Military Spending and Inequality: Panel Granger Causality Test

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Abstract

The relationship between military spending and economic inequality is not well documented within the empirical literature, while numerous studies have uncovered the linkages between military spending and other macroeconomic variables, such as economic growth, unemployment, purchasing power parity, black market premium, poverty and investment. The purpose of this article is to examine the causal relationship between military spending and inequality using BVC and SIPRI data across 58 countries from 1987 to 1999. Panel unit root tests indicate that two inequality measures (Theil and EHII) under consideration are likely to be non-stationary. The authors' work addresses the adverse implications of modeling with non-stationary variables, since this omission casts serious doubt on the reliability of the relationship between military spending and inequality. The recent developed panel Granger non-causality tests provide no evidence to support the causal relationship in either direction between the military spending and the change in economic inequality. The results are consistently robust to alternative data sources for military spending, to alternative definitions of the inequality measures, to the log transformation of the military spending, to the deletion of some data points, and to the division of OECD and non-OECD countries. Finally, the impulse responses and variance decompositions based on the panel vector autoregressive regression model are consistent with the findings relied on Granger non-causality tests.

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Introduction

The relationship between military spending and inequality has received marginal attention among empirical and theoretical academicians, in spite of the surges in military spending in most countries both during and after the Cold War.[1] Due to the lack of a theoretical structure relating military spending to inequality, and vice versa, a few studies (e.g. Abell, 1994; Ali, 2007) have resorted to the reduced form regression analysis to uncover correlations and associations among variables, without relying on a detailed specification from economic theory.

Contrary to previous studies, in this article we adopt the concept of Granger causality (Granger, 1969) to empirically test the causal relationship between military spending and inequality. To the best of our knowledge, no prior work has been done to look into this causal relationship (in the Granger sense) using the panel data approach. In this article, we therefore collect the military spending information from the US Bureau of Verification and Compliance (BVC) and Stockholm International Peace Research Institute (SIPRI) data sets, as well as the Theil and EHII indices for economic and inequality measures from the University of Texas Inequality Project. By matching all these data sources, we compile a panel data set with 58 countries covering a period of 13 years from 1987 to 1999.

We attempt to apply the recently developed panel Granger non-causality test (Hurlin, 2004, 2005) to empirically justify the causal relationship between military expenditures and economic inequality.[2] The panel unit root tests indicate that the two inequality measures are likely to be non-stationary. The causal relationship between the military expenditures and economic inequality based on first-differenced inequality measures is subsequently analyzed. This study is the first to address the adverse implications of modeling with non-stationary variables, since this omission casts serious doubts on the reliability of the relationship between military spending and inequality. We also check the robustness of the causal relationship by dividing the whole sample of countries into OECD and non-OECD groups. By controlling for the country heterogeneity using the panel

[1] One of the essential reasons for empirical studies is the availability of data in regard to the inequality data (especially for the panel data). For instance, if one goes to the World Development Indicators website at the World Bank: `http://publications.worldbank.org/WDI`, one will find that the inequality data (such as Gini coefficients) are very limited. The limitations of the data could also be seen in Angeles-Castro (2006), who explores the relationship between economic growth and inequality by employing a balanced panel data set consisting of 31 countries over 1970-1998, even though there are a total of 161 countries in the sample.

[2] In fact, Hurlin's approach is not the only way of performing the panel Granger causality test. There are several alternatives. We will discuss the advantages of Hurlin's approach over the others in the section of econometric methods.

data approach, we hope this study will provide us not only with a clear picture of the relationship between the military spending and economic inequality, but also with a more accurate inference than would be provided by the time series or cross sectional data alone. Finally, impulse responses and variance decompositions based on the vector autoregression model are conducted to learn of the interrelations among variables without a prior commitment to established theories.

The remainder of this article is organized as follows. In the next section, we briefly review the literature and then discuss the relationship between military spending and economic inequality in the following section. The next section introduces the panel unit roots and panel Granger non-causality tests, which are used as vehicles to test for stationarity and causal relationships in this paper. The data sources, key variables under investigation, and the empirical results concern the section that follows. The final section offers some concluding remarks.

Literature Review

Numerous studies have uncovered relationships between inequality and economic and political institutions. Gradstein, Milanovic & Ying (2001) argue that democratization can reduce inequality. More generally, affluence has been correlated with the presence of democratic institutions (e.g. Diamond, 1992; Lipset, Seong & Torres, 1993). Rodrik (1999) strongly suggests that democratic institutions are associated with higher wages; institutions do matter to distributive outcomes. DiNardo, Fortin & Lemieux (1996) show that de-unionization is an important factor explaining the rise in wage inequality from 1979 to 1988. Differences in labor market institutions, mainly the relative decentralization of the wage-setting mechanism, provide a widely accepted explanation of wage inequality in the US as compared with other OECD countries (Blau & Kahn, 1996).

There is much work which has been done on the relationship between military spending and other macroeconomic variables, such as economic growth (Chan, 1985; Chowdhury, 1991; Dunne, Smith & Willenbockel, 2005; Yildirim, Sezgin & Ocal, 2005; Kollias & Makrydakis, 2000), unemployment (Dunne & Smith, 1990; Abell, 1990, 1992; Barker, Dunne & Smith, 1991; Hooker & Knetter, 1997; Yildirim & Sezgin, 2003), purchasing power parity (Bahmani-Oskooee & Goswami, 2005), black market premium (Bahmani-Oskooee & Goswami, 2006), poverty (Henderson, 1998), and investment (Smith, 1977).

As indicated in the previous section, the relationship between military spending and economic inequality is not well documented within the empirical literature. In fact, there are only two papers closely related to our work: Abell (1994) and Ali (2007). As far as we know, Abell (1994) is the first seminal work to examine the relationship between military spending and the distribution of income. Abell (1994) uses the time series data for the US during the post-Vietnam War period ranging from 1972 to 1991, and he finds that military spending is associated with increasing income inequality, after controlling for some macroeconomic variables such as economic growth, taxes, interest rates, non-military spending and inflation. The result of Abell (1994) relies on the assumption that military spending is not determined by income inequality.[3]

In a recent analysis of military spending and inequality with global panel data, Ali (2007) treats both military spending and inequality as endogenous variables in his model. Ali's results indicate that there is a positive effect of military expenditure on pay inequality, and vice versa. However, Ali incorporates the inequality as the right-hand-side endogenous variable without any empirical or theoretical justification for the causal direction from inequality to military spending. With the panel Granger non-causality test, our research aims to employ a global panel data set for 58 countries and to empirically test the relationship for two potentially endogenous variables.

Military Spending and Inequality

There are several ways in which military spending may affect economic inequality. First, from a Keynesian point of view, defense spending can boost the income in defense-related sectors and result in increased aggregate demand and employment. Since the level of income inequality increases during downswings in the economy and decreases during upswings, the implication is that the poor gain relative to the rich during peaks in the business cycle (Beach, 1977). Then by implication such spending should provide opportunities for individuals to live equally.

Secondly, increases in military spending could be at the expense of public spending on social programs such as health and education - which have an equalizing effect. The military as an institution, therefore, competes for scarce resources with other social entitlements and reduces the special advantages conferred by those social programs (Ali, 2004). For example, Drèze (2000) has criticized the Indian government's unwillingness to spend an additional 0.5 percent of GDP to ensure universal elementary education while it endorsed proposals for larger increases in military

[3]In Abell (1994), income inequality is a function of military spending but income inequality is not a key factor affecting military spending.

spending. However, there may exist a large number of simultaneous channels by which the crowding out effects and counter effects operate (Deger, 1985), so that the final causality is not clear-cut.[4]

Third, the aggregate military spending may hide conflicting labor effects among the components (personnel, procurement, R&D, operations, and maintenance) which result in different impacts on economic inequality.[5] For instance, military personnel spending generally absorbs the less-skilled labor. In particular, during an economic recession when unemployment increases, more people (the poor or less-skilled workers) join the armed forces and this increases military personnel spending while decreasing economic inequality. Military procurement and R&D expenditures are most likely to give rise to higher economic inequality since they tend to lead to the hiring of more highly skilled workers.[6] In addition, operations and maintenance (O&M) as well as procurement and R&D may be used as a counter-cyclical mechanism to ensure profits for monopoly capital and employment for organized labor (Griffin, Devine & Wallace, 1982). If the poor are among the unionized sectors, procurement, R&D, and O&M will decrease economic inequality. However, it is often the case that the poor dominate non-unionized sectors that do not benefit from the counter-cyclical spending. The economic inequality will thus be increased.

Finally, we can establish a causal relationship between the two based on standard microeconomic theory (Ali, 2007). Assuming that the defense-related sector is already the high-wage sector, if defense-related labor inputs are specialized and in inelastic supply, an increase in the demand for defense will increase the inter-sector dispersion in wages, at least over short or intermediate periods of time. In the developed countries in particular, for example, an increase in the demand for military personnel tends to drive up military pay because the supply of personnel to the military is inelastic. Likewise, higher outlays on procurement tend to drive up the wages of electrical engineers, aircraft and shipbuilding workers, and other specialized labor inputs related to defense production. The inequality measure is likely to increase as a result. The long-run inter-sector adjustments in labor supply might temper this effect on measured inter-sector wage inequality. To turn this around, if workers in the defense-related sector enjoy higher wages to begin with, a reduction in defense spending should lower their relative wages and reduce inequality. In general, the more the equipment-intensive military expenditure is, the more we expect the inequality-increasing

[4]The empirical findings in regard to the defense-welfare trade-off are classified into negative, positive or no trade-offs. For more details, refer to Yildirim & Sezgin (2002).

[5]Henderson (1998) analyzes the impact of the segregation of military spending on the issue of poverty.

[6]Abell (1994) provides empirical evidence for the US to support this point.

effects to dominate; the more labor-intensive the military is and the more home grown the military production, the more we might expect to find inequality-reduction effects in the data.

On the other hand, the relationship running from economic inequality to military spending is rarely discussed in the literature. However, from the standpoint of political economy, if the economic inequality is enlarged, this will destabilize the society and will be a source of social tension, thus fueling demands for social and political change (Ali, 2004). Therefore, an increase in military spending is the response of those in power to maintain social order. Suppressing the trade unions and other egalitarian social forces increases inequality and further fuels the need to increase military spending. In its quest for stability, the establishment expresses its preferences for preserving peace and the status quo by suppressing the dissident and consequently increasing inequality. Therefore, the level of inequality has an impact on the demand for military spending; as inequality increases, military spending might rise.

Recently, Caverley (2007) has attempted to link economic inequality with military capitalization through a micro-foundational argument that the median voter possesses the ability to reduce her costs of war. He sets up a neoclassical production function for defense to predict capital intensive defense preparation in democracies based on median voter preferences. One of the results suggests that military capitalization will increase as the inequality in the distribution of wealth rises.

From the above discussion, we know that the link between military spending and inequality is quite complex in that there are many variables that affect military spending and inequality through many channels, especially in the direction running from the former to the latter. Due to the lack of a formal testable model in the literature, it is difficult to empirically establish the interdependency between the two variables using a fully specified multivariate model. Furthermore, it could be the case that the relationship is specific to some regions (say, Western Europe and the US) such that we may not detect this link empirically.[7] Nevertheless, it is possible to have two opposite driving forces running from military spending to economic inequality that offset each other so that we are unable to detect the association in empirical studies.

[7] In our preliminary analysis, military spending and inequality in different regions of the world have been observed to exhibit different and unique patterns. We will leave a thorough investigation of this link based on regional analysis to future research.

Econometric Methods

From our previous theoretical arguments, the causal relationship between military spending and economic inequality could be in either or both directions. It is also possible to even have no interdependency. Abell (1994) utilizes US time series data with a single regression (inequality is treated exogenously), and Ali (2007) uses a global panel data with a simultaneous regression (inequality is ad hoc treated endogenously) to examine the relationship between military spending and economic inequality. In this article, we rely on the concept of Granger causality to empirically test the causal relationship between military spending and inequality without assuming the exogeneity or endogeneity of the underlying variables *a priori*. The military spending 'causes' economic inequality in the Granger sense if the lagged military spending helps forecast economic inequality. Even though the Granger causality test for time series data has been well developed, a better way of testing for causality is to combine both the cross sectional and time series data, and to perform the so-called panel Granger non-causality test (Hurlin & Venet, 2001; Hurlin, 2004, 2005). Consequently, the panel Granger non-causality test is more efficient than when only the time series data are used (Hurlin & Venet, 2001). Other advantages for using panel data include: 1) the ability to control for individual heterogeneity; 2) the increased precision of the regression estimates (using a large sample size relative to the cross sectional data); 3) a reduction in identification problems (identifying individual dynamics); and 4) the ability to model temporal effects without aggregation bias as in time series studies.[8]

To test the relationship between two variables in the Granger sense, consider the following linear panel data model:

$$y_{it} = \alpha_i + \sum_{k=1}^{K} \gamma^{(k)} y_{it-k} + \sum_{k=1}^{K} \beta^{(k)} x_{it-k} + \varepsilon_{it},$$

where α_i captures the individual specific effect across i and the coefficients $\gamma^{(k)}$ and $\beta^{(k)}$ are implicitly assumed to be constant for all i. The pioneering work on the panel Granger causality test by Holtz-Eakin, Newey & Rosen (1988) involves testing the null hypothesis that $\beta^{(1)} = ... = \beta^{(K)} = 0$ against the causality from x to y for all the cross-sectional units. However, this approach may result in several problems. First, to implement the panel Granger causality test, we need to obtain

[8] For the theoretical arguments made in the previous section, we basically look at links between in-country inequality and military spending. It is worth noting that with use of the panel approach in this article, we open up the possibility of other theoretical linkages between between-country inequality and military spending. We owe this remark to the Associate Editor.

the estimators for $\gamma^{(k)}$ and $\beta^{(k)}$. It is well-known that the fixed effect estimator is biased and inconsistent in the dynamic panel data model when there are a large number of cross-sectional units observed over relatively short time periods (Nickell, 1981). Secondly, for short time panels, the Wald-type statistic with respect to the null hypothesis is not a standard distribution (Hurlin & Venet, 2001). Finally, the panel Granger causality test proposed by Holtz-Eakin, Newey & Rosen (1988) imposes the homogeneous alternative, which is a very strong hypothesis (Granger, 2003). To overcome the above-mentioned disadvantages, Hurlin (2004) proposes testing the homogeneous non-causality (HNC) null hypothesis against the heterogeneous non-causality hypothesis (HENC). HENC allows some but not all of the individuals to Granger cause from x to y. The linear panel data model under consideration is given by:

$$y_{it} = \alpha_i + \sum_{k=1}^{K} \gamma_i^{(k)} y_{it-k} + \sum_{k=1}^{K} \beta_i^{(k)} x_{it-k} + \varepsilon_{it},$$

where $\gamma_i^{(k)}$ and $\beta_i^{(k)}$ are various coefficients of y_{it-k} and x_{it-k} for individual i, respectively. The idea behind Hurlin (2004) is to average the individual Wald statistics associated with the standard Granger HNC tests for units $i = 1, ..., N$. Hurlin (2005) also suggests a similar test statistic to deal with the unbalanced panel data set. In this paper, we apply the methods of Hurlin (2004, 2005) to conduct the panel Granger non-causality test.

The new procedure by Hurlin (2004, 2005) also follows a standard Granger causality where the variables that enter into the system need to be covariance-stationary. This could be accomplished by implementing the unit root test. In principle we can pool the data and conduct the traditional unit root tests such as the Dickey-Fuller, Augmented Dickey-Fuller, Phillips-Perron, and KPSS tests. However, the little power of the individual unit root test makes it difficult to detect the stationarity of the series. Pooling the individuals across time is one way to come up with a more powerful unit root test, which has been pioneered by Levin, Lin & Chu (LLC, 2002).[9] In addition, there are several types of panel unit root tests, for instance, see Im, Pesaran & Shin (LPS, 2003), Breitung (2000), Maddala & Wu (MW, 1999), Choi (2001), Hadri (2000).

[9] The original paper by Levin, Lin & Chu (2002) comes from the highly cited working paper by Levin & Lin (1992) in the literature.

Empirical Results

Data and Variables Description

Since the defense data are often considered to be unreliable, we try to use military spending data obtained from two different data sources. The first source is the US's BVC military spending, which has reported the world military expenditures for a decade. Another popular data source for military expenditures is SIPRI, which is an independent international institute for research into problems of peace and conflict. Both sets of military spending are in constant US dollars. The military expenditures are extended to cover a period of 13 years from 1987 to 1999 for 140 countries. Along the same lines as Ali (2007), we choose the per capita military expenditure and the logarithm of per capita military expenditure variables to test the causal relationships with the inequality measures.

As for the economic inequality measures, we focus on the Theil and EHII indices, both of which are available from the University of Texas Inequality Project (UTIP). The larger the two indices, the larger the levels of inequality. The Theil index is proposed by Theil (1979) and inherits several nice properties such as easy computation and decomposition into between-group and within-group components. For more details on this see Galbraith (1998), Galbraith & Kum (2004), Galbraith & Conceição (2001). Note that the Theil index in the UTIP data set is actually the industrial pay inequality, which measures the wage dispersion across industries in the manufacturing sector so that it is a component of overall economic inequality. The EHII index available in the UTIP is the Estimated Household Income Inequality, which combines the industrial pay inequality data and the Deininger & Squire (1996) Gini coefficient. On this see Galbraith & Kum (2004). The latest Theil and EHII inequality measures in the UTIP contain 156 countries covering the period 1963-99.[10]

The original data contain up to 140 countries covering 13 years and 156 countries covering 37 years obtained from the military spending and inequality data sources, respectively. Hurlin's (2004, 2005) panel Granger non-causality test is based on averaging the standard time series Granger non-causality test for all countries. This means that for a given country both the military and inequality information should be available and meet the requirement of lasting at least eight consecutive years for that country. The countries with insufficient military data (e.g. Iceland and Iraq) and inequality data (e.g. France, Sudan, Brazil and Argentina) are therefore excluded from this study.

[10]The EHII and UTIP-UNIDO (Theil index) data sets are available at `http://utip.gov.utexas.edu/data.html`.

Most of these countries are excluded due to the lack of sufficient inequality measures. We also consider the countries with both BVC and SIPRI military spending to see if the sources of the military data matter. Thus, to compromise those various data sets, we match them to generate our (unbalanced) panel of 58 countries covering a period of 13 years. The number of countries decreases slightly to 52 if we stick to the balanced panel. The countries in the data are presented in Table 1. The descriptive statistics of the underlying variables are listed in Appendix Table I in levels. The sample correlation coefficient between the BVC and SIPRI military expenditures is about 0.910 indicating that the linear relationship between these two military expenditures is strong and positive. Moreover, the correlation coefficient between the pair of inequality measures is found to be 0.753. This is conceptually intuitive since the former pair measures the same variable (military spending), but the latter pair uses different inequality definitions to approximate inequality.

[Table 1 is about here!]

Panel Unit Root Tests

The results in Table 2 show that all the military spending variables {BVC, ln(BVC), SIPRI, and ln(SIPRI)} pass four versions of the panel unit root tests, i.e., the four variables are stationary regardless of the military data sources or logarithmic transformations used. However, the LLC, IPS, and MW tests strongly show that the inequality variables (Theil and EHII) are non-stationary.[11] The non-stationarity in levels of the inequality measure is also found in Assane & Grammy (2003) and Nath & Mamun (2004).[12] We then adjust the inequality variables by taking the first differences. The last two rows in Table 2 show that the first-difference transformation will remove the potential non-stationarity. Note that Ali (2007) simply uses the Theil index in levels for the simultaneous determination of the link between military expenditure and economic inequality. In what follows, we will consider two scenarios to implement the panel Granger non-causality test. One is to ignore the possible non-stationarity of the inequality variables and the other is to utilize the first-differenced version of the inequality measures.

[Table 2 is about here!]

[11] We also find that the logarithms of the two inequality indices cannot reject the null unit root hypothesis. Furthermore, if we take the whole sample of Theil and EHII measures in the UTIP covering 156 countries from 1963-1999, non-stationarity is still found for the two measures.

[12] Assane & Grammy (2003) use U.S. annual data (1960-96) to determine the causal relationship between the growth and inequality. Nath & Mamun (2004) show that the EHII in levels are non-stationary in Bangladesh for the period from 1967 to 1992.

Panel Granger Non-causality Tests

To conduct the panel Granger non-causality test by Hurlin (2004, 2005), we note that the requirement, $T_i > 5 + 2K$ (T_i : time spans for country i) should be met. Since the maximum of T_i is 13 in our sample period, the possible choice of the autoregressive lag orders (K) remains 1, 2, and 3, e.g. if $K = 2$, one would need at least 10 consecutive observations ($T_i = 10$) for country i. Since we have relatively short panels, we are likely to run out of degrees of freedom. In what follows, the empirical results are based on the more reliable case of $K = 1$.[13] To exhaust all possibilities, we consider testing the Granger non-causality running from the military spending set {BVC, SIPRI, ln(BVC), ln(SIPRI)} to the inequality pair {Theil, EHII}, and vice versa. Both the balanced and unbalanced panels are taken into consideration. This enables us to implement 32 combinations of the panel Granger non-causality tests.

We temporarily ignore the possible non-stationarity and run the panel Granger non-causality tests. Table 3 indicates that the causal relationships between two versions of the per capita military spending (and its logarithm) and the inequality measures are significantly bi-directional. Since the results are obtained by ignoring the potential non-stationarity of the inequality measures, we will not provide a further discussion.

[Table 3 is about here!]

We now take potential non-stationarity into account by first-differencing Theil and EHII. Table 4 indicates that changes in the inequality measures (i.e. ΔTheil and ΔEHII) do not Granger cause the military spending, and vice versa. In general, this finding holds for either balanced or unbalanced panels.[14] The exception is that there is a weak causality running from SIPRI to the change in EHII, and from ΔEHII to BVC. With that exception in mind, we find no evidence to support the causal relationship between military spending and changes in inequality measures. This implies that if we neglect the possibility of non-stationarity in the inequality variables, it is very likely that the true causal relationship will be distorted.

[Table 4 is about here!]

[13] The simulation in Hurlin (2004, 2005) shows that the size and power are reasonably good with small T. However, we occasionally face a shortage of countries (say, $N = 4$) if the inequality variables are first-differenced.

[14] To save space, the results for unbalanced panels are available upon request.

To check the robustness of the insignificant causal relationship between military spending and changes in economic inequality, we separate the countries into OECD and non-OECD countries. [15]Another reason for this exercise is that the causal relationship between the variables under consideration could be sensitive to the rich and poor countries. For details see Choe (2003); Hoffmann *et al.* (2005); Yildirim, Sezgin & Ocal (2005). There are 17 OECD and 35 non-OECD countries after the countries are divided up.[16] Table 4 again shows that in general there is no Granger causality between the two variables in the cases of both the OECD and non-OECD countries.[17] This is consistent with what we found for all countries as a whole. It is worth noting that no causality in either direction is perceived between military expenditure and ΔTheil, regardless of how countries are classified. Meanwhile, we also observe that ΔEHII occasionally exhibits a significance in terms of the Granger causality both in the BVC and SIPRI military expenditures.

Recently, in using data on US military expenditure, Brauer (2007) has found that even adding to or deleting one year from the data may drastically change the estimated coefficients. Thus, it is worth implementing a further robustness check. We conduct the experiment by considering three alternative time periods: 1987-97, 1987-98, and 1987-99. Note that time intervals 1987-97 and 1987-98 represent deleting two years and one year in terms of data points for each country from the original data period (1987-1999), respectively.[18] Most of the Granger non-causality test statistics are insignificant and provide no evidence of a uni-directional or bi-directional relationship between military expenditures and changes in economic inequality. For instance, the three test statistics for testing the null that BVC does not Granger cause ΔTheil are -0.825 (87-97), -0.946 (87-98), and -0.906 (87-99).[19] This result is consistent with our previous finding.

Since one cannot determine whether there exists a specific relationship between these two variables, we thus apply the concept of Granger causality to investigate this relationship. Consequently, our results of no significant statistical relationship between military spending and changes in eco-

[15]We thank Ron Smith for pointing out that 'there could be Granger causality in all countries in the sample from military expenditure to inequality but in half of the countries the effect is positive and half negative, so the global effect is zero'.

[16]The 17 OECD countries in our sample include Australia, Austria, Canada, Denmark, Finland, Greece, Italy, Japan, Mexico, the Netherlands, New Zealand, Norway, Spain, Sweden, Turkey, the UK, and the United States.

[17]The results for using the levels in the EHII and Theil indices are listed in Table 3, which has a very similar conclusion to the sample as a whole. Again, we cannot interpret the results here since the inequality variables in levels are non-stationary.

[18]Of course, we may want to see what happens to the Granger non-causality test if we add more recent data points (say, 1987-2000, 1987-2001). However, the EHII and Theil inequality data are reported by UTIP up to the year 1999. We therefore turn to the 'in-sample' instead of the 'out-of-sample' comparison.

[19]To save space, the results of the sensitivity analysis are available upon request.

nomic inequality depart from those in past studies such as Abell (1994) and Ali (2007). This may result from employing the approach of Granger causality and dealing with the possible non-stationarity of inequality measures, as well as expanding a panel data set with more observations. First-differencing the inequality variables is crucial for our findings. A significant relationship between military spending and economic inequality is consistent with previous studies if we neglect non-stationary inequality measures. Moreover, our insignificant results may simply reflect the fact that the two opposite forces in terms of the expansion of military expenditures on changes in inequality have just offset each other.

Impulse Response Analysis

In order to understand the reaction of the military spending or change in inequality to the innovations in another variable in the system, we set up a panel vector autoregression (VAR) model and perform an impulse response analysis. To draw a comparison with the Granger non-causality test, we adopt the panel VAR(1) model in standard form, which is given by:

$$Z_{it} = A_o + A_1 Z_{i,t-1} + e_{it},$$

where Z_{it} is the vector of any combination of military spending and change in inequality pairs, A_o and A_1 are coefficient vectors, and the e_{it} are composite error terms. For instance, we can take $Z_{it} = (\text{BVC}_{it}, \Delta\text{Theil}_{it})'$. The impulse response functions are plotted in Appendix Figure 1.[20] The figure shows that the response of military spending to the change in inequality (ΔTheil_{it}) shocks causes military spending to jump at the beginning and to die out quickly to the long-run value after 6 time periods. For instance, the response of changes in the Theil index to a one-unit increase of innovation in SIPRI per capita military spending increases first, declines in period 2, and increases again. On the other hand, the response of the change in inequality to shocks in military spending decreases and subsequently increases to the long-run equilibrium. Various combinations of the impulse responses in Appendix Figure 1 indicate that the patterns are invariant to the data sources of the military spending and economic inequality indices.[21] In general, the perturbation of innovations in military spending and in first-differenced inequality measures seems to have no statistically significant effects on the other variables. This result is comparable to that obtained

[20] We thank Insessa Love for providing the Stata code to estimate the panel VAR models.

[21] We also try the VAR(2) setting and yield quite similar results to the case of VAR(1). It is well known that the ordering of the variables is crucial in impulse response analysis. Our experiment shows that reversing the Cholesky decomposition does not have a significant impact on the impulse responses.

using the panel Granger non-causality approach. Moreover, the variance decomposition in Table 5 summarizes the percentage of variation in military spending explained by the change in inequality and vice versa. It is clear that a tiny proportion (below 10%) of the movements in a variable is due to the shocks of the other variable. However, in most of the cases, the variations due to the variable's own shocks are over 90%. This finding is again parallel to the fact that there is no causal relationship between military spending and the change in inequality according to the panel Granger non-causality test.

[Table 5 is about here!]

Conclusion

In this paper we contribute to the literature by examining the presence and direction of Granger causality between military spending and economic inequality for a larger data set of countries using more refined econometric techniques. This task is performed by considering both the BVC and SIPRI military spending data as well as the UTIP's Theil and EHII inequality measures across 58 countries from 1987 to 1999. Panel unit root tests indicate that the Theil and EHII inequality measures are likely to be non-stationary. The panel Granger non-causality tests (Hurlin, 2004, 2005) show that in general there is no Granger causality in either direction between military spending and changes in economic inequality. Our study is the first to address the adverse implications of modeling with non-stationary variables, since this omission casts serious doubt on the reliability of the relationship between military spending and inequality. We also perform an experiment by taking a logarithm of the military spending but this does not alter the results of the analysis. However, if we ignore the non-stationarity of the variables, the causal relationship runs significantly in both directions. This fact emphasizes that non-stationary income inequality measures should be borne in mind by researchers when they try to test the two variables empirically.

Furthermore, grouping data into OECD and non-OECD countries basically does not change our results, i.e., there is also no evidence of Granger causality in either direction within OECD and/or non-OECD countries. In addition, sensitivity analysis shows that our results are robust in that deleting one or two data points does not affect the outcome. Finally, the impulse response analysis and variance decompositions are conducted and the results are consistent with our previous findings in that the proportion of the movements in a variable being due to shocks in the other variable is very small.

Abell (1994) using US time series data, and Ali (2007) using panel data, show that military spending is indeed positively associated with income inequality. However, they both treat the inequality measures as stationary. It would be interesting for future work to re-examine the relationship in a regression model if the income inequality measures were to be treated as non-stationary variables. Another direction for future research would be to develop a testable economic theory which might first endogenize military spending and inequality and then examine the linkage between the two key variables empirically.

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Table 1: Countries in the Data

Algeria	Australia	Austria	Barbados*	Bolivia	Bulgaria
Cameron	Canada	Chile	Colombia	Costa Rica	Cyprus*
Denmark	Ecuador	Egypt	Ethiopia	Finland	Greece
Honduras*	Hungary	India	Indonesia	Ireland	Israel
Italy	Japan	Jordan	Luxembourg*	Kenya	Korea
Kuwait	Malawi	Malaysia	Malta	Mauritius	Mexico
Morocco	Netherlands	New Zealand	Norway	Panama	Philippines
Poland	Senegal	Singapore	South Africa	Spain	Sri Lanka*
Swaziland	Sweden	Syria	Taiwan	Turkey	UK
USA	Uruguay	Venezuela*	Zimbabwe		

The countries with asterisks are excluded for the balanced panel data.

Table 2: Panel Unit Root Tests for Key Variables

Variables	LLC	IPS	MW	Choi
Bpme	-15.314	-5.264	172.361	213.844
	(0.000)	(0.000)	(0.032)	(0.000)
Lbpme	-6.573	-2.501	141.984	181.201
	(0.000)	(0.006)	(0.008)	(0.000)
Spme	-11.028	-5.235	206.613	267.444
	(0.000)	(0.000)	(0.000)	(0.000)
Lspme	-26.439	-9.821	194.811	246.912
	(0.000)	(0.000)	(0.000)	(0.000)
Theil	5.164	3.183	119.680	142.437
	(1.000)	(0.999)	(0.140)	(0.007)
EHII	-0.267	1.570	121.512	145.202
	(0.395)	(0.942)	(0.116)	(0.005)
ΔTheil	-9.864	-9.527	318.334	429.094
	(0.000)	(0.000)	(0.000)	(0.000)
ΔEHII	-14.486	-10.313	310.872	433.038
	(0.000)	(0.000)	(0.000)	(0.000)

Bpme, Lbpme, Spme, Lspme, Theil, EHII, ΔTheil, and ΔEHII denote the BVC per capita military expenditure, the logarithm of Bpme, SIPRI per capita military expenditure, the logarithm of Spme, the Theil index, the EHII index, the first differenced Theil, and the first differenced EHII, respectively. p-values are in parentheses.

Table 3: Panel Granger Causality Tests – Military Spending vs. Inequality

(**A**) Military spending to Inequality

	Bpme $\nrightarrow$ Theil	Lbpme $\nrightarrow$ Theil	Spme $\nrightarrow$ Theil	Lspme $\nrightarrow$ Theil
Total countries	4.409***	4.009***	2.670***	3.299***
OECD countries	3.675***	3.940***	4.273***	4.896***
Non-OECD countries	3.030***	2.423**	0.734	1.113
	Bpme $\nrightarrow$ EHII	**Lbpme $\nrightarrow$ EHII**	**Spme $\nrightarrow$ EHII**	**Lspme $\nrightarrow$ EHII**
Total countries	3.235***	3.046***	1.756*	1.678*
OECD countries	1.700*	1.976**	1.704*	2.369**
Non-OECD countries	2.758***	2.393**	1.077	0.632

(**B**) Inequality to Military spending

	Theil $\nrightarrow$ Bpme	Theil $\nrightarrow$ Lbpme	Theil $\nrightarrow$ Spme	Theil $\nrightarrow$ Lspme
Total countries	5.621***	5.388***	3.188***	3.003***
OECD countries	5.736***	5.378***	1.769*	1.617
Non-OECD countries	3.298***	3.211***	2.668***	2.540**
	EHII $\nrightarrow$ Bpme	**EHII $\nrightarrow$ Lbpme**	**EHII $\nrightarrow$ Spme**	**EHII $\nrightarrow$ Lspme**
Total countries	5.373***	4.146***	4.233***	3.869***
OECD countries	4.719***	4.463***	2.189**	1.997**
Non-OECD countries	3.562***	2.294**	3.630***	3.319***

"$\nrightarrow$" is the panel Granger homogeneous non-causality (HNC) null hypothesis.
***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Panel Granger Causality Tests – Military Spending vs. Inequality with Correcting for Possible Non-stationarity

(**A**) Military Spending to Change in Inequality

	Bpme $\nrightarrow$ ΔTheil	Lbpme $\nrightarrow$ ΔTheil	Spme $\nrightarrow$ ΔTheil	Lspme $\nrightarrow$ ΔTheil
Total countries	-0.906	-0.787	0.516	0.685
OECD countries	-0.761	-0.697	-0.379	-0.309
Non-OECD countries	-0.591	-0.499	0.850	1.005

	Bpme $\nrightarrow$ ΔEHII	Lbpme $\nrightarrow$ ΔEHII	Spme $\nrightarrow$ ΔEHII	Lspme $\nrightarrow$ ΔEHII
Total countries	0.406	0.505	1.737*	1.846*
OECD countries	-0.722	-0.688	-0.623	-0.592
Non-OECD countries	0.937	1.041	2.449**	2.559**

(**B**) Change in Inequality to Military spending

	ΔTheil $\nrightarrow$ Bpme	ΔTheil $\nrightarrow$ Lbpme	ΔTheil $\nrightarrow$ Spme	ΔTheil $\nrightarrow$ Lspme
Total countries	0.923	-0.547	-0.210	-0.320
OECD countries	-0.376	-0.443	0.639	0.678
Non-OECD countries	1.330	-0.366	-0.652	-0.808

	ΔEHII $\nrightarrow$ Bpme	ΔEHII $\nrightarrow$ Lbpme	ΔEHII $\nrightarrow$ Spme	ΔEHII $\nrightarrow$ Lspme
Total countries	2.136**	0.245	0.389	0.241
OECD countries	1.949*	1.660*	2.075**	2.095**
Non-OECD countries	1.294	-0.772	-0.853	-1.039

"$\nrightarrow$" is the panel Granger homogeneous non-causality (HNC) null hypothesis.
***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Variance Decompositions

	Periods	Bpme	ΔTheil		Periods	Bpme	ΔEHII
Bpme	10	0.747	0.253	Bpme	10	0.949	0.051
ΔTheil	10	0.188	0.812	ΔEHII	10	0.018	0.982
Bpme	20	0.747	0.253	Bpme	20	0.949	0.051
ΔTheil	20	0.188	0.812	ΔEHII	20	0.019	0.981

	Periods	Spme	ΔTheil		Periods	Spme	ΔEHII
Spme	10	0.948	0.052	Spme	10	0.987	0.013
ΔTheil	10	0.281	0.719	ΔEHII	10	0.028	0.972
Spme	20	0.948	0.052	Spme	20	0.987	0.013
ΔTheil	20	0.281	0.719	ΔEHII	20	0.029	0.971

The numbers denote the percentage of variation in the row variable explained by the column variable.