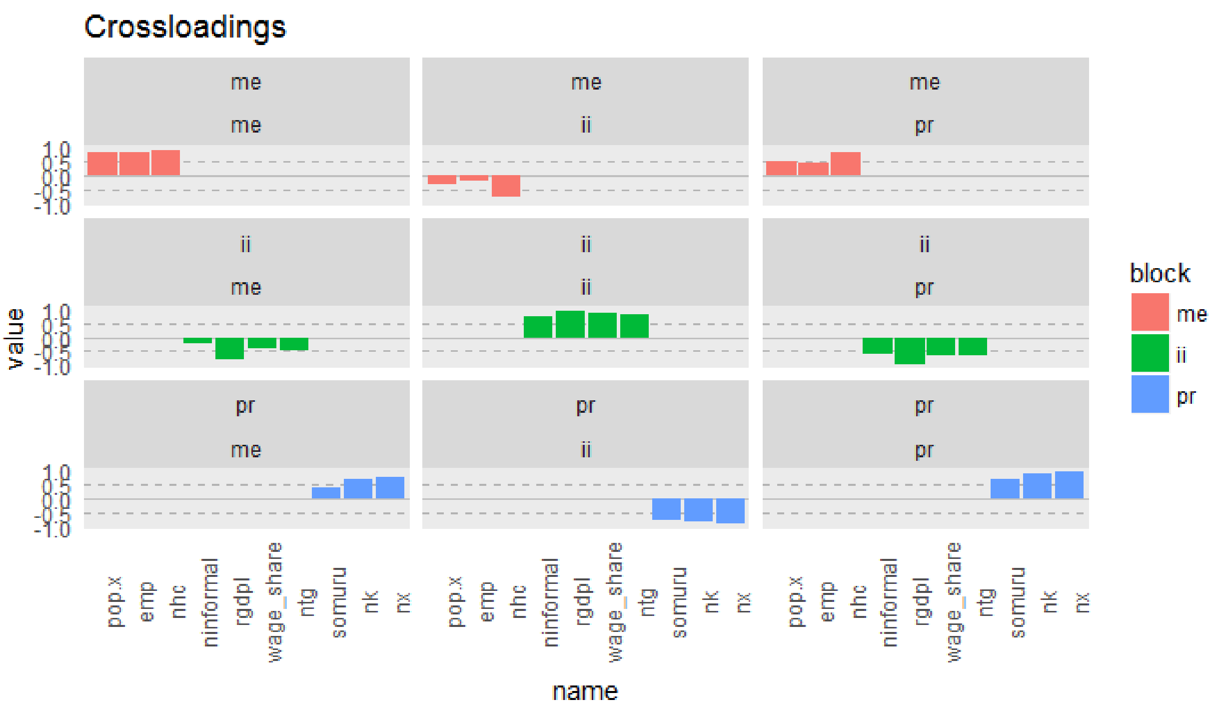
5.5.1 Bootstrapped results

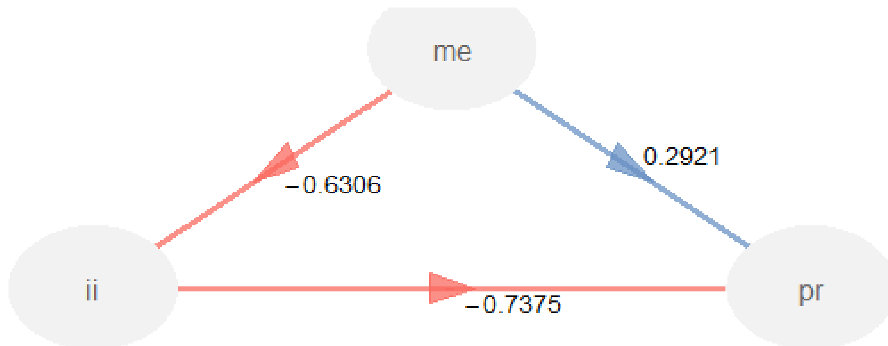
```
PARTIAL LEAST SQUARES PATH MODELING (PLS-PM)

----------------------------------------------------------
MODEL SPECIFICATION
1   Number of Cases      394
2   Latent Variables     3
3   Manifest Variables   10
4   Scale of Data        Standardized Data
5   Non-Metric PLS       FALSE
6   Weighting Scheme     centroid
7   Tolerance Crit       1e-06
8   Max Num Iters        100
9   Convergence Iters    6
10  Bootstrapping        TRUE
11  Bootstrap samples    200

----------------------------------------------------------
BLOCKS DEFINITION
    Block         Type   Size   Mode
1      me    Exogenous      3      A
```

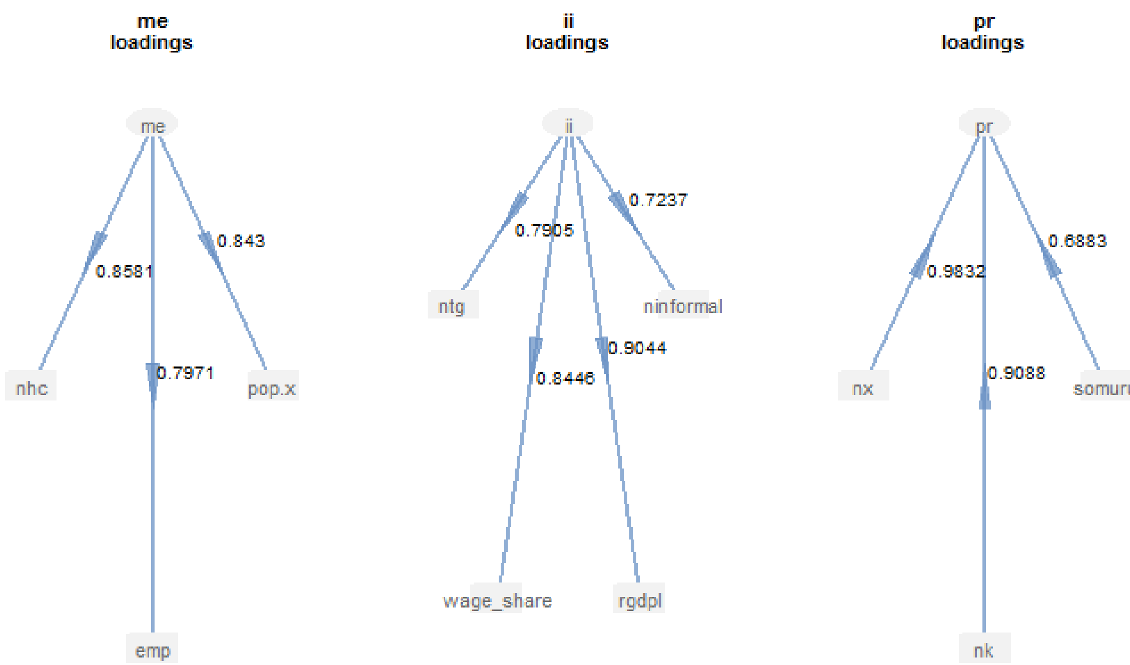
```
2      ii   Endogenous      4      A
3      pr   Endogenous      3      B

----------------------------------------------------------
BLOCKS UNIDIMENSIONALITY
    Mode  MVs  C.alpha  DG.rho  eig.1st  eig.2nd
me     A    3    0.820   0.898     2.25    0.728
ii     A    4    0.838   0.892     2.70    0.642
pr     B    3    0.000   0.000     2.33    0.585

----------------------------------------------------------
OUTER MODEL
                weight  loading  communality  redundancy
me
  1 pop.x       0.3089    0.843        0.711       0.000
  1 emp         0.2602    0.797        0.635       0.000
  1 nhc         0.6202    0.858        0.736       0.000
ii
  2 ninformal   0.2026    0.724        0.524       0.208
  2 rgdpl       0.4410    0.904        0.818       0.325
  2 wage_share  0.2732    0.845        0.713       0.284
  2 ntg         0.2831    0.791        0.625       0.248
pr
  3 somuru      0.2164    0.688        0.474       0.427
  3 nk          0.0372    0.909        0.826       0.744
  3 nx          0.8313    0.983        0.967       0.871

----------------------------------------------------------
CROSSLOADINGS
                    me      ii      pr
me
  1 pop.x        0.843  -0.300   0.483
  1 emp          0.797  -0.228   0.432
  1 nhc          0.858  -0.772   0.799
ii
  2 ninformal   -0.238   0.724  -0.568
  2 rgdpl       -0.772   0.904  -0.982
  2 wage_share  -0.396   0.845  -0.691
  2 ntg         -0.473   0.791  -0.653
pr
  3 somuru       0.387  -0.768   0.688
  3 nk           0.733  -0.792   0.909
  3 nx           0.777  -0.873   0.983

----------------------------------------------------------
INNER MODEL
$ii
             Estimate   Std. Error     t value   Pr(>|t|)
Intercept    4.19e-17       0.0392    1.07e-15   1.00e+00
me          -6.31e-01       0.0392   -1.61e+01   4.59e-45

$pr
             Estimate   Std. Error     t value    Pr(>|t|)
Intercept    2.46e-16       0.0159    1.54e-14    1.00e+00
me           2.92e-01       0.0205    1.42e+01    2.31e-37
ii          -7.38e-01       0.0205   -3.60e+01   4.73e-126
```

```
----------------------------------------------------------
CORRELATIONS BETWEEN LVs
        me      ii      pr
me   1.000  -0.631   0.757
ii  -0.631   1.000  -0.922
pr   0.757  -0.922   1.000

----------------------------------------------------------
SUMMARY INNER MODEL
          Type     R2  Block_Communality  Mean_Redundancy    AVE
me   Exogenous  0.000              0.694            0.000  0.694
ii  Endogenous  0.398              0.670            0.266  0.670
pr  Endogenous  0.901              0.755            0.681  0.000

----------------------------------------------------------
GOODNESS-OF-FIT
[1]  0.6755

----------------------------------------------------------
TOTAL EFFECTS
   relationships  direct  indirect   total
1       me -> ii  -0.631     0.000  -0.631
2       me -> pr   0.292     0.465   0.757
3       ii -> pr  -0.738     0.000  -0.738

---------------------------------------------------------
BOOTSTRAP VALIDATION
weights
               Original  Mean.Boot  Std.Error  perc.025  perc.975
me-pop.x         0.3089     0.3074     0.0111    0.2853     0.325
me-emp           0.2602     0.2594     0.0115    0.2364     0.278
me-nhc           0.6202     0.6227     0.0340    0.5604     0.690
ii-ninformal     0.2026     0.2018     0.0114    0.1778     0.222
ii-rgdpl         0.4410     0.4417     0.0218    0.4089     0.491
ii-wage_share    0.2732     0.2733     0.0121    0.2503     0.299
ii-ntg           0.2831     0.2825     0.0131    0.2601     0.309
pr-somuru        0.2164     0.2181     0.0261    0.1644     0.270
pr-nk            0.0372     0.0379     0.0417   -0.0507     0.106
pr-nx            0.8313     0.8289     0.0430    0.7496     0.912

loadings
               Original  Mean.Boot  Std.Error  perc.025  perc.975
me-pop.x          0.843      0.840    0.02790     0.784     0.887
me-emp            0.797      0.794    0.02855     0.734     0.841
me-nhc            0.858      0.859    0.00856     0.844     0.875
ii-ninformal      0.724      0.722    0.02527     0.670     0.766
ii-rgdpl          0.904      0.905    0.00596     0.894     0.916
ii-wage_share     0.845      0.845    0.02130     0.800     0.877
ii-ntg            0.791      0.790    0.02720     0.731     0.834
pr-somuru         0.688      0.688    0.03658     0.625     0.756
pr-nk             0.909      0.909    0.00769     0.892     0.924
pr-nx             0.983      0.983    0.00371     0.975     0.990

paths
          Original  Mean.Boot  Std.Error  perc.025  perc.975
me -> ii    -0.631     -0.633     0.0155    -0.663    -0.602
me -> pr     0.292      0.292     0.0258     0.243     0.340
```

```
ii -> pr    -0.738     -0.737     0.0210    -0.775    -0.697

rsq
    Original  Mean.Boot  Std.Error  perc.025  perc.975
ii     0.398      0.401    0.01966     0.363     0.440
pr     0.901      0.902    0.00815     0.886     0.917

total.efs
          Original  Mean.Boot  Std.Error  perc.025  perc.975
me -> ii    -0.631     -0.633     0.0155    -0.663    -0.602
me -> pr     0.757      0.759     0.0153     0.730     0.789
ii -> pr    -0.738     -0.737     0.0210    -0.775    -0.697
```




me
ii
pr
0.2921
−0.6306
−0.7375


me
loadings
ii
loadings
pr
loadings
me
0.8581
0.843
0.7971
nhc
pop.x
emp
ii
0.7237
0.7905
ntg
ninformal
0.9044
0.8446
wage_share
rgdpl
pr
0.6883
0.9832
nx
0.9088
somuru
nk

The results show that, first, milex has a relationship with employment, population and human capital index. Second, income inequality is associated with wage share, real GDP per capita, and size of the informal sector. Third, the relevant variables for profit are the marginal product of labor/wage share (i.e. Pigouvian exploitation), negative of labor productivity (expressed in real GDP in 2000 purchasing power parity per worker in 2005 purchasing power parity), and negative of capital-labor ratio (in 2005 purchasing power parity). The findings suggest that while increasing milex reduces income (inequality) it boosts profits. Also, increasing income inequality reduces profit rates. However, it is important to consider unobserved heterogeneity which may affect these general results. The following section deals with this issue.

5.6 Unobserved heterogeneity correction and classes of countries ranked after their scores

When we estimate PLS path models, we do it under the implicit assumption that all the observations in the data are more or less homogeneous. This implies that we treat all observations alike without considering any group structure, and we take for granted that a single model will adequately represent all the countries. Consequently, we are supposing that the same set of parameter values applies to all observations. The problem, however, is that this assumption may not be realistic in all cases; and it is reasonable to expect diversity in our data. This "diversity" in data receives the special name of heterogeneity.

Basically, unobserved heterogeneity implies that we have no clue whatsoever about the possible number of classes in which the observations can be grouped. Therefore, we cannot divide a priori the observations into groups. Although we are supposing that the data consists of different classes, we do not know beforehand which observations belong to which of the classes.

Fortunately, the PLS-PM approach have a number of options to handle unobserved heterogeneity by applying traditional clustering techniques, latent class analysis, and mixture models. The main idea behind these methods is to infer class memberships of observations by using some type of clustering-based procedure.

The simplest approach to tackle unobserved heterogeneity consists of a sequential two-step procedure; one in which we combine cluster analysis in the first step with a multi-group analysis in the second step. First, we form groups by performing typical clustering analysis on the data (on the manifest variables or on the latent variables). Then, we perform a multi-group analysis on the separate models for each cluster. Generally speaking, model-based techniques involve some clustering-based procedure that takes into consideration the cause-effect.

REBUS, 4 clusters using Bootstrapped results:

```
RESPONSE-BASED UNIT SEGMENTATION (REBUS)
IN PARTIAL LEAST SQUARES PATH MODELING
----------------------------------------------

Parameters Specification
  Number of segments:    4
  Stop criterion:        0.005
  Max number of iter:    100

REBUS solution (on standardized data)
  Number of iterations:  14
  Rate of unit change:   0
  Group Quality Index:   0.6546646

REBUS Segments
                 Class.1   Class.2   Class.3   Class.4
number.units         144        97        94        59
proportions(%)        37        25        24        15

----------------------------------------------
$path.coef
         Class.1   Class.2   Class.3   Class.4
me->ii   -0.7384    0.9107   -0.7860   -0.8842
me->pr   -0.1698   -0.2747   -0.6613   -0.6581
ii->pr   -1.0215   -0.6834   -1.2832   -1.3991

----------------------------------------------
$loadings
             Class.1   Class.2   Class.3   Class.4
pop.x         0.9338    0.9766    0.9157   -0.4699
emp           0.8355    0.9802    0.8886   -0.7164
nhc           0.6768   -0.8935    0.7494    0.9994
ninformal     0.9381    0.9201    0.7315    0.9614
rgdpl         0.8794    0.8311    0.6823    0.7885
wage_share    0.5650    0.6398   -0.2355    0.7896
ntg           0.3102   -0.4596    0.3785    0.7699
somuru        0.4689    0.5449   -0.3240    0.7128
nk            0.5430    0.6656    0.9584    0.9335
nx            0.8813    0.7995    0.9741    0.7951

----------------------------------------------
$quality
             Class.1    Class.2    Class.3    Class.4
Aver.Com
  Com.me   0.6760472  0.9042633  0.7299272  0.5775909
  Com.ii   0.5171881  0.5394748  0.2998395  0.6905714
  Com.pr   0.4304546  0.4596910  0.6574162  0.6705692
Aver.Redu
  Red.ii   0.2819515  0.4474219  0.1852269  0.5399399
```

```
  Red.pr    0.3512925  0.4066051  0.4930201  0.5111002
R2
  R2.ii     0.5451623  0.8293658  0.6177537  0.7818740
  R2.pr     0.8160967  0.8845184  0.7499361  0.7621886
GoF
  GoF       0.6069408  0.7373666  0.6201536  0.7063430
```

```
> ct1ds$country[ct1ds$segments==1]
  [1] "KOR" "KOR" "KOR" "KOR" "KOR" "KOR" "KOR" "KOR" "KOR" "KOR" "KOR" "KOR" "KOR" "KOR" "KOR"
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 [31] "AUS" "AUS" "AUS" "AUS" "AUS" "AUS" "AUS" "AUS" "AUS" "AUS" "NLD" "NLD" "NLD" "NLD" "NLD"
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 [61] "ESP" "ESP" "ESP" "ESP" "ESP" "ESP" "ESP" "ESP" "ESP" "ESP" "ESP" "ESP" "ESP" "ESP" "ESP"
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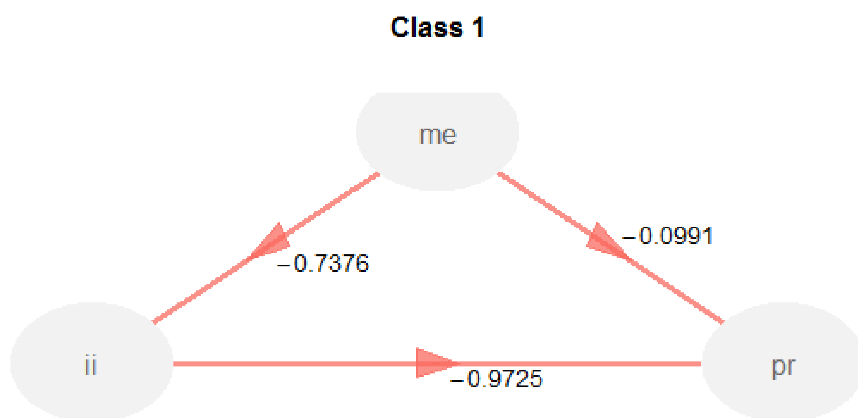


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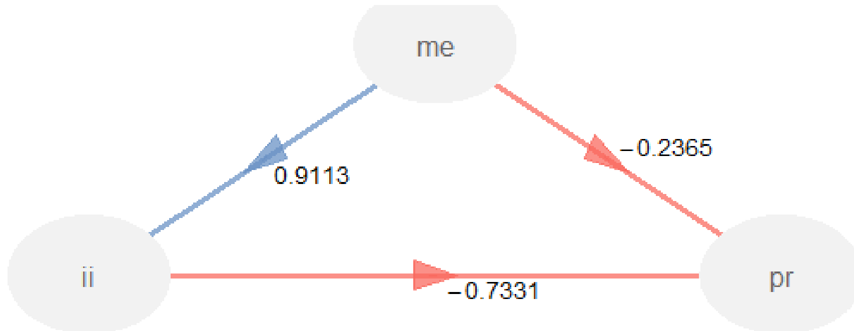
Class 2

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[16] "MEX" "MEX" "MEX" "MEX" "MEX" "RUS" "RUS" "RUS" "RUS" "TUR" "TUR" "TUR" "TUR" "TUR" "TUR"
[31] "TUR" "TUR" "TUR" "TUR" "TUR" "TUR" "TUR" "BRA" "BRA" "BRA" "BRA" "BRA" "BRA" "BRA" "BRA"
[46] "BRA" "BRA" "BRA" "BRA" "BRA" "BRA" "BRA" "BRA" "BRA" "BRA" "BRA" "BRA" "CHL" "CHL" "CHL"
[61] "CHL" "CHL" "CHL" "CHL" "CHL" "CHL" "CHL" "CHL" "CHL" "CHL" "CHL" "CHL" "CHL" "CHL" "CHL"
[76] "CHL" "ARG" "ARG" "ARG" "ARG" "ARG" "ARG" "ARG" "ARG" "ARG" "ARG" "ARG" "ARG" "ARG" "ARG"
[91] "ARG" "ARG" "ARG" "ARG"
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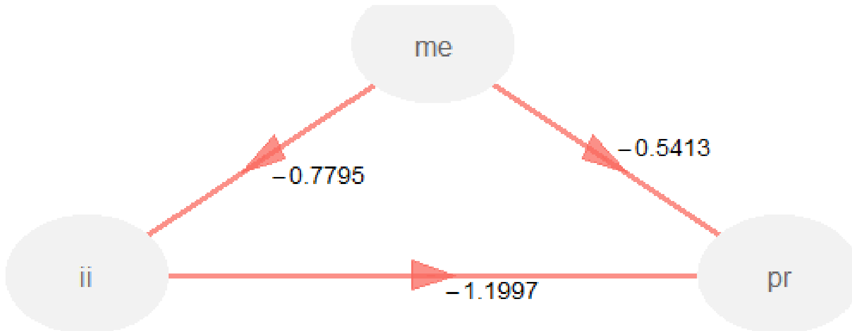
Class 3




```
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 [1] "CHN" "CHN" "CHN" "CHN" "CHN" "CHN" "CHN" "CHN" "CHN" "CHN" "CHN" "CHN" "CHN" "CHN" "CHN"
[16] "CHN" "CHN" "CHN" "CHN" "CHN" "IND" "IND" "IND" "IND" "IND" "IND" "IND" "IND" "IND" "IND"
[31] "IND" "IND" "IND" "IND" "IND" "IND" "IND" "IND" "IND" "IDN" "IDN" "IDN" "IDN" "IDN" "IDN"
[46] "IDN" "IDN" "IDN" "IDN" "IDN" "IDN" "IDN" "IDN" "IDN" "IDN" "IDN" "IDN" "IDN" "IDN"
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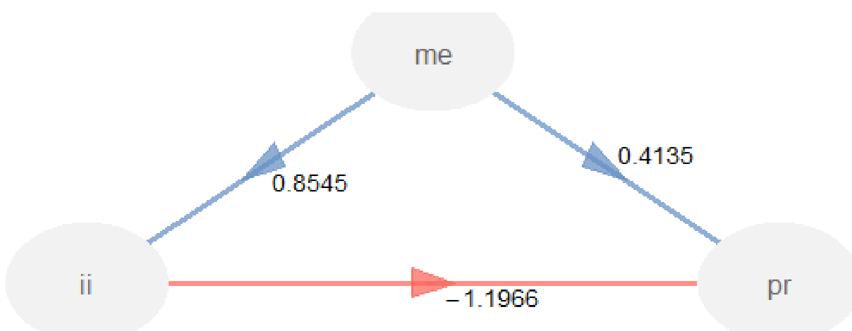
Class 4



Based on, clusters/classes, one can notice five important dynamics/causality between milex, income inequality, and profit:

First, milex has a larger negative effect on profits when overall profit rates are higher.

Second, milex has a positive effect on profits when milex is smaller.

Third, higher milex increases income inequality in countries with very large or very small military expenditures.

Fourth, when inequality is low, higher milex leads to both lower income inequality and profits.

Fifth, when inequality is high, higher milex leads to both higher income inequality and profits.

6. Conclusion

The goal of this paper is to provide some evidence on the dynamics of military expenditures, income inequality, and profit for the first time. The relationships between these three variables is very crucial. Although, the existing literature deals with the problem in bivariate settings, such as milex-inequality, milex-growth, or milex-profits, there is no single study that tries to analyze it at a Threevariate setting. This paper is the first attempt to do so. Military expenditures have direct and indirect effects on, economic growth, income distribution and profit rates.

Since different theoretical approaches lead to different conceptualization and therefore different measurement, it causes incorrect types of empirical distribution functions of the Threevariate. Current studies, therefore, analyze the dependent variables without discussing their distribution functions. That is why in this study, we prefer to utilize the non-parametric soft-modelling approach of PLS-PM. It is an appropriate technique in which the problems explored complex and theoretical knowledge is scarce and no detailed assumptions about the statistical distributions of the dependent variables could be made.

The findings of this study underscore the complex dynamics of these three variables as the results change significantly with respect to different country groups. The general findings that ignore the heterogeneity show that higher while higher milex leads to lower income (inequality), it increases. Income inequality, on the other hand, has a negative effect on profit rates.

Once heterogeneity is considered, for different country groups, the findings become much richer. Accordingly, our results suggest that, first, it is more likely that military expenditures have a negative effect on profit rates, particularly in countries with high profit rates. Also, higher military expenditures lead to lower profit rates when inequality is low, but it leads to higher profit rates when inequality is higher. These are some additional evidence to those provided by Elveren and Hsu (2016), and to some degree in line with their general findings that the effect of military expenditures on profit rates changes with respect to time period and country groups. Second, higher milex increases income inequality in countries with very large or very small military expenditures. Also, higher milex increases income inequality when inequality is high, but increasing milex causes decline in income inequality if inequality is lower. These findings challenge the early findings in the literature that higher military expenditures is associated with rising income inequality. Our findings suggest possibility of negative relationship between milex and inequality, pointing the need for further research on this issue.

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