Senior Project
Department of Economics

Exploring the Impact of Military Expenditure on Unemployment:
A Study Disaggregated by Industry

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May 2015

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Abstract

This study analyzes military expenditure both by per capita and as a percentage of GDP and how they affect the unemployment rates of different industries within the United States. More specifically, this study attempts to look at where the causality in this relationship is running from – military expenditure towards unemployment in the given industry, or from the industry's unemployment rate to the military expenditure. While simply using the Ordinary Least Squares Method proved to be inefficient in terms of efficacy, it was able to point out some complications that ensured the data was prepared properly for the granger causality tests through the implication of differencing for unit roots. The granger causality tests implied that military expenditure as a percentage of GDP and on a per capita basis both granger caused unemployment in the agricultural sector. There was no causation regarding the expenditure variables and the service industry and the production & operations industry. These tests also found that the professional and technologies industry granger caused the level of military expenditure, which I return to alternative previous literature in hopes to explain.

Table of Contents

I. Introduction

According to White House's Office of Management and Budget (2015), military and defense expenditure made up 51.3% of discretionary spending. While still high, military and defense expenditure is down from the record highs that were seen in the 1980's (BLS 2015). At the same time, unemployment levels have decreased and hovered just below 6%. At the time when military expenditure was at its all-time high, unemployment reached levels of 7% all the way up to nearly 11% (BLS 2015). The relationship between military spending and unemployment is a complex one because there is more than just one confounding factor that can mask its nature. There are several schools of thought on how military expenditure could affect unemployment or vice versa. The first theory is that increased levels of military expenditure will decrease unemployment because of the spillover from military R&D. These spillovers would result in increased labor productivity and therefore, the demand for this labor would increase and decrease unemployment (Tang et al. 2009). Another theory suggests that as the military experiences funding cuts, people originally employed in the military sector will seek employment elsewhere, thus resulting in elevated levels of frictional unemployment (Tang et al. 2009). In many cases taxes are used to help finance military expenditure during times of war. This increased taxation will either more heavily weigh on the employer (decreasing the demand for labor) or the employee (decreasing the supply of labor), in either case increasing unemployment (Tang et al 2009).

After reviewing the data and previous literature that has been published, the verdict is still out on what the exact relationship is between defense spending and unemployment. Some researchers believe there is a positive correlation between the two while others have findings that prove that a negative correlation exists. There is also a school of thought that the comparison between the two is negligible because no correlation exists between the two.

The intention of this study is to discover if increased levels of military expenditure affect the unemployment levels of different industries in different ways. More specifically, this study seeks to discover whether this uncertainty with causality cannot be seen at a macro level but is more visible when broken down into industry. In a previous study by Tang et al (2009), they found that there was a positive correlation between military expenditure as a share of GDP and unemployment, and they also provided thought-provoking possibilities on furthering their own research through the breakdown of unemployment by industry. Their recommendation is the basis for this study. The dependent variable will be the specific industry's unemployment, ranging from the professional and technical industry, the service industry, the agricultural industry and the production and operations industry. The dependent variables will be variations of military expenditure used similarly to that of the Tang et al (2009) paper. The aim is to answer the research question in a manner that will eliminate a gap in the literature regarding military expenditure and unemployment. The research question being investigated in this paper is, "Although many studies show there is no correlation between military expenditure and unemployment, does this correlation exist when broken down into industry?" The hypothesis being tested in regards to this question is: *The level of military expenditure will granger cause the level of employment in each industry except for the service industry.* I believe the service industry will largely be unaffected by the military expenditure because of the nature of serving jobs. Younger people and people experiencing cyclical or frictional unemployment fill many of these positions. I think these factors will be prominent than military expenditure in the service sector.

II. Literature Review

The methodology in which the previous literature has addressed their respective research questions has ranged over the years from simple OLS to the more complex Granger Causality test. One of the first papers on this topic, Hooker and Knetter (1994), looks at different effects that military spending and non-defense spending may have over unemployment using a panel dataset set from 1965 to 2002 for the 50 states in the U.S. In particular they focus on procurement spending by state, a contribution not seen before in the previous literature. Hooker and Knetter (1994) use the fixed effects model to estimate an equation of the unemployment rate as a function of real military contracts per capita, time and state variables, and the dummy variable for unemployment type. This dummy variable is used to observe the shift in unemployment rates as they differentiate across states and between sources. In a later fixed effect model used, they also include the independent variable controlling for exchange rates. Their findings indicate that defense spending has roughly twice the impact on overall unemployment levels than non-defense spending, though in different directions. These findings indicated that when military expenditures increase, unemployment would also increase (Hooker and Knetter 1994). They also found strong indicators that would suggest that the relationship between the latters is not linear and that any research done in the future that assumes they are linear will likely understate the effect of military expenditure on unemployment.

Silverberg (2010) hypothesizes that increases in the U.S. defense spending will help the unemployment rate, contrary to what many previous studies claim. She bases this hypothesis on the idea that federal spending will be and always has been a major proponent of employment in United States. This would seemingly put her in the school of thought that military and other federal expenditures are driven by unemployment and under-consumption by the public. She tests her hypothesis by using three different models; one for the change in unemployment, one for the change in government jobs, and one with the dependent variable of the change in private sector jobs. In each case, the independent variables being used are defense spending (and its lag), non-defense spending (and its lag), GDP, and the presence of war as a dummy variable. Current year defense spending proved to be highly significant in the model for the change in private sector jobs but not in the model for the change in government jobs. Silverberg (2010) found here that a one percent increase in current year defense spending was estimated to decrease the number of private sector positions by approximately forty thousand. Silverberg concluded that her hypothesis was, in fact, incorrect and that elevated levels of current year defense spending would increase unemployment. She attributes her findings to the fact that the government is protected because of its size and that the private market is much more susceptible to quickly increasing and decreasing numbers of employment opportunities than the government, thus changing more fluidly with these increased levels of defense spending.

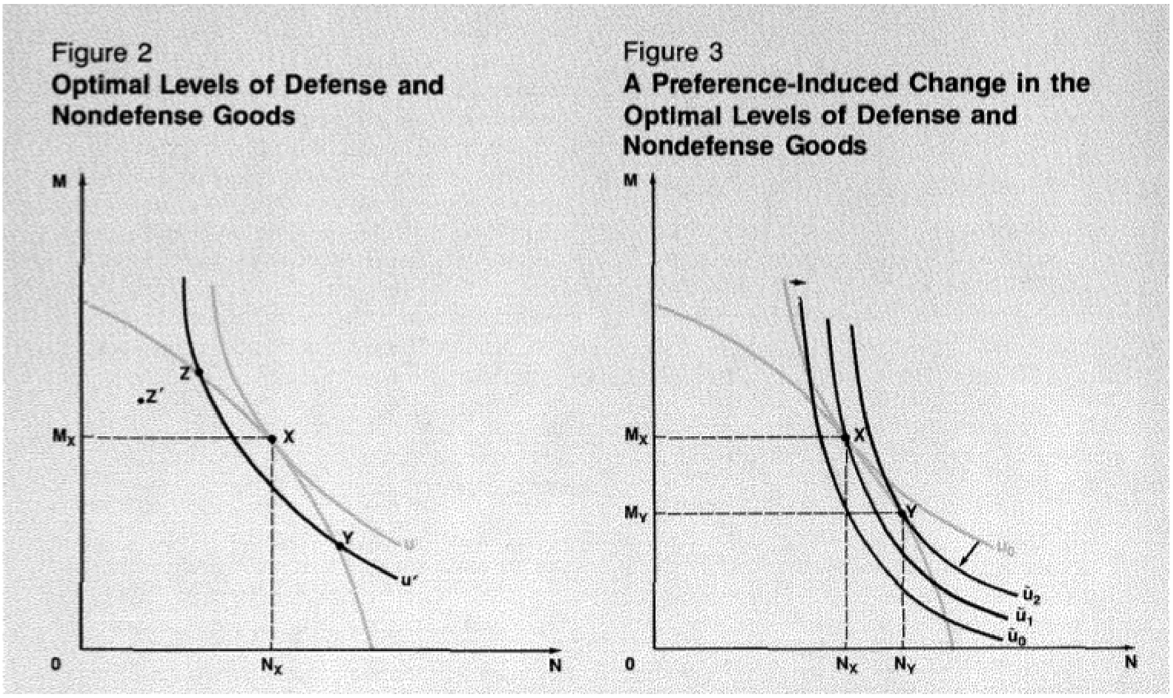
Prior to Abell (1990,1992) very little work had been done utilizing vector autoregression (VAR) to account for the possible dual causality running between defense spending and unemployment. In his first study (Abell 1990), he finds that the relationship between defense spending and unemployment did vary when disaggregated by race. More specifically, he found that as defense spending increased, blacks were more heavily burdened than whites. His findings even went so far as to say that whites benefitted by increased levels of defense spending. In his second study (Abell 1992), he furthers his own work by also disaggregating the unemployment rate not only be race but also by gender. Abell (1992) uses the VAR technique controlling for non-defense spending, the money supply, and defense spending. The results of this study, for the total unemployment rate, were very much what one would assume once the causality was established: unemployment rates are worsened in response to increases in defense spending (Abell 1992). His findings, once disaggregated by race and gender, told a more intriguing story. Abell found that increased levels of military expenditure were more likely to afflict minorities and women than white males. This result would be consistent with conclusions made by Silverberg (2010) since, she states, white males hold most government and technology-related positions.

Paul (1996) addresses the effects of defense spending on unemployment rates using OECD country data. The author also entertains the idea that unemployment could cause increased military spending and that military spending could cause elevated levels of unemployment. To address this issue, Paul (1996) uses a similar method to Abell (1992) in that VAR is used to model three different situations, each regarding causality in a different manner. The variables being used in this study are similar to those if the previously mentioned studies, but defense and non-defense spending are not measured in levels but rather as change from the previous year. The results of this study proved that the effect of military spending on unemployment varies by country. This, of course, is likely due to the number of things that are not controlled for in the study; things ranging from the type of government the country has to the level and policies regarding income tax. In Germany and Australia, there is an unemployment decrease when defense spending increased (Paul 1996). Conversely, there was a rise in unemployment in Denmark as military expenditure rose (Paul 1996). There were also countries like Japan, Canada, Sweden, and the United States that showed no significant correlation between defense spending and unemployment (Paul 1996). Paul believes this variation between countries is due to the relationship between the sizes of the defense spending, the overall size of the economy, and whether or not the bulk of the defense spending is being spent on foreign or domestic land.

Unlike the papers done in earlier years, Tang et al. (2009) acknowledges the possibility of reverse causality between unemployment and defense spending and uses a Granger Causality test to determine whether it is the military variables that are Granger causing the unemployment or if it the unemployment granger causing the increased levels of military expenditure. They use two alternative measure of military spending: (1) per capita military spending, and (2) the share of military spending in GDP. They found that if measured in per capita military spending there is no causation between military spending and unemployment. However if measured as share of GDP, increased military expenditure would increase unemployment. Thus, they found that defense spending as a share of GDP did Granger cause unemployment to increase. To further their research, they believe it would be beneficial to the topic to investigate how increased levels of military expenditure effect different sectors of the labor market rather than the labor market as a whole.

III. Theoretical Model

The theoretical model that the study will be based on is from the Federal Reserve Bank at St. Louis (Garfinkel 1990) and explains the relationship between defense spending, non-defense spending, public well being and the optimality among these three. The graphical version is shown here:



Source: Federal Reserve Bank at St. Louis

This model shows the optimal levels of defense and non-defense goods with point ‘x’ being the optimal level of ‘M’ (Defense) and ‘N’ (Nondefense). Aggregate utility is maximized here and any move away from ‘x’, either on or inside the production possibility curve would result in a loss of aggregate utility (Garfinkel 1990).. The model predicts a potential loss in employment in the non defense sector because of the law of the diminishing returns behind the model implies that the curve has a concave shape. Hence any move away from ‘x’ in favor of increased military spending means that a certain amount of non-defense goods must be forgone. In terms of this study, this loss of aggregate utility is translated into loss of employment and gives solid theoretical framework for the rest of the study to stand on. Using this framework and the methodology explained below, this study should successfully explain the causality between military expenditure (and its variants) and the unemployment levels of the different industries being used in the model. With this model clearly stating what has been explained above, it will aid in explaining how an increased level of military expenditure (which would lead to a deviation from point ‘x’ in the model) will lead to an overall decrease in welfare or in this study’s case, a change in unemployment specific to the industry being studied in the respective model.

IV. Description of Data & Methodology

The general model I plan to use in this study is a form of the Granger Causality test using time series data. The general model which was adapted from the Tang et al (2009) paper will look like the following:

$$Y_t = a_0 + a_1 Y_{t-1} + a_2 Y_{t-2} + b_1 X_{t-1} + b_2 X_{t-2} + e_t$$

$$H_o\text{: } b_1 = b_2 = 0$$

$$H_A\text{: At least one } b_t \neq 0$$

The subscript ‘t’ stands for time and is only going to be lagged twice in the model being used. This is due to an inference made by Tang et al. (2009) that correlations become very insignificant beyond two time lags. The dependent variables being used are the unemployment rates for the Professional & Technical industry (P), the Service industry (S), the Production and Operations industry (O), and the Agricultural industry (A). These sectors were selected following the suggestions made by the Tang et al. (2009) paper and after checking data availability. Ultimately these sectors were chosen because they all have possible ties to military expenditure, dealing with things like technology spillovers or infrastructure management. All of the data for unemployment rates by industry will be extracted from the LABORSTA Internet database, a database maintained by the International Labor Organization (ILO). The independent variables being used are military expenditure per capita and military expenditure as a share of GDP. These two variables are used in the Tang et al. (2009) study and carried over into the study currently taking place. The data for military expenditure per capita (M) will come from the Stockholm International Peace Research Institute (SIPRI) while the military expenditure as a share of GDP (G_m) is derived by taking 'M' and multiplying it by GDP for that year.

After estimating the model for each one of the sector specific unemployment rate one can compute the Wald statistic on the hypothesis that if the null hypothesis is rejected, then we can say that there is Granger causality running from military expenditure per capita to sector specific unemployment rate. After causality is determined, the same equations will be estimated using a vector autoregression model to determine the impact that each of the two variants of military expenditure has on the industry specific unemployment rate.

V. Empirical Analysis

I. OLS

The first step in determining the estimates on the effects of military expenditure per capita and military expenditure as a percentage of GDP on the various industries' unemployment levels is through the use of the Ordinary Least Squares method. My goal through the use of this method is to see if there is a significant effect on the industry's unemployment levels from each of the military expenditure variables. I ran four models for each of the four industries: (1) using military expenditure per capita; (2) the given industry's effect on the military expenditure per capita; (3) using military expenditure as a percent of GDP; and (4) the given industry's effect on the military expenditure as a percent of GDP. The reason the variables are run against each other in this way is because of the possibility of reverse causality. A similar method to running the models can be seen in the Tang et al (2009) study.

The results I found through using the Ordinary Least Squares method with this modeling example were consistent with what one would expect to see when cointegration is present. The only case showing a significant effect of military expenditure as a share of GDP is the model for the agriculture unemployment rate. This model yielded an adjusted R-squared of .8511 and an overall p-value of 5.868e-10. These values make the model appear very strong, but are clearly overstated due to the underlying cointegration and OLS's inability to handle it. The results for this model predict that with each percentage point increase in military expenditure as a share of GDP, the unemployment rate for the agriculture industry increases by .52 percentage points. Although this interpretation is probably far from the correct value, it is at least showing the correct direction in which the variable should be affected and matches the reaction we would expect from the theoretical model.

The common trend among all of the other results was that the only truly significant variable in the equation was the first lag of the variable that was actually being tested.. This is the expected result due to the high level of conintegration between the two variables and the significance that it absorbs from the significance of the other independent variables. In all of the results there was a very high R-squared with a range of 63% of the variation being explained to 94% of the variation being explained. Again, I believe this was largely due to the extreme level of cointegration between the dependent variable and the lagged versions of the dependent variables being used as independent variables in the model. One positive aspect of the results was that, although they were not significant, the direction the independent variables were influencing the dependent variable were in the correct or expected direction; that direction being that the military expenditure variables were causing increases in the unemployment levels of the industries.[1] Moving further, it can also be noted that many of these lagged versions of the dependent variable that are returned to be so highly significant are also have a coefficient that is dangerously close to being equal to 1 and indicate that unit roots may be needed. This suggests that something needs to be done in order to determine whether or not these variables are experiencing cointegration and to decide whether or not there needs to be some degree of differencing performed on the variables before continuing onto the Granger Causality Testing.

2. ACF and PACF

Before any differencing processes are performed on the data, there has to be a check for stationarity on the time series' so a before and after of the data can be seen. Through the use of both an autocorrelation function and a partial autocorrelation function, we can see if the data being used is non-stationary and decide to what degree differencing is needed. The autocorrelation function (ACF) gives us the correlations between the time series 'y' and the lags of time series 'y'. The partial autocorrelation function (PACF) gives us the graph of the amount of correlation between 'y' and the three lags of time series 'y' that is not explained by their shared correlations. Essentially, the graphs of these two functions can be used in tandem to decide if the designated time series is stationary or not. Before anything else, the PACF's of each of the time series was taken and their results interpreted. In the case of every time series, all of the autocorrelation that is present could be effectively explained by the first present lag of the dependent variable. The next step was to now take the ACF's of the time series' and continue to do so after differencing until the data appears stationary and can then be used in the Granger Causality Testing. Fortunately, the time series for each of the variables was successfully deemed

[1] OLS results can be seen in tables II – V in the appendix

stationary and ready for further testing after just one round of differencing.[2] These plots, both before and after differencing, can be seen in the appendix.

3. Granger Causality Testing

The next and final step of the empirical testing in this study is the Granger Causality Testing. According to the Granger Causality Test, ‘x’ granger causes ‘y’ if lagged values of ‘x’ are found to be accurate predictors of the future values of ‘y’. We are able to do this through the analysis of both the F- and t-values provided from the testing between the two elected time series’. At this point in the testing, all of the time series have been differenced once and show to be stationary and ready for testing. This differencing, as mentioned above, took place to control for the cointegration between the time series’ current variable ‘y’ and the lags being used in the regression necessary for the granger causality testing. The results of this testing were different for each industry in question except in the case of ‘ProOp’ and ‘Service’ where conclusions were much the same. In this testing, we will use the F- and t-values to decide if ‘x’ can be considered granger causal for ‘y’ with ‘x’ does granger cause ‘y’ being the null hypothesis. The results gave sufficient evidence that military expenditure as a percentage of GDP does in fact granger cause unemployment in the agricultural sector. There was also sufficient statistical results that point to the granger causality leading from military expenditure per capita to the agricultural unemployment level. The statistical significance for both of these tests are greater than 95% and 99%, respectively. On the neutral side of the testing, there was no statistical evidence that suggested there was any causality between either of the military expenditure variables and the ‘ProOp’ and ‘Service’ variables from either direction. Conversely, and to great surprise, there was causality found between the ‘ProTech’ variable and military expenditure as a percentage of

[2] The before and after of these ACFs can be seen in charts I – XII in the appendix

GDP with 90% statistical significance.[3] As stated in the motivation and literature review, the results from previous testing done between military expenditure and unemployment is largely under debate, especially regarding the United States. These variations in causality between defense spending and different industries could be the reason that many of the tests performed in the previous literature were deemed to be inconclusive when looking at the country as a whole. Perhaps there is a canceling-out effect as different industries are affected in different ways by defense spending but look to be independent of these causes when viewed from a macro approach.

VI. Concluding Remarks

This study investigates a relationship between military expenditure broken up by share of total GDP and the per capita value and how it affects the unemployment rates of specific industries. This analysis is derived from the study done by Tang (et al 2009) where they looked at the effects of military expenditure with the same variations used in this study and how they affected unemployment rates of different countries. They concluded that it would be interesting to see another near replication of their study but this time disaggregated by industry, a study that had yet to be done. Although the results from OLS were disappointing in terms of significance, they do give us a direction in which to move forward and what we might expect to see from the results. They do point to increased levels of military expenditure leading to increased levels of unemployment and, although the cointegration is obvious, future advanced regressions would hopefully provide similar, more accurate effects. Until then, it does appear that there is rampant

[3] The results for the Granger Causality Tests can be seen in tables XI – XII in the appendix

cointegration within the models due to lags of the dependent variables being so highly correlated with the independent variables.

After one round of differencing with each of the time series', granger causality testing returned some interesting results. The results revealed that both military expenditure as a share of GDP and on a per capita basis are both granger causal for the unemployment rate in the agricultural sector. The results from the granger causality test revealed that neither variations of the defense spending variable are related to the unemployment levels of either the 'ProOp' or 'Service' unemployment levels. Perhaps the most unexpected piece of information retrieved from the granger causality test is the causality found to run from the 'ProTech' variable to the level of military expenditure as a share of national GDP. Upon seeing this result, further research began to try and explain why this causality, being the opposite as initially predicted, would exist.

After researching to current status of the private technology sector, there was some evidence as to why this causality may exist. An independent research company called 'The Brookings Institute' did a study on the basis that many believe that the private sector has a higher proclivity to be more innovative than the public sector (West 2009). Their study yielded some interesting results, and more importantly, results that back up the results generated from my granger causality testing. With technology constantly evolving at the rate that it is today, innovation cannot happen without a substantial amount of financing. Brookings found that private technology firms were investing 2.5% of their overall budget towards innovation while government agencies were only found to invest 1.88% of their overall budget towards technology innovation. They also found out that through the interviewing of key leaders of both the private technology sector and those in charge of technology for the public sector that the private sector is much more concerned with leading the pack when it comes to technological advancement. Nearly all of the leaders of the private technology sector said they were most concerned with staying ahead of the curve within the industry. Conversely, they found that the leaders of the public technology sector were more concerned with handling turns and advancements in the field as they came to them. In brief, the private technology sector is more concerned with being proactive while the public the sector is largely concerned with being reactive to the market. This provides ample evidence and insight into why this causality may exist leading from 'ProTech' to military spending as a percentage of GDP. I think it would be interesting to look at this study again when the technology sector was not as advanced and privatized and see if the results were the same.

VII. Appendix

Table I

Variable Definitions, Descriptive Statistics and Data Sources

Variable	**Definition**	**Source**
ProTech	% of population unemployed in the professional and technical industry (.0639, .0121)	International Labor Organization (1965 – 2002)
Service	% of population unemployed in the service industry (.1636, .0144)	International Labor Organization (1965 – 2002)
ProOp	% of population unemployed in the production and operations industry (.3796, .0461)	International Labor Organization (1965 – 2002)
Ag	% of population unemployed in the agricultural industry (.0295, .01)	International Labor Organization (1965 – 2002)
MilCap	Military expenditure expressed in per capita terms (1460.62, 455.69)	Stockholm International Peace Research Institute (1949-2013)
MilGDP	Military expenditure expressed as a share of total GDP (.062, .024)	Stockholm International Peace Research Institute (1949-2013)

Table II

	Ag ➔…			
Variables	**MilCap**	**MilGDP**	**MilGDP ➔Ag**	**MilCap ➔ Ag**
Intercept	239.9219 (0.137)	0.009025 (0.098832).	-0.000239 (0.966691)	2.598e-03 (0.653205)
Ag_{t-1}	3998.8604 (0.503)	0.643329 (0.643329)	0.875966 (0.000974)***	8.272e-01 (0.000779)***
Ag_{t-2}	-1205.0632 (0.883)	0.194760 (0.510223)	0.015495 (0.961050)	8.220e-03 (0.978161)
Ag_{t-3}	-4536.3840 (0.403)	-0.210922 (0.231684)	0.045546 (0.807866)	5.580e-02 (0.807866)
$MilGDP_{t-1}$		0.932499 (0.000261)***	0.516370 (0.037871)*	
$MilGDP_{t-2}$		0.219910 (0.569412)	-0.162535 (0.695880)	
$MilGDP_{t-2}$		-0.275100 (0.257979)	-0.276234 (0.291043)	
$MilCap_{t-1}$	1.1320 (2.24e05)***			9.825e-06 (.225648)
$MilCap_{t-2}$	-0.1163 (0.750)			3.812e-07 (0.977219)
$MilCap_{t-3}$	-0.1234 (0.578)			-9.211e-06 (0.261434)

Table III

	ProTech ➔…			
Variables	**MilCap**	**MilGDP**	**MilGDP ➔ProTech**	**MilCap ➔ProTech**
Intercept	678.5691 (0.222)	0.009265 (0.586574)	0.033138 (0.122960)	-2.585e-02 (0.22919)
$ProTech_{t-1}$	-1769.5507 (0.716)	-0.070363 (0.645243)	0.698756 (0.000977)***	8.058e-01 (0.00023)***
$ProTech_{t-2}$	-9321.1174 (0.152)	-0.410330 (0.041264)*	0.193689 (0.41720)	3.118e-01 (0.21382)
$ProTech_{t-3}$	6674.7907 (0.289)	0.424918 (0.022420)*	-0.125378 (0.564696)	1.738e-01 (0.47277)
$MilGDP_{t-1}$		0.978302 (0.000106)***	-0.299347 (0.261789)	
$MilGDP_{t-2}$		-0.110811 (0.668071)	-0.041109 (0.897179)	
$MilGDP_{t-2}$		0.008396 (0.959822)	-0.008195 (0.968193)	
$MilCap_{t-1}$	1.0068 (8.06e-05)***			4.395e-06 (0.59814)
$MilCap_{t-2}$	-0.1235 (0.673)			-1.880e-06 (0.86794)
$MilCap_{t-3}$	-0.1015 (0.589)			2.390e-06 (0.74221)

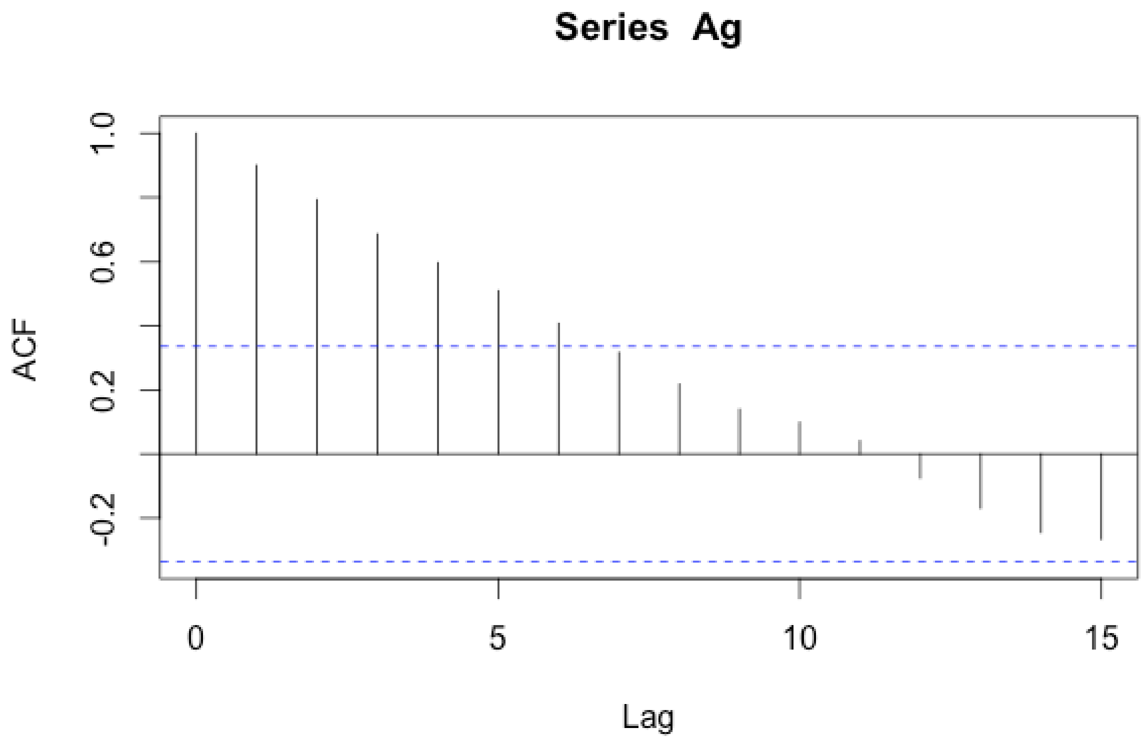
Table IV

	ProOp → …			
Variables	**MilCap**	**MilGDP**	**MilGDP → ProOp**	**MilCap → ProOp**
Intercept	20.8178 (0.917)	-.004253 (0.498594)	0.03450 (0.49859)	3.771e-02 (0.416474)
$ProOp_{t-1}$	-338.5934 (0.698)	-0.004809 (0.877)	0.89987 (0.000463)***	9.152e-01 (0.000124)***
$ProOp_{t-2}$	1926.4627 (0.100)	0.062884 (0.125)	-0.14157 (0.624263)	-2.170e-01 (0.414698)
$ProOp_{t-3}$	-982.5761 (0.283)	-0.027088 (0.393)	0.13882 (0.542045)	2.068e-01 (0.328905)
$MilGDP_{t-1}$		1.053394 (9.1e-05)***	0.37202 (0.820078)	
$MilGDP_{t-2}$		-.143056 (0.624263)	-1.70766 (0.428921)	
$MilGDP_{t-2}$		-0.073649 (0.677)	1.30784 (0.308734)	
$MilCap_{t-1}$	1.1442 (7.14e-06)***			4.892e-06 (0.91715)
$MilCap_{t-2}$	-0.1088 (0.711)			-3.171e-05 (0.641943)
$MilCap_{t-3}$	-0.1728 (0.335)			-0.1728 (0.335)

Table V

	Service → …			
Variables	**MilCap**	**MilGDP**	**MilGDP → Service**	**MilCap → Service**
Intercept	395.4942 (0.346)	0.005641 (0.761)	0.09926 (0.03452)*	6.706e-02 (0.0530) .
$Service_{t-1}$	-102.9934 (0.968)	0.019345 (0.828)	0.77638 (0.00124)**	8.550e-01 (0.0003)***
$Service_{t-2}$	-4550.2881 (0.159)	-0.150796 (0.175)	-0.07527 (0.7750)	-1.220e-01 (0.6303)
$Service_{t-3}$	3689.7014 (0.134)	0.119083 (0.176)	-0.20562 (0.32872)	-7.958e-02 (0.6794)
$MilGDP_{t-1}$		1.143662 (7.82e-06)***	-0.47597 (0.33860)	
$MilGDP_{t-2}$		-0.138577 (0.640)	0.77653 (0.28212)	
$MilGDP_{t-3}$		-0.086723 (0.643)	-0.60544 (0.18760)	
$MilCap_{t-1}$	1.1852 (2.09e-06)***			-1.203e-05 (0.4394)
$MilCap_{t-2}$	-0.1364 (0.647)			2.051e-05 (0.3916)
$MilCap_{t-3}$	-0.1763 (0.351)			-1.355e-05 (0.3708)

Chart I & II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0.2
-0.2
0
5
10
15
Lag

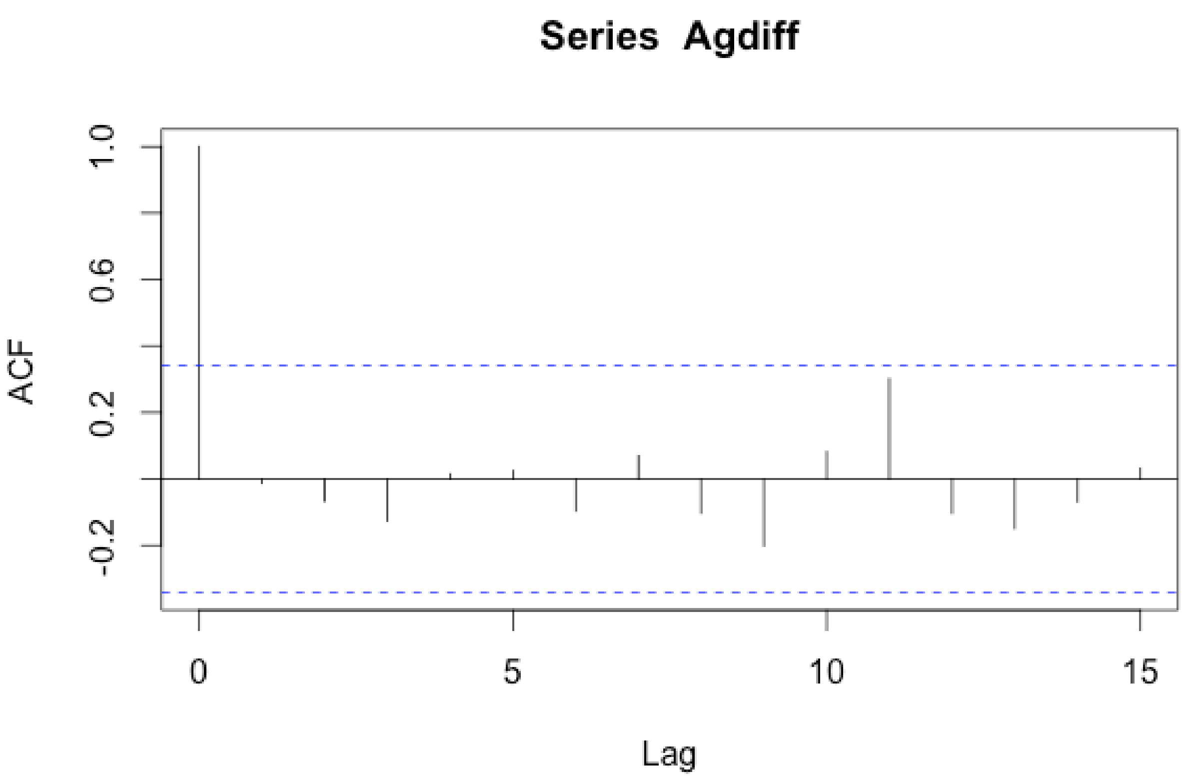
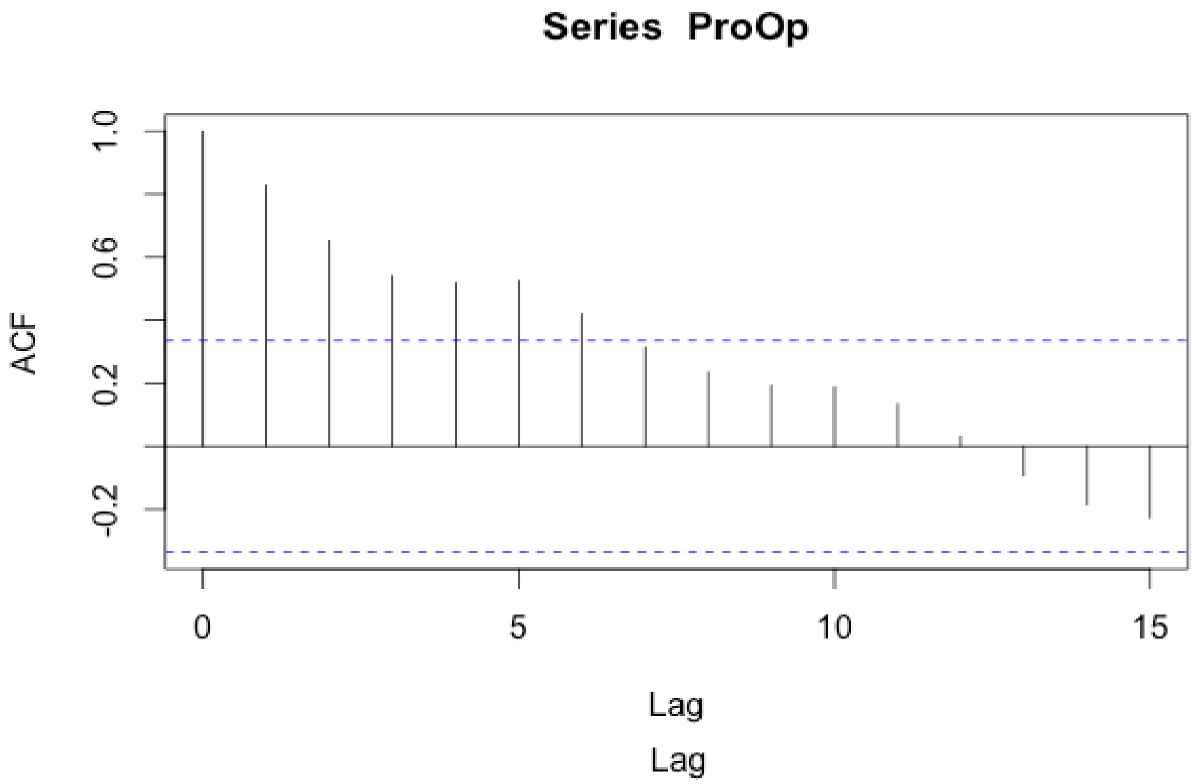

Series Agdiff
ACF
1.0
0.6
0.2
-0.2
0
5
10
15
Lag

Chart III & IV


Series ProOp
ACF
1.0
0.6
0.2
-0.2
0
5
10
15
Lag
Lag

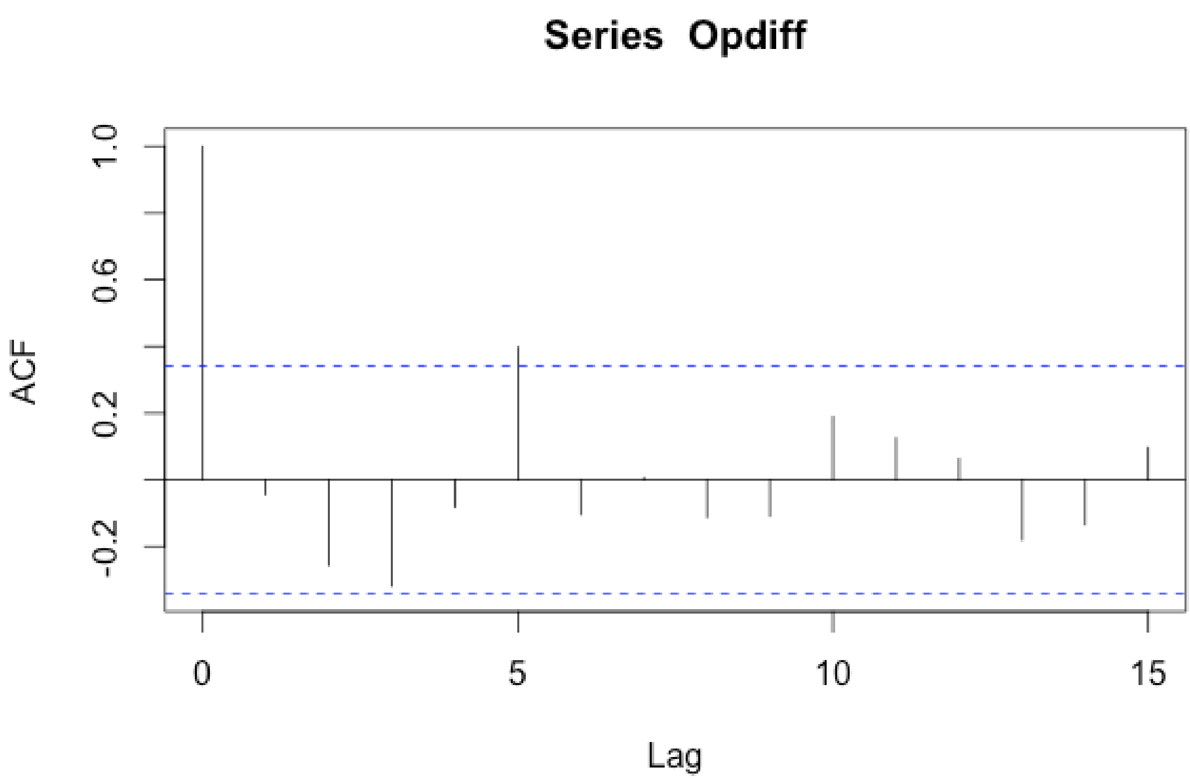
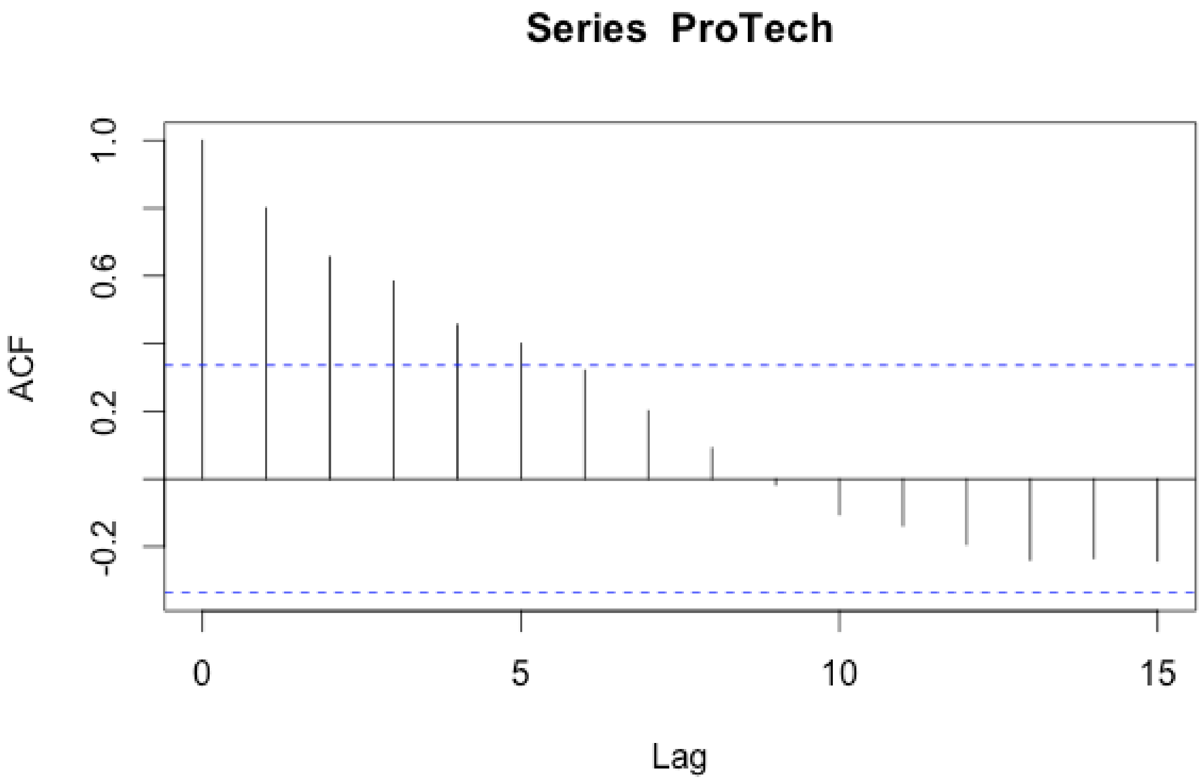

Series Opdiff
ACF
1.0
0.6
0.2
-0.2
0
5
10
15
Lag

Chart V & VI


Series ProTech
ACF
1.0
0.6
0.2
-0.2
0
5
10
15
Lag

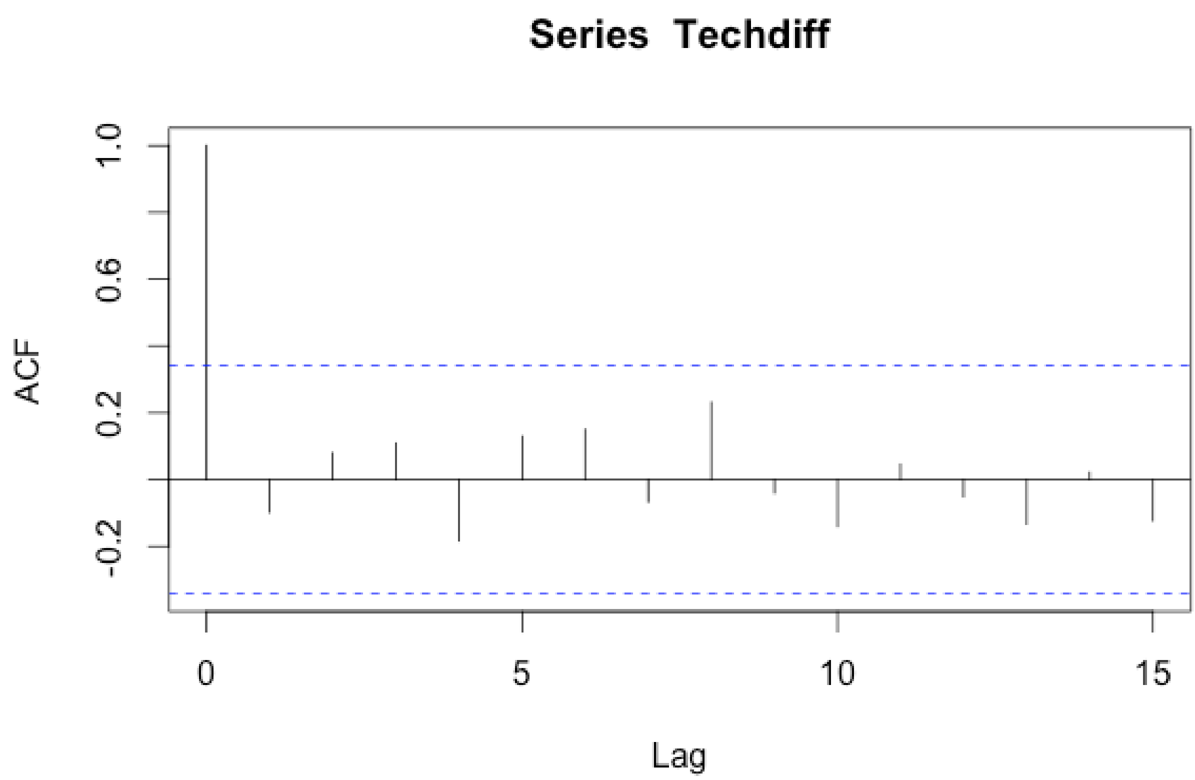
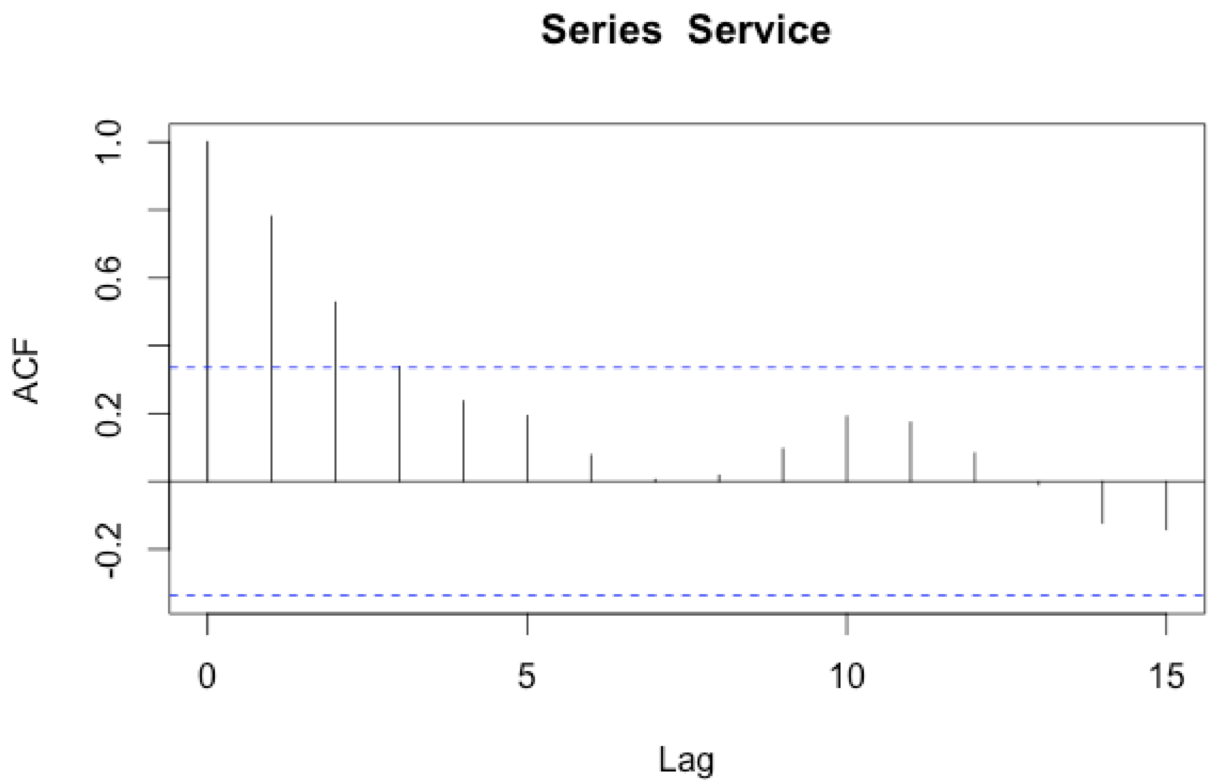

Series Techdiff
ACF
1.0
0.6
0.2
-0.2
0
5
10
15
Lag

Chart VII & VIII



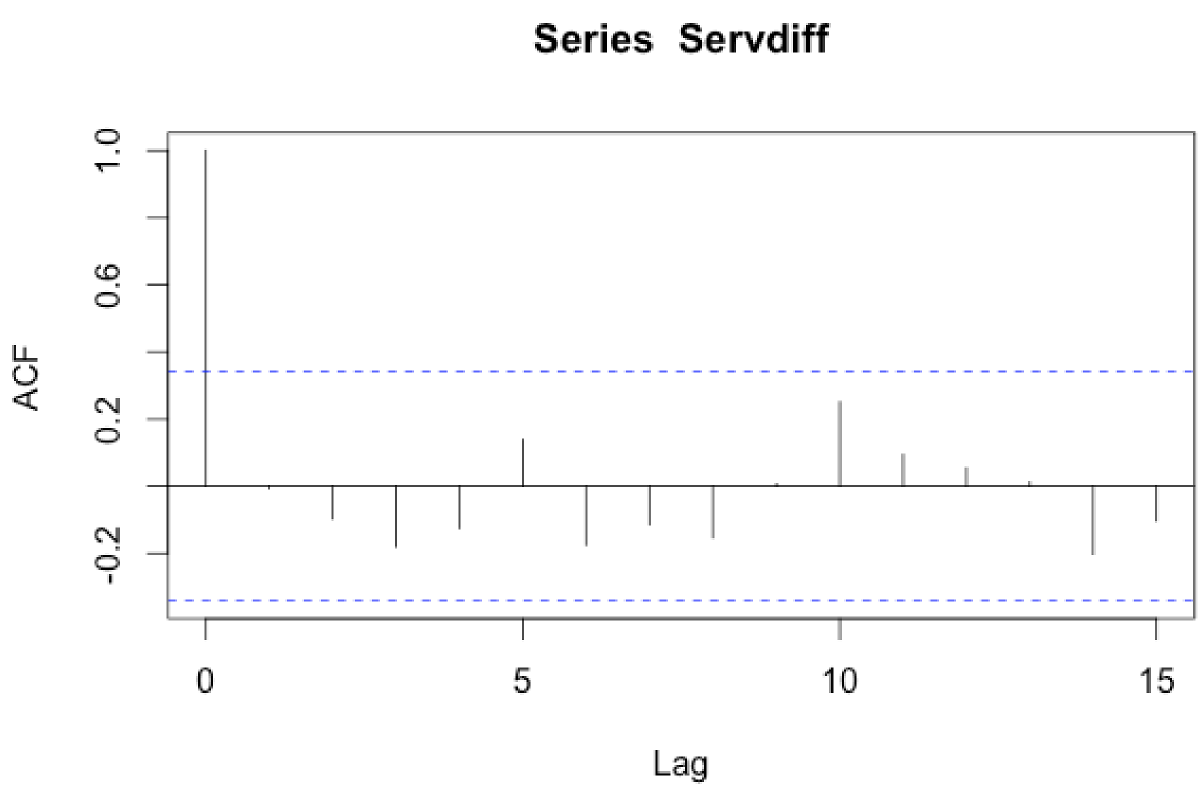
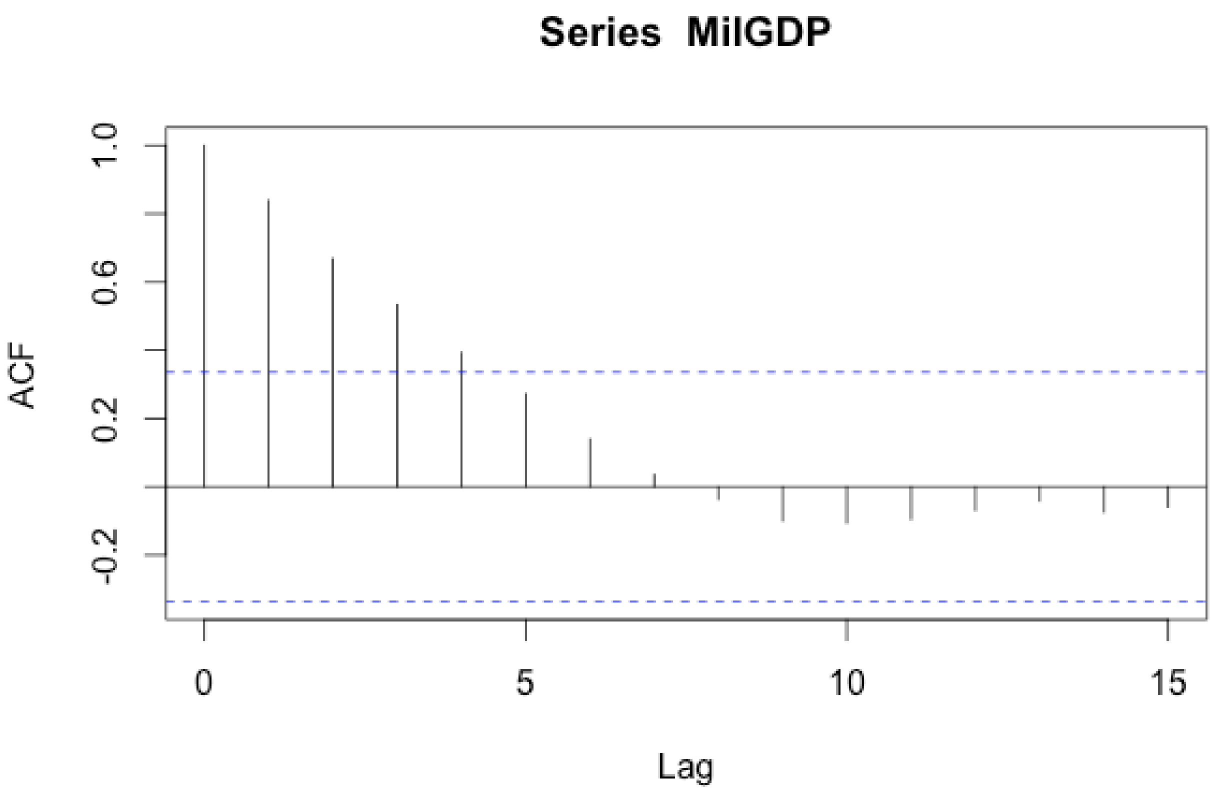


Chart IX & X


Series MilGDP
ACF
1.0
0.6
0.2
-0.2
0
5
10
15
Lag

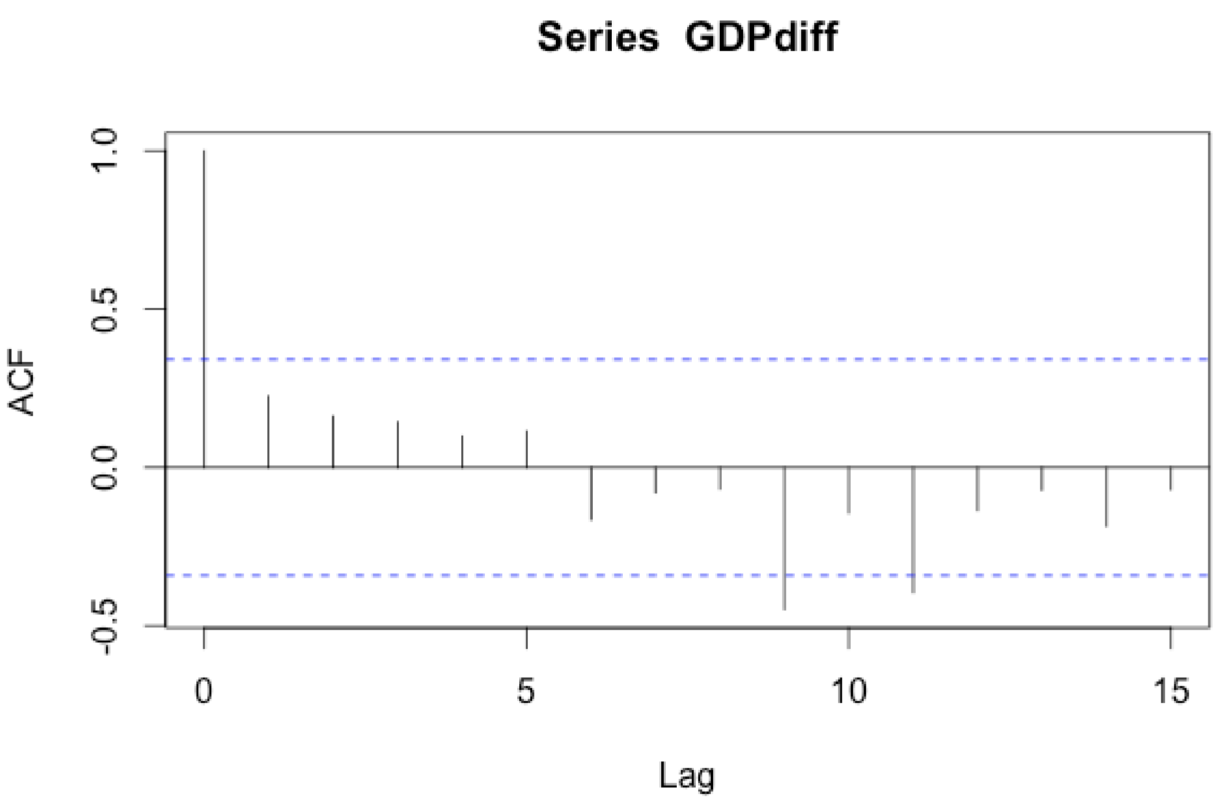
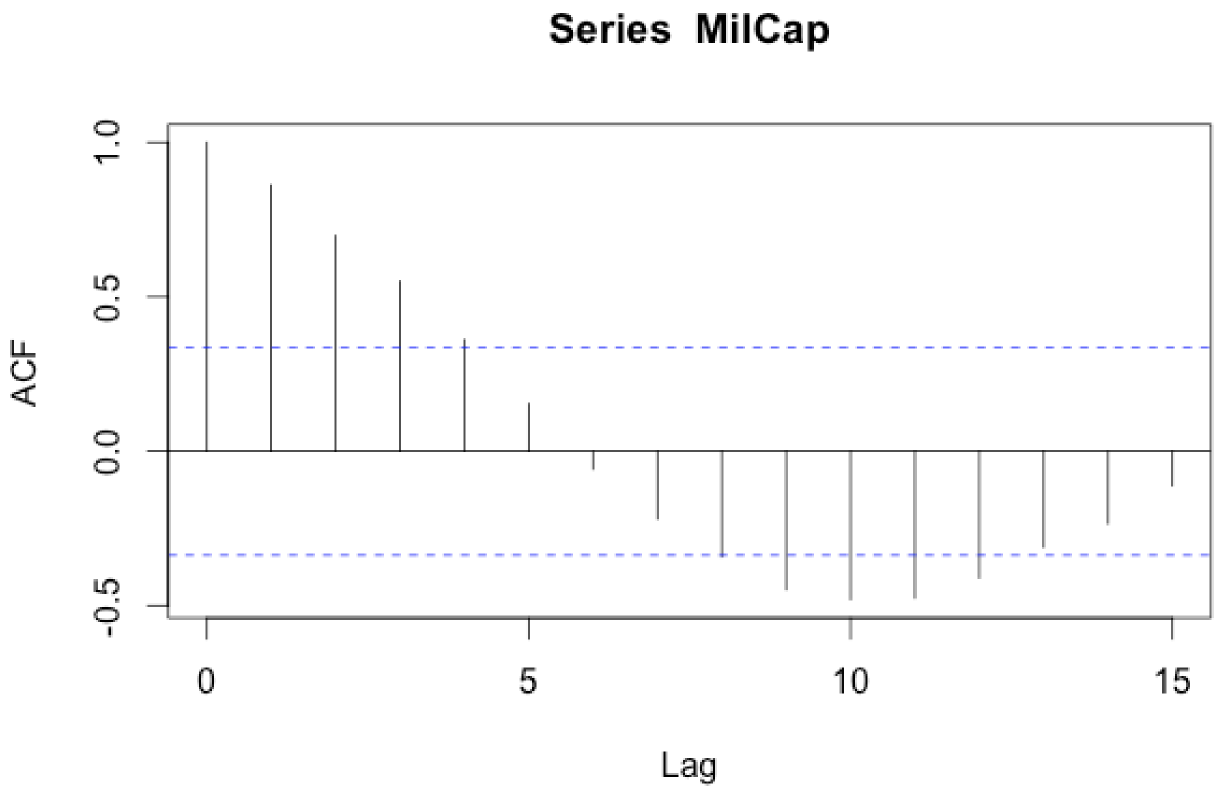

Series GDPdiff
ACF
1.0
0.5
0.0
-0.5
0
5
10
15
Lag

Chart XI & XII


Series MilCap
ACF
1.0
0.5
0.0
-0.5
0
5
10
15
Lag

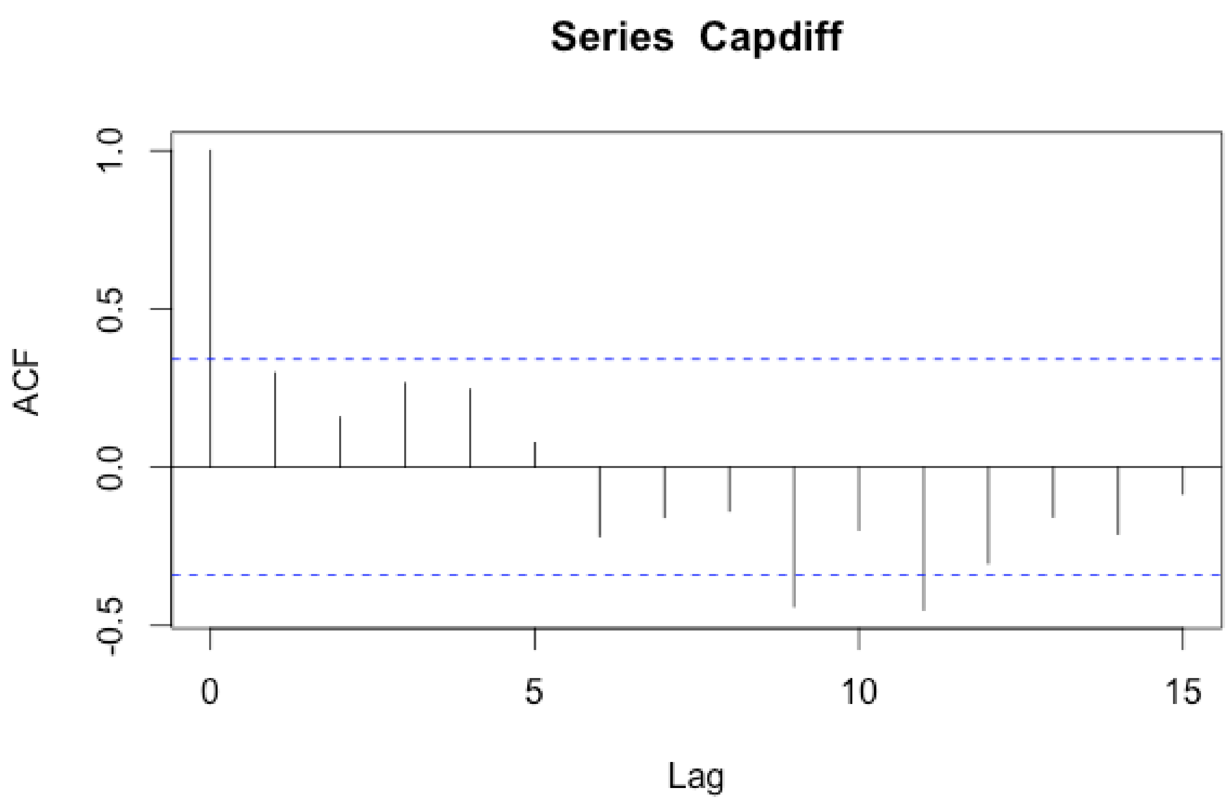

Series Capdiff
ACF
1.0
0.5
0.0
-0.5
0
5
10
15
Lag

Table VI

Variables	**Military Expenditure (GDP)**	**Military Expenditure (Capita)**
Agriculture	0.1286 (0.9421)	0.4338 (0.7308)
ProOp	1.8187 (0.1719)	1.0453 (0.3914)
ProTech	**2.7609** **(.06517)***	1.303 (0.2979)
Service	1.1302 (0.3576)	0.7874 (0.5133)

Table VII

Variables	**Agriculture**	**ProOp**	**ProTech**	**Service**
Military Expenditure (GDP)	**5.912** (**0.003821)*****	1.8502 (0.1663)	.0092 (0.9988)	0.8931 (0.4596)
Military Expenditure (Capita)	**4.2584** (**0.01567)****	0.9527 (0.4315)	1.2443 (0.3166)	1.2443 (0.3166)

VIII. Bibliography

Abell, John D. "Defense Spending and Unemployment Rates: An Empirical Analysis Disaggregated by Race and Gender." (1992): 25. Web. 5 Jan. 2015. <http://vl3fl6qn8e.search.serialssolutions.com/directLink?&atitle=Defense Spending and Unemployment Rates: An Empirical Analysis Disaggregated by Race and Gender&author=Abell, John D&issn=00029246&title=American Journal of Economics and Sociology&volume=51&issue=1&date=1992-01-01&spage=27&id=doi:&sid=ProQ_ss&genre=article>.

Barro, Robert, and Veronique De Rugy. "Defense Spending and the Economy." (2013): 18. Web. 9 Jan. 2015. <http://mercatus.org/sites/default/files/Barro_DefenseSpending_v2.pdf>.

Carter Jr., Richard E. "The Relationship Between Fiscal Spending and Unemployment." (2012). Web. 8 Jan. 2015. <http://search.proquest.com.lib.ezproxy.uakron.edu:2048/docview/926192339/D58140011AD945BCPQ/2?accountid=14471>.

Et al, Tang. (2007) Military expenditure and unemployment in the OECD. Defense and Peace Ecnomics, 1(1), 57-73. Doi:10.1080/10430719008404650

Hooker, M., & Knetter, M. (1994). How do changes in military spending affect the economy? Evidence from state-level data. Retrieved March 4, 2014, from https://www.bostonfed.org/economic/neer/neer1996/neer296a.pdf

Pollin, Robert, and Heidi Garrett-Peltier. "The U.S. Employment Effects of Military and Domestic Spending Priorities." (2007): 15. Web. 9 Jan. 2015. <http://www.peri.umass.edu/fileadmin/pdf/other_publication_types/PERI_IPS_WAND_study.pdf>.

Silverberg, Kristen. "Defense Spending as a Mechanism for Reducing U.S. Unemployment." 14 Apr. 2010: 41. Web. 5 Jan. 2015. <https://repository.library.georgetown.edu/bitstream/handle/10822/553917/silverbergKristen.pdf?sequence=1&isAllowed=y>.

IX. R Coding

```
>load("~/SeniorProject.RData")
```

CREATING THE VARIABLES

```
>ProTech <- ts(mydata$ProTech)
> Service <- ts(mydata$Service)
> Ag <- ts(mydata$Ag)
> ProOp <- ts(mydata$ProOp)
> MilCap <- ts(mydata$MilCap)
> MilGDP <- ts(mydata$MilGDP)
> ProTech.1 <- lag(ProTech,-1)
> ProTech.2 <- lag(ProTech,-2)
> ProTech.3 <- lag(ProTech,-3)
> Service.1 <- lag(Service,-1)
> Service.2 <- lag(Service,-2)
> Service.3 <- lag(Service,-3)
> Ag.1 <- lag(Ag,-1)
> Ag.2 <- lag(Ag,-2)
> Ag.3 <- lag(Ag,-3)
> ProOp.1 <- lag(ProOp,-1)
> ProOp.2 <- lag(ProOp,-2)
> ProOp.3 <- lag(ProOp,-3)
> MilCap.1 <- lag(MilCap,-1)
> MilCap.2 <- lag(MilCap,-2)
> MilCap.3 <- lag(MilCap,-3)
> MilGDP.1 <- lag(MilGDP,-1)
> MilGDP.2 <- lag(MilGDP,-2)
> MilGDP.3 <- lag(MilGDP,-3)
```

OLS MODELS

```
>dynlm(ProTech ~ MilCap.1 + MilCap.2 + MilCap.3 + ProTech.1 + ProTech.2 + ProTech.3)
>dynlm(MilCap ~ MilCap.1 + MilCap.2 + MilCap.3 + ProTech.1 + ProTech.2 + ProTech.3)

>dynlm(Ag ~ MilCap.1 + MilCap.2 + MilCap.3 + Ag.1 + Ag.2 + Ag.3)
>dynlm(MilCap ~ MilCap.1 + MilCap.2 + MilCap.3 + Ag.1 + Ag.2 + Ag.3)


>dynlm(Service ~ MilCap.1 + MilCap.2 + MilCap.3 + Service.1 + Service.2 + Service.3)
>dynlm(MilCap ~ MilCap.1 + MilCap.2 + MilCap.3 + Service.1 + Service.2 + Service.3)

>dynlm(ProTech ~ MilCap.1 + MilCap.2 + MilCap.3 + ProTech.1 + ProTech.2 + ProTech.3)
>dynlm(MilCap ~ MilCap.1 + MilCap.2 + MilCap.3 + ProTech.1 + ProTech.2 + ProTech.3)
```

DIFFERCING THE DATA

```
> ProTechdiff <- diff(ProTech,1)
> plot(ProTechdiff)
> ProTechdiff2 <- diff(ProTech,2)
> plot(ProTechdiff2)
> Protechdiff3 <- diff(ProTech,3)
> plot(Protechdiff3)
> ProTechdiff4 <- diff(ProTech,4)
> plot(ProTechdiff4)
> plot(Ag)
> Agdiff <- diff(Ag,1)
> plot(Agdiff)
> Agdiff2 <- diff(Ag,2)
> plot(Agdiff2)
> Agdiff3 <- diff(Ag,3)
> plot(Agdiff3)
> > acf(Ag)
> pacf(Ag)
> pacf(Service)
> pacf(ProTech)
> pacf(ProOp)
> pacf(MilCap)
> pacf(MilGDP)
> acf(Ag)
> acf(Service)
> acf(ProTech)
> acf(ProOp)
> acf(Ag)
> acf(Agdiff)
> acf (ProTech)
> acf(Techdiff)
> acf(ProOp)
> acf(Opdiff)
> acf(Service)
> acf(Servdiff)
> acf(MilGDP)
> acf(GDPdiff)
> acf(MilCap)
> acf(Capdiff)
```

GRANGER CAUSALITY TESTING

```
> grangertest(Agdiff ~ GDPdiff, order=3)
> grangertest(GDPdiff ~ Agdiff, order=3)
> grangertest(Agdiff ~ Capdiff, order=3)
> grangertest(Capdiff ~ Agdiff,order=3)
```

```
> grangertest(Opdiff ~ Capdiff,order=3)
> grangertest(Capdiff ~ Opdiff,order=3)
> grangertest(Opdiff ~ GDPdiff,order=3)
> grangertest(GDPdiff ~ Opdiff,order=3)
> grangertest(Opdiff ~ GDPdiff,order=2)
> grangertest(Techdiff ~ Capdiff,order=3)
> grangertest(Techdiff~GDPdiff,order=3)
> grangertest(GDPdiff~Techdiff,order=3)
> grangertest(Capdiff~Techdiff,order=3)
> grangertest(Servdiff ~ Capdiff,order=3)
> grangertest(Servdiff~GDPdiff,order=3)
> grangertest(Capdiff ~ Servdiff,order=3)
> grangertest(GDPdiff ~ Servdiff,order=3)
```