Alabama Districts and COVID-19:
Exploring the Impact of Pandemic-Related Disruptions on
K-12 Student Achievement

by

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Abstract

The COVID-19 pandemic presented several challenges to U.S. public school districts, particularly those characterized as low-income or high-poverty, that negatively impacted academic achievement in English Language Arts (ELA) and mathematics (math). This pre-post study, aimed to investigate the extent to which socioeconomic inequalities, district characteristics, and pandemic-induced changes in instruction and financial support influenced the change in academic proficiency scores before and after the pandemic by conducting two separate multiple regressions, one per subject area, while also incorporating an ANCOVA methodology. In the ELA model, results indicated that predictors for the pre/post change included the amount of Elementary and Secondary School Emergency Relief or ESSER funding awarded per student and pre-COVID proficiency scores. For the math model, a two-way interaction between the proportion of districts serving students receiving free and reduced lunch and pre-COVID proficiency scores, emerged as important for explaining the same pre/post change.

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Thank you.

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List of Abbreviations

ALSDE	Alabama State Department of Education
ANCOVA	Analysis of Covariance
APA	American Psychological Association
ARP	American Rescue Plan of 2021 Act; section 2001(e)
CARES	Coronavirus Aid, Relief, and Economic Security Act of 2020
CCR	College and career readiness
CDC	Center for Disease Control
COVID-19	Coronavirus disease
CRRSA	Coronavirus Response and Relief Supplemental Appropriations Act of 2021; section 313(d)
DLE	Discourses on Learning in Education
ECA	Economically-advantaged
ECD	Economically-disadvantaged
ELA	English Language Arts
ESEA	Elementary and Secondary Education Act of 1965
ESSA	Every Student Succeeds Act of 2015
ESSER	Elementary and Secondary School Emergency Relief
HMM	Hidden Markov Model
K-12	Kindergarten to 12th-grade levels
NASSP	National Association of Secondary School Principals
NCLB	No Child Left Behind of 2002
NCES	National Center for Educational Statistics
NEA	National Education Association
NSLP	National School Lunch Program
NTPS	National Teacher and Principal Survey
RQ	Research Questions
SNAP	Supplemental Nutrition Assistance Program
GAO	U.S. Government Accountability Office
U.S.	United States
USDA	U.S. Department of Agriculture
USDOE	U.S. Department of Education
WHO	World Health Organization

CHAPTER 1. INTRODUCTION

For nearly six decades, numerous legislative efforts have been aimed at decimating persistent achievement gaps, notably observed in low-income public-school systems, by repositioning college and career readiness (CCR) as a primary focal point of educational strategies (English et al., 2016). Federal laws such as the Elementary and Secondary Education Act (ESEA) of 1965[1] and No Child Left Behind (NCLB)[2] of 2002 were established to mitigate achievement gaps while reinforcing a connection between societal values and educational attainment, with Every Student Succeeds Act (ESSA) of 2015, a more recent initiative, sparking a shift in how accountability is viewed in education (Darling-Hammond et al., 2016; Anderson, 2005). The enactment of ESSA provided state and local education agencies flexibility in adopting CCR standards that were relative to the needs and underlying dynamics of their school systems (GAO, 2014 & 2017; NGACBP & CCSSO, 2010). This policy also expanded upon previous NCLB efforts by incorporating more purposeful academic and nonacademic components into state CCR definitions, and thus, creating an interrelated framework that supported districts providing a comprehensive, challenging, high-quality education experience that theoretically, would be accessible to all students (Cushing et al., 2019; English et al., 2016). While the intent behind policies like NCLB and ESSA promoted equitable access to high-quality education and training,

[1] The Elementary and Secondary Education Act (ESEA) of 1965, a federal anti-poverty initiative, promoted equal educational opportunities for children from economically disadvantaged backgrounds outlined in six sections, from Title I to Title VI, addressing various education aspects. Out of the sections, Title I was the most substantial, providing financial aid to LEAs to support the education of children from low-income families (Yell, 2014).

[2] The No Child Left Behind (NCLB) Act of 2002, a modification of the Elementary and Secondary Education Act (ESEA), implemented rigorous academic standards, assessment requirements, and teacher qualifications. This initiative signaled a shift in federal responsibilities from funding sources to overseeing and enforcing educational accountability and student outcomes (USDOE, n.d.).

this expectation required local education agencies or school districts to ensure that every student across the U.S. received rigorous instruction, which thereby, would increase the likelihood of students becoming college and career ready (Conley, 2012). It is evident that school systems that offer high quality learning opportunities will also likely help students foster knowledge and skills that are essential to engaging in various postsecondary outcomes. However, it is also evident that some districts may be ill-equipped to offer these educational opportunities to their students, and that, ecological differences may influence a district's ability to provide instruction to students (Mishkind, 2014; Darling-Hammond et al., 2016). For districts to be in line with legislative mandates (e.g., ESSA), it is important they examine various district-specific characteristics to identify potential hinderances and opportunities for districts to grow their capacity to provide a high-quality, rigorous educational experience that accessible to all students.

Socioeconomic Inequities and Public-School Systems

Two primary factors impact school districts' ability to meet the expectation in providing a learning experience that prepares students for college and careers: (1) the financial capacity to sustain day-to-day operations (e.g., maintaining and offering access to facilities) and (2) adequate access to state and community resources (e.g., funding, technology, and curricular materials) (Darling-Hammond, 2017; USDOE, 2017). The influence of these factors on student achievement becomes more evident as some districts are able to allocate the necessary funds for recruiting highly qualified teachers, providing sufficient resources, and granting access to technology with ease, while other districts may encounter more financial challenges that impede their execution of these goals (NEA, 2021). To better understand how these challenges may affect school districts' capacity to offer students opportunities for academic and vocational growth, a closer look at the contexts behind these dynamics is required.

Public school systems in the United States are structured similarly; yet district-specific differences (e.g., pedagogical approaches and teacher experience) and accessibility concerns (e.g., funding, resource shortages, access to technology) appear to be factors that contribute to variations in how districts operate. These differences impact the overall quality of instruction districts provide to students, which in turn, negatively impacts student achievement across all academic subject areas (Lavy & Sand, 2015). A closer examination of these district-level differences in characteristics is imperative, especially for poorer districts, as it would provide various stakeholders an opportunity to identify potential barriers to achievement.

Many studies have explored connections between education quality and their impact on academic outcomes. In a recent policy brief, Morgan (2022) proposed that adequate funding play a crucial role in school systems providing students with a high-quality education. Investigating district-specific factors, such as locale and free and reduced lunch rates, is essential to identifying potential disparities in education quality but to also evaluate plans for allocating resources to school districts that need more support (Snyder & Musu-Gillette, 2015; Morgan & Amerikaner, 2018; Morgan, 2022; Crosnoe & Cooper, 2010; Rumberger, 2014). Historically, students from low-income backgrounds have attended poorly-funded, ill-equipped public schools, while those from wealthier backgrounds often have access to schools with better funding, facilities, instructional materials, and technology (Ferguson et al., 2007; Smith, 2010; Alexander & Jang, 2020). Recent education reform efforts to improve financial operations have led to increased federal funding, and thus, have mitigated some issues school districts have experienced with limited funding (Tyner, 2023). However, when compared to more affluent areas, districts in low-income and rural areas still have less access to resources and funding, leading instruction being provided in poor facilities with outdated technology and fewer academic opportunities being offered, both of which, may contribute to an education that is poor in quality (Goldhaber et al., 2018). Students attending school systems in high-poverty areas are also more likely to face other barriers to learning, such as poor nutrition, inadequate healthcare, and limited access to early childhood education, further widening the achievement gap (NASSP, 2019).

Public School Districts and Locale

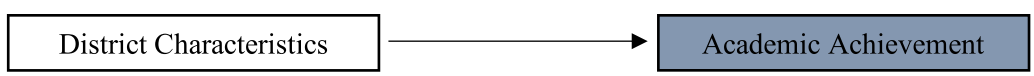
There are notable differences in student performance when comparing school systems by locale (Pendola et al., 2022). For instance, suburban districts are found to be high-performing academically than those in rural and urban areas. This difference in academic performance was mostly due to suburban systems having optimal funding and access to more resources, both of which, support an enriched, rigorous learning environment (i.e., offering of advanced coursework and extracurricular activities) (KewalRamani et al., 2018). Achievement disparities observed in urban and rural districts may also be attributed to higher poverty and crime rates, and limited resources within their community, a direct contrast to their suburban counterparts (Schwartz et al., 2012).

Bronfenbrenner's Ecological Systems Model

When further examining the interchanges between the environmental factors, school system, and student (i.e., academic achievement), one could liken them to the interplay observed among the macro-, exo-, meso-, micro-, and individual systems seen in Bronfenbrenner's Ecological Systems Model (1979). This ecological approach posits that human development is influenced by personal traits and sociocultural contexts within an individual's environment, such that their social interactions with others and personal characteristics may directly or indirectly affect their development over time (Rosa & Tudge, 2013). This ecological exchange is similar to that between district-specific characteristics and achievement, as school districts could be viewed as an ecological system that is often influenced by internal and external factors, both of which, would impact academic achievement.

Figure 1 shows that an intricate interchange exists between various layers of an ecological system (e.g., differences in district-level characteristics) and academic achievement. Emphasis on this connection is related to differences that may be observed with school districts as underlying dynamics may be more complex depending on the geographic region in which it is located, leadership efforts, access to resources and funding opportunities. Public school systems grappling with limited resources and funding may resort to pedagogical approaches that do not support the development of critical competencies. Furthermore, these districts are susceptible to experiencing cycles of low achievement, especially in the wake of a natural disaster (Crosnoe & Cooper, 2010).

Figure 1



Note. Conceptual model highlighting a cause-and-effect relationship between district-specific characteristics such as locale, insufficient access to community resources, and limited funding; and changes in student achievement (i.e., academic proficiency).

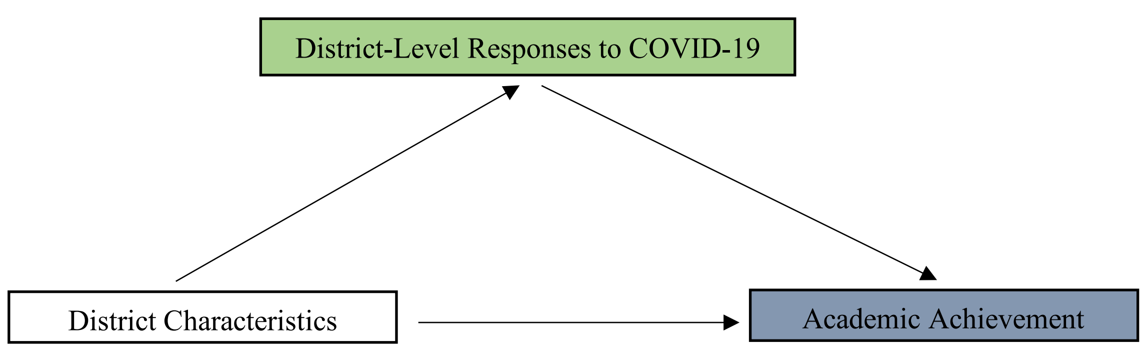
Pandemic-Induced Disruptions

The COVID-19 pandemic has been characterized as an unexpected, catastrophic public health crisis that affected millions of people (Alimohamadi et al., 2020). By November 2019, the Coronavirus Disease, or *COVID-19 virus,* had infected more than 178 million people leading to approximately 4 million deaths worldwide (Hale, 2021; Pustake et al., 2022). These high rates of cases and deaths were also observed in the U.S., with over 100 million individuals being infected and close to 1.5 million individuals dying from the virus (JHUM, 2023).

The 2019-20 outbreak of this virus sparked several global and national changes, several of which, exacerbated pre-existing challenges for school districts already grappling with limited funding and resources. Examples of these pandemic-related impacts included new federal regulations such as nationwide lockdowns, mandatory mask-wearing, protocols for social distancing, and mandated quarantines for those who were diagnosed suspected to have been exposed to someone diagnosed with COVID-19. While these lifestyle changes differed by intrusiveness and duration, they were still significant deviations from the norm, and thereby warranted the implementation of new measures for adjusting to the constant threat of the highly infectious virus (WHO, 2020; Gostin & Wiley, 2020).

As the pandemic progressed, disruptions to learning became more frequent and pervasive for U.S. K-12 education systems, leading to this period being described as the "largest disruption" in education history (Pokhrel & Chhetri, 2021). Districts were forced to adopt alternative instructional methods and strategies to mitigate COVID-related impacts to learning, however, it remains unclear as to the effectiveness of these strategies (Pressley et al., 2022; Shamir-Inbal & Blau, 2021).

Figure 2



Note. An expansion of the previous conceptual model depicted in Figure 1. In addition to the causal relationship between district level characteristics and achievement, this model displays the introduction of district-level responses to pandemic-related changes, particularly the provision of ESSER funding and alternative learning modalities.

Statement of the Problem

Federal and state governments imposed numerous mandates during the COVID-19 pandemic, creating many challenges for U.S. education systems (Gostin & Wiley, 2020). As many businesses were ordered to shut down nationwide, school systems also began grappling with intrusive school operations disruptions, impacting student performance (García & Weiss, 2022). Many U.S. K-12 school systems faced many difficulties with strategically delivering high-quality instruction while adhering to copious, restrictive COVID-related mandates (HHP & HMS, 2020)

Since its emergence in 2019, several studies have explored how the pandemic has affected the population nationally. However, state-specific impacts have yet to be fully examined, which may inadvertently result in an incomprehensive view of how COVID-19 impacted them separately. Previous studies have cautioned against generalizing national findings to individual states, emphasizing the importance of acknowledging unique characteristics and dynamic that are contextual to each state (Pendola et al., 2022). Morgan (2022) further noted that while summaries of national data may showcase notable funding dipartites, reviewing these patterns for each state may provide a more nuanced understanding of local and state revenue allocation disproportionalities. Differences that were observed in how school districts handled these pandemic-related disruptions may have also sparked a myriad of challenges relative to the implementation of alternative teaching practices that replaced ones that were more traditional and based on in-person instruction (Leech et al., 2020).

As school shutdowns became more frequent and prolonged, adopting alternative learning modalities such as virtual and hybrid instruction became critical to ensuring that instruction was sustained at home (Huck & Zhang, 2021). However, employing such methods may have become especially problematic for public-school districts in Alabama, as it is a state widely known for high poverty rates, disparities in access to community resources, and low academic performance

(ALSDE, 2019a; Morgan & Amerikaner, 2018; Hagedorn & Torres, 2014). Furthermore, pre-existing educational inequities in Alabama related to limited access (e.g., resource allocation, school funding) likely worsened during pandemic-induced school shutdowns (Kim, 2020; Norman et al., 2022). These disruptions have resulted in negative impacts on student learning, and thus, may have further deepened gaps in achievement and opportunity, especially with those from historically marginalized communities (Archibald, 2022; Davis, 2023; Morgan, 2022).

Despite school districts nationwide working diligently to acclimate to the pandemic, the pervasiveness of mandated school closures amidst other COVID-related interruptions, may have significantly impacted students attending poorer districts more than those at more affluent ones. In fact, several studies have suggested a potential connection between instruction quality and the potential for school systems to swiftly, yet effectively respond to pandemic-related disruptions (Hammerstein et al., 2021). Districts located in high poverty states, such as Alabama, were likely impacted differently by these disruptions, making it important to explore which, if any, of their characteristics may be connected to COVID-related impacts on learning and achievement. This dynamic understandably becomes more complex as these districts are more likely to provide students a low-quality education; yielding negative impacts on their academic performance.

Purpose of the Study

To assess the potential impact that COVID-19 had academic achievement for public K-12 school systems in Alabama, the purpose of this study was to investigate whether district-level characteristics, namely the district's locale and poverty rates, and the implementation of learning modalities, yielded significant changes in academic proficiency scores, before and after the pandemic. Alabama districts were targeted in this study given their history of high poverty and underperformance in multiple academic areas. Findings from this study may not only illuminate other underlying complexities that contribute to the persistent cycle of socioeconomic inequities observed in districts that serve higher concentrations of students from disadvantaged backgrounds, but they may also provide valuable insight that can inform future endeavors in education and public policy (see Figure 2).

U.S. Census Bureau (2021) data for 2019 showed that Alabama was one of the ten poorest states in the nation, with a poverty rate of 15.8%, a rate significantly higher than that which was reported nationally, 10.5%. While these are a sample of instances, a consistent pattern of high poverty rates emerges, further indicating the potential for deeper issues, namely inadequate access to resources and funding. Focusing improvement efforts on educational practices presents an opportunity to target resolving current issues with socioeconomic disparities while mitigating potential impacts from future pandemic-related disruptions that may amplify inequities in resource allocation and SES-related differences further. Policy reform may also encourage long-overdue modifications to resource and funding management strategies implemented in education (Morgan, 2022; Simon, 2021). While these changes may promote more opportunities to increase equity with social capital and mobility, they ultimately allow individuals from all backgrounds to reach their full potential (Clouston, et al., 2021; Adler & Stewart, 2010).

Research Questions

It is evident that COVID-19 posed a myriad of challenges for public school systems nationwide. While many studies have provided additional insight into how this dynamic impacted learning, few have targeted Alabama, a state widely known for persistent cycles of poverty and low achievement. Pandemic-related research has provided valuable insights into the short and long-term impacts COVID-19 had on learning. However, information may not fully capture the true essence of what these impacts mean for districts in Alabama or the degree in which they had the capacity to handle these unforeseen challenges posed to student learning and progress. For those reasons, the study explored whether characteristics observed at the district-level for systems in Alabama influenced changes that may be seen when comparing pre- to post-COVID academic proficiency scores for ELA and math while controlling for pre-COVID proficiency? How might changes in learning modalities impact the previously noted relationship?

Relevance of the Study

K-12 education systems have been viewed as sociocultural transmission agents intended to promote skills (e.g., academic/college, career, and interpersonal) that are necessary for ensuring students transition into society as productive citizens and workers upon exiting high school (Silliman & Schleifer, 2018; Pai & Adler, 1997). Furthermore, students who successfully master fundamental K -12 concepts are presumed to be more likely to experience personal growth, successfully navigate society, and attain economic prosperity (Spring & Spring, 2008).

According to 2019 American Community Survey findings, 58.6% of Alabama's population lived in urban areas, 28.9% in suburban areas, and 12.5% in rural areas (U.S. Census Bureau, 2021). Previous research suggests that despite urban schools serving more diverse student populations and offering a more comprehensive range of academic programs, suburban schools typically achieved higher test scores and access to more resources (e.g., technology and extracurricular activities) than their urban counterparts (Logan & Burdick-Will, 2017). Rural schools often face more unique challenges, such as teacher recruitment and retention issues and limited access to educational resources (Davis, 2023; García & Weiss, 2020; NASSP, 2019; ALSDE, 2020). In general, poor school districts often encounter more complex challenges with providing high quality educational opportunities (McKenzie, 2019; Reardon & Portilla, 2016; Brito & Noble, 2014). This notion appears to align with our position that poor districts in Alabama may experience challenges that are likely nuanced by differences in characteristics that occur at the district-level, such as pre-existing issues with limited resources, inadequate funding, and scarce curriculum options (Ciuffetelli Parker & Conversano, 2021).

Despite the pandemic transitioning into a perceived endemic phase (Pressley et al., 2022), new and old variants remain a threat to districts state-wide. Moreover, it is highly likely that as COVID-19 transmissions persist, school districts will be forced to continue devising contingency plans that account for learning modality changes that may stem from potential disruptions in the future. Delivering instruction during pandemic-induced lockdowns posed many challenges for public school systems, particularly those in high-poverty areas. These challenges likely became compounded as these lockdowns led to an unexpected shift from to traditional "in-person" instruction models and alternate learning modalities. Examining the relationship between district characteristics, COVID-related adaptations, and academic proficiency may offer valuable insights that may help inform discussions on education policy (Alexander & Jang, 2020). Furthermore, evaluating the extent in which differences in these characteristics in conjunction with these disruptions in learning adversely impacted academic skill development will be crucial in shaping how districts educate students moving forward.

These unprecedented changes from COVID-19 have led to several studies, aimed at examining pandemic-related impacts, mainly short-term, on learning and school functioning. However, states like Alabama, which have historically experienced high poverty rates, extensive rurality, and issues with low achievement; must be studied to more to determine the extent in which these pandemic-related disruptions compound pre-existing characteristics that were counterproductive to academic achievement.

Definition of Terms

Below are definitions of key terms featured in this paper. Terms #1, #2, #7, and #8 were devised from different sources. However, terms 3-6 were adaptations of definitions found in the Wisconsin Department of Public Instruction (2022) and Center for Disease Control and Prevention (2022), and terms #7 & #8 were adapted from other sources (USDOE, 2015; APA, 2023).

1) *District-level characteristics:* factors specific to the district that impact may negatively or positively impact academic achievement. Examples of these factors include, but are not limited to sufficient financial support, adequate staffing, working learning facilitates, access to instructional materials, reliably technology, and state and community resources (Darling-Hammond, 2017; Nicola et al., 2020; USDOE, 2017).

2) *District-level responses to COVID-19*: instances where school districts employed various curricular strategies, re-allocated resources, implemented alternative emergency contingencies, etc. to sustain instruction and mitigate potential learning loss resulting from unforeseen interruptions in school operations related to the outbreak of COVID-19 during the 2019-2020 AY (Crepeele, 2022; Pressley et al., 2022; Bozkurt et al., 2022; Daniel, 2020).

3) *School learning modality refers to* how students engage in instruction. During the pandemic, instruction was presented as one of three primary types: in-person, remote, or hybrid.

4) *In-person learning modality:* Districts required schools to offer every student face-to-face instruction five days weekly.

5) *Remote learning modality:* Districts mandated schools to conduct instruction at home/online; no face-to-face option was offered.

6) *Hybrid learning modality:* Districts provided access to in-person and remote instruction, with the former offered to a subgroup of students or for less than five days each week.

7) *Achievement:* defined in terms of English Language Arts (ELA) and mathematic assessment proficiency scores; often used to measure achievement as they reflect students' knowledge and skills in specific subject areas.

8) *Socioeconomic status:* the position of a group or individual based on a socioeconomic scale; contains factors such as income, education level, and geographic region.

Organization of The Study

This study is divided into five chapters, with Chapter One providing an overview of the COVID-19 pandemic and the global challenges that resulted from its unexpected arrival. It also describes how differences in district characteristics and pandemic-related changes within a district's structure could impact student achievement. Chapter Two reviews relevant literature that describes potential factors that elicited challenges observed in U.S. K-12 public school districts. Additionally, it describes the degree to which poverty rates, differences in locale, and variations in the amount of time (in terms of remote and hybrid instruction) posed acute or continuous challenges to student achievement. Chapter Three outlines the procedures for procuring, preparing, and describing secondary data for analysis. This chapter also described how data were analyzed, including how variables were selected, a description of the statistical test(s) that were performed, and a process for determining the appropriateness of the methodology. Chapter Four provides the results from the analysis, while Chapter Five shares conclusions that can be made given the study's results and future implications for K-12 school systems and other relative ecosystems within the educational network.

CHAPTER 2. LITERATURE REVIEW

Despite legislative efforts being levied to address issues with accessibility, public-school districts in low-income areas have faced persistent cycles of socioeconomic inequalities that ultimately yielded poor achievement. Given the extensive history of low-income districts struggle to improve academic performance and educational opportunities with limited funding and resource availability, the question arises: How did these districts navigate the significant changes induced by the COVID-19 pandemic, especially in terms of the shifts in the K-12 instruction model?

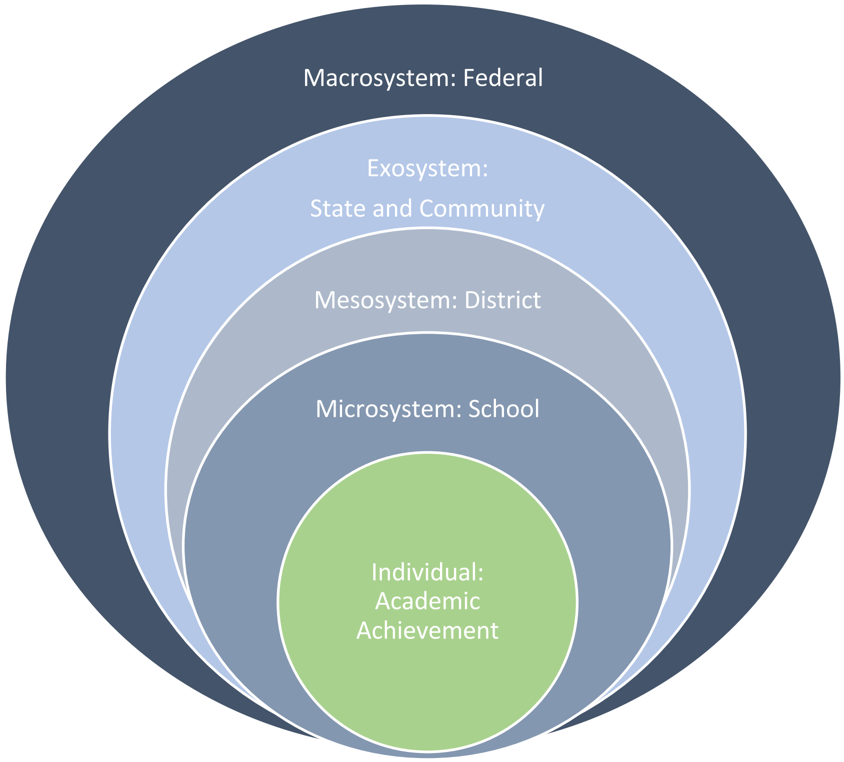
The pandemic significantly affected various aspects of daily life, especially in K-12 education. While national studies have shed light on the pandemic's impact on systems, limited attention has been given to this aspect concerning Alabama, one of the poorest states in the United States. This study closely examines how school systems adapted their instruction amidst widespread disruptions, exploring the impact of district-specific characteristics and COVID-induced changes on academic achievement in ELA and math. The primary focus of this chapter is to provide a comprehensive view of the study including the theoretical foundation, methodology, and detailed descriptions of the independent and dependent variables.

Theoretical Framework

This study is based on the Bronfenbrenner's Ecological Systems theory (EST), a framework that depicts human development as a function of an intricate interplay between an individual and their environment, representing an integrated, comprehensive view that may be presented as biological, psychological, and social perspectives (Crawford, 2020; Turner, 2019; Guy-Evans, 2022; DLE 2023). This multifaceted framework may also be applied in a variety of ways depending on the type of research being done (e.g., qualitative, quantitative, and mixed research) (Onwuegbuzie et al., 2013). Although there are few studies that focus on the connection between EST and Alabama districts specifically, findings from previous studies seemingly suggest a connection between high-poverty rates and negative impacts on educational outcomes, especially with academic proficiency. This notion, in conjunction with pandemic-induced disruptions, further implies that districts in Alabama, a predominately rural and poor state, would likely adhere to these same notions (Golden et al, 2023; Dorn, 2020; Broer et al., 2019; Archibald, 2022). The inherent and complex, yet dynamic, nature of these multi-faceted district-level phenomena make the EST framework an optimal approach as it may help position these interconnected layers in such a way that offers a clearer picture of how these factors may have influenced academic proficiency collectively, not exclusively, of each other.

To paint this picture, this study follows the same environmental structure seen in Figure 3, which consists of five layers of nested systems: microsystem, mesosystem, ecosystem, macrosystem, and the chronosystem, the "school" entity represented the school system (Bronfenbrenner, 1994). A student's microsystem includes their closest interactions, whether at school (e.g., peers, school personnel), at home with parents and siblings, or larger systems surrounding the student like school districts, the communities in which the student lives, and their local economy (Morgan, 2022; Strayhorn, 2010; Hampden-Thompson & Galindo, 2017).

Figure 3



Note. Adaptation of Bronfenbrenner's Bioecological Systems Theory (1979) from Davis & Francis (2023) showing multi-directional flow among the five layers of the individual's environment.

Despite these ecosystems appearing to function independently of each other, they are arguably interconnected and dynamic constantly influencing one another (Bronfenbrenner, 1979; Bronfenbrenner & Evans, 2000). Given the interdependent nature of these systems or levels, and the significant disruptions that COVID-19 caused to the education, strong consideration must be given to the unique characteristics and intricacies of the school systems, especially in case of Alabama systems. (Lindahl, 2018; Johnson, 2008). Moreover, while recommendations for instruction may have been presented at the national level, they may have been being there is often significant variations across and within each state (Pendola et al., 2022). For Alabama, a state widely known for high poverty rates and scarce resources, it is imperative that emergency plans, financial budgets, school system operations use a nuanced, not universal, approach to better ensure resource and funding strategies account for these differences to not only ensure that instruction may be sustained in the case of another outbreak, but that the instruction is high-quality and accessible to all students (Bertolini et al., 2012; Berkes, 2004 as cited in Ostrom, 2009).

COVID-19 had a tremendous impact on resource allocation for K-12 students, especially with those living in communities that had previous experiences with inequitable access (Adger et al., 2020; García & Weiss, 2020). Pandemic-related disruptions led to global supply chain shortages, impacting resource availability food and economic insecurities (Andersson, 2021; USGLC, 2020; Nicola et al., 2020; Bauer et al., 2015; Kakaei et al., 2022; Reardon & Portilla, 2016). To address these interruptions in supply, districts modified their strategies for managing resources to accommodate unexpected closures and an instructional shift that required implementing alternative methods. Some systems invested in new technologies and tools that supported remote instruction (e.g., learning management systems), while others implemented policies and programs such as expanded technology access and internet connectivity and academic support, and mental health services (Ciuffetelli Parker & Conversano, 2021). However, the adoption of new learning modalities and operational changes posed challenges for school systems in Alabama, potentially augmenting existing socioeconomic disparities, and impeding academic achievement. Using the EST to frame our study allows us to describe the type of districts that were impacted by pandemic-induced changes and the potential for these changes to compound challenges that existed prior to the pandemic. This frame of reference may also help us view this information in a more contextual manner, which is also helpful in exploring to what degree did Alabama districts endure changes in their pre-to-post proficiency.

Background

Persistent socioeconomic disparities public K-12 education systems in the U.S. that span over 60 years worsened during the COVID-19 pandemic. In 2020, pandemic-related cases rose to 4 million and 300,000 deaths globally, sparking widespread job losses and school closures (WHO, 2020 & 2021; Nicola et al., 2020). At one point, school closures impacted over 700,000 students statewide (Ballotpedia, 2020). These disruptions, compounded with existing socioeconomic disparities, likely amplified achievement gaps, especially in high-poverty areas with limited resources, particularly in Alabama. (Brito & Noble, 2014; Reardon & Portilla, 2016; Melchior et al., 2014). This period was particularly transformative for K-12 systems as they transitioned from in-person to remote and hybrid instruction (Yani, 2021; Francom et al., 2021).

Prior to the pandemic, U.S. public K-12 systems largely centered on in-person instruction. Alternative learning modalities such as hybrid and remote instruction were rarely implemented, with only 20% of K-12 systems using remote instruction under special circumstances (Hua et al., 2017; Hart et al., 2019). However, this significantly changed during 2019-20, the COVID year, as 83% of public-school systems employed remote instruction, further underscoring the impact of pandemic-related closures on school operations and student learning (Berger et al., 2022).

While it is widely known that the poverty rate of Alabama, one of the poorest states in the nation, has been consistently higher than the United States, 16.2%, compared to 10.5%, reflecting ongoing resource disparities in K-12 education (Davis, 2023; U.S. Census Bureau, 2023; KFF, 2023). Comparisons of per-pupil spending also showed that Alabama ($9,717.00) spent significantly less per student than what was reported nationally ($12,585.00), further signaling a higher potential for insufficient access to educational resources and the provision of instruction that was poor quality (NSB, 2021; NEA, 2023; Morgan, 2020). Staff shortages and limited learning resources persist due to an unfair funding formula (SPLC & ELC, 2021). Low achievement rates in reading (33% vs. 35%) and math (15% vs. 19%) for 4th and 8th graders emphasize the challenges, continuing to illuminate a pattern of underperformance with K-12 students that ultimately hinders their ability to grow academically and achieve positive educational outcomes (NCES, 2019a; Woolley et al., 2008; Banerjee, 2016; Ladd, 2012).

Literature Review

Repeated, and often, extensive school closures led to significant disruptions in the day-to-day operations of K-12 education systems in 2019-20. These pandemic-induced closures prompted school systems to adopt alternative educational practices, especially in terms of instruction. While many systems were able to adapt to these new changes, many studies on COVID-related topics have suggested otherwise. Additionally, public systems that have been studied may not be fully inclusive or representative of those that experience deep-rooted socioeconomic inequities. The main purpose of this study is to examine whether ESSER funding, FRL, and locale, all of which will function as direct or proxy measures for resource availability and funding, and the adoption of alternative learning modalities may have impacted achievement for public school districts. The focus is placed on Alabama public school districts, specifically, due to the state's history of low achievement and high poverty rates and rurality. For these school systems, responding to pandemic-related school closures was unavoidable, begging the question what degree these changes exacerbated existing achievement gaps for these systems (Johnson, 2020).

Differences in District-level Characteristics

Over the years, researchers have studied student achievement in relation to differences in characteristics at the district level, especially with community resource availability. Gustafsson (2003) found an association between global resources and school-specific factors, such as class size, noting that these two things often influenced teacher quality and, consequently, academic achievement. Duncombe's (2017) systematic review of over 1,800 public schools in Virginia revealed that resource deficits negatively affected course offerings, when comparing high- and low-poverty school systems. Results from that review suggested that high-poverty systems were less likely to offer advanced classes or have experienced teachers, making it evident that resource accessibility in surrounding communities directly impacts student learning. Although the Alabama population was not specifically focus of these, or other studies, their emphasis on the unique challenges that high-poverty school systems experienced aligned with what has been historically observed with ones in Alabama. Moreover, these findings collectively show a consistent pattern of these challenges with school systems in high-poverty areas, which further underscores the significance of examining Alabama districts, as they were also prone to encountering similar challenges prior to the pandemic.

Previous studies have not only emphasized the link between resource accessibility, school systems, and achievement but have also emphasized a central position of this study: socioeconomic disparities within K-12 education present greater challenges to poor school systems than to their counterparts (Rosen et al., 2018). Furthermore, environmental factors are connected to learning opportunities, suggesting a complex interplay between communities and schools. Accounting for socioeconomic challenges is critical to providing a high-quality education experience, namely for high-poverty or rural school systems (Pokropek et al., 2015), and may require tailored support efforts, as these strategies may be crucial to day-to-day operations, and in adapting to catastrophic events like the 2019 COVID-19 pandemic.

Pandemic-related school closures impacted public education systems nationwide, however, they were especially problematic for those in Alabama, a state with high percentage of rural and high-poverty areas and a persistent pattern of low achievement. A recent interview with Alabama

Superintendent Eric Mackey revealed that the average ACT score for 11th grade students dropped from 18.2 to 17.2. Additionally, the percentage of 2nd to 8th grade students considered to be proficient in ELA was under 53% for each grade level, and for math, the proficiency percentage ranged from 34% of 2nd grade students to only 14% of eight grade students (Chandler, 2021).

To gain a better understanding of how district-level factors, COVID-induced changes to instruction, and changes in achievement before and after the pandemic, this study included two types of achievement, for both ELA and math. The first was student achievement documented for AY 2020-21, post-COVID achievement, as the dependent variable. While achievement data provided both the "number of students who completed a reading or language arts assessment and for whom a proficiency level was assigned and the "midpoint of the range used to report percentage of students scoring proficient on ELA or mathematics assessments, measured using a scale from 0 to 100 (NCES, 2021b & 2023), the latter was selected to account for differences in district size (Dougherty & Shaw, 2016).

Locale Differences

Socioeconomic disparities, persistent contributor to K-12 achievement gaps, may have intensified due to instructional modifications school systems made in response to the pandemic. Most high-performing systems transitioned smoothly to alternative learning modalities (e.g., remote learning), however, low-income communities struggled due to having limited access to funding and resources (Zota & Granovskiy, 2021; Reardon & Portilla, 2016 & 2019). There are many variations in how 'socioeconomic' is defined, however, this construct is usually described in terms of a person's or a family's position in a social hierarchical structure which is associated with their level of societal control and/or access to resources such as like wealth, prestige, power, and social and cultural capital (APA, 2023; Brito & Noble, 2014; Woolley et al., 2008).

These disparities were more pronounced in high poverty areas, underscoring the need to explore socioeconomic disparities' potential impact on student achievement. Schwartz et al. (2021) found that during school closures, students from urban communities needed more access to devices and quiet spaces essential to learning. Additionally, studies found that rural school systems often needed a better infrastructure to provide students with high-speed, broadband internet (Ogundari, 2023; Litchfield et al., 2021; Mueller et al., 2021). Students living in low-income areas were also likely to experience inequitable access and, therefore, were less likely to participate in remote or hybrid instruction. Poor participation in instruction, in turn, impacted their opportunities to achieve academic success and their academic performance overall (Krishnan, 2023).

Braxton et al. (2014) further noted that many rural and urban districts needed more funding, leading to many challenges in providing students with a quality educational experience. Students living in rural areas experienced internet issues and longer travels for food and other support services, showing a need for more necessities (Azevedo et al., 2021). Additionally, studies found that those living in rural areas had a higher proportion of families characterized as "essential workers," meaning, during shutdowns, they were more likely to work longer hours and less likely to adequately supervise and support their children as they learned remotely (Levine, 2020).

While this study uses free and reduced lunch as a proxy for poverty and resource access, other studies have cautioned against relying solely on it alone as a poverty measure. Prior research recommends analyzing it alongside other relative factors such as education level, income, and occupation to accurately identify accessibility issues at the district level (APA, 2023). For this study, locale, a geographic indicator, was selected to help classify and compare school systems with respect to resource availability and independent variable, extracurricular access, teacher quality, and community involvement (Roscigno et al., 2006). Galobardes (2006) noted three primary ways socioeconomic status could be measured as (1) a dependent variable, (2) an independent variable, or (3) an adjustment or control variable. Option number two aligns with the quantitative, correlational approach of this study, and will provide insight into the relationship between socioeconomic measures, district level characteristics, COVID-related instruction modifications, and academic achievement. Locale served as another descriptor for districts, following the NCES format, which categorized locale into four groups: (1) city, (2) suburban, (3) town, and (4) rural (Geverdt, 2015).

Free and Reduced Lunch and District-Based Poverty

The overarching theme of this study posits that school systems located in high-poverty areas faced more challenges in accessing necessary resources, services, and funding, all of which, contributed to achievement gaps prior to the COVID-19 pandemic. Pandemic-induced, extensive school closures prompted AL public school systems to swiftly shift from traditional in-person instruction to alternative learning modalities, leading to low achievement in high poverty systems. Examining how K-12 systems in Alabama, a state recognized for its high poverty rates, adjusted to the instructional changes brought on by COVID-19 may offer more insight into how these difficulties affected student achievement.

Previous research has suggested a connection between technology access and effective online learning in the United States. However, COVID-related shutdowns exacerbated a pre-existing digital divide, particularly with groups that already experienced socioeconomic disparities in access. Golden et al. (2023) found that during the initial pandemic stages, numerous school systems faced significant delays in providing technology to students living in U.S. households earning less than $25,000/year, leaving roughly two thirds of these students with insufficient technology access and supplies that were essential to engaging in remote learning. This delay also led to numerous school closures, specifically in low-income communities, in addition to inconsistent assignment offerings (e.g., paper assignments, paper and online work), complicating task instruction and assignment submission methods. These accessibility challenges persisted into the 2020-2021 academic year, mainly due to ongoing supply shortages and external factors such as the political atmosphere.

Free and reduced lunch, a product of the National School Lunch Program (NSLP), data are accessible and follow the assumption that families that have financial difficulties are more likely to participate. As of 2020, roughly 300,000 students across 100,000 public and non-profit school systems, participate in the NSLP (Kamelhar & Tanen, 2020). Free and reduced lunch is commonly used to measure student poverty in education research and has allowed school systems and policymakers to identify areas that have higher concentrations of economically-disadvantaged students, helping to ensure resource allocation and interventions are more (NCES, 2023).

While free and reduced lunch has been widely viewed as a viable estimate for school-based or district poverty, there have been conflicting accounts on its validity, especially when examining the connection between free and reduced lunch and educational outcomes such as student achievement. Cruse & Powers (2006) conducted a correlational study to gauge the reliability of FRL as an indicator of "intercensal poverty" by examining the relationship between NCES FRL data and Census 2000 poverty estimates, finding that while certain aspects of free and reduced-price lunch (FRPL) eligibility counts could help estimate district-level poverty, their results did not support using FRPL data as a poverty estimate for school-age children. They further noted that differences in reporting periods (annual for poverty versus monthly for FRPL), income thresholds (e.g., 100% for poverty versus 130% and 185% for FRPL), and school district population versus enrollment, were among the various factors that appeared to account for various disparities that have been observed at the district-level.

Snyder & Musu-Gillette (2015) found that despite the average proportion of free and reduced lunch students (per district) being a viable indicator for children poverty rates, it may not adequately account for the child poverty level or changes in these rates over time. Students may be eligible to receive FRL through direct certification, meaning they already receive benefits from state and federal programs (e.g., Medicaid, food stamps) or by completion of school-administered surveys (USDA, 2017). However, inflated FRL counts, and in essence, district poverty rates, may be attributed to district-administered surveys verifying income amounts, the United States Department of Agriculture (USDA) taking a more lax approach with enforcing income verification practices when determining FRL eligibility, school systems and parents receiving incentives, such as increased funding for schools and cheaper food prices for parents (Parsons, 2023).

Some studies support using free and reduced lunch data as a district-level poverty measure. Initially, district poverty estimates were created synthetically from aligning sub-county data with the Small Area Income and Poverty Estimates (SAIPE) program's model (NRC, 2000). To improve the accuracy of this estimate, FRL eligibility was identified as a viable district poverty indicator (Snyder & Musu-Gillette, 2015). A 2022 RAND study found a strong correlation between FRL rates and various poverty measures, including the percentage of 5- to 17-year-olds in poverty (r = 0.65), families below the poverty line (r = 0.63), average income-to-poverty ratio, median family income, families with incomes between $15,000 and $25,000 ($r$ = 0.61), and households receiving food stamps or Supplemental Nutrition Assistance Program (SNAP) benefits (r = 0.61). Survey results (n = 1,626) showed significant associations between school-level FRL eligibility rates and these poverty indicators (Doan et al., 2022).

Due to this study's focus on student achievement, free and reduced lunch was also selected as a variable because students in these programs are more likely to have lower achievement, which emphasizes how influential socioeconomic factors may be when looking at educational outcomes. For instance, students living in high poverty areas often encounter challenges such as limited resources and inadequate nutrition, affecting their academic performance (Ballotpedia, n.d.). Mitigating negative patterns observed in achievement will likely involve school systems offering additional support such as tutoring and mentorship to level the playing field for these students academically.

District-Level Reponses to COVID-19

The adoption of alternative learning methods in K-12 education became more pronounced during the COVID-19 pandemic when it was no longer feasible to provide in-person instruction due to school closures. Prior to the pandemic, U.S. public school systems followed an in-person instruction and training model, making remote learning relatively uncommon. National Teacher and Principal Survey (NTPS) results for AY 2015-16 showed that roughly 6% of public and 8% of charter schools offered most of their courses online (Taie & Goldring, 2017). Results from the 2017-18 NTPS slightly showed only 21% of public, 13% of private, and 30% of charter schools offered any of their courses virtually (Taie & Goldring, 2019). Results from the Spring 2020 NTPS showed a significant difference from previous years with public schools offering virtual courses increasing to 83% (Berger et al., 2022). Remote learning is often provided off-campus, virtually (Black et al., 2021). Furthermore, schools and/or school districts seldom used virtual learning methods prior to the COVID-19 outbreak. The drastic increase in the implementation of virtual learning coupled with the introduction of COVID-19 further suggests a potential connection between pandemic-related school closures and the shift in learning modalities.

Remote Learning

In-person instruction became less feasible during prolonged pandemic-related shutdowns, leading to widespread implementation of remote learning methods, including live video conferences, pre-recorded lectures, and online forums (Hodges et al., 2020). To ensure equity, schools provided devices and internet access for remote learning (Coleman, 2021). Some studies indicated that some students benefited from remote learning, reporting that this approach offered flexibility, immediate feedback, and accessibility, benefiting students with diverse needs and disabilities (Saikat et al., 2021; Dhawan, 2020; Bowen et al., 2014). It also provided access to more resources, fostered self-directed learning skills, and encouraged creative teaching approaches, enhancing student engagement and motivation (Gray & DiLoreto, 2016; Sahu, 2020; Johnson et al., 2023; Kim, 2020).

Hybrid Learning

Districts utilized hybrid instruction, combining of both in-person and remote methods, to offer more learning opportunities that were flexible, yet, tailored to meet the needs of students while also comporting with new instructional standards that were based on pandemic-induced federal mandates (Allen et al., 2021; WDPI, 2022). One of the benefits of this approach was that it allowed students to progress at their own pace with teacher support, which not only promoted engagement, but it also led to positive student performance (Li et al., 2022; Katsarou & Chatzipanagiotou, 2021). Hybrid learning, like remote learning, also accommodated diverse learning styles, fostered collaboration, and improved academic achievement, promoted a positive learning environment (Tong et al., 2022). Teachers also perceived that hybrid methods improved their teaching effectiveness as this modality often required the integration of technology (Jaggars et al., 2013). Hybrid instruction was also cost-effective due to their being less time spent using school facilities and related resources, helped improve learning and engagement, which ultimately led to students performing well both in-person and online (Halverson & Graham, 2019; Wang et al., 2022; Attard & Holmes, 2022).

ESSER Funding and Learning Implications

Pandemic-related impacts led to numerous disruptions in K-12 education, making it more costly to sustain day-to-day operations and instruction. In 2021, section 18003(d) of the Coronavirus Aid, Relief, and Economic Security Act (CARES), section 313(d) of the Coronavirus Response and Relief Supplemental Appropriations (CRRSA) Act, and section 2001(e) of the American Rescue Plan (ARP) Act established the Elementary and Secondary School Emergency Relief or ESSER funds, which played a critical role in assisting K-12 education systems across the United States response to the pandemic (USDOE, 2022). Roughly $200 billion federal dollars were distributed to schools receiving Title I funding to address COVID-related challenges relative to promoting the safe reopening of schools, mitigating learning loss, enforcing health protocols, and softening the digital online learning gap and thus, increase educational equity (Gordon & Reber, 2021; Merod, 2022; OESE, 2022).

While the provision of ESSER funds was intended to support learning during COVID, whether these efforts yielded positive impacts on student achievement is still unclear. Goldhaber et al., (2022) used student level data (n = 2,100,000) from 10,000 schools in 49 states, including Washington, D.C., to compare growth in student achievement during COVID-19 (AY 2019-20) and to what was recorded prior to COVID (AY 2017 to 2019). Results showed that high poverty school systems faced more negative impacts on student achievement during the switch to remote learning, widening the gap between low and high poverty schools (SD = .168). Findings also indicated that slight disparities in math achievement gains when considering other factors such as race (Black and Hispanic students, .014+.016), and that baseline achievement scores appeared to be a contributing factor in the differences observed in achievement. Overall, roughly one-third of the total achievement difference (.051/.168) was likely due to the increase in remote/hybrid learning in high-poverty schools.

The sustainability of the provision of ESSER funds was also questioned, especially with respect to its potential to reduce funding disparities and its impact on student learning for the long-term. Schwalbach (2021) found that Congress provided more than $200 billion in new, COVID-related spending, making it the most substantial influx of federal education funds ever documented. Dorn et al. (2020) further noted that, historically, deep-rooted socioeconomic inequities have hindered several legislative efforts, and that, these pandemic-related, short-term initiatives may not yield lasting improvements on educational quality.

This study emphasizes that existing socioeconomic gaps were amplified during the pandemic, likely impacting academic performance in ELA and math. The total amount of ESSER funds awarded per district served as a measure of resource availability for those located in economically-disadvantaged areas for three key reasons (1) only school systems that received Title I funds were eligible to receive ESSER funds (Smith Duffy, 2022), (2) ESSER funding was primarily provided to help mitigate learning loss and cover other COVID-related costs that may have been otherwise difficult to shoulder, and (3) Title I and ESSER funding are associated with poverty measures including income, restricted funding, inadequate access to resources, etc., which aligns with the overarching purpose of this study.

To better prepare this variable for analysis stage of this study, a new version of the total amount of ESSER funds awarded per AL K-12 system, ESSER funding awarded per pupil/student, served as an independent variable. The original variable, ESSER funds awarded per district, was converted into ESSER funding awarded per pupil/student by dividing the total number of students by the total amount of ESSER funds awarded per district. The resulting percentage represented the proportion of funds that were awarded, which helped account for size differences among the districts.

Chapter Summary

Despite numerous national studies examining the impact of free and reduced lunch, locale, ESSER funds per pupil, learning modality changes, on academic achievement, few studies focus on all these variables, collectively, with respect to public school systems in Alabama. A key objective of this chapter was to illustrate how Bronfenbrenner's Ecological Systems Theory (1979) aligned with various aspects of this study. Additionally, this approach was adopted to account for the underlying intricacies that occur in the surrounding layers of a district, as these internal dynamics offer insights into how these factors collectively influence academic achievement. Despite national data offering valuable insights into how COVID-19 has impacted learning, they may not be relevant to Alabama specifically. Furthermore, without these data being relevant to this state, these same insights may fail to fully capture the essence of the challenges that district face, and thus, may also fail to adequately meet their needs and experiences specific to this state. To gain a better understanding of how underlying challenges impacted low-income school systems' capacity to sustain instruction during pandemic-related closures, research efforts must dive deeper into state-specific intricacies of each system, especially for those in Alabama.

Furthermore, this study examined how these characteristics coupled with pandemic-related instructional shifts impacted pre/post proficiency changes, while controlling for pre-COVID scores, for Alabama public school districts. Additional details, including the research design, rationale, supplemental information on the methodology, including an in-depth description of the independent and dependent variables and data preparation process are provided in the Chapter 3. Chapter 3 also outlines the analysis procedure, potential threats to validity, and other ethical measures taken to mitigate these threats.

CHAPTER 3: RESEARCH METHODOLOGY

Public school systems developed and implemented emergency contingency plans that outlined strategies for handling current and future pandemic-related disruptions in response to a myriad of concerns that were relative to systems operating nationwide (Pressley et al., 2022). However, the extent in which these strategies have mitigated negative impacts on student achievement is not fully understood, especially for those attending Alabama public school systems. Although public school systems in Alabama fundamentally follow the same educational structure as that in other states, long-standing socioeconomic disparities have contributed to Alabama's pattern of low achievement. To fully understand COVID-related impacts on learning, it is imperative that we first examine whether there are district-level differences statewide.

When looking at academic proficiency at the district level, various exchanges, including differences in district-level characteristics and their subsequent responses to COVID-19 must be considered. Two regression models, one for ELA and one for math, were constructed to model the relation between these district-level variables. Specifically, these two models focused on the degree in which free and reduced lunch status, locale, the implementation of alternative learning modalities, and Elementary and Secondary School Emergency Relief (ESSER) funds contributed to changes in ELA and math proficiency (pre-and post-COIVD) for Alabama public school districts. Pre-COVID proficiency scores for ELA and math served as covariates that controlled for existing variations in proficiency before the pandemic. The research questions guided the model development process are as follows:

1) Do differences in district-level characteristics, such as locale and Free and Reduced Lunch proportions per district, predict the changes in pre-to post-COVID proficiency scores while controlling for pre-COVID proficiency scores for Alabama public school districts?

2) To what degree did district-level responses, such as changes to learning modalities and the addition of ESSER funds per student, influence changes that were observed in pre-to-post academic proficiency?

The next section in this chapter will describe various aspects of the study, including the research design, additional information on the data sources, and procedures for preparing and analyzing these data.

Research Design

Previous studies have used various quantitative methodologies to explore the impact of COVID-19 on student achievement. For instance, Fisher et al. (2022) conducted a multivariate logistic regression to identify changes in students' grades based on school and student-specific characteristics relative to each learning modality type while controlling for environmental characteristics. Ludwig et al. (2022) used a multi-level imputation multi-group model in addition to conducting an IRT analysis to examine pandemic-related impacts on 4th grade reading achievement. A systematic review of literature of 49 studies showed that roughly 39% (*n* =19) used quantitative approaches to explore topics related to challenges with implementing remote instruction (Huck et al., 2021). Siripipatthanakul et al. (2023) also found that quantitative approaches are commonly used in educational research, mainly to support or not support a theory. The systematic, structured nature of quantitative methods are also conducive to preparing and analyzing potential trends, patterns, and relationships within a dataset (Codiroli Mcmaster & Cook, 2019). Researchers have also used quantitative results to make inferences about a larger population based on findings from a smaller sample (Williams, 2021). Inferences made from these findings, have been used to inform policy decisions and educational practices that may improve achievement on a larger scale, which is also a future implication of this study.

Secondary data were selected to represent measures for district-specific characteristics, district-level responses to pandemic-related changes, and the change between district-level pre-to-post academic proficiency were used in this study. Additionally, this relationship among these data was analyzed over a specified time period, making it appropriate for the study to follow a pre-post research design, which is quantitative in nature. Pre-post designs have been widely used when evaluating impacts of interventions on a variable or a set of variables in addition to estimating these changes on specified outcomes (Jennings & Cribbie, 2021a & b).

Data Sources

The analysis involved performing descriptive statistics and a multiple regression using secondary data. Data were procured from the Center for Disease Control and Prevention (CDC), National Center for Educational Statistics (NCES), Elementary and Secondary School Emergency Relief (ESSER). Although this study used solely involved secondary data that were publicly available, IRB determination (or approval) that this study did not involve collecting data from live humans was obtained prior to engaging in any research-related activities (AU IRB #23-499 NHSR).

District-Level Characteristics

Title I, Part A of the ESEA, requires that state education agencies or SEAs report student achievement data to the U.S. Department of Education annually for grades 3-8 and at least once in high school, using state assessments that measures student performance against state standards (USDOE, 2017 & 2022). To meet this expectation, National Center for Educational Statistics (NCES), an affiliate of the U.S. Department of Education, was established to collect, analyze, and report education data. This study included variables from NCES datasets to measure achievement and district level characteristics (NCES, n.d.a & 2021a). Moreover, the change in ELA and math pre-to-post proficiency was the outcome variable (achievement) while ELA and math pre-COVID proficiency, another achievement measure that was documented prior to the pandemic, served as a covariate. These variables were presented at percent proficient (achievement) which was defined in the 2022 *EDFacts* Data Documentation as "the percent of students proficient or above on the state assessment," with "proficient or above" defined as the number of students achieving at the "proficient" or "advanced" levels, as defined by each SEA" (USDOE, 2022; p. 6). Other variables such as local education agency (LEA) name, and locale, were used to describe the geographical makeup of public-school districts in Alabama. This study also included data such as student enrollment and full-time teacher counts to describe student body and personnel characteristics for each district.

While the U.S. Department of Education is the primary source that establishes educational and curricula standards for K-12 and higher education programs, the NCES is the primary source for educational data in the United States (NCES, n.d.a & 2021a). The NCES collects, analyzes, and reports data for various aspects of education, including student and teacher demographics, academic achievement scores, and educational attainment level. These data, which are publicly available on the NCES website, were procured from various reports, surveys, and databases, including Common Core Data (CCD, 2018). Policymakers, researchers, educators, and the public have used these data to inform various decisions ranging from educational policies to instructional practices.

The NCES regularly performs rigorous procedures to ensure data collection, analysis, and reporting is reliable and valid (USDOE, 2022). Steps in these procedures include establishing clear, explicit research questions, designing sound research methods and instruments, assessing instruments for clarity and comprehension, and conducting extensive data cleaning and analyses with statisticians and content-specific experts to further confirm that data collection and analytical processes have met reliability and validity standards (NCES, n.d.a & n.d.b). External researchers have also been encouraged to replicate and validate NCES findings to further strengthen the credibility and robustness of the use of their data in prior studies (NCES, 2017b). Overall, the NCES review process is systematic and comprehensive, further supporting the notion that their datasets are high quality and appropriate for analysis by policymakers, researchers, and practitioners (NCES, n.d.a, 2017b, & 2021b).

Additionally, NCES data have been used to track trends in K-12 systems over periods of time to illuminate potential racial, ethnic, and socioeconomic inequities in educational outcomes which in turn have been used to inform subsequent improvement efforts targeting educational quality, access, and student achievement (NCES, n.d.b). Furthermore, identifying data trends may underscore racial, ethnic, and socioeconomic disparities in education, which may be the focus of initiatives (e.g., No Child Left Behind (NCLB) of 2007) aimed at lessening achievement gaps and improving education opportunities for all students. Furthermore, legislative efforts have utilized NCES data to evaluate policy and program effectiveness in relation to student achievement, making the NCES a viable data source for describing district-level characteristics in this study (Abdulkadiroglu et al., 2011; USDOE, 2020).

Free and Reduced Lunch Data

The NCES database was also used to find information on the proportion of students receiving Free and Reduced Lunch (FRL) data which, for this study, served as a measure for district-based poverty. These data were provided by the National School Lunch Program (NSLP), a U.S. program that offers students school meals for free or discounted pricing and have widely used in educational research as an indicator of poverty levels in schools and districts (Greenberg et al., 2019). Free and Reduced Lunch counts may also be indicative of districts access to resources, which was frequently discussed throughout this paper.

According to a 2023 NCES report, students coming from households with incomes under 185% of the poverty threshold are likely to be eligible for free and reduced lunch. School districts in high-poverty areas often face distinct challenges related to limited resource accessibility and funding availability. These challenges not only impact the quality of educational experiences for students, but they help perpetuate continuous disparities in academic achievement and may further contribute to lower educational attainment rates (Morrissey et al., 2014; Doan et al., 2022; Crosnoe & Cooper, 2010). A key focus of this study was to explore the degree in which public school districts in Alabama lacked access to resources and funding as both may heavily influence the quality of instruction provided to students.

Given that lower-income families are more likely to participate in this program, factors such as family income and household size have often been linked to FRL enrollment (Nicholson et al., 2014). However, variable eligibility determination processes, across states and districts, may suggest that FRL rates is not a precise measure for school- or district-based poverty (Snyder & Musu-Gillette, 2015). While this concern is valid, FRL has repeatedly been used when assessing the socioeconomic background of student bodies, informing policy decisions aimed at addressing educational inequalities, and exploring how low-income districts adaptations to COVID-related changes may have impacted academic proficiency. For these reasons, FRL was selected in this study to help identify districts in high-poverty areas as they would more likely encounter higher instances of socioeconomic challenges during the pandemic.

District-Level Responses to COVID-19 Data

One of the ways that districts responded to COVID-related changes was by implementing alternative learning modalities. Learning modality data, specifically, in-person, remote, and hybrid learning, provided information on the number of instances where public school districts in Alabama offered traditional and alternative instruction. These data were taken from the CDC School Learning Modality dataset, available via the *CDC School Learning Modalitie*s webpage, and have been used in past studies aimed at ascertaining the degree in which the pandemic impacted various aspects of education.

The School Learning Modalities dataset, which was based on data collected from August 2021-Sept 2022, was created using Hidden Markov Modeling (HMM), a statistical test that used past learning modality data patterns to estimate and infer when districts likely offered learning modalities each a week (CDC, 2022; Parks et al., 2021). To account for instances of missing data or conflicting results, researchers also used information on pandemic–related school closures that they found during systematic internet searches. The dataset was representative as it included information for 57,419 public and private K-12 schools, approximately 76% of the total number of schools in the U.S. (CDC, 2021b).

Prior to 2020, no formal pandemic-related dataset, with respect to COVID-19 data, existed, making it more difficult to assess of its impact on student learning (Miller et al., 2022; Gross & Opalka, 2020; Aristovnik et al., 2021). The School Learning Modalities dataset, one of many initiatives focused on identifying indicators of COVID-related impacts on learning, involved a high level of statistical rigor in its creation. The consistency of its learning modality types, and the ones examined in this study, coupled with the strong concurrent validity that was found between the dataset's classification of school learning modalities and other measures of instructional models made it a viable data source for this study (Parks et al., 2021).

ESSER Funding Data

The introduction of ESSER funding was another method districts employed to lessen the impact that COVID-related changes may have had on instruction and learning. Initially, the amount of ESSER funding awarded to districts was included in this study to measure district-level COVID-relief funding. However, the version of this variable that was used in the analysis was the amount of ESSER funds awarded per student for each district. Details on the construction of this variable will be addressed further in the *Variable Creation* section of this chapter.

Data Preparation Procedure

Preparing data for analysis requires several steps, often beginning with data cleaning. Kelleher and Tierney (2018) described cleaning data as involving the identification/correction of any errors, inconsistencies, and missing values. Proactively resolving these issues will not only likely improve the quality of your dataset by making the data more complete and consistent, but it would also more likely yield accurate results during the analysis phase. The next sections of this chapter will further describe each component of the data preparation process, including handling missing values, dataset restructuring, and data merging.

Handling Missing Values

Prior to this step in the preparation process, variables that were not pertinent to the study, especially those with numerous missing values, were removed to reduce each dataset. While it is typical to find missing data in datasets, their presence can significantly impact the validity and quality of analysis results. Imputation or replacing missing data with plausible estimations of their values, has been largely used in handling missing values (Little & Rubin, 2019; Schafer & Graham, 2002). While there are several ways to utilize the next method, listwise deletion, however, this approach typically involves excluding cases with missing values observed in variables that are not pertinent to the study (Enders, 2010; IBM, 2020). While many studies have examined the pros and cons of employing imputation or listwise deletion, the prevailing view in the literature suggests that both methods may potentially introduce bias into the results, and therefore may adversely impact the validity of the analysis (Pepinsky, 2018). In addition to concerns about biases, methods such as listwise deletion, may also affect the parameters of the model, namely the sample size, which may further impact how each regression model is interpreted, compared, and selected (Kang, 2013).

Researchers using any method to handle missing values must carefully consider the nature and characteristics of their datasets to determine the best, most appropriate approach for handling missing data (van Buuren, 2018; Graham, 2009). In addition to consideration of biases, having a large sample size, which represents a proxy for the proportion of cases from the population, is commonly pursued in quantitative analyses. Past literature suggesting that a larger sample may increase its representativeness and generalizability, as well as improve the accuracy of the results (Andrade, 2020). Listwise deletion was used to handle missing values due to having only one missing district from the population of districts in Alabama. Variables were excluded based on many factors, including their suitability for performing descriptive statistics and a multiple regression, and their potential impact on sample size upon exclusion.

Restructuring the Datasets

Some datasets required restructuring to improve our ability to manipulate and visualize the data. Restructuring data helps "melt" data frames into a long format, making them easier to use as well as primed for more complex analyses (Wickham, 2014). Two different statistical software programs, R and SPSS, were used to restructure the CDC learning modality dataset, specifically, from a long-to-wide format, as a wide format would support conducting a multiple regression (Harrell, 2015).

Merging Datasets

While data were selected from multiple sources to contributed to the robustness of the analysis, analyzing them individually would not be conducive to developing a comprehensive understanding of the data. Merging separate data files into one is a method that may improve the analysis (Carpenter, 2014). In addition to restructuring the datasets, all the datasets were merged into one file, which was essential to performing the multiple regression.

Prior to merging the data, at least one variable was identified across all datasets and used to "bridge" or join them together. Statistical programs such as SPSS and R were used to merge each individual dataset together, two at a time, until only one fully-merged dataset remained. The final dataset was also presented in a wide format, with each row representing data for each Alabama public school district.

Once the data merge was complete, data were exported as a spreadsheet into Microsoft excel to determine whether the merge was properly performed. The bridge variable in addition to excel features, mainly conditional formatting, allowed us to visually examine variables and cases in the final dataset for potential errors by providing the ability to select unique or duplicate cases while comparing two variable columns at a time. Discrepancies that were found were fixed by manually entering in values or by re-joining each individual dataset, two at a time, to see if the issue resolved itself.

Variable Creation

Once the data were merged into one file, additional variables were created and added to provide a more nuanced understanding of district-level differences and responses to COVID, which in turn, improved the analysis and interpretation of the data. For instance, learning modality data, originally presented as weekly estimations of the number of instances where in-person, remote, and hybrid learning occurred in Alabama public school districts, was recoded, and transformed to reflect a count of the number of instances where instruction was provided either in person or not (remote/hybrid). The latter of the two categories was coded as such after descriptive statistics highlighted a sizable discrepancy between in-person and alternative learning modalities (remote and hybrid).

ESSER data provided a measure for how Alabama districts', especially those that classified as rural and/or high poverty, responded to pandemic-related changes in school operations. However, it was evident that its original format was not conducive to analyzing this effect. As previously stated, the total amount of ESSER funds awarded per district was the original version of the ESSER funding variable. To better account for district-level differences in size, and make these data more comparable for analysis, we created a version of the variable that reflected the amount of ESSER funding awarded *per student*. This variable was created by dividing the total amount of ESSER funding awarded by the total number of students enrolled (per district).

The analysis involved conducting a multiple regression that followed an ANCOVA framework with the pre-COVID proficiency as a covariate. Covariates in multiple regression function as an independent variable, that is considered in conjunction with other independent variables, to explain its impact on the dependent variable (Witte & Didelez, 2019). Adding covariates to multiple regression also enhances the accuracy and reliability of the analysis by controlling for other effects and accounting for potential confounding variables, and thus, making it easier for researchers isolate and identify the direct relationship between the independent and dependent variables (Glymour & Weuve, 2018).

Academic year 2019-20 was designated as the “pandemic year” due to the continuous nature of COVID-19, creating respective two time periods for proficiency scores: (1) pre-and (2) post-COVID. Pre-COVID proficiency variable, specifically, was created by averaging proficiency scores reported prior to the pandemic, AY 2015 to 2019, for four academic years into one score. We recognized that variations in students’ academic backgrounds may inadvertently influence the dependent variable, making it imperative that we included the pre-COVID proficiency score as a covariate rather than including it as an independent variable to help increase the accuracy of our results (BUSPH, 2013).

The dependent variable had to be created as well. Originally, academic proficiency scores documented for the AY after the pandemic could have served as the dependent variable; however, we determined that it may be best to use a different version of that variable to better capture pre-to-post differences. In addition to the covariate, the change in pre-to-post proficiency, which was not included in the NCES dataset, served as the dependent variable. This variable was calculated for both subject areas by subtracting pre-COVID proficiency scores from the post-COVID scores.

We also created a variable to reflect the average proportion of free and reduced lunch students per district. Like other studies, such as Snyder & Musu-Gillette (2015) free and reduced lunch data served as an indicator of district-based poverty. These data were originally presented as school level data, creating a misalignment with the unit of measurement designated for this study. To resolve this issue, we aggregated the FRL data up to the district level using a 5-step process that was provided in the *Aggregating National School Lunch Program (NSLP) Eligibility Data* document (NCES, 2021). More specifically, the following steps were completed (1) the ElSi or Ethical, Legal and Social Implications Research Program tablegenerator was used and thus, created a school-level table of pertinent variables, (2) a new column named “NSLP” was added by using Free and Reduced-Price Lunch data that were available; including zeros, and the direct certification number, (3) school data that met criteria in the previous step were aggregated up to the district level, and (4) the total number of operational schools and the number of schools was calculated for each district using schools that met criteria in step 3. If Free and Reduced-Price Lunch data were unavailable, data from operational schools were used instead.

Multiple Regression Analysis

Statistical models offer a way to mathematically summarize the properties of variables and their relationships with one another (Vrieze, 2012). A multiple regression is a method commonly used to construct statistical models that may be used to analyze the degree in which two or more independent variables predict the variation observed in a dependent variable (Hair et al., 2017; Hanson, 2010). The primary purpose of this study was to understand whether district-specific and pandemic-induced changes contributed to differences in pre/post achievement, while controlling for differences in pre-COVID proficiency, at the district level. Moreover, a multiple regression that followed an Analysis of Covariance (ANCOVA) framework was conducted to examine how these predictors might explain the change in pre-and-post-COVID proficiency (dependent variable) while controlling for ELA and math pre-COVID proficiency scores (covariate).

Research Questions

The study examined whether district-level characteristics and district-level responses to pandemic-related changes explained changes that were observed in pre- to post-COVID academic proficiency scores. Past studies have consistently suggested that high levels of poverty are more likely to lead to negative impacts on student performance (Ziller et al., 2019; Rorrer et al., 2018). Rural and urban geographic regions have been associated with scarce resources, lower rates of educational attainment, and more instances of health disparities became more of an issue for districts who were forced to offer remote and hybrid instruction; all of which, have been linked to poor student achievement (Eamon, 2005; Sirin, 2005).

Descriptive Statistics

Descriptive statistics were performed in addition to the multiple regression. These findings provided information conducive to summarizing and organizing the data, in addition to observing any notable patterns or trends. Central tendency measures (e.g., mean, median, mode, standard deviation) were used to visualize and describe the shape and nature of a distribution including its dispersion, skewness, and/or kurtosis (Gravetter & Wallnau, 2016).

Assumptions

The multiple regression, like other parametric tests, requires a set of conditions be met, such as the assumption of linearity, normality, homoscedasticity, and absence of multicollinearity, to improve the accuracy of the results. While plots are often used to visually check for assumptions being met, it has also been suggested that this method alone may be insufficient for informing the researcher (Tranmer et al., 2020). Moreover, the analysis for this study included diagnostic plots, statistical tests, or a combination of both, to assess if each assumption was met.

Linearity was checked mainly using histograms and scatterplots (visual aspect) and correlations (i.e., statistical confirmation) (Yang, 2012). Normality may be checked a variety of ways. Q-Q plots were used to visually assess normality in conjunction with Shapiro-Wilks testing, a method providing a statistical or mathematic way of confirmation (ERIC, 2000; Shapiro & Wilk, 2024; Royston, 1992). Homoscedasticity was checked by plotting the residuals against fitted values, while VIFs were calculated to determine if there were multicollinearity violations (CFA

Institute, 2024; ERIC, 2000). Violating these assumptions can result in biased results and incorrect conclusions; (Field, 2018; Cohen et al., 2013).

Multiple Regression Procedure

In this study, we predicted that districts in low-income areas, likely experiencing socioeconomic inequities, would likely struggle to adjust to COVID-induced changes to instruction and general operations. As a result, academic achievement for these districts would worsen. To investigate this notion, district level variables that represented district-specific characteristics, COVID-induced changes, and academic achievement were included. Specifically, independent variables (IVs) included the following: (1) locale, (2) the proportion of free and reduced lunch students, (3) the amount of ESSER funds awarded per student, and (4) learning modalities (in-person vs. remote/hybrid). The dependent variable (DV) the degree in which these IVs explained changes observed in pre-and post-COVID proficiency scores when controlling for differences in the pre-COVID proficiency scores (covariate).

Model Comparison and Selection

Several factors were considered during the model comparison and selection phase of the analysis. The comparison and selection approach involved a combination of examining R-squared and adjusted R-squared values, in addition to backwards elimination, an iterative selection procedure that where the initial model includes all of the predictors and then, using a chosen criterion value, removes them based on the model that shows notable improvement, and terminates when no removal improves the criterion compared to the previous iteration (Lindsey & Sheather, 2010; Shieh, 2006; Thompson, 1978).

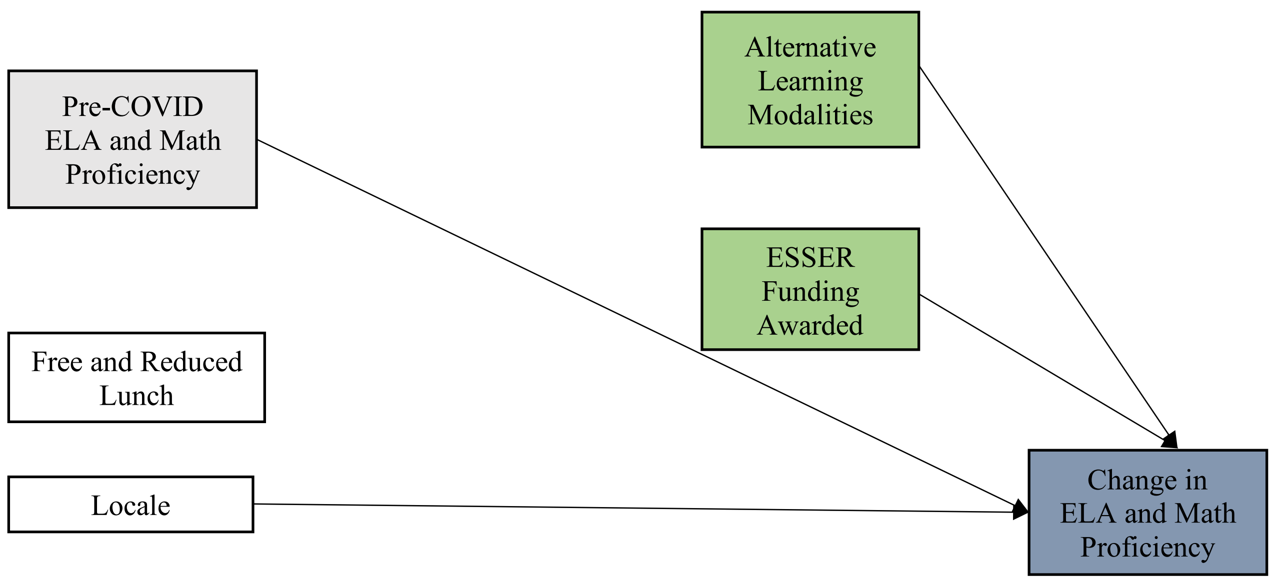
During the comparison phase, the R-square value was utilized to assess the extent to which the independent variables explained the variance observed in the dependent variable (Chessa, 2021; Wall, 2020; Akossou & Palm, 2013). This was done in tandem with the adjusted R-squared value as it accounted the number of predictors in the model by penalizing unnecessary variables, and thus, providing a more accurate measure of the model's goodness of fit (Karch, 2020; Ricci, 2010). This combination was especially beneficial for models containing two or more IVs, which aligned with the type of analysis conducted in this study.

In addition to using the R-squared and adjusted R-squared values, backwards elimination procedure was utilized to the compare and select the ELA and math models. The backwards elimination procedure involves beginning with a model that includes all the IVs and their interactions, and then progressively removing a regressor (i.e. IVs and their interaction terms) based on specified criteria (Jurečková & Picek, 2007). As the regressors are removed, the number of models decrease until the model that has the best fit remains. For this study, regressors were removed or eliminated based on two primary pieces of evidence (1) prioritizing regressor complexity (i.e. a four-way interaction term would be the most complex while the individual IV term the least complex) and (2) the regressor with the highest p-value. For example, the last section or type of IV combination in a full ELA model, a model with all the IVs included, along with all two, three- and four-way interactions. First, the highest order interactions are examined to identify the one with the highest p-value. Once that interaction is identified, it was removed from the model given the combination of IVs was not statistically significant. This pattern continued until the best fitting model was identified. Moreover, after removing regressors no longer improved the model fit, that model was selected as the model with the best fit.

Hypotheses for ELA and Math Models

Figures 1 and 2 were earlier iterations of models that illustrated different contingencies between district-level characteristics, district-level responses to COVID-19, and academic achievement or proficiency. Figure 4, the final iteration, provides a comprehensive, yet, succinct, view of two separate regression models, one for ELA and one for math. These models focused on the degree in which free and reduced lunch, locale, alternative learning modalities implemented during lockdowns, and Elementary and Secondary School Emergency Relief or ESSER funding awarded potentially contributed to a change in ELA and math proficiency. Additionally, this model also shows pre-COVID ELA and Math proficiency, the average of proficiency scores for AY 2015-2018, as a covariate to control for existing variations in pre-COVID proficiency.

Figure 4



Note. This diagram expands upon Figures 1 and 2 and shows a causal relationship between independent variables that (a) existed prior to the pandemic (e.g., free and reduced lunch rates and locale), (b) district-level responses to the pandemic (e.g., alternative learning modalities, ESSER funding per student), and (c) the outcome, changes observed in the outcome while controlling for pre-pandemic proficiency, the covariate.

In essence, the following hypotheses apply to the ELA and math models:

- ***Change in ELA achievement score*** = *a* + *free and reduced lunch proportions* + *locale* + *ESSER funding per student* + *learning modalities*
- ***Change in Math achievement score*** = *a* + *free and reduced lunch proportions* + *locale* + *ESSER funding per student* + *learning modalities*

Chapter Summary

This study aimed to describe to what degree did differences in district-level characteristics, often influenced by interactions with factors from within and outside of the district (e.g., school, local, and federal levels) and pandemic-related responses, at the district level, influenced changes in pre-to-post achievement in ELA and math. The first few chapters, including this one, have established the fundamental structure of this study in addition to highlighting a persistent history of issues with socioeconomic inequities and achievement gaps that, combined with COVID-related changes to instruction, may have significantly influenced the districts in Alabama's capacity to respond to these changes. Understanding the interconnectedness of these layers may further offer insight into how pre-to-post proficiency, measured at the district level, was impacted in the areas of ELA and math. While this chapter positioned these inquiries with respect to research methodologies, the results are presented in Chapter four, which will highlight notable patterns and trends found after conducting the analyses.

CHAPTER 4: RESULTS

Amidst several pandemic-induced school closures, public education systems in Alabama, a state known for high poverty rates and low student achievement, adopted alternative learning methods, such as remote and hybrid instruction, to sustain instruction during times where it was harder to meet in person. National studies have explored the impact of these changes on districts with pre-existing socioeconomic disparities, however, few studies have focused on those challenges in relation to districts in Alabama. Having little to no representation in literature is especially problematic given the consensus that these pandemic-induced changes may have posed more complex challenges to poorer states like Alabama. Furthermore, given the state's history of high poverty rates and rural areas, these changes may have significantly affected Alabama school systems' ability to provide quality learning opportunities when day-to-day operations were paused. ESSER funds may have been allocated to these districts to mitigate the negative impacts on learning for those located in low-income areas. However, these funds may not have fully accounted for pre-existing socioeconomic inequities, and therefore, may have negated these efforts.

This chapter will summarize the results that were found. The study explored the degree in which district-level characteristics and district-level responses to COVID-related changes explained changes observed in ELA and math pre- and post-COVID proficiency while controlling for pre-COVID proficiency. The next section will provide additional information on characteristics that are specific to public school districts in Alabama.

Descriptive Statistics

The study included data for 137[3] public school districts in Alabama. As anticipated, districts varied in size, with the smallest one consisting of 10 operational schools and the largest with 92 schools. The sample size may be considered small by more traditional standards; however, it was appropriate given this study targeted Alabama public school districts. Additionally, all but one district was included in the analysis, creating a more nuanced sample that was in fact representative respective to this state.

Table 1 presents aggregated data for students and teachers by locale for each district. Viewing the data by district and locale allowed us to do three things: (1) compare economically-advantaged and-disadvantaged districts, (2) identify characteristics that potentially supported the existence of socioeconomic inequities, and (3) provide information as to the degree in which these districts varied by locale. Most of the districts in Alabama were rural (45%, n = 60), while 24% were town (n = 32), 24% were suburban (n = 20), and 13% were city (n = 17). Although there were fewer city districts, city and rural districts served the higher numbers of students, while town districts served the lower numbers of students. City and rural districts also had more full-time equivalent (FTE) teachers, support staff, and district-and school-level administrators.

[3] As of this study, the total number of public-school districts in Alabama was 138. One district, Gulf Shores City, was excluded during the data preparation phase because it was established as a district outside of the designated time frame for scores that were selected to calculate the pre-COVID achievement score.

Table 1

District Descriptive Statistics by Locale

Local Education Agencies			Students		Teachers		Administrators		Support Staff	
	N	%	N	%	N	%	N	%	N	%
City	16	12%	228,286	31%	13,511	32%	1,439	28%	4,313	29%
Rural	64	46%	218,842	30%	12,561	30%	1,709	33%	4,529	30%
Suburb	28	20%	195,257	27%	11,450	27%	1,327	26%	3,832	25%
Town	32	23%	87,259	12%	4,729	11%	689	13%	2,424	16%
Total	138	100%	729,644	100%	42,251	100%	5,164	100%	15,098	100%

Table includes Common Core Data (CCD) data, from the National Center for Educational Statistics (NCES) website. These results are the total frequencies and percentages for each group. Student totals were from six categories, American Indian (*N* = 6,789; 1%), Asian & Pacific Islander (*N* = 10,966; 2%), Hispanic (*N* = 68,821; 9%), African American (*N* = 233,613; 32%), Caucasian (*N* = 388,970; 53%), and Multi-racial (*N* = 19,576; 3%). The teacher group included total counts for pre-kindergarten (*N* = 1,202; 3%), kindergarten (*N* = 4,772; 11%), elementary (*N* = 16,881; 40%), and secondary (*N* = 19,391; 46%) teachers. Administrator totals included counts for LEA (*N* = 1,132; 22%) and school level (*N* = 4,028; 78%) administrators. Support staff included totals for paraprofessionals (*N* = 6,779; 45%), instructional coordinators (*N* = 49; 0%), guidance counselors (*N* = 1,764; 12%), LEA administrative support staff (*N* = 2,117; 14%), school administrative (*N* = 2,209; 15%), student support service staff (*N* = 2,169; 14%). Total percentages may be slightly over or under 100% due to rounding.

Achievement

Table 2 displays means and standard deviations for ELA pre-and post-COVID proficiency scores by locale to offer a closer look into patterns of achievement. When comparing pre-and post-COVID proficiency across all locales, ELA scores showed a slight increase. Based on ELA pre-and post-COVID scores, rural districts were the least proficient of the group. ELA pre-and post-COVID scores revealed that city and suburban districts were the most proficient of the group. Despite city, suburb, and town districts outperforming rural districts, it is worth noting that ELA pre-and post-COVID scores also appeared to show slight more variation in their mean scores based on their standard deviations.

Table 2

Mean ELA Pre-and Post-COVID Proficiency

	Pre-COVID Proficiency		Post-COVID Proficiency	
	Mean	SD	Mean	SD
City	43.93	12.73	44.54	15.14
Rural	37.30	9.90	39.46	12.12
Suburb	42.20	18.22	45.79	20.11
Town	40.78	11.91	43.61	13.71

In addition to Table 2,Table 3 presents math pre-and post-COVID proficiency scores by locale. Off first glance, there were some similarities. For instance, rural districts were still the least proficient of the group based on math pre-and post-COVID scores. There also appeared to be some variability with math pre-and post-COVID scores. While the two subject areas shared some similarities, it is worth noting that there were also some salient differences. One difference was that pre-and post-COVID math scores showed a sharp decline in proficiency regardless of locale.

Table 3

Mean Math Pre-and Post-COVID Proficiency

	Pre-COVID Proficiency		Post-COVID Proficiency	
	Mean	SD	Mean	SD
City	47.00	14.99	23.85	13.60
Rural	39.80	11.94	16.92	10.17
Suburb	44.49	20.46	22.97	19.14
Town	42.44	13.25	20.84	11.74

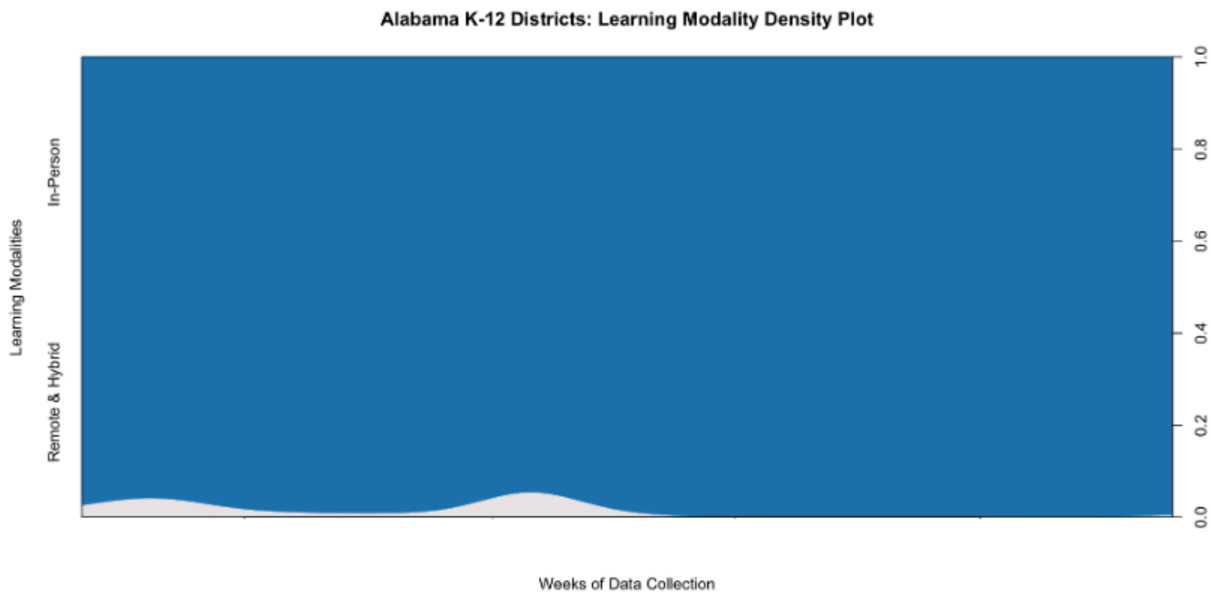
Free and Reduced Lunch

Free and reduced lunch is one of many measures for school- or district-based poverty (Snyder & Musu-Gillette, 2015). Alabama has a history of being one of the poorest states in the nation, and thus, it can be assumed that the public-school districts in this state are predominately poor as well (NEA, 2023; U.S. Census Bureau, 2021; NCES, 2023). When comparing districts by locale, results indicated that rural districts served a higher average proportion of FRL students than other locales. On the other hand, suburban districts served lower average proportion of FRL students. Findings from this study were consistent with previous reports describing Alabama as predominately rural and poor.

Learning Modality

Figure 5 and Table 4 presents results for learning modality data. In general, results indicated that instruction was provided in-person (98%; n = 7,111) more frequently than with the other modalities (remote and hybrid; 2%; 103). Overall, the results showed minimal variability, which carried important implications for subsequent regression results.

Figure 5



Note. The conditional density plot showed data that were collected from August 2021 -September 2022.

Table 4

Learning Modalities by Locale for Alabama Districts

	In Person		Remote and Hybrid	
Locale Type	N	%	N	%
City	903	98%	14	2%
Rural	3129	98%	70	2%
Suburb	1590	98%	14	2%
Town	1489	98%	5	2%

ESSER Funds Per Student

Results also showed that the total amount of ESSER funds awarded, for all the districts combined (*n* =137), was $194,862,127.00. As previously stated, the amount of ESSER funds per student was calculated to adjust for the large differences in the number of students per district. Of the locales, districts in rural areas received the highest average amount of ESSER funds awarded per student ($360.47) in comparison to those located in city ($314.69), suburban ($292.44), and town ($288.13) areas. One of the key eligibility requirements for receiving ESSER funds was that districts must be receiving Title I funds, another measurement of poverty (NCSL, 2022; USDOE, 2022; Malkus, 2021; OESE, 2022). Moreover, trends that were observed in the total amount of ESSER funds awarded to Alabama districts provided insight into the degree in which these districts are in areas with high poverty rates.

The descriptive analyses outlined in this chapter provided valuable insight on potential trends or patterns in environmental factors relative to public school districts across Alabama. Variations in the environment (e.g., locale, resource access, and funding availability) may have contributed to negative consequences for student achievement. The following section will present results from the multiple regression analysis to further illustrate how the instructional adjustments public-school districts in Alabama, a state categorized as predominantly low-income, combined with COVID-induced changes potentially impacted ELA and math achievement. While some may argue that multiple regression results primarily reveal “statistical associations” rather than causations (Pendola et al, 2022, p. 20), they can still provide more nuanced view of how low-income districts, already burdened by socioeconomic inequalities in resources and funding, maneuvered shifting from traditional to alternative instructional methods during the pandemic, a change that may have influenced student learning, and subsequently, affected academic proficiency in ELA and math.

Multiple Regression Results

To assess the impact on academic achievement in Alabama's low-income and high-income public-school systems, examining the relationship with district-specific factors and pandemic-induced changes; and pre/post ELA and math proficiency scores is crucial. A multiple regression following an ANCOVA framework was performed to further examine this complex relationship. Regression models were evaluated separately, resulting in one model for ELA and one for math.

Assumptions

The overall theme of the MR was that the data were all at the district level. Other assumptions that were checked to ensure that a multiple regression was appropriate included (a) linearity, (b) normality, (c) homoscedasticity, and (d) multicollinearity (CFA Institute, 2024; Osborne & Waters, 2019; ERIC, 2000). This section will examine various plots and tables to check these assumptions.

Linearity

Linearity was viewed using scatterplots and a correlation table. Figures 6 and 7 illustrate the linear patterns observed for both subject areas. Results indicated that there was a strong positive correlation between comparing ELA and math pre and post pandemic proficiency scores, within each subject area, (r = 0.97; r = 0.94, respectively). Initial scatterplots for both subject areas showed a strong, positive linear relationship between pre-post proficiencies, however, observing these results by locale provided additional insight into district-level differences statewide.

Figure 6

Alabama Public-School Districts: ELA Pre-Post Proficiency Comparisons

Alabama K-12 Districts n = 137

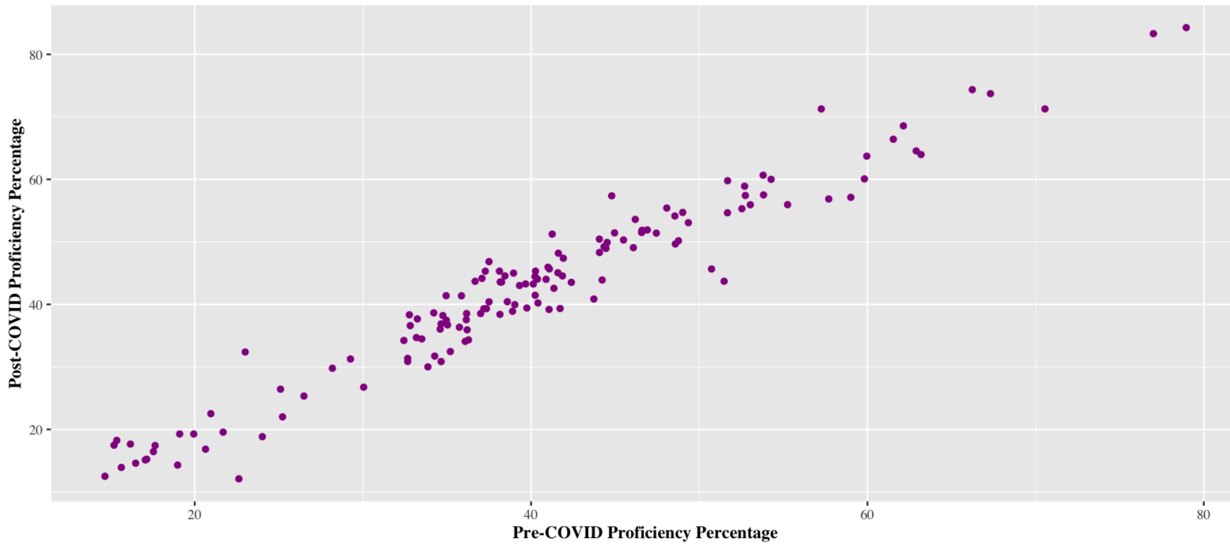


Figure 7

Alabama Public-School Districts: Math Pre-Post Proficiency Comparisons

Percentage of Students Deemed Proficent

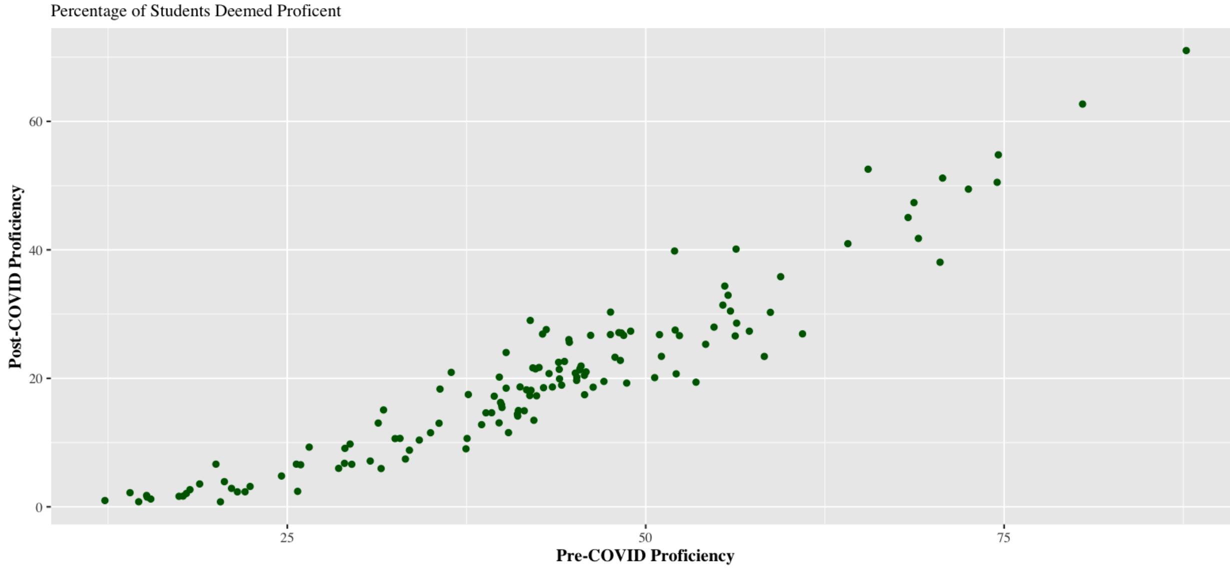


Figure 8

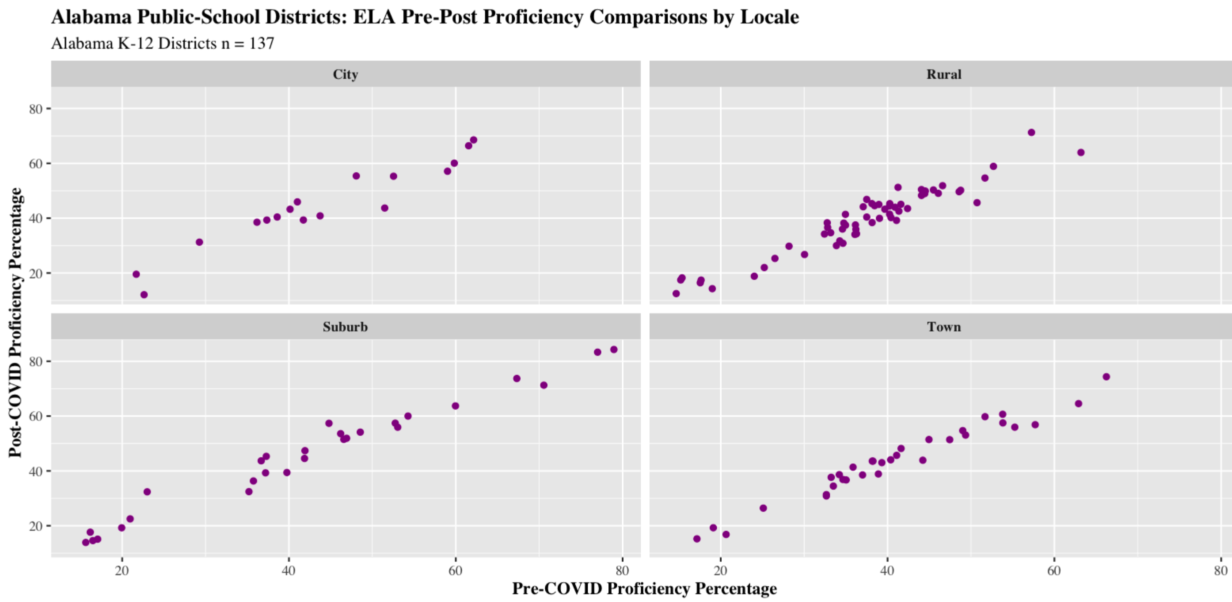


Figure 9

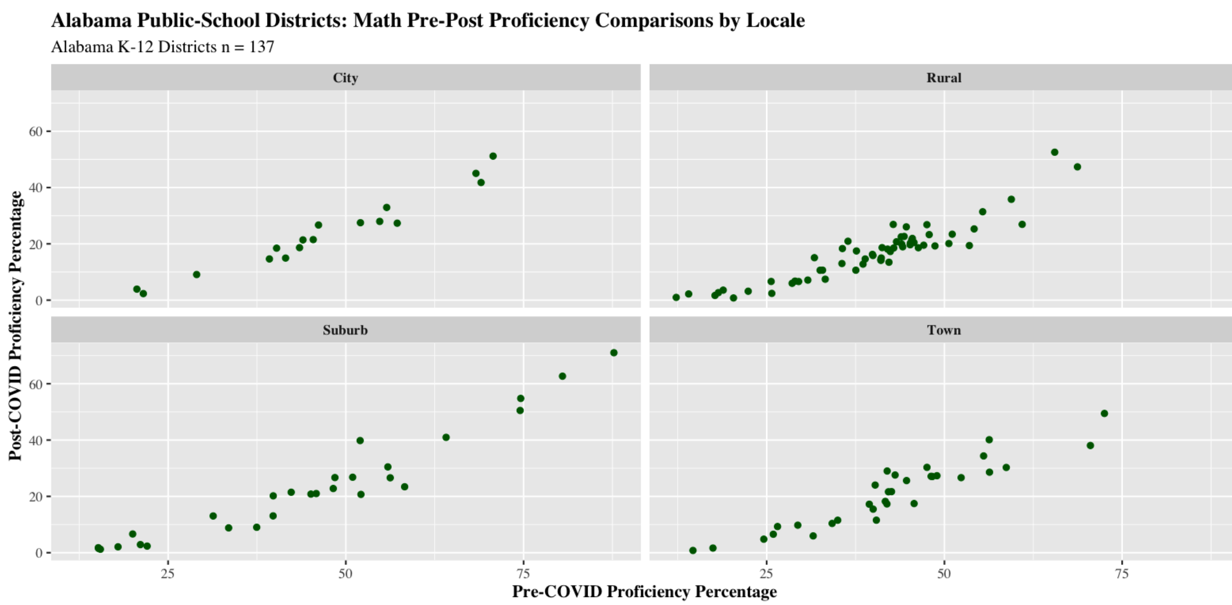


Figure 8 showed ELA pre and post COVID proficiency comparisons by locale to which, the overall pattern was strong, positive, and linear. There were no notable differences by locale. Figure 9 showed the same linear pattern as the ELA pre-post comparison and the findings for both subjects were consistent with the ones reported in the correlation table. It is also worth noting that, for both subjects, there were clusters of data points that were closest to the lower end of both plots, for ELA at 20% and Math at 0%; meaning, several districts regardless of the locale and subject were already low in proficiency. This piece of information appeared to be evidence of a floor effect and would be important in the interpretation of the regression results.

Figures 10 and 11 showed the correlation between the average proportion of students receiving free and reduced lunch per district and post-COVID proficiency scores for ELA and math. In general, both subject areas, showed a strong negative correlation between average proportion of FRL per district and post-COVID proficiency (*ELA r* = -0.86; *math r* = -0.82). for ELA and math, there were two consistent findings: 1) overall, districts with higher average proportions of students receiving free and reduced lunch had lower proficiency scores after COVID, and 2) out of all the locales, rural districts consisted of higher average proportions of FRL students in comparison to what was observed with city, suburb, and town districts. Moreover, both findings suggest that the assumption that rural districts catered to more significant proportions of high-poverty students is very likely.

Figure 10

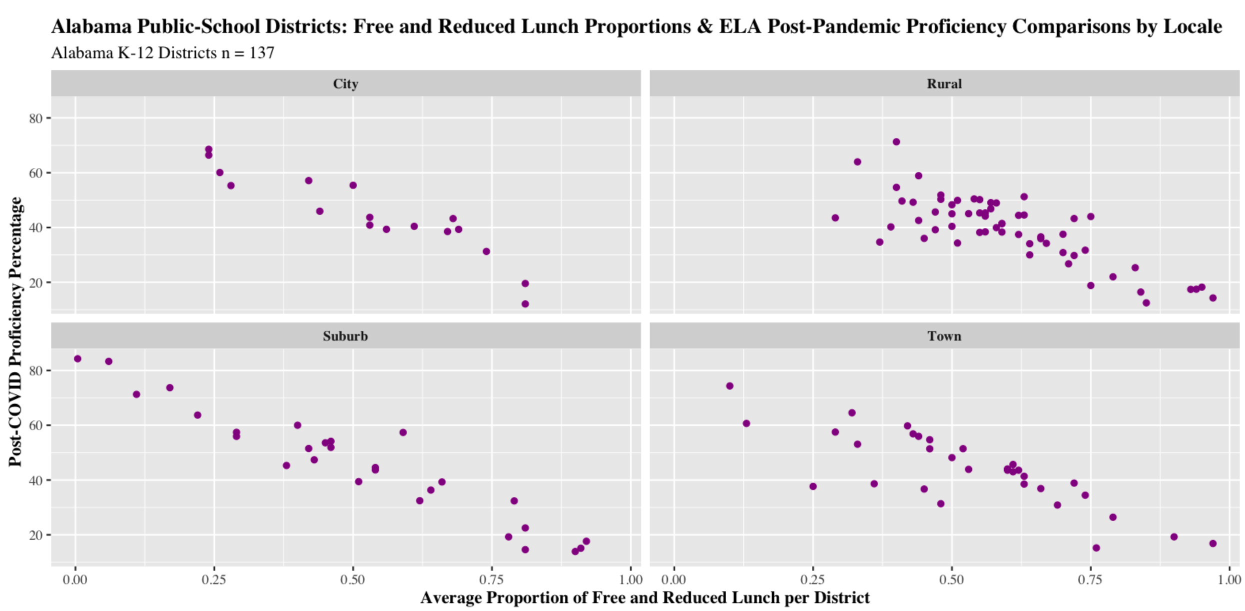
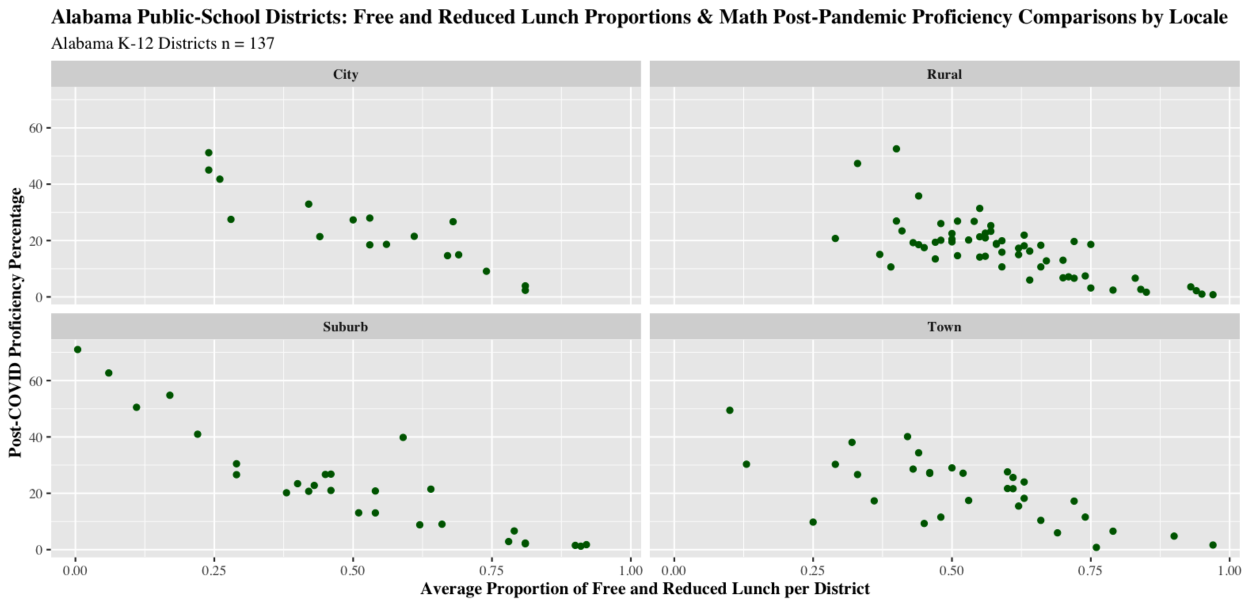


Figure 11



Figures 12 and 13 show comparisons between the amount of ESSER funding awarded per student (ESSER) and post-COVID proficiency scores for both ELA and math. Results showed a strong negative correlation between ESSER funds and proficiency scores reported after the pandemic when comparing these findings by locale. In general, both subject areas, showed a robust negative correlation between FLR proportions and proficiency scores (r = -0.86; r = -0.82; ELA and math, respectively).

Figure 12

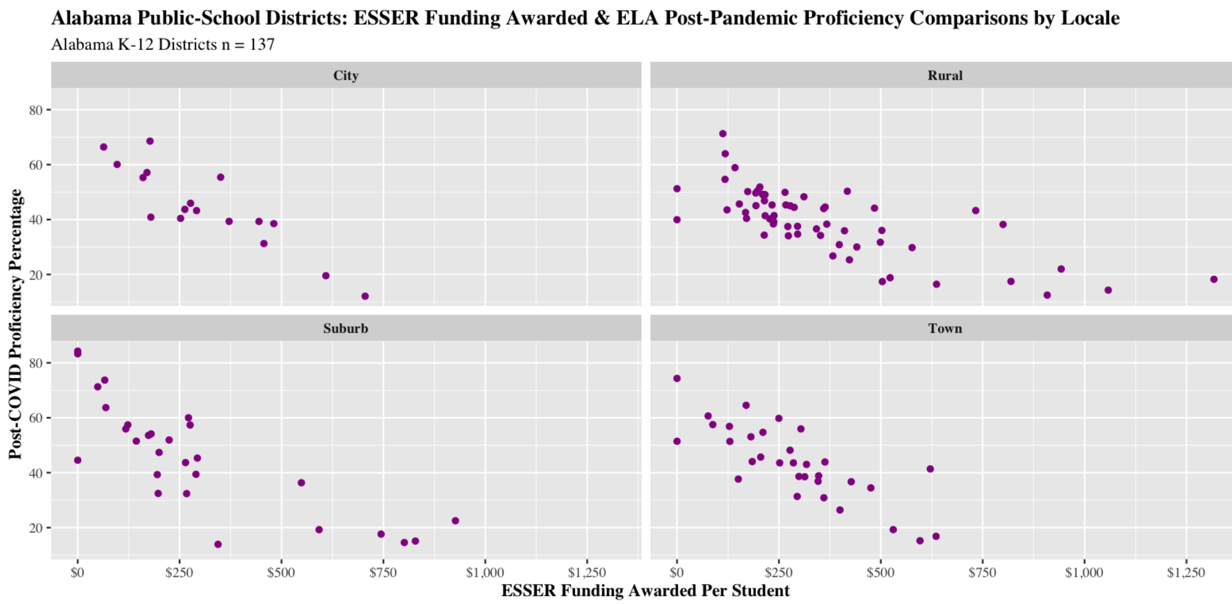


Figure 13

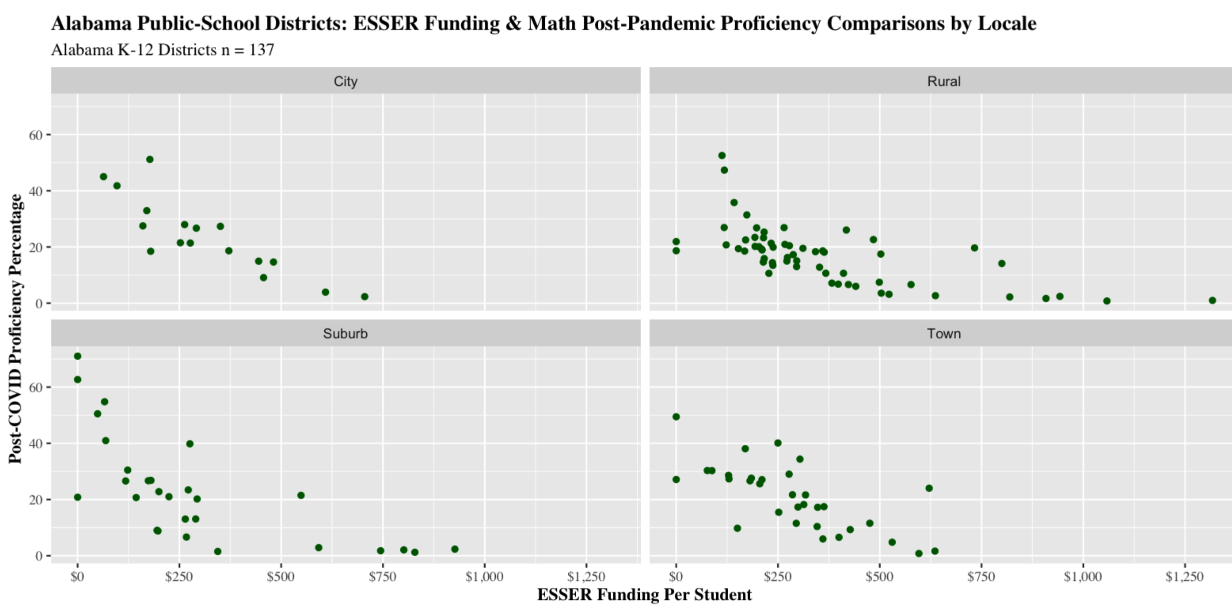


Table 5 showed the correlations for all the variables in three tiers; ones that are strongly, weakly, and not correlated. Results indicated that pre and post proficiency levels for ELA and math, FRL, and ESSER funds per student were strongly correlated. ESSER funds was however, weakly correlated with the change in pre-to-post proficiency for both ELA and math. Learning modalities and locale showed little to no correlation with any of the variables. Scatterplots were completed to provide a visual for potential linear patterns.

Normality

Common ways to check for normality, another assumption, is to use Q-Q plots and Shapiro-Wilks testing to assess if the residuals are normally distributed (Osborne & Waters, 2019). Results from the Q-Q plots, for both ELA and math, did not indicate that this assumption was violated. Results from Shapiro-Wilks tests also did not signal a potential issue with normality.

Homoscedasticity

In the sample, the residuals should demonstrate homoscedasticity, meaning, they should be consistently distributed throughout the range of the independent variables (Sinn, 2020). Residuals and fitted values were plotted against each other, for both subject areas, to check if this assumption was violated. Results indicated that homoscedasticity was met for both subjects.

Multicollinearity

In a multiple regression, the independent and dependent variables being correlated is ideal. However, it is not ideal for the independent variables to be highly correlated with each other (i.e., multicollinearity), as it may make it more challenging to isolate the individual effects of each IV on the dependent variable (ERIC, 2000). Variance inflation factors (VIF) were checked to identify potential issues with multicollinearity to which, there was no indication of any violations. Other assumptions such as all data being at the district level, the predictors having normal distributions, relationships between variables being linear, and the data being randomly sampled from the population (n = 137) were also met.

Table 5

Correlations

	ELA Change Pre-to-Post	Math Change Pre-to-Post	ELA Pre-Test	ELA Post-Test	Math Pre-Test	Math Post-Test	Free and Reduced Lunch	ESSER Funds per Student	Learning Modalities	Locale
ELA Change Pre-to-Post	--									
Math Change Pre-to-Post	.093	--								
ELA Pre-Test	$.389^{**}$	$-.398^{**}$	--							
ELA Post-Test	$.599^{**}$	$-.321^{**}$	$.971^{**}$	--						
Math Pre-Test	$.437^{**}$	$-.438^{**}$	$.973^{**}$	$.960^{**}$	--					
Math Post-Test	$.516^{**}$	-.119	$.929^{**}$	$.943^{**}$	$.945^{**}$	--				
Free and Reduced Lunch	$-.408^{**}$	$.319^{**}$	$-.886^{**}$	$-.877^{**}$	$-.845^{**}$	$-.817^{**}$	--			
ESSER Funds per Student	$-.396^{**}$	$.368^{**}$	$-.757^{**}$	$-.762^{**}$	$-.728^{**}$	$-.670^{**}$	$.749^{**}$	--		
Learning Modalities	.058	$-.199^{*}$	.035	.046	.047	-.021	-.043	-.047	--	
Locale	$.173^{*}$	.128	.029	.070	-.004	.043	-.094	-.098	-.118	--

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Multiple Regression Models

As previously noted in Chapter 3, models were compared and selected using a combination of examining R-squared and adjusted R-squared values and employing a backwards elimination. The R-squared and adjusted R-squared values provided two important pieces of information (1) the degree in which the independent variables predicted the observed variance in the dependent variable and (2) a more accurate representation of the model's goodness of fit by accounting the number of predictors, and penalizing unnecessary variables (Chessa, 2021; Robert Wall, 2020; Akossou & Palm, 2013). Additionally, backwards elimination was used to isolate the best fitting model through a series of removals by looking at the combination of IV and the (highest) p-value (Karch, 2020; Ricci, 2010). Subsequent sections will provide additional information on the ELA and math models.

English Language Arts Model

Tables 6 and 7 present the results for the final ELA (*E*) regression model. In reference to the first research question, main effects were noted for the ESSER funds per student, or $ESSER_{ST}$, ($b = -0.005$, $t_{(134)} = 29.09$, $p < .001$) on the change in pre-to-post-COVID proficiency scores ($R^2 = 0.16$; 16%) while controlling for pre-COVID proficiency. In addition to main effects, this model was checked for potential interactions. No interactions were found. Theoretically, when holding pre-COVID proficiency constant, districts that spent $100.00 in ESSER funds per student, would likely see a 0.50% decrease in the pre-to-post scores. Moreover, there would be a relatively small change observed in ELA proficiency. The final equation for the ELA regression model is:

$$\textit{Change in Pre-to-Post } {}_{E}\textit{Achievement} = 1.296 - 0.005(\textit{ESSER}_{ST}) + 1.066\ (\textit{Pre-Covid } {}_{E}\textit{Achievement}) + 3.55$$

Table 6

ELA ANOVA Table

	Df	Sum of Squares	Mean Squares	F-value	P-value
ELA Pre-COVID Score	1	28258.10	28258.10	2194.5066	< 2e-16 ***
ESSER Funds per Pupil	1	64.20	69.10		0.02205 *
Residuals	134	1725.50	12.90		

*** Significant at 0.001; [NS] not significant. The response variable is the change in ELA achievement score (ELA Post-COVID score – ELA Pre-COVID score) and FRL = Free and Reduced Lunch.

Table 7

ELA Regression Coefficient Table

	Estimate	Std. Error	t-value	P-value
(Intercept)	1.296132	2.027213	0.639	0.524
ELA Pre-COVID Score	1.066433	0.036662	29.088	<2e-16 ***
ESSER Funds per Student	-0.004685	0.002022	-2.317	0.022 *

*** Significant at 0.001; [NS] not significant. The response variable is the change in pre-to-post ELA proficiency and Free and Reduced Lunch (FRL). Proficiency is a percentage. $F = 14.26_{(2, 134);}$ *p-value* = 2.418e-06; R = 0.404; $R^2 = 0.163$.

Math Regression Model

Tables 8 and 9 in addition to Figures 14 and 15, illustrate the results for the final math (*M*) regression model. Results showed two-way interaction (Math Pre-COVID proficiency * FRL) ($F_{(3,133)} = 26.07$, $p < .001$) when controlling for pre-COVID proficiency constant. The two-way interaction found with this model prompted post hoc testing which will be explicated in the next section. Figure 14 presents a visualization for the two-way interaction found in the math regression model, Math Pre-COVID * FRL, as a plot to provide additional insight into the relationship between this interaction and pre-COVID proficiency on the change in math pre/post proficiency scores.

Table 8

Math ANOVA Table

	Df	Sum of Squares	Mean Squares	F value	P-value
Math Pre-COVID Score	1	622.02	622.02	40.547	2.883e-09***
Free and Reduced Lunch	1	30.14	30.14	1.965	0.1633^{NS}
Math Pre-COVID * FRL	1	547.50	547.50	35.689	1.996e-08***
Residuals	13	2040.34	15.34		

*** Significant at 0.001; ^{NS} not significant. The response variable is the change in math achievement score (math Post-COVID score - math Pre-COVID score) and FRL = Free and Reduced Lunch.

Table 9

Math Regression Coefficient Table

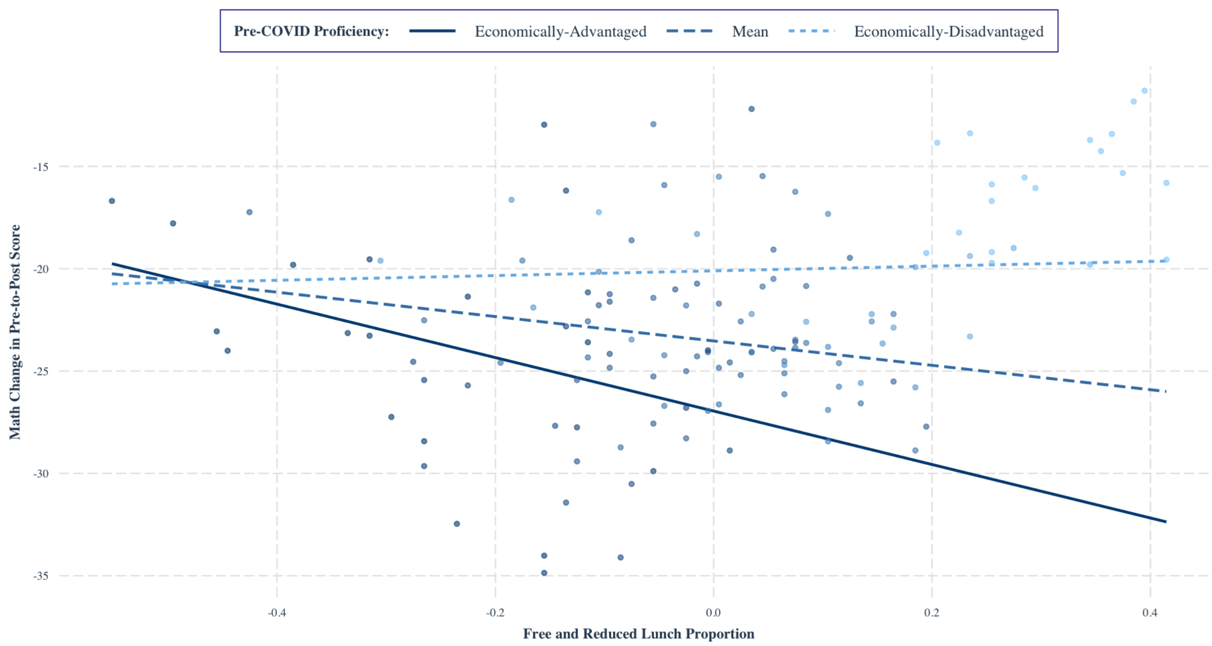
	Estimate	Std. Error	t value	P-value
(Intercept)	-23.52786	0.38892	-60.496	< 2e-16 ***
Math Pre-COVID Score	-0.23203	0.04295	-5.402	2.95e-07 ***
Free and Reduced Lunch	-5.95459	3.16878	-1.879	0.0624^{NS}
Math Pre-COVID * FRL	-0.48136	0.08058	-5.974	2.00e-08 ***

*** Significant at 0.001; ^{NS} not significant. The response variable is the change in pre-to-post math achievement score and Free and Reduced Lunch (FRL). $F = 26.07_{(3, 133)}$; *p-value* = 2.511e-13; $R = 0.60$; $R^2 = 0.36$.

Figure 14 provides an illustration of the two-way interaction found in the math regression model. Results from this interaction plot indicate that a relationship between the average proportion of FRL per district and change in pre-to-post math scores depends on the district's proficiency prior to the pandemic. Overall, two key findings emerged with the first involved economically-disadvantaged (ECD) districts, which were represented by the light blue dotted line and data points. Here, the results indicate that ECD districts are ones that likely began with low pre-COVID proficiency scores. These and results from previous plots are consistent with a floor effect with this group and since they are starting at a lower math proficiency, they cannot go any lower than where they are currently at which may explain why these scores did not look strongly related to FRL or the outcome, and, the average proportion of FRL did not appear to impact how much scores changed or decreased for ECD districts..

Another key finding was that (ECA) economically-advantaged districts, represented by the dark blue solid line and data points, or districts that started with higher math proficiency prior to the pandemic, showed more of an effect with the FRL and the outcome. Moreover, the ECA districts with higher average proportions of FRL, showed more notable losses in their change in pre-to-post math scores.

Figure 14

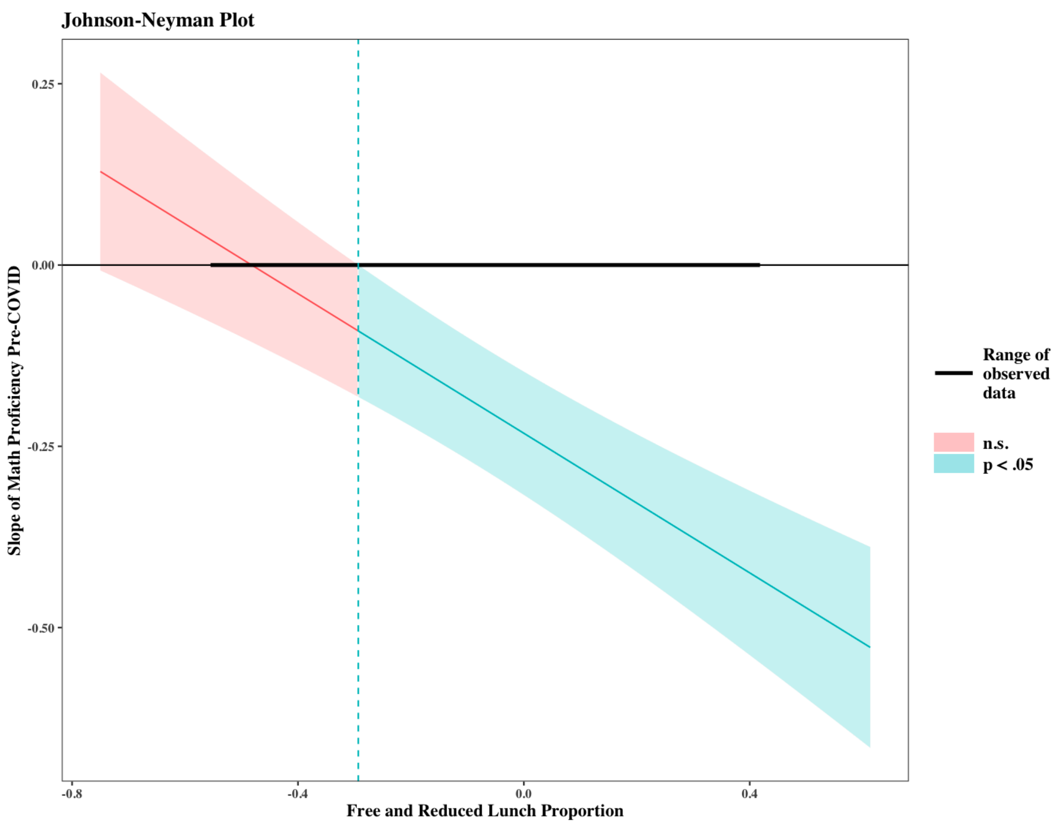


Johnson-Neyman Test

In addition to the interaction plot, a Johnson-Neyman test, Figure 15, was conducted to identify regions of significance given the multiple regression followed an ANCOVA framework, pre-COVID proficiency served as the covariate, when evaluating regression lines that are not parallel in addition to providing a means to assess the significance of the difference between two independent variables for one dependent variable, while holding two other variables constant (Toyama, 2023; D'Alonzo, 2004). Results indicated that the range of observed values for the average proportion of FRL students (per district) was expected to fall within this interval [-0.55, 0.41]. Additionally, when FRL values are outside of the interval [-0.77, -0.29], the slope of pre-COVID math proficiency is $p < .05$. or statistically significant. Ultimately, the final math regression formula is as follows:

$$Change\ in\ {}_{m}Achievement = 23.53 - 0.23({}_{m}Pre\text{-}COVID\ Achievement) - 0.481({}_{m}Pre\text{-}COVID\ Achievement) * (Free\ and\ Reduced\ Lunch) + 3.91$$

Figure 15



Chapter Summary

In conclusion, the findings discussed in this chapter partially supported the initial conjecture that environmental factors would explain the variability found in pre-and post-COVID achievement scores for English Language Arts (ELA) and math (while controlling for variation in pre-COVID scores, covariate). Ultimately, ELA regression findings differed than those found for math. ELA results indicated that little change in pre-to-post scores was observed with the addition of ESSER funds when controlling for pre-COVID proficiency; whereas math results showed that when controlling for pre-COVID proficiency, a two-way interaction, that included the average proportion of FRL students (per district), explained the pre-to-post proficiency changes that were observed. While these results differed by subject area, it is important to position these results using the EST framework when making inferences. The next chapter, Chapter Five, will further discuss these inferences in term of potential limitations of the study, future theoretical and practical implications, and recommendations.

CHAPTER 5: DISCUSSION

Given its history of persistent cycles of high poverty and low achievement rates, this study aimed to examine the degree in which district-level characteristics and district-level responses to pandemic-related disruptions affected academic achievement, especially with public-school districts in Alabama. This chapter highlights key findings from this, as well as previous studies to further emphasize the significance of exploring pre-existing challenges within these dynamics that may otherwise hinder districts' capacity to mitigate and prevent COVID-related learning loss while maintaining instruction that is high quality and that may still contribute to learning opportunities that are optimal for academic growth. Additional information on theoretical and practical implications, potential study limitations, suggestions for future research, and a brief conclusion will also be addressed in this chapter.

Summary of Findings

It is widely known that poorer districts often lack adequate access to resources and funding, making them predisposed to poor instruction quality and low achievement (Morgan, 2022). Initially, there were several assumptions that were initially made about each of the variables included in the study including that locale could serve as one of the indicators for economically-disadvantaged districts. Alabama is predominately rural and poor, making it more likely that districts in this state encountered more challenges as they navigated COVID-related disruptions to learning. Results from this study supported this notion as most of the school districts in Alabama were found to be rural (roughly 44%). Findings from past studies also suggest that rural and poor districts are more likely to experience similar challenges given their inherent struggles with accessibility (Morgan, 2022; Conway et al., 2019; Rosen et al., 2018). However, despite the evidence from our study indicating high rurality, regression results did not show a significant relationship between locale and the change in pre-to-post-COVID proficiencies in either ELA or math. This same result was observed when looking at the impact of learning modality shifts on the outcome.

In addition to learning modality changes and locale differences not being statistically significant, another finding from this study showed some notable disparities in achievement when comparing ELA and math proficiency scores at different phases of the analysis. For instance, pre- and post-COVID mean score comparisons across all locales for districts in Alabama, results showed a slight increase in ELA mean scores while the opposite occurred with math as the scores instead showed a significant decrease. This disparity based on subject area can also be seen when in the regression results as ESSER funds per student was the only predictor found to explain the change in pre-to-post-COVID proficiency scores when controlling for pre-COVID proficiency (R^2 = 0.16). This was different for math regression results as we found evidence of a two-way interaction between the average proportion of free and reduced lunch per district and the covariate, pre-COVID proficiency (R^2 = 0.36).

Pandemic-related research has explored several themes related to the impact of COVID and socioeconomic disparities on learning; however, few studies have done so with respect to public school districts in Alabama. Examining the impact of COVID-19 on public school districts in this state is ideal given Alabama's history of high poverty rates and poor achievement would make it likely this group experienced more challenges in responding to pandemic-related changes, specifically when looking at changes in pre-to-post proficiency in ELA and math. Skill development in these two areas is crucial to the development of skills in other subject areas. It is pertinent that as pandemic-related research continues, that we also examine these impacts with relation to public school districts in Alabama. The following sections further elaborate on the key findings in relation to both research questions.

Research Limitations

While the results found in this study were promising, they also indicated that fully understanding the impact of COVID on achievement or learning for Alabama districts may be more complicated given there are underlying issues that are often multi-layered and interconnected. Several steps were taken to ensure procedural fidelity, however, we also found potential limitations related to both areas of interest: district-level characteristics and district-level responses to COVID-19. More specifically, this section will discuss three potential limitations regarding the quality of the selected measures, granularity of the sample, and concerns with the generalizability of the results.

Quality of Measures

The first of the potential limitation involves the quality of the measures included in this study. Several the assertions suggested a domino effect with the intricacies of Alabama public school districts such as socioeconomic inequities, may restrict their ability to adapt to COVID-related changes, and how their restricted capacity could likely negatively impact academic achievement in ELA and math. ELA regression results from this study indicated that only FRL, when controlling for pre-COVID proficiency explained roughly 16% of the variability observed in our outcome while math regression results showed that ESSER funding per student, when controlling for pre-COVID proficiency, explained roughly 36% of the outcome. These results suggested that neither locale, an indicator of poverty, nor learning modalities, an example of district-level response to COVIDwere were important for predicting ELA proficiency above and beyond FRL.

Including pre-COVID proficiency in both models as a control for variations in scores prior to the pandemic and in conjunction with ESSER funds per student (ELA model) and FRL (math model), may hAVE explained some variation observed in the outcome which suggests that we may need to identify different measures than the current ones we included as indicators of poverty and COVID-related responses. The low percentage of variability in the outcome further hints towards a potential issue with measure quality given pre-COVID proficiency served as a covariate, it became evident that that controlling for pre-COVID proficiency did not fully stop differences in these scores from influencing proficiency in math.

Regression results further indicated districts with higher FRL proportions showed less improvement in their scores, which was the opposite of their affluent counterparts signaling evidence of a potential floor effect that stemmed from differences in pre-COVID scores. It is common that poor districts serve higher numbers of FRL students. It is also common that these same districts struggle to offer high quality instruction and learning environments that foster academic growth. Moreover, these districts often show low academic achievement rates across all subject areas. While the floor effect that we observed in the math regression model showed that these same students who started out with low proficiency were not likely to be worse than off than their affluent counterparts in math, they did not experience significant improvements either. This floor effect combined with its statistical significance in both models suggest that including pre-COIVD proficiency as a covariate did not fully control for previous differences in scores.

Sample Granularity

District level data can provide valuable insight used to inform educational decisions of various stakeholders (LSU, 2020), which supported the unit of measurement for this study reflecting as such. However, the granularity of district-level data may have been too large to fully capture the variability of the schools within each district regarding various aspects, including the implementation of alternative learning modalities. As noted in Figure 5 and Table 4, we did not see significant variation in the data that were collected, which may explain why we did not see the locale and learning modalities account for a higher amount of the variability in our dependent variable.

Potential Issues with Generalizability

In research, typically quantitative, generalizability refers to the extent to which results from a sample can be used to make inferences about a larger population (Andrade, 2020; Gobo, 2004; Staines, 2008; Shavelson et al., 1989). A larger sample size helps improve generalizability by increasing statistical power, reducing the likelihood of chance variations, and increasing the representativeness of the sample (Degtiar & Rose, 2023). It also allows researchers to make inferences that are more reliable and accurate about the broader population or context of interest (Tipton et al., 2017). That said, the sample of this study was 137 public school districts in Alabama, which to some, the sample size may be viewed as relatively small with respect to more traditional standards and may present issues with generalizability. However, it is important to note, that the study included all but one district, making the sample representative and generalizable to districts in this state.

Future Implications

Findings from this study emphasized that while districts and other ecosystems may have functioned independently and exhibited characteristics specific to that group, these systems are still interconnected, making the introduction of COVID a strong antagonist as it intensified underlying complexities relative to districts providing instruction. Moreover, ultimately impacting proficiency in ELA and math. Variations in environmental characteristics, such as differences in resource availability, personnel, and community engagement, played a critical role in the degree in which districts in this state had the capacity to respond to pandemic-related disruptions, and thus, impacted educational outcomes. Furthermore, this concept of interconnectedness is supported by Bronfenbrenner's (1979) ecological systems theory (EST), which provided a framework for examining "developmental changes" in individuals (e.g., students, parents, and teachers) (pg. 2) (Brigandi et al., 2022; as seen in Bronfenbrenner, 1977, 1979, & 2001). In this case, we posit that at the meso- level, Alabama districts have functioned as an its own ecosystem, which may have differed from other relative ecosystems due to their unique socioeconomic characteristics (e.g., locale, socioeconomic status, student performance) (Nicola et al., 2020; De Meo Hoyt, 2020; TCI, 2017; García & Weiss, 2017). These variations in characteristics led to districts in Alabama encountering more complex functional and instructional challenges than those in other states; especially with introduction of COVID. From there, districts that were already prone to low rates of achievement became more vulnerable, and thus, experienced varying degrees of learning loss across various subject areas (Hatch & Harbatkin, 2021; Halloran et al., 2023; Johnson, 2008). While this study may not have focused on other levels (e.g., individual or microsystem), based on EST, it could be implied that pandemic- changes to policies and procedures made existing challenges more complex across all levels; especially within the district or meso-level.

Improving the Quality of Measures

While results from this study appeared to partially align with key themes of the EST perspective, including how the interchange between these ecosystems coupled with challenges posed by pandemic-related changes, may have affected student achievement when examining the changes in scores before and after the onset of the pandemic. Proactively preparing for potential challenges may help not with only the application of this framework, but also in research designs moving forward. Although selecting measures for studies is important, it is worth noting that a strong focus should also be placed on the sample itself. As previously noted, granularity concerns arose when some of the findings from this study presented as different from that of prior ones. This incongruency suggested a potential issue with using district level data and that, this level may have been too large to adequately capture the effect of these predictors on the dependent variable (Agostinelli et al., 2022; Caldas & Bankston, 1999). Variability within schools within the district may have made it more difficult to get a clearer understanding of the degree in which district-specific characteristics impacted student learning. Examining the data at a smaller granularity, such as at the school level, may result in findings related to achievement that depict similar themes observed with previous studies.

Adjust the Granularity of the Sample

In addition to improving the quality of the measures that are included moving forward, results from this study may be inform considerations related to sample size with respect to the overall aim of the study. While some may view these results best reflect characteristics of districts in this state and may find them generalizable to other states or regions with similar socioeconomic characteristics (Charter, 1999; Shavelson et al., 1989; Gobo, 2004). In contrast, some may find that using these findings to draw conclusions about districts in other states is inappropriate as Alabama's small size and high rurality may be considered too nuanced (Tipton et al., 2017; Staines, 2008).

More Representation in Literature

Despite having a longtime history of poor achievement as well as limited funding and resources, few pandemic-related studies focus on Alabama public school systems. It was evident from the results found in this study that COVID had a more detrimental impact on math proficiency across all locales than on ELA proficiency and that, districts with higher average proportions of FRL were impacted more negatively in math than in ELA. More studies should continue to examine why districts fared better with ELA proficiency but not with math. While this study hinted at something impacting achievement, the reality is that more information is needed to fully gain an understanding as to specifically sparked these variations in pre and post proficiency. Increasing the body of work on Alabama districts can also provide more insight on how different policies and procedures for the implementation of alternative learning modalities, COVID-related absenteeism, and teacher preparation and support potentially impacted achievement.

Furthermore, findings from this study showed the importance of decomposing findings from a national to smaller level and illuminated the potential for exploring continuing this work through the lens of this state moving forward. Furthermore, consideration of these implications in subsequent research efforts may not only highlight COVID-related impacts on Alabama districts, but it may also provide additional insight into the interplay between existing socioeconomic inequities, pandemic-induced disruptions, and the potential for learning loss, thus, broaden the current body of literature.

Recommendations

The unexpected, destructive nature of the pandemic led to many challenges, especially for school systems who had to quickly identity alternative ways to sustain learning while comporting to mandates that contradicted traditional teaching pedagogies (Lugo, 2022; Gürhan & Çankaya, 2020; Castroverde & Acala, 2021). Despite it being four years since its initial emergence, it remains unclear as to the extent to which these pandemic-related interruptions impacted student achievement in states high in poverty and limited in resources, such as Alabama. This section offers recommendations for stakeholders based on findings from this study on next steps for

Alabama districts as time progresses and the pandemic continues to have some degree of impact on day-to-day operations.

Strategic Contingency Planning is Necessary

During the pandemic, school districts developed and implemented emergency contingency plans that not only helped them adapt to constant changes to operations, but it also helped ensure instruction was sustained (Pressley et al., 2022). While this planning often centered on school-level protocols, challenges relative to poorer, more rural districts that may potentially impede their ability to respond to pandemic-induced changes must be considered. There was insufficient evidence that supported significant improvements across all subject areas. This finding was concerning given there at least four primary subject areas that public school districts are required to address in CCRS instruction, and further signals that there may be issues with the allocation of these funds or that, the provision of high amounts of these funds may not be an efficient way to use of them. Both must be addressed to not only ensure districts in high financial need receive additional support, but to also ensure funds may be efficiently provided now and moving forward as necessary.

These findings further allude to the importance of continuing state-specific research that consider contextual differences in subsequent emergency planning and improvement efforts (Daniel, 2020). It is imperative that contingency plans, financial budgets, school system operations use a nuanced, not universal, approach to better ensure resource and funding strategies account for these differences to not only ensure that instruction may be sustained in the case of another outbreak, but that the instruction is high-quality and accessible to all students (Bertolini et al., 2012; Berkes, 2004 as cited in Ostrom, 2009).

A Re-Examination of COVID-Relief Funds Usage

Educational decisions and practices are largely driven by legislation, making it imperative that federal initiatives shift their focus towards state-specific characteristics when targeting challenges with resource availability and allocation (Tyner, 2023; Garcia & Weiss, 2020). These legislative efforts, especially those tied to funding must be tailored to the needs of each state as their experiences and underlying dynamics are more nuanced in nature rather than those presented nationally (Cairney & Kippin, 2022; Gee et al., 2023). Furthermore, public K-12 systems' capacity to respond to subsequent pandemic-related disruptions to operations will largely depend on these educational policies, further emphasizing the importance of developing mandates and legislative efforts that incorporate contextual, not universal approaches to ensuring resource and funding strategies adequately address the needs of all students, regardless of their socioeconomic background (Agostinelli et al., 2022; SPLC & ELC, 2021; Bozkurt et al., 2022).

COVID Relief funding initially came in the form of three government-funded grant opportunities related to the Elementary and Secondary School Emergency Relief Act (ESSER) (ESSER I: $13.2 billion, ESSER II: $54.3 billion, ESSER III: $122 billion). ESSER funds were provided to eligible, high poverty districts, to not only offset expenses tied to pandemic-related disruptions, particularly with making it more financially feasible to access supplies and materials that would help sustain instruction during mandated closures and subsequent reopenings (Smith Duffy, 2022). Additionally, the provision of ESSER funds was also viewed as a means of lessening COVID-related impacts on student learning for districts that historically experienced persistent cycles of low achievement (Hanushek et al., 2019; Doan et al., 2022; Reardon & Portilla, 2016).

While these efforts appeared to have promising impacts on achievement, several studies have noted issues related to sustainability and the practicality of providing large amounts of funding over an extended period of time. Shores & Steinberg (2022) and Merod (2022) both noted that while receiving large amounts of ESSER funding could be applied to improving instructional support and materials, results have suggested that examining how COVID relief funds were spent instead of the total amount awarded may help give clarity on how much of these funds were spent directly on instruction materials and support. The total amount of funds that were received appeared to be insufficient in accounting for the degree in which these funds targeted learning loss. In addition to mitigating learning loss, ESSER funds could have been used to enforce health and safety measures, create or maintain a infrastructure for technology, provide professional development to school personnel, offer social and emotional support to school personnel and students, engage parents and families, and ensure facilities meet COVID-related health codes (NCSL, 2022; USDOE, 2022; OESE, 2022; Gordon & Reber, 2021).

Without taking a closer look at how these funds are being used, we cannot (1) ensure they are being used appropriately, (2) understand the degree in which they are used to directly support instruction and (3) identify what may improve the likelihood of this funding significantly improving academic proficiency across all subject areas in this state. The results from this study are not meant to serve as the definative analysis for this topic. However, they do serve as a promising start towards a path filled more opportunities that explore those three notions, should opportunities for ESSER funding or other types of COVID-relief funding continue to be offered.

Conclusion

The impact of COVID-19 on academic proficiency in public K-12 systems was substantial and multifaceted. Despite Alabama consistently demonstrating high rates of poverty and low achievement across all subjects, K-12 education systems in this state have largely been underrepresented in pandemic-related literature. Results from this study indicated, to some degree, that differences in characteristics not only perpetuate socioeconomic inequities, but they also sustain gaps in achievement and opportunity. While it was clear that results regarding impacts on ELA and math proficiency varied, it was also evident that inherent challenges related to socioeconomic disparities played a role in the degree in which academic proficiency was achieved prior to the pandemic and that the addition of COVID posed new threats to traditional teaching practices. Some districts adapted to that transition effectively, while others did not. Ultimately, research must continue to further examine short and long-term implications that these dynamics may pose to these persistent gaps in achievement may have on Alabama education systems. Furthermore, findings can be used to inform subsequent legislative efforts that target K-12 improvement and increasing equity in Alabama and other high poverty states. The dispersion of ESSER funds, albeit different in its effect on the outcome, still appeared to be a reliable predictor for changes observed in ELA pre-to-post-COVID achievement, however, the degree in which these funds are helpful across multiple subjects, feasible, and sustainable for an extended time period, may also need consideration. Understanding the intricacies of these dynamics may help tailor interventions and strategies to meet the needs of students in Alabama, and thus, will offer an opportunity for districts to help them maximize their potential to achieve.

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