USING ALPHABET KNOWLEDGE AND PHONEMIC AWARENESS ASSESSMENTS TO PREDICT WORD READING FLUENCY IN KINDERGARTEN

by

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A DISSERTATION

Presented to the Department of Educational Methodology, Policy, and Leadership
and the Graduate School of the University of Oregon
in partial fulfillment of the requirements
for the degree of
Doctor of Education

June 2016

DISSERTATION APPROVAL PAGE

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Title: Using Alphabet Knowledge and Phonemic Awareness Assessments to Predict Word Reading Fluency in Kindergarten

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DISSERTATION ABSTRACT

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Doctor of Education

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June 2016

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This dissertation study examined the predictive validity of alphabetic knowledge and phonemic awareness assessments on word reading fluency. The participants were approximately 900 kindergarten students from a suburban school district in Oregon. The study used extant curriculum-based measure (CBM) reading assessment data collected during the 2013-2014 school year to examine the predictive validity of measures of letter naming fluency (LN), letter sound fluency (LS), and phoneme segmentation fluency (PS) on word reading fluency (WRF). Linear regression was employed to examine the amount of variance that early reading skills (LN, LS, and PS), measured during the fall and winter, explained in WRF measured in the spring of kindergarten. The relation of non-performance demographic data to student spring WRF was also examined. Results of this research are intended to inform practitioners implementing early reading instruction and interventions through an equity lens.

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ACKNOWLEDGMENTS

I would like to express gratitude to Dr. Keith Hollenbeck for guiding me through the research and writing processes, and for his assistance in the preparation of this manuscript. Dr. Hollenbeck helped me integrate my core values and professional experiences in education as we developed this research topic. I would like to thank my committee. Special thanks are due to Dr. Julie Alonzo for providing input that helped me frame my research within the larger context of promoting equity. I also thank Dr. Brian Megert for connecting me with the necessary data from the school district, and for helping develop research questions that reflect relevant problems of practice. I owe deep thanks to the Department of Educational Methodology, Policy, and Leadership, for working with me over the years as a student in Portland. Special thanks to Dr. Mike Bullis and Dr. Jo Smith for their assistance during my doctoral research and writing coursework. I also would like to thank Dr. Nancy Heapes for reframing and deepening my understanding of change. I would like to thank my family. I thank my parents, Mom and Abba, for giving me the foundation of a love of learning and questioning. Lastly, I thank my husband Joe. His friendship and dedication provided me with the courage to complete this dissertation.

For Grandpa Ray, whose commitment to education was matched only by his conviction to do the right thing.

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CHAPTER I

INTRODUCTION

The gap in student literacy achievement by third grade reflects a significant problem in Oregon. Emergent literacy behaviors relate to later reading ability (Cunningham & Stanovich, 1997; Whitehurst & Lonigan, 1998). Reading words fluently, or with accuracy and speed, is one aspect of emergent literacy, and an important correlate to reading skills later in school (Savage, Frederickson, Goodwin, Patni, Smith, & Tuersley, 2005). Facilitating the development of children's automatic word reading skills in kindergarten is likely to support children in becoming skilled readers later in school. Identifying students with difficulties reading words automatically early in elementary school can allow educators to provide students with targeted interventions that may prevent future reading difficulties.

To support the development of children's fluent word reading, it is necessary to understand the early reading skills that foster that particular skill. Tindal (2013) noted that early literacy skills taken together reflect a "complex constellation with a relatively brief shelf life" (p. 8) because the relative importance of each skill changes as the child transitions from earlier skills to fluent reading. It follows that measuring young children's literacy development requires the use of different measures according to developmental transitions. Code skills, including phonological awareness, letter naming, phonological decoding, emergent writing, and print awareness, enable successful decoding of written text, and are important predictors of later reading skill (National Institute of Child Health and Human Development, 2005). Successful reading comprehension involves an ability to both decode words and access meanings of words simultaneously (LaBerge &

Samuels, 1974, 1994). Thus, there is a relationship between a child's observable early literacy skills and later reading comprehension. Designing interventions for students at risk for later reading difficulties involves examining the predictive relations between code skills and word reading fluency in kindergarten.

In many school districts in Oregon, teachers measure students' early literacy skills throughout the kindergarten year using easyCBM interim assessment measures. These assessments include measures of letter naming fluency (LN), letter sound fluency (LS), phoneme segmentation fluency (PS), and word reading fluency (WRF). See Table 1.1 for a seasonal schedule of assessment availability through easyCBM.

Table 1.1

Kindergarten easyCBM Assessment Subtest Schedule

	Fall	Winter	Spring
Letter Names	X		
Letter Sounds	X	X	X
Phoneme Segmenting	X	X	X
Word Reading Fluency		X	X

Prior research on the predictive validity of CBMs points to opportunities for future research. One study related group differences in passage reading fluency (PRF) in grade 2 and word reading fluency (WRF) in grade 1 to kindergarten LS scores (Saéz, Nese, Alonzo & Tindal, 2015). Although researchers found that fall kindergarten LS scores were significant predictors of grade 1 WRF scores, they did not include demographic data and non-performance indicators in their study. It is relevant to consider the role that nonacademic demographic factors (i.e. student race/ethnicity, SES, special education status, English learner status, or attendance) may play in these predictions. It may be that nonacademic demographic variables contribute to the variance in student performance on word reading fluency measures. If it is the case that nonacademic variables significantly change the relations between word reading fluency and the preceding early literacy measures, then two possible conclusions arise: (a) either the measures might not function equally for all groups of students, as intended, or (b) the differences in the relation between the early literacy measures and WRF, as a function of student demographic characteristics, likely indicate inequities elsewhere in the educational system.

Anderson et al. (2014) provided validity evidence that the LN and LS measures are appropriate for use within the Response to Intervention (RTI) framework. Discovering the relations among academic predictors of WRF may support the development of targeted interventions within school systems using RTI. Describing the emergent literacy skills that best predict children's WRF in kindergarten will enable educators to design interventions to target these skills. Discovering patterns among student performance on measures of different skills during the kindergarten year might allow for multiple points of intervention, while examining the patterns of achievement among students from high-risk circumstances will reveal the extent to which demographic variables may influence performance.

The purpose of my dissertation study was to examine the validity of three emergent literacy measures (a) LN, (b) LS, and (c) PS to predict children's skill in fluent word reading in kindergarten. In this study, I examined student scores on these assessments as related to differences in fluent word reading measured during the spring of the kindergarten year. I also examined the influence of nonperformance indicators on students' scores on the kindergarten WRF CBM. Through this study, I read a variety of empirical literature in order to discover salient relationships between academic and nonacademic variables related to student word reading skill. This review provided a foundation to develop my research questions about early and emergent literacy processes and their relations.

Literature Synthesis

In my literature search I used online databases from the University of Oregon (UO) Library to locate research about academic and nonacademic factors promoting early and emergent literacy skills. I limited my literature review to peer-reviewed research, although I also consulted technical reports, review articles, and policy briefs to help deepen my understanding of reading skills.

Key words and search parameters. I searched within PsychNet, ERIC, and the UO library advanced search functions for peer-reviewed journal articles using the following search terms: *alphabet knowledge*, *letter naming*, *letter sound identification*, *letter fluency*, *graphophonic*, *kindergarten*, *reading*, *phonemic awareness*, and *emergent literacy*. An initial search through the UO library of journal articles using *alphabet knowledge* AND *kindergarten* AND *reading* returned a list of 83 articles. Removing the term *kindergarten* returned 137 articles. I removed the term *kindergarten* because I wanted to target research that referred to the developmental ages and stages of children rather than grade level. I also did not want to exclude research from other English-speaking countries that might not use the term *kindergarten*.

Reviewing results for possible inclusion in my review. I reviewed the abstracts of the research articles to select articles meeting criteria for inclusion in this review. Of the 137 peer-reviewed journal articles returned from my search of the electronic databases, I systematically eliminated research about *nonsense word reading* because decoding nonsense words was not a component of the easyCBM reading assessment in Oregon, where I conducted my research study. I also eliminated research articles about English Language Learners, dual language education, and research about reading in languages other than English. Because student phonemic awareness was found to be an important skill in learning to read and including alphabet instruction with phonemic awareness instruction made phonemic awareness instruction more effective (Ehri, Nunes, Willows, Schuster, & Yaghoub-Zadeh, 2001), I also reviewed the abstracts of articles that included phonemic awareness and alphabetic knowledge as variables.

Based on the rules articulated in the above paragraph, I created a list of 31 journal articles and abstracts. I used the following criteria to pare the initial list of 31 articles down to 16: (a) measured literacy skills of children in grades K-2, (b) described student reading achievement over time, (c) described early reading predictors of later reading achievement, and (d) related specific early literacy skills to other specific early literacy skills. The number of participants in each study varied. Of the 16 research articles reviewed, five included reports of results from studies with fewer than 100 subjects. Ten research articles included a sample size greater than 100 subjects, and one research article included a sample size greater than 1,000 subjects

The Link Between Phonological Sensitivity and Developing Reading Skills

Phonemic awareness is most likely a single aspect of phonological sensitivity, an ability children develop along a continuum (Cunningham & Stanovich, 1997; Lonigan, Burgess, Anthony & Barker, 1998). Importantly, the development of student skills in phonological sensitivity is a salient variable influencing reading development. I will use the term *phonological sensitivity* to refer to the construct measured by the phoneme segmenting (PS) easyCBM assessment, and *phonemic awareness* to refer to the specific skill measured by the PS assessment. Phonemic awareness, the awareness of the distinct sounds of spoken words, is a skill within the construct of phonological sensitivity. Lonigan, Burgess, and Anthony (2000) defined phonological sensitivity as "sensitivity to and ability to manipulate the sound structure of oral language" (p. 597). Phonological sensitivity develops along a continuum (Lonigan, Burgess, Anthony, & Barker, 1998) and contributes to later reading skill because of the role of decoding processes in reading achievement (Whitehurst & Lonigan, 1998). Viewing children's language development along a continuum supported the predictive validity of measurements across time. Phonological sensitivity skills measured in kindergarten refer to the same underlying construct as phonological sensitivity skills measured when a student is older.

Another important point to make is that code skills, the written alphabetic knowledge skills necessary for later fluent reading, including skills such as letter naming and letter sound identification, are associated with phonemic awareness and reading ability (Storch & Whitehurst, 2002; Wood, 2004). Practice with code skills facilitates the process of automaticity, decreasing the amount of attention the student needs to devote to decoding and comprehending text (Samuels, 1994). For example, Ehri et al. (2001) found that phonemic awareness instruction was more effective in helping students learn to read when paired with alphabetic instruction in small groups of students. In a meta-analysis of 52 articles summarizing results of research investigating phonemic awareness, Ehri et al. (2001) reported that teaching the skills of blending and segmenting using both sounds and letters showed the greatest effect size on student phonemic awareness knowledge. The finding that a child's knowledge of how printed language functions can impact a child's phonemic awareness has implications for future research. Code skills and phonemic awareness are thus important literacy skills that children begin to develop before formal academic instruction, and that influence students' later reading.

Alphabetic Knowledge and Phonemic Sensitivity. Schatschneider, Fletcher, Francis, Carlson, and Foorman (2004) used a quantitative methodology to explore the predictive relationship between early literacy skills and reading ability, including 10 predictor skills, many of which are similar to the skills measured in my study. The following six skills were assessed four times during kindergarten: (a) phonological awareness, (b) alphabetic knowledge, (c) rapid automatized naming (RAN), (d) vocabulary, (e) visual-motor integration, and, (f), recognition-discrimination. Four skills were assessed once during the spring of kindergarten: (a) expressive syntax, (b) syntactic comprehension, (c) letter-word identification, and, (d) timed word reading. The authors found that the most important skills in kindergarten for predicting reading ability in Grades 1 and 2 were phonological awareness, letter sound knowledge, and rapid automatized naming (RAN). RAN pointed to the construct of automaticity, similarly measured by the easyCBM LN and WRF assessments.

Schatschneider et al. (2004) designed their study using multiple published and unpublished measures. Among the published measures they used was the Woodcock-Johnson Reading (WJ-R), with a reported reliability level of .90 (Schatschneider et al., 2004). They found that the highest correlation between early literacy skills measured was between letter naming and letter sound identification, with a correlation coefficient of (*r*

= .70). They also found a stronger correlation for students in Grade 1 between reading fluency and RAN letters (r = .43) than between reading fluency and phonological awareness (r = .25), letter name knowledge (r = .29), or letter sound knowledge (r = .31). These results support the conclusion that the letter naming, letter sound identification, and reading fluency assessments measured constructs with more similarities than phonological awareness. These findings might also suggest that, as children become more skilled readers, automaticity (e.g., RAN) becomes more important than other skills.

Contrary to findings relating RAN skill in kindergarten to reading ability later in elementary school, MacDonald, Sullivan and Watkins (2013) found rapid serial naming to be a nonsignificant predictor of word identification skills at the end of Grade 1. MacDonald et al. (2013) studied a population of 131 students in Grade 1 at nine elementary schools. The researchers found kindergartners' cognitive ability, phonemic awareness skills, and letter knowledge were significant predictors of word reading fluency in Grade 1.

Academic and Non-Academic Variables and Word Reading Fluency

In this section, I synthesize results of research probing the relation between academic (reading) variables and student word reading fluency. Of the 16 articles reviewed, 12 included measures of word reading fluency, and 10 of these included quantitative descriptions of the relation between the constructs phonological sensitivity and word reading fluency. Stahl and Murray (1994) found that students scoring lower on measures of phonemic awareness were also more likely to score below the cutoff on a test of word reading fluency. Letter naming was also found to be an important predictor of word reading fluency. Of the 16 articles reviewed, 14 included measures of letter name knowledge. Storch and Whitehurst (2002) found that alphabetic knowledge, measured by letter naming and letter sound naming, exhibited a path coefficient of (β = .76) to word reading skill in Grade 1.

The role of multiple measures. Multiple measures were found to be better predictors of outcomes including reading skill as compared to using single measures alone (MacDonald, Sullivan & Watkins, 2013; Schatschneider, Fletcher, Francis, Carlson & Foorman 2004). MacDonald et al. (2013) examined multiple models of variables to predict word-reading skill in first grade from data collected during the kindergarten year, and found that the model that included a combination of phonemic awareness and letter knowledge was the best predictor of word-reading skill. In a meta-analytic study, Ehri et al. (2001) found that phonemic awareness instruction had a moderate effect on the acquisition of phonemic awareness (effect size d = .53). Ehri et al.'s (2001) analysis showed a combined effect of curricular interventions designed to target phonemic awareness. These results, taken together, suggest that there is not a single variable that can be isolated as the best predictor of later word reading, but rather a combination of variables that best capture the complex relation of early and emergent skills.

Academic predictors of reading achievement. Researchers conducting longitudinal studies examining the influence of variables measured during kindergarten on student reading achievement in the elementary grades found letter identification to be an important predicting variable of later reading (Adolf, Catts & Lee, 2010; Bowey, 1994; MacDonald, Sullivan, & Watkins, 2013). For example, Adolf et al. (2010) found letter knowledge to be an important predictor of later reading ability, and the variance in the relation between phonological awareness and reading ability could be explained by differences in letter knowledge. Additionally, Adolf and colleagues found a moderate correlation between kindergarten phoneme deletion skills and Grade 8 reading comprehension, (r = .49), and a slightly lower correlation between kindergarten letter naming skills and Grade 8 reading comprehension, (r = .36), while phonemic awareness in kindergarten was more highly correlated with eighth grade reading comprehension compared to letter naming knowledge (Adolf et al. 2010). Similarly, among students in kindergarten, Bowey (1994) noted statistically significant correlations between word identification tasks and letter knowledge (r = .52). The ability of students in kindergarten to recognize letters and words emerged as a salient indicator of later reading achievement in the literature synthesis.

Nonacademic predictors of reading achievement. Contrary to the robust research relating academic predictors to later reading achievement, fewer researchers have reported on the role of nonperformance indicators on later reading achievement. Of the 16 articles reviewed, only two included results related to demographic questions (Lonigan, Burgess, Anthony, & Barker, 1998; NICHD, 2004). Lonigan et al. (1998) compared the performance of students from middle-income and lower-income families on measures of phonological sensitivity, alphabetic knowledge, and word reading using a cross-sectional research design. Lonigan and colleagues found that children from a middle-income sample of preschoolers performed better on phonological awareness tasks than did children from the lower-income sample of preschoolers across four age groups. However, the researchers also reported no statistical significant difference between the performance of boys and girls on the phonological awareness tasks.

The National Institute on Child Health and Human Development (NICHD, 2005) included socioeconomic status (SES) as a variable in a study on early literacy skills. NICHD (2005) grouped children by family income level into higher, middle, and lower income families to test a hypothesis that language skills at 54 months of age would predict later reading assessment scores better than would vocabulary scores as measured by assessments alone. Surprisingly, NICHD found that oral language skills at 3-years of age were a better predictor of reading ability at 54 months for children from low- and medium-SES homes than for children from high-SES homes (NICHD, 2005). One possible interpretation of this finding may be that a way to raise student achievement in reading in elementary school is to target interventions in kindergarten and preschool to children from low- and middle-income communities.

The roles of academic and nonacademic variables are important to consider. Taken together, these findings mean that early literacy behaviors such as naming letters, identifying the sounds of letters, and discerning the sounds of language are valuable predictors of word reading fluency, which in turn is predictive of students' reading ability in the elementary years. Further research should investigate the specificities of the ability of alphabetic knowledge skills and phonological awareness to predict word reading fluency in kindergarten. Questions remain as to which skills are the most useful predictors, and if nonacademic variables influence the outcomes of such predictions.

More specifically, the research reviewed prompts further questioning into the role of nonacademic demographic variables on the level of student word reading fluency in kindergarten. There exists an observable gap in student literacy achievement among students of color by the end of high school, yet, surprisingly, the research synthesized in this review did not examine differences in student achievement in literacy according to race or ethnicity at the start of formal schooling (i.e., kindergarten). A direction for future research includes exploring the extent to which nonacademic demographic variables influence the role of early literacy skills on later developing emergent skills, such as word reading fluency. Discovering the relations among academic indicators and nonacademic variables might provide insights needed to prevent the perpetuation of gaps in student achievement related to demographic characteristics.

Theoretical Framework

Information processing theory can provide a theoretical framework to approach questions regarding young children's reading skill acquisition. Swanson (1987) noted that information processing theory provides an approach that can explain the performance patterns of children both with and without learning disabilities. Invoking the information processing model of learning, Swanson (1987) described how a student learns "through various stages of cognition such as encoding, organizing, storing, retrieving, comparing, and generating (reconstructing) information" (Swanson, 1987, p. 155). Under this theory, linguistic units such as phonemes and graphemes (i.e., letters) are bits of information that the student is able to remember, organize, and retrieve for future use. The information-processing model explains the relations among observed differences in student performance on measures of reading skills (Swanson, 1987).

Automaticity. Information processing theory provides a theoretical framework for automaticity theory as explained by LaBerge and Samuels (1974, 1994). Automaticity theory holds that performing a task takes limited cognitive resources (LaBerge & Samuels, 1974, 1994; Samuels & Flor, 1997). Acquiring skill in a task means that gradually fewer resources are needed to complete the task (Samuels, 1994; Samuels & Flor, 1997). When fewer resources are needed to complete a task accurately, a person has more cognitive resources available to multitask (LaBerge & Samuels, 1974, 1994). An assumption of the LaBerge-Samuels automaticity theory is that cognitive processes require resources from a set of *finite* cognitive resources (Swanson, 1987). Automaticity in performing a task supports the completion of tasks that are more cognitively complex because there is a surplus of cognitive resources, such as attention, available (Samuels & Flor, 1997).

Swanson (1987) and Gray (2004) noted that the term *automaticity* has been used in literature to refer to a number of different cognitive processes. In this paper, I use the Samuels and Flor (1987) definition of automaticity "as the ability to perform complex skills with minimal effort and attention" (p. 108). Under this view of automaticity, fluent reading becomes possible when decoding letters and then words becomes automatic. Children learn first to automatically recognize letters, then words. I illustrated the variables contributing to word reading fluency below, in Figure 1.1.

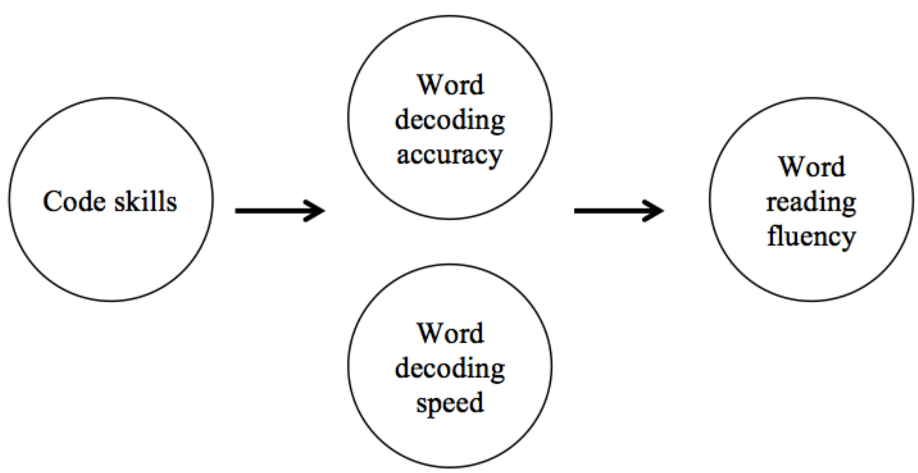

Figure 1.1. Model of automaticity theory. Automaticity is the cognitive process that facilitates the development of fluent word reading.

The role of attention in automaticity. Automatic word decoding supports fluent reading because the student is better able to direct attention to comprehension, instead of switching between attending to decoding and comprehending (LaBerge & Samuels 1974, 1994). LaBerge and Samuels (1974, 1994) explained the process of automatic reading in terms of the relations between features of print and types of memory (Samuels, 1994). Attention is required to relate information among the visual, phonological, and semantic memory in order to yield meaning to the reader.

When less attention is required to process linguistic information, the skill becomes more automatic. Samuels and Flor (1997) offered Stanovich's (1990) concept of *encapsulation* as a way to explain why automaticity in reading also involves memory. Under this view of automaticity, repeated exposure to the written sign (i.e., the word) contributes to a memory of the written sign, which the reader attaches to a meaning. The reader forms a high-quality representation of the written units and can eventually access these representations automatically.

Rapid naming. Stanovich (1990) identified rapid speed of recognition as a salient component of automatic word recognition. RAN assessment tasks can be used to measure automaticity. In RAN tasks, students are asked to name items (i.e., letters or pictures) under a timed condition. Savage, Frederickson, and Goodwin, et al. (2005) found that RAN skill was a moderate predictor of spelling ability for 61 British students in grades 3 and 5, and RAN measures could be used to distinguish below-average readers from average readers. Researchers have found a relation between RAN skill and word reading skill, providing evidence for automaticity theory as a way to explain early reading processes (Catts, Gillispie, Leonard, Kail, & Miller, 2002; Savage et al., 2005).

Taken together, information processing theory and the literature describing automaticity theory provide a theoretical framework from which to begin to understand the assumptions and inferences embedded in my research design. Automaticity theory explains the pathways by which early literacy competencies such as alphabetic knowledge contribute to a student becoming a fluent word reader.

Study Context and Research Questions

The role of automatized processes in reading development presents a need to find out which early reading skills best predict word reading fluency, a measure of automaticity. Literature synthesized in this review points to the role of the early literacy skills of letter name fluency, letter sound fluency, and phoneme segmenting fluency on word reading fluency, and the role of word reading fluency on reading achievement in elementary school. Taken together, these findings suggest that knowledge of alphabetic principles and phonological sensitivity in kindergarten are indicators of later reading ability. Findings from my study have the potential to inform practitioners designing kindergarten curricula and targeted interventions.

I designed this study to address the following research questions:

RQ1 Which early literacy skills assessed in the fall of kindergarten best predict spring word reading fluency?

RQ2 Which early literacy skills assessed in the winter of kindergarten best predict spring word reading fluency?

RQ3 What is the relation between student demographic characteristics and spring word reading fluency?

CHAPTER II

METHODS

Research Design

In this descriptive study, I used multiple regression to examine the relation of early reading and demographic variables on word reading fluency. Figure 2.1, below, presents a visual representation of the design and constructs measured.

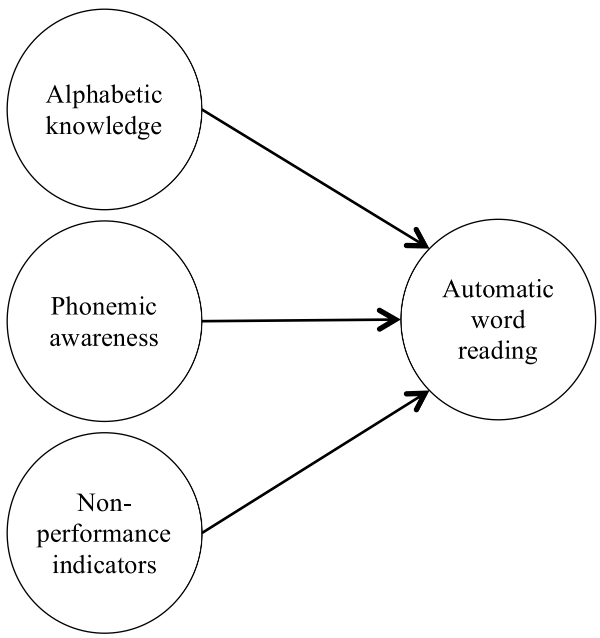

Figure 2.1. Dissertation research design.

This study used a predictive validity design to examine the role of student alphabetic knowledge, phonological awareness, and non-performance indicators on word reading fluency. The unit of analysis targeted by my proposed research questions was groups of students in kindergarten. I selected this as the unit of analysis because I was interested in discovering patterns of performance for groups of students. Babbie (2013) likened the unit of analysis to “those things we examine in order to create summary descriptions of all such units and to explain differences among them” (p. 98). Examining student group level data at two points during the school year helped answer my research questions because as children’s skills develop, some skills have been previously shown to be more or less important in predicting the outcome of word reading over time. One advantage of considering student level data is that group performance trends can be disaggregated to reveal specificities unique to the population studied. Considering student group level data allows for comparisons between groups of students when predicting word reading fluency, and may reveal the impact of nonperformance indicators of risk on student word reading.

Variables

I used multiple variables to predict the outcome of spring word reading fluency scores among the study participants. Predictive variables included: (a) fall LN fluency score, (b) fall LS fluency score, (c) fall PS fluency score, (d) winter LS fluency score, (e) winter PS fluency score, (f) special education status, (g) English learner status, (h) attendance, (i) free/reduced meal status, and (j) race/ethnicity (see Table 2.1, below).

Research Questions 1 and 2 examined the role of multiple academic variables on the outcome variable of word reading fluency measured in the spring of kindergarten using the easyCBM WRF Spring Benchmark assessment. These two questions addressed the role of different early literacy skills measured at different time points (fall and winter) of the kindergarten year. Research question 3 explored the role of student nonperformance indicators on word reading fluency. Only students with complete assessment data for each research question were included in the analytic sample.

Table 2.1

Research Questions and Analytic Methods

Research Question	Statistical Analysis	Variables
1. Which early literacy skills in the fall of kindergarten best predict spring word reading fluency?	Multiple regression	Fall LN Fall LS Fall PS Spring WRF
2. Which early literacy skills in the winter of kindergarten best predict spring word reading fluency?	Multiple regression	Winter LS Winter PS Winter WRF Spring WRF
3. What is the relation between student demographic characteristics and spring word reading fluency?	Multiple regression	Special education status English learner status Attendance Free/Reduced meal status Race/ethnicity Spring WRF

Timeline. My research study used a descriptive design to examine the relations between student performance on measures of alphabetic knowledge, phonemic awareness, word reading fluency, and non-performance indicators in kindergarten. Data were collected during the fall, winter, and spring of the 2013-2014 school year during the seasonal benchmark assessment administration practices of the participating school district in Oregon (See Table 1.1).

Setting. This study explored characteristics of a sample of kindergarten students from a mid-size suburban school district neighboring a large research university in Oregon. The school district serves a city of about 59,000 residents, and enrolls about

10,900 students total. Of these students, approximately 900 attended kindergarten during the study period.

Participants. As noted above, the participants in my study included a non-random convenience sample. Approximately 5,000 students were enrolled in grades K-5, at 12 elementary schools in the district where the study was set. Of these, over 900 students participated in the district half-day kindergarten program. The participants in my study included all kindergarten students in a school district who had assessment and demographic data on all measured variables included in my study. Table 2.2 presents a summary of the demographic data in the school district.

I used a non-probability sampling plan because I was interested in describing aspects of reading achievement for the entire population of kindergarten students in the participating school district. My sampling strategy followed what Babbie (2013) called "Reliance on Available Subjects" (p. 128) because I wanted to describe patterns of student reading achievement from the available students in the district. To describe trends among all the kindergarten students in the district, it followed that relying on all available subjects was an appropriate sampling method for this inquiry. The sampling method fits my analytic strategy of using multiple regression because participants were not randomly assigned to a treatment or control group within my analyses. I measured the predictive validity of student non-performance indicators on WRF for the population of kindergarten students within the district described above.

Table 2.2

Demographic Characteristics of Student Population

Demographic characteristic	Percentage of K-3 students in district
Student race/ethnicity	
White	68%
Hispanic/Latino	21%
Multi-racial	7%
Black/African American	2%
Asian	1%
American Indian/Alaska Native	1%
Native Hawaiian/Pacific Islander	< 1%
Students receiving free and reduced meals	69%
English Language Learners	11%
Students with identified disabilities	14%
Students attending 90% or more of enrolled days	91.6%

Instruments

The measures used in my research study were interim assessment measures of early and emergent literacy development typically administered in kindergarten classrooms in Oregon, and that were part of regular practice in the district where my study was set. Kindergarten classroom teachers administered the measures to their assigned students. The literacy instruments used in this research study were four easyCBM reading subtests: LN fluency, LS fluency, PS fluency, and WRF. Appendix B includes sample student and assessor copies of the measures (Figures A.1-A.4).

Typically, each of these measures is administered one-on-one for one minute. The assessor marks student errors, and scores self-corrections as correct. For LN, the student verbally states the name of each letter presented in a matrix of uppercase and lowercase letters. For LS, the student verbally states the sound made by each of the letters in the matrix. For the PS, the assessor says a word and the student is asked to say each phoneme. In the WRF task, the assessor presents the student with a list of words and asks the student to correctly read as many words as possible. Table 1.1 shows when students are administered the LN, LS, PS, and WRF assessments during the kindergarten year.

Constructs measured. The easyCBM subtests of LN fluency and LS fluency measure aspects of the alphabetic knowledge construct. The PS fluency assessment measures a student's phonemic awareness, or awareness of the sounds in spoken language. The WRF assessment measures a student's ability to fluently name grade-level appropriate single words. Students who have mastered the alphabetic principle will be able to demonstrate rapid (automatic) naming of letters, sounds, phonemes, and words.

Reliability of easyCBM. Researchers from the UO developed multiple forms of the LN, LS, PS, and WRF subtests (Alonzo & Tindal, 2007). Table 2.3 shows reliability information regarding the included easyCBM measures. The reliability coefficients for each of the LN, LS, PS, and WRF subtests indicate that the assessments are likely to yield consistent results across test administrations and students.

Validity. A technical manual documents the validity properties of the easyCBM assessments for use within RTI contexts (CITE manual here). The easyCBM measures of LN, LS, PS, and WRF are valid indicators of a student's progress. DIBELS (Dynamic Indicators of Basic Early Literacy Skills) was used as the comparative measure in order to evaluate criterion validity (Lai, Alonzo, & Tindal, 2013). The criterion and predictive validities of the easyCBM measures were established by using the Stanford-10 test of word reading (SAT-10) as the criterion measure (Lai et al., 2010). Lai et al. (2013) explored the concurrent validity of the easyCBM PS measure with the DIBELS PSF, finding the correlation to be high, at r = .85. Table 2.3 summarizes the available validity information for easyCBM early and emergent reading measures. Taken together, these findings indicate the use of kindergarten reading easyCBM assessments are valid for the purposes of measuring student reading ability.

Table 2.3

Psychometric Properties of Kindergarten easyCBM Measures

	LN	LS	PS	WRF
Reliability				
Alternate form	r = .61 to .90	r = .53 to .92	r = .31 to .90	r = .89 to .97[a]
Test-retest	r = .79 to .82	r = .64 to .68	r = .45 to .47	r = .94 to .95
Generalizability	--	r =.87 to .95	r = .50 to .83	r = .96 to .98
Validity				
Criterion	rho = .86	rho = .55	rho = .85	r > .60
Predictive	R^2 = .35 to .40	R^2 = .10	R^2 = .41 to .51	R^2 = .48 to .58
Concurrent	73% variance	R^2 = .10	Small percentage	20.16% variance
Construct	Factor loadings of .80 to .90	--	Factor loadings of .50s	Factor loadings of >.95[b]

Note. a = Data provided for Grade 1 only; b = Data provided for Grades 2-3 only.

Data Analysis

I calculated descriptive and inferential statistical analyses for the fall, winter and spring easyCBM assessments using IBM SPSS. I included the mean, range, and standard deviation of the scores of the fall LN, LS, and PS, and the spring WRF assessments.

The inferential statistical test I used to answer Research Questions 1, 2, and 3 was multiple regression. Multiple regression is an appropriate statistical method to use to evaluate the relation between multiple predictor variables and a continuous outcome variable (Creswell, 2014; Wampold & Freund, 1987). I performed three separate multiple regression analyses, using (a) fall assessment predictor variables and the spring outcome, (b) winter assessment predictor variables and the spring outcome, and (c) student non-performance indicators and the spring outcome.

Multiple regression, the statistical method that I employed, carries a number of assumptions in order to derive statistically valid findings. Three assumptions necessary for a valid interpretation of data analyzed using multiple regression include: (a) a linear relationship between independent and dependent variables, (b) errors are normally distributed, and (c) lack of multicollinearity between variables (Morgan, Leech, Gloeckner, & Barrett, 2013). Violations of these assumptions can be observed through visual representations of the data. A response to potential violations of statistical assumptions is to perform the appropriate statistical tests prior to performing the multiple regression analysis, and reporting the results. Visual representations of data such as histograms and scatterplots can support the evaluation of assumptions of linearity and normality. I checked variables for multicollinearity by (a) comparing zero-order correlations, and the variance inflation factors (VIFs).

To code nominal demographic data, I used a dichotomous system. I assigned a value of either *0* or *1* to each of the variables measured, with 0 indicating the lower risk. In the case of the marker race/ethnicity, I considered White students to be the low risk group while other students were of the higher risk group. I also coded student attendance dichotomously, using Oregon's criteria for chronic absenteeism. Attendance data for students attending 90% or more school days enrolled were coded as 0, and data for students attending fewer than 90% of enrolled school days were coded 1. The results of the multiple regression analyses displayed the predictive validity of measures of alphabetic knowledge and phonemic awareness on word reading fluency in the form of shared variances between predictor variables, and the extent to which non-performance indicators related to academic outcomes.

Interpretation of findings. I interpreted the findings with respect to accepted levels of statistical significance. Given the statistical methods employed in my research study, it is necessary to set appropriate levels of statistical significance including confidence intervals, p-values, and desired effect sizes. Quantitative researchers investigating early literacy skills often report a 95% confidence interval, with $p < .05$ for statistical significance (Ehri, Nunes, Willows, Schuster, & Yaghoub-Zadeh, 2001; NICHD 2005). Thus, I set the level for statistical significance at alpha equal to 0.05. I reported effect sizes for the findings of the ability of alphabetic knowledge and phonemic awareness to predict word reading. I discussed the effect sizes of the statistical findings to bring a practical understanding to the relative strength of the relation between early literacy skills as children develop over the kindergarten year, and the relations between non-performance variables and the academic outcome.

Academic variables predictions. I predicted that each academic assessment (i.e., letter name fluency, letter sound fluency, and phoneme segmenting fluency) would moderately predict spring word reading fluency. Bowey (1994) found a .52 correlation between letter identification and word identification in-group of 5-year-old English speakers in Australia. Similarly, Lonigan, Lonigan, Burgess, and Anthony (2000) reported on the relations between early literacy skills, finding that early phonological sensitivity was most likely mediated by letter name knowledge in predicting later skills. Lonigan et al found a .64 correlation between letter knowledge and phonological sensitivity for students ages 4 and 5. In a later study, Anthony, Lonigan, Burgess, Driscoll, Phillips, and Cantor (2002) found a .61 correlation between letter-name knowledge and phonological sensitivity in a study of 149 preschool children between ages 4 and 6. Anthony et al. (2002) measured the relation between print features, alphabetic knowledge, and phonological sensitivity, finding the highest correlation between letter-name knowledge and phonological sensitivity. From this research, I predicted that there would be a moderate positive correlations between the academic variables in my study.

Demographic variables predictions. My second prediction was specific to the effects of demographic variables on spring word reading fluency. I predicted that the non-performance indicators would contribute some variance to the ability of the fall and winter reading measures to predict spring word reading fluency. In my study, I used Free and Reduced Meals (FaRM) status as a proxy for poverty. At the time of publication of this study, there were plans in the district to change from using FaRM status to a community eligibility designation, but the transition to the community eligibility designation had not yet taken place when data for this study were collected.

Lonigan, Burgess, Anthony, and Barker (1998) reported the number of boys and girls in their study on phonological sensitivity and noted that there was no significant difference between the performance of boys and girls on four tasks of phonological awareness. Contrary to Lonigan et al.'s (2007) findings, Madhabi (2006) examined the role of student sex, race/ethnicity, and poverty on reading achievement in kindergarten and first grade using data from the Early Childhood Longitudinal Study and found that upon kindergarten entry, student scores on reading measures varied according to demographic variables. During kindergarten and Grade 1, African-American students scored lower than White students, boys scored lower than girls, and children from poverty scored lower than children not from poverty.

Thus, I predicted that the addition of the demographic variables to the regression modeling would alter the ability of fall and winter reading measures to predict word reading fluency at the end of kindergarten. Interestingly, Madhabi (2006) found that the combined demographic variable explained 56% of the variance in students' reading scores at the start of kindergarten, 32% at the end of kindergarten, and 5% at the end of first grade. The decreasing ability over time of demographic data to explain variances in reading achievement may be evidence of some young children's resilience, and of the importance of school in creating equitable outcomes. As children progress in school, demographic factors may contribute less variance to academic performance, and prior exposure to instruction may begin to contribute more variance (Madhabi, 2006). By controlling for differences in non-performance indicators, Madhabi (2006) showed that over time these characteristics became less significant in predicting student achievement outcomes. This means that exposure to instruction is likely more important than student background in predicting academic achievement. Examining student test score data in conjunction with student demographic characteristics will reveal the extent to which non-performance indicators influence academic outcomes. If non-performance indicators are shown to not be important contributing factors to student academic outcomes, then it follows that the instruction received at school may be a more relevant factor in student achievement. If non-performance indicators contribute a significant amount of variance to spring word-reading scores, then the data can be used to help support the design of targeted interventions to foster equity before students begin kindergarten.

CHAPTER III

RESULTS

In the paragraphs that follow, I provide a report of the results of the analysis. I first provide descriptive statistics for each of the variables used in the study. I next used multiple linear regression to analyze the relation between student scores on easyCBM assessments, non-performance indicators, and spring word reading fluency. The first research question probed the relation between student fall scores in (a) LN, (b) LS, and (c) PS and spring WRF. The second examined the ability of student winter scores in (a) LN, (b) PS, and (c) WRF to predict spring WRF scores. To answer the final research question, I performed a third linear regression using non-performance indicators as predictor variables, and spring WRF as the outcome variable. The third model included the student-level non-performance variables (a) special education status, (b) English learner status, (c) attendance, (d) free and reduced meal status, and (e) race/ethnicity.

Description of Cases Included

A total of 931 students participated in at least one fall or spring CBM during the school year. Of these students, 663 had complete scores for fall and spring and were entered into the first regression model. I provided the demographic data dichotomously coded as entered into the regression model for Research Question 1, see Table 3.1. Among students with complete fall and spring scores, 13.9% were English learners, and 14.9% of students were identified as needing special education services. Similarly, among the 268 students with incomplete fall and spring assessment data, 10% were English learners and 12.7% were identified for special education.

Table 3.1

Demographic Data for Students in RQ1 Sample

	Included[a]	Not included[b]
English Learners	13.9%	10.0%
Attendance < 90% enrolled days	3.6%	13.4%
Eligible for FARM	63.5%	70.5%
Not White	33.5%	28.0%
Special education status	14.9%	12.7%

Note. a. n = 663. b. n = 268.

A total of 778 students had complete score sets to enter in Research Question 2, probing the relation between winter and spring CBMs. Table 3.2 provides demographic data for participants included and not included in the analyses related to Research Question 2. Of the students with complete winter and spring assessment data, 13.5% were English learners and 14% were identified for special education services. Among the 153 students without complete winter and spring assessment data, 22.9% of students were chronically absent, as defined by missing more than 10% of enrolled school days, while among the 778 students with complete scores only 3.2% of students were chronically absent. There were also fewer English learners and more students eligible for free and reduced meals among the students with missing winter or spring assessment scores.

Table 3.2

Demographic Data for Students in RQ2 Sample

	Included[a]	Not included[b]
English Learners	13.5%	9.2%
Attendance < 90% enrolled days	3.2%	22.9%
Eligible for FARM	62.6%	80.4%
Not White	32.0%	31.4%
Special education status	14.0%	15.7%

Note. a. n = 778. b. n = 153.

The 828 participants whose data were used in relation to Research Question 3 included any student with a spring WRF CBM score and demographic data. The demographic characteristics of students included in the analysis for research question three were quite similar to the characteristics of students included in the analyses for research questions one and two, see Table 3.3. In all, the dataset included 111 students without spring CBM scores who were thus not included in the analyses related to any of the three research questions, see Table 3.3.

Table 3.3

Demographic Data for Students in RQ3 Sample

	Included[a]	Not included[b]
English Learners	13.3%	8.7%
Attendance < 90% enrolled days	3.7%	28.2%
Eligible for FARM	64.0%	77.7%
Not White	32.5%	27.2%
Special education status	14.4%	13.6%

Note. n = 828. b. n = 111.

Common to the demographic information for students not included in each research question was the percentage of students absent for more than 10% of the school days. In each of the three regression models, the student score sets without complete assessment data were not entered. The regression models reflect the predictive relationship of the CBM scores and non-performance indicators for students who were present for each of the assessments in the model.

Descriptive statistics. I computed descriptive statistics for fall, winter, and spring assessments in LN, LS, PS, and WRF according to sample used in each research question. For a visual representation of assessment data, see Appendix B, figures B.1-B.7. Table 3.4 shows the descriptive statistics for assessment scores of student scores entered into Research Question 1. A total of 663 students participated in Research Question 1 using the fall and spring assessments. Table 3.5 shows descriptive statistics for the student assessment scores used in Research Question 2, a total of 778 students. To answer Research Question 3, 828 student scores were entered into the regression model. Table 3.6 shows the descriptive statistics for student spring WRF scores entered into Research Question 3.

Table 3.4

Descriptive Statistics for RQ1

Measure	*n*	Minimum	Maximum	*M*	*SD*
Fall LN	663	0.0	72.0	16.66	15.21
Fall LS	663	0.0	46.0	5.80	8.87
Fall PS	663	0.0	64.0	11.00	13.08
Spring WRF	663	0.0	109.0	13.12	12.31

Table 3.5

Descriptive Statistics for RQ2

Measure	*n*	Minimum	Maximum	*M*	*SD*
Winter LS	778	0.0	66.0	20.08	12.46
Winter PS	778	0.0	68.0	33.46	15.95
Winter WRF	778	0.0	118.0	4.80	8.16
Spring WRF	778	0.0	109.0	12.92	12.33

Table 3.6

Descriptive Statistics for RQ3

Measure	*n*	Minimum	Maximum	*M*	*SD*
Spring WRF	828	0.0	109.0	12.73	12.25
Sped status	828	0.0	1.0	0.14	0.35

Multicollinearity Analysis

Before answering my three research questions, it was important to determine if multicollinearity was problematic for my statistical conclusion validity. Analyzing for multicollinearity shows the degree of the relation between independent variables included in the model (Tabachnik & Fiddell, 2001). If the correlation between variables was .90 or larger, then the variables would exhibit high multicollinearity and be measuring similar constructs in the regression analysis (Tabachnik & Fiddell, 2001).

I analyzed data for multicollinearity using (a) correlations, and (b) a variance inflation factor (VIF). Table 3.7 presents a zero order correlation matrix for the assessment variables. In Table 3.8 I present a zero order correlation matrix for the non-performance indicators and target variable, spring word reading fluency. The information presented in tables 3.7 and 3.8 showed that the highest correlation exhibited was between winter and spring Word Reading Fluency ($r = .81$). In Table 3.7, the correlations ranged from .33 to .81. In Table 3.8, the correlations were between -.17 to .53. Because none of the correlations exceeded a value of .90, I assumed that the data did exhibit multicollinearity, and all the variables could be used in the linear regression models.

Table 3.7

Zero Order Correlation Matrix for Assessment Variables

Variables[a]	Fall LN	Fall LS	Fall PS	Wint LS	Wint PS	Wint WRF
Fall LS	.70*					
Fall PS	.51*	.52*				
Wint LS	.66*	.56*	.48*			
Wint PS	.42*	.37*	.46*	.55*		
Wint WRF	.48*	.53*	.41*	.55*	.33*	
Spg WRF	.54*	.56*	.41*	.65*	.38*	.81*

* $p < 0.01$, 2-tailed. a. $n = 658$.

Table 3.8

Zero Order Correlation Matrix for Non-Performance Variables

Variables[a]	Spg WRF	EL	Attendance	FaRM	Race/Eth
EL	-.15*				
Attendance	-.05	-.02			
FARM	-.13*	.20*	.15*		
Race/Eth	-.07**	.53*	.04	.21*	
SPED	-.17*	.03	.05	.12*	-.01

*$p < 0.01$, two-tailed. ** $p < 0.05$, two-tailed. [a]$n = 828$.

For the second test of multicollinearity, I assessed the tolerance and variance inflation factor (VIF). Table 3.9 presents results of the tests of tolerance and VIF. A VIF of 10 or above shows multicollinearity (Tompkins, 1992). Tolerance and VIF Tolerance and VIF have an inverse relationship, so a tolerance close to 1.0 means that little of the variable is explained by other variables, while a tolerance close to 0.0 shows multicollinearity with other variables (Tompkins, 1992).

Both the tolerance and VIF values presented in Table 3.9 show that multicollinearity was not a concern for models 1, 2, or 3 because tolerance statistics ranged from .48 in Model 1 (Fall LS) to .98 in Model 3 (special education status). Similarly, the range of VIF values presented in Table 3.9 are within an acceptable range to rule out multicollinearity. VIF values ranged from 1.02 to 2.08. Under Model 3, special education status exhibited the lowest VIF value, at 1.02. Because special education status under Model 3 exhibited the highest tolerance it will also exhibit the lowest VIF, as VIF and tolerance exhibit an inverse relation. Taken together, the tolerance and VIF statistics demonstrated the amount of multicollinearity among variables was within an acceptable range to be included in my regression statistics.

Relations Among Variables

The research questions posed were answered using three multiple regression analyses. Because none of the variables exhibited multicollinearity, they were all entered into the regression models. Tables 3.7 and 3.8 show the correlations among the variables in Research Question 1 and Research Question 2. The correlations among the variables demonstrate the relations of the skills measured within the population, and the way these skills relate to each other within young children's reading development.

Table 3.9

Tolerance/VIF Matrix

Model	Tolerance	Variance Inflation Factor (VIF)
1		
Fall LN	.49	2.05
Fall LS	.48	2.08
Fall PS	.69	1.46
2		
Winter LS	.52	1.93
Winter PS	.68	1.47
Winter WRF	.67	1.48
3		
EL Status	.71	1.41
Attendance	.97	1.03
FaRM Eligibility	.91	1.10
Race/ethnicity	.71	1.41
Special education Status	.98	1.02

Correlations between fall and spring CBM variables. A total of 658 student score sets were included in the correlation statistics for Research Question 1 (see Table 3.7). All correlations were found to be statistically significantly different than zero at the 0.01 level of statistical significance. Of these correlations, the size of the correlations ranged from $r = 0.33$, Winter PS and Winter WRF, to $r = 0.81$, Winter WRF and Spring WRF. Of the fall assessments, the alphabetic knowledge CBMs (LN and LS) each exhibited slightly higher correlations with spring WRF ($r = 0.54$, $r = 0.56$) than did the measure of fall phonemic awareness, PS ($r = 0.41$). Among predictor variables, Fall LN and Fall LS displayed a moderately high correlation of $r = 0.70$.

Correlations between winter and spring CBM variables. Of the winter assessments, Winter PS and Spring WRF exhibited the lowest correlation at $r = 0.38$. Winter LS and Spring WRF exhibited a moderate correlation, at $r = 0.65$, whereas Winter WRF and Spring WRF showed the highest correlation at $r = 0.81$. Winter LS was found to have a higher correlation with Spring WRF ($r = 0.65$) than Fall LS ($r = 0.54$), although both correlations were in the moderate range. In the sections to follow, I present the results of the linear regression modeling and Analysis of Variance (ANOVA) used to answer the research questions.

Research Question 1 Regression Analysis

Research Question 1 asked which early literacy skills in the fall of kindergarten best predicted spring word reading fluency. To answer this research question, I entered student fall scores in (a) LN, see Figure B.1, (b) LS, see Figure B.2, and (c) PS, see Figure B.3, into a regression model with spring Word Reading fluency (WRF) as the target variable, see Figure B.7. Table 3.10 shows the ANOVA statistics for this model, and Table 3.11 shows the linear regression coefficients. According to the ANOVA statistics in Table 3.10, one or more of the fall assessments was a significant predictor ($p < .001$) of spring WRF.

Table 3.10 presents the standardized and unstandardized regression coefficients of the first regression model. Table 3.11 presents the model summary. The results in Tables 3.10 and 3.11 indicated that the fall CBMs were statistically significant predictors of Spring WRF in kindergarten.

Table 3.10

ANOVA Statistics for Fall LN, LS, PS and Spring WRF

Model	Sum of Squares	*df*	Mean Square	*F*	Sig.
Regression	37132.50	3	12377.50	128.86	.00
Residual	63301.56	659	96.06		

The standardized coefficients in Table 3.11 shows that fall LS fluency was the most predictive ($\beta = .33$) of the three variables on spring WRF. The R^2 value in Table 3.13 is .37, meaning that 37% of the variance in spring WRF scores was accounted for by the combined CBM assessments in alphabetic knowledge and phonemic awareness. Table 3.13 provides additional information related to the regression model for Research Question 1. Comparing the values of the part and partial correlations for each of the fall CBMs revealed the same relative importance of measures: fall LS fluency was more highly correlated with spring WRF (part correlation = 0.23), than were either fall LN fluency or fall PS fluency (0.19 and 0.08, respectively). In order to discover the unique contribution of each of the fall variables to this model, I calculated the square of the part correlations in Table 3.13. LN fluency accounted for 3%, LS fluency accounted for 5%, whereas PS fluency accounted for <1% of the variance in Spring WRF.

Table 3.11

Regression Model for RQ1

	Unstandardized Coefficients		Standardized Coefficients	*t*	Sig.
	B	*Std. Error*	*Beta*		
(Constant)	5.86	0.59		10.00	.000
Fall LN	0.22	0.04	0.27	6.00	.000
Fall LS	0.46	0.06	0.33	7.33	.000
Fall PS	0.10	0.04	0.10	2.70	.007

Table 3.12

Model Summary for RQ1

R	R^2	Adjusted R^2	*Std. Error of the Estimate*
.61[a]	.37	.37	9.80

Table 3.13

Part and Partial Correlations: Spring WRF on Fall CBMs

	Correlations		
	Zero-order	Partial	Part
LN	.54	.23	.19
LF	.56	.28	.23
PS	.41	.11	.08

Research Question 2 Regression Analysis

Research Question 2 asked which early literacy skills in the winter of kindergarten best predicted spring WRF. I entered student winter scores in (a) LS fluency, see Figure B.4, (b) PS fluency, see Figure B.5, and (c) WRF, see Figure B.7, into a second regression model with spring WRF as the outcome, see Figure B.7. ANOVA statistics are presented in Table 3.14. The combined winter CBMs in LS, PS, and WRF were a significant predictor of student Spring WRF ($p < .001$).

Table 3.14

ANOVA Statistics for Winter LN, LS, PS, and Spring WRF

Model	Sum of Squares	*df*	Mean Square	*F*	Sig.
Regression	85466.35	3	28488.78	674.42	.000
Residual	32695.22	774	42.24		
Total	118161.57	777			

Table 3.15 presents standardized and unstandardized regression coefficients for Model 2. The standardized regression coefficients demonstrate the magnitude of the relation between each predictor variable and spring WRF. As shown in Table 3.15, winter WRF was the most predictive of spring WRF ($\beta = .65$), and PS fluency was the least predictive of the three variables on Spring WRF ($\beta = .00$). Interestingly, Winter PS was not a statistically significant predictor of spring WRF ($p =.93$).

Table 3.15

Regression Model for RQ2

	Unstandardized Coefficients		Standardized Coefficients		
	B	*Std. Error*	*Beta*	*t*	Sig.
(Constant)	2.45	.56		4.35	.000
LS	.28	.02	.29	10.86	.000
PS	.00	.09	.00	.08	.938
WRF	.99	.04	.65	28.40	.000

Information provided in Table 3.16 contributed to the analysis of the relation between winter and spring reading skills in this population. The model summary presented in Table 3.16 shows an adjusted $R^2 = .72$, indicating that 72% of the variance in spring WRF scores is accounted for by the combination of winter CBMs in LN, PS, and WRF. It should be noted that Winter PS was not a statistically significant contributor ($p = .94$) to Spring WRF. Table 3.17 displays the part and partial correlations for model 2, the predictive relation between winter CBM assessments and Spring WRF. The highest zero-order correlation is observed between winter and spring WRF ($r = 0.82$), indicating that the partial and part correlations between these variables will also be the highest, at $r = .71$ and $r = .54$, respectively. By squaring the part correlations, I obtained the unique contribution of each variable in this model, finding that LS fluency accounted for 4% and Winter WRF accounted for 28% of the variance in spring WRF. PS fluency was not a significant predictor of Spring WRF.

Table 3.16

Model Summary for RQ2

R	R^2	Adjusted R^2	*Std. Error of the Estimate*
.85	.72	.72	6.50

Table 3.17

Part and Partial Correlations Winter CBMs Against Spring WRF

	Zero-Order	Partial	Part
LS	.66	.36	.21
PS	.39	.00	.00
WRF	.82	.71	.54

Research Question 3 Regression Analysis

The third research question asked about the relation between student demographic characteristics and student spring WRF scores. The demographic information provided for each student included: (a) attendance, (b) special education status, (c) English learner status, (d) participation in the free and reduced meals program, and (e) race/ethnicity.

The zero-order correlations in Table 3.8 indicated that attendance was not a statistically significant contributor to the model at the 0.01 level. EL status, FaRM eligibility, race/ethnicity, and special education status all were significant contributors and showed a weak, negative correlation with spring WRF. Of these variables, the strongest correlation was between Special Education status and Spring WRF (r = -.17). Race/ethnicity was a statistically significant contributor at the .05 level (r = -.07), but not at the .01 level. Among contributing variables, EL status and race/ethnicity were highly correlated at r = .53.

The ANOVA statistics provided in Table 3.18 showed that one or more of the non-performance indicators were statistically significant in predicting Spring WRF when the set of indicators were entered together. Further information about the contributions of this demographic information is presented by the regression coefficients in Table 3.19.

Table 3.18

ANOVA Statistics for Spring WRF and Nonperformance Indicators

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	7064.54	5	1412.91	9.93	.000
Residual	116985.43	822	142.32		
Total	124050.01	827			

The standardized beta coefficients presented in Table 3.19 present the relative contributions of each of the non-performance indicators on Spring WRF when all the variables were entered simultaneously into the regression model. Of the non-performance indicators entered, attendance (p =.38) and race/ethnicity (p = .71) were not statistically significant. FaRM eligibility was significant (p =.02). Also, EL status (p =.00) and Special Education status (p =.000) were both statistically significant. Within the regression model, although FaRM eligibility was statistically significant, it had a low beta weight at β = -.09. Special Education status (β = -.15) and EL status (β = -.13) each displayed the ability to predict Spring WRF, although neither of these beta weights were as high as the weights in the prior two models using only CBM variables (see Tables 4.11 and 4.15). Taken together, the adjusted R^2 value of the non-performance indicators was .05, see Table 3.20.

Table 3.19

Regression Model for RQ3

	Unstandardized Coefficients		*Standardized Coefficients*	*t*	*Sig.*
	B	*Std. Error*	*Beta*		
(Constant)	15.49	.72		21.44	.000
EL	-4.75	1.45	-.13	-3.28	.001
Attendance	-1.95	2.21	-.00	-.88	.380
FaRM	-2.20	.91	-.09	-2.43	.016
Race/Eth	.39	1.05	.02	.37	.713
Special education status	-5.37	1.19	-.15	-4.50	.000

Table 3.20

Model Summary for RQ3

R	R^2	Adjusted R^2	*Std. Error of the Estimate*
.24	.06	.05	11.93

Results Summary for RQ1 and RQ2

A total of six variables were entered into two linear regression models in an attempt to discover the predictive relation between alphabetic knowledge and phonemic awareness CBMs on spring WRF in kindergarten. The first model included 663 student scores from fall assessments in (a) LN fluency, (b) LS fluency, and (c) PS fluency, with the outcome variable of Spring WRF. Of these measures, all fall assessments were statistically significant contributors to Spring WRF. LS fluency displayed the highest beta weight, $\beta = .33$. In the fall, PS fluency showed the smallest standardized Beta weight, at $\beta = .10$, with a statistical significance of $p = .007$. By the winter of kindergarten, PS was no longer a statistically significant predictor of Spring WRF (see Table 3.16). Instead, Winter WRF Fluency became a highly significant predictor of Spring WRF ($\beta = .65$). Taken together, these findings point to a decreasing contribution of PS to predict student WRF over the kindergarten year.

Results Summary for RQ3

A total of five non-performance indicators were included in the analysis of research question two: (a) attendance, (b) EL Status, (c) FaRM eligibility, (d) race/ethnicity, and (e) Special Education status. Of these non-performance indicators, only EL status, FaRM eligibility, and Special Education status were statistically significant contributors. Attendance and race/ethnicity did not make significant contributions to the model when all five non-performance indicators were entered into the model simultaneously. The beta weights revealed that, although none of the indicators were strong contributors, Special Education status was the strongest among relatively weak beta weights, $\beta = -.15$. The model summary presented in table 3.20 shows that the total contribution of non-performance demographic indicators on Spring WRF is 5% (adjusted $R^2 = .05$). The contribution provided by combined non-performance indicators was less than either the contribution provided by Fall (36%) or Winter (72%) CBMs.

CHAPTER IV

DISCUSSION

The results of my research show a moderate predictive relation between alphabetic knowledge, phonemic awareness, and word reading fluency-based CBMs in kindergarten. In this section, I present a discussion of the findings of my research questions. First, I review findings from my results section, and note limitations that should be taken into consideration when interpreting and applying findings from my study. I then explore practical implications of these findings and make suggestions for districts using student CBM assessments to plan and evaluate instructional leadership.

Review of Findings

The purpose of this dissertation research was to investigate the predictive relations between measures of alphabetic knowledge and phonological awareness in kindergarten among a population of kindergarten students in one suburban school district in Oregon. I explored the role of alphabetic knowledge and phonemic awareness CBMs during the fall and winter of kindergarten as predictive of Spring WRF. I also analyzed the nature of nonperformance indicators on Spring WRF for these students. A benefit of my research design is that I was able to explore the role of different early literacy skills measured at different points in the year in predicting performance at the end of the kindergarten year. Additionally, I explored the function of demographic characteristics in explaining differences in reading performance at the end of kindergarten.

Fall measures and spring WRF. My first research question asked about the predictive relations between fall measures of LN, LS, and PS fluency on Spring WRF. I found that all fall variables were statistically significant predictors of Spring WRF (see

Table 4.6). The combined contribution of Fall LN, LS, and PS on Spring WRF was 36.7%. Of these relations, Fall LN accounted for the highest amount of variance in Spring WRF (β = .32, p = .000), and Fall PS accounted for the smallest amount of variance (β = .10, p = .007).

Winter measures and spring WRF. Unlike the contributions of fall predictors to the spring outcome, the winter variables did not all exhibit statistically significant contributions to the regression model (Table 4.10). Winter PS was not a statistically significant predictor of Spring WRF (p = .938) when this combination of variables was entered into the model. Expectedly, Winter WRF was a strong predictor of Spring WRF, (β = .65, p = .000), while Winter LS fluency accounted for a smaller amount of variance on Spring WRF (β = .29, p = .000). When entered into the regression model together, Winter LS, PS, and WRF explained 72.3% of the variance in Spring WRF scores.

Nonperformance indicators and spring WRF. The third research question explored the role of demographic nonperformance indicators on Spring WRF. The total contribution of the five nonperformance indicators entered into the regression model was about 5% (adjusted R^2 =.05). Of these variables, only EL status, Special Education status, and FaRM eligibility contributed significantly to the model. Attendance and race/ethnicity did not make significant contributions to the model.

Study Limitations

Though my study has practical implications, it is also subject to several limitations, which must be considered when interpreting results. It is unknown the extent to which variability in instrumentation may impact the reliability of conclusions. The students' classroom teachers administered the LN and LS assessments at the start of the kindergarten year. Different teachers may administer the test slightly differently while remaining within the testing protocol, leading to variability within the results. For example, some teachers may use a screen to cover certain items and only leave visible the current assessment item for the student, and some teachers might leave the entire item matrix visible to students.

Furthermore, each classroom has a different teacher. Because there are likely a number of people responsible for assessing students, there is a possibility of differences in implementation. For example, two teachers may interpret differently a child’s response to the sound that the letter /*h*/ makes, resulting in the two of them giving different scores to the item. In response, I cannot report levels of internal consistency for the measures or levels of inter-rater reliability for the scores from assessment administered in this study.

Internal Validity Limitations

Threats to the internal validity of the claims made in response to the research questions include: history, maturation, attrition, instrumentation and reactive effects. Creswell (2014) explained internal validity threats as features of the procedures, treatments, or experiences of the participants that impact the ability to arrive at justified and true inferences to the population studied. The research design employed in this study presents a number of threats to internal validity and opportunities to reduce validity concerns through the research design.

History. Despite the cross-sectional nature of the research design, there is necessarily a time lag between the administration of the measures used as predictor variables, and the measure that is the outcome variable. During the time lag between the administrations of the measures, students in the study are likely to have had different experiences with the school curriculum. I further limited my sample selection of participants to only students enrolled in half-day kindergarten programs. Students may also have different experiences with the kindergarten curriculum because of different teachers. The degree of implementation of the district kindergarten curriculum varies by teacher and school. Because I could not control for implementation of curriculum, I cannot answer questions relating instructional practices to assessment outcomes.

Maturation. Related to the time lag between the administration of the measures in the study is the idea of maturation as a threat to the internal validity of the findings. Young children's skills develop along a continuum, so it may be hard to tell the extent to which the patterns of predictability between alphabetic knowledge and phonemic awareness observed at the end of the year were influenced by the kindergarten curriculum compared to an expected course of child development. The way to combat this threat to internal validity is to exercise caution when discussing results of the regression analysis. I do not make the claim that the kindergarten curriculum or children's levels of letter name or letter sound knowledge *caused* the level of phonemic awareness at the end of the kindergarten year. Instead, I limit my claims to discussing the relations between levels of alphabetic knowledge, phonemic awareness, and word reading fluency as measured by easyCBM and nonacademic variables.

Mortality. It is expected that students enter or leave the school district during the course of the study, because the study bridges the entire kindergarten year. Students may have incomplete assessment data because of attrition, or because of English language learner status. Students who speak Spanish may take the Spanish Letter Names and Spanish Letter Sound identification assessments in the fall in lieu of the English LN and

LS assessments. Such students taking the Spanish LN and LS assessments would have incomplete scores for the fall for the purposes of this study, but would have scores for the spring PS assessment because easyCBM data is collected for all students. In response to anticipated attrition of students during the year, I intentionally selected a large district for the study. Selecting a large district provided a sample size large enough to be able to generate appropriate levels of statistical significance, despite student attrition.

I observed differences between the demographics of my included population and excluded population. Notably, the percentage of students missing 10% or more of enrolled school days was higher in each of the excluded groups than in the included groups. This is expected because a student who has missed 10% or more of school days is more likely to miss a day of CBM administration. Additionally, student mobility may be a contributing factor to some students having incomplete scores.

External Validity Limitations

The threats to external validity present challenges for making generalizations to other situations, and future opportunities for research. Creswell (2014) attributed threats to external validity to three sources of attempted generalization: other persons, other settings, and to situations at different points in time. Messick (1995) framed external validity as the adequacy and appropriateness of the interpretations and actions based on assessments. In considering the implications for the external validity of this study, it is necessary to consider the direction of the influence the claims purport. Because this research study was not experimental and did not employ a control group, I cannot attribute causality to the results of the linear regression. In this study, variables were studied, but not manipulated. Thus, I made claims about the percentages of shared variance of the independent variables on the dependent variable, but I did not make claims that alphabetic knowledge causes word reading fluency. Specific threats to external validity I describe are: the interaction of the setting and the treatment, the interaction of the selection and treatment, and the interaction of history and treatment.

Interaction of setting and treatment. The testing situation might influence the behaviors and demonstrable skills of the participants. Students at the start of kindergarten build new relationships with teachers, and this varying level of trust that young children have for new adults may influence the extent to which the assessment is able to measure what the student knows about alphabetic knowledge. By selecting 2013-2014 as the school year, I included only participants from half-day kindergarten programs in the data analysis. Therefore, the results of this research study likely do not generalize to students in full-day kindergarten programs. The degree of predictive validity of early reading skills on emergent word reading may differ when children are attending school in different settings. Students who participate in a curriculum emphasizing the instruction of letter names and letter sounds may have scores demonstrating a stronger relation to later word reading compared to students attending play-based kindergartens with less curricular emphasis on alphabetic principles.

History and treatment. The results and generalizability of this research study are bound to the time and place in which the data were collected, the 2013-2014 school year. Conducting a similar study in different districts over future years will provide data needed to be able to make larger scale generalizations about patterns in students' early literacy skills. In a 2005 study by the National Institute of Child Health and Human Development (NICHD), early reading skills were found to be more related to later reading ability for children from lower SES homes than for children from higher SES homes (NICHD, 2005). Replicating the study in areas of the state with different proportions of students from lower or higher SES homes may lead to different results. Appropriately restricting claims about the generalizability of the results of this study will support the credibility of the external validity of the findings.

Statistical Conclusion Validity Limitations

Threats to statistical conclusion validity are incurred from inadequate statistical power or violations of statistical assumptions (Creswell, 2014, p. 176). One way to combat inadequate statistical power is to minimize the risk of Type II error, or the probability of incorrectly accepting the null hypothesis. Statistical power is calculated by $1-\beta$, where β is the level of Type II error. Type II error and power have an inverse relationship, so minimizing Type II error increases statistical power. One practical implication of reporting findings with low statistical power is that it may not be as possible to answer the research questions, as a high Type II error rate can limit the detection of the relationship between the predictor and outcome variables.

Type II error also exhibits a relationship with Type I error. Type I errors occur when the null hypothesis is incorrectly rejected; the researcher finds there to be a statistically significant relationship between variables when in fact there is not (Babbie, 2013). A response to combat the presence of Type I error is to set an appropriate alpha level of statistical significance. Setting an alpha level that is too large will have the effect of inducing a higher Type I error rate because more results will be considered statistically significant. A higher Type I error rate means that there is an increased likelihood of accepting some null hypotheses that should be rejected, or, that some instances of relationships between independent and dependent variables will be found to be statistically significant when in fact they are not. Type I and Type II errors are related because of the role of alpha in determining statistical significance. Increasing alpha will decrease Type II error while increasing Type I error, and decreasing alpha may increase Type II error while decreasing the likelihood of Type I error occurring. In this study, I set alpha at .05.

Findings

In this section, I interpret findings of my research questions. I discuss the outcomes of each of the three research questions with respect to my initial predictions. I include relevant references to prior research in a comparison of my findings to expected results. I also address the changing role of phonological awareness and alphabetic knowledge skills as students become fluent readers.

Alphabetic knowledge and word reading. The existing body of research in the area of early reading development suggested a moderate connection between students' alphabetic knowledge, phonemic awareness, and word reading skills. Prior research supported my predictions and findings about the statistically significant, moderate correlations between young children's alphabetic knowledge and word reading (Bowey, 1994; Schatschneider, Fletcher, France, Carlson, & Foorman, 2004). For example, Bowey (1994) found a 0.52 correlation between student performance on word identification and letter knowledge tasks, and Schatschneider, et al. (2004) found a higher correlation between grade 1 students' reading fluency and rapid letter naming (r = .43) than between reading fluency and phonemic awareness tasks (r = .25). Similarly, I found a .54 correlation between fall LN Fluency and Spring WRF. The results of my first two research questions further confirm the moderate correlations between early alphabetic knowledge skills and word reading skills.

The results of my research study confirmed my prediction that alphabetic knowledge and word reading in kindergarten would exhibit a statistically significant relation. I found a .48 correlation between fall LN and winter WRF, and a .54 correlation between fall LN and spring WRF. Furthermore, my research supported previous published research establishing that alphabetic knowledge and phonemic awareness are distinct constructs. Testing variables for collinearity also showed that LN, LS, PS, and WRF measured different constructs.

The role of phonemic awareness. Prior research pointed to the decreasing role of phonemic awareness as children become fluent readers. Blailock (2004) found decreasing correlations between student rhyming scores, a measure of phonemic awareness, and reading ability measured time intervals of one and two years later. The un-adjusted correlation between rhyme categorization and reading at time 4 was .44 at the time of administration, .40 one year later, and .23 at the end of year two (Blailock, 2004). Importantly, the role of phonemic awareness in predicting students' word reading skills decreased over time. Muter, Hulme, Snowling and Stevenson (2004) also showed the decreasing importance of phonemic awareness skills as students become fluent readers. Compared to measures of alphabetic knowledge (i.e., letter naming), phonological sensitivity measures administered to a group of London students at the age of school entry (5 years old) displayed a less predictive relationship to word reading measures. Muter et al (2004) found a .21 path correlation between student scores on a measure of phonological sensitivity at time one and word recognition at time two. My findings coincide with previous research on the role of phonological awareness and word reading fluency, showing that as students develop word reading fluency, the relative contribution of phonemic awareness to this skill lessens (Blailock, 2004; Muter, et al, 2004).

The results of Research Question 1 and Research Question Two showed that phonemic awareness contributed a slight amount of variance to Spring WRF. I found Fall PS scores to be statistically significant contributors to Spring WRF scores (p = .007, Standardized β = .10), whereas Winter PS scores were not statistically significant contributors to Spring WRF scores (p = .94, Standardized β = .00). I found a .41 correlation between Fall PS and Spring WRF. My pattern of winter to spring results demonstrated comparable outcomes to prior research (Blailock, 2004; Muter, et al, 2004) with the correlation between the PS fluency and Spring WRF decreasing from .41 in the Fall to .39 in the Winter. The lowest correlation (0.33) was between PS and winter WRF, and may provide evidence to support the decreasing importance of phonemic awareness as children become fluent readers.

By spring of the kindergarten year, skills more advanced than phonemic awareness may become more important in students' word reading fluency. The relative rapid pace at which students develop early reading skills means that as students become proficient in some skills, looking at performance on simpler skills will no longer be an indicator of student achievement in other areas of reading development. When students reach a maximum threshold of segmenting phonemes, for example, segmenting any more phonemes in that minute does not necessarily predict being able to read more words in the minute. By the winter of kindergarten, phonemic awareness has decreased in importance to the point of being a non-significant contributor.

Nonperformance indicators and word reading fluency. Prior researchers have shown connections between student demographic characteristics and student outcomes on early reading measures. Poverty impacts educational outcomes, as there are differences observed in performance in kindergarten between students who are and who are not from poverty (Lonigan, et al., 1998; Madhabi, 2006; NICHD, 2004). These researchers all noted differences in student achievement on reading measures among students from different socioeconomic levels, as defined by income. My analysis of Research Question 3 demonstrated that among students in the population studied, student SES as measured by FaRM eligibility was a statistically significant contributor to observed variance in student Spring WRF scores (β = -.09, p = .016), although not as large a contributor as either Special Education status (β = -.15, p = .000) or EL status (β = -.13 p = .001).

It is of interest to note the constrained sample of students included with a designated special education status. At the start of kindergarten, students identified for special education commonly have one or more of three disability codes: (a) communication disorder, (b) autism, or, (c) intellectual disability. In order for a child to be identified for early childhood special education services in one or more of these areas, the child must have scored at least two standard deviations below the mean in at least one of the above qualifying categories. The significance is that students identified for special education in kindergarten may present different academic profiles than those students identified during the mid-primary years. Those students identified later are usually categorized as learning disabled (reading, writing, or math). Thus, any academic intervention suggestions based upon the special education sub-groups from my study must implemented with caution.

Two nonperformance indicators, attendance ($\beta = .00$, $p = .38$) and race/ethnicity ($\beta = .02$, $p = .71$), were not significant factors in the regression model. There is no inherent reason why student performance should vary based on race/ethnicity. There was also a noticeable lack of impact of attendance on Spring WRF. This is likely due to the systematic elimination of students with missing CBM scores from the population in Research Question 3. Students with chronic absenteeism were more likely to have not participated in a CBM and, thus, the impact of attendance on the scores of these students could not be represented in the analysis.

When entered into the regression model together, (a) Special Education status, (b) EL status, (c) FaRM eligibility, (d) race/ethnicity, and (e) student attendance accounted for only 5.1% of the variance observed in spring WRF scores. Despite coming from circumstances of higher risk, the combined impact of this risk was no more than 5%. A plausible alternative explanation for this low percentage of the variance could be that the vast majority of all students were served well by the district. This result points to the protective role of the district in promoting equitable student achievement.

Practical Interpretations

In this section, I discuss the practical significance of my statistical findings. Recommendations may support school districts in instructional leadership planning. I make suggestions for districts regarding the use of CBM data in resource allocation, curriculum and instruction, and principal evaluation. Finally, I discuss practical interpretations with respect to an equity framework.

Instructional planning. It is of practical significance that there exist relationships among early literacy and emergent reading variables. The results of Research Questions 1 and 2 demonstrate the important role that alphabetic knowledge has on word reading fluency in kindergarten. Based on this finding, instructional leaders should be concerned with establishing and maintaining systems that can effectively identify students not meeting benchmark expectations and provide early intervention opportunities targeted at improving alphabetic knowledge skills.

Resource allocation. School districts and building administrators can use the results of my research to inform allocation of staff and instructional time. My results show that there is a connection between alphabetic knowledge, phonological awareness, and end of year word reading skills, but that their contributions shift over time. It follows that providing instruction targeting these core skills will support student learning in these areas, but the academic emphasis areas will change across the school year accordingly. Within an RTI framework, allocating personnel to leading small instructional groups focusing on these time-sensitive skills is likely to have significant effects on student performance and skill mastery. Instructional activities within the kindergarten core ELA curriculum should include daily opportunities for instruction and practice in alphabetic knowledge, phonemic awareness, and word reading skills. Students should be matched with interventions targeting these skills according to performance on interim CBMs.

Within an RTI system, schools have the opportunity to adjust resource allocation mid-year based on data demonstrating student need. The results of Research Questions 1 and 2 taken together show that as phonemic awareness becomes less important in predicting Spring WRF, Winter WRF scores become more important. Schools can focus instruction and interventions on developing the skills needed for automatic word reading by winter of the kindergarten year, and use the winter interim assessments to adjust allocations based on individual student progress. Progress monitoring using CBMs to measure skill growth in alphabetic knowledge and phonemic awareness will allow educators to adjust instruction/interventions to help students become fluent readers.

Early intervention. Early intervening on children's letter naming and letter sounding identification skills in kindergarten might help to increase word reading fluency by the end of the kindergarten year, but should not be the only instructional focus for the entire year. Within a RTI framework, instructional leaders can use indicators of student knowledge on letter naming, letter sounding, and phonemic awareness to create differentiated groups and targeted instruction. Increased student performance on these measures will be a likely result of targeting instruction and specific interventions to the level alphabetic knowledge and phonemic awareness skills in each group. In addition to providing interventions to students as identified by performance on reading CBMs, my findings for Research Question 3 invite the possibilities to target interventions to students with disabilities, students learning English, and students experiencing poverty at the pre-kindergarten age.

Student growth and educator evaluation. CBMs can be used as indicators of student achievement. Technical research on reading CBMs supports the use of CBM data to make instructional decisions (Lai, et al., 2010). Using CBM data to check for progress among subgroups may in some cases promote equity. Student CBM scores should not vary based on race/ethnicity or free/reduced meal eligibility. Performance variation baed on these indicators would be evidence of inequitable gaps in student achievement, and a school's effectiveness at reducing these inequities could be measured in part using disaggregated CBM data. However, administrators must exercise caution when guiding teachers to use CBMs to establish student learning and growth goals (SLG Goals). Students with a designated disability might not be expected to show the same growth patterns as students without disabilities. The same is true for students learning English; the relations between early reading skills may not hold the same pattern for all groups of students over the entire school year. When tying student performance on CBMs to SLG Goals and principal evaluations, districts must exercise extreme caution.

Equity. The influence of nonperformance variables on WRF in kindergarten shows the impact of inequities present among the student population during kindergarten. It is necessary to consider how assessments are functioning within a district from the perspective of accountability for student subgroups. If assessments are showing a large degree of variance due to nonperformance indicators, and if this variance is not similar between districts, then it is likely that there are other factors that are influencing student performance on the assessment. It is on these variables that schools must focus in order to decrease discrepancies in achievement among subgroups.

Future Research

The conclusions from my research questions invite possibilities for future research on the role of early reading skills and the predictive relationships between CBMs for students from different subgroups. The moderate correlations observed between alphabetic knowledge, phonemic awareness, and word reading fluency in kindergarten are a starting point for further research questions. In the sections to follow, I describe future research possibilities generated from discussion of my results.

Study Design and Methods. The population of my research included half-day kindergarten students from one school district in Oregon. Future studies should examine the relations between reading CBMs among students attending full-day kindergarten. I used a static model to examine relations among early reading skills, and future research could consider student growth on alphabetic knowledge and phonemic awareness skills in relation to word reading fluency. The benefit of considering growth on certain skills would be to be able to describe changes in performance for students receiving scores of 0 on CBMs at the start of the year. Also, repeating the study in other districts with different demographic characteristics would increase the external validity (generalizability) of my findings to the diversity of communities in Oregon. Statewide, it would be relevant to consider the role of early reading skills on reading fluency in kindergarten. Expanding the scope of this study to include all districts using CBMs would expand the applicability of the findings.

In addition to expanding the populations studied, practitioners may benefit from increasing knowledge about the role of early reading skills on fluency indicators measured later in elementary school. Researchers have demonstrated a connection between early reading skills and reading outcomes in elementary and secondary school (Adolf et al., 2010; Bowey, 2004; Cunningham et al., 1997). Repeating my study with the outcomes of word reading fluency beyond kindergarten would support practitioners in designing a continuum of curriculum and instruction.

Alphabetic knowledge, phonemic awareness, and fluency. My first and second research questions both included Spring Word Reading Fluency as the outcome measure. Creating an additional regression model using this data with Winter Word Reading Fluency as an outcome and fall reading skills as predictor variables would show practitioners which skills are most important for students to have mastered by the middle of the year in order to be on track to meet spring benchmarks in reading. Furthermore, finding out the early reading skills that predict fall scores in alphabetic knowledge and phonemic awareness would provide insight to early childhood practitioners working with students before kindergarten. Lonigan et al. found (1998) that phonemic awareness is an aspect of the construct phonological sensitivity. In concert with this finding, it is relevant to inquire about the early literacy constructs that predict performance on phonological awareness CBMs. Future research may lead to the development of phonological awareness screening items for the pre-kindergarten population.

Population and subgroups. I included the third research question in order to probe the relations between nonperformance demographic characteristics and student achievement in kindergarten. Although I found that special education status and English learner status both contributed significantly to the model predicting WRF scores in spring, I did not inquire as to the role of specific disability codes on student performance. Future research is needed to examine the impact of specific learning disabilities early reading skills. This research would be relevant for practitioners to be able to progress monitor students with specific disabilities, with confidence that the results correspond meaningfully to probabilities of achieving year-end outcomes.

English learners. In addition, research to uncover student growth rates among the English Learner subgroup would support practitioners in making decisions within an RTI framework. Future research may find out more about the English reading development of speakers of languages other than English, and help establish indicators by which practitioners can measure likelihood for risk of not meeting grade level expectations in reading. As students gain proficiency in the English language, it may be the case that the relative importance of each reading skill changes, and that these patterns differ from trends observed among children whose first language is English. Designing inclusive systems for instruction and intervention incorporates disaggregating assessment data.

There are opportunities to investigate the impact of poverty on student achievement using different methods and constructs. I used the free/reduced meals eligibility variable to approximate poverty, and found this to have only a slight contribution to student performance on the word reading CBM. Future research should address other ways in which poverty impacts student achievement, and ways to effectively allocate resources to alleviate these impacts before kindergarten. New models for traditional elementary Title programing may develop as a result of research linking risk and achievement in early childhood.

Linking academic and demographic variables. I measured the relations between academic predictors and Spring WRF separately from nonperformance indicators and Spring WRF. A possibility for future research is to include both academic and demographic variables in the same regression model. Including both types of variables in the same analysis with word reading fluency as the outcome would show the relative contributions of each variable when entered simultaneously. Additionally, there are future research opportunities to test for interactions among the variables. It is possible that the correlations observed among nonperformance indicators represented an interaction of variables in which certain combinations of factors predict Spring WRF with a higher probability than other factors.

Curriculum and instruction. My research questions addressed the role of assessments in predicting word reading fluency in kindergarten without reference to specific curriculum or instruction. There exist possibilities to direct research towards the effects of different instructional strategies, interventions, and core reading curricula on student outcomes on CBMs. In particular, it is in the interest of equity to ask about the role of various interventions on increasing performance for students with disabilities and students learning English. Future research can measure the impact of curricular choices on student achievement.

One consideration in evaluating student outcomes on CBMs may include the relative impact of the differences in quality of teaching on student performance. Additionally, fidelity of implementation to multi-tiered systems of support among schools in the district may impact the relations among student performance on CBMs. Future research should measure such variables as the use of instructional time as related to student outcomes on CBMS and fidelity of implementation of curricular interventions tied to the CBMs. The measuring of fidelity of implementation should be across the multi-tiered systems of support in instruction and intervention, and the impact of differences in fidelity have on student outcomes as measured by CBMs.

Conclusion

Promoting reading fluency for all students by third grade is an expressed priority of the state of Oregon (Oregon Department of Education, 2009). It is a matter of social justice that educational systems align to promote this goal equitably for all students across the state. Systematically examining student achievement data is a component of effective educational decision-making. My study added to the body of research on the relations between early reading skills and the use of interim CBMs to mark student progress toward the outcome of fluent word reading in kindergarten. Results of my study added to the body of prior research on early reading skills and assessment in early childhood.

The population I studied included the kindergarten students in a mid-size suburban school district in Oregon. All the students in my study participated in the half-day kindergarten program. I used three linear regression models to explain the relationships between reading CBMs, nonperformance indicators, and word reading fluency for these students. I found moderate correlations between alphabetic knowledge, phonemic awareness, and word reading fluency variables. My research confirmed prior research showing moderate relationships among early reading skills (Castles & Coltheart, 2004; Ehri et al., 2001).

Moreover, the results of my study can inform system leaders and practitioners in both elementary and early childhood education settings. Instruction in kindergarten must include alphabetic knowledge, letter sound knowledge, phonemic awareness, and word reading. Students who are not making adequate progress toward mastery of these skills should receive an adjustment to instruction or intervention. Interventions targeting students with disabilities and English learners are likely to impact achievement for students in these subgroups, because these variables contribute significantly to student outcomes and, unlike poverty, can be addressed at the school system level. The combination of alphabetic knowledge, phonemic awareness skills, and student nonperformance indicators are significant predictors of student word reading fluency.

APPENDIX A

SAMPLE CBM STUDENT AND ASSESSOR FORMS

Sample Student Copy-English Letter Sounds

s	D	m	M	H	b	o	k	S	c
p	h	e	Z	O	U	z	n	A	T
g	J	t	G	N	I	a	r	L	y
k	f	I	th	Sh	Ch	z	qu	sh	wh
u	w	v	Th	ch	V	Ph	E	g	F
f	ph	s	i	X	R	Y	K	u	P
d	c	k	S	o	H	b	M	D	m
r	n	T	A	U	z	O	e	Z	h
a	y	r	L	g	I	G	t	N	J
t	sh	qu	wh	z	Ch	th	I	Sh	f
Ph	V	u	E	g	F	w	v	Th	ch

Figure A.1. Letter Sound Identification Assessor Form

Sample Student Copy—English Letter Names

o	X	A	s	O	B	E	a	T	x
e	r	Z	S	L	t	R	N	p	C
m	D	P	n	F	I	M	f	K	i
k	c	G	v	z	W	U	h	Q	u
w	y	l	V	d	J	b	j	q	A
T	a	O	s	X	o	B	x	A	E
Z	L	N	r	S	p	t	e	C	R
K	M	F	P	m	i	f	I	n	D
W	h	u	v	c	k	G	z	U	Q
A	y	g	j	b	d	J	V	l	A

Figure A.2. Letter Name Identification Student Form

Item	Teacher Says	Student Says	Number Correct
16	straight	/s/ /t/ /r/ /aigh/ /t/	_5_ / 5
17	first	/f/ /ir/ /s/ ~~/t/~~	_3_ / 4
18	lamb	/l/ /a/ /mb/	_2_ / 3
19	bide	/b/ /i/ /de/ s	_3_ / 3
20	soak	/s/ /oa/ ~~/ks/~~	_2_ / 3
21	mess	/m/ /e/	_0_ / 3

Figure A.3. Phoneme Segmentation Assessor Form

the	or	will	number
of	about	remain	no

Figure A.4. Word Reading Fluency Assessor Form

APPENDIX B

DISTRIBUTION OF FALL, WINTER, AND SPRING ASSESSMENTS

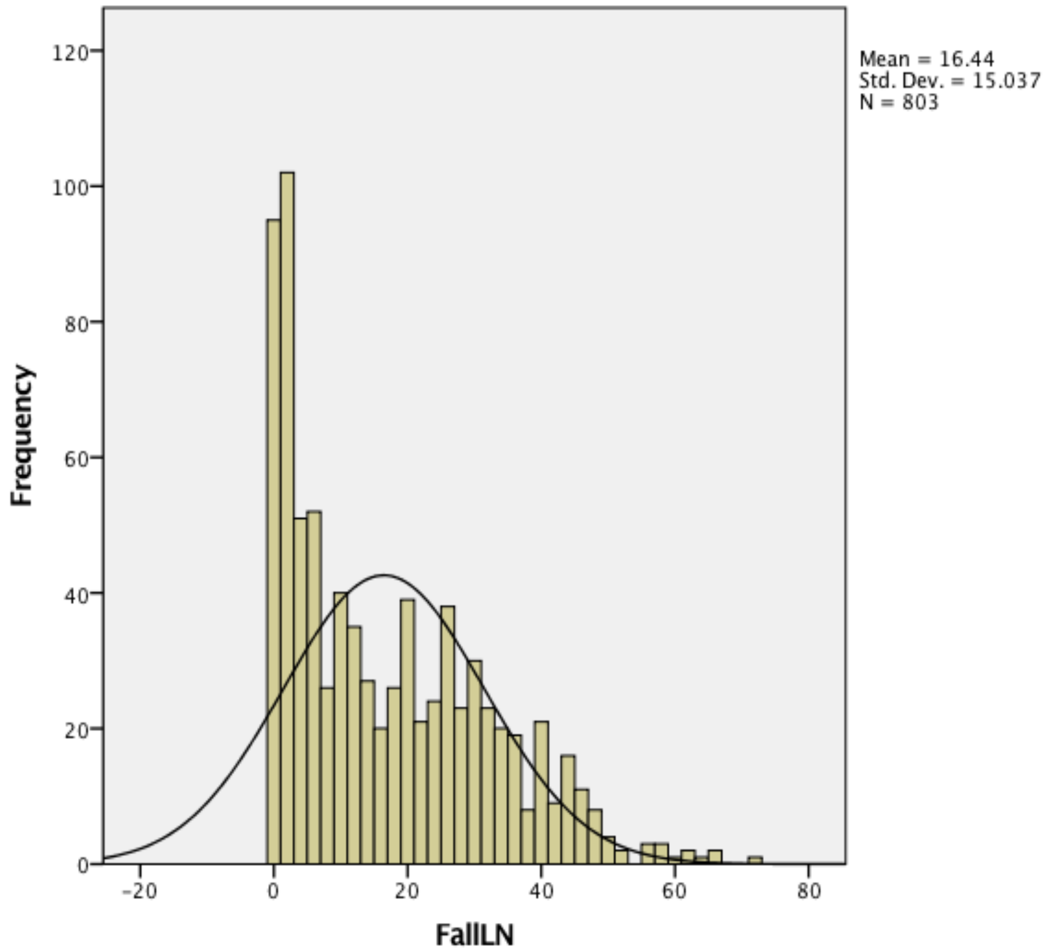

Figure B.1. Fall LN Distribution. The Mean, standard deviation, and number of cases are included.

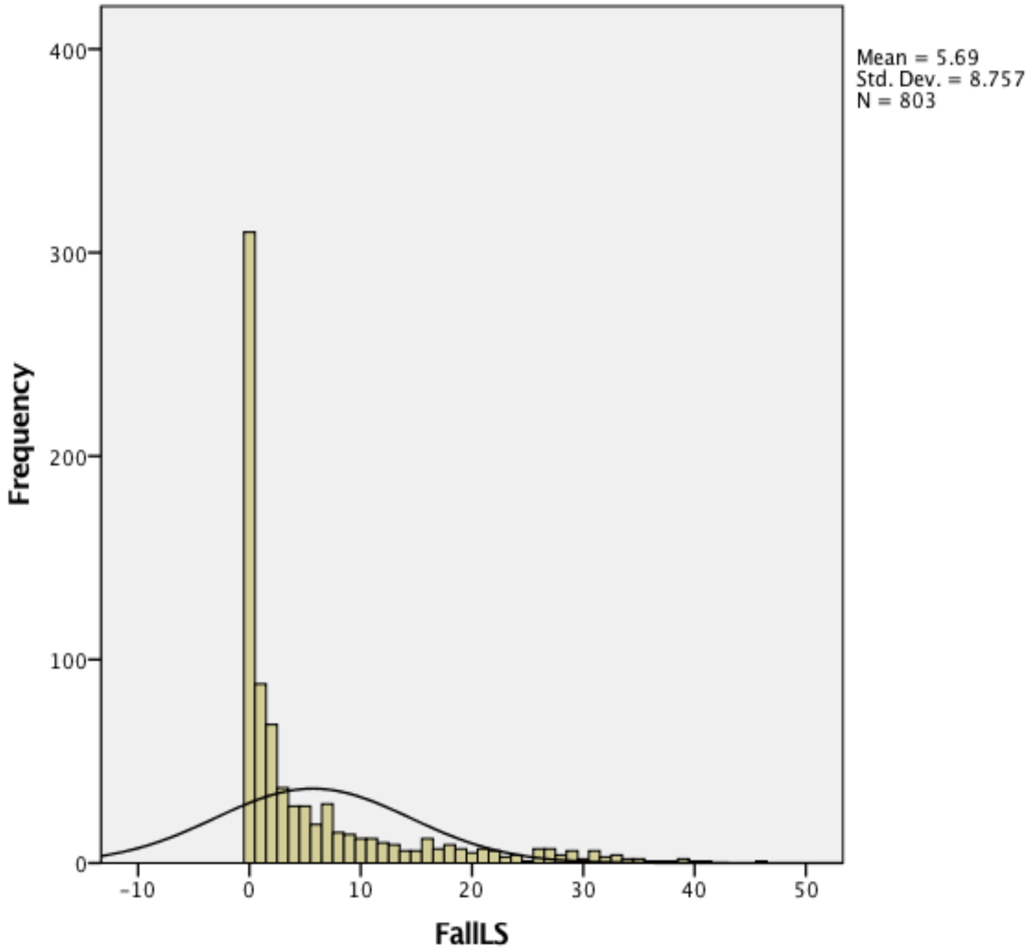

Figure B.2. Fall LS Distribution. The Mean, standard deviation, and number of cases are included.

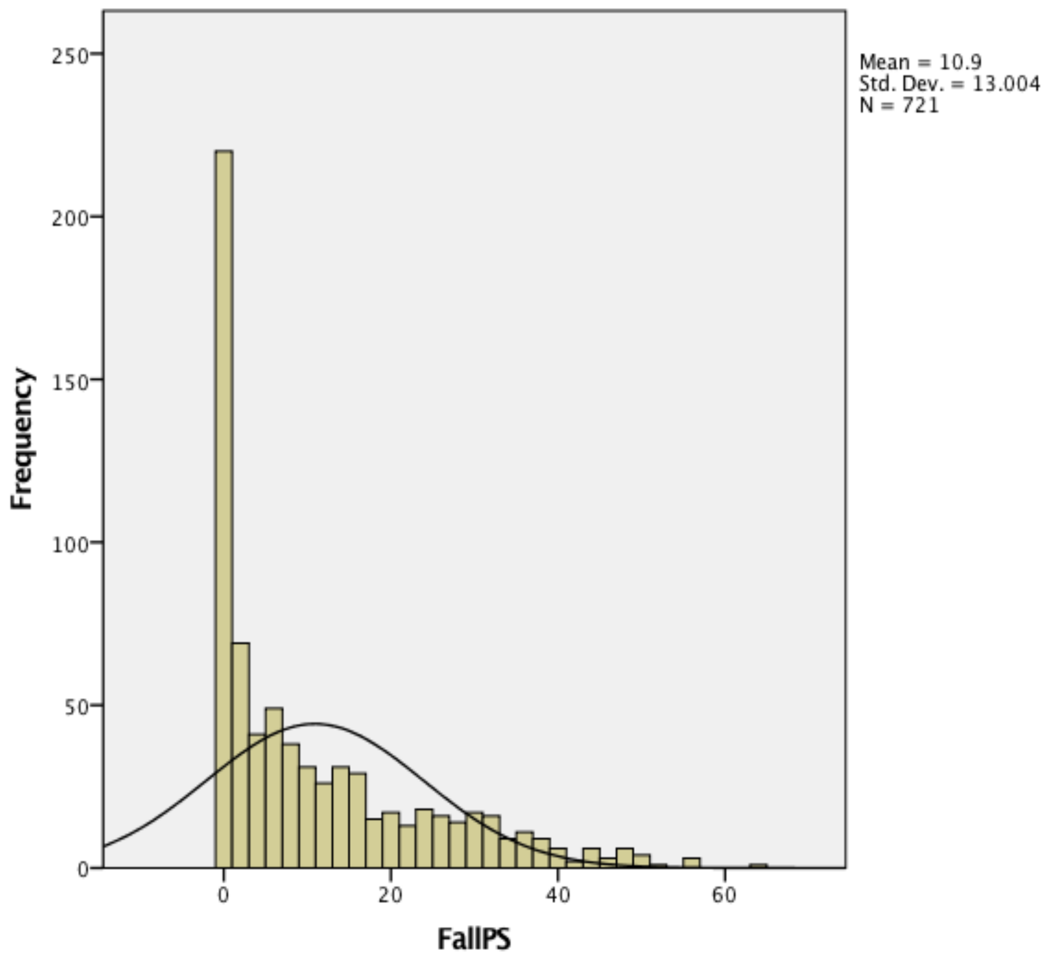

Figure B.3. Fall PS Distribution. The Mean, standard deviation, and number of cases are included.

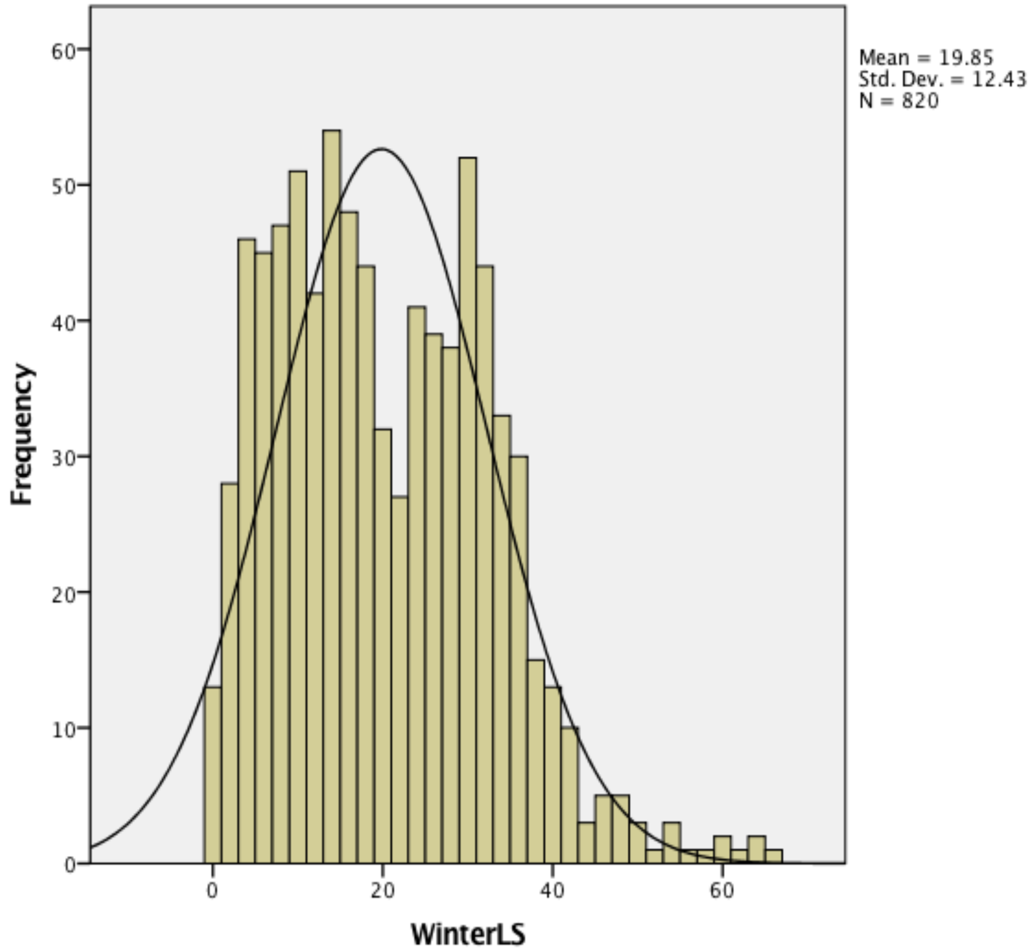

Figure B.4. Winter LS Distribution. The Mean, standard deviation, and number of cases are included.

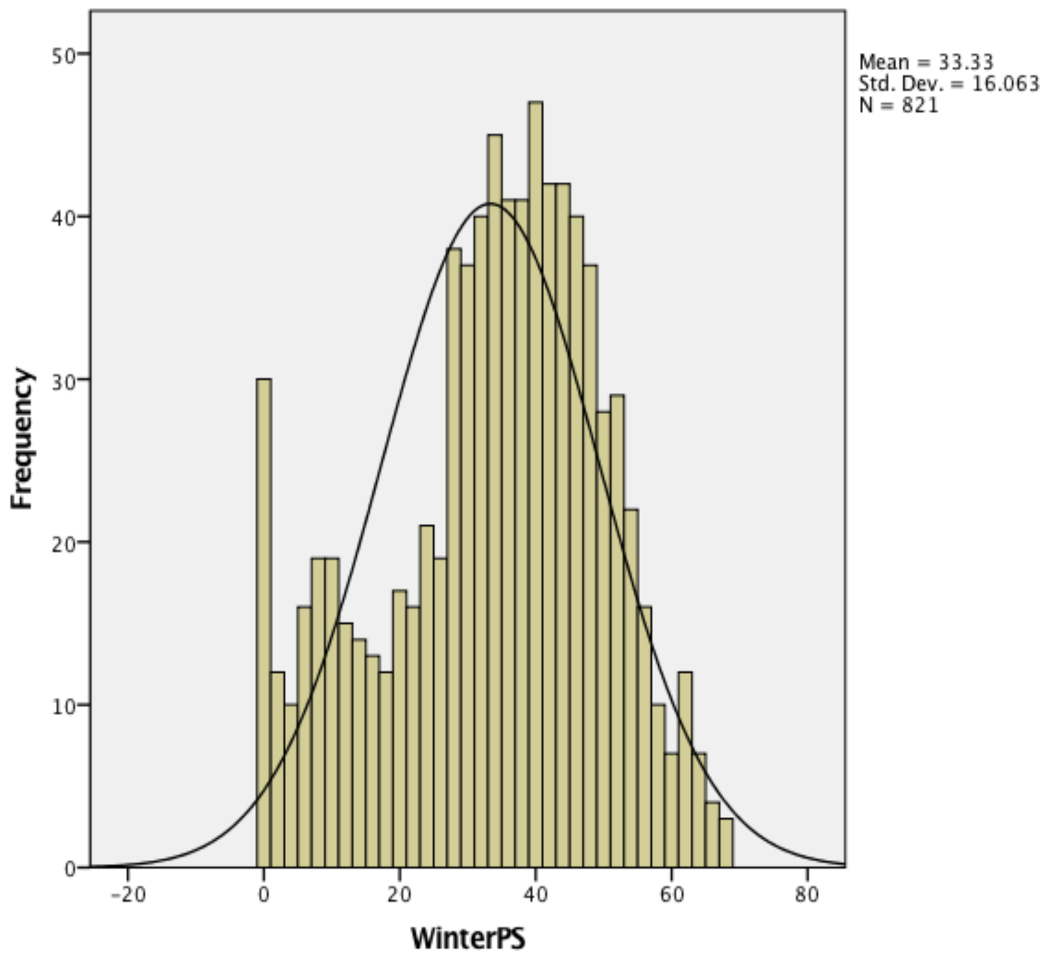

Figure B.5. Winter PS Distribution. The Mean, standard deviation, and number of cases are included.

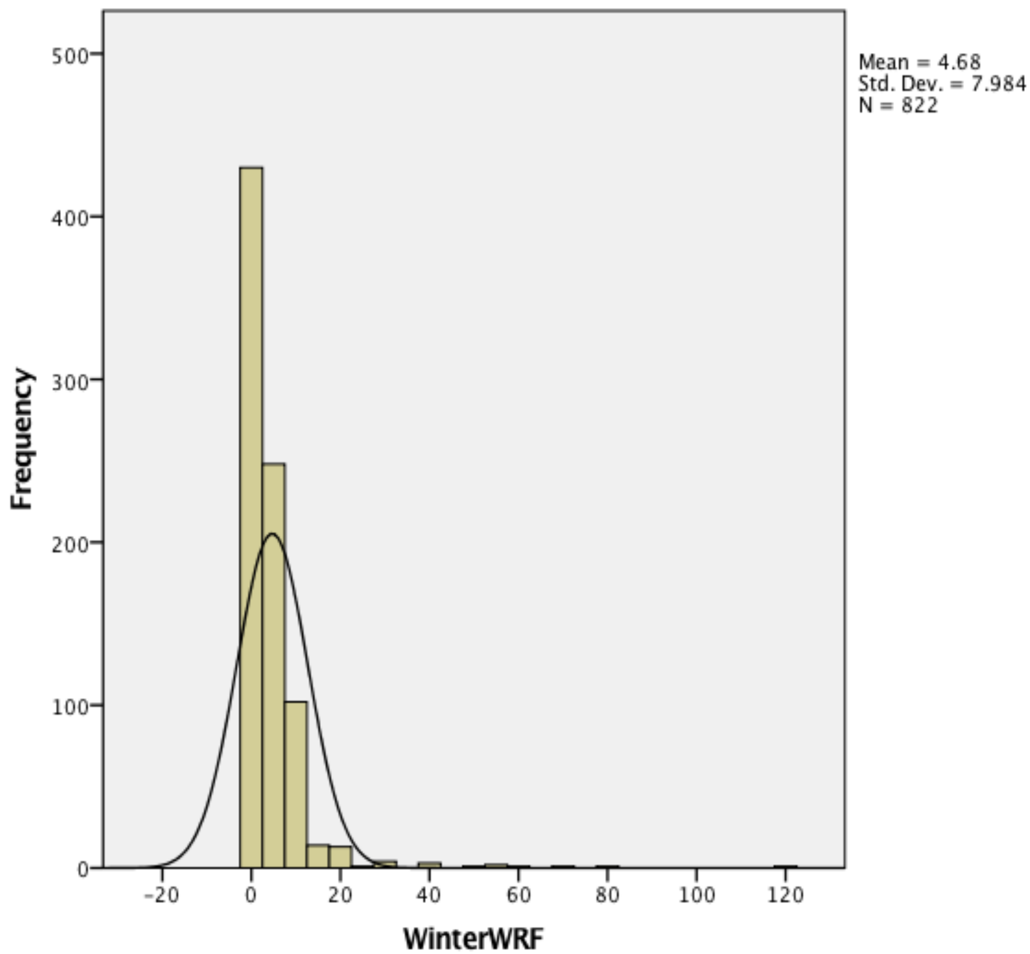

Figure B.6. Winter WRF Distribution. The Mean, standard deviation, and number of cases are included.

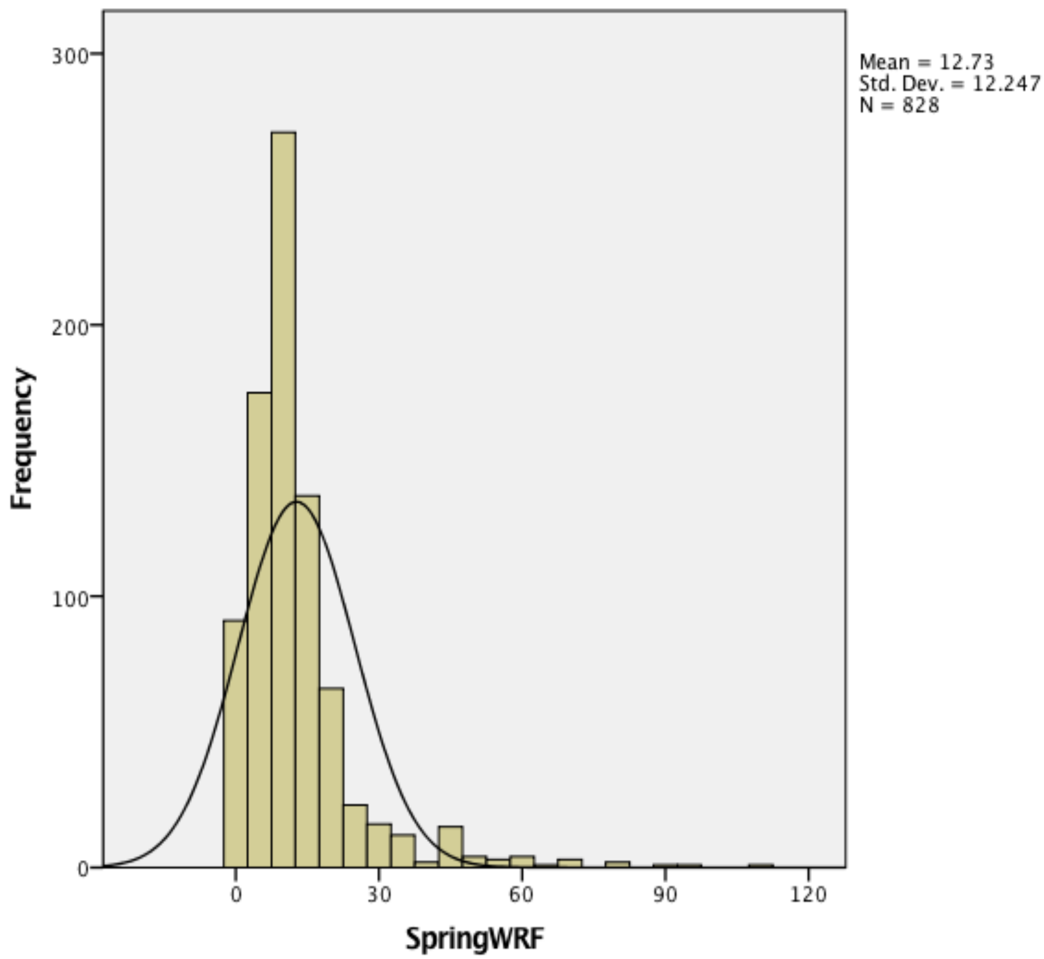

*Figure B.7***.** Spring WRF Distribution. The Mean, standard deviation, and number of cases are included.

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