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A MULTILEVEL NONLINEAR APPROACH OF PIECEWISE REGRESSION FOR DETECTING TURNING POINTS: DEVELOPING AN ALTERNATIVE PLATFORM WITH AN APPLICATION OF TIMSS

JING ZHANG
University of Kentucky, zjing1982@gmail.com
Author ORCID Identifier:
https://orcid.org/0009-0004-6279-1028
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JING ZHANG, Student

Dr.Xin Ma, Major Professor

Dr. Sherry Rostosky, Director of Graduate Studies

A MULTILEVEL NONLINEAR APPROACH OF PIECEWISE REGRESSION FOR DETECTING TURNING POINTS: DEVELOPING AN ALTERNATIVE PLATFORM WITH AN APPLICATION OF TIMSS DATA

DISSERTATION

A dissertation submitted in partial fulfillment of the
requirements for the degree of Doctor of Philosophy in the
College of Education
at the University of Kentucky

By
Jing Zhang
Lexington, Kentucky
Director: Dr. Xin Ma, Professor of Quantitative and Psychometric Methods
Lexington, Kentucky
2023

https://orcid.org/0009-0004-6279-1028

ABSTRACT OF DISSERTATION

A MULTILEVEL NONLINEAR APPROACH OF PIECEWISE REGRESSION FOR DETECTING TURNING POINTS: DEVELOPING AN ALTERNATIVE PLATFORM WITH AN APPLICATION OF TIMSS DATA

Studies in recent years have explored the methods of identifying the turning points when dealing with the non-linear relationship. Four approaches applied by researchers, the eyeball approach, the establishment approach, the theory-driven approach, and the data-driven approach, are all under the traditional piecewise regression framework when seeking turning points. Thus, the purpose of this study is to introduce a multilevel piecewise regression model to identify the turning point beyond the traditional piecewise regression, as a completely non-linear approach.

Data used for this study is TIMSS 2019 United States sample. TIMSS is a project guided by the International Association for the Evaluation of Educational Achievement (IEA) (TIMSS 2007 Technical Report). In the United States, the sample size of fourth graders was 8,776 students from 287 schools. Students enrolled in the fourth grade have four years of schooling, and the average age in the United States sample is 10.2 years.

Under the present approach, the empirical findings confirmed the results in the literature review of previous research that certain factors impacted achievement. In this case, Students Like Learning Mathematics (SLM), Student Confidence in Mathematics (SCM), and Self-Efficacy for Computer Use (SEC) had a positive effect on mathematic achievement, but also indicated the different patterns of the effect change with and without control of the student and school factors. Students with the highest level of SLM, SCM, and SEC did not conclusively demonstrate the highest mathematics achievement. When students' SLM, SCM, and SEC reached a certain degree, their mathematics achievement progress slowed down, indicating after the turning point, more effort invested to increase the SLM, SCM, and SEC measurement level for higher mathematic outcomes might not effective.

KEYWORDS: Multilevel Piecewise Regression, Non-linear, TIMSS, Mathematics Achievement

Jing Zhang

(Name of Student)

April 11th, 2023

Date

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By
Jing Zhang

Dr. Xin Ma
Director of Dissertation

Dr. Sherry Rostosky
Director of Graduate Studies

4/11/2023
Date

For my grandparents and my family, thanks for all your love.

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CHAPTER 1. INTRODUCTION

1.1 Introduction

A turning point is defined as a point at which a significant change occurs, according to the Merriam-Webster dictionary. Since monitoring change, especially significant change, is demanding in many fields, defining or detecting the turning point is often the main focus of many researchers. Psychologists who focus on behavioral science tend to anchor their research on behaviors that emerge at a certain age. Thus, children's development is expected to reflect a significant behavior or skill change when they reach a specific age group (Cole et al., 2005). Educators who emphasize the relationship between study time and academic achievement are interested in the effect of a threshold study time on how well a child performs academically. They hold that the minimum time invested in study could produce the highest academic outcome, other than spending extra time studying, even though time investment in study is considered a key element of academic success (Ma, Jong, & Yuan, 2013). However, the non-linear trend revealed by the turning point requires a non-traditional procedure to examine the effect of X (independent variable) on Y (dependent variable), since a normal regression line is not suitable to capture the non-linear relationship. Regarding the importance of the turning point, researchers have conducted different approaches to define or detect when it occurs. Piecewise regression, evolved from the general regression model, has been applied as a useful tool for detecting the turning point.

1.2 Practical Examples

Example One. In the education field, the relationship between teaching quality and student outcomes has been discussed by many researchers, with inconsistent results. Some research showed a weak relationship between quality and outcome (Burchinal, Kainz, & Cai, 2011; Keys et al., 2013), while other literature offered strong evidence that children can benefit more from a high-quality preschool resource (Yoshikawa et al., 2013). The requirement of a proper statistical model has been raised since models applied in the studies above might not meet the model property. The pending research question here is whether there is a threshold requirement of preschool quality that, when reached, would positively influence child outcomes.

To answer this research question, Li et al. (2019) applied a piecewise regression model in their research to test such 'thresholds' of preschool education quality on child outcomes in China. This study overcame many limitations in previous studies, such as failure to conduct the threshold estimation, produce proper slopes before and after the potential turning point, and include covariates into the model. In this study, the piecewise regression was conducted under the following steps.

First, the linear relationship between preschool quality and child outcomes was tested by a multilevel modeling technique. A three-level hierarchical linear model (HLM) analysis was applied here. Several selected covariates were included in the HLM model, and then a non-linear trend was confirmed. Second, a piecewise regression model (PRM) was applied to test the threshold in quality-outcome associations. The PRM estimated the threshold of CECERS (Chinese Early Childhood Environment Rating Scale) factor scores, which is the measure of preschool quality. The separate linear association of preschool quality and child outcomes before and after the threshold was also estimated by the PRM. The same dependent variables, independent variables, and covariates used in HLMs were included in the PRM estimation. To examine whether preschool quality has a stronger impact on child outcomes in higher quality classrooms than lower quality classrooms, the Davies test was conducted to do the post-hoc comparisons of the slopes within the two segments (Davies, 1987).

Example Two. In behavioral science, piecewise regression also has been applied to test the trajectory of problem behaviors of adopted Korean children (Ahn et al., 2017). This study aimed to investigate how problem behaviors among adopted Korean children changed across their different developmental stages and demonstrate which variables accounted for these changes. The data selected for this research purpose was a longitudinal three-waved data set, the Panel Study on Korean Adopted Children (PSKAC). To estimate the pattern of change, considering the data hierarchy and three time points, the piecewise hierarchical linear growth model was proper for the estimation. Raudenbush & Bryk, (2002) also indicated that when assuming the rates of change are different for clear time periods, a piecewise approach is useful. According to the statement of their previous research results, a non-linear behavior change was recommended, along with different time points. In fact, two time periods were determined in the growth trajectory. For that reason, the breakpoint for the piecewise regression is firm, rather than following a statistical detecting approach. The two time periods were ages five to seven years (coded as Time 1), and ages seven to ten years (coded as Time 2).

The model development process was suggested by Singer & Willett (2003). The first step was to test whether there was adequate variation in the dependent variable by an unconditional mean model (model 1). The purpose was to determine if it was proper to put all other explanatory variables into the model. The main focus of the testing was to determine the random effects significance in the level 1 and level 2 models of within-person and between-person variations. The second step was to test another model (model 2) as an unconditional change model, with the assumption that the individual changes over time. In the level 1 model, three fixed effects were tested – the baseline of the behavior problem status when children were five years old, the rate of change between five and seven years of age (Time 1), and the rate of change between seven and ten years of age (Time 2). In the level 2 model, the random effect indicated the significant variation between-person within the respective coefficient. If the random effect were significant, then the between-person variables could be used to predict variation. Finally, to demonstrate the variations of behavior problems among children in the initial status as well as the change rate, predictors of sex and older-age adoption variables were added into the level 2 model.

Summary. Comparison, based on the two literatures, shows that the level of complexity of the data structure highly correlated with the selection of the piecewise regression model. Meanwhile, the uncertainty of the breakpoint increases the complexity of the model. The data in the second example (behavioral science) had three waves of data to measure adopted children's behavioral problems. Also, the data hierarchy showed the structure of children nested within families. To test the change pattern of children's behavioral problems, the piecewise hierarchical linear growth model was applied in this paper. For the breakpoint, it was also fixed into two time periods of age, according to their previous study results. In contrast, the piecewise regression model applied in the first example (education) was much more complicated than the second, since the breakpoint is uncertain and the data is nationally wide with many years of repeated measures. Because of the hierarchical data structure, the non-linear trend cannot be seen visually. A three-level hierarchical linear model (HLM) was used to test the non-linear relationship. Then, the threshold of the relationship between preschool quality and children's outcome was conducted by using the piecewise regression model (PRM). In sum, the non-linear relationship, breakpoint detection and the data structure are three main aspects for the application of different types of piecewise regression.

1.3 Traditional Piecewise Regression

Piecewise regression can be called segmented regression or broken-stick regression. The principle for this method is that the independent variable would be split into different intervals, and then a separate regression line would fit each segment.

The traditional piecewise regression model is evolved from the regression model:

$$Y = \pi_0 + \pi_1 X + \varepsilon$$

where Y is the outcome variable, X is the independent variable that contains the potential turning point, and π_0 is the intercept (i.e., the Y value when X takes the value of zero). π_1 is the coefficient of X, indicating the effect of X on Y. ε is the error term, representing the effect of the variable that is not explained by the model. For the simplest example, suppose a visual inspection confirms a point as the breakpoint of the effect. Then the X will be divided into X_1 (below that point) and X_2 (above that point). The data are split into two segments, and the equation would be:

$$Y = \pi_0 + \pi_1 X_1 + \pi_2 X_2 + \varepsilon$$

where π_1 and π_2 are two different slopes of X, representing the different effects before and after the breakpoint.

The necessity of conducting a piecewise regression is often due to the non-linear relationship. The non-linear relationship can be identified by the naked eye according to the data scatter plot or based on the theory recommendation, whereas statistical testing is required when the breakpoint is not clear or a data-driven approach has been chosen.

1.4 Determination of Breakpoints

The non-linear relationship can be detected or supported by various practices of determining breakpoints. The commonly used approaches are illustrated here. The practice of each approach is discussed first, followed by an example from the research literature.

Eyeball Approach. Visual inspection is often applied to predict the number of segments, as well as the position of the breakpoints (Crawley, 2012). In some cases, it works well to use the naked eye to manually specify the breakpoint between piecewise segments for piecewise regression analysis (i.e., the linear regression would be performed independently based on the separate dataset). Generally, the scatter plot offers a rough picture of the dataset, serving as preparation for the further statistical exploration of the breakpoint. However, in reality, some datasets are not ideal for the eyeball approach, especially when the patterns underlying the data are subtle. As an example of visual inspection, a polynomial hierarchical model was conducted to examine discontinuity of mother-infant relationship change during different periods of time (Hernández, Colmenares & Martínez, 2004). The eyeball approach provided the initial suggestion of the polynomial degree; then the hypothesis tests of the fixed effect of the model decided the specification of the final model.

Establishment Approach. This approach means that a breakpoint has been naturally established. Compared with the eyeball test, some cases naturally contain a breakpoint that would divide the data into stages. Therefore, the breakpoint has been established without any identification process. Burke, Shrout & Bolger (2008) offered an example of the turning point of life, the conjugal loss. The researchers demonstrated the pre-and post-effect of conjugal loss on people's wellbeing by using a large cross-sectional sample. The loss could be considered as a trigger of traumatic symptoms, so a discontinuity of wellbeing would be expected, according to the psychological theory. Between the pre- and post-time period, many time-varying variables had non-linear relationships. For instance, the pre-loss depression symptoms level could be relatively low whereas, at the time of loss, the depression level would escalate, then gradually decrease in the following years.

Theory-Driven Approach. In social sciences, one essential element of social theory is to examine the relationship between humans and society, with one of the main goals being to identify how the relationship changes over time (Elliott, 2014). For that reason, there are (prior) theories that provide important hypotheses of certain relationships, and further statistical methods to conduct the confirmation of the hypotheses. For example, in the development of autonomy in emerging adults, contact with families tends to decline.

This decline is based on the separation individuation theory (Mahler et al., 1975). Further, gender differences were emphasized during the autonomy development, such as the fact that men tended to separate from their families faster than women and had less family contact, compared with women. Two crucial age points were highlighted by Sneed et al. (2006) to suggest that a 17-year-old represents a high rate of family contact with the same level between men and women, whereas a 27-year-old represents the low rate of family contact, with very significant differences between these two gender groups. Such theories and research discovery offered the foundation for the research of Rindskopf & Sneed (2008). In this study, they generated family contact data from 240 young adults' narrative interviews. Their narrative supported the assumption, based on the theory that a sudden change was rare, and they validated the existence of the turning point at age 17, when a large proportion of participants in their sample started to show decline in family contact.

Data-Driven Approach. In some cases where the breakpoint is neither clear nor identified by theories, a data-driven approach would be chosen to detect the breakpoint for a piecewise regression. This approach relies heavily on statistical testing to detect the breakpoint. As an example, Li et al. (2019) indicated that there might be a threshold of teaching quality that had an effect on preschool children's outcomes, such as early math, language, and social cognition. The threshold here was defined as a significant difference in children's outcome displayed below and above the threshold. However, where the thresholds do not have any theory support, a data-driven approach was adopted that used piecewise regression to estimate these points. After the thresholds were determined, the slopes in the higher and lower quality classrooms were estimated.

The four approaches discussed above illustrate the procedure of detecting the turning point due to the data structure complexity. The eyeball approach and establishment approach are suitable for situations where data structure is cross-sectional and the turning point is known. By contrast, the theory-driven approach and data-driven approach tend to test the turning point, requiring relatively complicated statistical methods. When the turning point is known, the piecewise regression is very similar to the regression discontinuity design.

1.5 Regression Discontinuity and Piecewise Regression

A regression discontinuity design (RDD) is a quasi-experimental method that normally is used for extracting the causal effects by means of an intervention assigned by a cutoff point or threshold. The procedures to conduct the RDD and piecewise regression are similar when the threshold is known, and the effect of X on Y is examined separately below and above the threshold. However, a regression discontinuity design emphasizes the causal effect of an intervention, whereas a piecewise regression focuses on the changing trend below and above the breakpoint, such as the different coefficients and different slopes.

Another difference is the identification of the breakpoint or the cut-point. A regression discontinuity design (RDD) is a proper method when the intervention assignment is under the condition that the "cut-point" is exogenous with a variable. The treatment group and control group (comparison group) would be defined by the cut-point. If the assignment variable for an individual's value belongs to one side of the cut-point, then the individual would belong to the treatment group; otherwise, the individual belongs to the compassion group. For example, Angrist & Lavy (1999) conducted research to explore whether class size had an effect on student study outcome. Maimonides' Rule was applied to define the cut-point for class size, and the rule was one teacher (one class) should contain only 40 students. When the class size surpassed 40 students, even at 41 students, the classroom should be divided into two teachers (two classes). The requirement for the assignment variable is that it should be a continuous variable, in order to guarantee a range of values at each side of the cut-point. In this case, when every class of 40 students increased, the cut-point would show up continuously. Simultaneously, the cut-point of the large classroom and small classroom is 40 to 41 students. For piecewise regression, the breakpoint can be identified, based on the theory or the previous research, or by depending on an eyeball test of the scatter plot, as previously discussed. The sample research question for a discontinuity design can be "Does summer remedial coursework have an effect on student academic achievement?" (Jacob & Lefgren, 2004). Similarly, the research question for piecewise regression research can be "What is the effect of age on the length of time that children talk on the phone?" However, when breakpoints are not clear, the research question will turn out to be "What is the quality effect of thresholds testing of preschool education on child outcomes?" (Li et al., 2019). The unknown threshold requires very different statistical methods compared with a discontinuity design.

1.6 Methodological Significance of the Study

The purpose of this study is to introduce a new method to identify the turning point beyond the traditional piecewise regression from a completely non-linear approach. The traditional approach is limited in several ways.

First, the traditional piecewise regression usually defines a single or a couple of breakpoints. Although this parsimonious practice is reasonable especially under theoretical considerations, what researchers get from traditional piecewise regression is oversimplified non-linear relationships. For instance, the eyeball approach and the establishment approach from previous discussion only provide rough information about the turning point and, for that reason, the model has many restrictions on explaining the data.

Secondly, when more breakpoints are desired, a traditional piecewise regression approach can become quite demanding for the determination of breakpoints, as well as for data management for traditional piecewise regressions. Researchers prefer to employ comprehensive models to identify all the turning points; however, these methods are relatively complicated (Muggeo, 2008).

Thirdly, even though the data-driven approach is a legitimate method to detect turning points, this approach may identify unrealistic turning points. For example, in a Likert type of measurement, a decimal has no measurement meaning, thus less applicable to social policies and practices. Finally, the combination of multilevel modeling and piecewise regression tends to be univariate in nature (i.e., conducted separately) (Li, Zhang et al., 2019). Multilevel piecewise regression in a multivariate fashion is not very common in the literature (Muggeo, 2008).

The first research question that arises here is whether there is another way to more "naturally" check for non-linear relationships of X on Y that is also suitable for the multilevel data structures, such as students nested within classrooms or schools.

The contribution of the new model to be developed here is to provide the solutions to the limitations discussed above. What's more, it is a multilevel framework, which could explain the data more effectively and more efficiently. This approach is simpler, comprehensive, and naturally non-linear in terms of model specification. It is capable of identifying multiple turning points if a certain threshold can be established or is available. It is also an easy integration into HLM. Local regression may not possess these advantages. The only weakness is a possible need to collapse data when the independent variable is continuous, which loses some information. This weakness can be improved by setting up an adequate number of potential points. However, the flexibility of the data type would be another advantage when researchers need to generate many categories of data in order to have a precise estimation. If researchers were allowed to define the data categories, that would yield a practical significance from this study.

1.7 Practical Significance of the Study

The purpose of studying the turning point is to capture the crucial point in the non-linear trend. The crucial point is defined as showing the greatest change below and above this point. When the effect of X on Y completely follows the non-linear relationship, there might be several peaks across the measure that unite. It is important for practitioners to have a fuller understanding of the whole non-linear relationship for better evidence-based decision making, as well as for conducting more complicated research questions.

In this study, the application of the new model will focus on the effect of psychological variables, Students Like Learning Mathematics (SLM), Student Confidence in Mathematics (SCM), and Self-Efficacy for Computer Use (SEC) on mathematics achievement. The dependent variable Y is mathematics outcomes, which make up the mathematics score. The independent variables X are SLM, SCM, and SEC, which have been reported in three categories by TIMSS 2019, ranging from one to three. The new method will allow researchers to test the effect of X on Y from each new category. A graph of all the peaks under different levels of SLM, SCM or SEC could be illustrated as the electrocardiogram (ECG). The second research question that arises here is whether there is a turning point that reflects the best mathematics outcome change when students maintain a specified category of SLM, SCM or SEC.

Another advantage of this new model is that researchers can define the categories according to their research requirement. The TIMSS 2019 reported the students' data of SLM, SCM and SEC in two types, index categories and scale score. The three index categories were aggregated from the scale score. The SLM index includes Very Much Like Learning Mathematics, Somewhat Like Learning Mathematics, and Do Not Like Learning Mathematics. SCM index includes Very Confident in Mathematics, Somewhat Confident in Mathematics, and Not Confident in Mathematics. SEC index includes High Self-Efficacy, Medium Self-Efficacy, and Low Self-Efficacy. (See Appendix 1). Since the index is a rough description of the SLM, SCM and SEC by three categories, the turning point identification might not be precise. If a more detailed result is required, the scale score can be divided into demanding categories for the research purpose. For example, the SLM scale score ranges from 3.85 to 13.14, which can be divided into five or seven categories for a more precise estimation. (See Table1). In that case, the new model will provide flexibility of the data type, suitable for continuous variable and ordinal variable.

Literature about the relationship of math outcome and SLM, SCM, or SEC can only explain the general relationship, such as a positive or moderate effect on mathematics achievement (Kadijević, 2008; Çiftçi & Yildiz, 2019; Nurhikmah et al., 2021). The new model is effective in revealing more information during the research by estimating the certain level of SLM, SCM, and SEC that have the most significant effect on students' mathematics achievement. Further, the new model can handle data hierarchy while detecting the turning point, since data hierarchy is very common in social science and education fields, such as residents nested within communities and students within classrooms and schools. Even in the medical field, the encounter of patients nested within hospitals is common as well. Another advantage of multi-level modeling is that individual and group covariates can be controlled separately in different levels. For example, the TIMSS 2019 sample contains student's covariates and school covariates, which will be controlled separately in student level and school level.

1.8 Organization of Dissertation

This dissertation includes five chapters. Chapter One is an introduction to the study and provides an overall picture of piecewise regression, as well as four approaches of detecting the turning point. It states the purposes and significance of the study, while indicating the difference between regression discontinuity design (RDD) and piecewise regression. Chapter Two presents the new piecewise regression model under multilevel analysis settings. It displays the model framework and illustrates the non-linear trend through an EKG graph. Chapter Three presents the research design, including the data source, the sample, and analytic procedures, while reviewing the effect of students' attitudes towards mathematics on students' mathematics achievement when applying the model to mathematics education. Chapter Four reports and interprets research findings and draws conclusions. Chapter Five presents the conclusions, implications, and recommendations for future research.

CHAPTER 2. MULTILEVEL PIECEWISE REGRESSION

Hierarchical linear models (HLM) can handle data when the observations are not independent and can model correlated error correctly. The violation of uncorrelated error often occurs in general linear models when, for example, students nested within classrooms or schools share certain similarities, and the clustering results in correlation of error, thus disproving any prediction parameters calculated based upon it. The HLM model would allow the outcomes to vary within and between groups, which would release the assumption of independency of observation. If we test students' mathematics achievement by using the HLM model, we can identify the variation of students' mathematics achievement within the school in which they are nested, as well as their mathematics achievement variation between schools. This chapter serves as an introduction to the piecewise regression model under hierarchical linear model settings. The format of a two-level, multilevel piecewise regression model will be presented, as well as the model assumption and estimation. The six illustration graphs of the multi-level piecewise regression also display the advantage of this new model, compared to traditional piecewise regression.

2.1 The Model

The multilevel piecewise regression can take the form of a two-level HLM model. The first level is focused on the individual, and the second level is focused on the institution. Take the example of a data structure with students nested within schools. A level 1 variable of X is sought for a turning point in the effects of X (X_{nij} precisely) on the dependent variable of Y (Y_{ij} precisely). Suppose that X_{nij} is measured by a five-point Likert type scale (1, 2, 3, 4, 5). The multilevel piecewise regression reconstructs the traditional piecewise regression by applying the dummy coding to represent each measuring point. The student (level-1) model is a set of separate piecewise regressions, one for each school. The level-1 model was expressed as

$$Y_{ij} = \pi_{1j}x_{1ij} + \pi_{2j}x_{2ij} + \pi_{3j}x_{3ij} + \pi_{4j}x_{4ij} + \pi_{5j}x_{5ij} + \sum_{p=1}^{m} \pi_{(5+p)j}x_{(5+p)ij} + e_{ij}$$

$$x_{nij} = \begin{cases} 1, & for\ x = n\ (n = 1, 2, 3, 4, 5) \\ 0, & for\ x \neq n\ (n = 1, 2, 3, 4, 5) \end{cases}$$

where Y_{ij} is the outcome variable value for student *i* in school *j*, x_{nij} are the dummy variables to indicate response points, $x_{(5+p)ij}$ (p = 1, 2, … *m*) are all the individual variables controlled in level-1, and e_{ij} is the error term.

The school (level-2) model adjusts π_{1j}, π_{2j}, and π_{3j}, over school-level variables:

$$\pi_{1j} = r_{10} + \sum_{q=1}^{n} r_{1q}z_{qj} + U_{1j}$$

$$\pi_{2j} = r_{20} + \sum_{q=1}^{n} r_{2q}z_{qj} + U_{2j}$$

$$\pi_{3j} = r_{30} + \sum_{q=1}^{n} r_{3q}z_{qj} + U_{3j}$$

$$\pi_{4j} = r_{40} + \sum_{q=1}^{n} r_{4q}z_{qj} + U_{4j}$$

$$\pi_{5j} = r_{50} + \sum_{q=1}^{n} r_{5q} z_{qj} + U_{5j}$$

$$\pi_{(5+p)j} = r_{(5+p)0} + \sum_{q=1}^{n} r_{(5+p)q} z_{qj} + U_{(5+p)j} \quad (p = 1, 2, \dots m)$$

where the *r* parameters (r_{10}, r_{20}, r_{30}, r_{40}, r_{50}, $r_{(5+p)0}$) are adjusted for school-level variables, z_{qj} (q = 1, 2, … m) are all the school variables controlled in level-2, and U_{1j}, U_{2j}, U_{3j}, U_{4j}, U_{5j} and $U_{(5+p)j}$ were school-level error term.

Based on this multilevel piecewise regression model, the significance of coefficient r_{10}, r_{20}, r_{30}, r_{40}, r_{50}, $r_{(5+p)0}$ will suggest whether these points, with adjustment over school-level variables, are the effect of turning points of *X on Y*. There appear to be two advantages for this multilevel piecewise regression model. First, the identification of turning points is determined with adjustment over both student-level variables and school-level variables. Second, the statistical approach for determining a turning point here is entirely non-linear (i.e., there could be multiple turning points dependent on the specification of a turning point).

2.2 The Assumption

Because the multilevel piecewise regression model takes the form of a two-level HLM model, the model needs to meet assumptions of multilevel modeling. According to Bryk & Raudenbush (2002), the assumptions of error forms should be normally distributed in both level 1 and level 2. Suppose students' social class is in the multilevel piecewise regression model above. The key assumptions of the two-level Hierarchical Linear Model described above are that:

1.Each $e_{ij}$is independent and normally distributed with a mean of 0 and variance for every level 1 unit *i* within every level 2 unit *j,* meaning the students' social class is conditional and that the within-school errors are normal and independent with a mean of 0 in each school, as well as equal variance across schools.

2.The level1 predictors are independent of e_{ij} ,meaning the error term e_{ij} is independent of student social class.

3.The residual school effects U_{1j} , U_{2j} , U_{3j} , U_{4j} , U_{5j}, and $U_{(5+p)j}$ are assumed independent and normally distributed.

4.The predictors in level 2 are independent of U_{1j}, U_{2j}, U_{3j}, U_{4j}, U_{5j}, and $U_{(5+p)j}$, meaning the effects of any school predictors are excluded from the model for the intercept, and slopes are independent of the school characteristics.

5.The errors at level 1 and level 2 are also independent, meaning the error at level 1, e_{ij} is independent of the residual school effects of U_{1j}, U_{2j}, U_{3j}, U_{4j}, U_{5j}, and $U_{(5+p)j}$.

The five assumptions offer a systematic explanation of the inquiry of validity. The first two assumptions target the internal of the level 1 model. Meanwhile, assumptions 3 and 4 target the level 2 models. In contrast, the last two assumptions focus on cross-level associations. The discussion of the tenability of assumptions could be worthwhile for both the structural and random parts of the model. Regarding the structural part in Hierarchical Linear Models, the specification of the model should avoid predictors in the model associated with the component in the error term. Regarding the random part of the model, the assumption of independent errors with equal variances at both level 1 and level 2 would reduce the poor estimation of standard errors and inferential statistics (Bryk & Raudenbush, 2002).

2.3 The Estimation

In reference to the estimation approach, Raudenbush and Bryk (2002) detailed the estimation methods in HLM, including maximum likelihood (ML), restricted maximum likelihood (REML), and fully Bayesian estimation. Normally, the default setting for HLM software estimating is ML or REML (Raudenbush et al., 2000), while fully Bayesian estimation can be conducted by the R package (Lock, Kohli & Bose. 2018).

The foundation of ML estimation is to select parameter estimates in order to maximize the likelihood of the data (Ferron et al.,2004). ML estimation provides fixed and random components simultaneously by maximizing the likelihood function of the data (Corbeil & Searle, 1976). ML would have a better performance when sample sizes are large, as would many groups at level 2. However, when either or both the sample size and group number are small, the variances are biased (Raudenbush & Bryk, 2002). Owing to these limitations, REML would be recommended.

The estimation of variances is the main difference between ML and REML (Peugh, 2010). The variances in ML are estimated based on the assumption that they are measured without error because the fixed components were known. In contrast, the fixed components in REML were estimated when estimating variances. Because of the estimation difference, REML estimates can be considered as less biased when compared to ML estimates, especially when the sample contains a small number of groups.

Regarding Bayesian estimation, probability distributions are normally applied to model the reliability of possible parameter values. The application of prior and posterior distributions is the primary difference when comparing Bayesian estimation and the other estimation techniques discussed above (Boedeker, 2017). The first distribution is the prior distribution, and each possible parameter value is true before any new data analysis that is the modeling of prior belief. The prior belief can be drawn from previous research or theories. Data likelihood is the second distribution, and the data collected in a specified study offer the only source upon which the likelihood of parameter values may be based. The likelihood applied here was the same as ML and REML for the maximization. The third probability distribution, posterior, is the outcome of a Bayesian analysis. The probability of each possible parameter value was modeled as being true by the posterior, and the prior and likelihood are decided according to this approach.

The number of groups is the primary factor for deciding the estimation technique. If the dataset is small, the estimation of less-biased estimates can be produced by REML, when compared with ML. However, if a Bayesian estimation were applied, the posterior mode should be used as the variance estimate instead of the posterior mean (Browne & Draper, 2006). In this study, the dataset would come from the mathematics achievement of TIMSS (International Results in Mathematics and Science), which provides a large amount of both student data and school information. The group number will not be a concern of the restriction for certain estimation techniques.

2.4 The Interpretation

The non-linear trend of the data can be illustrated by a plot very similar to the electrocardiogram (EKG) graph. Here is a hypothetical illustration of the multilevel piecewise regression model discussed earlier (see Figure 2.1). In this graph, X has an effect of 2 on Y at X = 1; X has an effect of 4 on Y at X = 2; and X has an effect of -1 on Y at X = 3. The EKG graph has the advantage of showing specific effects on Y across values of X. For the illustration purpose, the segments were seemingly joined together at the turning points by the dotted line, but the discontinuity at the changepoint was expected, meaning those changepoints were not necessarily to join together.

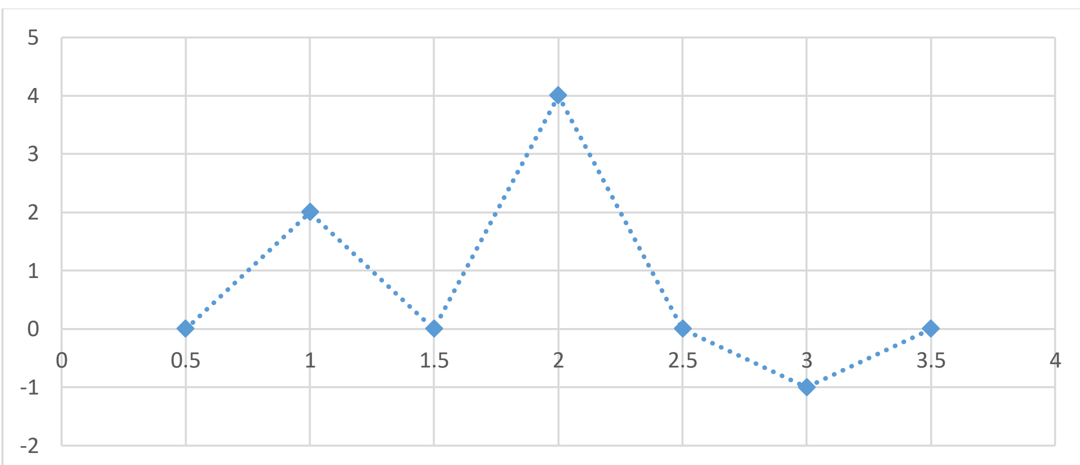

Figure 2.1 EKG Graph Showing Non-Linear Turning Points

Turning Point Showing Linear Positive Change. Because the EKG graph indicates specific effects on Y across values of X, non-linear (or linear) change can be easily detected. Figure 2.2 is a typical (traditional) linear positive change with a turning point at X = 3. There is an effect of 1 on Y at X=1 and X=2; X has an effect of 3 on Y at X = 3; X has an effect of 4 on Y at X = 4; and X has an effect of 5 on Y at X = 5. So, there is a linear positive change from X = 3 (turning point). When the number of X values increases, the linear positive change can be more easily detected.

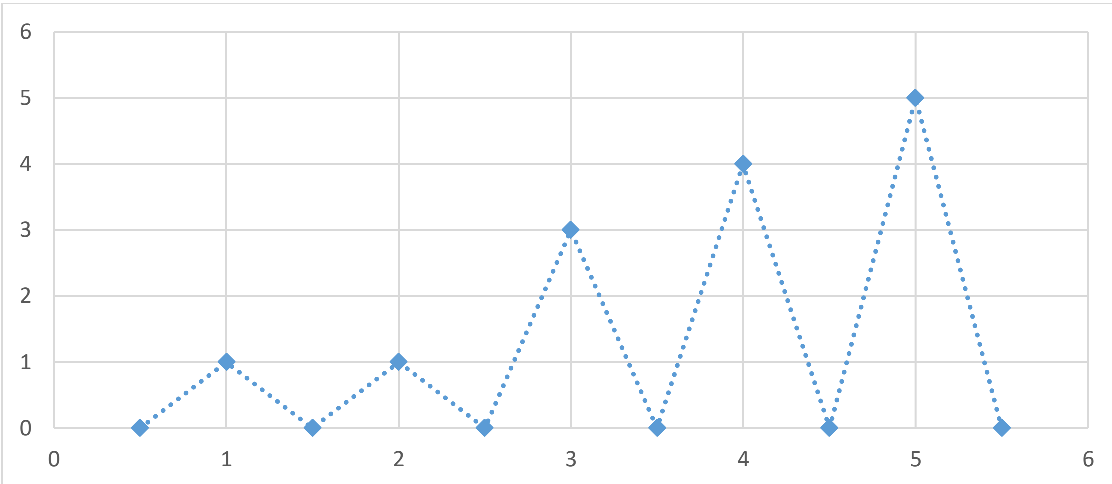

Figure 2.2 EKG Graph Showing Turning Point with a Linear Positive Change

Turning Point Showing Linear Negative Change. Figure 2.3 is a typical (traditional) linear negative change with a turning point at X = 4. X has an effect of -1 on Y at X=1, X has an effect of -2 on Y at X =2; X has an effect of -3 on Y at X = 3; X has an effect of -5 on Y at X = 4; and X has an effect of -5 on Y at X = 5. So, there is a linear negative change from X = 4 (turning point). When the number of X values increases, the linear negative change can be more easily detected.

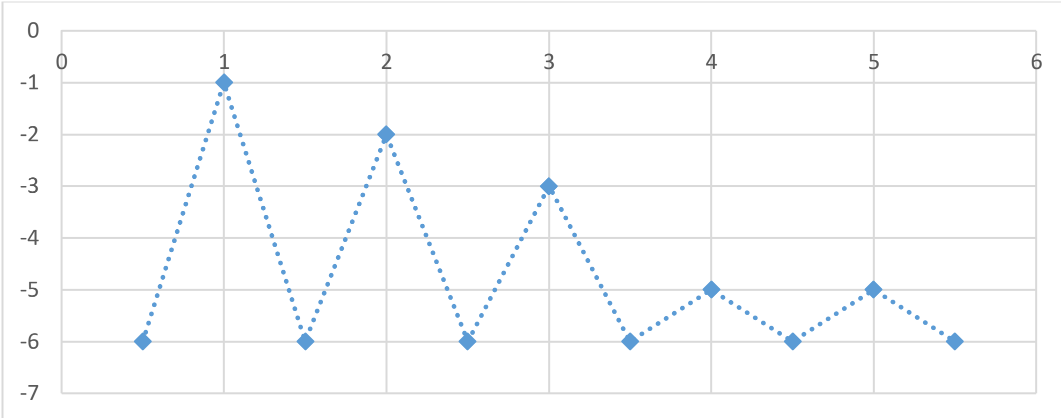

Figure 2.3 EKG Graph Showing a Turning Point with Linear Negative Change

Turning Point Showing Non-Linear Positive Change. Figure 2.4 is a non-linear positive change with a turning point at X = 3. X has an effect of 0.5 on Y at X=1; X has an effect of 1 on Y at X=2; X has an effect of 3 on Y at X = 3; X has an effect of 4 on Y at X = 4; and X has an effect of 5 on Y at X = 5. So, there are two linear positive changes (X = 1 and 2 versus X = 3, 4, and 5). However, the two linear changes show different rates. The two linear positive changes break at X = 3 (turning point). When the number of X values increases, the non-linear positive change can be detected more easily.

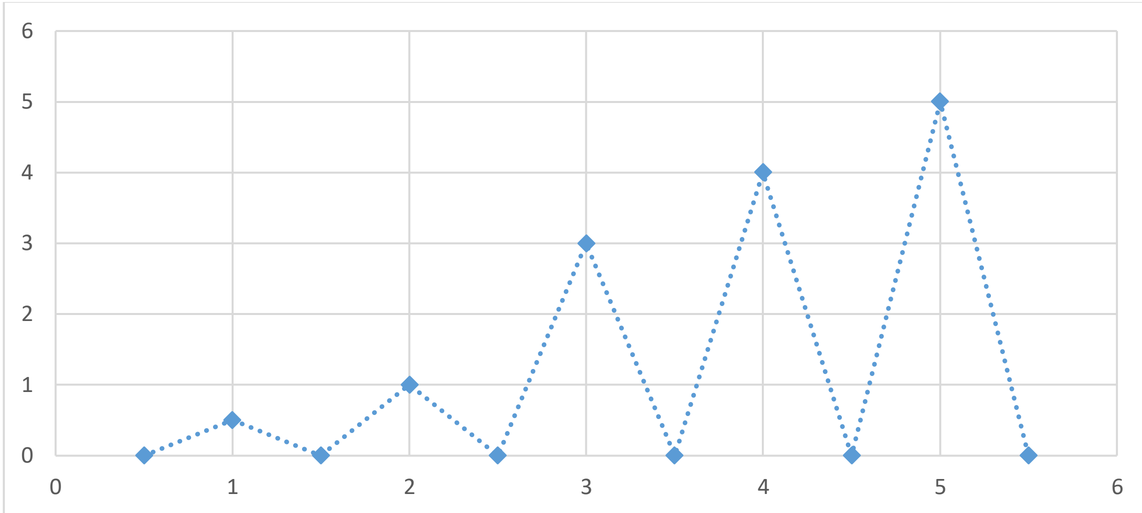

Figure 2.4 EKG Graph Showing a Turning Point with Non-Linear Positive Change

Turning Point Showing Non-Linear Negative Change. Figure 2.5 is a non-linear negative change with a turning point at X = 4. X has an effect of 5 on Y at X=1; X has an effect of 4.5 on Y at X=2; X has an effect of 4 on Y at X = 3; X has an effect of 1.5 on Y at X = 4; and X has an effect of 1 on Y at X = 5. So, there are two linear negative changes (X = 1, 2 and 3 versus X = 4 and 5). However, the two linear changes show different rates. The two linear negative changes break at X = 4 (turning point). When the number of X values increases, the non-linear negative change can be detected more easily.

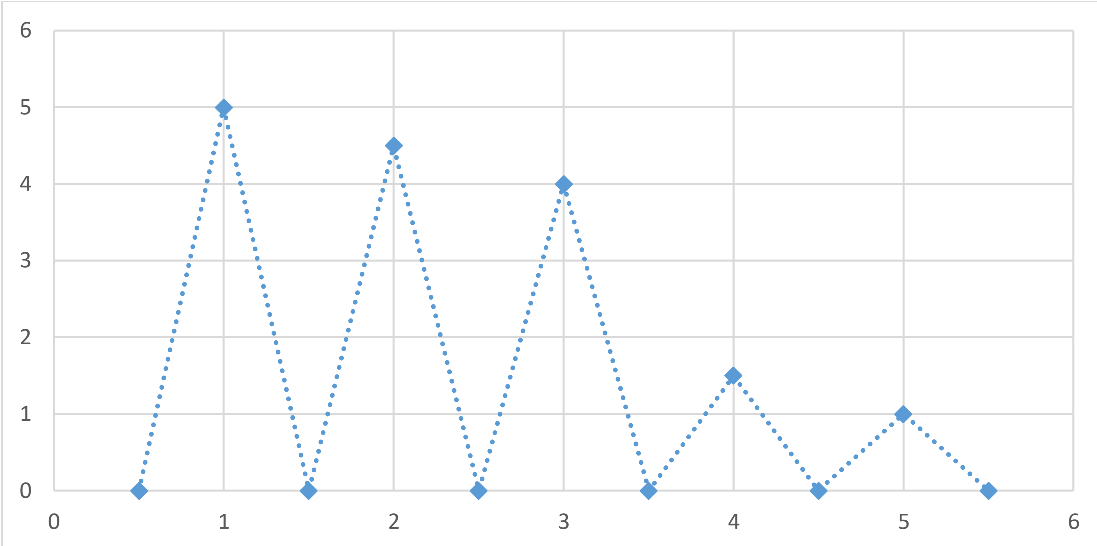

Figure 2.5 EKG Graph Showing a Turning Point with Non-Linear Negative Change

Turning Point Showing Non-Linear Mixed Change. Figure 2.6 is a non-linear mixed change with a turning point at X =3. X has an effect of 7 on Y at X=1; X has an effect of 6 on Y at X=2; X has an effect of 1 on Y at X = 3; X has an effect of 2 on Y at X = 4; and X has an effect of 4 on Y at X = 5. There is a non-linear mix change from X = 3 (turning point). So, there are two linear changes, one positive (X = 1 and 2) versus one negative (X = 3, 4, and 5), but the two linear changes show different rates. The two linear mix changes break at X = 3 (turning point). When the number of X values increases, the non-linear mix change can be detected more easily.

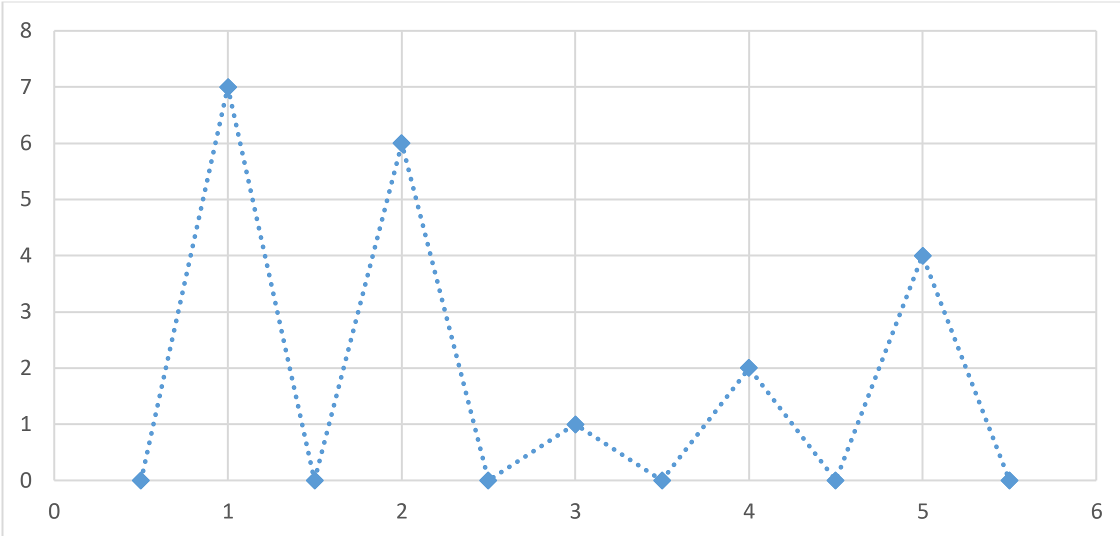

Figure 2.6 EKG Graph Showing a Turning Point with Non-Linear Mixed Change

The six figures show different patterns of the turning point. The coefficient of each point will be estimated in the new model, and the pattern can be identified by comparing each coefficient as the discussion in each figure. If the coefficient is significant for certain points, those points will be the expecting turning points.

CHAPTER 3. APPLICATION OF MULTILEVEL PIECEWISE REGRESSION

The purpose of this study is to introduce a new method to identify the turning point beyond the traditional piecewise regression as a completely non-linear approach. By building upon the strength of methodology while avoiding some limitations of traditional piecewise regression, this study applied the new model to a large assessment data, TIMSS (Trends in International Mathematics and Science Study). This chapter begins with the introduction of the data source and sample examined, identifying the variables applied in this study. The review of the three independent variables, Students Like Learning Mathematics (SLM), Student Confidence in Mathematics (SCM), and Self-Efficacy for Computer Use (SEC) on mathematics achievement enhances the practical contribution of this study and aims to provide a comprehensive understanding of the analytical procedure.

3.1 Data Source

Data used for this study is TIMSS 2019 United States sample. TIMSS is a project guided by the International Association for the Evaluation of Educational Achievement (IEA) (TIMSS 2007 Technical Report). Since 1995, TIMSS has collected and analyzed the data every four years (in 1995, 1999, 2003, 2007, 2011, 2015 and 2019), thus TIMSS 2019 is the seventh assessment circle. This project is a global assessment that evaluates international students' achievement in mathematics and science at two grade levels — grade four and grade eight. In 2019, TIMSS underwent a transition to computer-based assessment, meaning some countries have two options to organize their assessment — the new computer-based version (eTIMSS) and previous paper-and-pencil version (paperTIMSS). Sixty-four countries participated in TIMSS 2019. In this study, fourth graders in the U.S. are the focus sample. TIMSS collects data not only from students, but also from teachers and school principals. The measure includes home and classroom contexts, as well as school contexts.

3.2 TIMSS Sampling

According to TIMSS Technical Report, TIMSS adopted a rigorous sampling with a two-stage random sample design. The first stage chose a sample of schools. At the second stage, one or more entire class of students was selected from each school in the sampled schools. Each country provided its own plan for determining its target population under the TIMSS sampling procedure. The purpose was to achieve a sample that could represent schools and students nationally. In the United States, the sample size of fourth-graders was 8,776 students from 287 schools. Students enrolled in the fourth grade have four years of schooling, calculated from the baseline of ISCED (International Standard Classification of Education) Level 1(UNESCO, 2012), and the average age in the United States sample is 10.2 years. Since TIMSS 2019 was the beginning of the computer-based assessment (eTIMSS) for some countries, including the United States used in this study, an additional sample called "bridge" data was required to compare with the eTIMSS versions of the assessment. The "bridge" data was measured by a paper version of the trend items, which is considered as an equivalent data sample under the main data sampling settings. The bridge sample of the United States was 1,652 students from 79 schools. The population of the United States school is divided by poverty level (high or low), school type (public or private), census regions within public schools (west, midwest, northeast, south), and whether school funding is Catholic or non-Catholic within private schools. Within schools, schools are stratified by school location (city, suburb, town, rural), ethnicity status (proportion of non-white students is above or below 15%), and state (52).

3.3 Variables

TIMSS measured mathematics achievement by focusing on content and cognitive domains for both fourth graders and eighth graders. In this study, the outcome variable is mathematics achievement of the fourth graders. The content domains include number, measurement and geometry, and data. The cognitive domains include knowing, applying, and reasoning. For fourth graders, the assessment emphasis is number, and the introductory or pre-algebra topics are served as part of the number as well. The data domain focuses on collecting, reading, and representing data. The cognitive domains are the same for both grades; however, the fourth grade puts more emphasis on the knowing domain (Mullis & Martin, 2017). To minimize testing time, TIMSS applied a limited number of items to assess each student, which cannot produce accurate individual content-related scale scores but is sufficient to produce group content-related scores. Plausible values are transformed from these scores. TIMSS produces five mathematics achievement plausible values for each student. Since plausible values cannot be directly used as test scores, integration of the five plausible values is required to produce a student mathematics achievement score.

Independent variables included student and school levels in the TIMSS. Student-level variables included key predictor variables and student background variables as control variables. Key predictor variables pertain to student attitude toward mathematics learning with three variables, Students Like Learning Mathematics (SLM), Student

Confidence in Mathematics (SCM), and Self-Efficacy for Computer Use (SEC) on mathematics achievement. Student Like Learning Mathematics (SLM) was measured by a four-point Likert type scale containing nine items, and the item example is "I enjoy learning mathematics." Student Confidence in Mathematics (SCM) was measured by a four-point Likert type scale containing nine items. The item example was "I am good at using a computer."

Other student background variables and school level variables were control variables. Student background variables included student characteristics of gender, age, student socioeconomic status (SES), language at home, and immigration status. These variables partially explained individual differences in academic achievement (Ma et al., 2008). Specifically, gender was a binary measure of boy or girl. Age was a continuous variable, measured by year and month. Student SES measured home resource for learning. Language at home measured the use frequency of test language. Immigration status measured whether students were born in the test country (U.S. in this study). A detailed explanation for each student variable can be seen in Appendix 1.

School-level variables included school contextual variables and climate variables. Contextual variables were school location, school composition by socioeconomic background, and majority student proportion. Climate variables included institution affected by math resource shortage, school emphasis on academic success, as well as school discipline and safety. Specifically, school location measured the density of population of school area. School composition by socioeconomic background measured school facility of learning resource. Institution affected by math resource shortage measured by a four-point Likert type scale containing five items, and the sample item was

"Teachers with a specialization in mathematics." School emphasis on academic success was measured by a five-point Likert type scale containing 11 items, and the sample item was "Teacher's understanding of the school's curricular goals." School discipline and safety measured problems among students by a four-point Likert type scale containing 10 items. The sample item was "Arriving late at school." A detailed explanation for each school variable can be seen in Appendix 2.

3.4 Review of Mathematics Attitude and Mathematics Achievement

Mathematics attitude was defined as a positive or negative inclination toward mathematics (Hart 1989). Positive attitude is considered as important as mathematics knowledge to acquire a better mathematics achievement (Tarmizi & Tarmizi, 2010.) Researchers claimed that factors of students, families, and schools would affect students' mathematics attitude as much as their mathematic achievement. Generally, gender is a factor with much controversy. Boys are normally expected to have a more positive attitude than girls (Nosek et al., 2002), whereas there is no significant attitude difference (Orhun, 2007) or mathematics outcome difference (Lindberg et al., 2010) found between gender. Otani (2020) indicates that parental involvement has an indirect effect on mathematics achievement through influencing students' attitudes toward mathematics. Mathematics classroom instructions also play a role in students' attitude toward this subject (Bakar et al., 2010). Teachers' instruction methods in the classroom affect students' mathematics attitude (Akinsola & Olowojaiye, 2008). In addition, technology use in a mathematics class can increase students' interest in remaining in the classroom (Eyyam & Yaratan, 2014). A meta-analysis of 46 studies examining the relationship between computer technology and mathematic instruction in K-12 classrooms showed a positive computer technology effect on mathematics achievement (Li & Ma, 2010).

TIMSS 2019 measured mathematics attitude from two aspects, Student Likes Learning Mathematics (SLM) and Student Confidence in Mathematics (SCM). These two variables are generated from two subscales in the student questionnaire. According to Key (1993), mathematics attitude measurement should consist of three domains—cognitive, behavior, and emotion. Items in TIMSS 2019 represent the three aspects independently (e.g., "I learn things quickly in mathematics," "I learn many interesting things in mathematics," and "Mathematics makes me nervous"). Ma & Kishor (1997) demonstrated the relationship between attitude towards mathematics and achievement in mathematics through a meta-analysis by testing 113 relevant studies, with the results showing a moderate positive relationship. Al-Mutawah & Fateel (2018) found a positive and significant correlation between attitude and academic achievement in mathematics by examining TIMSS 2011 Bahrain sample. Students' confidence and interest in mathematics also have a positive effect on mathematics achievement (Kadijević, 2008). Çiftçi & Yildiz (2019) analyzed 336 dependent studies of TIMSS assessment data from 2003 to 2015, and their research offered more evidence that students' confidence in mathematics is crucial in mathematics learning, indicating a positive and moderate effect on mathematics achievement.

3.5 Review of Computer Self-Efficacy and Mathematics Achievement

Computer self-efficacy has been conceptualized as a person's capability to manage computer-related tasks and perform computer-based skills (Liao et al., 2018; Murphy et al., 1989). Gurcan (2005) indicated that computer self-efficacy would influence individuals' interests and desire to use computers as a tool and also affect students' determination to overcome difficulties when encountering computer-related challenges. In addition, computer self-efficacy significantly affected the computer use outcome expectations of individuals, their computer practice, and their emotions related to computer use (Compeau & Higgins, 1995). Individuals with higher computer self-efficacy would expect higher performance and further increase their time spending on computers. Meanwhile, their positive attitude towards computer use can reduce their computer anxiety (Martocchio 1994).

TIMSS 2019 measured computer self-efficacy by variable Student Self-Efficacy for Computer Use (SEC). This variable is generated from one additional subscale for students taking E-TIMSS, which is a computer-based test. According to Liao et al., (2018), self-efficacy is measured in three dimensions: magnitude, strength, and generalizability. Items in TIMSS 2019 represent the three aspects independently (e.g., "I can use a touchscreen on a computer, tablet, or smartphone," "It is easy for me to find information on the internet," and "I am good at using a computer.") Regarding students' academic achievement, researchers found that students with higher computer self-efficacy were more likely to use computers and learn related skills. (Hill, et al., 1987). Chen (2017) provided additional evidence that computer self-efficacy had a positive effect on learning performance and engagement. Moreover, a mathematics outcome comparison between the experimental group (computer-based test) and the control group (paper-based test) showed that computer self-efficacy had a positive effect on mathematics learning outcomes

(Nurhikmah et al., 2021). Students with higher computer self-efficacy skills would obtain better mathematics learning outcomes using the computer-based test.

The literature review of the student's confidence, interest or computer self-efficacy on mathematics indicated a positive or moderate positive effect on mathematics achievement. These studies consider the psychological variables of confidence of mathematics, interest in mathematics or computer self-efficacy on mathematics as a whole, meaning they can only explain the relationships in general, showing positive or negative effects. The new model will precisely estimate under which level of these psychological variables the best mathematics achievement change will show up. The development of this new model will explore more detailed research questions for future study, which would be an extension of the relationship between mathematics attitude and mathematics achievement, as well as computer self-efficacy and mathematics achievement.

3.6 Analytical Procedure

The TIMSS sampling procedure provides data hierarchy for students nested within schools. Considering the data hierarchy, a two-level, multi-level piecewise regression model would be used to seek the threshold of mathematics attitude and computer self-efficacy level for the outcome of mathematics learning. Students Like Learning Mathematics (SLM), Student Confidence in Mathematics (SCM), and Self-Efficacy for Computer Use (SEC) on mathematics achievement will be used to examine the effect on the outcome variable Y, mathematics achievement. The first-level model will focus on the student model, and the second-level model will focus on the school model. Data analysis will proceed in three steps, building a null model in the first step, and a full model in the second and third step.

In the first step, a null model will be built without any independent variable at level one (student level) and level two (school level). The model contains only the outcome variable, measuring the variance within and between schools for mathematic achievement. Afterwards, a two-step full model will be built. In the second step, student variables will be included in the null model, in order to test at what point the coefficient becomes significant after controlling all other student covariates in the model. The specific point will be the threshold effect of mathematics confidence on students' mathematics achievement, meaning the greatest change of mathematics outcome happens at this point. The last step is to model school-level variables that include school climate and context variables. The purpose is to analyze the effects of school-level variables in addition to the student variables.

Plausible values integration is a necessity for the five plausible values of mathematics outcome of TIMSS 2019, since plausible values cannot be directly used as test scores. The application of the matrix sample technique split a long list of items into a limited number of items. In order to reduce the test time as well as students' burden, each student only finished one small test out of the whole test booklet. The five plausible values for each student are randomly drawn from an empirically derived distribution of scores. Students' responses to the items and their background have been taken into consideration for the scores. The integration of each plausible value follows four steps.

The first step is the parameter estimation. The resulting parameter is estimated and then averaged. This average is the "real" parameter estimate.

$$t^* = \frac{\sum_{m=1}^{M} \hat{t}_m}{M}$$

Secondly, the resulting variance of the parameter estimates is averaged.

$$U^* = \frac{\sum_{m=1}^{M} U_m}{M}$$

Thirdly, the variability of these parameter estimates is calculated.

$$B^* = \frac{\sum_{m=1}^{M} (\widehat{t}_m - t^*)}{M - 1}$$

Finally, the variance of the "real" parameter estimate is calculated. The standard error is the square root of this final variance.

$$V = U^* + (1 + \frac{1}{M})\, B_m$$

After integration, plausible values can be specified in HLM, then the model can be viewed as a regular HLM model.

CHAPTER 4. RESULTS

4.1 Descriptive Statistics of Student and School Characteristics

At the student level, among 8,776 students, 49% were girls, 93% were born in the U.S., 64% always spoke English at home, and the mean age was 10.25 (SD = .43). Student SES was measured by the number of books at home—42% of students had less than 25 books at home, 32% of students had books amount between 25 to 100 books, and 26% of students had more than 100 books. Moreover, the mean Student Likes Learning Mathematics (SLM) was 9.86 (SD = 2.18), more than 60% of students below the average score of SLM. Mean Student Confidence in Mathematics (SCM) was 10.00 (SD = 2.09), with more than 60% of students below the average score of SCM. Mean Self-Efficacy for Computer Use (SEC) was 10.14 (SD = 1.81), and more than 40% students below of the average score of SEC. (see Table 1).

At the school level, among 261 schools, 61% of schools had a proportion of socioeconomic disadvantage background larger than 50%, and 79% of schools had a proportion of white students larger than 50%. Regarding the school location, 19% of schools were located in the urban area, which was densely populated; 51% of schools were located in the suburban area, which was on the fringe or outskirts of urban area; and the rest of the schools (30%) were located in the medium-sized city or large town, small town, village or remote rural area. Moreover, the mean score of Instruction Affected by Math Resource Shortage was 11.38 (SD = 2.35), mean score of School Emphasis on Academic Success was 10.05 (SD = 2.38), and mean score of School Discipline was 9.85 (SD = 1.47). (See Table 1).

Table 1 Descriptive Statistics of Independent Variables at Student and School Level

Variables	Mean	SD
Student-level variables (N = 8776)		
Age (continuous)	10.25	0.43
Gender (male = 0, female = 1)	0.49	0.01
Immigration status (yes = 1, no = 0)	0.93	0.27
Less Books at Home (vs. Median Books at Home)	0.42	0.49
More Books at Home (vs. Median Books at Home)	0.26	0.44
Home Language (English = 1, others = 0)	0.64	0.48
SLM (Student Likes Learning Mathematics)	9.68	2.18
SLM 20 percentile (3.85-7.98)	6.75	1.23
SLM 40 percentile (7.98-8.96)	8.57	0.28
SLM 60 percentile (8.96-9.97)	9.53	0.30
SLM 80 percentile (9.98-11.74)	10.97	0.56
SLM 100 percentile (11.76-13.14)	13.13	0.08
SCM (Student Confidence in Mathematics)	10.00	2.09
SCM 20 percentile (2.80-8.30)	7.56	0.90
SCM 40 percentile (8.31-9.19)	8.75	0.22
SCM 60 percentile (9.20-10.11)	9.67	0.31
SCM 80 percentile (10.12-11.70)	10.99	0.48
SCM 100 percentile (11.74-14.41)	13.70	0.90
SEC (Self-Efficacy for Computer Use)	10.14	1.81
SEC 20 percentile (3.29-8.49)	7.75	0.85
SEC 40 percentile (8.49-9.79)	9.38	0.37
SEC 60 percentile (9.83-10.39)	10.38	0.05
SEC 80 percentile (10.56-11.23)	11.22	0.05
SEC 100 percentile (11.43-12.92)	12.91	0.09

School-level variables (N = 261)		
Instruction Affected by Math Resource Shortage (continuous)	11.38	2.35
School Emphasis on Academic Success (continuous)	10.05	2.38
School Discipline (continuous)	9.85	1.47
School Composition by Socioeconomic Background Disadvantage Proportion (> 50% = 1, < 50% = 0)	0.61	0.49
Majority Student Proportion (> 50% = 1, < 50% = 0)	0.79	0.41
School Location-Urban (vs. others)	0.19	0.39
School Location-Suburban (vs. others)	0.51	0.50

4.2 The Null Model

The following steps of analysis aimed to address the second research question regarding whether there is a turning point that reflects the best mathematics outcome change when students maintain a specified degree of Students Like Learning Mathematics (SLM), Student Confidence in Mathematics (SCM), or Self-Efficacy for Computer Use (SEC).

The null model was following the traditional two-level multilevel model that included only the dependent variable.

Level-1 Model

$$\boldsymbol{S1_{ij}} = \beta_{\boldsymbol{0j}} + \boldsymbol{r_{ij}}$$

Level-2 Model

$$\beta_{0j} = \gamma_{00} + u_{0j}$$

For the interpretation purpose, the plausible values were standardized based on the TIMSS scales reports that set the mean of the U.S. average scores to 500 and with a standard deviation of 100. The purpose of the null model was to test the model performance by calculating the Pseudo R2, which is the proportion of variance that would be explained by the new model.

$$Pseudo\ R^2 = \frac{Var_{null} - Var_{new}}{Var_{null}}$$

4.3 The Two-Steps Full Model

There were two steps in building the new models after the null model was specified. The first step was to build new models by adding three independent variables, Students Like Learning Mathematics (SLM), Student Confidence in Mathematics (SCM), and Self-Efficacy for Computer Use (SEC) respectively. Based on the continuous scale score, the three independent variables mentioned above were divided into five points with an interval of 20 percentile. For example, the five points of SLM, SLM 1 to SLM 5 represented each interval before the point at the 20th, 40th, 60th, 80th, and 100th percentile, respectively (See Table 1). Since the purpose of the new model was to compare each point of the independent variable, the intercept was removed from the model to generate the pattern of effect of the five points. (See Chapter 2 regarding the model specification.) For each independent variable, SLM, SCM, and SEC, the five points effect was estimated, and the results of the step one model can be seen in Table 2. The second step was to add control variables: student characteristics at level one and school characteristics at level two. The results of the five points effect can be seen in Table 3. The purpose of setting up two steps in building full models was to estimate the unique contribution of SLM, SCM, and SEC.

4.3.1 Students Like Learning Mathematics as the Independent Variable

4.3.1.1 Pattern Identification

Table 2 showed the results of the effect of each point after adding SLM without school and student characteristics. All effects were significant and showed a non-linear positive change pattern as discussed in Chapter 1. Figure 4.1 illustrated this pattern with a turning point at X = 4; X had an effect of 0.13 on Y at X = 1; X had an effect of 0.22 on Y at X = 2; X had an effect of 0.34 on Y at X = 3; X had an effect of 0.57 on Y at X = 4; X had an effect of 0.6 on Y at X = 5. So, there were two linear positive changes (X = 1, 2, and 3 versus X = 4 and 5). The two linear changes showed different rates and the positive changes break at X = 4 (turning point).

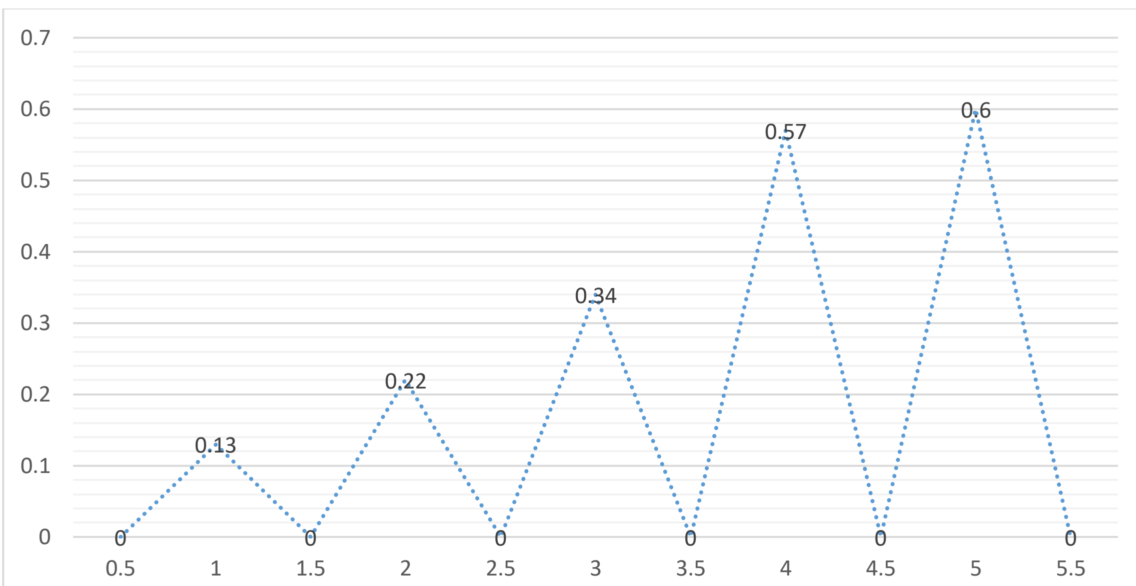

Figure 4.1 EKG Graph of the Trend of SLM without Control of School and Student Characteristics

The second step was adding student and school characteristics into level 2 as the full model. Table 3 showed that all effects were significant as well, but a non-linear mix change pattern was illustrated in Figure 4.2, with a turning point at X = 4; X has an effect of 0.23 on Y at X = 1; X has an effect of 0.3 on Y at X = 2; X has an effect of 0.35 on Y at X = 3; X has an effect of 0.67 on Y on Y at X = 4; X has an effect of 0.66 on Y at X = 5. So, there was one linear positive change (X = 1, 2, and 3) and one linear negative change (X = 4 and 5). The two linear changes showed different rates and the mix changes break at X = 4 (turning point). The step two model (full model) showed a different pattern of the second line composed by X = 4 and 5, which was a decreasing trend (negative change) compared with the step one model with an increasing trend (positive change).

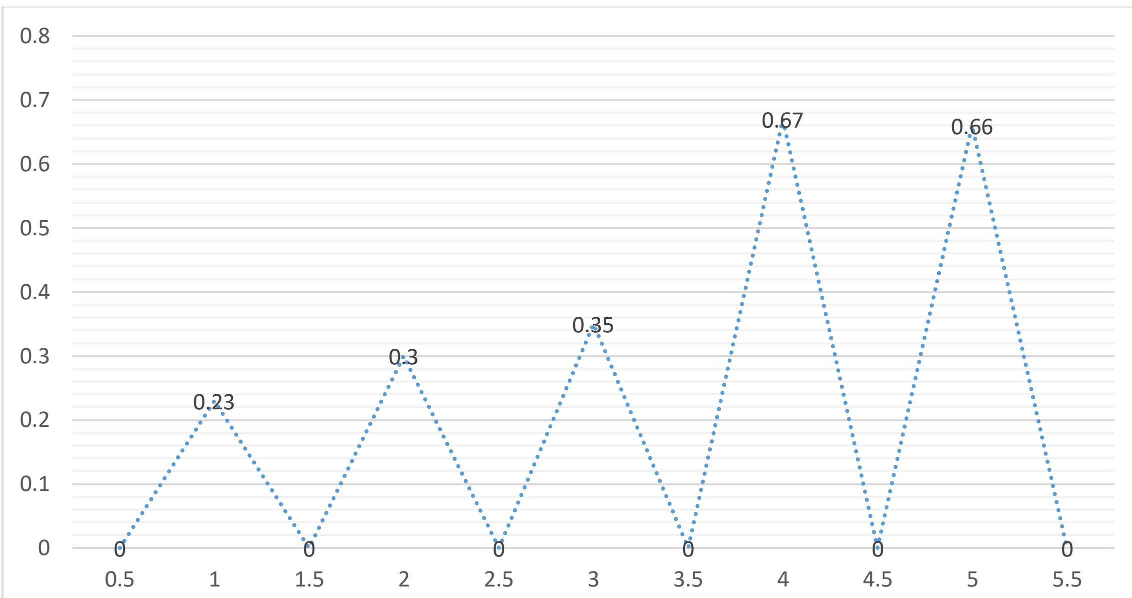

Figure 4.2 EKG Graph of the Trend of SLM with Control of School and Student Characteristics

4.3.1.2 Neighborhood Comparison

The neighborhood effect comparison aimed to test if the effect difference between the two points were significant. Table 4 showed that the first three pairs of comparisons under SLM were all significant in the step one model (the model without control of student-level and school-level variables). However, the last pair of the comparison was not significant, meaning the effect of SLM 4 was not different from SLM 5. This is a clear indication that SLM 4 represented a turning point, which is consistent with the results in Figure 4.1. In the step two model (the model with the control of student-level and school-level variables), the significant comparison was the third pair, which is between SLM 3 and SLM 4, meaning the effect of SLM3 was different from SLM 4. Whereas, the comparison between SLM 4 and SLM 5 was not significant. This is a clear indication that SLM 4 represented a turning point, which is consistent with the results in Figure 4.2. The results of the neighborhood compassion provided more evidence, based on statistical significance tests, to verify SLM 4 (X = 4) as the turning point, which is also consistent with the former discussion.

4.3.1.3 Model Performance

Table 5 illustrated the model performance of the two steps. The step one model overall explained 8.4% of the variance in level one. Regarding each SLM point, they explained 64%, 58.6%, 56.2%, 60.8%, and 70% of the variance, which was the unique contribution of the variable SLM. The step two model overall explained 19.8% of the variance in level one. Regarding each SLM point, they explained 65.7%, 67.2%, 57%, 64.3%, and 64.2% of the variance in the full model.

4.3.2 Students Confident in Mathematics as the Independent Variable

4.3.2.1 Pattern Identification

The results of the effect of each point after adding SCM without school and student characteristics were also shown in Table 2, all effects except SCM 2 were significant and showed a non-linear positive change pattern. Figure 4.3 illustrated this pattern with a turning point at X = 3; X has an effect of -0.14 on Y at X = 1; X has an effect of 0.03 on Y at X = 2; X has an effect of 0.4 on Y at X = 3; X has an effect of 0.72 on Y at X = 4; X has an effect of 0.91 on Y at X = 5. So, there was one non-linear positive change (X = 1, 2, and 3) and one linear positive change (X = 4 and 5). The two mix changes showed different rates and the positive changes break at X = 3 (turning point).

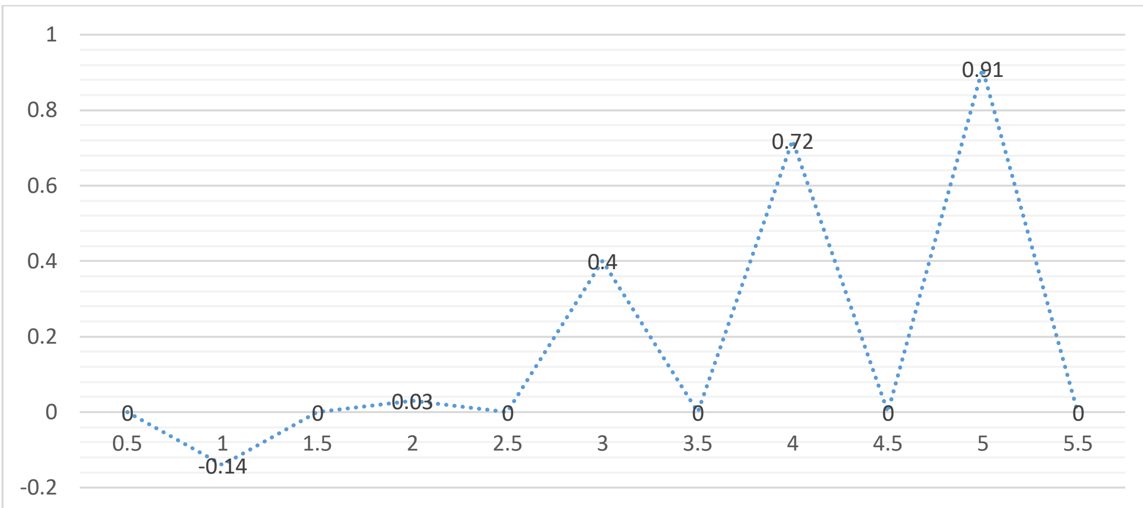

Figure 4.3 EKG Graph of the Trend of SCM without Control of School and Student Characteristics

The second step was adding student and school characteristics into level 2 as the full model. Table 3 showed that not all effects were significant, SCM 1 and SCM 2 were not significant. However, the non-linear mix change pattern remained as the step one model. Figure 4.4 illustrated this pattern with a turning point at X = 3. This trend was more apparent when compared with Figure 4.3; X had an effect of -0.05 on Y at X = 1; X had an effect of 0.1 on Y at X = 2; X had an effect of 0.49 on Y at X = 3; X had an effect of 0.75 on Y at X = 4; X had an effect of 0.83 on Y at X = 5. So, there was one non-linear positive change (X = 1, 2, and 3) and one linear positive change (X = 4 and 5). This mix-change pattern showed different rates and the mix changes break at X = 3 (turning point). The step two model (full model) showed the same pattern of the trend as the step one model, also indicating the turning point (X = 3) much clearer than the step one model.

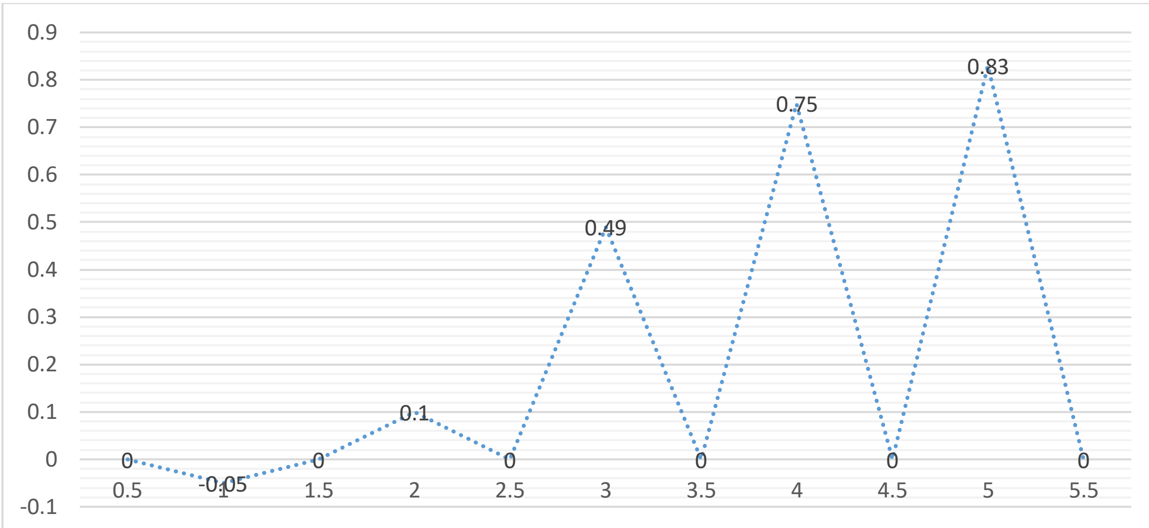

Figure 4.4 EKG Graph of the Trend of SCM with Control of School and Student Characteristics

4.3.2.2 Neighborhood Comparison

The neighborhood effect comparison under SCM can be seen in Table 4, which showed that four pairs of comparisons under SCM were all significant in the step one model. This is a clear indication that SCM 3 represented a turning point, which is consistent with the results in Figure 4.3. In the step two model, the significant comparison was the second pair, which was between SCM 2 and SCM 3, and the third pair, which was between SCM 3 and SCM 4. This is a clear indication that SCM 3 represented a turning point, which is consistent with the results in Figure 4.4. The results of the neighborhood compassion provided more evidence, based on statistical significance tests, to verify SCM 3 (X = 3) as the turning point, which is also consistent with the former discussion.

4.3.2.3 Model Performance

Table 5 illustrated the model performance of the two steps. The step one model overall explained 27.9% of the variance in level one. Regarding each SCM point, they explained 69.1%, 66.4%, 70.8%, 75.3%, and 74.4% of the variance, which was the unique contribution of the variable SCM. The step two model overall explained 35.2% of the variance in level one. Regarding each SCM point, they explained 71.8%, 67.2%, 57%, 64.3%, and 64.2% of the variance in the full model.

4.3.3 Self-Efficacy for Computer Use as the Independent Variable

4.3.3.1 Pattern Identification

The results of the effect of each point after adding SEC without school and student characteristics were also shown in Table 2, all effects were significant and showed a non-linear mix-change pattern. Figure 4.5 illustrated this pattern with a turning point at X = 2; X has an effect of 0.14 on Y at X = 1; X has an effect of 0.38 on Y at X = 2; X has an effect of 0.46 on Y at X = 3; X has an effect of 0.49 on Y at X = 4; X has an effect of 0.4 on Y at X = 5. So, there was one non-linear positive change (X = 1, 2, and 3), and one linear negative change (X = 4 and 5). The mix-change showed different rates and the mix-changes break at X = 2 (turning point).

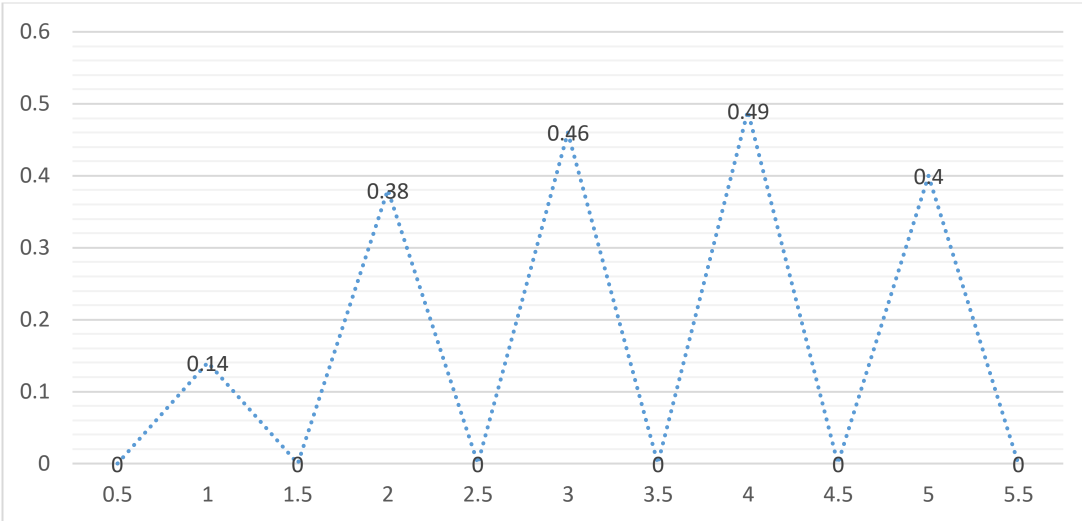

Figure 4.5 EKG Graph of the Trend of SEC without Control of School and Student Characteristics

The second step was adding student and school characteristics into level 2 as the full model. Table 3 showed that all effects were significant, and the non-linear mix-change pattern remained as the step one model. Figure 4.6 illustrated this pattern with a turning point at X = 2; X had an effect of 0.28 on Y at X = 1; X had an effect of 0.51 on Y at X = 2; X had an effect of 0.59 on Y at X = 3; X had an effect of 0.57 on Y at X = 4; X had an effect of 0.42 on Y at X = 5. So, there was one non-linear positive change (X = 1, 2, and 3) and one linear negative change (X = 4 and 5). This mix-change pattern showed different rates and the mix changes break at X = 2 (turning point). The step two model (full model) showed the same pattern of the trend as the step one model, also confirming the turning point (X = 2) as discussed in step one model.

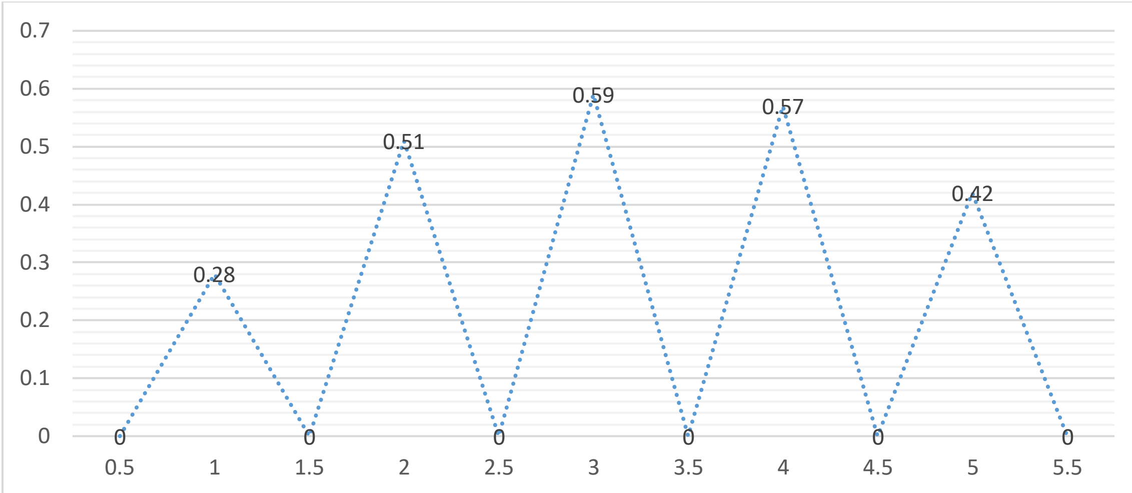

Figure 4.6 EKG Graph of the Trend of SEC with Control of School and Student Characteristics

4.3.3.2 Neighborhood Comparison

The neighborhood effect comparison under SEC can be seen in Table 4, which showed that, except for the third pair, the other three pairs of comparisons under SEC were all significant in the step one mode. This is a clear indication that SEC 2 represented a turning point, which is consistent with the results in Figure 4.5. In the step two model, the only significant comparison was the first pair, which was between SEC 1 and SEC 2, meaning the effect of SEC 1 was much different from SEC 2; whereas, the comparison between SEC 2 and SEC 3 was not significant. This is a clear indication that SEC 2 represented a turning point, which is consistent with the results in Figure 4.6. The results of the neighborhood compassion provided more evidence, based on statistical significance tests, to verify SEC 2 (X = 2) as the turning point, which is also consistent with the former discussion.

4.3.3.3 Model Performance

Table 5 illustrated the model performance of the two steps. The step one model overall explained 4.7% of the variance in level one. Regarding each SEC point, they explained 51.2%, 69.3%, 70%, 68.5%, and 60.6% of the variance, which was the unique contribution of the variable SEC. The step two model overall explained 17.1% of the variance in level one. Regarding each SCM point, they explained 49.3%, 64%, 62.9%, 69.1%, and 62.5% of the variance in the full model.

Table 2 Multilevel Piecewise-Regression Modeling of Student Psychological Measure Change Patterns without Control of School and Student Characteristics

Fixed Effects	Effect	SE	
SLM (Students Like Learning Mathematics)			
SLM 1	0.13*	0.03	
SLM 2	0.22*	0.04	
SLM 3	0.34*	0.04	
SLM 4	0.57*	0.03	
SLM 5	0.60*	0.03	
SCM (Students Confident in Mathematics)			
SCM 1	-0.14*	0.04	
SCM 2	0.03	0.03	
SCM 3	0.40*	0.03	
SCM 4	0.72*	0.03	
SCM 5	0.91*	0.03	
SEC (Self-Efficacy for Computer Use)			
SEC 1	0.14*	0.04	
SEC 2	0.38*	0.03	
SEC 3	0.46*	0.03	
SEC 4	0.49*	0.04	
SEC 5	0.40*	0.04	
Random effects	Variance	$\chi2$	df
SLM (Students Like Learning Mathematics)			
SLM 1	0.19*	796.59	231
SLM 2	0.22*	938.66	231
SLM 3	0.23*	875.97	231
SLM 4	0.21*	907.89	231
SLM 5	0.16*	584.92	231
SCM (Students Confident in Mathematics)			
SCM 1	0.16*	874.76	234
SCM 2	0.18*	924.13	234
SCM 3	0.15*	830.70	234
SCM 4	0.13*	698.55	234
SCM 5	0.14*	621.43	234
SEC (Self-Efficacy for Computer Use)			
SEC 1	0.26*	950.28	231
SEC 2	0.16*	872.82	231
SEC 3	0.16*	523.12	231
SEC 4	0.17*	504.39	231
SEC 5	0.21*	781.88	231

Note. * $p < 0.05$.

Table 3 Multilevel Piecewise-Regression Modeling of Student Psychological Measure Change Patterns with Control of School and Student Characteristics

Fixed Effects	Effect	SE	
SLM (Students Like Learning Mathematics)			
SLM 1	0.23*	0.11	
SLM 2	0.30*	0.09	
SLM 3	0.35*	0.10	
SLM 4	0.67*	0.09	
SLM 5	0.66*	0.09	
SCM (Students Confident in Mathematics)			
SCM 1	-0.05	0.09	
SCM 2	0.10	0.08	
SCM 3	0.49*	0.09	
SCM 4	0.75*	0.08	
SCM 5	0.83*	0.08	
SEC (Self-Efficacy for Computer Use)			
SEC 1	0.28*	0.11	
SEC 2	0.51*	0.08	
SEC 3	0.59*	0.10	
SEC 4	0.57*	0.10	
SEC 5	0.42*	0.09	
Random effects	**Variance**	**$\chi 2$**	**df**
SLM (Students Like Learning Mathematics)			
SLM 1	0.18*	212.02	152
SLM 2	0.17*	218.21	152
SLM 3	0.23*	226.22	152
SLM 4	0.19*	229.24	152
SLM 5	0.19*	198.81	152
SCM (Students Confident in Mathematics)			
SCM 1	0.15*	241.55	157
SCM 2	0.16*	238.25	157
SCM 3	0.15*	221.25	157
SCM 4	0.14*	214.55	157
SCM 5	0.14*	214.38	157
SEC (Self-Efficacy for Computer Use)			
SEC 1	0.27*	263.12	151
SEC 2	0.19*	232.08	151
SEC 3	0.20*	223.41	151
SEC 4	0.16*	221.76	151
SEC 5	0.20*	233.23	151

Note. * $p < 0.05$.

Table 4 Multilevel Modeling of Student Psychological Measure Change Points Neighboring Comparison Without and With Control of School and Student Characteristics

	Step1 Model		Step 2 Model	
	t	SE	t	SE
SLM				
SLM 1 vs SLM 2	0.09*	0.02	0.07	0.09
SLM 2 vs SLM 3	0.13*	0.03	0.05	0.09
SLM 3 vs SLM 4	0.22*	0.03	0.32*	0.10
SLM 4 vs SLM 5	0.03	0.03	0.00	0.09
SCM				
SCM 1 vs SCM 2	0.17*	0.03	0.15	0.10
SCM 2 vs SCM 3	0.37*	0.03	0.40*	0.09
SCM 3 vs SCM 4	0.31*	0.02	0.25*	0.09
SCM 4 vs SCM 5	0.19*	0.03	0.11	0.10
SEC				
SEC 1 vs SEC 2	0.25*	0.03	0.23*	0.09
SEC 2 vs SEC 3	0.07*	0.03	0.08	0.08
SEC 3 vs SEC 4	0.04	0.03	-0.03	0.11
SEC 4 vs SEC 5	-0.10*	0.03	-0.15	0.09

Note. The comparison of neighboring points is in terms of effects on the outcome.

Table 5 Proportion of Variance Explained (R2) for Multilevel Piecewise-Regression Modeling of Student Psychological Measure Change Patterns

Multilevel Piecewise-Regression Models	Step1 Model	Step2 Model
SLM (Students Like Learning Mathematics)	0.084	0.198
SLM 1	0.640	0.657
SLM 2	0.586	0.672
SLM 3	0.562	0.570
SLM 4	0.608	0.643
SLM 5	0.700	0.642
SCM (Students Confident in Mathematics)	0.279	0.352
SCM 1	0.691	0.718
SCM 2	0.664	0.699
SCM 3	0.708	0.718
SCM 4	0.753	0.736
SCM 5	0.744	0.736
SEC (Self-Efficacy for Computer Use)	0.047	0.171
SEC 1	0.512	0.493
SEC 2	0.693	0.640
SEC 3	0.700	0.629
SEC 4	0.685	0.691
SEC 5	0.606	0.625

CHAPTER 5. DISCUSSION

Some studies in recent years have explored the methods of identifying the turning points when dealing with the non-linear relationship. I have discussed the four approaches in Chapter One, the eyeball approach, the establishment approach, the theory-driven approach, and the data-driven approach for seeking the turning points. However, each approach applies only under certain circumstances, with restrictions such as the suitable data structure, theory-defined breakpoints, or complicated procedures for uncertain turning points. The four approaches mentioned above are also under the traditional piecewise regression framework, lacking the flexibility to interpret the data details and reconstruct the data format that meets the research purpose. Thus, the main goal of this study was to develop a new method to identify the turning point in a completely non-linear approach and beyond the traditional piecewise regression. The primary research questions as guidance for the analysis are as follows:

1. Is there is a more "natural" way to check the turning point for non-linear relationships of X on Y that is suitable for multilevel data structures, such as students nested within classrooms or schools?
2. Regarding the application of mathematics education, is there is a turning point that reflects the best mathematics outcome change when students maintain a specified category of SLM, SCM, or SEC?

In this chapter, I first summarize the present approach to identifying a turning point under the multilevel framework introduced in Chapter Two. Then, I discuss the strength and limitations of the present approach. I also discuss the application of the present approach based on practical considerations presented in Chapter Three. Next, I summarize the empirical findings from the application and their implications. I end this chapter by discussing future research.

5.1 Review of the Present Approach to Identify a Turning Point

The present approach, a multilevel piecewise regression, was under the format of a two-level HLM model. Taking the example of a data structure with students nested within schools, the first level was focused on the students, and the second level was focused on schools. The multilevel piecewise regression reconstructed the traditional piecewise regression by applying dummy coding to represent each measuring point. The student (level-1) model was a set of separate piecewise regressions, one for each school. Also, all the individual variables were controlled in level 1, and all the school variables were controlled in level 2. This model included all the potential turning points and allowed testing these turning points individually, which was discussed in Chapter Two. The assumptions of the multilevel piecewise regression were also the same as the two-level HLM model. Regarding the estimation method, the software conducting the statistical analysis was HLM 8, and the default setting for estimation was the maximum likelihood (ML) suitable for a large sample size and group number. This study used the U.S. data in TIMSS 2019 measuring international results in mathematics and science. TIMSS 2019 provided a large amount of data for student assessment, as well as student and school information. Compared with the traditional piecewise regression, the interpretation of the present approach provided the effect change of each turning point and the neighborhood comparison, while illustrating the non-linear trend of the data by the plot, which is very similar to the electrocardiogram (EKG) graph.

5.2 Strengths and Limitations of the Present Approach

The present approach is completely non-linear and beyond the traditional piecewise regression in many ways. The multiple potential turning points test in the present approach are not defined by eyeball or theory; instead, they were grouped from the original data and assigned to the model for comparison. The present approach could also test multiple turning points in one model, which is convenient for preparing the data structure and reducing the data management effort. It is an easy integration into HLM software. Meanwhile, this model is under a multilevel framework that allows individual and group covariates to be controlled separately at different levels. In this study, the TIMSS 2019 sample contains student covariates and school covariates, which are controlled separately at the student level and school level.

Another strength of the present approach is that the categorical variables can be applied to the model for both the dependent variable and the independent variable. The dependent variable in this study is mathematic achievement measured in scale score, a continuous variable. The turning point indicates where the mathematics scale score would become nonlinear (increase or decrease). Sometimes, the dependent variable can also be measured categorically with two groups, such as proficient in mathematics or not proficient in mathematics. The current approach is also suitable for such a situation where the dummy dependent variable can be modeled. The turning point will indicate where the probability of becoming proficient in mathematics would show a different increasing or decreasing pattern.

An additional advantage is that researchers can redefine the category of the independent variable according to their research requirements. In this study, the original

TIMSS 2019 data reported the students' data of SLM, SCM, and SEC in two types, index categories, and scale scores. (The original three index categories were aggregated from the scale score.) In order to have precise comparisons of the turning point, the scale score was divided into five categories by percentile for each independent variable, then made five tentative turning points that represented a range of SLM, SCM, and SEC scores. The original three categories served as the reference benchmark after the turning point has been identified, which increases the level of detail when discussing the effect of SLM, SCM, and SEC on students' mathematic achievement. Instead of discussing in general whether SLM, SCM, and SEC would positively affect students' mathematic achievement, the present approach discusses under which level of SLM, SCM, and SEC students would have received better mathematic achievement progress.

In this approach, continuous variables must be converted into categorical variables. This has both positives and negatives. The positive is that researchers can simplify a continuous variable by highlighting the most likely regions for effects. Oftentimes, "categorical effects" are also easier to interpret by researchers and to understand by educators, parents, administrators, and policymakers than "continuous effects." An additional advantage is that researchers can decide the turning point categories according to their research requirements. The negative is that there is information lost when converting the continuous variables into categorical variables.

Even though the present approach had many advantages beyond the traditional piecewise regression and brought flexibility to the type of data, the limitations of this study remain. The independent variable must be a categorical variable in order to apply this model, reconstructing data when the independent variable is continuous, which will lose some information and require extra data management effort. Also, the present approach is under a multilevel framework that is suitable for samples with data hierarchy. Further, in this study, the sample must be divided into five groups for testing five potential turning points, so a larger sample size is required to meet the sample property for the model structure. Lastly, the present approach uses HLM software to conduct the data analysis. In order to have more precise comparisons and generate all results in a single analysis, the neighborhood comparison is requested during the analysis. Each pair comparison is selected manually, which is not complicated for the null model but slightly inconvenient for the full model with its many covariances. Because the manual operation needs to select each pair from the correlation matrix, the more variables included in the model, the larger the matrix, which increases the risk of selecting the wrong pair and causing incorrect results.

5.3 An Application of the Present Approach with Practical Considerations

The multilevel piecewise regression model's application deals with the second research question – Is there a turning point that reflects the best mathematics outcome change when students maintain a specified category of SLM, SCM, or SEC? Data used for this study is the TIMSS 2019 United States sample of fourth graders. The TIMSS sampling procedure provides a data hierarchy for students nested within schools. The sample used in this study was composed of 8,776 students from 261 schools, an appropriate sample size for this study. In order to suit the present approach, the data was split into five categories using percentile as an interval (See Table 1). The original index benchmarks were used as a reference for interpretation after deciding the turning point.

The literature review in Chapter Three discusses the relationship between mathematic attitude and mathematic achievement, as well as computer-use self-efficacy and mathematic achievement in general. Mathematics attitude has a positive effect (Ma & Kishor, 1997; Kadijević, 2008; Al-Mutawah & Fateel, 2018), and a moderate effect (Çiftçi & Yildiz, 2019) on mathematic achievement. Regarding computer-use self-efficacy, researchers found that higher computer self-efficacy had a positive effect on mathematics learning outcomes (Hill, et al., 1987; Chen, 2017; Nurhikmah et al., 2021). The present approach dug deeper into the relationship mentioned above, when SLM, SCM, and SEC were tested respectively for the turning point that represented the best student mathematics outcome change under a multilevel framework. The three-step data analysis procedure was discussed in Chapter Three. The first step was the null model to measure the variance within and between schools for mathematic achievement. The second and third steps were to build the two-step full model to test the turning point, with and without control student and school variables in the model. Plausible values were also discussed in Chapter Three, which is used for reporting student assessment in TIMSS, HLM 8 software has integrated plausible values simultaneously when conducting the data analysis.

5.4 Summary of Empirical Findings from the Application and their Implications

By using the present approach, the results of the empirical findings confirmed the results in the literature review of previous studies that showed SLM, SCM, and SEC have a positive effect on mathematic achievement, but the results also indicated different patterns of the effect change, with and without control of the student and school factors. Students with the highest level of SLM, SCM, and SEC did not conclusively demonstrate the highest mathematics achievement. When students' SLM, SCM, and SEC reached a certain degree, their mathematics achievement progress slowed down, indicating after the turning point, more effort invested to increase the SLM, SCM, and SEC measurement level for higher mathematic outcomes might not be effective.

SLM analysis results showed that, in this sample, students made the greatest mathematic achievement progress with their SLM status at the fourth point, in which students' SLM scores ranged from 9.98 to 11.74. After students reached this SLM level, their mathematics progress slowed down. The pattern is clear in Figure 4.2 when controlling student and school variables in the model, SLM 4 not only represents the turning point of SLM on mathematics outcomes but also the peak of students' mathematic achievement related to SLM. Regarding the original index benchmarks to define the three categories of SLM, Very Much Like Mathematics is above 10.2, Somewhat Like Mathematics is 8.4 to 10.2, and Do Not Like Mathematics is below 8.4, Most students at the turning point SLM 4 fit into the first category of Very Much Like Mathematics, and some students fit into the second category of Somewhat Like Mathematics. In sum, when students near the benchmark of 10.2, their mathematics achievement progress is near the peak, and more investment in increasing students' SLM degree would return very limited growth of students' mathematic outcomes.

Results from the analysis of SCM showed a similar pattern with SLM in this sample. Students made the greatest mathematic achievement progress with their SCM level at the third point, in which students' SCM scores are between 9.20 and 10.11. After students reached this SCM status, their mathematics progress slows down. The pattern is shown in Figure 4.4 when controlling student and school variables in the model. SCM 3 represents the turning point of SCM on mathematics outcomes; however, it is not the peak of students' mathematic achievement. Even though the mathematics achievement progress has slowed down after the turning point of SCM 3, students still have a large growth space between SCM 3 and SCM 4. Thus, considering the implication, the effort to increase the SCM level should reach SCM 4, yielding scores between 10.12 and 11.70 in order to have better students' mathematic achievement. Regarding the original benchmarks to define the three categories of SCM, Very Confident in Mathematics is above 10.7, Somewhat Confident in Mathematics is 8.5 to 10.7, and Not Confident in Mathematics is below 8.5. Most students at the SCM 4 fit into the first category of Very Confident in Mathematics, and few students fit into the second category, Somewhat Confident Mathematics. In sum, when students near the benchmark of 10.7, their mathematics achievement progress is near the peak, and more investment in increasing students' SCM degree would return very limited growth of students' mathematic outcomes.

SEC analysis results showed a very different pattern compared with SLM and SCM. Students made the greatest mathematic achievement progress with their SEC status at the second point, when student SEC core was between 8.49 and 9.79. After students reach this SEC level, their mathematics progress slows down. The pattern is shown in Figure 4.6 when controlling student and school variables in the model. SEC 2 represents the turning point of SEC on mathematics outcomes, and nearly reaches the peak of students' mathematic achievement. Students' mathematics achievement progress then slows down significantly after the turning point of SEC 2. In addition, a new pattern emerges in Figure 4.6 that shows, after reaching the peak near SEC 3, there is a visible decrease in students' mathematics outcomes at SEC 5. This pattern is also shown in Table 4, the neighborhood comparison. Regarding the original benchmarks to define the three categories of SEC, High

Self-Efficacy in Computer Use is above 9.7, Medium Self-Efficacy in Computer Use is 6.6 and 9.7, and Low Self-Efficacy in Computer Use is below 6.6. Most students at the SEC 2 fit into the first category High Self-Efficacy in Computer Use, and very few students fit into the second category of Medium Self-Efficacy in Computer Use. In sum, when students near the benchmark of 9.7, their mathematics achievement progress is near the peak, and more investment in increasing students' SEC degree would result in very limited growth or even a decline in students' mathematic outcomes,

The results of this study have certain implications for teachers and schools that devote resources to improving students' mathematics achievement. This study shows consistent results with former researchers, that students with a high degree of SLM, SCM, and SEC are more likely to have better mathematics achievement. However, when regarding the magnitude, all three analyses recommended only reach to the benchmark of the first category of SLM, SCM, and SEC in the original TIMSS data index. The analyses also illustrate more details within the student groups with high degrees of SLM, SCM, and SEC, indicating that seeking a higher level of the three measurements is not efficient in supporting students' mathematics achievement when students reach the benchmark. Teachers and schools should pay attention to other factors that will affect students' mathematics outcomes.

Considering the validity of this study, the sample applied in this research was the U.S. sample, thus the results of SLM, SCM, and SEC effect threshold on mathematics achievement only restrict to the U.S. as a national reference. If researchers are interested in other countries' results, they should select their target country as the data sample. However, TIMSS provided the international assessment sample, and the international threshold of the three psychological measurements SLM, SCM, and SEC on mathematics achievement could be calculated using as an international reference for comparison. It will be also another advantage of this study, researchers can conduct the comparison between countries, as well as with the international threshold.

5.5 Future Research

From the model development perspective, the current study was univariate, meaning it tested only one variate – mathematics achievement – whereas the multilevel piecewise regression in a multivariate fashion is not very common in the literature. This will be another contribution of the current approach in the future. Multilevel, multivariate piecewise regression will be the extension of the current approach, having the ability to test two school subjects, for example, mathematics and science achievement, simultaneously under certain turning points. The research question will focus on both mathematics and science achievement, attempting to discover whether, at the turning point of a certain independent variable, a student who achieves a higher mathematic score also attains high achievement in science, and which student and school characteristics influence this consistency or inconsistency. Compared with the current univariate approach, the multilevel, multivariate piecewise regression will be a three-level hierarchical model. The first level will model mathematics and science with two dichotomous variables; and the second level will include two sets of linear regression models, one representing mathematics and the other representing science. Each linear regression model will apply the same approach as the univariate model discussed in this study; that is, the second level modeling turning points and student characteristics, and the third level modeling school characteristics.

From the application perspective, as shown in this study, multilevel piecewise regression provides more precise and effectiveness of the turning point modeling. The application of this approach also indicates the importance of considering the magnitude of students' measurement of SLM, SCM, and SEC when teachers and schools intend to invest effort into increasing the levels of the three psychological factors to increase students' mathematics outcomes. Therefore, when researchers focus on the threshold effect of X on Y under a multilevel situation, this model can provide more detailed information.

This study adopted TIMSS 2019 data, a large-scale dataset with fruitful measurement of many factors related to mathematics and science education. This study tests only three of them, focusing on mathematics. In addition, other student measurements related to mathematics education are also reported in TIMSS 2019, such as Students Value Mathematics and Instructional Clarity in Mathematics lessons. TIMSS 2019 also reports data from parents regarding Early Literacy and Numeracy Activities and Home Resources for Learning. Classroom teachers also contribute to reporting Classroom Teaching Limited by Students Not Ready for Instruction and Teachers' Job Satisfaction. The turning point identifying process for the variables above can also adopt the current approach when the threshold is the main interest. The parallel study of science can also apply the current approach since the TIMSS measures science and mathematics as parallel cohorts.

Other large-scale assessments with benchmark measurements are also suitable for the present approach. PISA 2022, Program for International Student Assessment, would focus on mathematics assessment and factors that affect mathematic outcomes. Thus, the multilevel piecewise regression could provide more detailed analysis results for researchers to explore certain thresholds when considering PISA 2022 as a data resource.

APPENDICES

APPENDIX 1. DESCRIPTION OF INDEPENDENT VARIABLE AT THE STUDENT LEVEL

Variable	Item	Coding
Age	When were you born?	continuous
Gender	Are you a girl or a boy?	1=Girl, 2=Boy
Immigration Status	In what country were you and your parents born?	1=Yes 2=No
Student SES	About how many books are there in your home?	1=None or very few (0-10 books) 2= Enough to fill one shelf (11-25 books) 3= Enough to fill one bookcase (26-100 books) 4= Enough to fill two bookcases (101-200 books)
Language at Home	How often do you speak (language of test) at home	1= Always 2= Almost always 3= Sometimes 4= Never
Students like learning mathematics	How much do you agree with the statements about learning mathematics? 1. I enjoy learning mathematics. 2. I wish I did not have to study mathematics. 3. Mathematics is boring. 4. I learn many interesting things in mathematics. 5. I like mathematics. 6. I like any schoolwork that involves numbers. 7. I like to solve mathematics problems. 8. I look forward to mathematics lessons. 9. Mathematics is one of my favorite subjects.	1=Very Much Like Learning Mathematics 2=Somewhat Like Learning Mathematics 3=Do Not Like Learning Mathematics

Students confident in mathematics	How much do you agree with these statements about mathematics? 1. I usually do well in mathematics. 2. Mathematics is harder for me than for many of my classmates. 3. I am just not good at mathematics. 4. I learn things quickly in mathematics. 5. Mathematics makes me nervous. 6. I am good at working out difficult mathematics problems. 7. My teacher tells me I am good at mathematics. 8. Mathematics is harder for me than any other subject. 9. Mathematics makes me confused.	1=Very Confident in Mathematics 2=Somewhat Confident in Mathematics 3=Not Confident in Mathematics
Self-Efficacy for computer use	How much do you agree with these statements? 1. I am good at using a computer. 2. I am good at typing. 3. I can use a touchscreen on a computer, tablet, or smartphone. 4. It is easy for me to find information on the internet. 5. I can look up the meaning of words on the internet. 6. I can write sentences and paragraphs using a computer. 7. I can edit text on a computer.	1= High Self-Efficacy 2= Medium Self-Efficacy 3= Low Self-Efficacy

APPENDIX 2. DESCRIPTION OF INDEPENDENT VARIABLE AT THE SCHOOL LEVEL

Variable	Item	Coding
Instruction Affected by Math Resource Shortage	Resources for Mathematics Instruction 1. Teacher with a specialization in mathematics. 2. Computer software/applications for mathematics instruction. 3. Library resources relevant to mathematics instruction. 4. Calculators for mathematics instruction. 5. Concrete objects or materials to help students understand quantities or procedures.	1=Not Affected 2=Somewhat Affected 3=Affected A Lot
School Emphasis on Academic Success	How would you characterize each of the following within your school? 1. Teachers' understanding of the school's curricular goals. 2. Teachers' degree of success in implementing the school's curriculum. 3. Teachers' expectations for student achievement. 4. Teachers' ability to inspire students. 5. Parental involvement in school activities. 6. Parental commitment to ensure that students are ready to learn. 7. Parental expectations for student achievement. 8. Parental support for student achievement. 9. Students' desire to do well in school. 10. Students' ability to reach school's academic goals. 11. Students' respect for classmates who excel academically.	1= Very High Emphasis 2=High Emphasis 3=Medium Emphasis

School Discipline and Safety	To what degree is each of the following a problem among (fourth-grade) students in your school? 1. Arriving late to school. 2. Absenteeism (i.e., unjustified absences). 3. Classroom disturbance. 4. Cheating. 5. Profanity. 6. Vandalism. 7. Theft. 8. Intimidation or verbal abuse among students (including texting, emailing, etc.). 9. Physical fights among students. 10. Intimidation or verbal abuse of teachers or staff (including texting, emailing, etc.)	1=Hardly Any Problems 2=Minor Problems 3=Moderate to Severe Problems
School Composition by Socioeconomic Background	School resources and technology such as computers, science laboratory, on-line learning systems, school library, digital learning resources.	1= More Affluent 2=Neither More Affluent nor More Disadvantaged 3= More Disadvantaged
Majority Student Proportion	Approximately what percentage of students in your school have <language of test> as their native language?	1=More than 90% 2=76 to 90% 3=51 to 75% 4=26-50% 5=25% or less
School Location	Which best describes the immediate area in which your school is located?	1=Urban–Densely populated 2=Suburban–On fringe or outskirts of urban area 3=Medium size city or large town 4=Small town or village 5=Remote rural

APPENDIX 3. MULTILEVEL PIECEWISE-REGRESSION MODELING OF STUDENT AND SCHOOL CHARACTERISTICS EFFECT ON MATHEMATICS ACHIEVEMENT

	SLM		SCM		SEC	
Student Characteristics	Effect	SE	Effect	SE	Effect	SE
Age (continuous)	-0.08*	0.02	-0.07*	0.02	-0.09*	0.03
Gender (male = 0, female = 1)	-0.13*	0.02	-0.07*	0.02	-0.16*	0.02
Immigration status (yes = 1, no = 0)	0.28*	0.04	0.24*	0.04	0.26*	0.04
Less Books at Home (vs. Median Books at Home)	-0.28*	0.02	-0.20*	0.02	-0.29*	0.03
More Books at Home (vs. Median Books at Home)	0.05*	0.03	0.03	0.02	0.06*	0.02
Home Language (English = 1, others = 0)	0.01	0.02	-0.01	0.02	-0.02	0.02

	SLM1		SLM2		SLM3		SLM4		SLM5	
School Characteristics	Effect	SE	Effect	SE	Effect	SE	Effect	SE	Effect	SE
Instruction Affected by Math Resource Shortage (continuous)	-0.01	0.01	-0.02	0.01	-0.02*	0.01	-0.01	0.01	0.01	0.02
School Emphasis on Academic Success (continuous)	0.03*	0.01	0.06*	0.01	0.04*	0.01	0.04*	0.01	0.02	0.01
School Discipline (continuous)	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.03

School Composition by Socioeconomic Background Disadvantage Proportion (> 50% = 1, < 50% = 0)	-0.24*	0.06	-0.20*	0.06	-0.18*	0.07	-0.26*	0.06	-0.21*	0.07
Majority Student Proportion (> 50% = 1, < 50% = 0)	0.05	0.07	0.04	0.06	0.13	0.08	0.03	0.07	-0.03	0.07
School Location-Urban (vs. others)	-0.28*	0.02	-0.24*	0.08	-0.34*	0.10	-0.21*	0.08	-0.16	0.10
School Location-Suburban (vs. others)	-0.01	0.07	-0.03	0.06	0.01	0.07	-0.03	0.06	0.03	0.06

	SCM1		SCM2		SCM3		SCM4		SCM5	
School Characteristics	Effect	SE	Effect	SE	Effect	SE	Effect	SE	Effect	SE
Instruction Affected by Math Resource Shortage (continuous)	-0.01	0.01	-0.01	0.01	-0.01	0.01	-0.01	0.01	-0.03*	0.01
School Emphasis on Academic Success (continuous)	0.04*	0.01	0.04*	0.01	0.04*	0.01	0.04*	0.01	0.04*	0.01
School Discipline (continuous)	0.03	0.02	0.01	0.02	0.01	0.02	0.02	0.02	0.02	0.02
School Composition by Socioeconomic Background Disadvantage Proportion (> 50% = 1, < 50% = 0)	-0.20*	0.05	-0.25*	0.06	-0.20*	0.05	-0.18*	0.06	-0.18*	0.06
Majority Student Proportion (> 50% = 1, < 50% = 0)	0.06	0.06	0.07	0.06	-0.01	0.06	0.01	0.05	0.09	0.07
School Location-Urban (vs. others)	-0.30*	0.07	-0.22*	0.08	-0.21*	0.08	-0.16*	0.07	-0.12	0.10
School Location-Suburban (vs. others)	-0.03	0.06	0.01	0.06	-0.03	0.06	-0.01	0.05	0.01	0.06

School Characteristics	SEC1 Effect	SEC1 SE	SEC2 Effect	SEC2 SE	SEC3 Effect	SEC3 SE	SEC4 Effect	SEC4 SE	SEC5 Effect	SEC5 SE
Instruction Affected by Math Resource Shortage (continuous)	-0.01	0.01	-0.02	0.01	-0.01	0.01	-0.01	0.01	-0.02	0.01
School Emphasis on Academic Success (continuous)	0.06*	0.02	0.05*	0.01	0.03*	0.01	0.03*	0.01	0.05*	0.01
School Discipline (continuous)	0.02	0.02	0.03	0.02	0.03	0.02	-0.02	0.02	0.04*	0.02
School Composition by Socioeconomic Background Disadvantage Proportion (> 50% = 1, < 50% = 0)	-0.18*	0.07	-0.17*	0.05	-0.18*	0.07	-0.25*	0.07	-0.21*	0.06
Majority Student Proportion (> 50% = 1, < 50% = 0)	0.12	0.08	0.03	0.06	0.01	0.08	0.10	0.07	0.08	0.08
School Location-Urban (vs. others)	-0.34*	0.10	-0.27*	0.08	-0.26*	0.09	-0.23*	0.11	-0.15*	0.09
School Location-Suburban (vs. others)	-0.09	0.07	-0.02	0.05	-0.03	0.06	0.03	0.06	0.06	0.06

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VITA

JING ZHANG

EDUCATION

2007 Master of Arts, Media Management, Communication University of China

2005 Bachelor of Science, Economics, Tianjin Commercial University

PROFESSIONAL POSITIONS

2018-2021 Research Assistant, High-Impact Leadership for School Renewal, University of Kentucky

2021-now Graduate Assistant, Student Organizations and Activities, Student Success. University of Kentucky

AWARDS, FELLOWSHIP, AND HONORS

2020-2021 Doris Nowak & William E. Stilwell, III Graduate Fellowship in Counseling & Educational Psychology, University of Kentucky. ($1,500)

2019-2020 John Edwin Partington and Gwendolyn Gray Partington Scholarship, University of Kentucky. ($500)

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Under review

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