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THE APPLICATION OF CROSS–LAGGED PANEL ANALYSIS IN EDUCATIONAL RESEARCH

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Abstract. *Cross–lagged panel analysis is found in the main stream of social, behavioral, medical, business and educational research. It is a form of quasi-experimental design used to determine whether the relationship between two variables is spurious i.e., due to a third variable and not due to causation. Cross–lagged panel analysis is a process used to determine which variable is the cause and which variable is the effect. It is an exploratory method of collecting information at two points in time i.e., time 1 and time 2, to clarify the causal relations between uncontrolled variables which could be tested more rigorously in an experimental setting. The Cross–lagged Panel Correlation (CLPC) is a low power test but better adapted than either multiple regression or factor analysis for answering many questions in longitudinal studies. It captures the dynamic relationship among the variables and allows the model to be controlled over time. This paper focuses on the 2w2v (two wave & two variable) design to describe a research method which can be used to explore the causal predominance relationship in the absence of a true experimental design, but only in a passive manner.*

Key words: *cross–lagged panel correlation, spurious correlation, synchronous correlation, autocorrelation, stationarity, synchronicity.*

A human being is not alone on this planet, which is why several factors including the psychological, social, economical etc., affect his behavior at every moment of his life. So it is hard to say whether a particular person will express specific behavior in a particular situation due to a particular reason. Similarly, in the field of education, all researchers who have conducted correlational studies have been aware of this situation, where a particular relationship is found between two or more correlated variables. It is difficult to ascertain the extent to which the resultant correlation is due to the mutual influence of the two variables or due to the influence of some other extraneous variables. A large number

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of studies have employed simple correlational techniques as the basis for inferring causality because many variables of interest are difficult to manipulate experimentally.

In recent times, an important goal of educational research is to determine the causal relationships among variables which occur in natural settings. Wide extent use has been made of two kinds of studies to achieve this goal: the correlational and experimental. Correlational studies have been especially useful in describing relationships among variables. For instance, a simple correlation technique has been used to investigate the significant statistical relationship between mathematical creativity and mathematical aptitude. But what does this fact tell us about a possible preponderance of causal relationship between them. It tells us nothing about causality because it may be due to a number of different extraneous variables. An experimental study has been advocated as a way to detect causal relationships. But due to ethical reasons, in an experiment, a "true" experimental design in the natural setting is formidable.

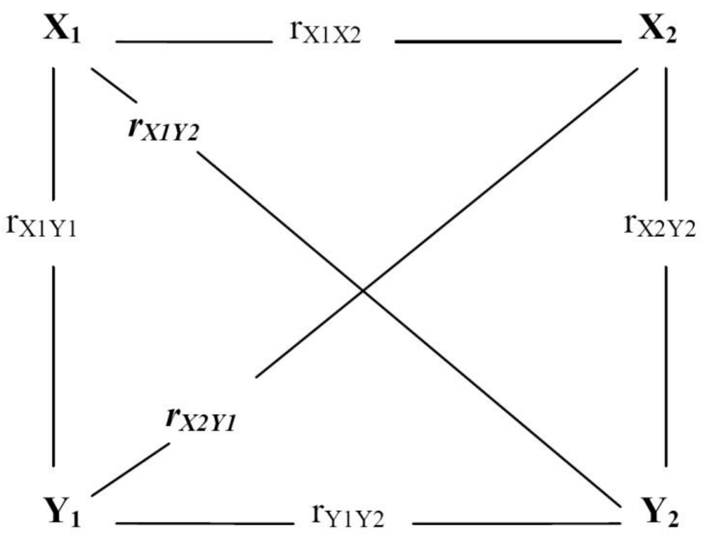
In a series of cross–lagged panel analysis, Crano et al. (1972) found that abstract skills cause concrete skills for suburban students while the opposite holds for inner–city students. Eron and his coauthors (1972) have given us a landmark study in their attempt to test causal relationships and found a probable causative influence of watching violent television programs on later aggression. Kellaghan (1973) found no preponderance relationship between intelligence and achievement. Calsyn (1973) found no causal relationship between a general self–concept and achievement but found evidence to suggest that achievement causes academic self–concept. Crano & Mellon (1978) pointed out that teacher expectations influenced children's achievement to an extent appreciably exceeding that to which children's performance impinged on the teacher's attitude. Rosenberg & Rosenberg (1978) concluded that self–esteem was a powerful predominant causal factor of delinquency but that the reverse was not true. Preece (1979) found that the anxiety of a science student teacher was the cause of the discipline problem that they encountered. Wolf et al. (1981) investigated that perceptions of quality of school life temporally preceded perceptions of Intellectual Academic Responsibility (IAR) than the converse. By using a cross–lagged panel analysis, Chan (1985) reported that depression, irrational beliefs and cognitive distortions co–varied but were not causally related, rather that the relationship among these three variables is spurious, it seems implausible because previous research has demonstrated that they are related. Pottebaum et al. (1986) found a spurious relationship between self–concept and achievement; i.e., a third variable may be causally predominant over both variables. Quinn & Jadav (1987) explored no predominant causal relationship (a spurious correlation) between attitude and achievement for elementary grade mathematics and reading. Verma (1994) found an asymmetrical relationship between scientific aptitude and scientific creativity and career interest, and indicated that scientific aptitude predicts scientific creativity, and scientific aptitude and scientific creativity both affect career interest while the reverse is not true. Yoon & Eccles (1996) found a reciprocal relationship among the concept of self–concept, value and academic achievement of early adolescents. Ma & Xu (2004) concluded that prior low mathematics achievement significantly predict later high mathematics anxiety but that the reverse is hardly true. Neopmmyaschy (2007) found a strong positive reciprocal relationship between the likelihood & frequency of father–child contact and the likelihood of the amount of informal support. Watkins et al. (2007) investigated that psychometric intelligence cause of future achievement but the reverse was not true. Martin & Liem (2010) investigated that academic personal bests saliently predict engagement and achievement over time but in some instances, evidence of a reciprocal effect was found to exist while in some others it was non–existent. Volmar et al. (2011) found a reciprocal relationship between leader member exchange and job satisfaction. Ahmad et al. (2012) concluded that a high self–concept leads to low anxiety, which in turn, leads to a high self–concept. McKinnon (2012) concluded that an increase in average relative standing in academic achievement predicted an increase in average relative standing on perceived social support but two years later the reverse was not true. Ye, Yu & Li (2012) also concluded that self–esteem consistently predicted subsequent life–satisfaction of both genders while the reverse is not true.

Specifically the causal direction of an obtained correlational relationship may be indeterminable and doubts about whether the relationship could have been produced through the operation of some spurious third variable. Control over these problems, standard powerful correlational research design is needed in the case of causal relationship among the given variables to give a good result about the prediction and predicted variable. Probably the most significant advancement in the methodology of a cross–lagged panel analysis was the development of a regression, as opposed to a correlational approach. Due to its indispensible role, application of a cross–lagged panel analysis in educational research is needed. A cross–lagged panel analysis might have the potential of combining the major advantages of the correlational and experimental methods.

Thus the main purpose of this paper is to focus on the technique of analyzing data in educational research especially, which can be used to investigate causal relationships without experimental manipulation.

1. CROSS–LAGGED PANEL CORRELATION [CLPC]

Cross–lagged panel analysis has been used in the beginning of 20^{th} century. Perhaps, Hooker (1901) was the first person who used cross–lagged panel analysis in economics. Lazarsfeld & Fiske (1938) and Lazarsfeld (1940) investigate the bi–directional influence between family characteristics and child problem behavior and it became popular as a means of assessing bi–directional causal effects in a non–experimental context exclusively for longitudinal data. Having attracted earlier attention in sociology and economics, the cross–lagged panel analysis is now becoming increasingly popular in the field of psychology, education and behavioral sciences. Wright (1921) developed path analysis in biology, and Blalock (1963), Duncan (1966), and Heise (1970, 1975) have elaborated this model for sociologists (as cited in Marmor & Montemayor, 1977). In behavioral science, CLPC was first suggested by Kenny (1973); Rickard (1972) and Rozelle & Campbell (1969) which in turn was motivated by the seminal work of Lazarsfeld (1948) on the analysis of panel studies involving discrete variables. They used factor analysis and multiple regressions to estimate structural parameters in a longitudinal context, but they were primarily developed to analyze cross–sectional data. A cross–lagged panel analysis is a valuable statistical technique for ruling out the plausible rival hypothesis of spuriousness. The rudiments of a cross–lagged panel correlation necessitates two constructs, X and Y measured at two different points in time, say 1 and 2. The two variables and two lags (time) generate four variables (X_1, X_2, Y_1, and Y_2) and the four variables generate six correlations: two auto correlations (r_{X1X2}, r_{Y1Y2}); two synchronous correlations (r_{X1Y1}, r_{X2Y2}) and two cross–lagged correlations (r_{X1Y2}, r_{X2Y1}). A cross–lagged panel correlation is a method for testing spuriousness by comparing the cross–lagged differential: r_{X1Y2} minus r_{X2Y1}. It is very clear that the attribution of causal predominance in CLPC is based on the difference between cross–lagged correlations ($r_{X1Y2} \sim r_{X2Y1}$). Campbell suggested if the data indicate a 2w2v panel, that the cross–lagged differential is positive, concluding the causal predominance to be that of *X* causing *Y*, and if the cross–lagged differential is negative, concluding causal predominance to be that of *Y* causing *X*.



Cross–lagged Panel Correlation Paradigm (X and Y are variables and 1 and 2 are times)

Usually, the above conclusions are made only when the null hypothesis of equal cross–lagged correlation (Ho: $r_{X1Y2} = r_{X2Y1}$) is rejected. But equal cross–lagged correlations indicate a conclusion of a spurious (non–existent) pattern of causal influence between *X* and *Y*. It means that both variables are not causally related but are affected by some other set of common causes or a "third variable".

An important feature of the cross–lagged panel design is that, while estimating the cross–lagged or instantaneous effects, the researcher controls the initial correlation between the two variables, as well as the auto regressive effects of both variables. Because of its strengths, the design was classified as "quasi–experimental" (Campbell and Stanley, 1963). A problem for the researcher is how to analyze the panel data such as cross–lagged panel analysis, multiple regressions, factor analysis or the 16–fold table. A cross–lagged analysis is a test for spuriousness, by which we mean that the relationship between X and Y is not due to the causal effects of either but due to the effects of a third variable Z. Alternative terms for spuriousness are third–variable, common factoredness, or "co–symptomatic" effects.

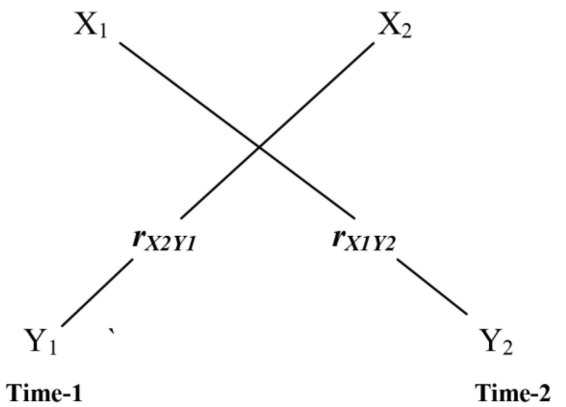
Let us consider two variables, mathematical creativity (*X*) and mathematical aptitude (*Y*) measured at the same point in time. During this time the question arises "what is the possible causal relationship between *X* and *Y*". The association between *X* and *Y* tells us nothing about causality. It could be due to a number of different causal relationships.

Case 1. Mathematical creativity may cause mathematical aptitude.

Case 2. Mathematical aptitude may cause mathematical creativity.

Case 3. Mathematical creativity may cause mathematical aptitude or vice–versa. They may influence each other equally.

Case 4. The relationship between mathematical creativity and mathematical aptitude may be influenced by a third variable. Mathematical creativity may not cause mathematical aptitude or vice–versa; both are influenced by third variable e.g. mathematical intelligence, mathematical imagination, and mathematical curiosity.



Cross–lagged Correlations between two factors measured at two points of time

Farris (1967) examined the strengths of the relationship between X and Y at two points of time and also described the interpretation.

If r_{X1Y2} is substantially different from zero, case 1 holds (*X* cause *Y*)

If r_{X2Y1} is substantially different from zero, case 2 holds (*Y* cause *X*)

If r_{X1Y2} & r_{X2Y1} are both substantially different from zero, case 3 holds (*X* cause *Y* and *Y* cause *X*).

If r_{X1Y2} & r_{X2Y1} are equal case 4 hold. (*X* and *Y* are not causally related but both are affected by a third variable, i.e., a spurious correlation) But it cannot assert any priority; perhaps both influence each other ($X \leftrightarrow Y$), or both are determined by a third factor ($X \leftarrow Z \rightarrow Y$).

What may be concluded if X and Y are related but neither r_{X1Y2} nor r_{X2Y1} shows sufficient extent of a relationship to indicate that *X* causes *Y* or *Y* causes *X*. The time lag needed for *X* to affect *Y* or vice–versa is longer or shorter than the interval chosen between time 1 and time 2.

Soelberg (1967) also examined the strength of the relationship between X and Y measured at time t and again at t+k (k = arbitrary re–measurement interval) and gave the interpretation of a cross–lagged correlation effectively.

1. If $r_{X1Y2} \neq 0$ and $r_{X2Y1} = 0$, X causes Y.
2. If $r_{X1Y2} = 0$ and $r_{X2Y1} \neq 0$, Y causes X.
3. If $r_{X1Y2} \neq 0$, $r_{X2Y1} \neq 0$ and $r_{X1Y2} > r_{X2Y1}$, X causes Y more than Y causes X.
4. If $r_{X1Y2} \neq 0$, $r_{X2Y1} \neq 0$ and $r_{X1Y2} < r_{X2Y1}$, Y causes X more than X causes Y.

5. If $r_{X1Y2} \neq 0$, $r_{X2Y1} \neq 0$ and $r_{X1Y2} = r_{X2Y1}$, Y causes X as much as Y causes X. (Reciprocal relationship).They may influence each other equally.
6. If $r_{X1Y2} = 0$ and $r_{X2Y1} = 0$, then X and Y are causally unconnected.

But Farris (1967) does not agree with the sixth possibility, namely, that both $r_{X1Y2} = 0$ and $r_{X2Y1} = 0$. Perhaps this case is not possible due to a significant correlation. It was revealed from the Soelberg work that there are three types of factors: causal, intervening, and resultant, which are found in a causal relationship. If *X* and *Y* are related and *X* causes *Y*, *X* is the causal factor and *Y* is the resultant factor. If *Y* is a resultant factor in a causal relationship with *X*, and *Y* is a causal factor in a causal relationship with Z, *Y* is an intervening factor between *X* and *Z*.

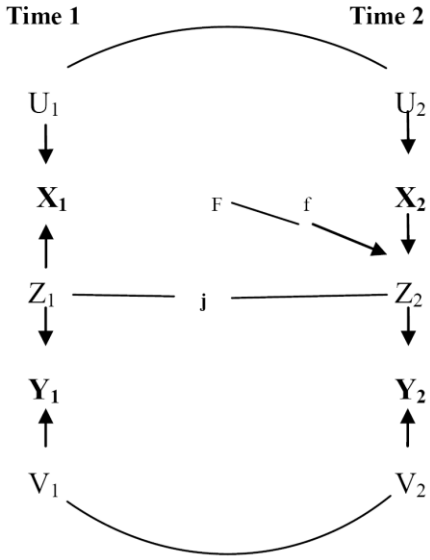
Lazarsfeld (1946) was an early proponent of causal analyses of panel data and suggests a clear cut causal relationship between two attributes. If we have a relationship between "X" and "Y"; and if for the antecedent test factor the partial relationship between X and Y do not disappear, then the original relationship should be called a causal one. It makes no difference whether the necessary operations are actually carried through or made plausible by general reasoning.

Simon (1957) writes that causality is an asymmetrical relationship among certain variables, or subsets of variables, in a self–contained structure; there is no necessary connection between the asymmetry of this relation and asymmetry in time, although an analysis of the causal structure of dynamical systems in econometrics and physics will show that lagged relations can generally be interpreted as causal relations.

2. Why Should CLPC Be Used?

A cross–lagged panel analysis helps to answer some important questions like; (1) Is a given factor causal, intervening, or resultant with respect to other factors? (2) Is it a causal relationship with each of the other factors it is associated? Although the answer of the first question can be given by a path analysis and regression analysis, the answer to the second question can be given by cross–lagged panel analysis only. It should be viewed as an exploratory method that may be used to uncover simple causal relations between uncontrolled variables which could then be tested more rigorously in controlled settings (Kenny, 1979). A cross–lagged analysis is a quasi–experimental design (Campbell & Stanley, 1963; Kenny, 1975). At the heart of a quasi–experimental inference is the attempt to rule out plausible alternative explanations of a causal effect. In a correlational analysis the chief alternative explanations of any causal effect is spuriousness. Any statistical relationship – be it a product moment correlation, partial correlation, multiple correlation, or regression coefficient – can be attributed not to causality but to spuriousness. True experiments control for spuriousness by random assignment to treatment conditions. Although random assignment permits researchers to make strong causal inferences, it brings with it some potentially burdensome methodological limitations. Due to ethical considerations, it is not possible to randomly assign and manipulate any variable. For instance, mal–nutrition has been proposed as an important cause of children's cognitive ability, but it would be highly unethical to randomly assign children to levels of malnutrition. Thus, it is not always possible to use random assignment to control for spuriousness due to practical and ethical reasons.

The null hypothesis of the CLPC tested by equality of the cross–lags is that the relationship between X and Y is due to an unmeasured third variable and not causation. Due to the inapplicability of true experimentation in numerous areas CLPC can be used to test for spuriousness. Kenny's model of CLPC is very important for investigators in education and social sciences is given below:



Model for 2w2v Panel Data Used to Represent Spuriousness in CLPC

Where U, V, and Z are all uncorrelated with each other but are auto–correlated because each takes on a different role.

Z is the unmeasured variable that brings about the relationship between X and Y and is also called the third variable.

U includes all the causes of X besides Z, and true cases as well as errors of measurement.

V plays the same role for Y as well as U.

In model, at time 1 a third variable Z_1 causes X_1 and Y_1 simultaneously. In actuality Z may cause X and Y with a lag, and the lag would be the same for both Z and Y. Over time Z changes and at time 2, Z_2 causes X_2 and Y_2. For a given model of spuriousness, the structural equations for X and Y are as follows;

$$X_1 = a_1Z_1 + b_1U_1$$
$$X_2 = a_2Z_2 + b_2U_2$$
$$Y_1 = c_1Z_1 + d_1V_1$$
$$Y_2 = c_2Z_2 + d_2V_2$$

All models rest on a set of assumptions; and there are no assumptions of free models. Shingles (1976) stated that all CLPA, being of the same basic design, share a common set of assumptions for both the formulation and the testing of causal predictions. But Chaney et al. (2004) stated that a cross–lagged panel analysis involves three pivotal statistical assumptions: (1) reliability, (2) synchronicity, and (3) stationarity that must be met before the appropriate causal interpretation can be made. According to Kenny the effect of a hypothetical third variable can be minimized by making two assumptions – *synchronicity* and *stationarity*.

Stationarity indicates the fact that the same variables are measured at each point of time. It is meant that a variable's causal or structural equation does not change between the two measurement dates, i.e., its structural equation is the same at both points of time. But it is different from stability. Stability refers to unchanging levels/empirical values of a variable over time, while stationarity refers to consistency in the strength and direction of synchronous correlations between the target variables over time (cross–sectional correlation r_{X1Y2} & r_{X2Y1} in figure 1). According to Kenny there are three types of stationarity: *perfect stationarity* (no change in the causal structural equation of the variables over time); *proportional stationarity* (the causal coefficients of each variable change over time by the same constant); *quasi–stationarity* (the causal coefficients of each variable change by a proportional constant, but each measured variable has its own unique constant). They make different assumptions about the changes in causal structure over time and symptoms for the way in which the synchronous correlations change over time and for the difference between cross–lags.

An insignificant difference between the synchronous correlations suggests that the variables are stationary, and then the test for cross–lagged correlations could be conducted by using the Pearson–Filon (PF) test for dependent correlations.

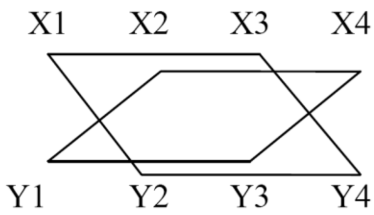
Synchronicity means that the two variables X and Y are measured at the same point of time and it involves attributes manifested at that point of time and not aggregated over some time prior to measurement.

$$X_t = aZ_t + bU_t \qquad 1$$
$$Y_t = cZ_t + dV_t \qquad 2$$
$$Z_t = jZ_{t-1} + fF_t \qquad 3$$

Where U, V, and Z are auto–correlated but not cross–correlated. The synchronous correlation is then ac from equations 1 & 2 and the cross–lag of $r_{Xt,Yt+k}$ is acj from equations 1,2 & 3. It is a special case of the cross–lag formula where k=0. Now if X is measured at times 1 and 3 and Y at times 2 and 4, but if X_1 and Y_2 are considered wave 1 and X_3 and Y_4 are considered wave 2, the "cross–lags" would not be equal because

r_{X1Y4} and $r_{X4Y1} = acj^3$

r_{X3Y2} and $r_{X2Y3} = acj$



The shared empirical findings indicate that variables measured closer together in time correlate more highly than those measured further apart in time, r_{X1Y4} should be greater than r_{X3Y2} (Similar for r_{X4Y1} and r_{X2Y3}) because the lag for the first correlation is smaller than that for the second. So synchronicity is then an important assumption of CLPC.

From the above discussion, it is clear that both a lack of synchronicity and stationarity are potential explanations of a difference between cross–lagged correlations. If the model is correct, then both synchronicity and stationarity together imply equal cross–lags. The null hypothesis that the cross–lagged differential is zero is then a test of spuriousness.

What if the cross–lagged differential is not zero? Asymmetrical cross–lags may indicate causal effects; they indicate that there is factor that causes one of the measured variables and causes the other measured variable at a later point of time. This factor is called a causal factor and the phrase "*X* causes *Y*" is shorthand for "something in *X* later causes *Y*" but the experiment does not necessarily tell what in *X* causes *Y*.

3. THE STRENGTH OF CLPC

Single–point–in–time correlational studies are feasible in the natural settings but they do not allow conclusions to be drawn about causal relationships with any ease or precision. What does a non significant difference between the cross–lagged correlations indicate? Researchers should not accept the null hypothesis of spuriousness, that is, the hypothesis that the variables do not cause each other but are co–symptoms of some set of common causes. There are some alternative explanations: *first*, it may be that both X and Y cause each other in a positive feedback loop. *Second*, it may be that X causes Y or vice–versa, but the magnitude of the effect is too small to be detected when the sample size is moderate (N=75 to 300). It is very difficult to obtain statistically significant differences between cross–lagged correlations.

Given the low power of CLPC, the researcher should design the longitudinal study to include many replications. Ideally, cross–lagged differences should replicate across (a) different time lags, (b) different groups of subjects, and (c) different operationalizations of the same construct. For instance, most of the causal effects in Crano et al.'s (1972) study of intelligence and achievement can be summarized as abstract skills causing concrete skills. In one of the best empirical applications of cross–lagged analysis, Calsyn (1974) demonstrated all to show that academic achievement causes academic self–concept. Watkins et al. (2007) concluded that psychometric intelligence is a causal inference of future achievement whereas achievement measures do not substantially influence future IQ scores. Ahmad et al. (2012) determined that higher self concepts leads to lower anxiety, which in turn, leads to higher self concept in mathematics. It is very important that the cross–lagged differential depends on the stability of the causal factor. So that cross–lagged analysis is, therefore, not appropriate for examining the causal effects of variables that do not change over time.

A cross–lagged analysis is a low–power test, better adapted than either multiple regression or factor analysis for many questions in panel studies. It has been assumed that the errors of the model are independent across waves. Mayer (1980) states that it contributes to this approach by extending the regression model to a multivariate model that captures the correlation among the variables and allows the errors in the model to be correlated overtime. Multiple regression must assume no errors of measurement in the independent variables and no correlated errors, while factor analysis must specify a particular factor structure.

4. ALTERNATIVES OF CLPC

Cross–lagged analysis is a quasi–experimental method designed to test the spuriousness and presumes as a null hypothesis that the relationships between X and Y are spurious (i.e., due to unmeasured third variable). Multiple regressions, factor analysis and cross–lagged panel correlation are usually viewed as a means for the analysis of panel data. In a multiple regression, there is a set of predictors (I.V.) and criterion (D.V.) which are interpreted as the predictors to be causes of the criterion. The goal of the application of factor analysis is to estimate factor loadings and factor correlations.

There are two difficulties with the application of multiple regressions to panel data: measurement error and unmeasured third variables and these difficulties make inference from panel data by the problems of multiple regressions. Although multiple regressions is a powerful method for non–experimental inference, a cross–lagged panel correlation is better adapted for panel data analysis. Although the model of cross–lagged panel correlation is a factor model in that it assumes that unobserved variables (factors) bring about the relationships, a cross–lagged panel correlation does not use factor analysis in the estimation of factor loadings and factor correlations. The orientation of CLPC is to put constraints not on the number of factors, as in factor analysis, but to put constraints on the pattern of loadings over time. A cross–lagged panel analysis assumes invariant factor structure over time. Some statistical analysis like multiple regression, path analysis, analysis of variance, and factor analysis though very general may not be easily adaptable to panel studies. The aforementioned discussion indicates that cross–lagged analysis is a better statistical technique/method to especially investigate the causal relationship for longitudinal context.

5. USES OF CLPC

There are two distinct advantages of this method over others: (1) It does not permit only a symmetrical causal relationship like the common applications of other methods; (2) It forces us to study time lags between cause and effect. The most important uses of CLPC are: (1) the test of significance; (2) to study background variables; and (3) missing data.

6. LIMITATIONS OF THE CROSS–LAGGED PANEL ANALYSIS

Quinn and Jadav (1987) indicated the discrepancy in using this approach because it only provides information about having chief power of causation between two variables in longitudinal context. It does not rule out the possibility of both variables having some causal influence on the other, or equal causal influence on each other. *Secondly*, this technique tests confounded pairs of hypothesis against each other. If one observes that $r_{X1Y2} > r_{X2Y1}$, it is possible either that *X* is a direct cause of *Y* or that *Y* is an inverse cause of *X* while it is possible for other factors to mask an inverse relationship. To reduce these boundaries the additional information is needed from other research and theory to distinguish between the confounded hypotheses. Rogosa (1980) also states that due to complications resulting from measurement error, specification error and multiple indicators, CLPC is not a useful procedure for the analysis of longitudinal panel data. Chaney et al. (2004) levied the two crucial criticisms against this approach centered around as inappropriate causal interpretation based on data that fail to satisfy the restrictive set of statistical assumptions on which the cross–lagged method is based (reliability/stability, synchronicity and stationarity) and (b) the use of simple bi–variate correlations as a basis for making causal inferences.

7. Concluding Remarks

A cross–lagged panel analysis is a formal method with an assumption and an exploratory strategy of data analysis for ruling out the plausible rival hypothesis of spuriousness. It is a method for testing spuriousness by comparing cross–lagged correlations. A cross–lagged analysis is helpful in answering the questions: (1) to determine generally what is associated with what; and clarify which factor is causal, intervening or resultant with respect to the criterion and (2) to study time "lags" between cause and effect in the natural setting so that cycles can be indicated, which show, for instance, how mathematical creativity changes over time and how mathematical aptitude changes over time. A positive, zero or negative correlation may occur between them at a single point of time. But in the case of exploring causal relationships between mathematical creativity and mathematical aptitude it is very important that variables be measured at intervals corresponding to the time lag needed for one factor to affect the other. But treating several factors at the same time and proposing a scheme for causal analysis among factors all of which are not measured on the same two occasions, it overcomes some limitations of cross–lagged panel analysis in its current formulation. It allows conclusions to be drawn with larger assurance when correlation coefficients are relatively large and third factors are controlled; due to linking the low–extent correlations and long–term possibility of spurious correlations, its applications are reasonably victorious.

It is clear that this method will not work better if the variables involved are highly inconsistent over time and the interval of remeasurement does not match the underlying interval of causation. Finally, a cross–lagged analysis plays an important role in solving the chicken–egg type problems with respect to an educational context. A cross–lagged panel correlation is a special case of the multi–trait and multi–method matrix (Campbell & Fiske, 1959). Much of the logic of Campbell's early articles on longitudinal analysis can be understood in this context. Due to its indispensible role to investigate/explore causal relationship on the basis of the statistical dominance of one variable related to another over time, the cross–lagged panel analysis is a low power test but better competitor than path analysis, multiple regression or factor analysis, especially in the longitudinal context.

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UPOTREBA STATISTIČKE ANALIZE POVEZANOSTI ČINJENICA U PEDAGOŠKIM ISTRAŽIVANJIMA

Statistička analiza povezanosti činjenica (engl. Cross–lagged panel analysis, CLPC) koristi se u glavnim tokovima društvenih, bihejvioralnim, medicinskih, poslovnih i pedagoških istraživanja. U pitanju je vrsta kvazi–eksperimentalnog istraživanja koje se koristi kako bi se odredilo da li je odnos između dve varijable prouzrokovan trećom varijablom, ili je slučajan. Ova vrsta analize spada u procese za određivanje varijabli koje su uzročnici i varijabli koje su posledice. To je metod objašnjavanja prikupljenih podatka u dva različita vremenska perioda, periodu 1 i periodu 2, kako bi se razjasnio uzročno–posledični odnosi između varijabli koje bi se mnogo strože kontrolisale u eksperimentalnom okruženju. CLPC je test slabe snage ali je od testova regresije ili faktorske analize bolje prilagođen potrazi za odgovore na mnoga pitanja u longitudinalnim istraživanjima. On obuhvata dinamički odnos među varijablama i omogućava kontrolu modela tokom vremena. Fokus ovog rada bio je dizajn 2w2v koji je opisao istraživačku metodu koja se može koristiti kako bi se istražio uzrok odnosa dveju varijabli u odsustvu pravog eksperimentalnog istraživanja, ali samo u pasivnom smislu.

Ključne reči: *statistička analiza korelacije, korelacija, sinhrona korelacija, auto–korelacija, stacionarnost, sinhronija.*