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Who Comes Back? Exploring Reengagement within the School Year

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Who Comes Back? Exploring Reengagement within the School Year

by

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B.A., Wilfrid Laurier University, 1993

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A thesis submitted to the

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This dissertation entitled:
Who Comes Back? Exploring Reengagement Within the School Year?
Written by Heather Lorraine MacGillivray
has been approved for the School of Education

Dr. William Penuel, Co-Chair

Dr. Kenneth Howe, Co-Chair

Date_____

The final copy of this thesis has been examined by the signatories, and we find that both the content and the form meet acceptable presentation standards of scholarly work in the above mentioned discipline.

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MacGillivray, Heather Lorraine (Ph.D., School of Education)

Who Comes Back? Exploring Reengagement Within the School Year?

Thesis directed by Professor William Penuel & Professor Ken Howe

Engagement, dropout, and reengagement within the school year are explored using records and survey data for students in grades seven through twelve. Reengagement is defined as returning to school after an episode of dropout and remaining continuously enrolled until the end of the school year. An episode of dropout is considered to be 20 consecutive unexcused absences. The inquiry explored factors that differentiate students who reengage from end-of-year dropouts or students who never return to school. Using both descriptive and predictive analyses, three key findings emerged. First, students who reengage after an episode of dropout have higher proportions of behavioral incidents, enrollment in low-track coursework, being overage for grade and the lack of course failure. Second, the only school-level predictor of significance in predicting reengagement is the school performance rating. Third, the results from this research are not consistent with existing literature about between-years students who reengage two to twelve years after dropping out. This research details the challenges of using with-year data, drawbacks of using advanced modeling techniques with limited data, and potential misuses of early warning systems. The research was exploratory and as such has substantial limitations including extensive missing data and measurement concerns with the student survey. In spite of the challenges, limitations and weak predictive models, continued research is recommended in this area because little research is available about what factors predict student reengagement with school. More research is needed to understand reengagement with school in order to close resistant racial and socioeconomic achievement gaps.

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CHAPTER I

INTRODUCTION

Our greatest weakness lies in giving up. The most certain way to succeed is to always try just one more time.

~Thomas A. Edison

In the United States, one-third of students who start the ninth grade do not obtain a traditional high school diploma (Barton, 2005). High school dropouts are more likely to have negative life outcomes, including a lack of post-secondary education, substance abuse issues, lower wages, periods of unemployment, welfare dependency, and incarceration (Catterall, 1985; Chavez, Oetting, & Swaim, 1994; Ekstrom, Goertz, Pollack, & Rock, 1986; Elliott, Huizinga, & Ageton, 1985; Rumberger, 1987).

Dropouts are costly. Some estimate that each high school dropout costs society \$200,000 dollars over a lifetime in public health and welfare expenditures, and aggregated can cost a large city \$3.2 billion in lost tax revenues (Catterall, 1985; Vernez, Kropp & Rydel, 1999). These costs are estimated assuming a healthier economic climate than we are currently experiencing. With a shrinking job market and poor youth employment opportunities, we might theorize that it is a critical time to incentivize adolescents to return to school in order to prevent delinquent behaviors.

Recently, student engagement has been promoted as essential to academic achievement and the key to preventing chronic absenteeism and dropout (Arreaga-Mayer & Perdomo-Rivera, 1996; Connell, Spencer, & Aber, 1994; Finn, 1989; Fredericks, Blumenfeld, & Paris, 2004; Furlong, Whipple, Jean, Simental, Soliz, & Punthuna, 2003; Henry, Knight, Thornberry, 2012; Libbey, 2004; Marks, 2000; Skinner, Wellborn, & Connell, 1990; Wang & Eccles, 2011). *The Handbook of Research on Student Engagement* (Christensen, Reschly, & Wylie, 2012)

defines student engagement as more than simply “academic-engaged time” and includes aspects of emotion, behavior, and cognition. Emerging concepts of student engagement have led the field to question the construction of dropping out as a one moment-in-time, irreversible event. Instead, it is better understood as a cycle of disengagement and reengagement (Berliner, Barrat, Fong, Shirk, 2008; Chan, Kato, Davenport & Guven, 2003; Christenson, Sinclair, Lehr & Godber, 2001; Ross & Gray, 2005; Suh & Suh, 2004; Wayman, 2001, 2002). Student engagement is not only critical for student success but it is recognized as an important consideration in the dropout prevention, intervention, and recovery field (Henry, Knight & Thornberry, 2012; Stout & Christenson, 2009; Wang & Eccles, 2011). Recovery or retrieval of dropouts occurs when students reenroll in the education process at either a traditional school setting or an alternative education option. Reenrollment can happen quickly, within weeks, or may take years. The current study focuses on reenrollment or recovery from dropout within the school year after a minimum of 20 days of consecutive unexcused absences. For the purposes of this dissertation, 20 days of consecutive unexcused absences is referred to as an ‘episode of dropout’, and returning to school for the remainder of the school year after such an episode is referred to as ‘reengagement’.

Recent legislation and corresponding accountability metrics create the need for early warning systems to flag students who may dropout. In addition to early warning systems for prevention, legislation and accountability systems were designed to encourage intervention with dropouts who are likely to reengage with school. Federal and state accountability metrics include on-time graduation rates, which are part of district and school performance frameworks. New technological investments in state longitudinal data systems create opportunities to track within-year data and to monitor students across districts, (see <http://nces.ed.gov/programs/slds>).

Reengagement of students is a positive goal for schools and districts to promote, in addition to preventing dropout and truancy.

Many practitioners see an unmet need for the early identification of students who are disengaging from school (Colorado Department of Education, 2009; National Council of LaRaza [NCLR], 2009). To that end, there has been a great deal of effort to develop early warning systems for schools to identify potential dropouts or students who are not on-track for on-time graduation (Allensworth, & Easton, 2005; Balfanz, Herzog, & MacIver, 2007; Heppen & Therriault, 2009). Forewarnings help schools and districts provide targeted interventions (Stout & Christenson, 2009). Four national groups have been leading the early warning field:

- the Consortium on Chicago School Research;
- the Center for Social Organization of Schools at Johns Hopkins University;
- the National High School Center; and
- Achieve, Inc.

Each of these groups has proposed similar indicators for being on-track to graduation and, importantly, their sources of data are almost exclusively culled from year-end school data systems. Consequently, the early warning systems developed from their work are based on between-years data and focus on predicting dropout. The current study provides an empirical basis for predicting within-year reengagement after an episode of dropout – a unique contribution to the field. Furthermore, understanding factors that predict within-year reengagement allows schools and districts to intervene earlier to keep students in school. Even if interventions are provided after a student drops out, such as GED completion or employment, students' opportunities are significantly limited by not obtaining a traditional high school diploma. Reengagement is ethically right for kids because it provides an on ramp back to a

potentially more successful future. Moreover, since all states use a cohort model for calculating graduation rates for school and district accountability frameworks, reengaging students helps schools and districts meet the demands of high-stakes accountability.

Conceptualizations of reengagement can be derived from the engagement and dropout recovery literature. Reengagement is defined as continuous enrollment, GED acquisition, or high school graduation after dropping out of school. Each of these outcomes is potentially significant but at different times in a student's educational pathway. Compared to simple re-enrollment or student seat time, authentic student engagement insulates students from later dropout and is hypothesized to increase student's pursuit of post-secondary education (Reschly & Christensen, 2012). However, there is limited research exploring the processes of reengagement, especially within a given school year. The proposed research addresses the following research questions:

1. What are the patterns of episodic dropout within the school year at a large, mountain-west school district?
2. What factors predict the successful reengagement of dropouts within the school year? Specifically,
 - a. Controlling for ethnicity and poverty, how does having a behavioral incident, being overage for grade, being in remedial course work or having a course failure predict reengagement?
 - b. Controlling for ethnicity and poverty, do the two specific school-level climate factors of affective engagement; school connection and staff student relationships, predict reengagement?

- c. Controlling for ethnicity and poverty, do three specific school-level climate factors of behavioral engagement, perceptions of safety, discipline practices and school participation, predict reengagement?
 - d. Controlling for ethnicity and poverty, do three specific school-level climate factors of cognitive engagement; perceptions of academic challenge, teacher feedback and future aspirations, predict reengagement?
 - e. Controlling for ethnicity and poverty, does a school's performance on state accountability frameworks predict reengagement?
 - f. Controlling for ethnicity and poverty, and based on results of Models addressing questions 2a through 2e, what combination of student-level and school-level factors best predict reengagement?
3. How does this exploratory study explain distinctions between reengagers and those who do not reengage with school?

The remainder of the dissertation is divided into four parts: literature review, method, results and discussion. In the literature review, a conceptual framework situates the study in accountability policies and educational equity issues, followed by an in-depth description of predictors of reengagement. The methods section describes how district data were used to identify the factors that predict reengagement after an episode of dropout but within the school year. The results section provides a description of district data to help understand the nature of dropout and reengagement. Additionally, factor analysis was used as a tool for lowering the number of distinct unobserved variables for use in the logistic regression modeling to predict reengagement within the school year. Finally, the discussion section suggests potential explanations for the results from an educational policy framework.

CHAPTER II

LITERATURE REVIEW

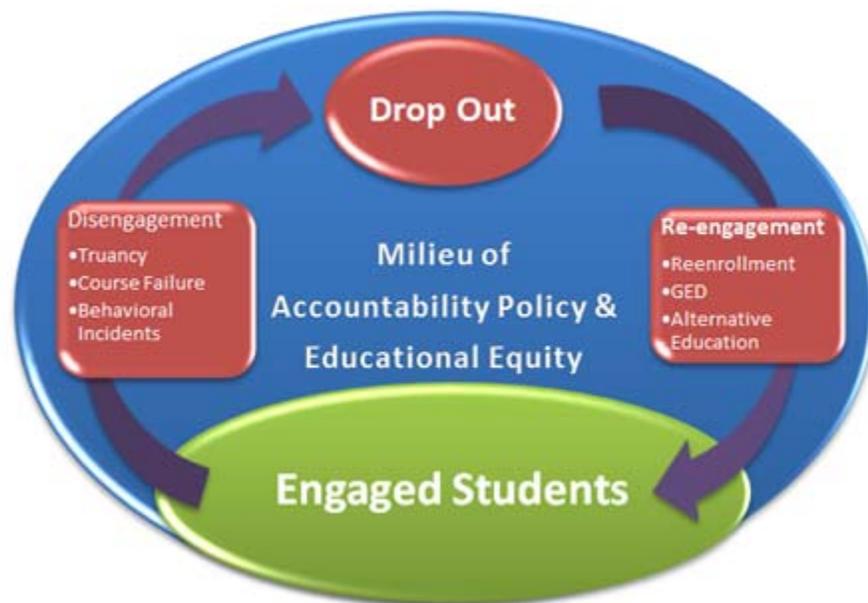
The purpose of my dissertation is to understand reengagers and how they are different from long-term dropouts using data available in school district systems. While we do not have rich literature on reengagement, an abundance of research is available on dropping out. The hope is to identify predictors of students who will reengage and to develop warning systems for students who are likely to experience long-term dropout. To that end, key terms need to be defined. First, end-of-year dropout is defined as students who are coded as dropouts at the close of the school year or during the summer clean-up of district data. Episodic dropout is characterized by an extended unexcused absence from school, which is distinguished from statutorily defined habitual truancy in terms of the length of absence and is restricted to consecutive days absent.

State statutes for habitual truancy are typically four unexcused days in a month or 10 unexcused days in a calendar year. These days accumulate across periods and/or days and habitual truants may still be attending some classes or days. My logic for defining episodic dropout as 20 consecutive days of unexcused absence is that, at some point, a student is not merely absent but has effectively dropped out; whether she is coded by the school as continuously enrolled or not. Furthermore, all students included in this study are chronic truants; therefore, habitual truancy does not sufficiently set apart the two groups.

Another important conceptual distinction made in this dissertation is the differentiation of between-years reengagement from within-year reengagement. Between-years reengagement is defined as students who are end-of-year dropouts but reengage in the following school year. The focus of this study is within-year reengagement, which is defined as reengagement prior to the end of the year after an episode of dropout (20 days consecutive of unexcused absence).

The conceptual framework in Figure 1 describes the theoretical basis for my literature review. Engaged students comprise the largest circle because the majority of students in America, probably two thirds, are engaged with the educational process. Continuously enrolled students are not the focus of this inquiry. Instead, my purpose is to compare students who reengage after an episode of dropout to those who do not. Although much literature has compared dropouts to continuously enrolled students, my dissertation breaks from this tradition to focus solely on students who cycle through one or all stages of disengagement, dropout, and reengagement in the hope of deepening our understanding of how these two groups differ. Figure 1 depicts the dropout cycle as occurring within the milieu of accountability policy and continuing concerns about educational equity.

Figure 1. Conceptual Framework



The Current Accountability Milieu

Recent federal and state policies have established a need to identify students who reengage within the school year. No Child Left Behind (NCLB) created mandates for student

performance and on-time, adjusted-cohort graduation rates. The American Recovery and Reinvestment Act of 2009 (ARRA) and Race to the Top (RttT) funding enticed states to implement substantial reforms connecting student engagement and performance to high stakes accountability for districts, schools, and teachers.

No Child Left Behind (NCLB). NCLB accountability policies increased the incentive to retain students throughout the school year as a result of three mechanisms: student absenteeism decreases performance on standardized tests that are the basis for accountability indices (Caldas, 1993; Lamdin, 1996); graduation rates and dropout rates are included in school accountability frameworks; and states are required to meet 95% participation rates to meet their annual yearly progress requirements (AYP). Therefore, even if schools and districts are not motivated to reengage students from a moral imperative, promoting within-year reengagement is still prudent from an accountability standpoint.

However, policy levers play out in more complex ways than well-intentioned policy makers might foresee. About the time that states were fully implementing NCLB's required accountability frameworks, events in the Houston Independent School District (HISD) eroded national trust in the accuracy of reported graduation rates, focusing attention on the calculation of both graduation and dropout rates and motivating districts to identify strategies for re-engaging youth in school. HISD was lifted up in the early stages of NCLB as an example of a district that benefited from an NCLB-like accountability system, particularly because they apparently raised test scores while increasing graduation rates for African American and Latino students (McNeil, 2005). In 2005, a whistle blower at HISD exposed the fact that twelve schools in the Houston Independent School District miscoded students as transfers instead of dropouts (Hursh, 2005). Subsequent research has confirmed this account and has further shown that that

students were ‘pushed out’, retained in ninth grade, advanced past tenth grade, or coded as transfers even though they dropped out in order to ‘game’ the accountability requirements (Vasquez Heilig & Darling-Hammond, 2008; Vasquez Heilig, 2007; Haney, 2002). By removing these low performing students from state tests and dropout calculations, it appeared that test scores and graduation rates were increasing. As a result, the National Governor’s Association created a compact declaring that these graduation metrics should include not only a cohort graduation rate but also an on-time graduation rate (graduating within four years).

True to the Texas Miracle on which it was fashioned, NCLB in its original form was eventually shown to encourage many school administrators to transfer, push-out or retain-in-grade low performing students thereby increasing the dropout rate and lowering graduation rates, especially for minority students (McNeil, Copplola, Radigan, Heilig, 2008; Shriberg & Shriberg, 2006; Darling-Hammond, 2006). Push-out practices were exacerbated when accountability frameworks were coupled with high stakes exit exams that require students to pass in order to matriculate or graduate (Haney 2002, Gotbaum, 2002). Others found that NCLB’s AYP provisos that held schools accountable for specific subgroups (e.g. minority students) actually widened the achievement gap between minority and white students (Orfield et al. 2004).

In response to the emergence of the detrimental impacts of NCLB on dropout rates, state and federal policy makers implemented three key changes. In 2008, revisions to the No Child Left Behind Act required all states to incorporate a four-year on-time graduation rate into their school accountability systems, necessitating continuous enrollment in school for all students by school year 2011-2012. Annual school accountability frameworks and on-time graduation rates encourage schools and districts to reengage students within the school year. Secondly, state policy makers heavily weighted their accountability frameworks with growth metrics as opposed

to solely achievement status. The intent was to reward schools for improvement. Some states now weight growth as high as 75% of the overall points on school accountability frameworks. Lastly, US Department of Education began accepting waivers, particularly waivers from the AYP provisos. Currently, over 44 states have a waiver from a variety of NCLB requirements. It is too early to gauge the impact of cohort graduation rates, NCLB waivers, and the inclusion of growth metrics on school practices regarding low performing students or dropouts looking to return to school. However, it is worth noting that each of these policy changes was designed to reduce push-out and support school reengagement.

American Recovery and Reinvestment Act of 2009 (ARRA). President Barack Obama's strategic policy direction for education was set through the ARRA and the Race to the Top (RttT) funding program administered by the United States Department of Education (ED). ARRA reinforced the need for reengagement practices not through the NCLB-like mandates but through funding enticements in the midst of an economic crisis. In 2009, 4.35 billion dollars in RttT funds were exceedingly attractive to states, resulting in over 40 states and the District of Columbia applying in Phase I. These 'stabilization funds' required states to make the following assurances: develop rigorous college and career ready assessments, establish longitudinal data systems to track students from preschool to college, improve teacher effectiveness, and provide supports to low performing schools (Center on Educational Policy, 2009). Participating states in the State Longitudinal Data Systems (SLDS) pilot are creating the infrastructure that will allow for more temporally sensitive, within-year data at the state educational agency than is currently being collected via annual submissions (see http://nces.ed.gov/programs/slds/grant_information.asp). This lays the groundwork for

temporally sensitive systems to monitor the progress of schools and districts, including early warning systems for within-year dropout and the potential for successful reengagement.

Colorado policy milieu. This dissertation study is based in a large school district in Colorado, and thus a brief overview of the enactment of national policies in Colorado is required. Colorado has been at the forefront of national policy developments. Colorado developed its own accountability frameworks prior to NCLB requirements. Colorado is a Phase III winner of RttT funds and one of 41 states to receive a waiver from NCLB. Colorado has received \$17 million to develop a State Longitudinal Data System (SLDS) with the intent to create a student centric collection system that captures real time information, aptly called a ‘data pipeline’ (Colorado Department of Education, April 11, 2012).

In Colorado, the District and School Performance Frameworks (DPF & SPF) incentivize within-year reengagement of students paralleling similar mechanisms established under NCLB; including student achievement and growth as well as graduation and dropout rates on annual accountability framework. Additionally, Colorado HB 09 -1243 set an ambitious goal of cutting the dropout rate in half by the 2017-2018 school year. To help meet this goal, the state recently created new metrics designed to measure precursors of dropout (e.g. truancy rates), changed the data submission process and the formula for calculating graduation rates.

The Colorado state house has also enacted many legislative policies to promote reengagement. In 1990, significant legislation was developed to prevent dropping out (Neumann, 1992). Almost 20 years later, in 2009, legislators developed policies to address reengagement: a concept that had not previously been defined (CDE, 2009). Recently, a staggering number of legislative changes occurred because of HB09-1243 entitled Concerning Measures to Raise the Graduation Rate in Public High Schools in Colorado. These changes include creating an Office

of Dropout Prevention and Reengagement at Colorado Department of Education (CDE) (C.R.S. §22-14-103); (re) defining dropout and reengagement (C.R.S. §22-14-102); demanding research and dissemination on best practices for dropout and reengagement (C.R.S. §22-14-104.3); encouraging collaboration across districts to create comprehensive interventions for dropout and reengagement (C.R.S. §22-14-104.2); and establishing a reengagement grant program of approximately fifteen million dollars (C.R.S. §22-14-109).

National and Colorado accountability policies have laid the foundation for a discussion of re-engaging youth in school. Specifically, NCLB, ARRA, and teacher effectiveness legislation have created the necessity to keep students continuously enrolled in order to meet high stakes mandates. Arguably, these accountability policies have been enacted to effect educational equity and close achievement gaps for low-income students and students of color.

Educational Equity

Student engagement, dropout, and graduation rates are beset by racial and socioeconomic (SES) disproportionality and to a lesser extent, disproportionality related to gender, with males only “slightly more likely” to dropout (Rosenthal, 1998 as cited in Christenson, Reschley & Wylie, 2012). African American and Hispanic students are disproportionately less engaged and tend to be more alienated in the classroom environment than white or Asian students (Yair, 2000). Students of color disproportionately drop out of school compared to their white counterparts (Orfield, 2004). Numerous researchers have used data from the Common Core Data (CCD) to examine a sample of the largest school districts in the country. Although results differ, all indicate minority under-representation in the graduating population (Balfanz & Letgers, 2004; Greene, 2001; Swanson, 2004). According to the Current Population Survey (CPS), the graduation gap shrinks when we look beyond the traditional high school years but remains substantial and concerning (Mishel & Roy, 2006). These data suggest that students of color may

reengage in school later than the four-year high school window and in alternative educational settings.¹

Because students of color drop out at higher rates, reengagement with school is a necessary step toward closing the achievement gap and thereby increasing educational equity. The achievement gap is mediated by adolescent identity development and resiliency in spite of systemic disadvantage (Spencer, 2008). The discomfort around issues of race and ethnicity prevalent in American culture plays out in educational settings where teachers may not acknowledge the diversity of students, beyond ‘heroes and holidays’, to include a deeper recognition of social injustice and the privilege of European American students (Spencer, 2008; Tatum, 1997, McIntosh, 1998). Resiliency can act as a protective factor to help students of color reengage quickly within the school year (Spencer, 2008). Positive risk taking behavior, such as returning to persist in a learning environment, facilitates success and can lead to a successful transition to adulthood (Spencer & Tinsley, 2008).

Reengagement

Reengagement refers to the path back to being an engaged student (see Figure 1) which is a more expansive definition than how reengagement is defined in this dissertation. Unfortunately, such an expansive definition is difficult to measure using available data especially when some engagement theorists include a student agency and ecological influences (e.g. peer, community, family aspects (Lawson & Lawson, 2013). However, the majority of the literature

¹ The Current Population Survey (CPS) is data collected by the U.S. Census Bureau for the Bureau of Labor and is consistently collected each month. As such, it is one of the only data set that can provide long-term trends on dropouts and completion rates (Kaufman, 2004).

describes between-years reengagement as returning to some kind educational experience - either to obtain a GED or a traditional diploma (Berkold, Geis & Kaufman, 1998; Berliner et al., 2008; Borus & Carpenter, 1983; Chan et al., 2003; Chuang, 1997; Lee & Ekstrom, 1987; Kolstad & Owings, 1986; Kolstad & Kaufman, 1989; McIver & Wang, 2011; National Center for Education Statistics (NCES), 2004; Suh & Suh, 2004; Wayman, 2001; Wayman 2002). Between-years reengagement has been broadly defined as re-entry, re-enrollment, retrieval, credit recovery, returning to school, or eventual school completion either by obtaining a GED or a high school diploma. I am focused on within-year reengagement defined as being coded 'continuously enrolled' in school at the end of the school year, 'transferred' to another education experience or 'graduated' because of achieving a traditional high school diploma. Each of these end-of-year statuses are reflected as codes in district data systems that can drive early warning systems and each reflect a desirable end-of-year educational outcome for a student who may be struggling with dropping out.

Between-years reengagement researchers typically followed students who dropped out and subsequently returned to schooling two to twelve years later (Berkold et al., 1998; Borus & Carpenter, 1986; Chan et. al., 2003; Kolstad & Owings, 1986; Kolstad & Kaufman, 1989; NCES, 2004; Wayman, 2001; Wayman, 2002). Although this work has framed dropping out as reversible and part of an identifiable life pattern (CDE, 2009; Christenson, et al., 2001; Balfanz et al., 2007; Suh & Suh, 2004; National Council of LaRaza, 2009), current research on between-years reengagement is so distant from the event of dropout, it is difficult to generate early warning systems for schools and districts useful for intervention.

Research on the correlates, causes, prevalence, and even the very definition of within-year reengagement with school is sparse compared to the literature on between-years dropout.

However, we know that the event of episodic dropout must precede reengagement, and so the current study attempts to distinguish between dropouts who reengage within the school year and those who do not.

Disengagement & Dropout

School disengagement may be conceived as a composition of many dynamic and interacting constructs such as detachment, disconnection from norms and expectations, lessened involvement, and withdrawn commitment to completion (Balfanz, Herzog, & MacIver, 2007). Disengagement is understood as occurring long before actual dropout. Latino youth who reenrolled in school after dropping out explained in focus groups that they had begun a process of ‘mental disengagement’ as early as elementary school (NCLR, 2009).

School disengagement is a series of conflicting factors (Balfanz et al., 2007). The factors of interest in this inquiry are those that facilitate reengagement, including persuasive, caring and persistent school staff, mandates from the courts (juvenile justice and child welfare), poor employment prospects, and the amelioration of the specific reasons for leaving (Berkthold, Geis, & Kaufman, 1998; Berliner et al., 2008; Ross & Gray, 2005). I hypothesize that factors associated with engagement draw students back to school. For example, strong student-teacher relationships may enable a student to approach a teacher with whom she has a strong connection in order to reenroll in school or resolve a conflict that may be a barrier to remaining in school. Aspects of school engagement, specifically affective, behavioral, and cognitive engagement are of interest in this study because engagement insulates students from dropping out.

Factors Predicting Reengagement

Within the body of research on between-years reengagement, many of the data sets used to identify predictors are representative samples from across the United States (NCES, 2004; Berkthold, Geis & Kaufman, 1998; Chan et al., 2003; Suh & Suh, 2004; Kolstad & Owings, 1986;

Kolstad & Kaufman, 1989; Borus & Carpenter, 1983; Lee & Ekstrom, 1987; Chuang, 1997), and both state and district data find similar factors associated with reengagement (Wayman, 2001, Wayman 2002; Berliner, 2008; McIver & Wang, 2011). Factors associated with between-years reengagement can be categorized as

- demographic (low socioeconomic status, minority status, and English Language Learners, overage for grade);
- academic (grades, credits, test scores, etc.); and
- related to school engagement (affective, behavioral and cognitive).

Student demographic characteristics (poverty, minority status & ELL). Consistent with the dropout literature, students from lower socioeconomic backgrounds are less likely to reengage in school (Chan et al., 2003; Berkold et al., 1998; Kolstad & Owings, 1986; Kolstad & Kaufman, 1989; NCES, 2004; Suh & Suh, 2004; Wayman, 2001; Wayman 2002). Students living in poverty may leave school to seek employment to support themselves and their families. Perhaps not surprisingly, students living in communities with high unemployment are more likely to return to school (Chuang, 1997). Low youth employment opportunities characteristic of an economic downturn could be considered a prime opportunity for educators to reengage dropouts and suggests that decision makers invest in reengagement interventions that connect education and employment.

Unlike predictors of dropout, which clearly indicate minority students are more likely to drop out, there is some disagreement regarding minority status and between-years reengagement. One study found that Hispanics are less likely to reengage with school and complete high school than African Americans or Whites (Kolstad & Kaufman, 1989). Another study found that students who are English Language Learners (ELL) and Hispanic are less likely to reenroll

(Berliner, et al. 2008). Most found a weak connection between minority status and reengagement especially when SES is controlled (Berkold et al., 1998; Chan et al., 2003 NCES, 2004; Suh & Suh, 2004; Wayman, 2001, 2002).

Explanations for minority student disengagement from school may include a lack of identification with the people and structures in schools (Tatum, 1997) or the lack of resiliency to persist in a system that privileges European American students (MacIntosh, 1990; Spencer, 2008; Spencer & Tinsely, 2008). Although similar mechanisms may apply to English language learners, another explanation may be that immigrant students may return to their home country for long periods to visit family before returning and re-engaging with school.

Retention in early grades is correlated with dropout and is often taken to be the basis for the correlation with being overage for grade and dropping out (Grissom & Shepard, 1989; Jimerson, 1999; Roderick, 1994; Stearns, Moller, Blau & Potochnick, 2007). Retention in middle school years is associated with failure to meet requirements to pass state assessments in order to move to the next grade level and subsequent increased dropout rates for retained students (Allensworth, 2005). Being overage for grade at the time of dropout may deter students from re-engaging with school due to increased employment opportunities available to older teens (Barro and Kolstad 1987; D'Amico, 1984; Pallas, 1987; 1984; Rumberger, 1983). Retention in elementary or middle school is a good indicator of eventual dropout but may not be associated with reengagement.

Academic factors. A strong predictor of between-years reengagement is academic performance as measured by grades, GPA, test scores, hours spent doing homework, and credit hours earned prior to dropping out (Chan et al. 2004; Chuang, 1997; Kaufman, 1989; Kolstad & Owings, 1986; NCES, 2004; Wayman, 2002). Course failure results in fewer credits earned and

has been identified with a higher likelihood of dropping out (Balfanz & Letgers, 2004; Balfanz et al, 2007; MacIver, Balfanz, & Byrnes, 2009). Additionally, timing of dropout has a consistent impact on reengagement. Students who drop out in the early grades, such as middle school or 9th grade, have less likelihood of returning to school than those who drop out in 11th or 12th grade. Overall, the higher the grade at the time of dropout, the more likely a student is to return to school (Berliner, 2008; Berktold et al., 1998; Chan et al. 2003; Chuang, 1997; Kolstad & Kaufman, 1989; Murnane, Willet & Tyler, 2000; Suh & Suh, 2004; Wayman, 2002). In fact, for each additional year of schooling, students increase their likelihood of completing school by 124% (Suh & Suh, 2004).

Relegating at risk students in remedial coursework as well as school wide tracking practices have long been associated with increased dropout rates (Quinn, 1991). Remedial programs often include scripted curriculum that may drive down student engagement and demotivate students. On the other hand, if done right, remedial coursework can help students retrieve lost credits and accelerate learning to ensure students are back on track to graduation. Closely related to remedial coursework is the systemic practice of enrolling students in low-track courses which is more prevalent among minority students and the perceived need for which is attributed to the recalcitrance of the achievement gap (Welner, Oakes & Lipton, 2005). Low-track, remedial courses of low quality may drive students to drop out of school due to lack of relevance and perceived future opportunity.

Academic factors may predict reengagement because students may be more likely to reengage with school if they stand a better chance of graduating (based on having more credits) or have experienced more success than failure. Perhaps, the longer a student is in school before

dropping out, the more likely she is to have peers who are actively engaged with school, the more credits she is likely to have, and the less effort it might take to graduate (Wayman, 2002).

School engagement factors. School engagement has been connected to academic achievement (Fredericks et al., 2004; Libbey, 2004), decreased dropout (Connell et al., 1994; Fredericks et al., 2004; Klem & Connell, 2004), avoidance of risk behavior (Connell et al., 1994; Furlong et al., 2003; Gottfredson & Hirshi, 1990), reduced disruptive behavior (Hudley, Daoud, & Hershberg, 2002; Klem & Connell, 2004), and higher self-perceptions of students' competence (Connell et al., 1994). In an extensive review of the literature, Fredericks et al. (2004) conceptualized school engagement as encompassing affective, behavioral, and cognitive components, in what was later termed a "multidimensional" view (Fredericks, 2011). Recent work has provided supporting evidence for the multidimensionality of school engagement as conceptualized by Fredericks et al. (2004, 2011) (Archambault, Jonosz, Fallu, Pagani, 2009b; Blondal & Adalbjarnardottir, 2012; Christensen, Reschly, & Wylie, 2012; Fall & Roberts, 2012; Wang & Eccles, 2011; VanRyzin, 2011).

Affective engagement. For the purposes of this study, affective engagement is conceptualized as connection to school, strong teacher - student relationships, and family support for learning.

Connection to school. Several descriptors have been identified as school connection including school belonging, student voice, peer relations, and liking school (Libbey, 2004). School connection has been identified with promoting educational resilience despite risk factors like high poverty, family dysfunction, mobility, or substance abuse (Wang, Haertel, and Walberg, 1997). Hirshi's (1969) landmark book *Causes of Delinquency*, presents an argument that a lack of school bonding breaks students' connection to conventional society and thereby

leads to delinquency behavior. Since that time, many researchers have found evidence of this link (e.g., Cheney, Abbott, Hawkins, Catalano, Neel & Peterson, 1997; Empey, 1982; Loeber & Farrington, 1998; Farrington, 1996; Thornberry, 1996). Van Ryzin (2011) identified student perceived academic autonomy and peer support as predictors of engagement, demonstrating that increasing autonomy and peer support generates a positive feedback loop resulting in beneficial engagement changes. One might expect that students are more likely to return to a school setting if they have some sense of emotional attachment and belonging, whether due to peers or teacher relationships.

Teacher-student relationships. Positive teacher-student relationships are a necessary precursor for engagement (Skinner, Wellborn, & Connell, 1990). Teacher-student relationships are founded on supportive teachers who show interest, provide positive praise, and facilitate students' inclusion in the school community; each of which positively affect student engagement (Fall & Roberts, 2012). Hattie's (2009) meta-analysis of teacher-student relationships identified nine variables that improve student achievement: empathy, warmth, adapting to differences, genuineness, learner-centered beliefs, encouragement of higher order thinking, and encouraging learning. Relatedness develops students' confidence, coping, and industriousness (Furrer & Skinner, 2003). Strong student-teacher relationships promote interest in classroom activities, the pursuit of learning goals, and obedience to classroom rules (Wentzel, 1997). Student-centered teachers have more engaged students as demonstrated by more respect, less resistance, as well increased student initiated activities (Cornelius-White, 2007). It follows that a student who has good relationships with teachers or other school staff may be more likely to reengage with school. Sixty percent of students who reengaged between school years attempted to re-enroll in

the school from where they dropped out by approaching a staff member with whom they had a positive relationship (Berliner et al., 2008).

Family support for learning. Family support, defined as talking with children about school related matters, is correlated with student engagement (Fall & Roberts, 2012). Positive parent interactions and support increases the likelihood of school completion (Chan et al., 2004). Family support for learning is associated with better academic success, improved behavior, higher enrollment in post-secondary education, safer school environments, and enhanced parent support for teachers and schools (Sanders & Epstein, 2000; Minke & Anderson, 2005). Building collaborative relationships between schools and families takes time and resources, but is worthwhile because it empowers parents to support their child's educational progress over the long-term (Minke & Anderson, 2005). For example, trusting, two-way communication establishes supportive relationships between parents and the school, enhancing the family's capacity to be a "life-long advocate" for their child. Families who are supportive of education and their child's learning are more likely to encourage students to return to school to reengage with the learning process.

Behavioral engagement. Behavioral engagement is often conceptualized in terms of what it is not. For example, the opposite of engagement has been identified as alienation, rebelliousness, or burn out (Furrer & Skinner, 2003). Others incorporate the importance of physical disengagement from school as evidenced by unexcused absences or severe behavioral issues (Brewster & Bowen, 2004). For the purposes of this inquiry, I define behavioral engagement consistent with Fredericks et al.'s (2004) formulation as obeying discipline practices as measured by recorded behavioral incidences resulting in in-school or out-of-school suspensions, experiencing a sense of safety, and school participation.

School discipline & sense of safety. School discipline and classroom management practices enable student engagement by providing structures for student behavior and reduction in discipline referrals. These strategies include clear rules, consistent expectations, and a well-structured but not overly structured environment (Fredericks et al., 2004). While students must understand unacceptable behavior, overly punitive and disciplined settings are associated with disengagement of at risk students (Finn & Voelkl, 1993). A balance is needed to create an environment that allows for self-pacing and student-directed learning (Wang et al., 1997).

Rules and consequences need to be explicit or students may perceive discipline as inequitable, partial or inconsistent, which can undermine strong relationships between students and school staff (Ripski & Gregory, 2009). Re-engaging students who have experienced conflictual or adversarial interactions with school authorities is likely to be difficult. Furthermore, students who fear for their safety due to bullying or other violence are unlikely to reengage with school.

Student attendance and participation. Recognized as an aspect of behavioral engagement, participation is defined as a student's classroom attendance, participation in extracurricular and social activities, taking initiative in classroom activities, and preparation for class or school (Appleton, Christensen & Furlong, 2008; Finn, 1989; Fredericks et al., 2004). Strong attendance and participation in school has been found to be negatively correlated with dropout and positively correlated with engagement (Appleton et al, 2008; Balfanz, Herzog, and MacIver, 2007; Betts, Appleton, Reschly, Christenson, & Huebner, 2010; Sinclair et al, 1998, 2003). If students who attend and participate in school are less likely to dropout, one might suppose that those same students are more likely to return to school because of the intrinsic reward that fueled their previous participation.

Cognitive engagement. For the purposes of this inquiry, cognitive engagement is defined as academic rigor, teacher feedback, and future aspirations.

Academic Challenge². Challenge is considered necessary for student engagement (Blackburn, 2008). Engaged students enjoy challenges posed by complex content and persist in their learning despite educational setbacks (Klem & Connell, 2004; Skinner & Pitzer, 2012; National Research Council and the Institute of Medicine, 2004). School climates that are challenging students include an “environment in which each student is expected to learn at high levels, each student is supported so he or she can learn at high levels, and each student demonstrates learning at high levels” (Blackburn, 2008, pp. 52). Academic challenge is imperative for a number of reasons: students are not prepared for high school or college, employers complain that graduates lack basic skills and are not workforce ready, and students bound for today’s high tech workplace need just as challenging curriculum as students bound for college (Achieve, 2007; ACT, 2007; National High School Alliance, 2006). Challenging activities and classroom content cultivate interest and without interest, students may not stay in school. One study found that almost half of dropouts left school because their classes were not “interesting” (Bridgeland, Dilulio, & Morison, 2006). While this may seem high, a lack

² Academic challenge is a component of the more holistic concept of academic rigor which is defined by Strong, Silver and Perrini (2001) as “developing the capacity to understand content that is complex, ambiguous, provocative, and personally or emotionally challenging.” (pp. 7). For the purposes of this dissertation, classroom rigor data was not available. However, student’s perception of challenging content is available and consequently, challenge is the concept of interest.

challenging class work diminishes students' motivation (Ryan, 1995). Challenging curriculum drives students back to school to reengage with learning.

Teacher feedback. Student engagement is increased by teacher feedback that is goal focused, about the task or the processing of the task, and connected to self-regulation strategies (Hattie & Timperley, 2007). Feedback about the student as a person (e.g. unspecified praise or compliments) is not conducive to deeper cognitive engagement or eventual achievement (Hattie & Timperley, 2007). Students respect teachers who challenge them, not simply praise them without corresponding high expectations. Effective teacher feedback should facilitate students' metacognition about their learning and be specific enough to help students to progress their learning (William, 2011). It follows that students are more likely to reengage in a school setting that provides this kind of rich learning environment.

Future aspirations. Future aspirations are defined as the intent to graduate and continue with post-secondary education. It is included as a sub-construct of cognitive engagement because qualities such as self-efficacy and motivation facilitate student cognitive engagement (Brewster & Bowen, 2004; Caraway, Tucker, Reinke & Hall, 2003; Hudley et al., 2002; Miller, Greene, Montalvo, Ravindran, & Nichols, 1996; Skinner et al., 1990). Miller et al. (1996) found that if students did not have a clear incentive for school success, they were less likely to engage with learning. However, strong personal factors predicting reengagement were high self-reported educational aspirations and expectations, as well as concrete post-secondary plans (Borus & Carpenter, 1986; Chan et al. 2003; Kaufman, 1989; Kolstad & Owings, 1986; NCES, 2004; Wayman, 2002). Future aspirations create the motivation for reengagement with school.

School Climate. In combination with an individual student's experience, the school learning environment can have a big impact on student engagement with school and likely the

probability of a student re-engaging with school (Rumberger & Rotermund, 2012). School-level engagement factors are included in the current research and operationalized as the nine constructs described above. A positive school climate encompasses all three dimensions of student engagement and is associated with lower dropout rates (Worrell & Hale, 2001). School-level variables that align to the dimensions of engagement, include attendance rates (Rumberger & Thomas, 2000), positive teacher-student relationships (Croninger & Lee, 2001; Rumberger & Palardy, 2005), and rigorous academic climates as demonstrated by more homework and offering more advanced coursework (Bryk & Thum, 1989; Lee & Burkam, 2003; Rumberger & Palardy, 2005). Conversely, negative perceptions of safety and disciplinary climate are correlated with higher dropout rates (Bryk & Thum, 1989; Pittman, 1991; Rumberger, 1995; Rumberger & Palardy, 2005).

A school's climate should be mutually respectful and allocate a high percentage of time to academic tasks (Fredericks et al., 2004; Wang et al., 1997). According to Yair (2000), this works particularly well for students at risk of disengagement because it creates a learning climate that poses challenges and creates learning environments starkly in contrast with what Haberman (1991) describes as the "pedagogy of poverty" in which authoritarian teaching to low-income students results in passive and disconnected students.

School performance. Students with higher academic performance are less likely to drop out (Balfanz, Herzog, and MacIver, 2007). Therefore, one might also assume that higher performing schools have lower dropout rates. However, moving from a student-level to school-level characteristics may or may not result in expected outcomes. Creating a climate of rigor and academic press may reduce dropout and encourage reengagement because authentic, challenging, relevant instruction stimulates intrinsic motivation in students and reinforces continued

engagement with content (Skinner & Pitzer, 2012; Deci & Ryan, 1985). However, increasing rigor without also enhancing affective engagement may push struggling students to disengage because teachers must help these students keep up by encouraging their engagement and providing individualized assistance; in other words challenge these students “without overwhelming them” (McDill, Natriello, & Pallas, 1986, p 147). The concern about higher standards and its impact on at risk students is especially relevant as new, higher standards are being implemented across the country. The best approach seems to be to focus on both academic press and social cohesion, because increasing school belongingness without also increasing academic press can backfire and result in lessened achievement for low-income schools (Shouse, 1996).

School accountability frameworks demonstrating high growth do not necessary show an impact on reduced dropout and increased graduation (Rumberger & Palardy, 2005). Because of this finding and other policy developments, most state accountability frameworks now include both dropout and graduation rates in their accountability frameworks. For this reason, it is important to look at school performance as a potential predictor of both dropout and reengagement.

Summary of Literature Review

Accountability policies and issues of educational equity incentivize schools and districts to promote reengagement within the school year. Timely indicators of dropout and predictors of reengagement can help focus interventions and resources. Due to the lack of predictive research about within-year reengagement, the next best available research is predictors of dropout and between-years reengagement. Student-level predictors of between-years reengagement include demographics (poverty, minority status, and English language learners), academic achievement,

and affective, behavioral and cognitive engagement. School-level predictors include climate and overall performance on accountability frameworks.

CHAPTER III

METHOD

Accountability systems and recent technological developments have facilitated the expansion of early warning systems through classroom- and school-level dashboards as well as simple watch lists to help educators target their intervention and prevention efforts (Allensworth, 2013; Carl, Richardson, Cheng, Kim & Meyer, 2013; MacIver, 2013). Historically, early warning systems were simple flags using arbitrary cut points or composite risk indices based on research about dropouts and between-years reengagers. With new data systems and the development of various statistical models, the use of early warning indicators have greatly improved (Allensworth, 2013; Carl, Richardson, Cheng, Kim & Meyer, 2013; MacIver, 2013). This dissertation is the first to explore within-year reengagement using temporally sensitive data systems and statistical models. Furthermore, the proposed models are based on data that allow schools to use predictors for within-year reengagement instead of building ‘early’ warning systems on stale data that may span up to 12 years of time. Timeliness of data has been identified as a critical need by the latest developers in early warning systems (Allensworth, 2013; Carl, Richardson, Cheng, Kim & Meyer, 2013).

The current research considers methods and analytics from early warning of dropout research to understand between-years reengagement by developing statistical models that predict reengagement within the school year. For example, one study created composite indices of key variables and then conducted a MANOVA to identify subgroup differences (Chan et al., 2003). A few studies used binomial logistic regression modeling to ascertain the odds of reengaging students given factors such as their ethnicity, gender, SES, or academic performance (Kolstad & Kaufman, 1989; Suh & Suh, 2003; Wayman, 2001; Wayman, 2002). In some cases, formulaic calculations of risk indicators were provided to educators to flag students for intervention

(Henry, et al., 2011; Heppen & Therriault, 2008). Another common approach to modeling between-years reengagement is hierarchical logistic regression (Kolstad & Kaufman, 1989; MacIver et al. 2009; Suh & Suh, 2003; Wayman, 2001; Wayman, 2002). Only recently has research begun to apply these statistical models to early warning systems to enable early intervention with at-risk students who might otherwise go unnoticed in large schools and districts (Allensworth, 2013; Carl, et al., 2013; Henry, et al., 2011; MacIver, 2013). Past research has primarily identified individual warning indicators as opposed to holistic models that consider the probability of negative outcomes contingent upon a cluster of factors.

The intent of this research is to determine the utility of local education agencies (LEA) developing their own, time-and-place specific early warning systems. This research fits into a growing body of research on early warning systems similar to the work of Johns Hopkins who used data from multiple districts to ascertain the weight of certain factors in predicting dropout. For example, in Colorado, data were modeled for five school districts. While three key factors were identified as predictive of dropping out of school (e.g. poor attendance, having a behavior incidents and 9th grade course failure), each of these variables held different weight in the logistic regression model for each of the five districts (MacIver, Balfanz & Byrnes, 2009). Even though this research suggests the need for district specific analytics, many LEA's do not have the skills or the resources to conduct advanced analytics with their own data.

Factors motivating this dissertation were advances in early warning systems, new conceptualizations of student engagement, and the advent of accountability for on-time graduation rates. However, past research has focused on between-years data predicting negative outcomes. The current study is the first to propose the development of predictive models for within-year reengagement in school – a more desirable outcome than dropout. Timely data based

on within-year metrics are, in principle, more likely to be actionable for school staff. Of course, interventions would need to be evaluated to make inferences about the effectiveness of certain interventions and the accuracy of specific predictors to inform interventions.

Setting & Sample

A large Colorado school district is the site of this study. To protect the identity of the school district, I have provided an alias of Wellington County School District (Wellco). Wellco Schools is located on the front range of Colorado. In school year (SY) 2011-2012, Wellco’s student enrollment was over 75,000 students with the majority of students (being White, followed by Hispanic (see Table 1). The students are almost evenly split by gender. Approximately a third of the students are eligible for Free and/or Reduced Lunch (FRL). The five-year cohort graduation rate in Wellco is high for a district of this size while the dropout rate is relatively low (see Table 1).

Table 1
Wellco Public Schools Enrollment & End-of-Year Statistics

Demographic	Statistic
Gender	49% Female students 51% Male students
Ethnicity	68% White students 24% Hispanic Students .17% Pacific Islander 1.15% African American 3.15% Asian .77% American Indian/Alaskan Native 3.25% Multiple Races
Free and Reduced Lunch Percentage	32%
Five-Year Cohort Graduation Rate	81.4% (ranged from 75% to 81.4% over last five years)
Dropout Rate	2%

Source: District Official Data

Wellington County spans a large geographic area that includes rural mountains and a metro suburban ring, as well as an urban area. Wellco is one of the largest school districts in

Colorado, comprising 10% of the state's overall student population. As such, Wellco is often considered a test bed of potential policy ideas. For example, Wellco is currently piloting several components of the Great Teachers and Leaders Act (SB191) for the Colorado Department of Education, including the principal evaluation rubric and the teacher-student data link.

Wellco's efforts to reengage youth with school have been comprehensive. Six years ago, Wellco created the Office of Dropout Prevention and Recovery, which "is dedicated to re-engaging students." The office provides a neutral space for students and their families to begin the conversation about reengaging in school. Three dropout recovery specialists work with students to facilitate reentry into a neighborhood or alternative school setting. Staff members work with students who are either referred by school staff, are self-referred, or are identified by district data systems as at risk of dropout. Staff provides one-on-one counseling to students about options for reengagement in educational settings that are considered most appropriate to student educational and personal needs.

Recently, Wellco was recognized as having the fifth highest graduation rate of the nation's largest fifty school districts for the class of 2008 (EPE Research Center, 2011). Wellco uses early warning systems to identify:

- ninth graders at risk of not graduating high school;
- incoming high school freshman at risk of course failure;
- sixth and eighth graders in need of summer transition programs; and
- third through tenth graders at risk of not being proficient on state standardized tests in mathematics and English language arts.

Early warning systems have provided critical information for teachers and administrators, but no work has been conducted to examine within-year episodic dropout and reengagement.

This dissertation used within-year data to retrospectively study students who dropped out and then reengaged in school over the course of the 2011-2012 school year. Specifically, multilevel binomial logistic regression is used to model the odds of two possible student outcomes: 1) successful reengagement prior to the end of the school year (REENG), or, 2) end-of-year dropout status at the end of the school year (EOYDROP). As described in Table 2, initial predictors included both school-level and student-level variables from student records, a student survey, and school-level characteristics.

Table 2
Outcomes, Predictors, and Model Specification for Reengagement with School

Outcome or Predictor	Measure	Model
Outcome		
Reengagement	Students who had 20 consecutive days absence and were coded as continuous in school at the end of the school year (REENG)	REENG = 1 EOYDROP = 0
End-of-year Dropout Status	Students who had 20 consecutive days absent and were coded as a dropout by district staff at the end of the school year or in the state in the submission process (EOYDROP)	
Predictors		
Student-level		
<u>Poverty</u> : Poverty is associated with dropping out because students may need to seek employment to support their family or may not have the means to participate fully in the education process.	Eligibility for Free and/or Reduced Lunch (FRL)	<i>Unconditioned Model</i> $\log[P/(1-P)] = B0$ <i>Single Predictor Models</i> Level-1 Model $\text{Prob}(Y=1 B) = P$ $\log[P/(1-P)] = B0 + B1*(\text{Predictor}_{k...})$
<u>Minority</u> : The achievement gap between white students and students of color has been explained in many ways including a lack of identification with primarily white staff, a lack of culturally competent curriculum, and institutionalized racism in the classroom.	Students categorized as Native American, Alaskan native, Asian, Black or African American, Hispanic or Latino, native Hawaiian or other Pacific island or two or more races (MINOR)	Level-2 Model $B0 = G00 + U0$ <i>Model 2a: Student-level Data</i> Level-1 Model $\text{Prob}(Y=1 B) = P$ $\log[P/(1-P)] = B0 + B1*(FRL) + B2*(MINORITY) + B3*(ISS_OSS) + B4*(OVERAGE) + B5*(LOWTRACK) + B1*(COUSREFAIL)$
<u>English Language Learners</u> : ELL's tend to have higher mobility and may not receive adequate educational services to meet their unique needs.	Students identified as Non-English Proficient or Limited English proficient (ELL)	Level-2 Model $B0 = G00 + U0$ $B1 = G10$ $B2 = G20$
<u>Overage for Grade</u> : Students who are overage for grade are more likely to dropout. Being overage may be due to previous grade retention indicative of	Students who were one or more years older than the typical student in their enrolled grade as of October 1, 2011 (OVERAGEFORGRADE)	

Outcome or Predictor	Measure	Model
poor academic performance.		$B3 = G30$
<u>Course Failure</u> : A course failure results in fewer credits earned and is correlated with dropout.	At Least One Course Failure (COURSEFAIL)	
<u>Low-track Core</u> : Remedial coursework may demotivate students due to a lack of opportunity or provide necessary supports for credit recovery.	Enrollment in a remedial or intervention class for mathematics or English Language Arts (LOWTRACKCORE)	

School-level

<u>School Climate – Affective</u> : An overall positive climate in a school, as measured by connection and relationships, creates a welcoming environment for students to return to.	Mean of items from the MYVH survey under the following constructs: <ul style="list-style-type: none"> • School Connection (SCHCONCT) • Staff – Student Relationships (SS_REL) 	<i>Model 2b: School Climate of Affective Engagement</i> Level-1 Model $\text{Prob}(Y=1 B) = P$ $\log[P/(1-P)] = B0 + B1*(FRL) + B2*(MINORITY)$ Level-2 Model $B0 = G00 + G01*(SCHCONNECT) + G02*(SCHSSREL) + U0$ $B1 = G10$ $B2 = G20$ <i>Model 2c: School Climate of</i>
<u>School Climate – Behavioral</u> : An overall disruptive environment is less conducive to learning and students are less likely to return to a place where they do not feel safe.	Mean of items from the MYVH survey under the following constructs: <ul style="list-style-type: none"> • Discipline (DISCPERC) • Safety (SAFEPERC) • Participation and attendance (PART) 	

Outcome or Predictor	Measure	Model
<p><u>School Climate – Cognitive:</u> Students who are not challenged by the content or who do not get constructive feedback from teachers may value school less and be reluctant to return.</p>	<p>Mean of items from the MYVH survey under the following constructs:</p> <ul style="list-style-type: none"> • Academic Rigor (ACADRIG) • Teacher feedback (TCHRFEED) • Future Aspirations (FUTASP) 	<p><i>Behavioral Engagement</i></p> <p>Level-1 Model</p> $\text{Prob}(Y=1 B) = P$ $\log[P/(1-P)] = B_0 + B_1*(FRL) + B_2*(MINORITY)$ <p>Level-2 Model</p> $B_0 = G_{00} + G_{01}*(SCHDISC) + G_{02}*(SCHSAFE) + G_{03}*(SCHPART) + U_0$ $B_1 = G_{10}$ $B_2 = G_{20}$ $B_3 = G_{30}$
<p><u>School Performance:</u> This measure is the state-defined rating for school performance on key accountability indicators that include turnaround, priority improvement, improvement, and performance. This is relevant because a school that is high performing is likely to have higher academic press and lower acceptability of dropping out.</p>	<p>Rating on School Performance Framework (SCH_SPF)</p>	<p><i>Model 2d: School Climate of Cognitive Engagement</i></p> <p>Level-1 Model</p> $\text{Prob}(Y=1 B) = P$ $\log[P/(1-P)] = B_0 + B_1*(FRL) + B_2*(MINORITY)$ <p>Level-2 Model</p> $B_0 = G_{00} + G_{01}*(ACADRIG) + G_{02}*(TCHFD) + G_{03}*(FUTASP) + U_0$ $B_1 = G_{10}$ $B_2 = G_{20}$ $B_3 = G_{30}$ <p><i>Model 2e: School Performance on State Accountability Framework</i></p> <p>Level-1 Model</p> $\text{Prob}(Y=1 B) = P$ $\log[P/(1-P)] = B_0 + B_1*(FRL) + B_2*(MINORITY)$ <p>Level-2 Model</p> $B_0 = G_{00} + G_{01}*(SPFCAT) + U_0$ $B_1 = G_{10}$

Description of the Data

Extant data were extracted from multiple data systems in the district. Data for students in grades seven through 12 were used because these are the secondary school grade levels in Wellco and the state board defines ‘dropout’ as applying only to children in seventh through twelfth grade. For the purposes of this study, episodic dropout was defined as 20 consecutive days of unexcused absence from school using the threshold of 80% absenteeism each day (e.g. being absent 80% or more of the day, which is typically equivalent to attending only one period). Using an 80% threshold accounted for challenges with the accuracy and consistency of attendance data collected at the school and classroom level. A threshold approach also accounted for students who might have been marked in error as present for one or two periods in the midst of a long span of absenteeism.

After I pulled the data from district data systems, the various tables were linked using unique student identifiers. Subsequently, all student names were removed from the data set and their student ID’s were masked using a formulaic calculation. This masking resulted in a data set with no personally identifiable information (PII) that could then be removed from the district network while maintain the privacy of student data All data were analyzed on aggregate. Consent was not collected since the data set did not include PII. At the request of district leadership, the district name has been changed in this document to protect confidentiality of students and schools. Since the dropout data set is relatively small compared to the student population, any risk to identifiable student or school information was actively avoided.

Dependent Variable. As in Table 2, two outcomes were included in the logistic regression models: reengagement (REENG) and end-of-year dropout (EOYDROP), coded as 1 and 0 respectively. The most desirable outcome was student reengagement, which is why it was coded as 1. Colorado state statute defines reengagement as occurring when “a student reenrolls

in high school after dropping out prior to completion.” (C.R.S. §22-14-102.15) For the purpose of the study, within-year reengagement was defined as being coded ‘continuously enrolled’ in school at the end of the school year, ‘transferred’ to another education experience or ‘graduated’ by achieving a traditional high school diploma. Per state statute, students were considered early leavers if they exited three weeks or less prior to the close of the school year, (C.R.S. §301-1.02 C.2.f). Therefore, if a student had an episode of dropout and then subsequently returned to school only to exit within the last three weeks of the school year, that student was still considered as reengaged.

The other category of the dependent variable was end-of-year dropout (coded as 0) and was defined as continued dropout status at the end of the school year, as determined by the student’s end-of-year exit code. Historically, exit codes were considered unreliable. Consequently, the Colorado State Board rules have become extremely prescriptive about the dropout exit code specifying that:

“... students in grades seven through 12 who drop out shall be determined by adding the number of students who

“(b) (i) were enrolled in school at some time during the current reporting school year; and (b) (ii) were not enrolled at the end of the school year or June 30; and (b) (iii) have not graduated from high school or received a GED certificate, or completed a District-approved educational program; and (b) (iv) do not meet any of the following exclusionary conditions: (a) transfer to another Public School District or private school, home-based education program (home school) pursuant to § 22-33-104.5, C.R.S., GED program, vocational education program, licensed eligible facility, state-operated program

or detention center; (b) temporary absence due to serious illness or injury, suspension or expulsion; or (c) death.” (C.C.R.S. §301-1 2.02 C)

Students are considered a dropout if they are no longer attending school for more than the last three weeks of the school year and their educational records are not requested by another district or their whereabouts are unknown (C.C.R. . §301-1 2.02.C). If records are requested by another district, but the student does not subsequently enroll in that district, the Colorado Department of Education instructs the local education agency to change the student’s code from transfer to summer dropout. All of these circumstances results in an end-of-year exit code of dropout. The list of dropouts is not finalized until approximately six months after the end of the school year. Whereas, reengagers are confirmed at the end of the school year by school-based enrollment secretaries.

Independent Variables. As described in Table 2, single and multiple predictors for the binary outcome of reengagement (1) or end-of-year dropout (0) were modeled using multi-level logistic regression techniques to answer the research question *What factors predict reengagement within the school year?* As described in the literature, previous researchers looked at between-years reengagement using predictors such as demographic variables including poverty, minority background, and English Language Learner (ELL) status. Similar predictors were used in this dissertation.

It should be noted that for this study, the bulk of the predictors were malleable variables such as course failure, and student engagement defined as affective, behavioral, and cognitive. Malleable means that the variables are amenable to change by intervention (Crick, 2012; Oyersman et al., 2011). “ ‘Malleable’ also signals that school-desired dispositions are not

inherently stable. They may unravel over time, especially when students lack sufficient social supports and resources.” (Lawson & Lawson, 2013, pp. 448)

Make Your Voice Heard (MYVH) Survey Data. Since the late 1960’s and 70’s there has been ever-increasing attention to and appreciation for affective measures as indicators of school success (McCoach, Gable & Madura, 2013; Tyler, 1973). Student engagement is the affective domain of interest, and it was measured by Make Your Voice Heard Survey (MYVH) – a student survey designed by the school district to measure school engagement. MYVH has been administered on paper since the late 1990’s. However, district staff updated the survey with many new items in fall 2011. The MYVH survey development is not a unique contribution of this dissertation but it is being used as a secondary data source. With that in mind, a few comments are warranted about the theory guiding its design and development as well as its psychometric properties.

Using Kane’s (2006) theory-based validity argument, there are five inferences to be considered; scoring, generalization, extrapolation, theory-based interpretation and implications. Each of these inferences need to be considered within the overall purpose and intended use of a measurement instrument. MYVH was developed to measure school engagement as an indicator of school climate. The data are used at both the district and the school level to determine where efforts and resources should be allocated to improve student engagement with school. Data are reported to key stakeholders including student and parent committees who then interpret the data within their local context to make decisions about any needed changes such as interventions or supports. MYVH is not being used in a high stakes context (e.g. teacher evaluation or school accountability reports). Instead the information is used qualitatively within a body of evidence of other school climate indicators (e.g. attendance rate, number of behavioral incidents and

expulsions, participation in extracurricular activities, classroom based observations, etc.) to develop a reasoned interpretation consistent with available evidence for the purposes of policy and resource allocation decisions. More specifically, “different kinds of information from different sources are combined for an interpretation... in context” to make inferences about student engagement factors at the school level with MYVH as one critical source of information (Kane, 2006, p.47). For the purposes of this dissertation, scores generated from scales created from the MYVH data are being used to estimate whether student engagement constructs predict student reengagement with school after an episode of dropout. Inherent in that use, is the need to provide evidence for the validity of deriving school climate indicators from the MYVH data. To that end, the validation approach operationalized in the development of MYVH is discussed. Each of the five inferences is reviewed and contextualized within the stated purpose and use.

Scoring. Borrowing from previous student surveys designed to measure the identified nine constructs, Likert scales were intended to indicate more or less of a given construct on a scale of 1 to 4. Both agreement scales (e.g. strongly agree, agree, disagree, strongly disagree) and frequency scales were used (e.g. never, rarely, sometimes, often). Using Likert scales on a one to four, scaling provides a response scale that is easy for students to respond to within the time frame of the administration of the survey. Schools had a 30 -45 minute blocks to administer the survey within a computer lab environment. Students also commonly know these types of scales.

All other studies used these items with the underlying scoring assumption that a higher score on the 4-point scale indicated ‘more’ of a construct. In order to summarize many items into useable information, items were averaged together to create a mean score reflecting a construct at the individual level. The group mean of the individual student means was used as a school level indicator of the construct. If a student missed one item assigned to a construct that student’s

construct mean was not included in the overall school level mean. Students could not mark more than one answer because the online system would not allow for more than one response per item. These scoring rules were applied consistently across all student data.

Empirical evidence is not available to confirm that students consistently interpreted the scale for every item. No observations of students' engagement were used to triangulate their scores on MYVH. Nor were any attempts made to determine if the items failed to include important and relevant criteria. It is important to note that the mean response to the MYVH items typically have a small range indicating that the items may not be eliciting the full response possible for a particular construct.

Generalization. Generalizability as it relates to validity theory is the idea that “item response behaviors are samples” from a “well-defined universe”, yet achieving this ideal is rare (Markus & Borsboom, 2013, pp55). For MYVH, it is not possible to determine if the items selected adequately represent the potential observations within the domain. Nor is it clear that all components of variance; variance due to the universe of scores, sampling of items or within person, has been accounted for in the development or analyses of MYVH. However, claims can be made that the ‘observations’ occurred under consistent conditions which Kane refers to as the ‘ceterus paribus assumption.’ (Kane, 2006, pp35).

Regarding evidence of standardized administration, it is important to note that a uni-modal administration was used for all students in brick and mortar schools (e.g. all students took MYVH online, in classrooms proctored by school staff using specified proctoring instructions and scripts). However, students in the districts' online school took the survey in any number of potential environments (but all online). Since these data are being used at the school level, this

inconsistency in administration may pose less of a risk to the intended generalizability purpose but nonetheless warrants mentioning.

Also important are generalizability studies that include empirically collected samples over time in order to produce reliability estimates. “To the extent that reliability or generalizability studies indicate that the sampling errors associated with replication of the measurement procedure are large, inferences from the observed score to the universe score are uncertain.” (Kane, 2006, pp. 35) Multiple administrations of MYVH have not yet occurred. However, reliability estimates (e.g. Cronbach alpha’s) are reported in the results section with the ‘one-time’ dataset and serve as a limited source of reliability estimates.

Extrapolation. The analytical evidence for validity draws from the conceptual framework of student engagement proposed by Fredericks et al, 2004. As such, most of the evidence is theoretical only. Think-aloud procedures were used in the development of MYVH to ensure that students were interpreting the content of items similarly. Empirical evidence of comparing the observed MYVH scores to other similar indicators (e.g. attendance, behavioral incidents, etc.) is not available.

Theory based interpretation. Multidimensional student engagement theory of affective, behavioral and cognitive engagement guided the development of MYVH (Fredericks et al., 2004). Within the three construct conceptual frame of engagement were nine targeted constructs of connection to school (affective), staff-student relationships (affective), family support for learning (affective), perceptions of discipline practices (behavioral), perceptions of safety (behavioral), attendance and participation (behavioral), academic challenge (cognitive), teacher feedback (cognitive), and future aspirations (behavioral). As described in Table 3, the content of the MYVH items were purposefully aligned to the nine constructs. In addition to think-alouds, a

panel of subject matter experts reviewed these items to ensure the conceptual and theoretical fit of items to constructs.

The intention of MYVH was to create items that elicit behaviors consistent with theoretical constructs. For example, the following items about staff – student relationships were designed to elicit their experiences of supportive teachers who have shown an interest in them, provided positive praise, and facilitated their inclusion in the school community (Fall & Roberts, 2012). Students who have strong relationships with their teachers are respectful of them and initiative help-seeking behaviors for both schoolwork and personal issues (Cornelius-White, 2007). Hattie (2009) identified empathy, warmth, adapting to differences, genuineness, and learner-centered beliefs as characteristic of teachers who engendered strong student relationships. The following items, designed to measure staff – student relationships, address this theoretical content.

1. Staff members at this school care about students.
2. I am respected by most staff members.
3. I have a favorite teacher at this school.
4. There is at least one adult at school that I can go to when I need help with schoolwork.
5. When a student has a personal problem, someone at school is there to help.
6. I respect most of the staff at this school.

It was expected that the nine constructs nested within the affective, behavioral and cognitive engagement constructs, would correlate more strongly with each than with the other constructs. However, as described in the results section, empirical evidence from the CFA did not confirm the anticipated nested relationships. CFA did provide rudimentary empirical evidence for the clustering of items into nine constructs.

Implications. School based administrators have used MYVH within a body of evidence to build on constructs with relatively high means and provide support or interventions for construct areas with lower means. Anecdotally, principals have reported that the data seem to fit with other

evidence available to them. In this sense, MYVH has been used qualitatively to inform school level policy decisions. However, no systematic inquiry about the implications of MYVH has been conducted. Additionally program evaluation of interventions resulting from school-based interpretations or uses has been conducted. Nor have any experimental analyses been explored to determine if MYVH can be used to measure effects of intervention-based changes or to monitor trends over time.

MYVH Development Process. The development of MYVH used a collaborative design process in partnership with multiple stakeholders within the school district. At a series of several meetings, the MYVH survey committee came together to identify constructs designed to measure the goals of Wellco with particular attention to the goal of students being 100% college and career ready by the time they graduate. The group converged on Fredericks and colleagues' (2004) theory of student engagement; attracted by its comprehensiveness and the research connecting engagement to achievement. The committee selected constructs that aligned to the widely accepted multidimensional understanding of student engagement as affective, behavioral, and cognitive (Christensen, Reschly, & Wylie, 2012; Fredericks et al., 2004, 2011). District assessment and research staff searched existing student questionnaires as well as created a few new items for the committee to provide feedback. After a lengthy process, potential items were selected and were then tested with students. Results were brought back to the committee for their consideration before determining the final version of MYVH for the 2011-2012 school year. In this way, the committee served as a community review panel as described by Wilson (2005) and provided evidence for validity based on the content of MYVH.

MYVH was designed to generalize to all Wellco students in grades 7 – 12 for the purposes of ascertaining indicators of school climate. MYVH is a census of all students and is

required by the district. Participation rates were monitored throughout the administration window and schools were contacted if participation rates did not reach 80% of the total student body. A high total response rate does not guarantee representativeness. Therefore, the proportion of subgroup response rates should also be explored. MYVH was designed as a time-and-place specific survey; meaning it was designed for schools to assess school climate during a specific window of time. These data were not intended to generalize beyond that window of time or that specific school. The district did not use the MYVH data to compare schools because the context and climate of schools is unique and requires context based understanding to interpret the meaning of a particular score on a construct. Two other limitations worth noting are that the standard error of estimates is lacking and I cannot guarantee that data are missing completely at random.

Student engagement theory described in the literature review of this dissertation, guided the development of the survey (Christensen, Reschly, & Wylie, 2012). Affective engagement was conceptualized for the MYVH survey as including items to measure School Connection (SCHCONNECT), Staff – Student Relationships (SS_REL), and Family Support for Learning (FAMSUPP). Behavioral engagement was conceptualized for the MYVH survey as including items that measure Discipline (DISPERC), Safety (SAFEPERC), and Participation and Attendance (PART). Cognitive engagement was conceptualized for the MYVH survey as including items that that measure the latent variables of Academic Rigor (ACADRIG), Teacher Feedback (TCHRFEEED), and Future Aspirations (FUTASP). Each associated survey item is described in Table 2.

Another attempt to attain validity evidence based on content included adopting or slightly adapting items from existing student surveys – a common first step in developing affective

surveys (McCoach et al., 2013). The following student engagement surveys were reviewed including:

- the Student Engagement Instrument (SEI) (Betts, et al., 2010);
- Brown & Evans' (2002) school connection instrument;
- Jenkins' (1995) school delinquency and commitment survey;
- the Healthy Kids Colorado Survey which is administered by the University of Colorado (see <http://www.ucdenver.edu/academics/colleges/PublicHealth/community/CEPEG/UnifYouth/Pages/HealthyKidsSurvey.aspx>) and based on the Social Development Research Group's risk and protective factors (Arthur, Hawkins, Pollard, Catalano & Baglioni, 2002);
- the National Center for School Engagement's (NCSE) student school engagement survey (NCSE, 2006); and
- the MET Project's Tripod survey (MET project, 2012).

Table 3 identifies the source of each item, which was used either verbatim or adapted slightly. If an item is not identified with a source, meaning it does not have a superscript lower case letter at the end of the item stem, then it was either created for the purposes of the 2011-2012 survey or was a carry-over item from previous versions of the survey. As a reminder, the MYVH survey has been administered in the district on paper with non-identifiable data, for over a decade prior to the revised version developed in the 2011-2012 school year.

The survey was administered to all students in grades two through 12, electronically, using a unique login to be able to link data with individual students. In order to avoid extensive loss of instructional time and to fit within the scheduling constraints of schools, the survey was

limited to 60 items, which took students approximately 30 – 45 minutes. Note that five items were not used for the purposes of this inquiry as these items were ‘tagged on’ to meet specific needs of district staff (e.g. items about the lunch program and athletics). Additionally, question 60 was an open-ended question and was not used in this analysis.

Table 3

Make Your Voice Heard Constructs and Associated Items

Constructs	Items (Numbered According to Survey Sequence)
Teacher – Student Relationships	1. Staff members at this school care about students. ^a 2. I am respected by most staff members. 3. I have a favorite teacher at this school. ^c 4. There is at least one adult at school that I can go to when I need help with schoolwork. 5. When a student has a personal problem, someone at school is there to help. ^e 6. I respect most of the staff at this school. ^e
Academic Challenge	7. Homework assignments help me practice what I am being taught in my classes. 8. My teachers ask students difficult questions in class. ^f 9. My math work is challenging. 10. My writing assignments are challenging. 11. The reading materials in my classes are challenging.
Teacher Feedback	12. My teachers know when the class understands, and when we do not. ^f 13. In my classes, teachers give students time to explain our ideas. ^f 14. My teacher checks to make sure we understand what he/she is teaching us. ^f 15. My teachers encourage me to do my best. ^f 16. The comments that I get on my work help me understand how to improve. ^f
Discipline Practices	17. My teachers know a lot about the subject they teach. ^e 18. At school, there are clear rules for acceptable behavior. ^f 19. Students generally behave themselves while at school. ^f 20. The discipline practices at school are fair. ^e 21. I follow the rules at school. ^e 22. I would inform an adult at my school about bullies and students who threaten others.
Safety	23. I feel protected from harassment at school. 24. I feel protected from discrimination at school. ^a 25. I feel safe at school. ^a 26. Staff members do not tolerate students who threaten others at school. 27. During this school year, how often did you not go to school because you felt you would be unsafe at school or on your way to school? * ^d 28. During this school year, how often were you bullied or harassed at school or on your way to school? * ^d 29. During this school year, how often have you been

Constructs	Items (Numbered According to Survey Sequence)
Attendance & Participation	electronically bullied? (including being bullied through email, chat rooms, instant messaging, web sites, or texting)* ^d
	30. During this school year, how often has someone threatened or injured you with a weapon such as a gun, knife or club on school property? * ^d
	31. During this school year, how often has someone stolen or deliberately damaged your property such as your car, clothing or books on school property? * ^d
	32. During this school year, how often were you in a physical fight on school property? * ^d
	33. I think it is important to go to school every day. ^e
	34. I skip classes that I don't like. *
	35. I am rarely absent from school unless I am sick.
School Connection	36. When I am in class, I just pretend that I am working. * ^e
	37. My classes are very interesting.
	38. My schoolwork is meaningful to me.
	39. Students at this school respect what I have to say. ^a
	40. I feel like I have a choice about what happens to me at school. ^a
	41. I have some friends that I feel close to at school. ^e
	42. I feel like I belong when I am at school. ^e
Family Support for Learning	43. I generally feel happy when I am at school. ^e
	44. I often attend school activities or events. ^c
	45. Students of different racial and ethnic backgrounds get along at this school.
	46. My parents/guardians support me with my homework.
	47. My parents/guardians expect me to do well in school.
	48. My parents/guardians ask me about what I am learning at school.
	49. My parents/guardians want me to keep trying when things are tough at school.
Future Aspirations	50. My parents/guardians and I talk about the good things that I have done in school. ^a
	51. My parents/guardians and I talk about the problems I have in school. ^a
	52. I have a place at home to do my homework.
	53. I would like to quit school. * ^c
	54. Education is important for achieving my future goals. ^f
	55. I will graduate from high school. ^e

*These items were reverse coded.

a. SEI b. Brown & Evans c. Jenkins d. Healthy Kids Colorado Survey e. NCSE f. TRIPOD

A Likert (1932) scaling with four possible responses of agreement was used for most items (e.g. strongly disagree, disagree, agree, and strongly agree). Responses were then coded using a scale of one to four respectively. The response categories for items 27 to 32 were never, rarely, sometimes, and often and were also coded as 1 to 4. Some items were reverse coded depending on the wording of the item. Responses with more agreement (e.g. *Strongly Agree*) or more frequency (e.g. *Often*) were assumed to indicate more of the construct being measured and were hoped to provide validity evidence of a range of the construct within the target population.

The rationale for using Likert scales was to use existing survey items that have been developed and tested by other researchers — an approach to achieve validity evidence based on content (see Table 3). For the sake of consistency, new items identified in Table 3, also used similar Likert scales. Additionally, Likert scales were used because they are familiar to students and staff, arguably making it easier for students to respond within a bounded time. Furthermore, the necessary theory for Wilson's (2005) outcome space approach was not available to specify the levels in Wilson's construct modeling approach.

One strategy for developing validity evidence based on response processes was used in the development of the survey was cognitive testing with students. Understanding students' cognitive response to the proposed items can provide validity evidence as to whether students actually interpret an item about harassment as being connected to an overall perception of safety, for example. Fifty-six students across varying grade levels, academic abilities, and instructional programs (e.g. English Language Learners, Special Education or Gifted and Talented) were asked to take the survey while 'thinking aloud' about their cognitive processes for each item (Wilson, 2005). Cognitive interviews were conducted by four interviewers, who then came together to discuss and synthesize findings to modify and eventually propose the final items to

the district MYVH survey committee. Detailed description of these analyses and results are beyond the scope of this dissertation.

According to the Standards for Educational and Psychological Testing, validity refers to the “evidence and theory supporting the interpretation of scores entailed by the proposed uses” (AERA, APA, & NCMS, 1999, pp.9). MYVH was designed to monitor the progress of schools and student subgroups across the district with regard to student engagement. To this end, district staff compared MYVH with student proficiency levels on the Transitional Colorado Assessment Program (TCAP) to build the validity evidence based on relations to other variables. Each construct was compared to the proficiency on the state standardized test in each content using a correlational evidence approach. The guiding theory for this external validity evidence come from existing conceptual frameworks and empirical research indicating that student engagement is correlated and promotes academic achievement (Christensen, Reschly, & Wylie, 2012, Connell, Spencer, & Aber, 1994; Finn, 1989; Fredericks, Blumenfeld, & Paris, 2004; Furlong, Whipple, Jean, Simental, Soliz, & Punthuna, 2003; Henry, Knight, Thornberry, 2012; Libbey, 2004; Marks, 2000; Skinner, Wellborn, & Connell, 1990). Specifically, the *Handbook of Research on Student Engagement* (2012) describes the theoretical underpinnings best, stating:

There is a long history of research on the relevance of academic engaged time for improving student achievement (Fisher & Berliner, 1985). Indeed, many current definitions of student engagement (see Epilogue , this volume) are explicitly linked to academic tasks and activities. However, engagement has long been viewed as more than academic engaged time. From the earliest review to include the term engagement (Mosher & McGowan, 1985) , to the publication of seminal theory about the underpinnings of school dropout and completion (Finn, 1989) , to

more recent conceptualizations (see Epilogue, this volume), engagement is viewed as multidimensional, involving aspects of students' emotion, behavior (participation, academic learning time), and cognition (Fredricks, Blumenfeld, & Paris, 2004). ...Student engagement is the glue, or mediator, that links important contexts—home, school, peers, and community— to students and, in turn, to outcomes of interest (Reschly & Christenson, 2012. pp. 3).

Based on extensive previous research, one would therefore expect that evidence for a valid measure of engagement would exhibit associations with measures of academic achievement. While these types of analyses may provide convergent evidence, no evidence was available with regard to test criterion relationships (e.g. historically called predictive and concurrent designs). However, with nine proposed constructs and three content areas on the state standardized test, the full details and results of these correlational analyses are beyond the scope of this dissertation and not publically available from the district

Use of the MYVH survey data rely on a specific validity argument about the nature of the data. For the purposes of this dissertation, the intended use of the MYVH survey is to explore how student engagement might explain who reengages with school after an episode of dropout. With this intent, confirmatory factor analysis was conducted to summarize proposed constructs of engagement used to predict reengagement for students who have experienced an episode of dropout. Given longitudinal data and a strong relationship between low MYVH climate factors and high dropout rates at a school, one might obtain validity evidence for the survey based on the ensuing consequences.

The MYVH variables reflect the existing theoretical conceptualizations of student engagement and are used to make inferences about school climate using the total population of

the school who responded to the student survey. Interpretations about school climate are limited by underlying limitations inherent in using Likert scales and by missing data due to students not taking the MYVH survey or schools choosing not to participate in the survey. The extent of missing data is discussed in the results section. However, a note about school-level measures is warranted.

School-Level Measures. School-level measures used in the logistic regression modeling were organized by the theoretical model of affective, behavioral, and cognitive engagement.. The theory behind this approach is that school climate issues associated with student engagement are likely to have an impact on whether students reengage or not. Specifically, one of the factor models aggregated affective engagement at the school-level as a group mean of the school connection and staff-student relationships items. Family support for learning was not included as a school-level climate predictor because it occurs outside of the school setting. Behavioral engagement was measured using a group mean of the discipline and safety items as well as attendance and participation. Cognitive engagement was measured by the group mean of academic challenge, teacher feedback and future aspirations items. The School Performance Framework rating (SPF) was also included as a school-level predictor.

A critical consideration is that students who are marginalized from school and have dropped out or are experiencing inconsistent attendance may not have been present to respond to the MYVH survey; therefore, there could be biases in the response rates. In this case, the missing data would not reflect the students who are the focus of this dissertation. Of course, this concern also applies to the SPF rating because the rating largely reflects students' achievement that is present to take the state standardized tests. In any case, it is critical to consider these missing data in any interpretation of the results or findings from this research.

In summary, the development of the MYVH survey evidenced validity based on content through expert panels and the use pre-existing items and through response, processes elicited using cognitive interviews with students. Using the conceptual framework of student engagement, preliminary attempts were made to obtain validity evidence based on internal structures. Some propositions were made about which items clustered under the three and nine constructs. However, no hypotheses were proposed about how these construct interrelate. The next section looks at item interrelationships using factor analysis and reliability analyses.

Analytic Approach

The analysis had three components 1) descriptive statistics, 2) factor analysis, and 3) multilevel modeling. A thorough descriptive analysis identified patterns of episodic dropout and reengagement within school year 2011 – 2012 by comparing students with episodes of dropout who either successfully reengaged or not, in terms of the demographic variables such as gender, grade, ethnicity, age, FRL, ELL, etc. Descriptive statistics helped determine if there was an appropriate balance between students who reengage and those who do not, to allow for logistic regression modeling; meaning there was no group that had too few students to permit regression modeling.

Factor Analysis. Factor analysis was used to identify correlations between items in the MYVH survey and provide a summary of theoretical constructs outlined in the literature review of affective, behavioral and cognitive engagement (Fredericks, 2004; Ford, MacCallum, & Tait, 1986). The purpose of the factor analysis was determine if the proposed three-factor or nine-factor model of student engagement is supported by correlations in the data; an appropriate use of confirmatory factor analysis (McCoach et al., 2013). For the purposes of MYVH, the literature and theory about student engagement guided the constructs of interest and hypothesized internal structure as three factors or nine factors. The empirical data of the survey connects the theory to

people's responses on individual items, a crucial foundational assumption inherent in the validation argument (McCoach et al., 2013). While Fredericks et al.'s (2004) theory of student engagement does not have any expected pattern of correlations among the item responses, using CFA provides additional evidence for validity using proposed interrelationships between items and constructs.

A confirmatory factor analysis (CFA) were conducted in AMOS 20 to determine if the factor structure of the MYVH survey data fit the proposed nine and three-factor structures. The theorized nine-factor structure is outlined in Table 3 but each of the nine factors is subsumed underneath a theorized three-factor structuring of the survey items. Lastly, internal consistency was also examined using Cronbach's Alpha with alphas above .7 or .8 as the desired test statistic (Kline, 1999).

Multilevel logistic regression modeling (MLLR). Logistic regression was used because the outcome of interest, reengagement, is dichotomous, meaning it either happens or it does not. Logistic regression can be communicated using the log odds, probabilities or odds ratios (exponentiated logs odds). Odds and probabilities are relatively accessible to non-technical laypersons. The hope is that this approach facilitates the use of the results for practitioners and is understandable enough to generate rich dialogue. It is useful here because an anticipated application of this study is to be able to flag students who experience an episode of dropout and then to identify those who are most likely to reengage.

Logistic regression modeling tests a hypothetical set of relationships and the result can be reported as odds ratios of expected outcomes. For example, suppose that 25 ELL students reengaged while 75 did not, then ELL students would be estimated to have a one in four chance of reengagement or a .25 probability of reengagement. Probability of reengagement provides a

helpful metric because it ranges from zero to one. However, odds ratios are invariant to baseline odds whereas probability increases and decreases are variant to baseline probability making it difficult to interpret probabilities.

Another potential application of the logistic regression model is using the regression coefficients as weighting factors in an early warning system for end-of-year dropout status by identifying students who are most likely to reengage. Additionally, this same technique provides insight regarding which factors best predict successful reengagement. The intent is to provide a method for practitioners to identify students ‘at risk’ of end-of-year dropout or ‘at-promise’ of re-engaging and thereby focus their limited resources accordingly. The model specification for the MLLR can be found in Table 2.

A few comments about the underlying assumptions of multilevel logistic regression are warranted. Similar to single-level logistic regression, the dependent variable must be dichotomous and therefore, is not normally distributed. Observations are assumed to be independent conditional upon group membership. Independent variables should not be linear combinations of each other. Lastly, a relatively large sample size is needed (e.g. between 10 and 30 cases per variable in the equation) (Menard, 2002). A few assumptions that are presumed, are that no important variables are omitted or extraneous variables included, and the independent variables are measured without error.

When data is collected across individuals in the same classroom, schools, or regions, we expect these dichotomous outcomes to contain “within-context dependencies, yielding a situation that requires statistical adjustment for the effect through multilevel research designs and analyses.” (O’Connell, Goldstein, Rogers, & Peng, 2008, pp. 200) For the purposes of this dissertation, MLLR provides an analytic technique to model the variation expected in the

regression coefficients across schools. MLLR was used to determine what factors predicted the probability of reengagement for students who have experienced an episode of dropout – a comparison of the two groups of interest. Again, continuously enrolled students are not included because extensive research has been conducted that compares dropouts to continuously enrolled students. The unique contribution of this study is to compare students who reengage with school to students who do not, after each group has at least 20 consecutive days of unexcused absences.

MLLR uses both student-level and school-level predictors. The two school-level variables include the SPF rating and the nine factors measuring student engagement. Overall, affective, behavioral, and cognitive engagement were not used as factors since the factor analysis did not support this configuration of items (see the results chapter). Instead the nine-factor structure was used in the multilevel analyses which included school connection, teacher – student relationships, family support for learning, discipline practices, safety, attendance and participation, academic rigor, teacher feedback, and future aspirations. However, it should be noted that lacking the CFA results, this choice is can also be a matter of my preference for summarizing the survey data. Within the multilevel modeling, student-level data for these variables (affective, behavioral and cognitive engagement) are also not used for the same reasons as stated above (factor analysis did not support a three construct internal structure). Overall, individual data were not used for these students due to extensive missing data (78% of students with an episode of dropout did not take the MYVH survey). To clarify, all district data were used to create school level variables as opposed to simply data from the sample of dropouts and reengagers used for the majority of the analyses in this dissertation.

The analyses were designed to answer research question 2: *What factors predict the successful reengagement of dropouts within the school year?* The conditional and unconditional

level 1 and level 2 models are specified in Table 2. Additionally, each predictor was run on its own as a single predictor in the model controlling for ethnicity and poverty. Minority status and free and reduced lunch status are used as controls because of historical achievement gaps in educational outcomes. Recall that the outcome of interest is reengagement and the referent group is dropouts.

Limitations

The study had some pre-existing limitations that should be acknowledged. First, the majority of this extant data was collected in school buildings and entered into Infinite Campus, the school data system for managing student records. The accuracy of the data was assumed but cannot always be verified.

A second limitation is that information about course failure and enrollment in low-track or remedial courses was not available for all students because not all students attended enough school to have a documented record of coursework. This is a limitation of the study because students who dropped out are more likely than those who reengaged to have more missing data about their coursework (e.g. grades and schedule). This could bias or underestimate the impact of these predictors in the logistic regression models.

Another limitation of the design was the lack of data during an episode of dropout (20 days consecutive unexcused absence). Nonetheless, it is important to conduct exploratory research to answer the research questions with data that are readily available and interpretable to practitioners, teachers, and district leaders. For example, we do not know if a student has dropped out of school to seek employment to support themselves or their family. Although this study would be well supplemented with surveys or interviews of reengagers, this would not reflect a sustainable practice for districts to use in ongoing early warning systems.

A fourth limitation included the inability to complete inter-coder agreement processes with student record data. As an employee in the district, I was able to go into the student system to check individual students in an attempt to determine the reasons for the episode of dropout. This coding was based largely on key data elements in the student enrollment record. However, it was not possible for a third party coder to verify the coding due to the lack of permissions to access individual student records.

A fifth limitation is that I did not look at classroom-level effects. Presumably, there are teacher-effects impacting student engagement, disengagement, and reengagement. Since the data set is secondary students, and these students have multiple teachers throughout the school year, the granularity of this analysis was limited. Additionally, the effects of different teachers at the secondary level are likely to be variable and it would be difficult to interpret results unless students completed a survey about every classroom teacher, which was not the case for the MYVH survey.

A sixth limitation is that patterns of missing data were unable to be examined due to a lack of access to overall enrollment data at the time of the survey administration. Therefore, it is unclear if there are patterns of missing data that might bias the results of the factor analysis or the logistic regression. Finally, a seventh limitation of this research is the lack of knowing the stability of MYVH over time. MYVH was only administered one time and therefore this error cannot be considered in our interpretation.

CHAPTER IV

RESULTS

As briefly described above, three analytic techniques were used with the data set. First, extensive analyses allowed deep exploration of the data set with particular attention to missing data. These analyses were designed to address research question 1: *What is the incidence and prevalence of episodic dropout within the school year?* Second, factor analysis was conducted with the larger survey data set from the entire district. Third, multilevel binomial logistic regression was used. The results of each of these analyses are described in this section. Factor analysis and logistic regression analyses were conducted to answer research question 2: *What factors predict the successful reengagement of dropouts within the school year?* Research question 3: *How does this exploratory study explain distinctions between reengagers and those who do not reengage with school?* is addressed in the discussion section.

Initial Exploratory Analyses

Wellco had over 40,000 students enrolled in grades seven through 12 in school year 2011-2012. Of those students, 929 were identified as dropouts. A few (30) of those dropped out over the summer of 2011 and did not have any data for the school year under study. The remaining 899 students include 675 end-of-year (EOY) dropouts and 224 students who experienced an episode of dropout but reengaged prior to the end of the year, indicating that approximately 25% of students who had at least 20 consecutive absences (the criteria for my definition of an episode of drop outs), reengaged within the school year.

Table 4 describes all students included in the analysis as well as a comparison between EOY dropouts and students who reengaged. There are significantly higher proportions of minority students $X^2= 6.06$ (1, $n=899$, $p<.05$), ELL students $X^2= 15.12$ (1, $n=899$, $p<.00$), and students who are overage for grade $X^2= 12.14$ (1, $n=899$, $p<.00$) in the EOY dropouts group than

in the reengaged group. Additionally, grades seven through 10 have higher proportions of students who reengaged compared to eleventh and twelfth grades. Reengaged students had significantly lower proportions of IEP students $\Sigma^2= 23.46$ (1, n=899, $p<.00$). Fifty-nine percent of ethnic minority students were EOY dropouts, compared to 49.6% of white students, with Hispanic students being overrepresented among minority students at 52.7% compared to 38.4% of non-Hispanic students. This mirrors the overrepresentation of Hispanic students in the overall district's dropout rates with Hispanic students having a 3.9% dropout rate compared to white students with a 1.3% dropout rate.

Reengagers and EOY dropouts vary considerably with regard to enrollment patterns. While the highest proportions of students were enrolled in one school throughout the year, the percentage of reengagers having more than one school enrollment was double that of EOY dropouts (30.8% compared to 16.6%).

Academically, reengagers tend to have more course failure than EOY dropouts (66.1% compared to 56.4%, $\Sigma^2= 29.46$ (1, n=899, $p<.00$). However, high percentages of EOY dropouts did not obtain any course credit and did not have the opportunity to fail, which is likely due to absenteeism. This confounds the comparison of these two groups. While neither group has high proportions of enrollment in low-tracked courses, reengagers had higher percentages of low-track courses than EOY dropouts (33.6% compared to 12.6%, $\Sigma^2= 53.59$ (1, n=899, $p<.00$)). Behaviorally, the percentage of reengagers who had at least one in-school or out-of-school suspension was higher than EOY dropouts (33% compared to 12.9%, $\Sigma^2= 46.43$ (1, n=899, $p<.00$)). The number of expelled students was low overall, affecting only 30 students in the entire sample. However, there were more reengagers who had expulsions than EOY dropouts (11.6% compared to .6%, numbers are too small for Σ^2).

The majority of reengagers experience an episode of dropout while enrolled at a neighborhood school while end-of-year dropouts were enrolled more broadly in any of three options: a neighborhood school, options school, or charter school (see Table 4). Sixty-three percent of reengagers experienced dropout while enrolled at a school with a School Performance Rating of Improvement, whereas 51% of EOY dropouts left a lower ranked, Priority Improvement school.

Table 4

Description of the All Students compared to EOY Dropouts and Reengagers (n=899)

		All Students		EOY Dropout		Reengagers	
		#	%	#	%	#	%
Demographics							
Grade	7	22	2.4%	3	.4%	19	8.5%
	8	29	3.2%	3	.4%	26	11.6%
	9	61	6.8%	11	1.6%	50	22.3%
	10	114	12.7%	53	7.9%	61	27.2%
	11	253	28.1%	213	31.6%	40	17.9%
	12	420	46.7%	392	58.1%	28	12.5%
Gender	Female	384	42.7%	279	41.3%	105	46.9%
	Male	515	57.3%	396	58.7%	119	53.1%
Ethnic	Hispanic	442	49.2%	356	52.7%	86	38.4%
	White	391	43.5%	277	41.0%	114	50.9%
	Multiple Races	17	1.9%	9	1.3%	8	3.6%
	Black or African American	17	1.9%	11	1.6%	6	2.7%
	American Indian or Alaskan Native	16	1.8%	13	1.9%	3	1.3%
	Asian	14	1.6%	7	1.0%	7	3.1%
	Native Hawaiian or Other Pacific Islander	2	.2%	2	.3%	0	0.0%
Minority	Yes	509	56.6%	398	59.0%	111	49.6%
Free and/or Reduced Lunch	Yes	451	50.2%	330	48.9%	121	54.0%
English Language Learner	Yes	167	18.6%	145	21.5%	22	9.8%
Individualized Education Plan	Yes	101	11.2%	56	8.3%	45	20.1%
Gifted Talented	Yes	21	2.3%	5	.7%	16	7.1%
Over Age for Grade	Yes	841	93.5%	643	95.3%	198	88.4%
Number of Schools Enrolled in School year 2011-2012	One School	697	77.5%	547	81.0%	150	67.0%
	Multiple Schools	181	20.1%	112	16.6%	69	30.8%
	Multiple Enrollments in Same School	21	2.3%	16	2.4%	5	2.2%

		All Students		EOY Dropout		Reengagers	
		#	%	#	%	#	%
Academic Variables							
At least one Course Failure	Yes	529	58.8%	381	56.4%	148	66.1%
	No	131	14.6%	85	12.6%	46	20.5%
No Course Grades		239	26.6%	209	31.0%	30	13.4%
Low-tracked Courses	Yes	149	18.4%	74	12.6%	75	33.6%
	No	638	78.8%	490	83.5%	148	66.4%
No Enrolled Classes		23	2.8%	23	3.9%	0	0.0%
Behavioral Variables							
At Least One In School or Out of School Suspension	Yes	161	17.9%	87	12.9%	74	33.0%
	Expulsion	Yes	30	3.3%	4	.6%	26
School-level Variables							
Type of School	Neighborhood	429	47.7%	251	37.2%	178	79.5%
	Option	274	30.5%	241	35.7%	33	14.7%
	Charter	186	20.7%	180	26.7%	6	2.7%
	Special	8	.9%	2	.3%	6	2.7%
	Other	1	.1%	0	0.0%	1	.4%
	Placed out of District	1	.1%	1	.1%	0	0.0%
School Performance Framework	Turnaround	4	.4%	1	.1%	3	1.3%
	Priority Improvement	369	41.0%	345	51.1%	24	10.7%
	Improvement	121	13.5%	67	9.9%	54	24.1%
	Performance	403	44.8%	261	38.7%	142	63.4%
	No Assigned Rating	2	.2%	1	.1%	1	.4%

Enrollment patterns reveal that 22.5% of all students were enrolled (registered and attended) more than one school. Table 5 represents a duplicate count of enrollments, meaning the same student may be in different rows because they are included in the count if they have two enrollments as well as one enrollment. Note that all students have at least one enrollment, while one of those students has five enrollments. All 899 students had at least one enrollment. Of those 899 students, 202 had two enrollments. Of those 202 students, 50 had three enrollments. Of those 899 students, eight students had four enrollments and one student had five enrollments. Similar patterns are apparent across both groups with the exception of more reengaged students having at least one or more second enrollment than EOY dropouts. Of course, we would expect reengagers to have at least one other enrollment because reengagers often re-enroll in another school after an episode of dropout rather than the original school they started in at the beginning of the school year.

Table 5
Total Number of Enrollments for All Students

At least...			EOY Dropout		Reengaged	
	No. of Students	No. of Schools	No. of Students	No. of Schools	No. of Students	No. of Schools
One Enrollment	899	57	675 (100%)	37	224 (100%)	48
Two Enrollments	202 (22.4%)	32	128 (19%)	16	74 (33%)	29
Three Enrollments	50 (5.5%)	15	31 (5.6%)	8	19 (8.5%)	10
Four Enrollments	8 (<1%)	5	6 (<1%)	4	2 (<1%)	2
Five Enrollments	1 (<1%)	1	1 (<1%)	1	0 (0%)	0

Note. This is a duplicate count across rows. All students have at least one enrollment and the remaining rows indicate additional enrollments for those students.

The student data system was accessed manually to review each of the 224 reengaged students' records in an attempt to understand the reasons for an episode of dropout. For the majority of reengagers (75%), reasons were not discernible from the available district data. Table 6 describes the possible events leading up to or resulting in an episode of dropout for the 25% of reengaged students with reasons that were discernible. Similar data were not collected for EOY

dropouts because of the limited insights gleaned from district data for reengagers and the amount of time required to review 675 records manually. An important limitation of these results is that they could not be crosschecked to verify my coding due to a lack of permissions to access the school district's data system. Therefore, no inter-rater reliability data are available, and the categorizations in Table 6 should be treated as preliminary and exploratory only.

Table 6

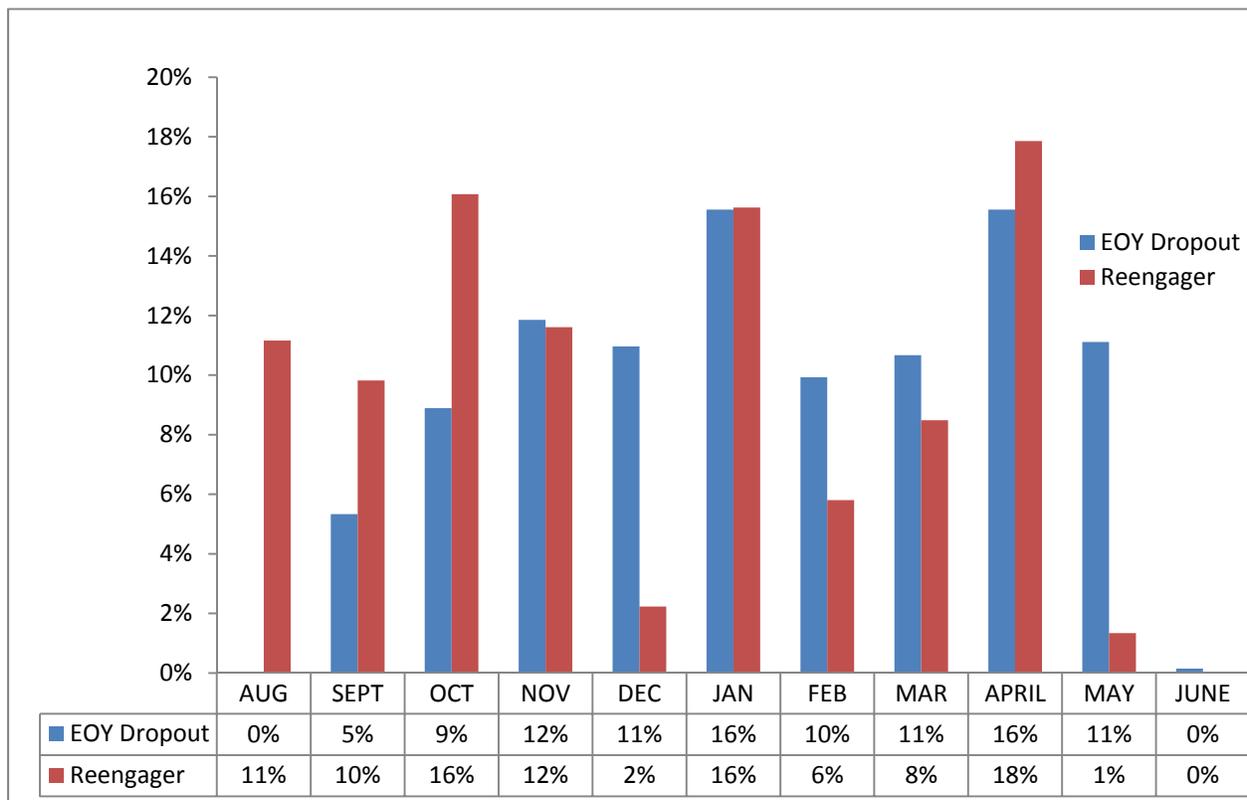
Circumstances Leading to an Episode of Dropout for Reengagers

Circumstances leading to an Episode of Dropout	#	%	Description
Behavioral issues	1	0%	Multiple behavioral incidents not resulting in out of school suspension.
Dual Enrollment	2	1%	Students who left their primary enrollment but reengaged at a school in which they were already secondarily enrolled.
Juvenile Justice Involvement	2	1%	Detention at a juvenile facility.
Medical Issues	18	8%	Medical issues that were not excused but often resulted in eventual homebound services.
Mental Health Issues	1	0%	Apparent mental health issues that resulted in placement in a facility.
Out of State	1	0%	Left the state (for Mexico) for an extended period.
Runaway	5	2%	Whereabouts unknown during the episode of dropout.
Multiple Out of School Suspensions	26	12%	One or multiple out of school suspensions occurring prior to the dropout episode.
Not discernible from district data systems	168	75%	Reason for the episode of dropout was not apparent from district data.
Total	224	100%	

The month in which the dropout occurred was explored for both groups. For EOY dropouts, the dropout is recorded by the school at the time a student is coded as a dropout. This event either occurs when the student completes an official withdrawal form or when school staff are unable to locate a student. For some large schools, this might occur at the end of the school year, as school staff begin to clean up files for the end-of-year submission to the state education agency. For reengagers, I manually reviewed each record to discern when their first episode of dropout occurred. Seven reengaged students had multiple episodes of dropout. Figure 2 displays

the month of dropout or the month of the first episode of dropout for EOY dropouts and reengagers respectively. Peak months include October for reengagers, as well as January and April for both EOY dropouts and reengagers. Notably, a large number of dropouts seemed to occur in May, immediately before the school year ends. It is unclear whether this is an artifact of end-of-year records clean up or the actual timing of dropout.

Figure 2. Month of Dropout Episode for EOY Dropouts and Reengagers



The month that students reengaged with school is a distinct temporal data point only available for reengagers and is presented in Table 7. A large number of students reengage (31%) with school at the end of the school year. Other peak months for reengagement were November and December. Otherwise, students reengaged somewhat evenly throughout the school year.

Table 7
Month Students Reengaged with School

Month of Reengagement	No. of Students	% of Students
SEP	9	4%
OCT	15	7%
NOV	24	11%
DEC	36	16%
JAN	15	7%
FEB	21	9%
MAR	14	6%
APRIL	20	9%
MAY	70	31%
Total	224	100%

Make Your Voice Heard Student Engagement Survey

Beyond the district data described above, the Make Your Voice Heard (MYVH) student engagement survey was also included in the analysis to determine patterns related to and factors predicting student dropout and reengagement. The MYVH survey was administered from January 9 to February 3, 2012. The overall district response rate on MYVH was 81%, with response rates as low as 66.3% in 12th grade and as high as 90.9% in seventh grade. School-level response rates ranged from 66% to 99%. Overall, of the 40,345 students enrolled at the beginning of the administration, 32,543 or 81% of secondary students took the MYVH survey. Of those who started the survey, 26,763 students had complete data with no missing responses across the 60 items. Although it would be informative to determine non-response bias within subgroupings of the population using student-level enrollment data, these data were not available. Despite the overall high response rate, these data may not be representative of the any or all subgroups within Wellco schools.

As one might expect in a study of at risk students, there was a concerning amount of missing data for those students. Since the MYVH survey is designed to measure engagement, only students who took the survey were included in the data set, resulting in the attrition of 704

students. Since this is such a substantial number, imputing the data was not considered worthwhile or appropriate. Table 8 demonstrates that overall both groups are missing MYVH data for more than 50% of students, which raises serious concerns about how the sample of students with MYVH data systematically differs from the rest of the population. A primary component of this inquiry is whether a survey of student engagement predicts reengagement. I did not impute missing data because I did not have a basis for inferring what the missing data could be. This approach is in alignment with MacIver and Messel (2013) who included only included students with non-missing data in their analyses.

Table 8
MYVH Student Engagement Survey Data

EOY Dropout				Reengaged			
Missing		MYVH		Missing		MYVH	
#	%	#	%	#	%	#	%
585	86.7%	90	13.3%	119	53.1%	105	46.9%

Although all schools in the district were required to complete MYVH, there are some systematic or non-random variations between schools. For example, detention facilities and mental health facilities did not complete MYVH. Additionally, the district cannot require charter schools to take the MYVH survey, although some do. School-level systematic differences between students with and without MYVH data are described in Table 9. Four areas of potential systemic bias are identified for EOY dropouts, as demonstrated by the greater than 10% difference between the groups. Differences are found for neighborhood schools, and schools with a rating of Turnaround or Priority Improvement.

Table 9

Characteristics of Schools attended by EOY Dropout and Reengaged Students with and without MYVH Data

		EOY Dropout				Reengaged			
		Missing		MYVH		Missing		MYVH	
		#	%	#	%	#	%	#	%
Type of School	Neighborhood	208	48%	43	10%	92	21%	86	20%
	Option	209	76%	32	12%	17	6%	16	6%
	Charter	165	89%	15	8%	4	2%	2	1%
	Special	2	25%	0	0%	5	63%	1	13%
	Other	0	0%	0	0%	1	100%	0	0%
School Performance Framework	NA	1	100	0	0%	0	0%	0	0%
	Turnaround	1	25%	0	0%	2	50%	1	25%
	Improvement	57	47%	10	8%	32	26%	22	18%
	Priority	313	85%	32	9%	11	3%	13	4%
	Performance	213	53%	48	12%	73	18%	69	17%
	NA	1	50%	0	0%	1	50%	0	0%

Based on these descriptive displays, it becomes clear that using MYVH at the student-level for logistic regression modeling is problematic due to systematic bias in the missing data. However, school-level data can be aggregated from all student responses across the district to create school climate factors. Indeed, MYVH was designed to be used by schools staff as an indicator of school climate not as a diagnostic tool for individual student engagement. Climate factors can be applied in inferential modeling because they are based on all students' data in the school. Obviously, using these data at the school level does not negate concerns about the missing data. In any case, a psychometric review of district level survey data is warranted before describing the inferential modeling (McCoach et al., 2013).

Make Your Voice Heard Psychometric Approaches

The MYVH data set used to test the hypothesized factor structures included data from all students in grades 7 through 12, not only the dataset of students who experience an episode of dropout (n=899). All data from all students were used because: a large number of cases was needed to conduct factor analysis; the application was to create school-level factors for the inferential modeling, and; there was a lot of missing data issue from the focal groups of

reengagers and EOY dropouts. Using all data, the number of students is large enough for factor analysis techniques, given that there are a minimum of 10 to 15 observations per variable (Field, 2009; Lingard & Rowlinson, 2006). Additionally, the number of students with complete data is large enough to be considered representative of the district. Missing data is problematic in AMOS; therefore, if students were missing data, the case was excluded from the analysis. Since the sample size is still large enough with 26,763 valid cases to allow for factor analysis, data were not imputed. I did not have the missing values module in SPSS so I could not run Little's Missing Completely at Random test with the data.

One assumption of CFA is that the data are normally distributed, and this is particularly important for Maximum Likelihood Estimates (MLE) because the advantages of MLE is that they “vary less widely around the actual parameter values than do estimates obtained by other methods” but only if “the distribution assumptions hold” and the sample is not too small (Briggs & MacCullum, 2003, pp.28). Using SPSS for verification of normality is difficult; therefore, skewness and kurtosis values for the variables were used as a proxy (Morgan, Barrett & Leech, 2011). Overall the skewness and kurtosis estimates for the items were generally acceptable indicating the responses to items are relatively normally distributed. Items 27, 30, 32, and 55 had distributions that were flatter than normal, with kurtosis estimates greater than 2. Item 32 had a negative skew of greater than -2, indicating a right skew in the data or larger values than expected in a normal distribution. Table 10 contains detailed descriptive information for each item.

Table 10
Descriptive Statistics of Survey Items
(*n*=26,763)

MYVH Item #	Minimum	Maximum	Mean	SD
1	1	4	3.16	.596
2	1	4	3.12	.631

MYVH Item #	Minimum	Maximum	Mean	SD
3	1	4	3.41	.727
4	1	4	3.26	.707
5	1	4	3.00	.719
6	1	4	3.16	.640
7	1	4	2.76	.804
8	1	4	2.88	.667
9	1	4	2.95	.849
10	1	4	2.83	.767
11	1	4	2.58	.799
12	1	4	2.77	.688
13	1	4	2.89	.634
14	1	4	2.91	.655
15	1	4	3.20	.638
16	1	4	2.88	.726
17	1	4	3.31	.608
18	1	4	3.16	.658
19	1	4	2.59	.745
20	1	4	2.77	.751
21	1	4	3.33	.633
22	1	4	2.96	.792
23	1	4	2.88	.771
24	1	4	2.93	.783
25	1	4	3.08	.681
26	1	4	3.21	.702
27	1	4	3.77	.607
28	1	4	3.50	.813
29	1	4	3.68	.692
30	1	4	3.89	.433
31	1	4	3.54	.770
32	1	4	3.85	.485
33	1	4	3.23	.717
34	1	4	3.47	.722
35	1	4	3.23	.760
36	1	4	3.11	.746
37	1	4	2.61	.760
38	1	4	2.95	.752
39	1	4	2.63	.744
40	1	4	2.86	.769
41	1	4	3.42	.674
42	1	4	2.92	.769
43	1	4	2.87	.758
44	1	4	2.65	.895
45	1	4	3.10	.684
46	1	4	3.19	.754
47	1	4	3.60	.551
48	1	4	3.04	.812
49	1	4	3.45	.605
50	1	4	3.12	.793

MYVH Item #	Minimum	Maximum	Mean	SD
51	1	4	2.97	.858
52	1	4	3.26	.663
53	1	4	3.43	.802
54	1	4	3.60	.598
55	1	4	3.74	.504

Evidence for Validity

Measurement provides “a reasonable and consistent way to summarize the responses that people make to represent their achievement, attitudes, or personal points of view through instruments such as scales, achievement tests and questionnaires, surveys and psychological scales.” (Wilson, 2005, p.5) According to McCoach et al. (2013), the steps of developing an affective instrument include the development of scales by selecting a large number of items, reviewing items with experts for validity evidence based on content, piloting items with the target population, and conducting item analysis including factor analysis and alpha reliability analyses. Each of these steps produces evidence for validity as specified by the standards for educational and psychological testing (the standards).

As previously discussed, evidence for validity based on content and response processes were actively sought with existing research and survey items, expert panels, and cognitive interviews. Again, the theorized structure of the data that factor analysis tested, is the three-factor affective, behavioral and cognitive engagement theory first proposed by Fredericks (2004) as well as the nine-factor model proposed. In the development of the survey, it was hypothesized that the nine factors were nested under the three factors. This section describes the next step in developing evidence for validity based on internal structures by exploring the item interrelationships. Item analysis includes the confirmatory factor analysis, the proposed factor model, and internal consistency statistics.

Confirmatory Factor Analysis. Confirmatory Factor Analysis (CFA) is used to determine the dimensionality of items in a survey developed with an *a priori* theoretical structure because it is designed to confirm that hypothesized structure. To better assess the proposed theoretical structure of the data and relationships between the latent variables, multiple CFA were performed using AMOS 21 program editor mode. Since the visual basic programming plug in was used, a pathway diagram of relationships was not produced, nor would it be practical to display due to the sheer number of items and nested nature of the hypothesized factor structure.

Three proposed models were tested; the three-factor model, the nine-factor model and a reduced nine-factor model. The three-factor model reflects Fredericks and colleagues' (2004, 2011) theory of affective, cognitive and behavioral engagement and is perhaps the simplest conception of engagement for school staff, parents, and students to understand. Table 11 displays the progression of fit indices over multiple models. The three-factor model (Affective, Behavioral, and Cognitive) fits poorly compared to the reduced nine-factor model. A statistical heuristic is that the goodness-of-fit-index (GFI), which indicates the fit between hypothesized and observed covariance matrix, should be greater than or equal to .9 and, while we are close with the nine-factor models, no model meets that criterion (Bryant & Yarnold, 1995; McCoach et al., 2013; Tabachnik & Fidell, 2005).

The normed comparative fit index (CFI), which adjusts for sample size in its analysis of the discrepancy between the data and the model, should be greater than .95 (Bentler, 1990; Tabachnick & Fidell, 2005). The CFI, estimated at .64 for the three-factor, .82 for the nine-factor and .85 for the reduced nine-factor models, does not provide strong support for any of the tested models. However, it does fit better for the nine-factor models than the three-factor models.

The preferred range of the root mean square error of approximation (RMSEA), which uses the parameter estimates to look at model fit, should be below .06 because this indicates that the average size of the residuals in the model is low (Browne & Cudeck, 1993; Tabachnick & Fidell, 2005). These criteria are met for the nine-factor models but not the three-factor model.

The Chi-square was 54,207.127 with 1394 degrees of freedom. The Chi-square was significant at $p < .001$, an undesirable p -value. Statistical significance could be due to the large number of students in the data set. The Chi-square statistics are reported in Table 11 as CMIN/DF, which should be under two or three (Tabachnick & Fidell, 2005; Garson 2008). All models had unacceptable high CMIN. However, Garson (2008) recommends that goodness-of-fit indicators other than CMIN, such as those already reported (e.g. GFI, CFI, RMSEA), should be given greater consideration especially for large sample sizes ($n > 250$).

Akaike Information Criterion (AIC) & Bayesian Information Criterion (BIC)³ are typically used to assess non-nested models (e.g. nine factors nested within three factors). These absolute fit indices cannot be interpreted in isolation; interpretation is facilitated by comparing multiple alternate models that are non-nested (McCoach et al., 2013). However, the AIC and BIC are reported in Table 11 (note that smaller is better). It is difficult to interpret AIC and BIC because these indices are highly variable even at large sample sizes (Preacher & Merkle, 2012). The AIC and BIC demonstrate a high variability across each model and should be considered with caution.

³ The default model was used as opposed to the saturated or independence model because it provides a more parsimonious explanation than the saturated model and better explanatory power than the independent model which assumes no relationships between the variables.

Table 11
CFA Fit Indices over Multiple Models

Instrument (and model design)	Iterations	GFI	CFI	RMSEA	CMIN/DF	$p (\Sigma^2)$	AIC	BIC
Theoretical (3 factor with all items)	10	.702	.654	.070	132.8	< .001	108,332	109,194
Theoretical (9 factor with all items)	11	.856	.829	.050	67.6	< .001	54,499	55,612
Reduced (9 factor with low loading items removed – item 7 & 53)	11	.875	.855	.050	67.6	< .001	37,616	38,562

Proposed Factor Model. CFA is a more rigorous test of the hypothesized relationships between items than Exploratory Factor Analysis (EFA) and allows for the comparison of alternative explanations. While it is relatively easy in AMOS to add additional paths from one item to another item and add correlations from a factor to an error term, these actions should be used cautiously, if at all. Excessive re-specification digresses from true CFA into EFA (McCoach et al., 2013). In any case,, excessive re-specification is not appropriate for testing an *a priori* theory, which is the purpose of CFA in this dissertation. It might be worth noting that factor analytic approaches are currently being implemented in the district for the next administration of MYVH in winter of 2014.

For the purposes of this dissertation, two hypothesized structures were proposed and tested with CFA. The nine-factor model with all items fit better in terms of GFI, CFI, and RMSEA than the three-factor model. The nine-factor reduced model provides slightly better fit for the data than the nine-factor model. Item 7 *Homework assignments help me practice what I am being taught in my classes*, seems to be substantively different than the other academic challenge items which reflect classroom practices of questioning and challenging materials. Upon further investigation into the cognitive interviews, it appears that at the secondary level students had to shift their frame of reference from the classroom environment to the home environment when answering this question. One might argue that homework was not seen as an

extension of the classroom but rather a separate activity required outside the classroom.

Surprisingly, this item was not qualitatively connected to support for learning at home in the cognitive interviews and did not have high cross loading with family support for learning. Item 7 was removed from subsequent analyses.

Item 53 *I would like to quit school* was reverse coded and could be considered an extreme statement compared to the other items that reflect students' perceptions of the importance of education and their expectations of high school graduation. However, item 53 could be considered as accessing the range of responses from students and was therefore left in for substantive reasons. After all, quantitative data can serve as a flag indicating the need for deeper qualitative inquiry (Wilson, 2005). Either way, additional cognitive interviews would be helpful to check item 53.

Table 12
Make Your Voice Heard Constructs and Associated Items

Constructs	Variable Name	Items ^a	Description Students Perceptions of:
Staff – Student Relationships	SS_REL	1,2,3,4,5,6	Positive relationships between students and school staff
Academic Rigor	ACADRIG	8,9,10,11	The rigor and challenge of classwork and homework
Teacher Feedback	TCHRFEEED	12,13,14,15,16,17	Feedback and questioning practices of their teachers
Discipline Practices	DISCPERC	18,19,20,21,22	School rules and discipline practices
Safety	SAFEPERC	22,23,24,25,26,27,28,29,30,31,32	Safety and experiences of delinquent acts (e.g. harassment, bullying, etc.)
Attendance & Participation	PART	33,34,35,36,37,38	Their attendance and on task behavior
School Connection	SCHCONCT	39,40,41,42,43,44,45	School belonging , connection to peers and emotional attachment to school

Constructs	Variable Name	Items ^a	Description Students Perceptions of:
Family Support for Learning	FAMSUPP	46,47,48,49,50,51,52	Their parents/guardians support for learning (e.g. help with homework) and dialogue with parents about schoolwork
Future Aspirations	FUTASP	54,55	Their intentions to stay in school, graduate and value education.

^aRefer to Table 2 for description of items.

Potential Next Steps to Obtain for Evidence for Validity. Another approach to bolster validity evidence for the proposed constructs is to collect other measures of same or similar constructs (McCoach et al., 2013). To further the evidence for validity based on relations to other variables, a suggested next step for the MYVH data could be to correlate or compare each of the nine constructs to district data systems such as grade point average, behavioral incidents, and attendance. These data points align with the constructs in the MYVH survey (e.g. attendance and participation could be correlated with actual attendance) and support the theoretical conceptualization of student engagement as promoting academic achievement, school attendance, and positive academic behaviors (Arreaga-Mayer & Perdomo-Rivera, 1996; Christensen, Reschly, & Wylie, 2012; Connell, Spencer, & Aber, 1994; Finn, 1989; Fredericks, Blumenfeld, & Paris, 2004; Furlong, Whipple, Jean, Simental, Soliz, & Punthuna, 2003; Henry, Knight, Thornberry, 2012; Libbey, 2004; Marks, 2000; Skinner, Wellborn, & Connell, 1990; Wang & Eccles, 2011). Further evidence for validity helps to secure buy-in from school staff, parents and the community and may encourage the use of the MYVH data.

Additionally, data could be collected from school staff and teachers to triangulate students' perceptions with the potential of obtaining other evidence for validity based on relations to other variables. Another line of inquiry is to explore the causal relationship between

the attributes intended to be measured by MYVH and students' responses with the hopes of developing more sophisticated item than Likert items (e.g. Guttman type items). Finally, the district will continue to administer MYVH to all students, as a census every other year and optionally in the 'off' years. Longitudinal analyses provide the opportunity to collect additional validity evidence of the MYVH constructs. For example, does the Future Aspirations construct predict educational outcomes for students (historically call predictive design)? The district might also explore the application of MYVH data to experimental designs used to evaluate programs producing convergent or discriminate evidence. Each of these approaches to collecting validity evidence can be applied to different subgroups within the student population to establish validity of the instruments for students of differing ethnicities, gender, and socioeconomic status. Of most interest to this inquiry is the applicability of MYVH to students who are at risk of dropping out of school. Perhaps, a more focused effort is needed to ensure representative data from this difficult-to-reach group of students.

Reliability of the Hypothesized Factor Structure. The next step in evaluating an affective instrument is to assess the reliability of the hypothesized structure (McCoach et al., 2013). According to generalizability (G) theory, two sources of error to consider are items and occasions (Shavelson & Webb, 1991). Error of occasions reflects the error over multiple administrations. For the purpose of this dissertation, error of occasions could not be explored because MYVH did not have more than one administration (parallel tests). However, internal consistency of the items was examined using Cronbach's Alpha for all factor models tested in the CFA to understand error in items (a separate facet considered important in G theory). The reliability coefficient derived using Cronbach's is the "average correlation of an item with all

other items in the domain” and can be interpreted similarly to an R-square (McCoach et al, 2013, pp. 282).

Cronbach Alpha’s for the nine-factor solution are described in Table 13 (Cronbach, 1951). All but two constructs are above .7 and are considered acceptable. The items designed to measure rigor and future aspirations do not meet that criteria and should be considered questionable. However, psychological constructs with alpha’s below .7 may be considered acceptable if diverse constructs are being measured by many variables (Kline, 1999) as is the case with these data using the reduced nine-factor model. Nonetheless, there remains error in the measurement, which makes estimates less precise, and this should be considered. As noted by Cortina (1993), constructs with small numbers of items are less likely to have high alphas. Five items were intended to measure the latent variable of academic rigor and future aspirations had three items. These limitations need to be considered moving forward due to alphas that are slightly less than .70. Attenuation of the estimated effects could also be present because of measurement error.

Table 13
Internal Consistency & Reliability of MYVH Constructs

Construct	C’s Alpha (Number of items)	Cronbach’s Alpha (if an item is deleted)
Staff Student Relationships	$\alpha = .751$ (6)	Remove Q3, $\alpha = .779$
Academic Rigor	$\alpha = .641$ (5)	Remove Q7, $\alpha = .700$
Teacher Feedback	$\alpha = .811$ (6)	
Discipline Practices	$\alpha = .712$ (5)	
Safety	$\alpha = .818$ (11)	This includes 6 reverse coded items
Participation	$\alpha = .757$ (6)	This includes 2 reverse coded items
School Attachment	$\alpha = .784$ (7)	
Family Support for Learning	$\alpha = .862$ (7)	
Future Aspirations	$\alpha = .678$ (3)	Remove Q53, $\alpha = .730$ (Q53 is reverse coded)

Psychometric Summary

Considering the fit indices and the theory of student engagement, the reduced nine-factor model was the model of choice for logistic regression modeling (removing item 7 only). The fit indices indicate an acceptable fit with a RMSE $>.90$, a CFI which is close to $.95$, and the lowest AIC and BIC of all models tested. While the Chi-square (CMIN/df) was significant, this statistic should be interpreted with caution, as large sample sizes are more likely to result in significance (Garson, 2008). Due to the lack of internal consistency with the construct of Academic Rigor, items 7 was removed from model, resulting in the reduced nine-factor model. The remaining items were aggregated into constructs by creating a mean for all items for each case (McCoach et al., 2013). Again, this theorized factor structure reflects the structure used to design the survey (for 54 out of 55 items) and was used for the predictive modeling in this study. The three-factor model of affective, behavioral, and cognitive engagement was not used because of a lack of good fit.

School-level Data

The CFA has suggested an acceptable nine-factor structure of the district wide student engagement survey. Now, we turn back to the subset of data containing students who have either reengaged after an episode of dropout or remained an end-of-year dropout. As mentioned earlier, due to extensive missing data, the MYVH nine-factor model data were not used at the individual level. However, using the nine-factor reduced model, the constructs were aggregated into a school-level mean for eight of the nine identified factors using all district data available. The intention of the aggregation was to reflect the culture of the school more broadly using school engagement climate indicators. The family support construct was omitted from the school-level variable since it occurs outside of the school setting and cannot be considered part of school climate.

The unit of analysis for the MYVH thus far has been students. In this next section, the data are being used at the school-level. The validity evidence for using MYVH at a school-level is predicated on the validity evidence established at the individual level. However, a description about the school-level results is warranted. The group mean for each school-level factor across the entire district is described in Table 14. Note that Table 14 does not report the 18 schools not represented in the reengagement subset because many of those schools (8) were very small (<80 students). Only 3,290 students are included in those 18 other schools for a total of 12% of the sample of students. Since data were applied to all students in the subset of dropouts, all but five students have group school-level means. The five missing students were enrolled in schools that did not administer the survey (e.g. charters or facilities).

Table 14
School-level Description of MYVH Constructs

MYVH Item	Sub Set of Students who Experienced an Episode of Drop Out (n=48)					All Secondary Schools in the District (n=66 schools)				
	#	Min.	Max.	Mean	SD	#	Min.	Max.	Mean	SD
SCH_SCHCONN	894	1.71	3.57	2.80	0.33	31586	2.89	3.48	2.92	0.51
SCH_SS_REL	894	2.86	3.67	3.23	0.16	31963	3.01	3.40	3.18	0.46
SCH_DISCPERC	894	2.65	3.40	2.99	0.14	31890	2.73	3.21	2.96	0.50
SCH_SAFEPERC	824	1.80	2.18	1.99	0.05	31071	1.85	2.25	1.99	0.27
SCH_PART	894	2.33	2.79	2.58	0.10	31610	2.43	2.58	2.58	0.32
SCH_ACADRIG*	894	2.25	3.20	2.79	0.10	31565	2.69	3.23	2.80	0.57
SCH_TCHERFEED	894	2.80	3.25	2.78	0.25	31942	2.80	3.36	3.00	0.48
SCH_FUTASP*	894	2.67	3.01	2.94	0.03	31801	2.96	3.89	3.66	0.50
Valid N (listwise)	824					27412				

*New reduced factors

Multilevel Binomial Logistic Regression

A primary research question is the extent to which each of the previously discussed variables predicts reengagement among dropouts and whether a multiple predictor model estimates reengagement better than any single variable. As a 2-category dependent variable, the

question is best answered by binomial logistic regression. Multilevel models, specifically random-intercept models, serve three primary research purposes 1) getting more accurate predictive estimates for individuals than only one level models that do not account for dependencies inherent in nested data, 2) accounting for effects that cut across the individual and school-level, and 3) partitioning the variance components into within and between schools (Raudenbush & Bryk, 2002). Essentially, variability among individuals within groups is not accounted for if we simply analyze the data as individual cases. This is problematic because clustered data, such as students within schools, may vary systematically. Random-intercept models include the typical fixed effect for the predictors found in standard logistic regression and a random effect at the group level. That is, schools in which individuals are clustered are treated as a random sample of all schools. Multilevel models estimate this variability using random effects at the school-level.

Multiple logistic regression models were explored and evaluated using standard model fit indices including Wald's t-test for significance, F tests for overall model significance test, AIC and BIC, and the strength of the OR's (Heck et al, 2012). Each model was run to address research question 2 and each of the sub questions, including:

2. What factors predict the successful reengagement of dropouts within the school year?

Specifically,

- a. Controlling for ethnicity and poverty, how does having a behavioral incident, being overage for grade, being in an intervention coursework or having a course failure predict reengagement?

- b. Controlling for ethnicity and poverty, do school-level climate factors of affective engagement, (specifically) school connection and staff student relationships, predict reengagement?
- c. Controlling for ethnicity and poverty, do school-level climate factors of behavioral engagement, (specifically) perceptions of safety, discipline practices and school participation, predict reengagement?
- d. Controlling for ethnicity and poverty, do school climate factors of cognitive engagement (specifically) perceptions of academic challenge, teacher feedback and future aspirations, predict reengagement?
- e. Controlling for ethnicity and poverty, does a school's performance on state accountability frameworks predict reengagement?
- f. Controlling for ethnicity and poverty and based results of research questions 2a through 2e, what combination of student-level and school-level factors provide the most parsimonious model for predicting reengagement?

Software Used for Multilevel Modeling. Multilevel models were run in SPSS (IBM's Statistics Package for the Social Sciences) using the generalized linear (GENLIN) mixed models analysis functionality. Since SPSS was the analysis package used, a few analytic notes should be made for those who typically use HLM or other multilevel modeling software. First, for multilevel models with dichotomous outcomes, active set method (ASM) with Newton-Raphson estimation is the estimation method not Maximum Likelihood Estimation (MLE). According to Heck, Thomas and Tabata (2012) ASM is a common theoretical approach which finds,

“a feasible starting point and repeating until it reaches a solution that is “optimal enough” according to a set of criteria. More specifically, at each iteration, the approach

proceeds by partitioning inequality constraints into an active (or sufficiently close to be deemed active for this iteration) or inactive set (Nocedal & Wright, 2006).” (pp. 137)

All students in the subset had complete data from the district data systems (e.g. demographics and enrollment information). Course failure (n=239) and, to a lesser extent, low-track or intervention course enrollment (n=112), was missing for many students because not all students attended enough school to have a documented record of coursework. Additionally, five students were missing a school-level performance rating because the school they attended did not have an SPF (e.g. a detention center). Listwise deletion for missing data was used by McIver & Messel (2013) to estimate graduation or non-graduation outcomes of high school students in Baltimore. Similarly, only those students with no missing data were included in the modeling because of the need to determine the strength of all predictors⁴.

Another benefit of SPSS is the ease of organizing the data files. One output file is produced by SPSS containing all models. The output file was exported to excel and formatted for the writing of the dissertation document. This process limits the transcription errors that can occur with the less flexible text files produced by HLM. Additionally, the syntax for every model

⁴ Note that in SPSS missing data are deleted listwise, meaning a case is eliminated if it has one missing variable. While add on packages are available to impute missing data, I did not have access to these expensive add-on's and more substantively, missing data are not missing at random in this study (as mentioned previously). Consequently, listwise deletion is preferred to using imputation method. Arguable, listwise deletion introduces its own biases. These biases can be taken into consideration in our interpretations.

was captured in SPSS syntax editor and can be found in Appendix B with the intent of providing transparency for external review.

Student and School-level Predictors. It is important to note that the student-level variables are dichotomous. Therefore, the interpretation is relatively straightforward. For example, if a student is overage for grade, she is coded as 1. If she is not overage for grade, she is coded as 0. Odds ratios (*OR*) can then be interpreted as the estimated ratio of the odds of the outcome if a student has that characteristic to the odds of the outcome if the student does not have that characteristic. The school-level predictor of school performance is similar to this because the school rating on the state's accountability framework was recoded into either high performing (1) or low performing (0). However, the other school-level predictors are on four-point ordinal scales and, as such, the interpretation for these predictors is inherently different. For these MYVH survey predictors, the variable represents the mean of the coded item response at the school from which a student has dropped out. Therefore, interpretation of the *OR* is that for each point increase on the school mean of the predictor, a student has X higher odds of re-engaging with school (Heck, et al. 2012).

As a reminder, the school-level predictors used in these models are the characteristics of the school from which the student drops out, meaning the models are built on the leaving school not the returning school. The rationale for this analytic approach is two-fold; 1) if school districts want to intervene with students, the only data available to them is the leaving school, and 2) the total number of students returning is too small to allow predictive modeling. Again, these analyses focused on the dichotomous outcome of either reengagement (1) or lack of reengagement (0), given that a student initially dropped out.

Evaluation of Model Fit. Several indicators of model fit were used including the classification table (percent correctly predicted), the statistical significance of the predictor, and the size of the log odds and corresponding odds ratio (*OR*). While there are many pseudo r-square formulas available for interpreting the value of particular models, there is a lively debate about the worth of these indices (Tabachnick & Fidell, 2007; Menard, 2002; Hox, 2010). Pseudo r-square cannot be interpreted similarly to a multiple regression model because a pseudo r-square does not explain the variance in the model (Tabachnick & Fidell, 2007). Additionally, a pseudo r-square cannot reach 1.0, and its range varies depending upon the data set, making it difficult to interpret. Additionally,

“variance at Level 1 is rescaled each time variables are added to the model, which also affects the variance estimate at Level 2 (Hox, 2010). Because of this, the notion of examining the reduction of variance as successive sets of predictors are added to the model can be misleading when estimating models with categorical outcomes (Hox, 2010).” (Heck, et al, 2012, pp. 161)

Another school of thought is to rely on the substantive interpretations of the models by looking at the evidence provided by all statistical output (Heck et al, 2012). For the purposes of this dissertation, a substantive approach is used to interpret results.

Another note about the use of the *OR* is warranted since interpretation relies heavily on the *OR*'s in the subsequent model. An *OR* greater than 1 indicates that a student with the referent characteristic (coded as 1) has *X* times higher odds of re-engaging. Odds ratios close to 1 indicate that a student with or without that characteristics has neither higher nor lower odds than the non-referent group (coded as 0). Negative odds ratios are easier to understand from the perspective of the non-referent group (Davies, Crombie, Tavakoli, 1998). It is easiest to

transform the *OR* into a number greater than 1 to get the *OR* for the non-referent group using the formula $1 / OR$ (McHugh, 2009). For example, an odds ratio of .15 for a student who is coded as eligible for free and reduced lunch (FRL=1) would indicate that students who are not FRL have 6.67 higher odds of re-engaging. Therefore, interpretation of *OR*'s, which is the focus of the interpretation of the subsequent multilevel logistic regression modeling, should attend to *OR*'s that diverge from 1.0. If a predictor is not a dichotomous predictor, the same logic applies. However, the interpretation of higher odds is applied to increases in the predictor variable (Heck et al, 2012).

A final interpretive note concerns the modeling. A single-predictor model can be interpreted as the odds of students with one characteristic. For example, if having a behavioral incident is the only factor entered into the model, then the odds ratio (*OR*) can be interpreted as a student with a behavioral incident having *X* higher odds of re-engaging. However, when multiple predictors are included in the models, interpretation hinges on all predictors in the model; meaning each predictor's effect is estimated while holding constant the effect of all other predictors in the model.

Analysis

First, the unconditional means model was run using no predictors, just the intercept. Second, each single predictor was run in SPSS GENLIN mixed models and finally each model reflecting the hypotheses outlined in research question 2 were run. Each of these models and the corresponding output are described in the next section.

The Unconditional Means Model. As specified in Table 1, the unconditional model (UCM) is an intercept only model. This model tells us whether there is enough variability across schools to substantiate a multilevel modeling approach. If not, simple binary logistic regression would be an appropriate approach. The fixed effects are not significant ($\beta = -.208, p=.40$).

However, the random effects are significant with an estimate of 2.21, $\sigma^2 = 0.666$, ($Z=3.33$, $p < .001$). Using the random effects estimate, an intraclass correlation (ICC) can be calculated to assess the proportion of variance that lies between schools in relation to the total variance (Heck, et al., 2013). The following formula will estimate the ICC (p)

$$p = \frac{\sigma_{Between}^2}{\sigma_{Between}^2 + 3.29_{Within}}$$

$$p = .167$$

Where:

$\sigma_{FBetween}^2$ = the estimate of the random effects variance component
 σ_R^2 = Error variance which cannot be estimated with dichotomous variables,
 and therefore is estimated as $\frac{\pi^2}{3}$ or 3.29

The ICC suggests that 16.7% of the variability in reengagement lies between schools; therefore, a multilevel model is a worthwhile analytic technique for this data set.

Single Predictor Analyses. Sixteen single predictor models were run controlling for FRL and Minority status using SPSS GENLIN mixed with random effects at the school-level to determine each factor or covariate's predictive utility. It is hoped that this exploratory approach may provide some insights to school based staff as to the effect of one predictor. Four student-level predictors and five school-level predictors were statistically significant; of the remaining predictors, none were close to significant at the .05 level (see Table 14). Several odds ratios were very high but only a few of those were statistically significant. One might expect that high odds ratios to result in statistical significance, estimates divided by their standard error are indicative of a significant effect. If an OR is high and suggests that it should be statistically significant, the problem could be a large standard error. This seems to be the case for the school level variable for safety and future aspirations in Table 15. While the OR is not statistically significant, upon further investigation, you can see that the standard error of the estimate are high suggesting that

the effect is not being well measured in the data set across the 48 schools. Table 14 provides an inkling that the safety and the future aspirations variables are not behaving well because it has little variability across schools with standard deviations of .05 and .03 respectively. Since the school level variable is based on the group-mean, it lacks the variability inherent in school level data derived linked to individuals in the data set. Recall that this was not possible due to extensive missing survey data. These anomalies call into question the utility of using school level means as a predictor in the model.

In Table 15, the percent total correct comes from the classification tables produced for each model and communicates how many students were correctly predicted to either reengage (REENG) or not (EOYDROP). All classification tables are not included since the percent correct is similar. However, classification tables will be provided for the hypothesized models designed to answer research question 2.

Table 15
Parameter Estimates for Individual Predictors

	<i>B(SE)</i>	<i>p-value</i>	<i>Odds Ratio</i>	% Correct
Student Characteristics (<i>n</i> =867)				
Minority	-0.12(.17)	.47	0.89	80.6%
Free & Reduced Lunch	0.23(.17)	.19	1.26	80.6%
Overage for Grade	-.60(.28)	.03*	0.55	81.1%
English Language Learner	-0.23(.20)	.27	0.80	81%
Behavioral Incident	0.67(.24)	.01*	1.95	81.9%
Course Failure	-1.09(.36)	.00*	0.34	79.5%
Low-track Core Coursework	1.10(.31)	.00*	3.01	79.5%
School Characteristics (<i>n</i> =892)				
High Performing	2.25(1.0)	0.03*	9.47	80.2%
Safety	2.60(3.7)	0.48	13.47	80.5%
Discipline	-3.40(1.41)	.017*	0.03	80.2%
Participation & Attendance	-6.82(5.76)	0.24	0.00	80.5%
Staff – Student Relationships	-5.64(1.83)	.002*	0.00	80%
Connection to School	1.89(1.64)	0.25	6.6	80.4%
Academic Challenge	-4.49(.17)	.001*	0.011	80.5%
Future aspirations	4.20(6.42)	0.54	66.80	80.1%
Teacher Feedback	-4.34(1.32)	.001*	0.013	80.1%

*Statistically significant at $p < .05$.

All single predictor models controlled for FRL and/or minority. While several Level 1 single predictors are worthy of discussion, it must be noted that the classifications for all models predict dropout better than reengagement. Our data points are better at predicting who will remain a dropout rather than who might reengage. Neither minority ($\beta = -.12$, $p = .47$) nor free and reduced lunch ($\beta = .23$, $p = .19$) eligibility was a significant predictor for reengagement. Being overage for grade was negatively associated with reengagement ($\beta = -.60$, $p = .03$). Again *OR*'s less than 1 are not directly interpretable. We can transpose this *OR* to ascertain that students who

are not overage for grade have 1.82 higher odds of re-engaging with school. Students with a behavioral incident have 1.95 higher odds of reengagement ($\beta = -.67$, $p=.01$). Students with course failure is negatively associated with reengagement ($\beta = -1.09$, $p=.00$). Therefore, students without course failure have 2.985 higher odds of reengagement. Students who were enrolled in low-track or intervention programs in ELA or mathematics have 2.98 higher odds of reengaging than students not in a low-track or intervention program ($\beta = 1.10$, $p=.00$). These somewhat unexpected findings are explored in the discussion section of this dissertation.

A final factor that was included as a single predictor was upper class student, meaning a student in grades 11 or 12. This factor was not included in our *a priori* hypotheses and was not included in subsequent models. Instead, it was added based on the exploration of the data after it was collected from district data systems. Upper class students have 2.04 higher odds of re-engaging than students in grades 7, 8, 9 or 10. Notably, the overall accuracy rate is 88.2% indicating that this one predictor has good predictive power.

School-level predictors were also entered individually into GENLIN mixed models in SPSS. As a reminder, the school-level predictor is based on the school from which the student dropped out not the school that the student reengaged. Several school climate predictors are worthy of note including high performing schools, discipline, academic challenge, and teacher feedback. Again, all classification tables indicate that the models predict end-of-year dropout better than reengagement.

Specifically, a student who drops out of a high performing school has 9.5 higher odds of reengaging than a student who drops out of a lower performing school ($\beta = 2.25$, $p=.03$). As a reminder, low performing schools are schools rated as turnaround or priority improvement on the state's accountability framework (SPF). Except for the predictor of high performing school, all

school climate predictors are negatively associated with reengagement. The school-level climate predictor of discipline was negatively associated with reengagement ($\beta = -3.4$, $p = .02$). Keep in mind that this is a scaled covariate not a dichotomous factor. Therefore, it can be interpreted using increases in the points on the response scale. A student with one decrease (because it is negative) on the discipline climate predictor (or .1 point on the 4-point scale) has 30.3 higher odds of re-engaging. Correspondingly, the school-level climate predictors of staff-student relationships and academic challenge and teacher feedback are all negatively associated with reengagement. For staff-student relationships, for every decrease, a student has 333.3 higher odds of reengaging. For every decrease on academic challenge, a student has 90.9 higher odds of reengaging. For every decrease on teacher feedback, a student has 83.3 higher odds of reengaging. These *OR*'s are high.

In summary, we have some surprising results from the single predictor modeling. Being in a low-track or intervention core course and having a behavioral incident are positively associated with re-engaging with school while being overage for grade and course failures are negatively associated with reengagement. Dropping out of a high performing school is positively associated with re-engaging, while other school climate variables are strongly negatively associated with re-engaging.

Multivariate Multilevel Modeling. Following the single predictor modeling, multiple predictors were used to assess various model fit with both the student-level and school-level data as specified by research question 2 and its sub questions (a through f). The results of each model are described below in Tables 15 through 20.

Model 2a: Student-level Data. Model 2a was designed to answer research question 2a. *Controlling for ethnicity and poverty, how does having a behavioral incident, being overage for*

grade, being enrolled in intervention course work or having a course failure predict

reengagement? Model 2a only contains student-level data but was run in SPSS GENLIN mixed.

Six fixed effects parameters were estimated in the following specified model:

Model 2a: Student-level Data

Level-1 Model

$$\text{Prob}(Y=1|B) = P$$

$$\log[P/(1-P)] = B_0 + B_1*(FRL) + B_2*(MINORITY) + B_3*(ISS_OSS) + B_4*(OVERAGE) + B_5*(LOWTRACK) + B_1*(COUSREFAIL)$$

Level-2 Model

$$B_0 = G_{00} + U_0$$

$$B_1 = G_{10}$$

$$B_2 = G_{20}$$

$$B_3 = G_{30}$$

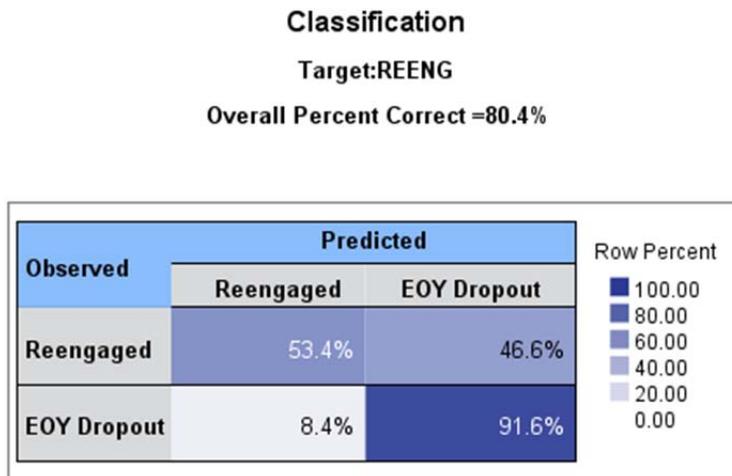
The output of this model is described in Table 16.

Table 16

Model 2a: Parameter Estimates of Student-level Data

Value	<i>B</i>	<i>p-value</i>	<i>Odds Ratio</i>
Student Characteristics			
Free and Reduced Lunch	-0.003(.19)	0.989	0.997
Minority	-0.268(.18)	0.143	0.765
Behavioral Incident	0.537(.35)	0.089	1.71
Overage for Grade	-0.0846(.31)	0.007	0.429
Low-track Core	1.015(.37)	0.006	2.759
Course Failure	-0.926(.37)	0.013	0.396

Figure 3. Classification Table for Model 2a



Since all predictors were entered into Model 2a together, the model must be evaluated holistically. First, it is important to note that 240 (27%) cases were excluded from the model due to missing data. Figure 3 displays the classification table, which conveys that the model accurately predicts 53.4% of reengagers and an overall accuracy rate of 80.3%. Note that three predictors are significant at the $p < .05$ level including a positive association for low-track intervention course in core ($\beta = 1.02, p = .01$) and a negative association for overage for grade ($\beta = -.085, p = .01$) and course failure ($\beta = -.926, p = .01$). Notice that having a behavioral incident is close to being significant with a p-value of .089. In terms of the *OR*'s, controlling for FRL and minority status, a student in a low-track core course has 2.76 higher odds of reengaging, adjusting for having a behavioral incident, course failure and being overage for grade. Similarly, a student without course failure has 2.52 higher odds of re-engaging and a student who is not overage for grade has 2.33 higher odds of re-engaging, adjusting for other predictors in the model.

In summary, the factors in Model 2a have a 53% accuracy rate for reengagers. The *OR*'s correspond to the single predictor modeling with significant log odds for being in a low-track or intervention course, not being overage for grade, and not having course failure. Although having a behavioral incident was significant as a single predictor, it is close to significant in Model 2a. A caution that must be considered for Model 2a is missing data. Twenty seven percent of the 899 cases were excluded due to missing data. The preponderance of missing data is due to course enrollment and grades because many students were not enrolled long enough to have a grades or full enrollment records. Excluding these students, Model 2a does provide a moderate explanatory framework for reengagement.

Model 2b: School Climate of Affective Engagement. Model 2b was run to address research question 2b. *Controlling for ethnicity and poverty, do school-level climate factors of affective engagement, (specifically) school connection and staff student relationships, predict reengagement?* Essentially, this research question addressed the effect of school-level affective constructs in predicting reengagement. Model 2b, also called the school climate of affective engagement model, estimates parameters for two fixed and two random effects in the following specified model:

Model 2b: School Climate of Affective Engagement

Level-1 Model

$$\text{Prob}(Y=1|B) = P$$

$$\log[P/(1-P)] = B_0 + B_1*(FRL) + B_2*(MINORITY)$$

Level-2 Model

$$B_0 = G_{00} + G_{01}*(SCHCONNECT) + G_{02}*(SCHSSREL) + U_0$$

$$B_1 = G_{10}$$

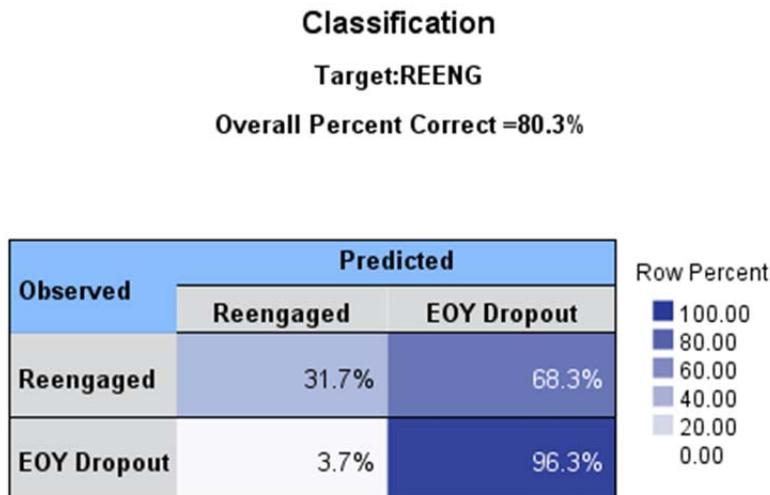
$$B_2 = G_{20}$$

Table 17 describes the output of this model and Figure 4 displays the classification table.

Table 17
Model 2b: Parameter Estimates of School Climate of Affective Engagement Constructs

Value	<i>B(SE)</i>	<i>p-value</i>	<i>Odds Ratio</i>
Student Characteristics			
Free and Reduced Lunch	0.179(.17)	0.289	1.197
Minority	-0.175(.17)	0.309	0.84
School-level Characteristics			
School Connection	2.918(1.48)	0.049	18.511
Staff- Student Relationships	-6.584(2.04)	0.001	0.001

Figure 4. Classification Table for Model 2b



Again, the multivariate models must be evaluated holistically, meaning the effect of one predictor cannot be teased out from the others. Unlike Model 2a, only five cases are excluded from Model 2b due to missing data. Figure 4 indicates a 31.7% accuracy rate for reengagers and an overall accuracy rate of 80.3%. Although the overall accuracy rate is similar to Model 2a, the affective engagement model is considerably less accurate in predicting reengagers.

Both school-level affective engagement predictors are significant at the $p < .05$ level but school connection has a positive association ($\beta = 2.918, p = .049$) while staff-student relationships

has a negative association ($\beta = -6.584$, $p = .001$). While these results are perplexing, the direction and strength of the association is similar to the single predictor models run initially. Controlling for FRL and minority status, a student has 18.5 higher odds of reengaging for each increase in school connection, adjusting for the school climate of staff student relationships. However, a student has 1,000 higher odds of reengaging for each decrease in staff student relationships, adjusting for the other factors and covariates in the model.

In summary, the factors in Model 2b have a low accuracy rate for predicting reengagers (32%) and provide perplexing results regarding affective engagement. While the hypothesized models reflect the three dimensions of engagement, the psychometric analyses did not support the three-factor model and similarly, Model 2b does not support a coherent affective model using the constructs of relationships and connection to school. The construct of staff student relationships is distinctly different in its predictive power for reengagement from school connection. Model 2b provides a weak explanatory framework for reengagement.

Model 2c: School Climate of Behavioral Engagement. Model 2c was run to address research question 2c. *Controlling for ethnicity and poverty, do school-level climate factors of behavioral engagement, specifically perceptions of safety, discipline practices and school participation, predict reengagement?* Model 2c or the school climate of behavioral engagement model estimates five parameters; two fixed and three random and can be specified as follows:

Model 2c: School Climate of Behavioral Engagement

Level-1 Model

$$\text{Prob}(Y=1|B) = P$$

$$\log[P/(1-P)] = B_0 + B_1*(FRL) + B_2*(MINORITY)$$

Level-2 Model

$$B_0 = G_{00} + G_{01}*(SCHDISC) + G_{02}*(SCHSAFE) + G_{03}*(SCHPART) + U_0$$

$$B_1 = G_{10}$$

$$B_2 = G_{20}$$

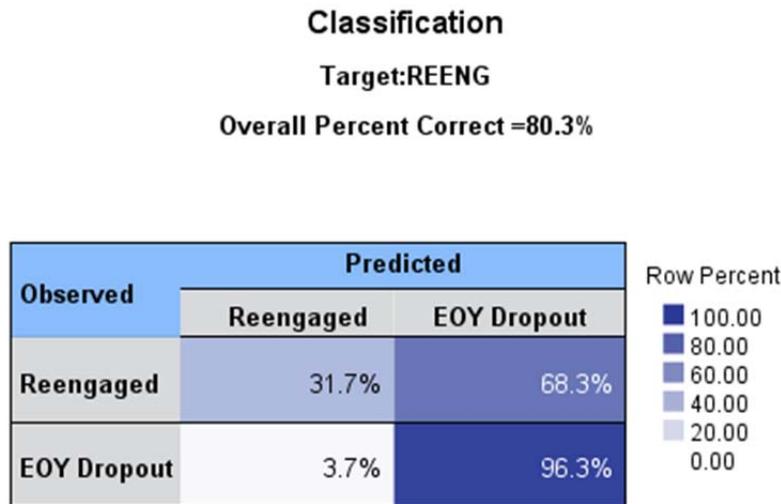
$$B_3 = G_{30}$$

Table 18 describes the parameter estimates of this model while Figure 5 describes the classification table.

Table 18
Model 2c: Parameter Estimates of School Climate of Behavioral Engagement Constructs

Value	<i>B</i>	<i>p-value</i>	<i>Odds Ratio</i>
Student Characteristics			
Free and Reduced Lunch	0.183(.17)	0.292	1.2
Minority	-0.176(.17)	0.304	0.838
School-level Characteristics			
Discipline	-2.547(3.01)	0.398	0.078
Safety	3.735(4.85)	0.441	41.874
Participation and Attendance	-4.395(7.16)	0.54	0.012

Figure 5. Classification Table for Model 2c



None of the predictors in Model 2c are not statistically significant or close to statistically significant and the accuracy and the overall accuracy is identical to the Model 2b (31.7%). Perhaps this is not surprising since in the single predictor models, discipline had negative but significant log odds while safety and participation were not significant at all. Again, this seems

to question the hypothesized modeling of behavioral engagement as a cohesive construct. Model 2c is a weak model for predicting reengagement.

Model 2d: School Climate of Cognitive Engagement. Model 2d was run to address research question 2d. *Controlling for ethnicity and poverty, do school-level climate factors of cognitive engagement, (specifically) perceptions of academic challenge, teacher feedback and future aspirations, predict reengagement?* The effect of school climate of cognitive engagement in predicting reengagement is modeled by estimating the parameter for two fixed and three random effects with the resulting specification:

Model 2d: School Climate of Cognitive Engagement

Level-1 Model

$$\text{Prob}(Y=1|B) = P$$

$$\log[P/(1-P)] = B_0 + B_1*(FRL) + B_2*(MINORITY)$$

Level-2 Model

$$B_0 = G_{00} + G_{01}*(ACADRIG) + G_{02}*(TCHFD) + G_{03}*(FUTASP) + U_0$$

$$B_1 = G_{10}$$

$$B_2 = G_{20}$$

$$B_3 = G_{30}$$

Table 19 describes the parameter estimates of this model and Figure 6 displays the classification table.

Table 19

Model 2d: School Climate of Cognitive Engagement Constructs

Value	<i>B(SE)</i>	<i>p-value</i>	<i>Odds Ratio</i>
Student Characteristics			
Free and Reduced Lunch	0.16(.17)	0.36	1.17
Minority	-0.18(.17)	0.27	0.83
School-level Characteristics			
Academic Challenge	-5.8(1.84)	0.002	0.005
Teacher Feedback	-3.57(1.43)	0.01	0.026
Future Aspirations	13.25(5.92)	0.03	569,221.14

Figure 6. Classification Table for Model 2d

Classification
Target:REENG
Overall Percent Correct =80.0%

Observed	Predicted		Row Percent
	Reengaged	EOY Dropout	
Reengaged	33.0%	67.0%	
EOY Dropout	4.6%	95.4%	

Three of the random effects are significant at the $p < .05$ level; academic challenge, teacher feedback and future aspirations. Both academic challenge and teacher feedback are negatively associated with reengagement. The effect of these two climate construct is negligible.

Controlling for minority and FRL status, students have .005 higher odds and .026 higher odds of re-engaging for each decrease in academic challenge and teacher feedback respectively. While future aspirations estimates indicate a strong, positive association with reengagement, and the logs odds are statistically significant. Notice that the overall OR is remarkably high (over 500,000 higher odds for each unit increase in the future aspirations construct). As a reminder, the standard deviation around future aspirations is small (see Table14) which may indicate an issue in the measurement of this construct. Therefore these OR's should be interpreted with caution.

The overall accuracy of the model for predicting reengagers is only 33%; meaning only a third of reengagers are predicted accurately with this model. Not surprisingly, the overall classification table indicates that this model classifies EOY dropouts better than re-engagers and

this could be due to the effect of the future aspirations predictor. Again, we are seeing that grouping our hypothesized structures into a construct of engagement is not providing a lot of explanatory power for reengagers.

Model 2e: School Performance on State Accountability Framework. Model 2e was run to address research question 2e. *Controlling for ethnicity and poverty, does a school's performance on state accountability frameworks predict reengagement?* Model 2e is the last of our hypothesized models and it is intended to estimate the random effect of school performance in predicting reengagement. The School Performance Rating was entered as a dichotomous variable with either high performing (1 = rated as Performance or Improvement⁵) or low performing (0 = rated as Priority Improvement or Turnaround). The rating data are an amalgamation of points related to test scores, academic growth, participation rates and graduation rates and should not be treated as continuous data. The model estimates two fixed effects and one random effect and can be specified as follows:

Model 2e: School Performance on State Accountability Framework

Level-1 Model

$$\text{Prob}(Y=1|B) = P$$

$$\log\left[\frac{P}{1-P}\right] = B_0 + B_1*(FRL) + B_2*(MINORITY)$$

Level-2 Model

$$B_0 = G_{00} + G_{01}*(SPFCAT) + U_0$$

⁵ State definitions of the SPF are Turnaround, Priority Improvement, Improvement or Performance. The Colorado Department of Education intervenes with schools that are turnaround or priority improvement; therefore, improvement and performance are typically considered as above the bar.

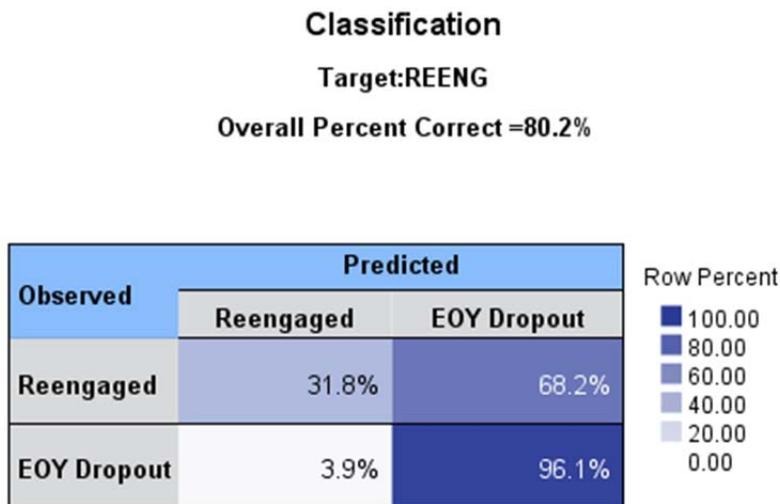
$$B1 = G10$$
$$B2 = G20$$

Notice that our two fixed effects of FRL and minority status continue to be our controls and distinguish this model from the single predictor model already specified. Table 20 describes the parameter estimates of this model and Figure 7 displays the classification table.

Table 20
Model 2e: School Climate of School Performance Rating

Value	<i>B(SE)</i>	<i>p-value</i>	<i>Odds Ratio</i>
Student Characteristics			
Free and Reduced Lunch	0.262(.17)	0.183	1.3
Minority	-0.082(.17)	0.687	0.922
School-level Characteristics			
High Performing	2.249(1.0)	0.001	9.474

Figure 7. Classification Table for Model 2e



The log odds are positive and statistically significant for high performing schools ($\beta= 2.249$, $p=.001$), indicating that the a student who drops out of a high performing school has 9.03 higher odds of re-engaging after controlling for FRL and minority status. However, the overall accuracy of the model is low at 31.8%. Model 2e suggests that perhaps additional models need to be explored that incorporate the school performance predictor with other significant predictors. The possibility of the need to model outside of *a priori* hypotheses was anticipated as reflected in

research question 2f. As a reminder, within-year reengagement has not been modeled before in this way so it is to be expected that some exploration would be necessary.

Model f & g: Combinations of Student and School-level data. It is likely that a combination of factors at both the student and the school-level predict reengagement, for that reason models f and g were run using predictors with statistically significant log odds in Models b through d. The rationale was to try to attain a parsimonious model that provides strong predictive power for reengagement. A key consideration for these more exploratory models is the missing data for two predictors. Additionally, interpretation of these models required a substantive approach that does not rely exclusively on statistical significance to ascertain model fit.

Model 2f, 2g, and 2h are new models developed based on the results of the single predictor models and Models 2a through e. Model 2f includes all statistically significant predictors in one model. Discipline was included because it was significant in the single predictor models and connection to school was included because it was significant in Model 2b. However, predictors with many missing cases were excluded including low-track in core and course failure. The following model estimated six fixed effects and six random effects and can be specified in the following way:

Model 2f: Significant Predictors Excluding Predictors with Many Missing Cases

Level-1 Model

$$\text{Prob}(Y=1|B) = P$$

$$\log\left[\frac{P}{1-P}\right] = B_0 + B_1*(FRL) + B_2*(MINORITY) + B_3*(ISS_OSS) + B_4*(OVERAGEFORGRADE)$$

Level-2 Model

$$B_0 = G_{00} + G_{01}*(SPFCAT) + G_{02}*(SCHCONNECT) + G_{03}*(SCHSSREL) + G_{04}*(SCHDISC) + G_{05}*(ACADRIG) + G_{06}*(TCHFD) + U_0$$

$$B_1 = G_{10}$$

$$B_2 = G_{20}$$

$$B_3 = G_{30}$$

$$B4 = G40$$

$$B5 = G50$$

$$B6 = G60$$

Model 2g includes the same four fixed effects of model f but excluded any non-statistically significant Level 2 predictors, resulting in two random effects. The model can be specified as follows:

Model 2g: Significant Predictors from Model 2f

Level-1 Model

$$\text{Prob}(Y=1|B) = P$$

$$\log\left[\frac{P}{1-P}\right] = B0 + B1*(FRL) + B2*(MINORITY) + B3*(ISS_OSS) + B4*(OVERAGEFORGRADE)$$

Level-2 Model

$$B0 = G00 + G01*(SPFCAT) + G02*(ACADRIG) + U0$$

$$B1 = G10$$

$$B2 = G20$$

A final model tested with these data was Model 2h that included all predictors from Model 2g but reintroduced the predictors of low-track or intervention course in core and course failure. Even though these predictors have missing data, the parameter estimates have been strong in previous models. Model 2h should be interpreted knowing that students who have limited time in the school are not included in the model. Model 2h has six fixed effects and two random effects and can be specified as follows:

Model 2h: Significant Predictors from Model 2h but includes Predictors with Many Missing Cases

Level-1 Model

$$\text{Prob}(Y=1|B) = P$$

$$\log\left[\frac{P}{1-P}\right] = B0 + B1*(FRL) + B2*(MINORITY) + B3*(ISS_OSS) + B4*(OVERAGEFORGRADE) + B5*(LOWTRACK) + B6*(COURSEFAIL)$$

Level-2 Model

$$B0 = G00 + G01*(SPFCAT) + G02*(ACADRIG) + U0$$

$$B1 = G10$$

$$B2 = G20$$

Table 21 describes the parameter estimates of Model 2f, 2g and 2h as well as the overall accuracy rate and accuracy rate for reengagers. Figures 8, 9 and 10 display the classification table for Models 2f, 2g, and 2h.

Table 21
Models 2f, g, and h: New Models Based on Results of Hypothesized Models

Value	<i>B</i>	<i>p-value</i>	<i>Odds Ratio</i>	<i>B</i>	<i>p-value</i>	<i>Odds Ratio</i>	<i>B</i>	<i>p-value</i>	<i>Odds Ratio</i>
Student Characteristics									
Free and Reduced Lunch	0.19(.2)	0.356	1.204	0.21(.2)	0.292	1.236	0.027(.23)	0.908	1.028
Minority	-0.15(.2)	0.481	0.864	-0.14(.2)	0.498	0.869	-0.23(.23)	0.33	0.792
Behavioral Incident	0.65(.22)	0.003	1.914	0.65(.22)	0.003	1.924	0.46(.25)	0.062	1.591
Overage for Grade	-0.66(.33)	0.043	0.516	-.67(.33)	0.4	0.51	-0.81(.41)	0.048	0.443
Low-track Core							1.01(.29)	0.001	2.75
Course Failure							-0.95(.37)	0.012	0.389
School-level Characteristics									
High Performing	2.04(.68)	0.003	7.695	2.71(.65)	.001	15.144	2.79(.63)	0	16.254
School Connection	0.79(1.85)	0.67	2.202						
Staff Student Relationships	-2.65(4.55)	0.56	0.071						
Discipline	2.26(3.16)	0.476	9.564						
Academic Challenge	-5.38(1.99)	0.007	0.005	-5.70(1.61)	.003	0.003	-3.93(1.76)	0.026	0.02
Teacher Feedback	-3.02(3.07)	0.326	0.049						
Overall Accuracy		81.3%			81.9%			79.3%	
Reengagement Accuracy		38%			38%			51.3%	

The three new models attempt to find the most parsimonious model for predicting reengagement. However, because two variables have high amounts of missing data it seems prudent to consider Models g and h as both worthy models. This is especially true since including low-track and course failure improve the accuracy rate for reengagers markedly.

The highest *OR*'s in both models are at the school-level with 15 and 16 higher odds of reengagement for students dropping out of high performing schools and 3333 and 50 times high odds of reengagement per decrease in one *unit of* academic challenge. With the inclusion of low-track and course failure in Model h, the *OR* for academic challenge is less astronomical and seems more reasonable. At the student-level, having a behavioral incident is significant in Model g but not Model h, indicating that perhaps the inclusion of low-track and course failure provide better parameter estimates when included in the model. As with other models, overage for grade and course failure continue to be negatively associated with reengagement while having a behavioral incident and being a low-track or intervention course in English Language Arts or mathematics is positively associated with reengagement.

Figure 8. Classification Table for Model 2f

Classification
Target:REENG
Overall Percent Correct =81.3%

Observed	Predicted		Row Percent
	Reengaged	EOY Dropout	
Reengaged	38.0%	62.0%	
EOY Dropout	4.5%	95.5%	

Figure 9. Classification Table for Model 2g

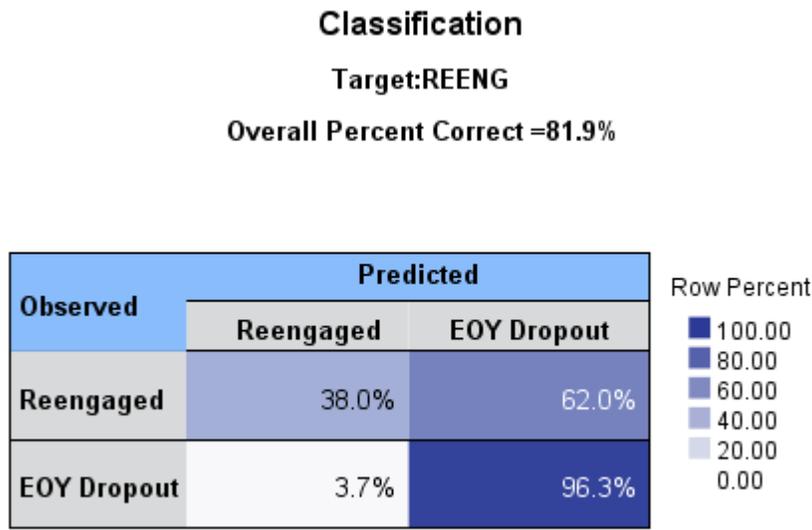
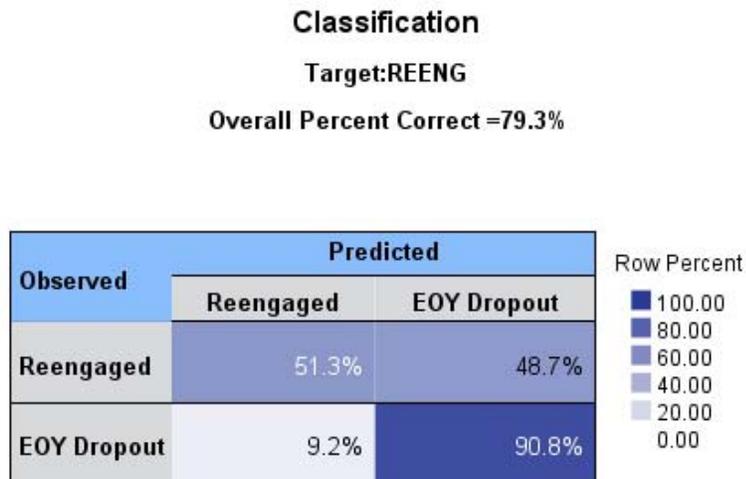


Figure 10. Classification Table for Model 2h



Summary

Initially, each predictor was run individually to determine its effect in predicting reengagement with school. Several single predictors had high odds ratios at both the student and school-level. At the student-level, having a behavioral incident (1.96) or being enrolled in a low-track or remedial course in ELA or mathematics (2.98) had the highest *OR*'s. All models controlled for poverty and minority status but, in no model, were the logs odds of poverty (FRL) or minority status even close to statistically significant when used as a single predictor.

School climate predictors were included within each of the engagement constructs (affective – Model b, behavioral – Model c, and cognitive – Model d) as well as school performance (high performing school – Model e). The predictor of a high performing school had a strong positive association with reengagement, with an *OR* of 9.27. Still, the remaining school-level results were surprising with several climate predictors having strong negative associations with reengagement. High negative *OR*'s including discipline (.033), staff – student relationships (.003), academic challenge (.011), and teacher feedback (.012).

Many constructs within affective, behavioral and cognitive engagement had conflicting effects on reengagement and in some cases, constructs within the same engagement dimension had opposite effects. The hypothesized models were developed *a priori* based on existing literature but the models only provided a starting point for the last three models which seem to fit the data better. Nonetheless, the MYVH survey data are not strong predictors of reengagement and this could be due to the measurement limitations mentioned above.

In summary, some student characteristics and school-level factors were predictive of reengagement. Student-level factors include behavioral incidents and being in a low-track or remedial course work for the core subjects of math and ELA. School climate factors are

academic press (high performing school) as well as school connection. Explanatory frameworks and interpretation of these results are provided in the discussion.

George Box is known for his quintessential saying, “all models are wrong, but some are useful.” (Box & Draper, 1987, pp.424) The initial multilevel modeling of these data was conceived to test hypotheses developed using existing research. At the same, very little research exists about reengagement within the school year. This was an exploratory study to determine the utility of district data in predicting reengagement within the school year. The purpose of the modeling was not only to test hypotheses but also to find useful models to inform policy and practice. Interpretation and discussion for the modeling results are provided in the next chapter.

CHAPTER V

DISCUSSION

The combination of descriptive analyses and logistic regression modeling conveys a complex and sometimes conflicting story about students who reengage with school and calls into question the utility of using models to predict reengagement. Overall, no logistic regression models were strong predictors of reengagement. However, there are some possible interpretations of the results and key findings to highlight. This chapter will cover those findings as well as corresponding policy and practice implications, concluding with limitations and recommendations.

Findings

Despite the intent of the dissertation, the evidence from this exploratory research does not support clear explanatory frameworks for predicting reengagement within the school year or distinguishing who will reengage from those who do not reengage. The results are mixed and require interpretation. Using the descriptive data in addition to the logistic regression models, a few suppositions can be derived from the research. First, within-year reengagers may be more likely to be on the radar screen of schools and districts as evidenced by their higher proportions and significance predictors of behavioral incident, enrollment in low-track coursework, not having a course failure and being overage for grade. Second, the only school-level predictor that can be considered when predicting within-year reengagement is school performance. Third, the results from this research is not consistent with existing literature about between-years students who reengage two to twelve years after drop out.

Reengagers may be on the radar screen of schools/districts. The reengagement group had a proportionally higher number of students with a behavioral incident, enrollment in a low track course, a lack of course failure or being overage for grade. Additionally, Model 2a

demonstrate these predictors are statistically significant but only accurately predict 53% of the reengaged group. Each of these predictors and their implications are discussed in the following paragraphs.

Behavioral Incident. A known predictor of school dropout, regardless of whether a student reengages with school or not, is having at least one behavior incident (Allensworth, 2013; Carl, Richardson, Cheng, Kim & Meyer, 2013; MacIver, 2013). Since reengagement after dropping out is a more positive outcome than never graduating from high school, one might expect that having no behavioral incidents would predict reengagement. However, the results from the individual predictor modeling and the student only data model both indicate that a predictor of reengagement is having at least one behavioral incident prior to experiencing an episode of dropout⁶. As a single predictor having a behavioral incident indicates that, a student has 1.96 higher odds of reengagement and within the student data only model (2a), 1.71 higher odds.

Low-track or intervention Coursework. A second incongruent finding was that being a low-track or intervention course in English Language Arts or Mathematics was a good predictor of reengagement. Tracking and remedial coursework are often attributed to limiting educational opportunity, de-motivating students learning, and leading to dropout. One explanation of this seeming incongruence is that determining if a student is ‘tracked’ requires historical data and this

⁶ It is important to understand that it is more likely for re-engagers to be coded as 1 on these variables given that they spent more time in school because the predictors are based on data prior to an episode of dropout (20 unexcused absences). The month of the episode of dropout is described in Figure 2.

study only included one year of data. Instead, we can only attest that remedial course work or intervention course work in core was a statistically significant predictor of reengagement.

Course Failure. Course failure has been demonstrated in previous literature to be predictive of dropout (McIver & Messel, 2013), and lack of course failure is a good predictor when modeling reengagement as an outcome for dropouts. In the models that predicted reengagement, course failure returned an *OR* of .34 as a single predictor and .40 in the student only model (2a). As a reminder, odds ratios less than 1 can be interpreted by transforming the *OR* into a number greater than 1 to get the *OR* for the non-referent group (in this case students who do not have a course failure) using the formula $1 / OR$. In this case, students who do not have a course failure have 2.94 higher odds (as a single predictor) of re-engaging. Within the student-level only data model, students have 2.5 higher odds of re-engaging.

Overage for Grade. Being overage for grade is also correlated with dropout because students who are overage for grade have typically experienced grade retention some time in their educational career and are no longer enrolled in the same grade as their student cohort. Typically, having grade retention on one's transcript puts students on the radar of school staff. As might be expected, there were higher proportions of students who were overage for grade in the end-of-year dropout group. Additionally, being overage for grade was negatively associated with reengagement with school. The strength of this predictor was moderate with an odds ratio of .56 as a single predictor and .43 in the student data model (Model2a). One might expect that this effect would be strong, considering that students may leave school for employment to support themselves because students "with adult responsibilities, such as being employed or having to take care of a child, are more likely to drop out than are their counterparts without these responsibilities." (Gleason & Dynarski, 2002, pp. 27; see also Barro & Kolstad 1987; D'Amico,

1984; Pallas, 1987; 1984; Rumberger, 1983) Moreover, students with work experience may be more cognizant of the purpose and potential of graduating from high school. However, without additional data, this is only supposition.

Surprisingly, ELL status was not predictive of reengaging because ELL status should place students on the radar screen of school staff. However, this could also be indicative of the lack of staff resources needed to support Spanish-speaking students at risk of dropout or at ‘promise’ of reengagement (Wellco’s dropout recovery staff do not speak Spanish).

Interestingly, ELL students were found in previous research to be less likely to reengage between-years as well, which does not provide evidence to support inferences one might make about long absences to Mexico or elsewhere, with intentions to return to school before the end of the school year. The descriptive data explored by manually culling through the district data system also would not support that theory (see Table 6). Keep in mind that even extensive manual review of data only provided potential reasons for dropout for 25% of students who reengaged providing limited utility of this labor-intensive effort.

School-level performance best predicts reengagement. School climate indicators were created from the state accountability framework and covariates collected through a student engagement survey. All predictors were aggregated at the school-level. School performance had a positive association with reengagement while the statistically significant school climate predictors aggregated from MYVH were negatively associated with reengagement. The significant school climate variables included teacher feedback ($\beta=.45$), discipline ($\beta=.75$), relationships ($\beta=.81$), and academic challenge ($\beta=.95$).

Perhaps not surprisingly, schools rated in the top two categories on their school performance framework (SPF) had higher odds for students who drop out to reengage,

supporting the belief that schools with a climate of rigor may encourage reengagement (Skinner & Pitzer, 2012). Previous research on dropout indicates that highly rated schools do not necessarily have lower dropout rates (Rumberger & Palardy, 2005). It may be that school performance plays out differently for reengagement. On the other hand, the school climate predictor did not accurately distinguish between dropouts and reengagers even when the coefficients were statistically significant—results that are perplexing. A potential explanation is that these school climate data are student perception data, aggregated at the school-level, and individual students' perceptions may vary greatly especially for students who are at-risk of dropout but have not actually dropped out. Additionally, student survey data aggregated at the school-level does not reflect extensive missing data from students who have dropped out or are consistently absent.

It should also be noted that even the school performance climate predictor result may also be an artifact of the data. A previous episode of dropout may increase the likelihood of permanent dropout (MacIver, 2011). In this vein, alternative schools have lower SPF ratings and are typically where many students reengage after dropping out. Nonetheless, it is worth remarking that in schools with strong relationships and limited academic expectations, students may be even less likely to reengage (McDill, Natriello, & Pallas, 1986).

Wellco within-year predictors do not consistently align with between-years predictors from previous research. Distinctions have been made in this study concerning between-year reengagement, occurring across school years, and within-year reengagement that occurs during the same school year. While the intention of this dissertation was not to generalize the results to other districts or schools, it is worth remarking that the predictors not consistent with between year reengagement research. The current research did not have empirical data

regarding between-years reengagement; however, drawing on the existing literature we can see that some predictors found to be significant are similar while others are different for these two groups. For example, the single predictor models indicated that students in upper grades (11-12) have double the odds of re-engaging within the school year than students in lower grades (7-10). This is a finding that concurs with previous research suggesting that students in upper grades are more likely than students in lower grades to reengage 2 to 12 years later (Chan et al., 2003; Berkthold et al., 1998; Kolstad & Owings, 1986; Kolstad & Kaufman, 1989; NCES, 2004; Suh & Suh, 2004; Wayman, 2001; Wayman 2002). This finding also suggests that there is a similar dynamic for students who seem to reengage within the school year compared to students who tend to reengage between years. Since the numbers of students who dropout in the early grades are proportionally lower than the upper grades, a possible implication is to focus efforts on upper grades students who have more course credit and a shorter route to graduation.

Logistic regression analyses indicated that minority students and low-SES students do not have significantly higher or lower odds of reengaging than students who are white or not eligible for free and reduced lunch. In contrast with existing research about between-years reengagement, socioeconomic status was not predictive of within-year reengagement (Chan et al., 2003; Berkthold et al., 1998; Kolstad & Owings, 1986; Kolstad & Kaufman, 1989; NCES, 2004; Suh & Suh, 2004; Wayman, 2001; Wayman 2002). Within the data set, about half of students in each of the referent categories were eligible for free and reduced lunch and half were of minority status, providing good variation across groups. Compared to the mixed findings from previous research about between-years reengagement of minority students (students who dropout and reengage two to eight years later), minority status was not a significant predictor in this exploratory study of within-year reengagement (Kolstad & Kaufman, 1989; Berliner, 2008). In previous research,

minority status was not a significant predictor of between-years reengagement when socioeconomic status was controlled. However, in this study, neither SES nor minority status were a significant predictor (Berkold et al., 1998; Chan et al., 2003 NCES, 2004; Suh & Suh, 2004; Wayman, 2001, 2002).

The inconsistency in the predictors for reengagers compared to dropouts and within-year reengagers compared to between-years reengagers may suggest the need for a different paradigm when considering within-year reengagers compared to between-years reengagers or it may suggest that place-based specifics should discourage the generalizability of overall models. According to the OR's, students overage for grade, and students with course failure, are less likely to reengage and the literature indicates that these students are more likely to dropout. However, students with behavioral incidents and low-track course work are more likely to reengage which corresponds with the literature indicating that these students are also more likely to drop out. These mixed results suggest that different frameworks or additional studies are needed to explain reengagers compared to dropouts, which could be more fully explored using deep qualitative inquiry.

Policy Implications

Many states, including Colorado, have explored the incorporation of a reengagement rate for school accountability frameworks, particularly for alternative education campuses' school performance framework. The current research would suggest that this is not a feasible application for a few reasons. First, the numbers of reengagers is just too small to hold any meaning as a rate on a school's accountability framework. Second, the processes used to identify students who had an episode of dropout and were subsequently reengaged were too labor intensive, involved extensive manual checking, and would not be easily verifiable for a district data submission to the state. Even with promises of real time data emerging as part of next-

generation State Longitudinal Data Systems, it is still a tall order to calculate a reengagement rate reliably.

Two predictors were surprisingly positively correlated with reengagement in the regression modeling, enrollment in low-track or remedial coursework and having a behavioral incident. Districts and schools could explore policies that balance the abilities of students with high expectations for achievement. While tracking students into low level coursework is not conducive to long-term equitable educational opportunity (Burriss & Welner, 2005), putting students in coursework without the needed scaffolds and differentiated instruction is also problematic. Additionally, it seems that having a behavioral incident might place students on a school's radar and facilitate reengagement. Systems might be developed that flag students who are equally at risk without the potential detriments associated with having an official suspension from school. Therefore, using these data in early warning systems might offer some promise.

Early 'Warning' Systems for Reengagement

An emerging dropout prevention policy is to integrate results from models that predict dropout and graduation into early warning systems designed to flag students for intervention (Allensworth, 2013; Carl, Richardson, Cheng, Kim & Meyer, 2013; McIver, 2013). For example, Chicago Public Schools (Allensworth, 2013) and Milwaukee Public Schools (Carl, et al., 2013) are assigning students to interventions based on the probability of failure in ninth grade and the probability of eventual dropout. However, school staffs do not simply receive a probability 'score' for each student; instead methods for communicating with school-based staff include "(a) focusing conversations and efforts on actionable problems, (b) identifying students for intervention, and (c) using indicator patterns to address low performance in a strategic way." (Allensworth, 2013, pp.68) The University of Wisconsin has worked with Milwaukee Public Schools to translate estimated probabilities predicted from course failure and credit accrual to an

interpretable index called total quality credits (TQC) (Carl, et al. 2013). The index is used by practitioners to have conversations with students and parents, inform individual interventions, and look at systemic practices. The index is also used at the school level to monitor improvements.

While this dissertation set out to use logistic regression models of within-year reengagement for early ‘warning’ systems to help schools focus their efforts on students who are either most or least likely to reengage, the results are too weak for that use even within Wellco schools. Early warning models have focused primarily on predicting dropout using historical data but these models often do not account for mobility across districts⁷ and the resultant missing data. In a special edition on early warning indicators in the *Journal of Education for Students Placed at Risk (2013)*, authors call for temporally sensitive metrics that can be applied during the school year when decisions and interventions could change the course of students’ lives (McIver, 2013). As presented in this dissertation, within-year predictive models do not draw on historical data and in theory could appropriately be used for highly mobile students. Nonetheless, the lack of strong predictive models for re-engagers in this study negates its application with Wellco district data. Other districts or states may want to consider the within-year approach to predictive modeling when emerging technological approaches to educational data systems (e.g. dashboards and push notifications) are fully developed.

Any future application of modeling for early warning systems must recognize that the use of results from logistic models should only occur in tandem with useful tools and dialogue that is

⁷ Although new state longitudinal systems promise cross district data, existing early warning research reflects within district data only with mobile students being excluded from analyses.

action-oriented and that can affect behaviors of administrators and school-based interventions (Allensworth, 2013). At the building level, systems could be used to build timely, meaningful, and actionable reports that alert school staff to not only episodes of dropout, but students who are likely to reengage in order to focus staff efforts. Focused conversations and coordinated efforts are needed between counselors, social workers, teachers, administrators and parents. While reengagement indicators may not help prevent an episode of dropout, in combination with systems that flag potential dropout, these indicators might quickly end an episode of dropout.

The current exploratory study did not uncover predictive models that correctly classified reengagers better than end-of-year dropouts. Therefore, this research is limited in its application to preventing dropout. However, this approach may hold merit for predicting other events. Reengagement is a rare occurrence, with only 224 reengagers out of 899 students who experience dropout from a total population of over 40,000 students. Reengagement follows a period in which school districts have no data about a student (during the episode of dropout). It is likely that those events that occur outside of school are the events that best predict whether a student engages. Few early warning systems currently use advanced statistical techniques to develop predictive models (McIver, 2013). Multilevel modeling, which accounts for the school-level effects, seems to be an appropriate application to predict student outcomes that are more common than reengagement (e.g. course failure, grade retention, proficiency on the state test, success in advanced placement classes, ACT score, graduation, and remediation and degree attainment in postsecondary education, etc.). However, there are some critical considerations necessary to ensure that these predictive models are not misused.

Misuses of Predictive Models

A risk of over-simplifying multiple, complex data points into one indicator is that the individual factors which should be acted upon are lost (Carl et al., 2013). As described above,

training, deep dialogue, and professional discretion are inherent components of most district-deployed early warning systems. Clearly, a body of evidence should be sought to understand the full context of an episode of dropout and potential intervention strategies. A critical method used in the current research was manually culling district data systems to understand the circumstances leading to an episode of dropout. Therefore, schools and districts must allow the time for dropout recovery staff to accomplish deep, data driven work that goes well beyond simple warning indicators. It is highly questionable whether current technological advancements could replace this work with automatic queries without creating additional data collection strategies. In either case, both additional data collection or manual culling requires extensive investment of staff time and resources.

Predictive information only provides a heuristic to guide practitioners' efforts. For example, early warning systems could identify students who may be falling through the cracks. Based on our models, students with suspensions or in remedial coursework may already be on practitioners' radar screens. Students who are overage for grade but do not have behavioral issues or need remedial course also merit attention. Since the models had many misclassifications and weak predictors, other systems to alert practitioners that a student might reengage are necessary. Because the models in this study were based primarily on district data, exploration of data outside of the school district may be needed, particularly data that reflect what is happening during an episode of dropout (e.g. involvement with the juvenile justice system, contact with child welfare, or mental health struggles).

Personal and environmental factors that influence reengagement are difficult to collect and rarely collected. Consequently, the cluster of predictors available to researchers may mask the 'real' reasons for reengagement. In light of this, practitioners might be encouraged to

consider student voice and lived experience as important as, or more important than any statistical model when designing comprehensive reengagement strategies. A possible method is to survey or systematically interview students when they reengage in school after an episode of dropout. At the district level, content specialists may be wary of assimilationist curriculum that does not engage background knowledge or experiences outside the classroom as this may silence student voices and promote alienation. Meanwhile as the application of standardized test scores continues to permeate to the teacher level with new educator effectiveness laws, unintended side effects such as student push-out needs to be considered.

Three methodological suggestions, which might reduce the misuse of early warning indicators, include not limiting modeling to descriptive background characteristics (non-malleable factors), checking the predictive accuracy of models, and using district or school specific data to determine predictive factors. Whenever possible, malleable predictors should always be included in predictive models (McIver, 2013). While demographic characteristics help to inform policy strategies, student-level interventions are best informed by predictors that can be ameliorated (e.g. course failure, behavioral incidents, remedial coursework etc.). Second, if probability estimates are used to identify students, those probabilities should be tested for accuracy post hoc to determine if predicted reengagers actually do reengage and vice versa. Testing the validity of logistic regression models may reveal critical missing data that might improve predictive precision. Finally, the culture and context of each district and school varies considerably. If the resources exist to conduct modeling, districts should use their own data sets to identify strong predictors for their unique student population.

Generalizability of the Research

In view of the many potential misuses of predictive models, much caution must be exercised when considering the application of the modeling presented in this dissertation. As

described in the previous section, the factors and their coefficients should not be generalized to other districts that may have significantly different contexts. Moreover, attempting to apply coefficients to other districts does not take into account the differences with which the data are collected across districts and more importantly, states. For example, state statutes vary with regard to what is considered an unexcused absence or what qualifies as an in-school or out-of-school suspension. Additionally, even if unexcused-absence definitions are similar, the aggregate of those data often varies by state (e.g. cumulative instructional minutes compared whole or half days). In this way, the data on which the factors are based are simply not comparable, undermining generalizability to other settings. Arguably, applying the weightages of the coefficients to other districts also conveys an artificial sense of precision around the measurement of these data.

Given that so many states and districts are moving toward early warning systems, it is worth mentioning that an approach that warrants exploration might be for other districts or states to explore the process used in this dissertation to determine its applicability and usefulness. At a minimum, districts could begin working with more temporally sensitive data than end-of-year data sets. Additionally, districts could consider investing efforts to develop foundational systems that include comprehensive and accurate data because many schools and districts do not have accurate data regarding attendance or behavioral incidents

Knowing the needed capacity and resources, other districts could run similar models with their own data to determine what factors are predictive of reengagement or dropout within their unique context and with their data sources. Moreover, it would be relevant to explore other factors that put a student on the radar screen of an interventionist and consequently provide a potential vehicle for reengagement. As data systems develop and more and more data become

standardized and systemically stored, districts and states will need to consider the use of those data. Specifically, what kind of analytics should be conducted? How much can those models be customized to the local context? And what predictive modeling can be borrowed from other settings? Modeling factors that predict reengagement is in its infancy. Consequently, few conclusions or recommendations can be substantiated except perhaps additional research.

Recommendations for Future Research

Reengaging dropouts quickly within the school year is an emerging area of inquiry. However, its importance is evident as educators struggle to meet accountability metrics for on-time graduation rates and address educational equity by eliminating the persistent achievement gap. While the current study explores reengagement using large district data sets to inform policy approaches, deep qualitative inquiry is also needed to identify the psychological characteristics that enable resilience and persistence necessary to reengage successfully. Large districts could survey reengagers or direct school counselors to conduct standardized interviews with students who return to school. Additionally, after a student has successfully reengaged, follow-up interviews or questionnaires might explain what circumstances averted future incidences of drop out.

While past research has compared dropouts to graduates, the current research begins to address differences within groups of dropouts to understand who reengages. Identifying how dropouts differ from one another can inform both prevention and intervention efforts and allow schools and districts to develop ameliorative policy approaches. Limited research has explored specific dropout typologies using a psychological lens (Fortin, Potvin, Marcotte, Royer, & Joly, 2006) but not in the context of large data sets or predictive modeling that might inform policy development.

Again, a critical piece of predictive models should be focused on malleable factors. This research explored student engagement using a student survey collected confidentially but not anonymously, thereby allowing data to be connected to individual students. While missing data limited the application of these data to predicting reengagement, it does not negate the importance of exploring student-level data within the context of other predictive analytics such as academic achievement. Student engagement surveys linked to individual students also provides numerous opportunities to study engagement longitudinally and its connection to on-time graduation and on-track to graduation outcomes.

Conclusions

While these models extend the work in the early warning indicators field from dropout and graduation to within-year reengagement, models were not able to accurately distinguish reengagers from end of year dropouts. Relying solely on descriptive data and modeled probabilities, students who are on the radar screen of schools for remedial coursework or behavioral issues have higher odds of reengaging even though these factors may also instigate an episode of dropout.

A growing body of research has reliably identified factors that place students at risk of dropout (attendance, behavior and course failure); equal efforts should focus on factors to reengage students. Issues of educational equity and the achievement gap cannot be addressed without emerging research in the area of successful reengagement. However, much of the early warning models rely strictly on data pulled from district level data systems. Studying reengagement requires additional manual exploration of individual student-level data because the reasons for dropping out and for reengaging are variable. Additionally, even manual exploration of students records did not provide reasons for 75% of the students in this study. Supplementary data collection beyond existing student data systems may be necessary.

While states and school districts continue to determine how to reengage students who have dropped out, the body of research around predictive models for reengagement needs to develop accordingly. It is not enough to predict dropout and long-term graduation. Focus must also be given to studying successful reengagement within the school year.

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APPENDIX A: Make Your Voice Heard Survey Items

Welcome to the Make Your Voice Heard survey. Thank you for your participation. For each sentence pick the one that describes how you feel.

1. Staff members at this school care about students.
2. I am respected by most staff members.
3. I have a favorite teacher at this school.
4. There is at least one adult at school that I can go to when I need help with schoolwork.
5. When a student has a personal problem, someone at school is there to help.
6. I respect most of the staff at this school.
7. Homework assignments help me practice what I am being taught in my classes.
8. My teachers ask students difficult questions in class.
9. My math work is challenging.
10. My writing assignments are challenging.
11. The reading materials in my classes are challenging.
12. My teachers know when the class understands, and when we do not.
13. In my classes, teachers give students time to explain our ideas.
14. My teacher checks to make sure we understand what he/she is teaching us.
15. My teachers encourage me to do my best.
16. The comments that I get on my work help me understand how to improve.
17. My teachers know a lot about the subject they teach.
18. At school, there are clear rules for acceptable behavior.
19. Students generally behave themselves while at school.
20. The discipline practices at school are fair.
21. I follow the rules at school.
22. I would inform an adult at my school about bullies and students who threaten others.
23. I feel protected from harassment at school.
24. I feel protected from discrimination at school.
25. I feel safe at school.
26. Staff members do not tolerate students who threaten others at school.
27. During this school year, how often did you not go to school because you felt you would be unsafe at school or on your way to school?
28. During this school year, how often were you bullied or harassed at school or on your way to school?
29. During this school year, how often have you been electronically bullied? (including being bullied through email, chat rooms, instant messaging, web sites, or texting)
30. During this school year, how often has someone threatened or injured you with a weapon such as a gun, knife or club on school property?
31. During this school year, how often has someone stolen or deliberately damaged your property such as your car, clothing or books on school property?
32. During this school year, how often were you in a physical fight on school property?
33. I think it is important to go to school every day.
34. I skip classes that I don't like.
35. I am rarely absent from school unless I am sick.
36. When I am in class, I just pretend that I am working.

37. My classes are very interesting.
38. My schoolwork is meaningful to me.
39. Students at this school respect what I have to say.
40. I feel like I have a choice about what happens to me at school.
41. I have some friends that I feel close to at school.
42. I feel like I belong when I am at school.
43. I generally feel happy when I am at school.
44. I often attend school activities or events.
45. Students of different racial and ethnic backgrounds get along at this school.
46. My parents/guardians support me with my homework.
47. My parents/guardians expect me to do well in school.
48. My parents/guardians ask me about what I am learning at school.
49. My parents/guardians want me to keep trying when things are tough at school.
50. My parents/guardians and I talk about the good things that I have done in school.
51. My parents/guardians and I talk about the problems I have in school.
52. I have a place at home to do my homework.
53. I would like to quit school.
54. Education is important for achieving my future goals.
55. I will graduate from high school.
56. The school lunch is a good value.
57. Healthy school lunch choices are available from the cafeteria.
58. How likely is it that you will do each of the following immediately after high school?
- Start working a full time job.
- Serve in the military (Army, Navy, Air Force, etc.).
- Attend a career, technical, or vocational school to prepare for a specific career like welding, cosmetology, or medical imaging, etc.
- Attend a 2-year community college for an Associate's degree or certificate.
- Attend a 4-year college or university for a Bachelor's degree.
59. What classes would you be interested in taking to help prepare you for your future career? Select any.
- Arts (music, drama, dance, photography, etc.)
- Science
- Technology & Computers
- International Studies / World language / Cultures
- Business (finance, marketing, starting your own business, etc.)
- Leadership & government (politics, public service)
- Education (teaching)
- Mathematics
- Engineering
- Automotive
- Building & Construction
- Hospitality (hotel, restaurant & culinary)
- Health Care & Nutrition
- Law & Law Enforcement
- Media & Communications (Radio, television, film, writer, reporter)

- ___ Athletics (football, basketball, volleyball, swimming, snowboarding, etc.)
___ Other, please specify

60. Is there anything else you would like to share about your school?

Response Categories include:

Strongly Disagree	Disagree	Agree	Strongly Agree
Never	Rarely	Sometimes	Often
Definitely Won't	Probably Won't	Probably Will	Definitely Will

Open ended text box for Question 60

APPENDIX B: SPSS Syntax Multilevel Modeling

*****Unconditional Model*****

Generalized Linear Mixed Models.

```

GENLINMIXED
  /DATA_STRUCTURE SUBJECTS=CDESchoolNumber.1
  /FIELDS TARGET=REENG TRIALS=NONE OFFSET=NONE
  /TARGET_OPTIONS DISTRIBUTION=BINOMIAL LINK=LOGIT
  /FIXED USE_INTERCEPT=TRUE
  /RANDOM USE_INTERCEPT=TRUE SUBJECTS=CDESchoolNumber.1
COVARIANCE_TYPE=VARIANCE_COMPONENTS
  /BUILD_OPTIONS TARGET_CATEGORY_ORDER=DESCENDING
INPUTS_CATEGORY_ORDER=DESCENDING
  MAX_ITERATIONS=100 CONFIDENCE_LEVEL=95 DF_METHOD=RESIDUAL COVB=ROBUST
  /EMMEANS_OPTIONS SCALE=ORIGINAL PADJUST=LSD.

```

*****Student-level Single Predictor*****

DATASET ACTIVATE DataSet1.

*Generalized Linear Mixed Models.

```

GENLINMIXED
  /DATA_STRUCTURE SUBJECTS=CDESchoolNumber.1
  /FIELDS TARGET=REENG TRIALS=NONE OFFSET=NONE
  /TARGET_OPTIONS DISTRIBUTION=BINOMIAL LINK=LOGIT
  /FIXED EFFECTS=MINOR USE_INTERCEPT=TRUE
  /RANDOM USE_INTERCEPT=TRUE SUBJECTS=CDESchoolNumber.1
COVARIANCE_TYPE=VARIANCE_COMPONENTS
  /BUILD_OPTIONS TARGET_CATEGORY_ORDER=DESCENDING
INPUTS_CATEGORY_ORDER=DESCENDING
  MAX_ITERATIONS=100 CONFIDENCE_LEVEL=95 DF_METHOD=RESIDUAL COVB=ROBUST
  /EMMEANS_OPTIONS SCALE=ORIGINAL PADJUST=LSD.

```

DATASET ACTIVATE DataSet1.

*Generalized Linear Mixed Models.

```

GENLINMIXED
  /DATA_STRUCTURE SUBJECTS=CDESchoolNumber.1
  /FIELDS TARGET=REENG TRIALS=NONE OFFSET=NONE
  /TARGET_OPTIONS DISTRIBUTION=BINOMIAL LINK=LOGIT
  /FIXED EFFECTS=FRL USE_INTERCEPT=TRUE
  /RANDOM USE_INTERCEPT=TRUE SUBJECTS=CDESchoolNumber.1
COVARIANCE_TYPE=VARIANCE_COMPONENTS
  /BUILD_OPTIONS TARGET_CATEGORY_ORDER=DESCENDING
INPUTS_CATEGORY_ORDER=DESCENDING
  MAX_ITERATIONS=100 CONFIDENCE_LEVEL=95 DF_METHOD=RESIDUAL COVB=ROBUST
  /EMMEANS_OPTIONS SCALE=ORIGINAL PADJUST=LSD.

```

DATASET ACTIVATE DataSet1.

*Generalized Linear Mixed Models.

```

GENLINMIXED
  /DATA_STRUCTURE SUBJECTS=CDESchoolNumber.1
  /FIELDS TARGET=REENG TRIALS=NONE OFFSET=NONE
  /TARGET_OPTIONS DISTRIBUTION=BINOMIAL LINK=LOGIT
  /FIXED EFFECTS=OverAgeForGrade USE_INTERCEPT=TRUE

```

```
/RANDOM USE_INTERCEPT=TRUE SUBJECTS=CDESchoolNumber.1  
COVARIANCE_TYPE=VARIANCE_COMPONENTS  
/BUILD_OPTIONS TARGET_CATEGORY_ORDER=DESCENDING  
INPUTS_CATEGORY_ORDER=DESCENDING  
MAX_ITERATIONS=100 CONFIDENCE_LEVEL=95 DF_METHOD=RESIDUAL COVB=ROBUST  
/EMMEANS_OPTIONS SCALE=ORIGINAL PADJUST=LSD.
```

DATASET ACTIVATE DataSet1.

*Generalized Linear Mixed Models.

GENLINMIXED

```
/DATA_STRUCTURE SUBJECTS=CDESchoolNumber.1  
/FIELDS TARGET=REENG TRIALS=NONE OFFSET=NONE  
/TARGET_OPTIONS DISTRIBUTION=BINOMIAL LINK=LOGIT  
/FIXED EFFECTS=ELL USE_INTERCEPT=TRUE  
/RANDOM USE_INTERCEPT=TRUE SUBJECTS=CDESchoolNumber.1  
COVARIANCE_TYPE=VARIANCE_COMPONENTS  
/BUILD_OPTIONS TARGET_CATEGORY_ORDER=DESCENDING  
INPUTS_CATEGORY_ORDER=DESCENDING  
MAX_ITERATIONS=100 CONFIDENCE_LEVEL=95 DF_METHOD=RESIDUAL COVB=ROBUST  
/EMMEANS_OPTIONS SCALE=ORIGINAL PADJUST=LSD.
```

DATASET ACTIVATE DataSet1.

*Generalized Linear Mixed Models.

GENLINMIXED

```
/DATA_STRUCTURE SUBJECTS=CDESchoolNumber.1  
/FIELDS TARGET=REENG TRIALS=NONE OFFSET=NONE  
/TARGET_OPTIONS DISTRIBUTION=BINOMIAL LINK=LOGIT  
/FIXED EFFECTS=COURSEFAIL USE_INTERCEPT=TRUE  
/RANDOM USE_INTERCEPT=TRUE SUBJECTS=CDESchoolNumber.1  
COVARIANCE_TYPE=VARIANCE_COMPONENTS  
/BUILD_OPTIONS TARGET_CATEGORY_ORDER=DESCENDING  
INPUTS_CATEGORY_ORDER=DESCENDING  
MAX_ITERATIONS=100 CONFIDENCE_LEVEL=95 DF_METHOD=RESIDUAL COVB=ROBUST  
/EMMEANS_OPTIONS SCALE=ORIGINAL PADJUST=LSD.
```

DATASET ACTIVATE DataSet1.

*Generalized Linear Mixed Models.

GENLINMIXED

```
/DATA_STRUCTURE SUBJECTS=CDESchoolNumber.1  
/FIELDS TARGET=REENG TRIALS=NONE OFFSET=NONE  
/TARGET_OPTIONS DISTRIBUTION=BINOMIAL LINK=LOGIT  
/FIXED EFFECTS=LowTrackCore USE_INTERCEPT=TRUE  
/RANDOM USE_INTERCEPT=TRUE SUBJECTS=CDESchoolNumber.1  
COVARIANCE_TYPE=VARIANCE_COMPONENTS  
/BUILD_OPTIONS TARGET_CATEGORY_ORDER=DESCENDING  
INPUTS_CATEGORY_ORDER=DESCENDING  
MAX_ITERATIONS=100 CONFIDENCE_LEVEL=95 DF_METHOD=RESIDUAL COVB=ROBUST  
/EMMEANS_OPTIONS SCALE=ORIGINAL PADJUST=LSD.
```

DATASET ACTIVATE DataSet1.

*Generalized Linear Mixed Models.

GENLINMIXED

```
/DATA_STRUCTURE SUBJECTS=CDESchoolNumber.1  
/FIELDS TARGET=REENG TRIALS=NONE OFFSET=NONE  
/TARGET_OPTIONS DISTRIBUTION=BINOMIAL LINK=LOGIT
```

```

/FIXED EFFECTS=ISS_OSS USE_INTERCEPT=TRUE
/RANDOM USE_INTERCEPT=TRUE SUBJECTS=CDESchoolNumber.1
COVARIANCE_TYPE=VARIANCE_COMPONENTS
/BUILD_OPTIONS TARGET_CATEGORY_ORDER=DESCENDING
INPUTS_CATEGORY_ORDER=DESCENDING
  MAX_ITERATIONS=100 CONFIDENCE_LEVEL=95 DF_METHOD=RESIDUAL COVB=ROBUST
/EMMEANS_OPTIONS SCALE=ORIGINAL PADJUST=LSD.

```

*****School-level Single Predictors*****

```

DATASET ACTIVATE DataSet1.
*Generalized Linear Mixed Models.
GENLINMIXED
  /DATA_STRUCTURE SUBJECTS=CDESchoolNumber.1
  /FIELDS TARGET=REENG TRIALS=NONE OFFSET=NONE
  /TARGET_OPTIONS DISTRIBUTION=BINOMIAL LINK=LOGIT
  /FIXED EFFECTS=SCH_SPF2CAT USE_INTERCEPT=TRUE
  /RANDOM USE_INTERCEPT=TRUE SUBJECTS=CDESchoolNumber.1
COVARIANCE_TYPE=VARIANCE_COMPONENTS
/BUILD_OPTIONS TARGET_CATEGORY_ORDER=DESCENDING
INPUTS_CATEGORY_ORDER=DESCENDING
  MAX_ITERATIONS=100 CONFIDENCE_LEVEL=95 DF_METHOD=RESIDUAL COVB=ROBUST
/EMMEANS_OPTIONS SCALE=ORIGINAL PADJUST=LSD.

```

```

DATASET ACTIVATE DataSet1.
*Generalized Linear Mixed Models.
GENLINMIXED
  /DATA_STRUCTURE SUBJECTS=CDESchoolNumber.1
  /FIELDS TARGET=REENG TRIALS=NONE OFFSET=NONE
  /TARGET_OPTIONS DISTRIBUTION=BINOMIAL LINK=LOGIT
  /FIXED EFFECTS=SCH_SCHCONNECT USE_INTERCEPT=TRUE
  /RANDOM USE_INTERCEPT=TRUE SUBJECTS=CDESchoolNumber.1
COVARIANCE_TYPE=VARIANCE_COMPONENTS
/BUILD_OPTIONS TARGET_CATEGORY_ORDER=DESCENDING
INPUTS_CATEGORY_ORDER=DESCENDING
  MAX_ITERATIONS=100 CONFIDENCE_LEVEL=95 DF_METHOD=RESIDUAL COVB=ROBUST
/EMMEANS_OPTIONS SCALE=ORIGINAL PADJUST=LSD.

```

```

DATASET ACTIVATE DataSet1.
*Generalized Linear Mixed Models.
GENLINMIXED
  /DATA_STRUCTURE SUBJECTS=CDESchoolNumber.1
  /FIELDS TARGET=REENG TRIALS=NONE OFFSET=NONE
  /TARGET_OPTIONS DISTRIBUTION=BINOMIAL LINK=LOGIT
  /FIXED EFFECTS=SCH_SS_REL USE_INTERCEPT=TRUE
  /RANDOM USE_INTERCEPT=TRUE SUBJECTS=CDESchoolNumber.1
COVARIANCE_TYPE=VARIANCE_COMPONENTS
/BUILD_OPTIONS TARGET_CATEGORY_ORDER=DESCENDING
INPUTS_CATEGORY_ORDER=DESCENDING
  MAX_ITERATIONS=100 CONFIDENCE_LEVEL=95 DF_METHOD=RESIDUAL COVB=ROBUST
/EMMEANS_OPTIONS SCALE=ORIGINAL PADJUST=LSD.

```

```

DATASET ACTIVATE DataSet1.
*Generalized Linear Mixed Models.
GENLINMIXED

```

```
/DATA_STRUCTURE SUBJECTS=CDESchoolNumber.1
/FIELDS TARGET=REENG TRIALS=NONE OFFSET=NONE
/TARGET_OPTIONS DISTRIBUTION=BINOMIAL LINK=LOGIT
/FIXED_EFFECTS=SCH_DISCPERC USE_INTERCEPT=TRUE
/RANDOM_USE_INTERCEPT=TRUE SUBJECTS=CDESchoolNumber.1
COVARIANCE_TYPE=VARIANCE_COMPONENTS
/BUILD_OPTIONS TARGET_CATEGORY_ORDER=DESCENDING
INPUTS_CATEGORY_ORDER=DESCENDING
  MAX_ITERATIONS=100 CONFIDENCE_LEVEL=95 DF_METHOD=RESIDUAL COVB=ROBUST
/EMMEANS_OPTIONS SCALE=ORIGINAL PADJUST=LSD.
```

DATASET ACTIVATE DataSet1.

*Generalized Linear Mixed Models.

GENLINMIXED

```
/DATA_STRUCTURE SUBJECTS=CDESchoolNumber.1
/FIELDS TARGET=REENG TRIALS=NONE OFFSET=NONE
/TARGET_OPTIONS DISTRIBUTION=BINOMIAL LINK=LOGIT
/FIXED_EFFECTS=SCH_SAFEPRC USE_INTERCEPT=TRUE
/RANDOM_USE_INTERCEPT=TRUE SUBJECTS=CDESchoolNumber.1
COVARIANCE_TYPE=VARIANCE_COMPONENTS
/BUILD_OPTIONS TARGET_CATEGORY_ORDER=DESCENDING
INPUTS_CATEGORY_ORDER=DESCENDING
  MAX_ITERATIONS=100 CONFIDENCE_LEVEL=95 DF_METHOD=RESIDUAL COVB=ROBUST
/EMMEANS_OPTIONS SCALE=ORIGINAL PADJUST=LSD.
```

DATASET ACTIVATE DataSet1.

*Generalized Linear Mixed Models.

GENLINMIXED

```
/DATA_STRUCTURE SUBJECTS=CDESchoolNumber.1
/FIELDS TARGET=REENG TRIALS=NONE OFFSET=NONE
/TARGET_OPTIONS DISTRIBUTION=BINOMIAL LINK=LOGIT
/FIXED_EFFECTS=SCH_PART USE_INTERCEPT=TRUE
/RANDOM_USE_INTERCEPT=TRUE SUBJECTS=CDESchoolNumber.1
COVARIANCE_TYPE=VARIANCE_COMPONENTS
/BUILD_OPTIONS TARGET_CATEGORY_ORDER=DESCENDING
INPUTS_CATEGORY_ORDER=DESCENDING
  MAX_ITERATIONS=100 CONFIDENCE_LEVEL=95 DF_METHOD=RESIDUAL COVB=ROBUST
/EMMEANS_OPTIONS SCALE=ORIGINAL PADJUST=LSD.
```

DATASET ACTIVATE DataSet1.

*Generalized Linear Mixed Models.

GENLINMIXED

```
/DATA_STRUCTURE SUBJECTS=CDESchoolNumber.1
/FIELDS TARGET=REENG TRIALS=NONE OFFSET=NONE
/TARGET_OPTIONS DISTRIBUTION=BINOMIAL LINK=LOGIT
/FIXED_EFFECTS=SCH_ACADRIGr USE_INTERCEPT=TRUE
/RANDOM_USE_INTERCEPT=TRUE SUBJECTS=CDESchoolNumber.1
COVARIANCE_TYPE=VARIANCE_COMPONENTS
/BUILD_OPTIONS TARGET_CATEGORY_ORDER=DESCENDING
INPUTS_CATEGORY_ORDER=DESCENDING
  MAX_ITERATIONS=100 CONFIDENCE_LEVEL=95 DF_METHOD=RESIDUAL COVB=ROBUST
/EMMEANS_OPTIONS SCALE=ORIGINAL PADJUST=LSD.
```

DATASET ACTIVATE DataSet1.

*Generalized Linear Mixed Models.

```

GENLINMIXED
  /DATA_STRUCTURE SUBJECTS=CDESchoolNumber.1
  /FIELDS TARGET=REENG TRIALS=NONE OFFSET=NONE
  /TARGET_OPTIONS DISTRIBUTION=BINOMIAL LINK=LOGIT
  /FIXED_EFFECTS=SCH_TCHRFEED USE_INTERCEPT=TRUE
  /RANDOM_USE_INTERCEPT=TRUE SUBJECTS=CDESchoolNumber.1
COVARIANCE_TYPE=VARIANCE_COMPONENTS
  /BUILD_OPTIONS TARGET_CATEGORY_ORDER=DESCENDING
INPUTS_CATEGORY_ORDER=DESCENDING
  MAX_ITERATIONS=100 CONFIDENCE_LEVEL=95 DF_METHOD=RESIDUAL COVB=ROBUST
  /EMMEANS_OPTIONS SCALE=ORIGINAL PADJUST=LSD.

```

DATASET ACTIVATE DataSet1.

*Generalized Linear Mixed Models.

```

GENLINMIXED
  /DATA_STRUCTURE SUBJECTS=CDESchoolNumber.1
  /FIELDS TARGET=REENG TRIALS=NONE OFFSET=NONE
  /TARGET_OPTIONS DISTRIBUTION=BINOMIAL LINK=LOGIT
  /FIXED_EFFECTS=SCH_FUTASPr USE_INTERCEPT=TRUE
  /RANDOM_USE_INTERCEPT=TRUE SUBJECTS=CDESchoolNumber.1
COVARIANCE_TYPE=VARIANCE_COMPONENTS
  /BUILD_OPTIONS TARGET_CATEGORY_ORDER=DESCENDING
INPUTS_CATEGORY_ORDER=DESCENDING
  MAX_ITERATIONS=100 CONFIDENCE_LEVEL=95 DF_METHOD=RESIDUAL COVB=ROBUST
  /EMMEANS_OPTIONS SCALE=ORIGINAL PADJUST=LSD.

```

*****Models for Research Question 2*****

*Generalized Linear Mixed Models.

```

GENLINMIXED
  /DATA_STRUCTURE SUBJECTS=CDESchoolNumber.1
  /FIELDS TARGET=REENG TRIALS=NONE OFFSET=NONE
  /TARGET_OPTIONS DISTRIBUTION=BINOMIAL LINK=LOGIT
  /FIXED_EFFECTS=MINOR FRL ISS_OSS OverAgeForGrade LowTrackCore COURSEFAIL
  USE_INTERCEPT=TRUE
  /RANDOM_USE_INTERCEPT=TRUE SUBJECTS=CDESchoolNumber.1
COVARIANCE_TYPE=VARIANCE_COMPONENTS
  /BUILD_OPTIONS TARGET_CATEGORY_ORDER=DESCENDING
INPUTS_CATEGORY_ORDER=DESCENDING
  MAX_ITERATIONS=100 CONFIDENCE_LEVEL=95 DF_METHOD=RESIDUAL COVB=ROBUST
  /EMMEANS_OPTIONS SCALE=ORIGINAL PADJUST=LSD.

```

*Generalized Linear Mixed Models.

```

GENLINMIXED
  /DATA_STRUCTURE SUBJECTS=CDESchoolNumber.1
  /FIELDS TARGET=REENG TRIALS=NONE OFFSET=NONE
  /TARGET_OPTIONS DISTRIBUTION=BINOMIAL LINK=LOGIT
  /FIXED_EFFECTS=MINOR FRL SCH_SCHCONNECT SCH_SS_REL USE_INTERCEPT=TRUE
  /RANDOM_USE_INTERCEPT=TRUE SUBJECTS=CDESchoolNumber.1
COVARIANCE_TYPE=VARIANCE_COMPONENTS
  /BUILD_OPTIONS TARGET_CATEGORY_ORDER=DESCENDING
INPUTS_CATEGORY_ORDER=DESCENDING
  MAX_ITERATIONS=100 CONFIDENCE_LEVEL=95 DF_METHOD=RESIDUAL COVB=ROBUST
  /EMMEANS_OPTIONS SCALE=ORIGINAL PADJUST=LSD.

```

*Generalized Linear Mixed Models.

```
GENLINMIXED
 /DATA_STRUCTURE SUBJECTS=CDESchoolNumber.1
 /FIELDS TARGET=REENG TRIALS=NONE OFFSET=NONE
 /TARGET_OPTIONS DISTRIBUTION=BINOMIAL LINK=LOGIT
 /FIXED_EFFECTS=MINOR FRL SCH_DISCPERC SCH_SAFEPERC SCH_PART USE_INTERCEPT=TRUE
 /RANDOM_USE_INTERCEPT=TRUE SUBJECTS=CDESchoolNumber.1
 COVARIANCE_TYPE=VARIANCE_COMPONENTS
 /BUILD_OPTIONS TARGET_CATEGORY_ORDER=DESCENDING
 INPUTS_CATEGORY_ORDER=DESCENDING
   MAX_ITERATIONS=100 CONFIDENCE_LEVEL=95 DF_METHOD=RESIDUAL COVB=ROBUST
 /EMMEANS_OPTIONS SCALE=ORIGINAL PADJUST=LSD.
```

*Generalized Linear Mixed Models.

```
GENLINMIXED
 /DATA_STRUCTURE SUBJECTS=CDESchoolNumber.1
 /FIELDS TARGET=REENG TRIALS=NONE OFFSET=NONE
 /TARGET_OPTIONS DISTRIBUTION=BINOMIAL LINK=LOGIT
 /FIXED_EFFECTS=MINOR FRL SCH_ACADRIGr SCH_TCHRFEED SCH_FUTASPr
 USE_INTERCEPT=TRUE
 /RANDOM_USE_INTERCEPT=TRUE SUBJECTS=CDESchoolNumber.1
 COVARIANCE_TYPE=VARIANCE_COMPONENTS
 /BUILD_OPTIONS TARGET_CATEGORY_ORDER=DESCENDING
 INPUTS_CATEGORY_ORDER=DESCENDING
   MAX_ITERATIONS=100 CONFIDENCE_LEVEL=95 DF_METHOD=RESIDUAL COVB=ROBUST
 /EMMEANS_OPTIONS SCALE=ORIGINAL PADJUST=LSD.
```

*Generalized Linear Mixed Models.

```
GENLINMIXED
 /DATA_STRUCTURE SUBJECTS=CDESchoolNumber.1
 /FIELDS TARGET=REENG TRIALS=NONE OFFSET=NONE
 /TARGET_OPTIONS DISTRIBUTION=BINOMIAL LINK=LOGIT
 /FIXED_EFFECTS=MINOR FRL SCH_SPF2CAT USE_INTERCEPT=TRUE
 /RANDOM_EFFECTS=CDESchoolNumber.1 USE_INTERCEPT=FALSE
 COVARIANCE_TYPE=VARIANCE_COMPONENTS
 /BUILD_OPTIONS TARGET_CATEGORY_ORDER=DESCENDING
 INPUTS_CATEGORY_ORDER=DESCENDING
   MAX_ITERATIONS=100 CONFIDENCE_LEVEL=95 DF_METHOD=RESIDUAL COVB=ROBUST
 /EMMEANS_OPTIONS SCALE=ORIGINAL PADJUST=LSD.
```