Identifying Factors Associated with Attendance of Professional Development for Early Childhood Professionals: Evidence from a Statewide Rollout of Online Professional Development

DISSERTATION

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Abstract

This research utilizes a natural experiment design to explore geographical differences in Early Learning Development Standards (ELDS) completion amongst registrants, both before and after an online delivery option is made available. Registrants were geocoded by workplace, and the employment zip code serves as a clustering variable. Spatial hierarchical linear modeling was utilized to explore the predictors of attendance while accounting for the significant spatial clustering within the sample of registrants. Accounting for the spatial clustering in the HLM reduced the ICC by nearly 50%. Results provide evidence that before the online option was made available, registering for the training in the county of employment increased the likelihood of a registrant attending the ELDS training. In the post-online sample, registering for the online delivery results in a statistically significant 12% lower likelihood that those registrants will complete the training when compared to those registrants choosing weekend face-to-face delivery. With all other model predictors held constant, rural registrants were not statistically different in their likelihood of attending compared to either suburban/urban cluster or urban center registrants. Policy implications include the lack of change in rural registrants in the three months after online delivery, and the need for further qualitative research to understand any technical barriers faced by rural registrants in accessing online professional development. Additional policy implications include the importance of face-to-face training locations, and the critical nature of how rural is defined in a research study. Methodological implications include the utilization of spatial methods in research concerning rural education professionals.

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Fields of Study

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Chapter 1: Introduction
Statement of the Problem

Professional Development (professional development) trainings serve as continuing education for many fields, including medicine, social work, the judicial system, and education. In order to maintain licensure or credentials, early childhood professionals must engage in a certain number of hours of professional development on new knowledge in the field, as well as new policies or strategies that are relevant to their work. In Ohio, early childhood professionals must receive at least 20 hours of approved training every two years in order to participate in Step Up to Quality (SUTQ), the rating and improvement system administered by the Ohio Department of Education (ODE) and the Ohio Department of Job and Family Services (ODJFS). Trainings are determined to be approved through the Ohio Approved process, the state's professional development approval process for early childhood professionals. Legislation passed in 2015 requires an increasing number of child-care settings receiving public funds be SUTQ certified, with 100% of settings receiving public funds being SUTQ certified by 2025[1]. While professional development sessions have historically been held in face-to-face environments; when organizing professional development sessions, geography must be considered in order to be accessible to professionals in different parts of the state.

[1] http://codes.ohio.gov/orc/5104.29

Predominantly holding trainings in a small number of areas within a state results in a loss of access to that training for individuals unable to attend training in those limited areas.

The focus of this dissertation is early childhood professionals (serving children from birth through kindergarten entry) within the education field in a single state (Ohio), for whom the state has taken responsibility for offering professional development related to a set of standards or policies set forth by the state. Adopted in 2012, the Early Learning Development Standards (ELDS) revolves around domains of school readiness to reflect the comprehensive development of children beginning at birth to kindergarten entry. The domains include: Social and Emotional Development, Physical Well-being and Motor Development, Approaches Toward Learning, Language and Literacy Development, and Cognition and General Knowledge. Descriptions of these domains are included in Appendix A (Ohio Department of Education, 2012). Ohio's ELDS standards "guide the design and implementation of curriculum, assessment, and instructional practices with young children" according to the Ohio Department of Education[2]. In order to educate early childhood professionals on the new standards that will guide their work, Ohio has developed no-cost trainings for professionals in the state.

[2] http://education.ohio.gov/Topics/Early-Learning/Early-Learning-Content-Standards/Birth-Through-Pre_K-Learning-and-Development-Stand

ELDS trainings are designed for professionals working with young children through the Ohio Department of Education, Ohio Department of Job and Family Services, Ohio Department of Health, Ohio Department of Mental Health, Ohio Department of Developmental Disabilities, and the Governor's Office of Health Transformation. These state agencies collaborated with the Governor's Office of Health Transformation on the standards, working with national experts and writing teams made up of Ohio-based content experts and stakeholders to revise and expand the standards. ELDS is a no-cost training targeted toward professionals working with children ages birth-5 through different agency affiliations; the population of ELDS participants includes, but is not limited to, Early Childhood Mental Health professionals, in-home family care providers, HeadStart instructors and Occupational Therapists, as well as preschool teachers licensed through the state of Ohio. A unique appeal of the ELDS trainings is the large audience of early childhood care providers . Professionals who work with any children aged birth-5 in Ohio will have their practice influenced by the ELDS, and should be motivated to take the training, given the lack of cost barrier. This is especially true for professionals who need to fulfill their training hours for SUTQ.

Early learning development standards exist in many other states, including Alaska, Arizona, California, Delaware, Georgia, Hawaii, Illinois, Iowa, Maine, Maryland, Massachusetts, New Jersey, New York, North Carolina, North Dakota, Oregon, Rhode Island, South Carolina, Texas, Washington, Wisconsin, and the District of Columbia (Build Initiative, 2015). There is at least one example of a free statewide ELDS online training, offered through Tennessee[3]. Research was not found that address the impact the online training had on Tennessee's ELDS attendance. The Ohio ELDS data offers a unique opportunity to take early learning development standards, adopted in different forms in many states across the United States, and see what effect the addition of online delivery options has on the predictors of attendance for the registered participants.

In the interest of reaching or educating as many early childhood educators as possible, the focus in this study is attendance. Specifically with no-cost trainings, the entrance barrier for registration is low. However, when registrants do not attend professional development trainings, an opportunity is lost to communicate policy, curriculum, and knowledge to individuals who at one point showed interest in that information. Attendance amongst registrants, as well as the important of what drives attendance, will be explored in the literature review.

Professional Development is a critical strategy employed in educational settings to advance the knowledge and skills of educators as well as to communicate policy

[3] http://www.tecta.info/tecta-services/online-training/

changes that impact the daily activities of education professionals' interactions with children or students (Zeichner, 2006). However, in Ohio, trainings are typically held in areas of higher population, as attendance is higher and the training is seen as more successful. Consequently, rural professionals can be faced with travel times upwards of two hours one direction for a training hosted in a more urban area. Faced with a four hour travel commitment for a three hour training, geography is a serious barrier in providing rural professionals the same opportunities to access professional development as their peers in urban center or suburban/urban cluster areas; this potentially affects their licensure and quality of work.

The issue of access to professional development is critical for early childhood professionals serving in rural areas (Askvig & Arrayan, 2002; Westling & Whitten, 1996). One strategy for reaching these rural professionals is to offer delivery of the professional development online, eliminating the travel barrier faced by rural professionals in search of professional development (Mollenkopf, 2009). Online professional development can be done in a live environment, or in a pre-recorded delivery that allows the participant to watch the training as their schedule allows within a certain time period. While there is the potential for loss of the learning community that exists within face-to-face professional development trainings, the online professional development option has gained momentum as a strategy to reach professionals with schedule or geography constraints that preclude them from participating in traditional face-to-face professional development sessions. However, little is known about how online delivery options mitigate the access issues faced by rural professionals.

Professional development is increasingly being offered in online settings; there is robust guidance on high-quality professional development within the traditional face-to-face setting (Garet, Porter, Desimone, Birman, & Yoon, 2001) with the warrant for a research agenda and online-specific framework set forth in literature(Dede, Ketelhut, Whitehouse, Breit, & McCloskey, 2009). The research agenda from Dede et al. (2009) includes recommendations surrounding research questions, strategies, models, designs, and methodologies that do not only replicate face-to-face professional development, but also create new research questions on issues of online collaboration, communication, and community (Dede et al., 2009).

Within Ohio's latest census population estimates[4], 6% of the 11,614,373 total population are under the age of 5.These 696,862 children constitute the population that could be served by Ohio's early childhood educators. Census estimates [5] that 22.08% of Ohio's population lives in rural areas. What Rural Matters states that Ohio in the 2015-2016 school year, had the fourth largest rural student population: 360,582, or 22.5% of all

[4] https://www.census.gov/quickfacts/OH
[5] http://www.census.gov/geo/www/ua/2010urbanruralclass.html

students. While the WRM is not limited to children under 5, and is therefore not a confident estimate of the percentage of Ohio's population under living in rural areas, it does provide a rough idea of the proportion of Ohio's young children living in rural areas. Early childhood professionals serving rural populations are in need of professional development, much as their peers in different geographic areas, but may have different professional development experiences based on their rural geography.

Rural educators, in addition to the common barriers of competing classroom responsibilities and lives outside of the classroom, are presented with additional barriers to receiving the professional development (Askvig & Arrayan, 2002; Westling & Whitten, 1996). An example of the additional barriers faced by rural professionals include limited budgets to support staff seeking professional development that have travel or registration expenses, or to pay staff taking professional development outside work hours. Distance is also a barrier for many rural professional development participants, as the travel distance from the training site to their workplace or home could be longer than the training itself. Staff coverage is an additional barrier for those in rural work settings; often, staffing limitations prevent adequate coverage of classroom responsibilities that would allow an early childhood professional to attend a professional development session during the 9am-5pm work day. These barriers contribute to what is identified here as the professional development professional development access gap.

Once in a professional development training, the rural educator may have a very different experience than other educators. There is evidence that rural educators may not have the same technology training that their peers have (Wallace, 2014) and they are lacking the professional learning community recommended as a best practice in effective professional development (Howley & Howley, 2005). One recommendation from Howley & Howley (2005) is to form a professional development community of local peers. This recommendation presents an interesting methodological opportunity in exploring the nature of professionals in geographically rural areas and the impact of neighboring professionals on their participation in a professional development training.

One promising approach to geography's relationship with access gaps is by incorporating spatial components into models examining these gaps. Spatial analytic methods allow data that are correlated across space or time to be analyzed in such a way that the geographic clustering of an outcome variable, professional development attendance, can be better explained. Spatial methods can be employed at the individual level, or in a multilevel setting.

Multilevel modeling has been used to explore spatial dependency and geographical variation among phenomena of interest (Verbitsky-savitz, & Raudenbush, 2012). A unique aspect of Verbitsky-Savitz and Raudenbush's research on crime reduction effort focused on the effects of treatment in a community on the neighboring, non-treatment community, known as neighborhood or spillover effects. In essence, their research was aimed at understanding how many neighborhoods needed the intervention in order to see the overall crime rate decrease across all communities, by taking into account the direct impacts on treated communities and indirect impacts through neighbor or spillover effects in areas near intervention communities, but not receiving the intervention. Spillover effects result in more than treated neighborhoods exhibiting treatment effects; this can be useful in research that may be limited by cost or logistics such that not all neighborhoods or geographical areas can be treated, but there is interest in impacting an outcome in all neighborhoods or geographical areas.

While there exists a robust body of literature on characteristics of effective professional development (L. M. Desimone, 2009; Porter, Garet, Desimone, & Birman, 2003) there is a significant gap in the literature related to our understanding of characteristics that explain access gaps for professional development across a state. Additionally, while the professional development barriers faced by rural educators have been explored in the literature, no exploration of online delivery as an intervention to mitigate those barriers was found within the literature. This study will contribute to a larger understanding of how online delivery shifts access patterns in a statewide professional development program, as well as how dosage (number of sessions or hours within a training), delivery method, and proximity to training relate to attendance for those registered. Methodologically, the study incorporates spatial methods with a dichotomous outcome situated in an education research setting; previous research of this nature was not found in the small amount of research comprising spatial methods within the education literature.

Objectives and Research Questions

The purpose of this study is to understand the determinants of professional development attendance amongst registered early childhood professionals. In other words, once an individual registers for training without the barrier of cost, what are the factors that predict whether or not that individual will ultimately attend the training? The professional development training considered here, Ohio's Early Learning Development Standards (ELDS), is one of many state-sponsored options that can be taken to fulfill licensing requirements set forth by the Ohio's Departments of Education and Job and Family Services. State-sponsored professional development options are the only ones that can be taken to fulfill requirements of licenses granted by the state of Ohio. As the training is voluntary, findings from this the self-selected sample are not intended to be applied to early childhood professionals who did not register for the ELDS training. Determinants will be assessed before and after the professional development is available online in order to examine if the determinants of attendance differ after the addition of the online training option.

This dissertation research will address the following research questions:

- Does the introduction of an online option for a professional development training reduce the access gap for this training amongst Ohio's early childhood professionals, and is this improvement related to geography types: rural, urbanized, and urban cluster? Related component questions include:
    - For the professionals who have the choice of online or face-to-face delivery (post-online sample), how does this choice affect professional development completion rates?
    - Based on the 3 months before the online delivery option and the 3 months after the online delivery options, how does the choice between online and face-to-face delivery affect dosage (number of sessions or hours of the professional development training) of the training?

In order to answer these questions, ELDS registration records were obtained by the state through the Ohio Professional Registry for 3 months prior and again 3 months after the initial offering of online delivery.

Significance of Study

Ultimately, the goal of this study is to identify factors that influence early learning professionals' professional development attendance once registered, particularly with regard to geography, and to assess whether the addition of online trainings address any access gaps that may exist in certain areas, such as areas of rural geography. Study results will contribute to work regarding access gaps, and policies employed to address those gaps. Methodological contributions include the incorporation of geographic or spatial effects into analyses of professional development opportunities.

Study Limitations

The scope of this study is limited to professional development access. Questions about professional development quality, as well as the student of teacher level impacts of professional development participation, are outside the scope of this study. Additional study limitations exist in the sample, which includes only Ohio registrants of a single professional development training during a period of six months. The researcher did not collect the sample, which are administrative data, and data quality limitations exist with any secondary data use. Additionally, the self-reported nature of critical fields such as employer, may contribute to data quality limitations. The results of this study are not intended to generalize to the larger early childhood education workforce in Ohio, or outside Ohio. This limitation is specifically salient as not all early childhood professionals serve students in setting receiving public funds, and would not be impacted by the impending legislative requirement of those sites to be SUTQ certified. Individuals who run in-home childcare centers frequently do not serve publicly funded children, and while they are eligible for SUTQ certification, the incentive is markedly lower than setting receiving public funds for the children served.

Organization of the Chapters

The following review of the literature in Chapter 2 puts forth the justification to explore the geographical variability of educator professional development attendance, using spatial methods to identify factors (sessions within training, time of the training, geography type, and the training occurring within the participant's county of residence) as potential predictors of whether or not a registered participant attends ELDS training. Chapter 2 reviews literature of professional development frameworks and justifications, geography as a barrier to professional development access for rural professionals, and spatial autocorrelation as a way to account for clustering that occurs in geographic access patterns. Study methods and analysis plan are detailed in Chapter 3, identifying the particular spatial methods appropriate for use in this study. Chapter 4 addresses study results, and Chapter 5 explores the implications of the study findings.

Chapter 2: Literature Review

Educational expectations for teachers are in a state of near-constant change, as standards and policies shift rapidly on the federal, state, district and classroom levels. Reform efforts tend to focus on the goal of improved student performance in a subject, increased student graduation rates, or other student-centered outcome measures; however, in order to implement these efforts, teacher practice often must be altered. The role of the teacher, who serves as intermediary between education reform efforts and their intended student-level consequences, necessitates a vehicle to communicate the policy changes that influence instructional practice to those teachers charged with implementing the changes. This vehicle typically manifests as professional development, which can be delivered to teachers through a variety of places (onsite in-service trainings or offsite), times (weekends, during in-service days, or over the summer) or modalities (face-to-face, online trainings, or a hybrid combination of both). Subject matter includes content knowledge as well as additional topics including, but not limited to: classroom management, bullying, integrating technology into the classroom, serving students with exceptional needs, accountability efforts (in response to teacher evaluation policies) and curriculum changes. After these trainings, teachers return to their classrooms with new knowledge and more tools at their disposal for educating students. In order to obtain these new tools and knowledge, teachers must attend the professional development. As the need for trainings becomes larger with more individuals seeking credentials requiring professional development, the need to understand what influences attendance becomes salient. Professional development registration without attendance represents an awareness of a learning opportunity, and a lost learning opportunity. Literature in three areas will be examined here: professional development frameworks, geography and its impact on professional development access, and spatial methodology as a way to measure and assess access gaps that exist, perhaps due to geography.

Professional Development Frameworks

A necessary first step in a conversation around professional development is to articulate the elements of what constitutes professional development. Desimone (2009) states that measuring the core features of teachers’ learning experiences is a way to combat the complicated task of measuring the benefit that an educator takes from professional development activities. There are five core features that Desimone focuses on in her argument toward consensus on professional development definitions: content focus, active learning, coherence, duration, and collective participation, building on the conversation in literature working toward consensus on professional development characteristics that improve teacher practice and student achievement outcomes (Hawley & Valli, 1999,Kennedy, 1998; Wilson & Berne, 1999).

There is evidence that change in both knowledge and practice requires professional development activities to be of sufficient duration, both in total hours and the number of sessions (Cohen & Hill, 2000; Fullan, 1993; Guskey, 1995). While there is no rule of thumb on how long professional development needs to be in order for it to be effective, Yoon et al. (2007) analyzed 1,300 studies representing the existing landscape of professional development research in 2007 and found that professional development less than 14 hours had no effect on student achievement. Within the Cohen & Hill (2000) research, they used length of time that a teaching professional spent in a professional development session as the indicator of depth; this extended time gave more opportunity for greater learning.

The collective participation component of Desimone's core features is grounded in literature surrounding the learning communities for teacher learning communities. The discussions from teacher learner communities can serve as an effective form of teacher learning (Banilower et al., 2006; Borko, 2004; L. Desimone, Garet, Birman, Porter, & Yoon, 2003; Fullan, 1991; Guskey, 1995; Little, 1993; Loucks-Horsley, 1998; Rosenholtz, 1989). Borko (2004) argues that these discussions must be supportive of critical examination rather than simply report-outs of what was learned and potential applications. Guskey (1995) supports the high-level access of knowledge gained from professional development in his conclusion that professional development success lies in the intentionally and appropriately use the new knowledge, not simply the acquisition of new knowledge. He also communicates this teacher learning community in his statement of a professional development ideal, where schools are communities of learners with both teachers and students serving as learners (Guskey, 1995).

Desimone's core features are explored in the context of only one type of professional development: face-to-face delivery. The features of online professional development are not in conflict with the elements proposed by Desimone, and these elements could logically be applied across the different professional development delivery mechanisms. professional development goals, regardless of the method of delivery, are the same; sessions may also be offered in both online and face-to-face settings, typically after converting the face-to-face training into the online format (Donahue & Fox, 2011; U. S. Department of Education, 2010) . This is to say that the objectives and goals of a professional development do not vary across face-to-face and online delivery. There has not been research empirically testing a professional development framework such as Desimone's for both online and face-to-face trainings which can be attributed to the relatively new consideration of online professional development in the education field.

In the same year of Desimone's article seeking consensus on professional development, Dede et al. (2009) and colleagues observed that there is a lack of empirical research related to online teacher professional development. His proposed research agenda for online professional development is centered on two focal points: research questions concerning understudied areas and the methodological strategies for addressing these questions. Dede notes that online and face-to-face professional development warrant exploration in the empirical research, rather than taking findings from face-to-face professional development research and applying those findings to online professional development. He sets forth recommendations for a research agenda that will contribute to to online professional development literature more reminiscent of the evidence-based frameworks seen in face-to-face professional development literature.

The warrant for a research agenda focused on online professional development builds from the knowledge gained in face-to face professional development literature, but does not translate face-to-face findings to the online delivery setting. For example, implementation strategies are more diverse in online professional development. Some participants may 'find their voice' in an online setting while being quiet or non-contributory in face-to-face settings, simultaneous contributions can be made, and the discussion period is not limited in the ways seen in face-to-face settings (Dede et al., 2009). When more time is granted for discussion purposes, participants have more opportunity to respond meaningfully, creating opportunities specifically for those who process internally before vocalizing reactions or thoughts.

Dede et al (2009) called for research on online professional development that "address enablers of durable teacher change, such as interventions designed to increase pedagogical content knowledge; impact of professional development on teacher change, …; effects of teacher change on student learning; factors influencing the sustainability of teacher improvement and scalability" of online professional development programs (p. 16, Dede et al., 2009). Dede's research call does not specifically call for increasing access to high quality professional development, or take into account any specifics such as broadband internet access or technological literacy that may be needed to integrate professional development into areas that have not previously had access due to geographical barriers. Additional components of Dede's research agenda include: a) various research methods that incorporate formative and summative components, b) clarity of research design, c) including research questions, assumptions, and terminology that is explicitly set forth and a scope that allows for replicability and generalizability, d) expanding replicability beyond the methods included in face-to-face professional development, e) including issues of coordination and dissemination of knowledge surrounding online professional development to share lessons learned from online professional development research.

Dede's proposed research agenda for online professional development has been cited 79 times from its 2009 publication through April 2017. This is a marked increase from April 2016, when the article had been cited 48 times. This suggests that literature is more frequently exploring or advancing Dede's proposed research agenda. Though some researchers have begun to build upon the various tenants of Dede's recommended research agenda. For example, research questions in online professional development that concern changes in pedagogical content knowledge or practice transformation have been approached (Malanson, Jacque, Faux, & Meiri, 2014; Masters, Kramer, O'Dwyer, Dash, & Russell, 2010), various research methods incorporating formative and summative concepts (Teräs & Herrington, 2014), and scopes that allow for replicability utilizing methods outside those exclusive to face-to-face environments, (J. B. Fisher, Schumaker, Culbertson, & Deshler, 2010).

The final tenant of Dede's research agenda to be addressed demonstrated development through the Online Learning Consortium's Innovate Conference. This conference, first held in New Orleans in 2016, focuses on Innovations in Blended and Online Learning and includes research highlights as well as hands-on workshops to develop practitioner skills.

Professional Development Best Practices

Best practices within professional development have been identified by The Center for Public Education's *Teaching the Teachers: Effective Professional development in Era of High Stakes Accountability* (2013) include:

- Duration significant enough to allow for teacher learning and implementation planning (Darling-Hammond, Wei, Andree, Richardsom, & Ophanis, 2009; Corcoran, McVay, & Riordan, 2003;French, 1997),
- Support for professionals implementing strategies from professional development (Truesdale, 2003; Knight and Cornett, 2009),
- Active engagement of participants through active participation and various approaches within the training (French, 1997; Roy, 2005; Richardson, 1998; Goldberg, 2002; Rice, 2001; Black, 1998; Licklider, 1997),
- Modeling of new practice by instructor (Snow-Renner & Lauer, 2005; Carpenter et al., 1989; Cohen & Hill, 2001; Garet et al., 2001; Desimone et al., 2002; Penuel, Fishman, Yamaguchi, & Gallagher, 2007; Saxe, Gearhart, & Nasir, 2001; Supovitz, Mauyer, & Kahle, 2000), and
- Content relevant to grade or subject level for professional in the training (Blank, de las Alas & Smith, 2007; Carpenter et al., 1989; Cohen & Hill, 2001; Lieberman & Wood, 2001; Merek & Methven, 1991; Saxe,

Gearhart, & Nasir, 2001; Wenglinsky, 200; McGill-Franzen et al., 1999; Gulamhussein, 2013).

Speaking specifically to online learning, best practices have been identified as: a focus on learning and the learner, facilitating engagement resulting in reflective thinking, building a learning community, flexible learning environment and culture, enabling learners to engage with material at their own pace on any device, and promoted continued learning (Donahue & Fox, 2011).

Professional Development Usage Patterns

Clarke and Collins build professional development specifically on Desimone's fifth characteristic of professional development, the collective participation of multiple individuals from the same workplace. Clarke and Collins (2007) apply a complex systems framework to the student teaching practicum, and produce five implications for student teacher supervision: 1) redefining the practicum, 2) rethinking evaluation, 3) surrendering certainty, 4) acknowledging complicity, and 5) allowing for improvisation. The complex systems framework, originating with Weaver (1948), presents complex phenomena as "interactions of events, activities and practices that coalesce in ways that are unpredictable but nonetheless high patterned," is defined by phenomena displaying five characteristics: 1) network, rather than linear or hierarchical structures, 2) feedback loops, 3) capacity for self-organization, 4) disequilibrium consistent with an open system, and 5) nested nature (Clarke & Collins, 2007). Clarke and Collins (2007) look at patterns rather than substance in order to gain a clearer understanding of the dynamics of the student teaching practicum experience, and the pattern approach is relevant to exploration of professional development for early childhood professionals. A limitation of the Clarke and Collins (2007) study is that student teaching practicums are pre-service education, rather than training for skills development aimed at professionals in the early childhood field. Patterns referenced within the Clarke and Collins (2007) work are further developed within Davis and Sumara's framework of complexity thinking. Davis and Sumara (2006) describe complexity thinking as transdisciplinary in nature, indicating a research approach wherein researchers arrive with backgrounds in various disciplines and agendas, but are sufficiently informed about the various perspectives to be able to function as a collective team. Teacher learning is argued to happen simultaneously at the individual, collective grade level or subject team, and subsystem level (for example: buildings within districts within communities) (Davis and Sumara, 2006).This can be seen in scenarios where professional development is administered program or building wide, rather than individuals seeking out professional development independently. In these cases, both the individual practice and building or staff-level dynamics are impacted through not only the training content, but the shared experience of having attended the training. Acknowledging that simultaneous process, the charge is not that these levels must be controlled or accounted for in assessments of teacher learning, but that leaving the complexity and nested nature of the field out of efforts to understanding teacher learning is a limitation that is commonly seen in the professional development literature (Opfer & Pedder, 2011).

Opfer and Pedder's movement away from considering teacher learning as situated in the individual classroom and towards an understanding of teacher learning influenced by multiple elements or subsystems such as the teacher, school, or learning activity, is in keeping with many criticisms within the professional development literature (Borko, 2004;Clarke & Hollingsworth, 2002; Sykes, 1996; Opfer & Pedder, 2011; Timperley & Alton-Lee, 2008). One of Borko's research questions, concerning what is known about professional development programs and their impact on teacher learning, is couched within the situative perspective, a research tradition that allows for multiple units of analysis. Using this perspective allows Borko (2004) to examine communities of learners within professional development and posit that to understand teacher learning, it must be studied with the individual teacher as the unit of interest as well as the social system that the teacher exists within. Clark & Hollingsworth (2002)'s criticisms of models of professional development center around the lack of complexity exhibited in the models. They propose an interconnected model of professional development building from the four domains set forth in Guskey'(1986) article: staff development, change in teachers' classroom practices, change in student learning outcomes, change in teachers' beliefs and attitudes. The resulting model is non-linear and allows for identification of growth networks, which captures the more nuanced nature of individual teacher growth as a result of professional development(Clarke & Hollingsworth, 2002). While the impacts of teacher professional development on student learning outcomes is outside the scope of the research proposed here, the approach set forth in Hollingsworth's model is relevant to understanding teacher change outside of the individual silo.

Opfer and Pedder (2011) expand upon the idea that teacher learning exists in a complex system representing recursive interactions between systems and elements that coalesce in ways that are unpredictable but also highly patterned (Clarke & Collins, 2007) . Opfer and Pedder (2011) argue for an explanatory theory based on these predictable patterns that can be discerned when considering the nested nature of teachers' learning environments . The nested nature of teachers' learning, the collective learning element characterized when trainings are taken by multiple employees within a workplace, has not been addressed in the empirical literature on professional development.

Professional Development Efficacy

Considering the efficacy of professional development requires an understanding of the different metrics of how efficacy is determined. In a study examining empirical research on professional development for early childhood educators, Schachter (2015) found that out of 73 included studies, fidelity, or adherence to procedures set forth in the professional development, was the most common measure of professional development success. Other measures included environment, teacher knowledge, teacher practice, teacher beliefs, teacher satisfaction, children's knowledge, and children's behavior.

Professional development studies may focus on multiple measures of efficacy. A randomized controlled trial with 88 teachers and 759 students, where teachers were assigned the online or face-to-face professional development, utilized hierarchal linear modeling to reveal positive effects on general classroom environment, classroom supports for early literacy and language development, children's letter knowledge, blending skills, writing, and concepts about print. The professional development did not find significant effects on teaching practices and children's oral language outcomes (Powell, Diamond, Burchinal, & Koehler, 2010). A pertinent finding of this study was the lack of significant difference between the effects seen for the online and face-to-face teacher groups. In this study, the effects were not affected by the professional development delivery mode. Additionally, positive effects were found in children's' science growth through a professional development training, and positive association between children's learning with increased math and science opportunities in a random assignment study of 65 early child educators (Piasta, Logan, Pelatti, Capps, & Petrill, 2015).

In a random assignment experiment, 34 Head Start providers were assigned to control (n=16) or experimental (n=18) groups to determine fidelity to the professional development components and whether the coaching-based intervention improved teachers' instruction (Diamond & Powell, 2011). One of the components of their study in this iterative project found that Head Start providers delivered more vocabulary instruction, including defining or reviewing more new works (M=7.12 words defined), than control teachers (M=3.7 words defined, d=0.69) over the period of one semester.

Professional development has the ability to affect improvements in instructional practice, but in order to fully realize the limitations and possibilities of professional development, access and usability must also be considered. The professional development series that fulfills all best practices and is tailored to an appropriate audience is lost if that audience is not in a position to avail themselves of the lessons and knowledge in the professional development session. A significant barrier or constraint that prevents many teachers from accessing professional development is time constraints (Firestone, 2005). An additional complication to the time constraint come in the form of travel time required to attend the training, with rural teachers reporting travel time as a barrier to professional development (Wilson & Ringstaff, 2010). The impacts that professional development may have on instructional practice necessitates a close look at the characteristics of the professionals taking advantage of professional development opportunities, and those who are not.

Geography as a Barrier to Professional Development Access for Professionals in Rural Areas

Individuals who are not geographically close to where most of the professional development is administered are presented with a barrier in accessing professional development. If a teacher travels 2 hours for a professional development session, that teacher will be travelling 4 hours round trip for one session and 12 hours for a three-session professional development module. Even if the coaching component is conducted through email, online or over the phone, the travel time involved in this situation could easily match or surpass the time involved in the actual professional development session. This presents a substantial professional development barrier to professional development educators who have unique geographic barriers in addition to the competing responsibilities in their classrooms and lives outside of the classroom.

Rural teachers often face the most extensive travel times for professional development, as well as staffing limitations that serve as barriers to their receipt of high-quality, relevant professional development. These teachers, due to smaller staff sizes, often serve in roles outside of their trained specialization (Billingsley, 2004; Ingersoll, 2001; Thorton, Peltier, & Medina, 2007). For example, due to the lack of special education teachers, individuals licensed in another area may serve in this capacity under an emergency license. These individuals are in need of professional development, but due to the staffing shortage that led to hires under emergency licensure, coverage of classroom responsibilities may not be possible therefore limiting the teacher's ability to attend professional development during the day. Additionally, the limited economic growth in rural communities contributes to lower populations (Eddy, 2007). These lower populations often mean that teachers may be the district's only teacher in a grade or topic, leading to professional isolation and lack of support (Jean-Marie & Moore, 2004; Schmidt, 2004; Wilson & Ringstaff, 2010). Lower population densities also impact the budget of schools in that as the population size shrinks, so does the property tax base that contributed to a school's operating funds. Budget, distance from accredited higher education institutions, and time constraints present challenges to rural educators seeking professional trainings (Askvig & Arrayan, 2002; Westling & Whitten, 1996). This smaller sample size is reflected in the data for this study, in which only 70 of the 3,288 individuals who provided employer information indicated employment in a rural area.

Rural professional development participants cannot be assumed to share the same takeaways and experiences in the training as their urban or suburban peers. In an explicit comparison of the differences between rural and urban teachers' experiences, a survey of Kentucky teachers in high achieving urban and low achieving rural districts found that less than half the rural teacher reported having enough training to implement technology in their classrooms, while over 80% of urban teachers reported having enough technology training (Wallace, 2014). This is theorized to be connected to funding for technology training, as the rural districts in this study had a higher degree of students receiving free or reduced price meals compared to the urban districts. If a professional development assumes technology training to implement its learning goals in the classroom, Wallace's research provides evidence that the training may not be as useful for rural professionals.

The barriers faced by rural educators seeking professional development have led to researchers exploring ways to tailor professional development to diverse learner needs, much as educators are charged with adapting their material to the diverse needs of children in their care. Rather than avoid the issues that distinguish rural educators from their peers, rural-responsive professional development embraces the differences in order to make professional development useful for rural participants (Howley & Howley, 2005).These differences, left unaddressed, could lead to rural educators not seeing how professional development lessons fit into their classroom. Specific examples of challenges addressed in rural-responsive professional development include " (a) encounter in code-switching difficulties that students language of dialect and the formal between informal schooling, (b) the lack of appreciation among some parents and community members for certain academic subjects of study, and (c) limited exposure by some rural students to a diverse group of peers" (p.3,Howley & Howley, 2005).

Efforts have been made to address the professional development needs of rural educators and there is evidence that partnerships with existing higher education institutions are effective practices in reaching rural teachers and providing math educators with limited math backgrounds the skills needed to confront math anxiety and expand math content knowledge (Wilson & Ringstaff, 2010). However, these findings do not easily generalize to early childhood educators, as math teachers and early childhood educators do not necessarily have the same professional development needs, and Wilson & Ringstaff's findings rely on access to higher education institutions. The higher education partnership could present financial barriers if tuition is required for content that serves as professional development, which could be obtained without cost through other avenues such as the state technical assistance network, and is not as flexible with timing as online professional development, which can generally be taken at the participants' convenience. Specific outreach efforts have been made to understand the higher education needs for pre-service professionals being trained in rural areas (Warren & Hamlin, 2005). These efforts, in North Carolina, indicated challenges for pre-service professionals in the form of a two-hour roundtrip drive to the nearest institution that could grant teacher certification, which prompted the opening of a satellite certification program at a rural community college. This effort was focused on the pre-service education needs of rural professionals, rather than the in-service needs of those professionals. However, rural science teachers serving grades 4-8 listed lack of curriculum leadership, lack of learning communities, and travel barriers as professional development challenges (Wilson & Ringstaff, 2010). The travel barrier identified as a challenge is explored further here, as well as a potential modification to professional development designed to address the travel barrier: online professional development.

Considering Desimone's professional development elements of best practice, the community of learners is a salient barrier for rural educators. While not a barrier to professional development access specifically, the small sizes of rural teaching staff limit the use of professional learning communities recommended by Desimone. A department may consist of a single individual, leading to professional isolation (Howley & Howley, 2005). Howley & Howley (2005) recommend a) faculty from districts form their own cross-district professional learning communities, which may be better able to support the needs of professional in rural settings with unique characteristics and needs and b) online learning communities to allow isolated subject-specific professionals to communicate. A meta-analysis conducted on online professional development revealed success in fostering this professional learning community (Surrette & Johnson, 2015).

Does Online Delivery Impact the Rural Professional Development Access Gap?

A potential resolution to the travel barrier identified by rural teachers is online professional development. This is seen as cost-effective because there are no costs associated with renting the space or equipment, and there are no requirements for participants to travel (Dede, 2004; Treacy, Kleiman, & Peterson, 2002). Little is known about whether online delivery of professional development may address gaps in who has access and who is utilizing trainings. However, given that travel has been identified as a barrier to professional development access, online professional development and coaching could potentially alleviate the barrier of travel that stands between some educators and sustained administration of professional development with coaching as a component. However there is literature that advocates for the exploration of online professional development for rural teachers who are seeking additional training. Specifically, Mollenkopf (2009) advocates for alternative delivery methods, such as distance education and online delivery, for degree-seeking rural educators struggling with these barriers.

Online professional development options do not necessarily provide a mechanism through which rural access issues will be addressed (Askov, Johnston, Petty, & Young, 2003; Atkinson, 2008; Weigel, Weiser, Bales, & Moyses, 2012). While there is research that suggests that online and face-to-face instruction are equivalently effective (Askov et al., 2003; Drummond, 1993; Powell et al., 2010), engaging in online professional development requires that participants make an active decision on the method of professional development delivery that they attend and have background skills for accessing content online (e.g.: ability to turn device on, ensure online connectivity, navigating online learning platforms, forming an account within the online learning portal with an email address that may also need to be created, as well as any blocking programs triggered by the online learning platform). When online trainings were introduced into North Carolina's early childhood professional development landscape, qualitative results suggested that most early childhood professionals preferred using elements of traditional face-to-face professional development in conjunction with, or instead of, online options (Warren & Hamlin, 2005). Additionally, there are cautions with online learning that have been identified in the literature. Without face-to-face contact with peers or classmates, a student's self-discipline becomes more critical. Low levels of self-discipline may interfere with course completion (Press, Washburn, & Broden, 2001) and course retention has been noted as lower for online courses than retention rates attributed to traditional face-to-face classrooms (Lee, 2000; Mariani, 2001) . Additionally, the individual's level of comfort with technology is critical to online learning success with some evidence suggesting that students may overestimate their ability to succeed in online courses while not taking into account how difficult the online learning process may be for them (Merwe

& Merwe, 2008; Perreault, Waldman, Alexander, & Zhao, 2002). Additional literature shows online learning may take considerably more time than participants expect and despite their using online resources for other purposes, participants do not fully comprehend the dynamics, possibilities, and responsibilities until they engage in online learning (Palloff & Pratt, 2001). Perhaps most concerning is research suggesting that the perceived impersonal nature of distance education results in potentially isolated and detached adult learners (Press, et al., 2001). This compromises the community of learners or sense of community for online learners (Dawson, 2006; Hrastinski, 2009; Kear, Chetwynd, & Jefferis, 2014).

Geography as a Clustering Variable

Rural participants who experience barriers not seen by participants serving in non-rural settings provide an opportunity to explore the observations as a cluster rather than simply individual cases. Their service in rural settings provides a common trait and the geographical, or spatial, nature of the trait allows for examination using spatial patterns. As previously discussed, teachers do not function in silos, and taking into account shared workplaces allows for a more nuanced examination of professional development attendance across shared or neighboring workplaces. Of interest is whether participation is clustered in certain areas, that is to say, if participation is clustered in certain areas of space.

Spatial clustering has a unique history that traces back to the 1854 cholera epidemic in London. Dr. John Snow's theory about disease contagion led him to believe that some deadly diseases were being transmitted through a method other than air, a common belief of the time (Johnson, 2007). Snow mapped the public water pumps and the cholera deaths in London as they occurred, and concluded that cases tended to be clustered in one area of the map, in the area surrounding the Broad Street pump; Snow's tracking of cholera victims revealed that others used this pump rather than their closest pump, as the Broad Street pump water appeared cleaner, accounting for cases outside the area near the Broad Street pump. While the majority of the cholera victims lived near the Broad Street pump, the pump was not automatically thought of as the source of the cholera outbreak due to the cases that did not live near the pump. Once the victims furthest from the Broad Street pump were connected to the Broad Street pump water, this early example of clustering became part of epidemiological history. Statistically, clustering is commonly manifested as serial correlation, or correlation over time. Observations of a phenomenon can be clustered in any number of ways: within classrooms, doctors, or communities, to name just a few.

A disease cluster is defined as an unusual aggregation, real or perceived, of health events that are grouped together in time and space (CDC, 1990). Cholera victims not residing in the Broad Street pump area drank from the pump due to their proximity from work or shopping habits. Snow's theory was proven accurate when the pump handle was removed, and the cholera epidemic ended. Snow's contributions, largely through the mapping of the cholera epidemic and its relationship to water supply, have secured his place as a founder of modern epidemiology.

Here, the interest lies in whether professional development participation is clustered across space in the 3 months before and after the introduction of online versions of the professional development under examination. Statistical testing to determine if clustering contributes to an outcome or endpoint is conducted through a test of spatial autocorrelation, which is defined as "a measure of the degree to which a set of spatial features and their associated data values tend to be clustered together in space (positive spatial autocorrelation) or dispersed (negative spatial autocorrelation) (ESRI, 2015). Within the context of this study, it is hypothesized that online professional development reduces the access gap for teachers working in rural settings.

Spatial Autocorrelation

Spatial autocorrelation test statistics are extensions, or special cases, of Pearson product-moment correlation coefficient for 2 variables.

$$p = \frac{\sum_{i=1}^{N}(x_i - \bar{x})\,(y_i - \overline{y})}{[\sum_{i=1}^{n}(x_i - \bar{x})^2 \;\; \sum_{i=1}^{n}(y_i - \bar{y})^2]^{\frac{1}{2}}} \tag{1}$$

Where $\bar{x}$ and $\bar{y}$ are the sample means of both variables and p indicates if x_i and y_i are linearly associated, or correlated. Equation 1 is modified to incorporate spatial autocorrelation by adding j (neighbor) variables as well as i (case of interest). There are two well-known tests to assess the extent spatial autocorrelation: Geary's c and Moran's *I* (Geary, 1954; Moran, 1949). Both are special cases of the Pearson product-moment correlation coefficient applied to continuous data and both statistics are expected to be approximately normal (Bailey & Gatrell, 1995).

Moran's *I*, the most common spatial autocorrelation test statistic, will measure if x_i and x_j are spatially associated, or correlated (Paradis, 2015). I serves as a diagnostic statistic, which can be run on an outcome variable, or on residuals (Moran, 1949). The equation for Moran's *I* is:

$$I = \frac{N}{\sum i \sum j \omega_{ij}} \quad \frac{\sum i \sum j \omega_{ij}(X_i - \bar{X})(X_j - \bar{X})}{\sum i (X_i - \bar{X})^2} \tag{2}$$

Where N is the total number of cases in the data, ω_{ij}= weight (measure of similarity or closeness in space) between observation i and j, $\bar{X}$ *is* the sample mean of the variable.

The null hypothesis is that I=0, indicating no spatial autocorrelation within the data. The statistic ranges from approximately -1 to 1, and has a mean of -1/ (n-1). A significant *I* indicates the presence of spatial autocorrelation (Bailey & Gatrell, 1995).

Geary's c (Equation 3) measures the similarity between observations *I* and *j* via $Sim_{ij} = (Y_i - Y_j)^2$. If the observations have similar values, the similarity (Sim_{ij}) will be small (Waller, 2004). Equation 3 takes a weighted average of the similarity values observed for all pairs in a data set, and measures the overall variation around the mean observation $\bar{Y}$ (Waller, 2004)

The equation is given by:

$$c = \frac{N-1}{2(\sum i \sum j \omega_{ij})} \times \frac{\sum i \sum j \omega_{ij}(Y_i - Y_j)^2}{\sum i (Y_i - \bar{Y})^2} \qquad (3)$$

Where *N* is the total number of cases in the data, ω_{ij}= weight between observation *i* and *j*, $\bar{X}$ *is* the sample mean of the variable. The null hypothesis for Geary's c is that c=1, and only produces positive values. Values below 1 but greater than 0 indicate positive correlation, and values above 1 providing evidence of negative correlation (Bailey & Gatrell, 1995).

Assessing the extent of spatial autocorrelation in any data is prefaced by multiple decisions that researchers must defensibly make before analyzing the data: defining what constitutes a neighbor, and how to collect and use this information in the analysis.

Neighbor weights (ω_{ij}) are most commonly determined by Euclidian distance or k nearest neighbors. This decision contributes a significant amount to the interpretability of the model and its results; the construction of the weights matrix should be from a theoretical place.

K nearest neighbors and distance based neighbors both require point data, with distance determined by geographic proximity. The researcher determines either a set number of neighbors (k), which are populated by the points nearest to the focal point or case in question, or a set distance and all neighbors within that set distance.

Moran's *I* and Geary's c are global measures of autocorrelation, meaning that they indicate if a significant level of spatial dependency exists. Researchers interested in seeing where the dependency exists must use a local measure. A local indicator of spatial association (LISA) allows for the decomposition of global indicators (I or c) into the dependency for individual observations (Anselin, 1995). LISA statistics indicate local clusters or pockets of concentration and assess the how these clusters contribute to the global statistic, that is to say, the LISA statistic can help identify outlier pockets within a geographic data set. A global measure of autocorrelation, such as the Moran's *I*, reveals if significant autocorrelation exists, while a local measure, such as the LISA, indicates where those geographic pockets exist.

The global Moran *I* formula is:

$$I_i = z_i \sum_{j=0}^{N} w_{ij}\, z_j \quad (4)$$

Where $z_i = (x_i - \bar{x})/SD_x$, ω_{ij}= weight between observation i and j, and N = number of cases in the data set.

Once spatial autocorrelation has been tested for, if spatial autocorrelation does exist, the underlying processes can be examined. Spatial autocorrelation can be caused by either spatial dependence or spatial heterogeneity, and data are modeled under the assumption of one of these causes. Statistically, spatial dependence is seen through omitted spatially lagged variables or spatial autocorrelation in the error terms ; spatial heterogeneity occurs when spatial contextual variation results in heteroscedasticity (Anselin, 1988; Cliff & Ord, 1973). Heteroscedasticity is associated with cross-sectional data, and dependence is more appropriate with longitudinal data and multiple observations for each case. When the underlying process has been identified, the appropriate analysis is more easily identified.

Spatial Dependency Techniques

The first step in determining the appropriate techniques for spatially dependent data is assessing if the autocorrelation is due to spatial heterogeneity or spatial dependence. Bailey & Gatrell provide the classic historical example of how each of these processes work.

Bailey & Gatrell (1995) describe iron filings scattered randomly on a sheet of grid paper, with the number of filings in any particular grid square representing a spatial stochastic process. If the scattering of the filings is random, the differences in numbers of filings in any individual square will also be random. However, if magnets are placed under the paper before scattering the filings, the resulting pattern will not be random, but instead a spatial pattern with clustering around the placement of the magnets. This pattern is known as spatial heterogeneity, and is referred to by Bailey & Gatrell as first order effects. Characteristics of spatial heterogeneity or first-order effects are characterized as: non-uniform distribution of observations over space, significant variations in means over spatial units, values of the variables are not independent of their spatial location, and results from interaction of unique characteristics of the units and their spatial location. Spatial heterogeneity is caused by pattern of social interaction that create unique characteristics within spatial units (e.g.: economic development), differences in physical features, such as size, of spatial unit, or a combination of the two.

Going back to the iron filings and magnet example, one change in the scenario changes the spatial phenomenon at play. Once the magnets are removed and filings scattered again, a spatial pattern will again occur, with local clustering due to the now-magnetized filings attracting one another. This is known as spatial dependence, or second-order effects. Characteristics of spatial dependence or second-order effects are characterized by: localized covariance among statistics (e.g.: mean) within the region, tendency mean statistics to 'follow' each other in space, results in clusters of similar values. Causes of spatial dependence are underlying socio-economic processes leading to the clustered nature of the variable. Examples of the processes are diffusion processes, dispersal processes, grouping processes reflecting that residents of the same neighborhoods have similar demographics, and spatial hierarchies such as economic influences that bind people together. Spatially heterogeneous data is rarely found, and is handled primarily in theoretical contexts (Basile, Mínguez, Montero, & Mur, 2014)

Spatially dependent cases are primarily handled with models that have either spatially lagged dependent variables or spatially correlated errors. These models allow researchers to explore the impact that one observation has on a proximate observation. The approaches are valuable in its heuristics as well as the plausible relationship of dependency that it sets forth (Ward & Gleditsch, 2008). Ward & Gleditsch (2008) introduce the two different approaches, spatially lagged dependent variables and spatially correlated errors, in their book using the POLITY index which relates to social requisites for democracy, such as income; the comparison of the spatially lagged and spatial error models found non-significant differences between the -2LL models and the number of parameters was identical. Ward & Gleditsch (2008) do not make a recommendation on which model is the more appropriate fit; rather, they suggest that the model choice is an apriori theoretical decision.

One approach to handling spatially dependent data involves use of spatially lagged dependent/y variables. This is also known as the spatial autoregressive model (Anselin, 1988). The model is appropriate when there is the belief that the outcome variable for a case is dependent on the outcome variables for the case's 'neighbors' above the influence of covariates related to the outcome variable (Ward & Gleditsch, 2008). The model requires a continuous outcome variable.

The matrix notation equation for the spatially lagged or autoregressive model comes from Anselin (1988):

$$Y = \beta_0 + pWy + X\beta + e \qquad (5)$$

Where Wy is the spatially lagged dependent variables for weights matrix W, X is a matrix of observations (such as GDP in the above example), e is the error term, p is the spatial dependency. The spatial coefficient p will equal zero if there is no spatial dependence.

An alternative approach, the spatial error model, is contingent upon the spatial dependency entering through the error term. This model considers spatial correlation similar to how temporal serial correlation is typically treated, as a nuisance. This model is appropriate in situations where there is the belief that there is a spatial pattern that will manifest in the error term, but there is not a theory as to what contributes to that error.

The equation for the spatial error model is:

$$Y = X\beta + \lambda Wu + e \quad (6)$$

Where u is the error term vector, spatially weighted using the weights matrix W, λ is the spatial error coefficient, and e is the remaining uncorrelated error term (Ward & Gleditsch, 2008). It should be noted that the spatial error model does not seek to remove all error from the equation with spatial modeling, but the error term will be reduced compared to if spatially dependent data were analyzed under and OLS model.

These two models imply spatial processes that are quite dissimilar. The practical differences are explained by Sparks, Sparks, & Wiley (2010) within their examination of county mortality rates within the United States. A spatially lagged dependent variables model implies the value of a health outcome in one location is influenced by that health outcome in a neighboring location (Sparks, Sparks, & Wiley, 2010). The dependent variable being examined is lagged across all the neighbors for an area, while the spatial impact of unmeasured independent variables in the model is also considered in the remaining error term. The spatial error model would suggest that the spatial pattern observed results from unmeasured independent variables. In Sparks et al.'s research problem, the spatial error model would argue that the clustering of county mortality rates not accounted for by the independent variables included in the model is the result of correlated error terms among the independent variables and omitted independent variables from the model (Sparks et al., 2010,Anselin, 1998, Baller, et al., 2001). This means the mortality rate in one county does not increase the likelihood that a neighboring county will have a similar outcome. Indeed, the spatial process leading to spatial clusters in county mortality rates results from the spatial process inherent to the independent variables that are both measured and omitted from the empirical model specification (Morenoff, 2003).

The above example involved a continuous dependent variable. Issues of access or access gaps that take advantage of geographic connections to professional development may best be captured by using a dichotomous dependent variable: whether registrants complete the professional development training or not. For research questions concerning a dichotomous or categorical outcome options, the spatial error model can be modified to handle discrete choices as outcomes. A spatial probit-based maximum likelihood method has been proposed that allows spatial dependence using a structure that generates correlations within a region, but assumes no correlation between regions (Case, 1992). Additional work has been done to propose an expectation maximization (EM) algorithm to accommodate autocorrelation in a probit model, replacing the latent dependent variable of the probit structure with an expectation based on the observed binary choice, and then estimating the resulting model using standard maximum likelihood techniques for the case of a continuous dependent variable (McMillen, 1992).

Spatial models have been used to address research questions with binary outcomes (Dubin, 1995; LeSage, 2000). Lesage (2000), who in addition to Verbitsky and Raudenbush (2012) uses crime data, extends the EM approach used by McMillen by employing Monte Carlo Markov Chain for a Bayesian estimate. Dubin uses spatial methods to study diffusion of innovations. Additional spatial models with binary outcomes include the addition of copulas to accommodate heteroscedasticity and large datasets (Bhat & Sener, 2009) as well as bivariate components to the spatial probit model to account for dependence between multiple outcomes of interest (Neelon, Anthopolos, & Miranda, 2014).

Options for Analyzing Dichotomous Spatially Dependent Data

Multilevel Modeling of Spatially Dependent Data

Multilevel modeling (MLM), well-known from the education field (Raudenbush & Bryk, 1986), provides a method for handling nested data as well as the ability to treat time flexibly, which lends itself to examination of online learning, characterized by its self-paced nature. MLM has been used in professional development research with both online and in-person coaching elements and the time-varying characteristic of MLM allowed for the empirical conclusion that there was no difference between the two delivery methods of coaching (Powell et al., 2010).

The nested nature of multilevel models, including children within schools, patients within doctors, or residents within census tract, provides an opportunity for the assessment of spatial dependency being captured as part of level-1 impacts. Multilevel models are useful, in part, because they address within-group dependency while measuring individual-level or ecological effects. Multilevel models using spatial analysis are present within the literature, however the body of literature is relatively new (Arcaya, Brewster, Zigler, & Subramanian, 2012; Chaix, 2005; Dennett & Wilson, 2013; Diez & Pulliam, 2007; Latimer, Wu, Gelfand, & John A. Silander, 2006; Savitz & Raudenbush, 2009). A distinct benefit of the spatial multilevel models is the ability to parse out effects of spatial autocorrelation, which may impact both levels of a multilevel model, from the effects of other within-group variables. This may reduce bias in the associations made between state-level policy and certain outcomes (Arcaya et al., 2012). The research has been concentrated in areas outside of education research thus far.

Arcaya et al. (2012) use a county-level dataset with variables related to life expectancy, with findings that suggest life expectancy in the dataset are spatially correlated and affected by county-level variables separate from the spatial process (Arcaya et al., 2012). Chaix et al. geolocated individuals in their data examining mental disorders caused by psychoactive substances. Comparing the multilevel model to the spatial multilevel model, stronger associations were seen in the spatially defined areas surrounding an individual's geolocated address rather than pre-defined administrative neighborhoods (Chaix, 2005). Dennett and Wilson use multilevel spatial methods to model European migration across regions (Dennett & Wilson, 2013). Within the field of ecology, spatial hierarchical models are used to study two orchid species and predictors of their location and concentration (Diez & Pulliam, 2007). Accounting for the spatial nature of the orchids alters the strength of the relationships in the model, with the authors recommending its further use in ecology to understand relationships with both abiotic (non-living environmental characteristics that affects living organisms) and biotic processes (such as competition and disease). Again in ecology, two plant species' appearance is studied using spatial hierarchical models; Latimer et al. (2006) use a Bayesian framework in order to minimize uncertainty, contributing previously known information about parameters. Savitz and Raudenbush (2009) study crime rates within neighborhoods using hierarchical spatial methods, comparing ordinary least squares (OLS), empirical Bayes based on independence assumption (EBE), and empirical Bayes estimator with spatial dependence (EBS),along with their relative loss of mean squared error. A unique component of the Savitz and Raudenbush (2009) study is a cross-validation study, which allowed the authors to determine that the EBS estimator demonstrated higher levels of validity and consistency.

Oakes suggests that multilevel regression models are not able to identify regional or level-2 effects from observational data (Oakes, 2004) due to stable unit –treatment assumption (SUTVA) violations and regression to the mean threats. He demonstrates this by using neighborhood treatment effects, and arguing that multilevel models are not able to identify neighborhood effects from observational data because people cannot be randomly assigned to neighborhoods, only their contexts can. Oakes (2004) arguments are countered by Ana Diez-Roux (2004), who distinguishes the concerns raised by Oakes (2004) as associated with neighborhood-effects research, rather than multilevel analysis, which are often used interchangeably despite differences outlined in the Diez-Roux piece .

In the education field, multilevel model analyses have often explored geographic variability in access to a specific program, such as professional development, or intervention. Methodologically, spatial multilevel models are rarely employed to explore phenomena with binary outcomes. Here, the concept of MLM must be modified to accommodate for any potential spatial auto-correlation that exists between the different regions as well as spatial auto-correlation that may exist as the individual case level.

Spatial Logit Models

Studies with dichotomous outcomes and spatially dependent data can be problematic with the standard spatial error or spatially lagged models, as those models imply heteroscedasticity and autocorrelation (Klier & McMillen, 2008). However, a linearization of the generalized method of moments (GMM) (Pinkse & Slade, 1998) allows Klier & McMillen (2008) to estimate a model (the Klier-McMillen model) in two steps: the first is a probit/logit model which allows dichotomous dependent variables but ignores the spatial autocorrelation and heteroscedasticity, the second being a two-stage least square estimate of the linearized model. Klier & McMillen (2008) interpret the dependent variable as an underlying latent variable showing the propensity to adopt the treatment or experimental condition; this is then translated into a discrete variable as shown in Equation 7.

$$Y = X\beta + e, e = \theta W + \varepsilon = (I = \theta W)^{-1}\varepsilon \qquad (7)$$

Here, ε is a vector of independent and identically distributed errors. Θ is Pinske and Slade's GMM estimate and W is the weights matrix. Klier & McMillen (2008) use this as the basis for a probit/logit model, where discrete variable d =i if y>0 in Equation 8, and d=0 otherwise.

The probability that d_i=1 is given by

$$Pi = \exp(X * i\beta)/(1 + \exp(X * i\beta)) \qquad (8)$$

Where $X^*_i = X_i/\sigma_i$ (Klier & McMillen, 2008). Klier & McMillen (2008) linearize their model around p=0, where there is no spatial dependence. The linearized model is then estimated in two steps

a) Standard Logit. Calculate u_0 and the coefficient terms $G_{\beta i}=\hat{P}_i(1-\hat{P}_i)X_i$ and $G_{pi}=\hat{P}_i(1-\hat{P}_i)H_i\hat{\beta}$, where $H= WX$.

b) Regress G_β and G_p on Z. The predicted values ($\hat{G}_\beta$ and $\hat{G}_p$) are then regressed as follows: $u^0+\acute{G}_\beta\hat{\beta}_0$ on $\hat{G}_\beta$ and $\hat{G}_p$. This produces the estimated values of β and p.

The use of spatial methods is minimal within the education literature, but the opportunities for their use are rich, given the geographic data associated with school buildings and in certain cases, student-level addresses. Spatial methods are a powerful tool in assessing disparities associated with geography, with a focus in this study on the spatial nature of professional development attendance in a sample of early childhood professionals serving in different geographic areas around the state of Ohio.

Natural Experiment

The present research occurs as a natural experiment, in which a naturally-occurring contrast between a treatment and contrast condition exists (Fagan, 1990, Meyer, Viscusi, & Durbin, 1995; Zeisel, 1973). A registered participant's choice to attend a professional development course once registered, or to attend online versus face-to-face delivery options, is not manipulated. The comparison condition consists of participants who registered for sessions before the addition of online delivery option, and the treatment condition consists of individuals who registered for sessions after the online delivery option became available. An assumption present within the proposed experiment is that some professionals would have chosen the online delivery option if that choice had been made available in the time prior to the addition of online option.

This natural experiment is similar in setup to a discontinuity design wherein a policy is treated as the intervention, with pre and post policy comparisons. For example, Dynarksi (2003) considered policy change related to financial aid, and how that impacted students' decisions to attend college. Analyzing pre and post policy change data after the policy is put into effect allowed the researcher to take the average value for the intervention group from the average value from the control group and use this 'first difference' estimate as an unbiased estimate of the causal impact of the financial aid policy on college-going behavior for students in this sample.

Murnane and Willett (2011) set forth 3 characteristics of natural experiments with discontinuity design:

- "an underlying continuum along which participants are arrayed. We refer to this continuum as the 'assignment' or 'forcing' variable,

- an exogenously determined cut-point on the forcing variable that divides participants explicitly into groups that experience different treatments or conditions, and
- a clearly defined and well-measured outcome of interest" (p. 145, Murnane and Willett, 2011).

One threat to validity within a natural experiment of this nature is the lack of randomization which makes it more difficult to eliminate the effect of confounding variables that could be explaining the differences in outcome variables pre to post. An additional threat to validity is the possibility that predictor variability is not consistent across the pre and post online sample. In this study, there are no policies at the state level that would confound the impacts of the online delivery, but that is not to say that individual centers or schools employed policies surrounding other training requirements or encouraged Early Learning and Development Standards (ELDS) participation that could impact participation rates. Due to the lack of knowledge of local policies in place that could serve as a confounding factor, this natural experiment is not designed to speak to causal claims, as the Dynarski (2003) experiment does. It will speak to the effect of a statewide policy change on registered ELDS participants in the period surrounding the introduction of online modules.

Chapter 3: Methods

This dissertation research will address the following research question:

- Does the introduction of an online option for a professional development training reduce the access gap for this training amongst Ohio's early childhood professionals, and is this improvement related to geography types: rural, urbanized, and urban cluster? Related component questions include:
    - For the professionals who have the choice of online or face-to-face delivery (post-online sample), how does this choice affect professional development completion rates?
    - Based on the 3 months before the online delivery option and the 3 months after the online delivery options, how does the choice between online and face-to-face delivery affect dosage (number of sessions or hours of the professional development training) of the training?

Ohio Context

Population and Sample

The study sample consists of individuals who have registered for ELDS training in the three months before and after the online option for the professional development is made available on February 14, 2015. This pre-existing data has been made available from the Ohio Department of Education; the extant nature of the data has resulted in the study being exempt from IRB approval because the sample was pre-existing and unable to be identified through the identifiers in the sample. Researchers do not have a link or crosswalk between the identifiers in the sample and the person represented by the case. Data were obtained from the Ohio Professional Registry (OPR), which stores training information for the ELDS as well as other professional development trainings available statewide to early childhood professionals. The extract includes information about the training (title, training ID, instructor, number of sessions in the training, date, location and time) as well as information about the training registrant such as unique use ID, age, years of employment in early childhood, if a fee is paid, if registrant attended, city of residence, zip code of residence, employer name, job title, and county of employment. Due to the optional nature of the demographic fields such as age and years of employment, reliable demographics are not available. This sample is not intended to generalize to the larger early childhood population within Ohio.

The final data set consists of 4,479 cases. These 4,479 cases are 4,318 unique individuals participants nested within 440 zip codes in Ohio. The difference of 161 cases are individuals that registered for the training, did not attend the first time, and registered again. The most concentrated zip code has 79 registrants in the 6 month period, while 99 of the 440 zip codes have only one registrant in that time. There are 2,239 individuals in the Pre-Online sample, who registered for the ELDS training before the online delivery option was available. There are 2,079 individuals in the Post-Online sample, who registered for the ELDS training after the online delivery was available.

The title of the training is used to isolate only ELDS Level-1 trainings within the OPR extract. The title also distinguishes whether registrants chose online or face-to-face delivery; this is the only field that distinguishes delivery method within the OPR extract. This distinction is used to create a dummy field to indicate if individuals registered for online or face-to-face delivery.

Only the first part of a multi-session training is retained to ensure individuals participating in a 2-session training are not counted twice for that training; the number of sessions in a training is reflected in the created variable PDTSession.

Cases identified as test entries made by OPR staff to test OPR functionalities are eliminated as are entries where the training is canceled. Two hundred and twenty observations are removed due to training cancellation, which occurred for a number of noted reasons include weather, timing conflicts, and instructor illness. Not all cancelled trainings listed a cancellation reason.

Entries are assigned to a zip code, or geocoded, for place of employment when possible (EmployerZIP). Initially, employer names are cross referenced with publicly available data to assign a zip code. Subsequent entries are geocoded based on identifying private trainings hosted by a workplace and matching empty zip codes to that of their coworkers. Registrants who are able to be geocoded are assigned a geography type (a categorical variable representing rural, urbanized, or urban cluster) based on their place of employment.

Voluntary demographics information is collected from participants. As all of these variables have high levels of missingness (more than 20%), extrapolation of the reported information is not recommended. The registrants came overwhelmingly from childcare centers administered by ODJFS, with additional registrants from the home-based childcare setting. The most common degree reported (*n*=972) is high school diploma. The most commonly reported years of service is 2.81, but the average years of service reported is 6.5. While not collected in this dataset, the early childcare workforce is almost exclusively female (U.S. Department of Health and Human Services, 2016).

Study Variables

The outcome variable considered in this study will be attendance at Early Learning Development Standards (ELDS) professional development training session once registered for the session. Participants whose sessions are cancelled (*n*=220) were removed from the dataset, because they did not have a choice of whether or not to attend the professional development session. An additional 118 cases in the dataset (2.7%) are removed, as they registered for the session a second time after failing to attend the first registered session. A comparative analysis will be conducted to assess the impacts of removing duplicate cases.

Zipcode and Cluster Size

Ninety-nine of the 440 (22.50%) zip codes have only one participant reporting their workplace within that zip code. 253 or the 440 (57.95%) have 5 or less participants. Small sample sizes within clusters, or in this case zip codes, may result in biased parameter estimates (Hex, 2010). Gelman and Hill (2007) indicate that with small sample sizes, the estimates of variance parameters are of concern, but that multilevel modeling with small cluster sample size should perform no worse than OLS regression.

Snijders (2005) explores the small sample size within clusters in an effort to understand the consequences of sample size decisions in multilevel analyses, arguing that the level-1 sample is the primary focus within HLM. While larger numbers within clusters are advantageous, he argues that small numbers within clusters are not problematic for testing regression coefficients. Snijders (2005) parses out that while the regression coefficients are not compromised by low level-1 samples within clusters, the power for testing random slope variances at the cluster level is compromised. In the case of the current research, the small number of registrants within zip codes compromises the ability to speak to between-zip code variances of the predictor effects on attendance. This variance between level-2 units is not pursued of interest in this analysis.

Within applied education research, there is precedent for multilevel models with one individual in a cluster. Lohr, Schochet, and Sanders (2014) touch on this concept in their Institute of Education Sciences paper on partially nested designs. The example used involves students with disabilities who may be in a classroom with their educational professional and no other students; when the students of this school are clustered into classrooms this student would be a cluster of 1 (Lohr, Schochet, and Sanders, 2014). There are implications for the partially nested design that are not relevant to the current research, but the single case within a cluster is not compromising to the multilevel model discussed.

Workplace Geography

Independent variables include the geography type of participants' place of employment (EmployerZIP). This variable is categorized as urban, urbanized, or rural based on the zip code of participants' workplace. The United States Census defines an urbanized area as one that consists of densely settled territory that contains 50,000 or more people, an urban cluster consists of densely settled territory that contains at least 2,500 people, but fewer than 50,000 people, and rural areas consisting of territory with less than 2,500 people[6]. The United States Census defines zip codes within 14 urbanized

[6] http://www.gpo.gov/fdsys/pkg/FR-2012-03-27/pdf/2012-6903.pdf

areas and 132 urban clusters within Ohio; all zip codes not within an urbanized or urban cluster are considered ‘rural’[7].The data set includes an optional field for zip code of employment. Zip code information is able to be converted into geographic categories based on these publicly available geographic definitions, as defined by the United States Census. 23.8% of the registrants (*n*=1030) did not provide workplace information and are not able to be geolocated. Registrants’ workplace geography type is coded as two dummy variables. Rural is used as the reference category, as rural professionals are of specific interest within the context of this study. The definition or rural in this study is based on population, and does not take into account distance from an urban area, such as the definitions used by The National Center for Education Statistics[8].

Session Duration

Sustained duration of professional development has been shown to be a best practice of effective professional development (Carlisle & Berebitsky, 2010; D. Fisher, Frey, & Nelson, 2012; Knapp, 2003; Mashburn et al., 2008; Penuel, Fishman, Yamaguchi, & Gallagher, 2007; Porter, Garet, Desimone, & Birman, 1995; Powell & Diamond, 2013; Roehrig, Dubosarsky, Mason, Carlson, & Murphy, 2011; Wayne, Yoon, Zhu, Cronen, & Garet, 2008). Therefore, number of sessions over which a participant

[7] http://www.census.gov/geo/reference/urban-rural.html
[8] https://nces.ed.gov/surveys/ruraled/definitions.asp

took the ELDS training (1 or 2) is included as an additional independent variable (PDTSession). The 2-session version of the ELDS training is largely unavailable in the post-online sample. The decision to exclude PDTSession from the post-online sample results in the removal of this variable from the full and pre-online samples as well, to minimize confounds when comparing results across models.

Time of Training

The time of day in which professional development trainings are held (PDTTimeCoded) is a potential barrier to attendance. Time of training, categorized as Morning (12:01am-12:00pm), Afternoon (12:01pm-5:00pm), Evening (5:01pm-12:00am), or Weekend is included as an independent variable. Trainings whose dates fell on a Saturday or Sunday are coded as Weekend training. Time of training is coded in four dummy variables, with the Weekend option as the reference category. Weekend options are available for both pre-and post- online registrants, providing an equivalent reference category across both groups. The weekend option is also the most flexible, given that most registrants are employed in the early childhood field with working hours closely mirroring the traditional work week.

Travel Distance

Understanding that the amount of travel required for professional development presents barriers to high-quality professional development, an additional independent variable (EmploymentCountyMatch, EmpCtyMa) is whether or the training took place in participants' work county. Online entries do not have a county of training; however, as EmpCtyMa is intended to capture the effect of a travel barrier, and online participants do not have a travel barrier, they are coded as though the counties of training and employment do match. Whether the county of training and county of employment are the same is included as a dummy variable in the data set.

Variables from the dataset included in the study are detailed in Table 1. Indented variables indicate dummy variables for categorical predictors. Asterisks designate the reference category within categorical predictors.

Table 1: Description of Study Variables

Variable Name	Description
PolicyLever	Whether registrant is in the pre-online (0) or post-online (1) sample
RegAttend	Whether registrant attended training; 0= did not attend, 1=did attend
PDTTimeCoded	Time of training (1= Morning, 2=Afternoon, 3= Evening, 4= Online, *5=Weekend)
TimeD1AM	Training occurred 12:01am-12:00pm on a weekday,1=yes, 0=no
TimeD2AF	Training occurred 12:01pm-5:00pm on a weekday,1=yes, 0=no
TimeD3EV	Training occurred 5:01pm-12:00am on a weekday,1=yes, 0=no
TimeD4ON	Training occurred online, 1=yes, 0=no. Only in post-online sample.
ZipCategory	Geographic category of registrant's employer (1= suburban/urban cluster, 2= urban/urban center, *3=rural)
Geo1urb	Registrant employed in urban environment, 1=yes, 0=no
Geo2sub	Registrant employed in suburban/urban cluster environment, 1=yes, 0=no
EmpCtyMa	County of Training matches County of Employment, 1=yes, 0=no
Online	Whether participant took training online, 1=yes, 0=no

*Reference Category

Analysis Plan

Descriptive statistics on all study variables, as well as the relationship between predictors, will be produced using R 3.2.4. Maps and shapefiles will be produced in Arcmap 10.2.2, using WGS projection. Chi-square tests will be done to test for independence between predictors and the outcome variable (RegAttend). The analysis plan will be driven by two diagnostic statistics; Moran's *I*, to assess the level of spatial autocorrelation which may exist in the data, and the Intra-Class Correlation (ICC), to assess the degree of clustering in attendance at the zipcode-level. Given the expectation of significant autocorrelation through Moran's *I*, a spatial error model will be constructed with a binary outcome (attendance or non-attendance amongst those registered). Geography type, delivery method, time of training, number of sessions, and whether or not the training occurred in a participants' county of employment will be used as predictors.

To account for significant spatial autocorrelation, a multilevel model incorporating clustering by zip code will be employed with a spatially-weighted Level-2 characteristic. Subsequent adjustments to the model will be made based on ICC and significance of Moran's *I*. Neighbors for cases will be determined by a distance-based weights matrix. Participants working in zip codes whose centroids are within a 10 kilometer radius are considered neighbors. For the HLM component, a neighbor matrix with the zip code rather than case as the unit of interest is manually constructed using CDX ZipStream, determining the zip codes that are within 10 kilometers of an individual zip code. CDX ZipStream is an Excel plug-in that locates zip codes within specified distances, using zip code centroids.

It is possible that registrants may not have neighbors outside of their own zip code of employment. According to data from the United States Census Bureau's American Fact Finder[9] ZCTA (Zip Code Tabulation Areas), codes in Ohio cover anywhere

[9] https://factfinder.census.gov/bkmk/table/1.0/en/DEC/10_DP/G001/0400000US39.86000P

between 0.02 and 885 square km. The data from American Fact Finder is reported in square meters, the appropriate conversion to report the size in square kilometers is done in Microsoft Excel. If a registrant works in a zipcode larger than 10 square kilometers, that registrant will only have neighbors within their own zipcode, as the neighbors are registrants in zip codes within 10km. While employer information is reported as Zip codes (product of United States Postal Service) rather than ZCTA, the US Census Bureau reports that Zip Codes and ZCTAs are usually the same (U.S. Census Bureau, 2015). As this study is using the information to speak to variation in size of zip code, or ZCTAs, conversion between the two is not done. The variation in size of ZCTA is consistent with the variability seen in Ohio counties. Ohio counties span between 589 and 1817 sq km[10] . ELDS Professional development is most frequently held in counties with urban centers, which are not the smallest or the largest counties in terms of size. For example, Franklin County cover 1378 sq km and is on the larger end of county size (16 of Ohio's 88 counties are larger)

Model Justification

The research question itself will be addressed through the interpretation and significance of the PolicyLever variable, which captures the introduction of the online

[10] https://factfinder.census.gov/bkmk/table/1.0/en/DEC/10_DP/G001/0400000US39.05000

variable through the distinction of whether a registrant falls into the pre-online or post-online group. The significance of the PolicyLever variable will provide evidence to answer the question of whether membership in the pre-online or post-online group affected attendance amongst registrants. The distinction between pre-online and post-online membership, as shown by PolicyLever, will be expounded by interaction terms that explore whether the effect of the PolicyLever variable differs significantly across geographic categories (Geo1urb and Geo2sub).

The first component question of the Research Question will be addressed through the interpretation and significance of the dummy variable TimeD4On in the spatial HLM on the post-online sample, which accounts for whether the participant took the professional development Face-to-Face (0) or Online (1). If TimeD4On is a significant predictor within the post-online sample, this would indicate that the online option did have a significant impact on attendance amongst registered participants. For the post-online sample, the second component question was intended to be assessed through PDTSession. However, as noted earlier, PDTSession was removed from the full, pre-online, and post-online models due to lack of variation in the post-online sample.

Depending on the results of the spatial HLM ICC, the Research Question will be addressed either through a spatial hierarchical model or a spatial model handling binary outcomes, specifically the Klier-McMillen model (2008).

The spatial HLM, if warranted, would be a two-level Bernoulli model. In order to obtain the most accurate estimates with this type of model, both adaptive Gaussian quadrature (AGQ) and Laplace estimation methods would be appropriate, based on findings about superior AGQ performance for models with small cluster sizes (n_{ij}=2) (Yosef, 2001). The spatial HLM would therefore be estimated under full maximum likelihood, using adaptive Gaussian quadrature and Laplace estimation techniques. This is done to compare results across both techniques. If results are consistent across Laplace and AGQ, AGQ will be reported.

The current research is grounded within a natural experiment. Utilizing pre-existing data for a state-offered professional development both before and after the training sessions went online provides an opportunity to understand the effects of the policy decision to offer the professional development training online on whether registered participants ultimately attend the training. This is specifically interesting as it pertains to the geographic typology of those registered, as online delivery could potentially mitigate the travel barriers faced by rural participants. Spatial HLM is the initial analysis method due to suspected autocorrelation, as well as registrants clustering within zip codes.

Chapter 4: Results

Research Question: Does the introduction of an online option for a professional development training reduce the access gap for this training amongst Ohio's early childhood professionals, and is this improvement related to geography types (rural, urbanized, and urban cluster)? Related component questions include:

- A) For the professionals who have the choice of online or face-to-face delivery (post-online sample), how does this choice affect professional development completion rates?
- B) Based on the 3 months before the online delivery option and the 3 months after the online delivery options, how does the choice between online and face-to-face delivery affect dosage (number of sessions or hours of the professional development training) of the training?

Descriptive Statistics

There are 4,318 registrants in the sample, of which 3,288 registrants are geolocated within 440 zip codes. 1,030 entries are lacking geolocation and 654 of the registrants without geolocation are missing values for EmpCtyMa. Cases may have information for County of Employment and not provide an employer name that could be geolocated; the resulting cases may not be geolocated and still have information in the

EmpCtyMa field. The sample that was unable to be geolocated largely attended their trainings (*n*=945), was predominantly in the pre-online sample (*n*=569), and over half of them registered for morning or online trainings (*n*=363 and *n*=228, respectively).

There are 278 cases of duplicated registration. One individual registered five times, the other individuals registered for the ELDS training two or three times. These cases are eliminated by sorting the file by DemographicsID (a psuedoID in the dataset), then date of training, with the most recent date of training being retained. Table 2 shows comparative analyses conducted on the full sample with and without the duplicate IDs, utilizing a spatial HLM (described in detail in a later section).

Table 2. Comparative Analyses: Fixed Effects with and without Duplicate Cases

		With Duplicates	No Duplicates
Intercept	Coefficient	3.02	3.44
	Std.Error	0.99	1.22
	p-value	0.002*	0.005*
PolicyLever	Coefficient	1.02	1.04
	Std.Error	2.05	2.38
	p-value	0.61	0.62
EmpCtyMa	Coefficient	2.89	2.89
	Std.Error	1.99	2.33
	p-value	0.15	0.22
TimeD1AM	Coefficient	0.39	0.2
	Std.Error	0.25	0.28
	p-value	0.12	0.49
TimeD2AF	Coefficient	-0.33	-0.5
	Std.Error	0.28	0.32
	p-value	0.25	0.12
TimeD3EVE	Coefficient	0.12	-0.02
	Std.Error	0.25	0.29
	p-value	0.63	0.94
TimeD4ON	Coefficient	-2.25	-2.1
	Std.Error	0.29	0.32
	p-value	<0.001*	<0.001*
Geo1urb	Coefficient	-0.87	-1.05
	Std.Error	0.99	1.22
	p-value	0.38	0.39
Geo2sub	Coefficient	1.51	1.38
	Std.Error	1.18	1.4
	p-value	0.2	0.33
Geo1*Policy	Coefficient	1.14	1.54
	Std.Error	2.05	2.37
	p-value	0.58	0.52

Continued

Table 2 Continued

Geo2*Policy	Coefficient	0.35	-0.65
	Std.Error	2.17	2.62
	p-value	0.87	0.8
Emp*Policy	Coefficient	-2.01	-2.68
	Std.Error	0.66	0.83
	p-value	0.002*	0.001*
Geo1*Emp	Coefficient	-1.91	-1.78
	Std.Error	1.99	2.33
	p-value	0.34	0.45
Geo2*Emp	Coefficient	-3.42	-1.92
	Std.Error	2.2	2.59
	p-value	0.12	0.46

EmpCtyMa= Match of Training and Employment counties; TimeD1AM= Training taken in morning or not; TimeD2AF= Training taken in afternoon or not; TimeD3PM= Training taken in evening or not; TimeD4ON= Training taken online or not; Geo1urb = Workplace Suburban or not; Geo2sub= Workplace Urban or not; PolicyLever= Registered in Post-Online sample or not; Geo1*Policy= Interaction between urban workplace or not and whether case is in the pre or post-online sample; Geo2*Policy= Interaction between suburban workplace or not and whether case is in the pre or post-online sample; Emp*Policy= Interaction between workplace - training county match and whether case is in the pre or post-online sample; Geo1*Emp = Interaction between suburban workplace or not and workplace - training county match; Geo2*Emp = Interaction between urban workplace or not and workplace - training county match

There is no appreciable change in the direction or significance of predictors between datasets with and without the duplicate case, and the decision to remove duplicate cases ensures each registrant is a unique individual.

Table 3 contains frequency tables for the predictors within the pre-online and post-online samples. Chi-square (χ^2) tests between predictors and the outcome variable of attendance (RegAttend) are also included. In the majority of cases, the significance of the χ^2 value presents evidence that there is an association between attendance and the independent variables. Within the post-online sample, geography type has χ^2 values that do not provide enough evidence to suggest associations between this variable and attendance.

Table 3. Relationship Between Predictors and Attendance

	Pre-Online (*n*=2,239)						Post-Online (*n*=2,079)					
	Attended	Did Not Attend	Total Registered	Attendance Rate	χ^2	*df*	Attended	Did Not Attend	Total Registered	Attendance Rate	χ^2	*df*
PDTTimeCoded					22.56, p<.001	4					148.37, p<.001	4
Morning	930	31	961	96.77%			393	23	416	94.47%		
Afternoon	235	25	260	90.38%			198	14	212	93.40%		
Evening	399	34	433	92.15%			554	22	576	96.18%		
Online	NA	NA					463	130	593	78.08%		
Weekend	550	35	585	94.02%			272	10	282	96.45%		
Geography Type					13.20, p=.001	2					1.69, p=.430	2
Suburban	1284	82	1366	94.00%			1230	133	1363	90.24%		
Urban	264	2	266	99.25%			203	20	223	91.03%		
Rural	37	1	38	97.37%			31	1	32	96.88%		
EmpCtyMa/Travel Barrier					9.17, p=.002	2					28.72, p<.001	1
Yes	1237	59	1296	95.45%			1399	186	1585	88.26%		
No	485	43	528	91.86%			253	2	255	99.22%		
Online											146.20, p<.001	1
Yes	NA	NA	NA	NA			463	130	593	78.08%		
No	NA	NA	NA	NA			1417	69	1486	95.36%		

PDTTimeCoded=Time at which session occurred; Geography Type= Geography of workplace; EmpCtyMa= Match of Training and Employment counties; Online= session taken online or not

Within Table 3, a drastic change appears when looking at registrations by time of day. Within the pre-online sample, the vast majority of registrants chose training in the morning, before 12pm on a weekday. Afternoon registrations have the least number of registrants. Evening registrations are the most frequent when the online option became available, with online registration the second most common registration type. It is of note that the non-attendance rate across both the pre-and-post samples is >10% for all predictors except the online category within the post-online sample, who registrants have a 21.92% non-attendance rate. The online non-attendance rate is 28%.

Registration by geography type is relatively stable across the three geographic categories when comparing the pre-and-post samples in Table 3. Within EmpCtyMa, there are fewer registrants with a travel barrier (EmpCtyMa=0), as indicated by a lack of match between employment and training counties. Only two of the registrants with this travel barrier did not attend, which represents a drastic decrease from the pre-online registrants without a travel barrier. Forty-three pre-online registrants with a travel barrier did not attend. Of these 43 registrants, the majority were employed in suburban settings (*n*=34). Only 1 pre-online registrant employed in a rural setting with a travel barrier did not attend the ELDS training.

Within the post-online sample, all registrants who select online delivery are coded as not having this travel barrier. While there is only a 3.59% gap (Table 3) in attendance rate between those with and without a travel barrier in the pre-online sample, this gap almost triples to an 10.96% gap in attendance between those with and without the travel barrier in the post-online sample. Online registrants are predominantly employed in suburban/urban cluster environments (*n*=392). Eleven online registrants reported employment in rural settings, and 77 online registrants reported employment in urbanized settings.

Preliminary Analyses

Pre-Online

For the pre-online sample, predictor correlations (Table 4) indicate no strong (>.7) correlations amongst the variables that would suggest multicollinearity. RegAttend, the outcome variable, is significantly correlated with every predictor except Geo1urb.

Table 4. Pearson Correlations for Pre-Online Sample

		EmpCtyMa	TimeD1AM	TimeD2AF	TimeD3EVE	Geo1urb	Geo2sub	RegAttend
EmpCtyMa	Corr.	1						
	Sig.							
TimeD1am	Corr.	.01	1					
	Sig.	.73						
TimeD2AF	Corr.	-.21*	-.31*	1				
	Sig.	.00	.00					
TimeD3Eve	Corr.	.02	-.43*	-.177*	1			
	Sig.	.36	.00	.00				
Geo1urb	Corr.	.24*	-.05*	-.04	.03	1		
	Sig.	.00	.02	.07	.13			
Geo2sub	Corr.	-.18*	-.01	-.01	.04	-.46*	1	
	Sig.	.00	.78	.56	.06	.00		
RegAttend	Corr.	.07*	.09*	-.06*	-.05*	-.02	.08*	1
	Sig.	.002	.00	.003	.02	.28	.00	

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

EmpCtyMa= Match of Training and Employment counties; TimeD1AM= Training taken in morning or not; TimeD2AF= Training taken in afternoon or not; TimeD3PM= Training taken in evening or not; Geo1urb = Workplace Suburban or not; Geo2sub= Workplace Urban or not; PolicyLever= Registered in Post-Online sample or not; RegAttend=Whether registrant attended/completed the training

Concentrations of these registrants within zip codes of employment are visible in Figure 1. The most densely concentrated area of registrants occurs in a Columbus-area zip code. Visually, a majority of the zip codes have 1-5 registrants, with a few zip codes in urban areas containing more than 5 registrants. Concentrated clusters are seen in Cincinnati, Dayton, Columbus, Toledo, Cleveland, Youngstown, and Akron. These areas are amongst the more densely populated areas in Ohio.

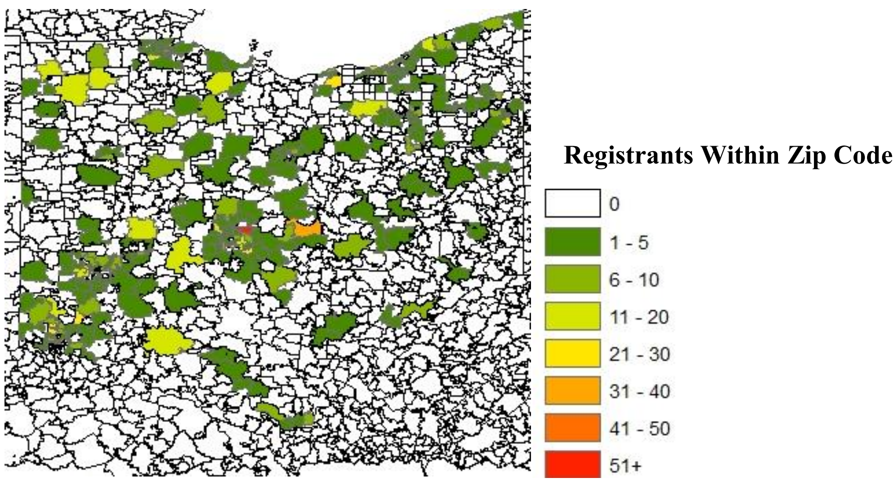

Figure 1. ELDS Registration by Concentration, November 13, 2014-February 13, 2015

Post-Online

In the post-online sample, predictor correlations (Table 5) indicate no strong (>.7) correlations amongst variables that would suggest multicollinearity. RegAttend, the outcome variable, is correlated with the majority of predictors. RegAttend is not significantly correlated to TimeD2AF, Geo1urb, or Geo

Table 5. Pearson Correlations for Post-Online Predictors Frequency

		EmpCtyMa	TimeD1AM	TimeD2AF	TimeD3EVE	TimeD4ON	Geo1urb	Geo2sub	RegAttend
EmpCtyMa	Correlation	1							
	Sig.								
TimeD1AM	Correlation	-.13*	1						
	Sig.	.00							
TimeD2AF	Correlation	.001	-.17*	1					
	Sig	.97	.00						
TimeD3EVE	Correlation	-.06*	-.31*	-.21*	1				
	Sig	.01	.00	.00					
TimeD4ON	Correlation	.28*	-.32*	-.21*	-.39*	1			
	Sig.	.00	.00	.00	.00				
Geo1urb	Correlation	.12*	-.02	.06*	.04	.01	1		
	Sig.	.00	.44	.01	.11	.74			
Geo2sub	Correlation	-.17*	-.01	-.01	-.01	.05*	-.48*	1	
	Sig.	.00	.52	.68	.66	.04	.00		
RegAttend	Correlation	-.13*	-0.69*	.03	.12*	-.27*	-.01	.01	1
	Sig.	.00	.002	.12	.00	.00	.69	.75	

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

EmpCtyMa= Match of Training and Employment counties; TimeD1AM= Training taken in morning or not; TimeD2AF= Training taken in afternoon or not; TimeD3PM= Training taken in evening or not; TimeD4ON= Training taken online or not; Geo1urb = Workplace Suburban or not; Geo2sub= Workplace Urban or not; PolicyLever= Registered in Post-Online sample or not; RegAttend=Whether registrant attended/completed the training

Concentrations of these registrants within zip codes of employment are shown in Figure 2. The most densely concentration of registrants occurs in Columbus-area and Akron-area zip codes. The bulk of the zip codes had 1-5 registrants, with a few zip codes in urban areas containing more than 5 registrants. Visually, more concentration of registrants are seen in the post-online sample. Visible concentrated clusters are in Cincinnati, Dayton, Columbus, Toledo, Cleveland, Youngstown, and Akron.

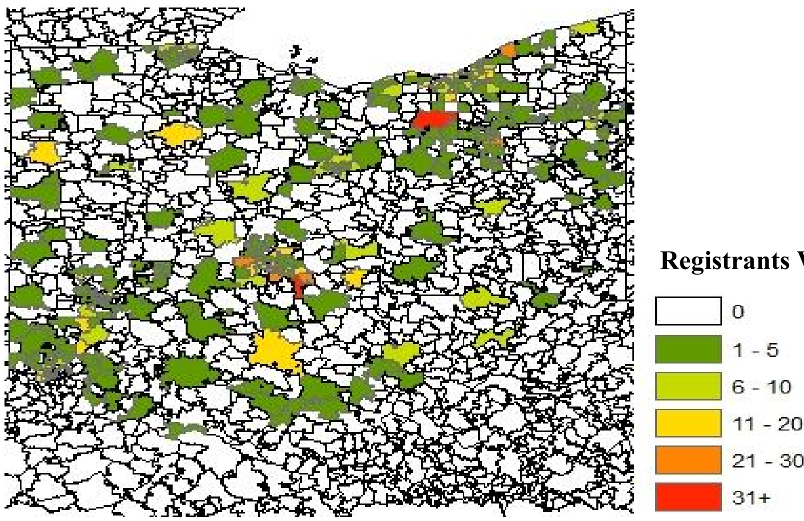

Figure 2. ELDS Registration by Concentration, February 14, 2015-May 14, 2015 Full

Pearson Correlations of predictors within the combined sample (Table 6) indicate no strong (>.7) correlations amongst variables that would suggest multicollinearity. The outcome variable, RegAttend, is significantly correlated with most of the predictors. RegAttend is not significantly correlated to TimeD2AF, Geo1urb, Geo2*Policy, Geo1*Emp, and Geo2*Emp.

Table 6. Pearson Correlations for Full Sample Predictors Frequency

		Policy Lever	EmpCt yMa	TimeD 1AM	TimeD 2AF	TimeD 3EVE	Time D4O N	Geo 1urb	Geo 2sub	Geo1* Policy	Geo2* Policy	Emp* Policy	Geo1 *Emp	Geo2 *Emp	RegAttend
PolicyLever	Corr	1													
	Sig.														
EmpCtyMa	Corr	.18*	1												
	Sig	.00													
TimeD1AM	Corr	-.25*	-.09*	1											
	Sig	.00	.00		.										
TimeD2AF	Corr	-.02	-.12*	-.24*	1	*									
	Sig.	.14	.00	.00											
TimeD3EVE	Corr	.10*	-.002	-.38*	-.19*	1	*								
	Sig.	.00	.89	.00	.00										
TimeD4ON	Corr	.41*	.23*	-.27*	-.14*	-.22*	1								
	Sig.	.00	.00	.00	.00	.00									
Geo1urb	Corr	.05*	.18*	-.05*	.004	.04*	.02	1	*						
	Sig.	.002	.00	.002	.79	.01	.11								
Geo2sub	Corr	-.02	-.18*	-.005	-.01	.01	.02	-.47*	1						
	Sig	.23	.00	.76	.49	.38	.17	.00							
Geo1*Policy	Corr	.71*	.19*	-.18*	.01	.09*	.30*	.52*	-.24*	1	*				
	Sig.	.00	.00	.00	.46	.00	.00	.00	.00						
Geo2*Policy	Corr	.24*	-.05*	-.06*	-.01	.02	.14*	-.31*	.65*	-.16*	1	*			
	Sig	.00	.001	.00	.46	.26	.00	.00	.00	.00					
Emp*Policy	Corr	.79*	.46*	-.26*	-.0	.04*	.52*	.21*	-.04*	.73*	.16*	1			
	Sig	.00	.00	.00	.30	.01	.00	.00	.02	.00	.00				
Geo1*Emp	Corr	.11*	.66*	-.05*	-.04*	-.001	.11*	.80*	-.38*	.49*	-.25*	.36*	1		
	Sig.	.00	.00	.001	.01	.97	.00	.00	.00	.00	.00	.00			
Geo1*Emp	Corr	.03	.15*	-.07*	-.03*	.06*	.10*	-.35*	.75*	-.19*	.59*	.09*	-.28*	1	
	Sig.	.06	.00	.00	.03	.00	.00	.00	.00	.00	.00	.00	.00		
RegAttend	Corr	-.08*	-.042*	.09*	-.01	.04*	-.22*	-.02	.04*	-.06*	-.01	-.12*	-.02	.01	1
	Sig.	.00	.01	.00	.51	.01	.00	.22	.01	.00	.39	.00	.28	.66	

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

EmpCtyMa= Match of Training and Employment counties; TimeD1AM= Training taken in morning or not; TimeD2AF= Training taken in afternoon or not; TimeD3PM= Training taken in evening or not; TimeD4ON= Training taken online or not; Geo1urb = Workplace Suburban or not; Geo2sub= Workplace Urban or not; PolicyLever= Registered in Post-Online sample or not; Geo1*Policy= Interaction between urban workplace or not and whether case is in the pre or post-online sample; Geo2*Policy= Interaction between suburban workplace or not and whether case is in the pre or post-online sample; Emp*Policy= Interaction between workplace - training county match and whether case is in the pre or post-online sample; Geo1*Emp = Interaction between suburban workplace or not and workplace - training county match; Geo2*Emp = Interaction between urban workplace or not and workplace - training county match; RegAttend=Whether registrant attended/completed the training

Concentrations of these registrants within zip codes of employment are shown in Figure 3. The most densely concentration of registrants occurs in a Columbus-area zip code, but a variety of concentrations levels are seen in the full sample. The bulk of the zip codes had 1-5 registrants. . Concentrated clusters are seen in Cincinnati, Dayton, Columbus, Toledo, Cleveland, Youngstown, and Akron.

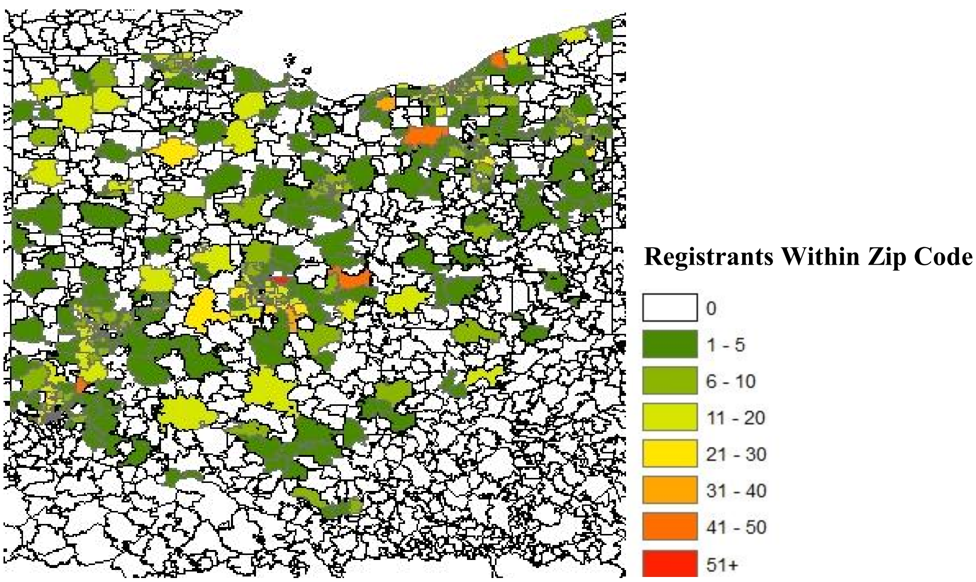

Figure 3. ELDS Registration by Concentration, November 13, 2014-May 14, 2015

Preliminary Diagnostics

Prior to analysis, preliminary diagnostics determined if multilevel, spatial, or a combination of both methods are the most appropriate choice for the data. Results from the preliminary diagnostics are shown in Tables 7 and 8.

Table 7. Moran's I for Full sample

	Moran's *I*	Sig
Full	-0.0004	<.01

A global Moran's *I* test assesses total spatial pattern autocorrelation in the attendance rates amongst professional development registrants. There are 3272 cases among 440 unique zip codes. Registrants have between 0 and 319 neighbor cases within 10 kilometers of their workplace. The global Moran's statistic (-0.0004, p<.01) indicates significant spatial autocorrelation within the dataset respective to the outcome variable of attendance amongst registrants.

In order to assess the other diagnostic, the Intra-Class Correlation (ICC), an additional neighbor weights matrix is required. Within Microsoft Excel, zip code centroids within 10km of each of the 440 unique employment zip codes in the sample are identified using CDXZipStream. Employment zip codes have between 0 and 59 zip codes whose centers are within 10km of their own. The neighbor weights matrix is imported into HLM7. The ICC is conducted with and without the neighbor weights matrix to evaluate the Level-2 variance with and without the spatial component taken into account. The difference between the non-spatial and spatial ICC values demonstrates how much of the Level-2 variance is accounted for by the spatial nature of the data.

Initial testing of the hierarchical linear model began with analysis of the empty model. Both the spatial and non-spatial empty models are shown in Table 8. There is no standard error for τ_{00} in the spatial model provided in the model output. In calculating the ICC for logistic models, the variance component (σ^2) can be treated as $\pi^2/3$, or 3.29 (Snijders & Bosker, 2012). The ICC for these models is calculated by $\tau_{00}/(\tau_{00}+3.29)$ (O'Connell, Goldstein, Rogers, & Peng, 2008).

Table 8. Fixed Effects of Spatial and Non-Spatial Empty Model

	Intercept/ τ_{00} (s.e.)	Coefficient	Std.Error	*t*-ratio	*df*	*p*	Odds Ratio	Confidence Interval
Non-Spatial	1.53 (.35)	3.12	0.15	20.66	439	<0.00 1	22.7 2	(16.82, 30.59)
Spatial	0.67	2.84	0.12	23.12	439	<0.00 1	17.2 0	(13.501,21.90)

The ICC, without taking into account the spatially dependent nature of the data is .316, indicating that 31.6% of the variance in participants' attendance once registered is attributed to variation between zip code. When accounting for the spatially dependent nature of the data, the ICC is .169, indicating 16.9 % of the variance in participants' attendance once registered is attributed to variation between zip codes. This tells us that including spatial dependency provides a better explanation of the individual and zip code level variance in the model intercepts.

Spatial HLM Results for Reduction of the Access Gaps

The spatial HLM is intended to show the predictors of attendance amongst registrants, accounting for the spatially dependent nature of data in the sample. The only difference in the pre-online and post-online models is the introduction of the online training option; keeping this as the only difference between models allows for attribution of model differences to the addition of online training. These differences were further tested via interactions for the analysis of the full sample.

Interaction terms (Geo1*Policy and Geo2*Policy) testing if the effects of location of employment differ across the pre-and post-sample are included in the combined model. Interaction terms (Geo1*Emp and Geo1*Emp) testing if the effects of location of employment differed across those who had a travel barrier (EmpCtyMa, training county different than county of employment) and those who did not have a travel barrier are included in the model. A final interaction term (Emp*Policy) testing if the effects of the travel barrier (EmpCtyMa) differed across pre-and post-samples is added to the combined model as well.

Geo1*Policy and Geo2*Policy are warranted for inclusion based on the research question, which asks if the effect of introduction of the online option (captured by PolicyLever) is related to geography (measured here by Geo1urb and Geo2sub). The question of whether the effects of geography are different for those with and without the travel barrier is addressed by the inclusion of Geo1*Emp and Geo2*Emp. Understanding the effect of the travel barrier for those in the pre-and post- online samples is accomplished by the inclusion of the Emp*Policy interaction term.

Pre-Online

The combined model for the pre-online sample is shown in Equation 9:

$$\eta_{ij} = \gamma_{00} + \gamma_{10}{*}\ POLICYLE_{ij} + \gamma_{20}{*}EMPCTYMA_{ij} + \gamma_{30}{*}GEO1URB_{ij} +$$
$$\gamma_{40}{*}GEO2SUB_{ij} + \gamma_{50}{*}TIMED1AM_{ij} + \gamma_{60}{*}TIMED2AF_{ij} + \gamma_{70}{*}TIMED3EV_{ij}$$
$$\rho{*}W{*}b_{0} + u_{0} \qquad (9)$$

Table 9 indicates that within the pre-online sample of registrants, the match between training and employment counties (EmpCtyMa) is a significant predictor of attendance ($p<0.001$). Odds of attendance for registrants who are taking the training in the county of their workplace are 2.85 times higher than for those who face a travel barrier of the training being in a county different from their county of employment. The positive value of Rho for this model indicates that attendance for one case makes attendance more likely for the surrounding cases.

Table 11 shows the amount of variance in intercepts explained by each of the models. Variance accounted for is calculated by $((\tau_{empty} - \tau_{conditional}) / \tau_{empty})$.Variance explained in intercepts amongst registrants for the pre-online model with all predictors in Table 11 is -11.8%. Negative variance in this sense is not interpretable, and serves as a sign that the model may need modification for the specific predictors included in the pre-online sample. None of the variance in intercepts for the pre-online sample is explained by the model.

Table 9. Fixed Effects Across Pre-Online, Post-Online, and Full Samples Predicting Attendance

		Coefficient	Std.Error	*t*-ratio	*df*	*p*-value	Odds Ratio	Confidence Interval	Rho/ ρ
Pre	Intercept	3.09	1.14	2.72	335	0.07*	21.97	(2.35,205.26)	
	EmpCtyMa	1.05	0.29	3.66	1328	<0.001*	2.85	(1.63,5.00)	
	TimeD1AM	0.55	0.36	1.52	1328	0.13	1.73	(0.853, 3.53)	
	TimeD2AF	-0.80	0.41	-1.96	1328	0.05	0.45	(0.20,1.00)	
	TimeD3EVE	-0.08	0.36	-0.23	1328	0.82	0.92	(0.46,1.87)	
	Geo1urb	-0.73	1.11	-0.65	1328	0.51	0.48	(0.05, 4.30)	
	Geo2sub	1.42	1.30	1.09	1328	0.28	4.14	(0.32, 53.18)	
									0.62
Post	Intercept	5.81	1.33	4.38	337	<0.001*	334.94	(24.52,457.54)	
	EmpCtyMa	-1.41	0.75	-2.89	1273	0.06	0.24	(0.06,1.05)	
	TimeD1AM	-0.17	0.57	-0.30	1273	0.77	0.84	(0.28,2.59)	
	TimeD2AF	-0.06	0.60	-0.10	1273	0.92	0.94	(0.29,3.08)	
	TimeD3EVE	0.37	0.58	0.63	1273	0.53	1.44	(0.46,4.49)	
	TImeD4ON	-1.85	0.51	-3.61	1273	<0.001*	0.16	(0.06,0.43)	
	Geo1urb	-1.24	1.08	-1.15	1273	0.25	0.29	(0.03, 2.41)	
	Geo2sub	-1.09	1.10	-0.99	1273	0.32	0.34	(0.04,2.93)	
									0.74
Full	Intercept	3.44	1.22	2.82	439	0.01*	31.34	(2.84,345.43)	
	PolicyLever	1.04	2.38	0.44	2835	0.66	2.83	(0.027,300.052)	
	EmpCtyMa	2.89	2.33	1.24	2835	0.22	18.01	(0.19,1737.53)	
	TimeD1AM	0.20	0.28	0.69	2835	0.49	1.22	(0.70,2.12)	
	TimeD2AF	-0.50	0.32	-1.56	2835	0.12	0.61	(0.32,1.14)	
	TimeD3EVE	-0.02	0.29	-0.08	2835	0.94	0.98	(0.55,1.73)	
	TImeD4ON	-2.10	0.318	-6.57	2835	<0.001*	0.12	(0.07,0.23)	
	Geo1urb	-1.05	1.22	-0.86	2835	0.39	0.35	(0.03,3.84)	
	Geo2sub	1.38	1.403	0.98	2835	0.33	3.97	(0.25,62.22)	
	Geo1*Policy	1.54	2.38	3.64	2835	0.52	4.65	(0.04,489.20)	
	Geo2*Policy	-0.65	2.62	-0.25	2835	0.80	0.52	(0.003,88.94)	
	Emp*Policy	-2.68	0.83	-3.227	2835	0.001*	0.07	(0.014,0.35)	
	Geo1*Emp	-1.78	2.33	-0.764	2835	0.45	0.17	(0.002,16.31)	
	Geo2*Emp	-1.92	2.59	-0.742	2835	0.46	0.15	(0.001,23.50)	
									0.71

EmpCtyMa= Match of Training and Employment counties; TimeD1AM= Training taken in morning or not; TimeD2AF= Training taken in afternoon or not; TimeD3PM= Training taken in evening or not; TimeD4ON= Training taken online or not; Geo1urb = Workplace Suburban or not; Geo2sub= Workplace Urban or not; PolicyLever= Registered in Post-Online sample or not; Geo1*Policy= Interaction between suburban workplace or not and whether case is in the pre or post-online sample; Geo2*Policy= Interaction between urban workplace or not and whether case is in the pre or post-online sample; Emp*Policy= Interaction between workplace - training county match and whether case is in the pre or post-online sample; Geo1*Emp = Interaction between suburban workplace or not and workplace - training county match; Geo2*Emp = Interaction between urban workplace or not and workplace - training county match

The wide confidence intervals in Table 9 are examined in Table 10, which displays cases in a three-way crosstabulation across the geographic categories, times of training, and attendance. The imbalance of cases across the different cells, specifically across the rural individuals in the 3rd geographic category who did not attend training, provides some insight into the confidence intervals displayed above.

Table 10. RegAttended * PDTTimeCoded * zipcategory Crosstabulation

			PDTTimeCoded					
zipcategory								
			1	2	3	4	5	
1	RegAttended	0	37	29	34	89	26	215
		1	788	272	637	303	514	2514
	Total		825	301	671	392	540	2729
2	RegAttended	0	0	1	5	13	3	22
		1	153	48	117	64	85	467
	Total		153	49	122	77	88	489
3	RegAttended	0	0	0	1	0	1	2
		1	36	2	9	11	10	68
	Total		36	2	10	11	11	70
Total	RegAttended	0	37	30	40	102	30	239
		1	977	322	763	378	609	3049
	Total		1014	352	803	480	639	3288

Table 11. τ, Across Models

		τ	Variance Accounted For In Intercepts
Pre-Online	Empty	0.76	-11.8 (0%)
	Conditional	0.85	
Post-Online	Empty	1.05	41.90%
	Conditional	0.61	
Full	Empty	0.67	16.42%
	Conditional	0.56	

Post-Online

The combined model for the post-online sample is shown in Equation 10:

$$\eta_{ij} = \gamma_{00} + \gamma_{10} * POLICYLE_{ij} + \gamma_{20} * EMPCTYMA_{ij} + \gamma_{30} * GEO1URB_{ij} + \gamma_{40} * GEO2SUB_{ij} + \gamma_{50} * TIMED1AM_{ij} + \gamma_{60} * TIMED2AF_{ij} + \gamma_{70} * TIMED3EV_{ij} + \gamma_{80} * TIMED4ON_{ij} \ \rho * W * b_0 + u_0 \tag{10}$$

Table 9 indicates that within the post-online sample of registrants, the match between training and employment counties (EmpCtyMa) is no longer a significant predictor of attendance (p=0.059). Online registration is a significant predictor of attendance (p<0.001), relative to weekend registrants. All other predictors in the model held constant, odds of attendance for registrants who are taking the training online (TimeD4ON) are expected to be 0.16 times less than the odds of attendance for those who register for in-person weekend training. The positive value of Rho indicates that attendance for one case makes attendance more likely for the surrounding cases.

41.90% of variance in intercepts amongst registrants in the post-online sample (Table 11) is accounted for with the inclusion of travel barrier (EmpCtyMa), time of training, and employment geography.

Full

The global Moran's statistic (-0.0004, p<.01) indicates significant spatial autocorrelation within the dataset respective to the outcome variable of attendance amongst registrants.

The combined model for the full sample is shown in Equation 11:

$$\eta_{ij} = \gamma_{00} + \gamma_{10} * POLICYLE_{ij} + \gamma_{20} * EMPCTYMA_{ij} + \gamma_{30} * GEO1URB_{ij} + \gamma_{40} * GEO2SUB_{ij} + \gamma_{50} * TIMED1AM_{ij} + \gamma_{60} * TIMED2AF_{ij} + \gamma_{70} * TIMED3EV_{ij} + \gamma_{80} * TIMED4ON_{ij} + \beta_{90j} * (Geo1 * Policy_{ij}) + \beta_{100j} * (Geo2 * Policy_{ij}) + \beta_{110j} * (Emp * Policy_{ij}) + \beta_{120j} * (Geo1 * Emp_{ij}) + \beta_{130j} * (Geo2 * Emp_{ij})\ \rho * \mathrm{W} * \mathrm{b}_0 + u_0 \quad (11)$$

Table 9 indicates that within the post-online sample of registrants, online registration is a significant, but negative, predictor of attendance (p<0.001). All other predictors in the model held constant, odds of attendance for registrants who are taking the training online (TimeD4ON) are expected to be 0.12 times less than the odds of attendance for those who register for in-person weekend training.

Neither the introduction of online options (PolicyLever) nor the travel barrier captured by EmpCtyMa have significant main effects in the full model. However, the interaction term Emp*Policy is significant, indicating that the effect of EmpCtyMa on the outcome variable of attendance (RegAttend) is contingent on the value of PolicyLever.

Additionally, the effect of PolicyLever on RegAttend is contingent on the value of EmpCtyMa. The positive value of Rho indicates that attendance for one case makes attendance more likely for the surrounding cases.

16.42% of variance in intercepts amongst registrants (Table 11) is accounted for with the inclusion of travel barrier (EmpCtyMa), time of training, employment geography type, and which sample the registrant is in (pre-or post-online).

The large confidence intervals for the full model shown in Table 9 provide evidence that a modified model may provide a more precise estimate of parameters for the full sample. Registrants who selected the online training (TimeD4ON) are entirely within the post-online sample (PolicyLever=1), therefore the modified-full model removes the time variables, which are the most likely theoretically to be the problematic variables in the model. The modified-full model is shown in Equation 12

$$\eta_{ij} = \gamma_{00} + \gamma_{10} * POLICYLE_{ij} + \gamma_{20} * EMPCTYMA_{ij} + \gamma_{30} * GEO1URB_{ij} + \gamma_{40} * GEO2SUB_{ij} + \beta_{90j} * (Geo1 * Policy_{ij}) + \beta_{100j} * (Geo2 * Policy_{ij}) + \beta_{110j} * (Emp * Policy_{ij}) + \beta_{120j} * (Geo1 * Emp_{ij}) + \beta_{130j} * (Geo2 * Emp_{ij}) \rho * W * b_0 + u_0 \qquad (12)$$

With the exception of the removal of the statistically significant predictor in the Full model (TimeD4ON), the significant predictor remains the same (Emp*Policy) (Table 12). The interpretation of the significant predictor does not appreciably change between the Full and Modified-Full models. This results in a larger degree of confidence that the conclusions drawn from the full model are not substantively influence by any the complete overlap of TimeD4ON with the PolicyLever variable.

Table 12.Fixed Effects Across Full Samples, with Full and Modified-Full Models Predicting Attendance

		Coefficient	Std.E rror	*t*-ratio	*df*	*p*-value	Odds Ratio	Confidence Interval	Rho / ρ
Modified-Full	Intercept	3.20	1.14	2.80	439	0.05*	24.70	(2.61,234,13)	
	PolicyLever	1.28	2.22	.58	2839	0.56	3.60	(0.05,279.07)	
	EmpCtyMa	2.58	2.20	1.17	2839	0.24	13.15	(0.18,981.53)	
	Geo1urb	-.96	1.16	-.83	2839	0.41	.38	(0.04,3.73)	
	Geo2sub	1.37	1.38	.99	2839	0.32	3.92	(0.26,58.48)	
	Geo1*Policy	1.43	2.22	.64	2839	0.52	4.17	(0.05,322.75)	
	Geo2*Policy	-.96	2.42	-.40	2839	0.69	.38	(0.003,44.21)	
	Emp*Policy	-3.81	.83	-4.59	2839	<0.001*	.02	(0.004,0.113)	
	Geo1*Emp	-1.41	2.20	-.64	2839	0.52	.24	(0.003,18.248)	
	Geo2*Emp	-1.67	2.41	-.69	2839	0.49	.19	(0.002,21.10)	
									0.57
Full	Intercept	3.44	1.22	2.82	439	0.01*	31.34	(2.84,345.43)	
	PolicyLever	1.04	2.38	0.44	2835	0.66	2.83	(0.027,300.052)	
	EmpCtyMa	2.89	2.33	1.24	2835	0.22	18.01	(0.19,1737.53)	
	TimeD1AM	0.20	0.28	0.69	2835	0.49	1.22	(0.70,2.12)	
	TimeD2AF	-0.50	0.32	-1.56	2835	0.12	0.61	(0.32,1.14)	
	TimeD3EVE	-0.02	0.29	-0.08	2835	0.94	0.98	(0.55,1.73)	
	TImeD4ON	-2.10	0.318	-6.57	2835	<0.001*	0.12	(0.07,0.23)	
	Geo1urb	-1.05	1.22	-0.86	2835	0.39	0.35	(0.03,3.84)	
	Geo2sub	1.38	1.403	0.98	2835	0.33	3.97	(0.25,62.22)	
	Geo1*Policy	1.54	2.38	3.64	2835	0.52	4.65	(0.04,489.20)	
	Geo2*Policy	-0.65	2.62	-0.25	2835	0.80	0.52	(0.003,88.94)	
	Emp*Policy	-2.68	0.83	-3.227	2835	0.001*	0.07	(0.014,0.35)	
	Geo1*Emp	-1.78	2.33	-0.764	2835	0.45	0.17	(0.002,16.31)	
	Geo2*Emp	-1.92	2.59	-0.742	2835	0.46	0.15	(0.001,23.50)	
									0.71

EmpCtyMa= Match of Training and Employment counties; TimeD1AM= Training taken in morning or not; TimeD2AF= Training taken in afternoon or not; TimeD3PM= Training taken in evening or not; TimeD4ON= Training taken online or not; Geo1urb = Workplace Suburban or not; Geo2sub= Workplace Urban or not; PolicyLever= Registered in Post-Online sample or not; Geo1*Policy= Interaction between suburban workplace or not and whether case is in the pre or post-online sample; Geo2*Policy= Interaction between urban workplace or not and whether case is in the pre or post-online sample; Emp*Policy= Interaction between workplace - training county match and whether case is in the pre or post-online sample; Geo1*Emp = Interaction between suburban workplace or not and workplace - training county match; Geo2*Emp = Interaction between urban workplace or not and workplace - training county match

Comparing Pre-and Post- Online Sample

Within the combined sample, online registration and the interaction between training-employment county match and the introduction of the online option (PolicyLever) are significant predictors of attendance. The significant predictors in the pre-and post- online samples reflect differences amongst the pre-and post- online samples. Within the pre-online sample, training-employment county match, used a measure of capturing travel barrier, is a significant predictor for attendance amongst registrants. Amongst the post-online sample however, only online registration is a significant predictor. It is noted here that all online registrants are coded as though training-employment counties matched, to indicate lack of travel barrier for these registrants.

Considering the Research Question at hand (for this study, does the introduction of an online option for a professional development training reduce the access gap?), there is no empirical evidence within this study to suggest that the online introduction significantly changed or improved the likelihood of attendance amongst registrants. The Research Question also inquired if the effect of online introduction is related to geography. The lack of significance in the interaction terms capturing this effect suggests that there the effect of the introduction of online professional development did not vary across the three geography types (rural, urban, and suburban) within this study.

Component Question A

Among registrants who had the choice between online or face-to-face delivery of the training (post-online sample), the only significant predictor of attendance is when comparing online registrants to weekend face-to-face registrants. Online registrants are statistically significantly less likely to attend once registered, compared to weekend registrants.

Component Question B

Unanticipated confound from lack of 2 session registrations in the post-online sample results in the current research's inability to speak to this question. The 2 session trainings are no longer offered once online options are available. The addition of the online option effectively results in a single, 3 hour session as the only training option. Post-online registrants did not have a dosage choice, as the 2 session ELDS was not offered, therefore the choice between online and face-to-face delivery cannot speak to impacts on training dosage in this study.

Chapter 5: Discussion

Now, we draw our attention to a discussion of the current research's results and implications of findings as it relates to the research question (does introduction of online offering reduce access gap, related to geography type?) and its two component questions (does the choice of online affect completion rates, and does the professional development dosage change across pre-and post-online samples?). Within the literature, a gap exists in understanding how online professional development shaped rural access patterns, that is to say: are more rural early childhood educators reached with the online professional development than with face-to-face alone?

These questions are addressed through descriptive statistics and spatial hierarchical linear modeling techniques.

Summary

The introduction of the online ELDS professional development (as measured by PolicyLever) is not significant in the spatial HLM, providing evidence that the introduction does not significantly affect attendance. Descriptive statistics in Table 3 demonstrate that the number of registrants remained fairly stable across geography types in the 3 months before online release when compared to the 3 months after its release. The large gap between rural registrants and their urban and suburban counterparts remains even after the introduction of the online professional development, which provide access without the travel barrier that may exist for many face-to-face professional development offerings.

A potential explanatory factor in why online offerings had a lower attendance rate than face-to-face offerings can be found in the assumptions behind online training. In order to successfully navigate an online course, an internet connection of sufficient bandwidth is necessary. Weak connection or reliance on cellular phone data may result in an unsuccessful attempt at online professional development. Additionally, the computing device such as desktop, laptop, tablet, or cell phone that a registrant uses to navigate the professional development can lead to an unsuccessful professional development attempt. The platform used for the training is not necessarily functional with mobile devices, meaning registrants accessing the training on mobile devices may not be able to complete the training. Older computers may not have the appropriate updates of software necessary for the training to work properly. Additionally, as mentioned in Chapter 2 there is evidence within the literature that rural participants may not have the same technology preparation as other educators. While the technology factor may be affecting rural registrants, the isolated nature and competing responsibilities noted in Chapter 2 may also be affecting the rate of both rural registrants and attendees in online trainings. Practically speaking, it is possible that rural participants simply took the ELDS training outside the time period considered for this study. Further data is required to understand if the online platform presents a barrier specifically to rural registrants.

The impact of the introduction of the online delivery option is not significantly different across the different geography types. The main effect of PolicyLever is not significant, the interaction effects of PolicyLever and the two geographic dummy variables (Geo1*Pol and Geo2*Pol) are also non-significant. The non-significance of the interaction terms indicates that the effects of the online introduction on the rural registrants is no different from the effect the online introduction has on urban or suburban registrants.

Geographic sector does not prove to be a significant predictor in attendance. This may be a function of the imbalance of rural registrants (n=70) versus that of the other geographical categories. Urban participants had 2,729 registrants over the 6-month period in question and 489 participants identified suburban workplaces. The outcome variable, RegAttend, is not strongly correlated with either of the geography variables in the full sample.

While neither geographic sector variable is a significant predictor of attendance, geographic clustering is significant within the ELDS registration sample. Taking into account the geographic clustering seen in the point maps, the ICC is cut by nearly ½.

In the pre-online sample when all registrants must attend face-to-face, travel barrier (EmpCtyMa) is a significant predictor of attendance. This is not unexpected, and consistent with the additional barriers to professional development faced by rural professionals discussed in Chapter 2. This travel barrier is not a significant predictor in the post-online sample, in which all registrants have a delivery option that avoids the travel barrier. Given the results of the geographic and travel barrier variables, evidence suggests the lack of rural participants is likely a function of the lack of local offerings. More information about the support provided to online registrants with the technological issues noted above would lend additional evidence to this conclusion.

Online registration is a statistically significant predictor of attendance, but in a negative direction. Online registrants are .12 times less likely to attend compared to those registering for weekend face-to-face training.

Ultimately, while the introduction of the online option did not statistically significantly affect attendance rates, those participants who took advantage of the online option are statistically significantly less likely to complete the training. The rate of attendance is lower for online registrants than that of any type of face-to-face registrant. It is unclear if these are individuals who registered and did not attempt the training, or individuals who attempted the training and were unsuccessful in completion because of possible technical barriers.

The small Moran's *I* indicates that across the state, the registration of early childhood educators' neighboring professionals in ELDS trainings does not significantly influence an individual's decision to attend the training. While the sample size would not have permitted the analysis to be restricted to only rural registrants, these findings provide evidence that early childhood educators are not forming their own professional development communities as recommended by Howley & Howley, at least not locally.

Conclusions

Methodologically, the large reduction in ICC resulting from the addition of spatial components suggests that spatial methods are useful in the examination professional development attendance. Much education research is studied within clusters (ex: classroom, district), and spatial dependency may exist. The current research provides a basis for examination of education research with geographical information such as zip codes with this important sense of space included. The sense of space is not new in education; one only needs to reflect on education funding issues, for example, to understand that in education, a student's location matters. The use of spatial methods allows for the integration of place in models of education phenomena, particularly for students in certain geographies (rural, urban, or suburban).

The parameters used to define geographic categories (rural, urban, and suburban) are not casual decisions in the research planning process. Defining these categories sets the stage for one of the most crucial distinctions within this study. Whether a registrant chooses online or face-to-face is a clearly defined distinction, but the geographic distinction is a construct determined by the research team. School districts that are identified by the Ohio Department of Education as rural may contain zip codes that fall under urban clusters or suburban using the Census definition used in this research. [11]

[11] http://education.ohio.gov/Topics/Data/Report-Card-Resources/Ohio-Report-Cards/Typology-of-Ohio-School-Districts

These district typologies are a convenient way to geographically classify students. However, because the current research involves education professionals serving children birth-age 5, many of the professionals are not employed through school districts. Given this information, the Census definition based on zip codes is used. A different definition of rural could have resulted in more rural participants, and therefore a different set of findings and conclusions.

Simply placing content online will not address the disparity between rural registrants and registrants from urban/suburban areas. Attendance in this study is significantly predicted by the travel barrier (EmpCtyMa), and would suggest that more rural face-to-face delivery options are more effective than an online delivery option. Alternatively, efforts to make computing requirements clear to registrants, and suggesting alternative locations to take the online training (ex: local public library) could mitigate the technology barriers noted above. This would compromise some of the flexibility embedded in taking a training from home, but leaves a great deal of flexibility in the time at which an individual takes the training. If online delivery is to be continued, support staff should be made available for those who experience technical difficulties. Clear instructions on account registration and navigating the training should also be made available to minimize the number of registrants who would like to attend the training but may face frustrating technical barriers that prevent completion.

The method of ELDS online delivery (pre-recorded material without interaction with an instructor) is inconsistent with many of the professional development features for which Desimone (2009) advocates. Without engaging with the instructor or fellow participants, this delivery does not develop a community of learners or situate learning or activities within participants' existing knowledge. While professional development quality is outside the scope of the current research, it is noted that the face-to-face delivery of the professional development with a physical instructor and classmates is better positioned to satisfy both of these features.

The current research extends one of the suggestions within Dede (2009)'s research agenda in exploring both online and face-to-face professional development participation empirically. ELDS delivery being offered face-to-face and online enables registration and attendance patterns of both delivery methods to be evaluated. The natural experiment design of the current research allows for an understanding of face-to-face registration patterns before and after the online delivery option is made available.

Given that time constraints present challenges to rural educators seeking professional trainings (Askvig & Arrayan, 2002), an expected finding is that time of training would have a significant impact on attendance. However, time of training is not a significant predictor of attendance amongst registrants. Weekend and Evening times are often times with more competing family or personal obligations, but generally with fewer competing professional obligations. Weekend and Evening times are the only times available to those working in environments without paid time for professional development or lacking in coverage for their professional development participation (ex: in-home providers). A potential explanatory factor in understanding the effect of time of day comes in the form of the demographics in Chapter 3. The majority of the registrants came from childcare centers that may provide support in the form on coverage of classroom or paid time for training for the professional development of their staff. Additionally, centers have the ability to make attendance at a specific training session a mandatory component of employment, effectively meaning the time of training is not the registrant's decision. This is in contrast to self-employed individuals running in-home childcare centers, who are not held to the training as a condition of their employment.

The message for policymakers that arises from this study concerns travel barriers, online delivery, and the impact of nearby early childhood professionals. The travel barrier is a significant determinant of registrants choosing to attend trainings, indicating that more face-to-face trainings in rural counties may be a more effective way to increase access to rural professionals. Online registration significantly decreased a registrant's odds of successfully completing and receiving the information within the ELDS training. More evidence is required to understand if this was a technology skills deficiency, hardware issue, or other barriers that led to the decrease in completion rates amongst online registrants. Registration was largely stable across pre-online and post-online samples, within all geographic categories. The addition of an online option did not result in more rural participants. While making the ELDS training available online did not result in significantly increased registration or participation rates amongst any geographic category it is possible that from a cost perspective roughly equivalent individuals accessed the training at a lower cost. That information was not available, and is outside the scope, of this study. That is to say, there may be benefits of the online addition that fall outside the scope of this study. The lack of clustering signified by the small Moran's *I* provides evidence that neighboring peers are not serving as a significant factor in an individuals' attendance. Neighboring peers registering for ELDS does not translate into a stronger likelihood that an individual will attend the training.

Complications/Qualifications/Limitations

As within any study, the sample presents complications. There is a potential confound in county of residence. The county of residence is a voluntary field, with too much missingness to be included in the data for this study. This lack of data results in the possibility that cases where the employment and training counties are mismatched could be instances where the county of training did match the county of residence, but did not match the county of employment. As EmpCtyMa informs the understanding of the travel barrier that a registrant faced in attending the ELDS session, the data may mistakenly indicate a travel barrier for individuals registering for sessions in their county of residence rather than their county of employment in the cases where individuals live and work in different counties.

Online registrants do not have county of training listed. All employment-training county matches are identified as matched, as the employment-training county match variable is intended to capture the travel barrier faced by registrants who attended face-to-face and those registering for online sessions face no travel barrier. Pre-Online sample does not have the option of online delivery, therefore TimeD4Online is not included in the pre-online analysis.

It is unable to be determined whether online registrants would have chosen a different face-to-face offering or simply not have registered without the online option. The online option could have brought the professional development to new individuals, or simply served as an alternative to those who would have pursued the professional development regardless of the online option's existence.

Entries that are geolocated are based on information supplied to the Ohio Professional Registry (OPR) by registrants. This information is not necessarily up to date; there is not a requirement for individuals to update their OPR profile with any regularity from November 2014- May 2015. Based on the high turnover in the early childhood profession (Miller & Bogatova, 2009), the information supplied may be reflective of a previous place of employment. For example, an individual who initially developed an OPR profile in January 2013 could volunteer the location of their then-current employer and when they register for an ELDS training 2 years later, that is the employer listed unless the registrant chooses to edit their profile to update the employer information.

Another limitation lies in the time of training variable. The times ELDS trainings are offered are pre-determined by training staff. Registrants have a list of times and locations to choose from but may not have a great deal of options to choose from, especially in areas with fewer training offerings. This is even further complicated if an early childhood professional does not receive paid time off to attend professional development or does not have coverage for their students (ex: in-home care provider) who may be restricted to hours outside of the traditional 9am-5pm, Monday-Friday.

The negative R^2 for the pre-online sample in Table 11 indicates that a different model would be useful for further examination of the pre-online sample. As the full sample produced an interpretable R^2, as did the post-online sample, the pre-online sample is included for comparison purposes. Caution is advised in drawing meaningful conclusions from the pre-online sample.

Future directions of this research could be using extended periods of data collection to understand if the effects of online introduction are delayed. A possibility would be to keep the natural experiment design, with extended data collection periods to reflect the 6 or 12 months before and 6 or 12 months after online introduction. The first 3 months of online introduction may not be enough time to capture the policy's effect.

An additional extension of the current research is a qualitative inquiry concerns the rural professional development registrants. Focus groups or individual interviews with individuals who registered for ELDS training online, including those who attended and those who did not attend, may shed considerable light on any barriers experienced that prevented completion.

Considering the gravity of how geographical categories are defined, additional research can be structured around the different geographical distinctions. Examining a subset of this data to only registrants who work with a school district would enable the Ohio Department of Education school typologies for rural, urban, and suburban distinction instead of the Census definition. Examining the same set of data under multiple definitions of what constitutes a rural geography has the potential to be powerful research in understanding rural educators, their needs, and their students. A different geographical categorization technique would provide additional evidence to understand the lack of correlation between attendance amongst registrants and workplace geography.

Interpretation Limitations

Limitations exist in the interpretation of study findings. Data on the quality of ELDS, from participant evaluations or external evaluations from observations, were not available, and conclusions about the quality of the ELDS training are outside the scope of this study. It is not possible to speak to how ELDS corresponds to Desimone's professional development best practices within the scope or the administrative data used in this study. The focus of this study is limited to the ELDS registrants, as they become either participants or non-participants.

Additional limitations to the interpretation of findings come in the form of the methods used. The extremely low Moran's *I* provides evidence that the analysis may not have been necessary.

The purpose of this study is to understand the determinants of professional development attendance amongst registered early childhood professionals. The travel barrier, as measured by the match between employment county and training county, is a significant predictor of attendance. Registrants without a travel barrier are more likely to attend the training. Selecting online delivery is also a significant predictor in a negative direction, with a statistically significant lower likelihood of attendance. The relationship of geography and attendance is a predictor of specific interest, as the online delivery of the training had the possibility of mitigating the access gap seen for rural professionals. Comparing the registration patterns of professionals across different geography types, as a policy is put into place that removes the travel barrier required for professional development, provided an excellent opportunity to understand how policies shape changes, and what other circumstances may be influencing a policy's impact.

Methodologically, the contributions of this study lie in the use of spatial effects for analyzing professional development opportunities and rural education professionals. These statistical methods, which take into account place, are warranted in education research, specifically research on policies that are often concerned with place, location, or geography. Ultimately, the hope is that this research provides a precedent for the incorporation of spatial method in education research as it moves forward.

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Appendix A: Ohio's Early Learning and Development Standards in All Essential Domains of School Readiness (Birth – Age 5)

Introduction[12]

In December 2011, Ohio was awarded the Race to the Top Early Learning Challenge Grant. To be awarded the funding, Ohio was required to have *Early Learning and Development Standards in all Essential Domains of School Readiness, Birth to Age 5*. These five domains included:

- Social and Emotional Development
- Physical Well-being and Motor Development
- Approaches Toward Learning
- Language and Literacy Development
- Cognition and General Knowledge

Ohio's Early Learning and Development Standards describe key concepts and skills that young children develop during the birth-to-five-year period. Their purpose is to support the development and well-being of young children and to foster their learning. The standards promote the understanding of early learning and development, provide a comprehensive and coherent set of expectations for children's development and learning,

[12] http://education.ohio.gov/getattachment/Topics/Early-Learning/Early-Learning-Content-Standards/The-Standards/Ohio-Early-Learning-and-Development-Standards-Introduction-9-October-2012-pdf.pdf.aspx

and guide the design and implementation of curriculum, assessment and instructional practices with young children.

The standards present a continuum of learning and development from birth to age five in each of the domains. Because the infant/toddler years are marked by rapid developmental change, the standards are divided into three meaningful transitional periods: Infants (birth to around 8 months), Young Toddlers (6 to around 18 months), and Older Toddlers (16 to around 36 months). The standards during the preschool years describe those developmental skills and concepts children should know and be able to do at the end of their preschool experience.

The Ohio Early Learning and Development Standards were created as part of a collaborative effort of state agencies serving young children including Ohio Department of Education, Ohio Department of Job and Family Services, Ohio Department of Health, Ohio Department of Mental Health, Ohio Department of Developmental Disabilities, and the Governor's Office of Health Transformation. The state agencies worked with national experts and writing teams made up of Ohio-based content experts and stakeholders to revise and expand the standards in the five developmental domains.

Ohio's revision of standards builds upon the strong set of existing standards in Ohio's Infant and Toddler Guidelines (for children birth to 36 months of age) and the Pre-Kindergarten Standards (for children ages 3 to 5). Ohio's *Infant and Toddler Guidelines* was the major source for the development of the infants' and toddlers' standards. Similarly, Ohio's *Pre-Kindergarten Content Standards* were revised and expanded in the Language and Literacy and Cognitive Development domains. The Cognition and General Knowledge standards were aligned with the kindergarten Common Core State Standards in English-Language Arts and Mathematics and Ohio's Revised Academic Content Standards in Science and Social Studies. Finally, the standards were reviewed and revised with particular attention to being appropriate for children with disabilities and for children with diverse cultural and linguistic backgrounds. Knowledge of the strengths and needs of each child is pertinent in order to implement differentiation strategies and culturally responsive pedagogy in a manner to help each child meet the standards.

<u>Organization of the Standards</u>

The standards within each domain are organized according to **strands**, the developmental or conceptual components within each domain. Each strand contains one or more **topics,** the area of focus within each strand, and the **standard statements,** those concepts and skills children should know and be able to do for the different age groups. Some topics reflect learning and development across the birth-to-five continuum, with standards for all age levels: infants, young toddlers, older toddler, and Pre-K, while other topics pertain only to a specific age- period. For example, some knowledge and skills such as *the ability to identify and describe shapes* or skills related to social studies and science emerge in preschool. Topics that address those competencies include standards only at the Pre-K level. Other topics such as *Self-Comforting* and *Social Identity* have standards only at the infant-toddler levels, because these foundational skills developed during the early years lead to more specific competencies at the preschool level.

An Overview of the Domains

Social and Emotional Development. The standards for Social and Emotional development involve behaviors that reflect children's emotional growth and their growing ability to successfully navigate their social worlds through interactions with teachers and peers. These standards include a focus on children's developing abilities to regulate attention, emotions, and behavior, and to establish positive relationships with familiar adults and with peers. Research indicates that early skills of social competence and self-regulation are foundational to children's long-term academic and social success (National Research Council, 2008). Strands in the social and emotional domain are *Self* and *Relationships.*

Physical Well-Being and Motor Development Physical Well-Being and Motor Development standards address motor skills and health practices that are essential for children's overall development. These skills include the ability to use large and small muscles to produce movements, to touch, grasp and manipulate objects, and to engage in physical activity. These standards also describe the development of health practices that become part of children's daily routines and healthy habits such as nutrition and self-help. These skills and behaviors play an important role in children's physical well-being and set children on a path leading toward a healthy lifestyle. Healthy children are more likely to attend school, to be physically active, and to learn more effectively (Bluemenshine and others, 2008). The two strands in this domain are *Motor Development and Physical Well-Being.*

Approaches Toward Learning. Approaches Toward Learning centers on the foundational behaviors, dispositions, and attitudes that children bring to social interactions and learning experiences. It includes children's initiative and curiosity, and their motivation to participate in new and varied experiences and challenges. These behaviors are fundamental to children's ability to take advantage of learning opportunities, and to set, plan, and achieve goals for themselves. This domain also includes children's level of attention, engagement, and persistence as they do a variety of tasks. These factors are consistent predictors of academic success (Duncan et al., 2007). Finally, children's creativity, innovative thinking and flexibility of thought allow them to think about or use materials in unconventional ways, and to express thoughts, ideas and feelings in a variety of media. The standards in the domain Approaches Toward Learning are organized in the following strands: *Initiative*; *Engagement and Persistence*; and *Creativity*.

Language and Literacy. The standards for language and literacy reflect knowledge and skills fundamental to children's learning of language, reading and writing. Young children's language competencies pertain to their growing abilities to communicate effectively with adults and peers, to express themselves through language, and to use growing vocabularies and increasingly sophisticated language structures. Early literacy skills include children's developing concepts of print, comprehension of age-appropriate text, phonological awareness, and letter recognition. Research has identified early skills of language and literacy as important predictors for children's school readiness, and their later capacity to learn academic knowledge (National Early Literacy Panel, 2008). The Language and Literacy domain consists of the following strands: *Listening and Speaking, Reading and Writing*.

Cognition and General Knowledge. This domain includes those cognitive processes that enable all other learning to take place, as well as children's knowledge of the social and physical world. This domain is organized into the strand, *Cognitive Skills* and those concepts and skills in **sub- domains**, *Mathematics, Social Studies* and *Science*.

Cognitive Skills. This strand refers to the underlying cognitive mechanisms, skills and processes that support learning and reasoning across domains, including the development of memory, symbolic thought, reasoning and problem-solving.

Mathematics. The sub-domain of mathematics encompasses the mathematical concepts and skills that children develop during the birth-to-five-year period, including children's developing understanding of number and quantity, number relationships, and basic algebraic concepts. A meta-analysis conducted by Duncan and colleagues (2007) suggests that specific early math skills such as knowledge of numbers and ordinality are important predictors of later achievement in math and reading. The Mathematics sub- domain also addresses children's developing knowledge of key attributes of objects, including size and shape, and the way objects fit, are positioned, and move in space. The standards in the domain of mathematics are organized in four strands: *Number Sense*, *Number Relationships and Operations*; *Algebra*; *Measurement and Data*; and *Geometry*.

Social Studies. The sub-domain of social studies includes basic skills and competencies that set the foundation for learning about concepts of social science. At a young age, children begin to develop their social identity and to think about their place in the social world. As they grow, they develop an increased awareness of their personal histories and heritage, and a sense of time and place. Through everyday interactions with children and adults, they develop an appreciation for rights and responsibility within a group, and how social rules help people in promoting safety and fairness (Mindes, 2005). Such competencies are described in the domain of Social Studies under the following strands: *History*; *Geography*; *Government*; and *Economics*.

Science. This sub- domain focuses on children's curiosity to explore and learn about their environment. It includes behaviors of exploration and discovery, and fundamental conceptual development such as problem solving and cause and effect. These early behaviors develop into increasingly systematic inquiry skills, and the ability to observe, investigate and communicate about the natural environment, living things, and objects and materials (Gelman and Brenneman, 2004). Early competencies in science are organized in four key strands: *Science Inquiry and Application*; *Earth and Space Science*; *Physical Science*; and *Life Science*.

Ohio's early learning and development standards illuminate the breadth of learning and development from birth to kindergarten entry that strengthens school readiness. An understanding of learning and development in each domain guides programs and teachers as they plan developmentally appropriate learning opportunities and environments for young children. In particular, teachers can use an understanding of standards to focus on the kinds of interactions and environments that support, for example, language development or approaches toward learning. While the standards facilitate a focused look at young children's learning in each domain, teachers and others responsible for the care and education of young children need to keep in mind that infants, toddlers, and preschool-age children learn holistically.

Moreover, social and emotional development stands at the center of their learning. For example, as an infant or toddler builds security in a relationship with a caring adult, that child is also learning to communicate with language and to use the relationship as a secure base for practicing new movement skills and building knowledge about the world through exploration. Likewise, as preschool-age children tell stories about family experiences they are expanding their self-awareness, using their growing cognitive capacity to remember the past, and practicing narrative skills. Such examples of integrated learning are endless. In addition to providing focused looks in each domain, the standards can help us see how learning occurs in different domains at the same time.

Teachers and others can use the standards as starting points for observing and understanding young children's learning and development. With each learning encounter teachers observe, they can refer to the standards and ask what knowledge and skills are the children gaining in the areas of language and literacy, cognition and general knowledge, social and emotional development, physical well-being and motor development, and approaches toward learning. Teachers can use their observations of integrated learning to plan new learning encounters for young children and support the building of knowledge in all essential domains of school readiness.

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