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Closure and the Roles of Student Performance and Enrollment Characteristics: A Survival Analysis of Charter Schools in Ohio's Largest Urban Counties

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Abstract: In this study, we seek to contribute to the literature on traditional charter school (TCS) closure by examining the potential relationships among racial and socioeconomic enrollment characteristics, TCS age and early adopter status, student achievement and the likelihood of closure within Ohio's "Big 8" Urban Counties (OBEUC). Using life tables and binary logistic regression, we examined 3,204 TCS school years (424 TCS) in OBEUC from the arrival of TCS in 1998 through 2015 to assess these relationships. While the Ohio Department of Education (ODE) reports that poor academic performance is the second most cited reason for TCS closure, we find no evidence that student performance predicts TCS closure in OBEUC. However, we find that compared to TCS with integrated enrollments, TCS with predominantly White or Black enrollments face higher risks of closure in OBEUC, even when controlling for other factors. This lack of a connection between student performance and TCS closure calls into question the argument that TCS closure is evidence that the accountability

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function of school choice policy is working.
Keywords: Ohio; Charter Schools; School Choice; Access to Education; Race; Poverty; Segregation; Closed Schools; Student Achievement

Cierre y los roles del rendimiento del estudiante y las características de inscripción: Un análisis de supervivencia de las escuelas *charter* en las regiones urbanas más grandes de Ohio

Resumen: En este estudio, buscamos contribuir a la literatura sobre el cierre tradicional de escuelas autónomas (TCS) mediante el examen de las posibles relaciones entre las características de inscripción racial y socioeconómica, la edad de TCS y el estado de adoptante temprano, el rendimiento estudiantil y la probabilidad de cierre dentro de Ohio "Grandes regiones urbanas de 8"(OBEUC). Usando tablas de vida y regresión logística binaria, examinamos 3,204 años escolares TCS (424 TCS) en OBEUC desde la llegada de TCS en 1998 hasta 2015 para evaluar estas relaciones. Si bien el Departamento de Educación de Ohio (ODE) informa que el bajo rendimiento académico es la segunda razón más citada para el cierre de TCS, no encontramos evidencia de que el rendimiento de los estudiantes prediga el cierre de TCS en OBEUC. Sin embargo, encontramos que en comparación con TCS con inscripciones integradas, las TCS con inscripciones predominantemente blancas o negras enfrentan mayores riesgos de cierre en OBEUC, incluso cuando se controlan otros factores. Esta falta de conexión entre el rendimiento del estudiante y el cierre de TCS pone en tela de juicio el argumento de que el cierre de TCS es evidencia de que la función de responsabilidad de la política de elección de escuela está funcionando.
Palabras-clave: Ohio; Escuelas *charter*; Elección de escuela; Acceso a la educación; Raza; Pobreza; Segregación; Escuelas cerradas; rendimiento del estudiante

Funções de fechamento e desempenho dos alunos e características das matrículas: Uma análise de sobrevivência de escolas *charter* nas maiores regiões urbanas de Ohio

Resumo: Neste estudo, buscamos contribuir com a literatura sobre o fechamento tradicional de escolas charter (TCS) examinando as possíveis relações entre características raciais e socioeconômicas da matrícula, a idade da TCS e status de adotante precoce, desempenho aluno e a probabilidade de fechamento em Ohio "Grandes regiões urbanas de 8" (OBEUC). Usando tabelas de vida e regressão logística binária, examinamos 3.204 anos escolares do TCS (424 TCS) no OBEUC desde a chegada do TCS em 1998 a 2015 até avaliar essas relações Embora o Departamento de Educação de Ohio (ODE) relate que o fraco desempenho acadêmico é a segunda razão mais citada para o fechamento do TCS, não encontramos evidências de que o desempenho do aluno preveja o fechamento do TCS no OBEUC No entanto, descobrimos que, em comparação com o TCS com inscrições integradas, o TCS com inscrições predominantemente brancas ou pretas enfrenta maior risco. sgos de fechamento no OBEUC, mesmo quando outros fatores são controlados. Essa falta de conexão entre o desempenho do aluno e o fechamento do TCS questiona o argumento de que o fechamento do TCS é uma evidência de que a função de responsabilidade da política de escolha da escola está funcionando.
Palavras-chave: Ohio; Escolas charter; Escolha da escola; Acesso à educação; Raça; Pobreza; Segregação; Escolas fechadas; Desempenho dos alunos

Introduction

The closure of traditional charter schools (TCS) is an expected occurrence since TCS, which are independently-operated public schools that are tuition-free and operate through a contract, are accountable for student performance in exchange for freedom from state and local regulations. TCS advocates argue that TCS closures provide evidence that the accountability function of the charter model is working. TCS that are poorly performing, have low enrollment or suffer from other financial or management pressures are intended to close since they are not fulfilling the terms of their charter. But, few studies examine the relationships among student performance, TCS characteristics, student enrollment demographics and the likelihood of TCS closure.

In this study, we seek to broaden the literature on charter school closure by examining the potential relationships among racial and socioeconomic enrollment characteristics, TCS age and early adopter status, student achievement and the likelihood of closure within Ohio's "Big 8" Urban Counties (OBEUC), the largest urban counties in Ohio that have experienced TCS development. Exploring these relationships and associations with TCS closure is important for several reasons. First, examining the connections between student performance and TCS closure helps researchers and policymakers to more fully understand the link between achievement and closure. Second, since TCS in OBEUC tend to serve larger percentages of disadvantaged and Black students, the potential displacement of these students and the number of school transitions they will have to make is of concern. Third, the association between early adopter status, TCS that opened within the first five years of charter law, and closure has yet to be examined in Ohio.

To learn more about the lifespans of TCS in OBEUC, we conducted a survival analysis. Using life tables and binary logistic regression, we examined 3,204 TCS school years (424 TCS) in OBEUC from the arrival of TCS in 1998 through 2015 to assess the relationships among the likelihood of closure and TCS characteristics (TCS age and early adopter status), student achievement (the percentage of students at or above the proficient level in math and reading and Performance Index scores), and enrollment characteristics (the percentage of students who are eligible for a free or reduced lunch, and three racial TCS enrollment categories: integrated TCS enrollment, Black TCS enrollment that is 75% or greater, and White TCS enrollment that is 75% or greater). OBEUC are an excellent setting for studying TCS closure because they are a mature education marketplace. TCS have been in place for nearly 20 years in Ohio's urban counties and Ohio's TCS closure law has been identified as one of the strictest in the nation because it requires the automatic closure of TCS that consistently fail to meet academic standards. Ohio is one of 15 states with laws requiring the automatic closure of TCS that fail to meet minimum academic performance standards (Ziebarth, 2015). Given this, Yost (2019) reported that TCS in Ohio have a 43% closure rate.

The results of this study make several contributions to the TCS closure literature. First, we find no evidence that student performance is linked to TCS closure in OBEUC. Additionally, we find that compared to TCS with integrated enrollments, TCS with predominantly White or Black enrollments face higher risks of closure in OBEUC, even when controlling for other factors. The implications of these findings are discussed.

Literature Review

Charter Schools, Accountability and Closure

Across the country, traditional charter schools (TCS) continue to expand within the landscape of public education. More than 300 new TCS opened in fall 2017, bringing the total operating in the 2017–2018 school year to more than 7,000 with nearly 3.2 million students (David & Hesla, 2018). Between the 2016–2017 and 2017–2018 school years, TCS enrollment increased by more than 150,000 students (David & Hesla, 2018).

TCS are public schools that receive federal and state funding but use their own curricula and are not required to follow all district regulations. Wells (2002) stated that TCS reform "fits into [an] autonomy-for-accountability framework" because charter school policies provide charter schools with autonomy "within a broader 'accountability' context" (Wells, 2002, p. 5). In exchange for greater accountability of student learning outcomes, TCS are granted flexibility to determine the use of public funding and freedom from state and local regulations (Wells, 2002).

The central idea behind school choice options, like TCS, is that by introducing choice into the public school system, parents can choose the school that is most appropriate for their children, which consequently creates incentives for all schools, TCS and traditional public schools (TPS) alike, to improve in order to compete for students (Apple, 2001). TCS that are unable to meet the terms of their charter, including meeting student performance metrics, must be closed by their authorizer. Therefore, "the threat of failure and the loss of the charter incentivize teachers and administrators to provide an effective and efficient education in order to meet the expectations and goals of the parents and students" (Schwenkenberg & VanderHoff, 2015, p. 300). Supporters claim that by closing TCS that are unable to meet their contractual obligations, students will leave unproductive school environments for higher performing schools, which will ultimately improve their academic achievement. Opponents of closures are concerned that closures will interrupt students' educational experiences, cause psychological stress and harm their academic outcomes (Ayala & Galletta, 2012; CREDO, 2017b).

While TCS are "incentivized" to meet the expectations set forth in their charters, some TCS close. Of the roughly 6,700 TCS that opened within the United States, 1,036 closed since 1992 (Consoletti, 2011). Historically, TCS have had a 15% closure rate, with closure occurring typically in their first five years of existence (Consoletti, 2011). Alison Consoletti (2011) from the Center for Education Reform, an education reform organization that collects, analyzes, and assesses the charter schools that are approved, opened and closed each year, published a report that identifies five primary causes of charter school closure: 1) Financial, 2) Mismanagement, 3) Academic Performance, 4) Facilities and 5) District Obstacles. The most common reason for TCS to close in the United States is financial, with 41.7% of closed TCS reporting that low student enrollment or low funding were the cause of closure (Consoletti, 2011). Mismanagement is the second most common reason for closure, with 24% of TCS closing due to administrator or sponsor misbehavior (Consoletti, 2011). TCS that are unable to meet academic goals and performance targets set by the state or written in their charter are closed due to academic performance, a reason that 200 (18.6 %) TCS closed (Consoletti, 2011). Poor school facilities are cited for 4.6% of closures and district obstacles, such issues with its school district sponsor, represent 6.3% of TCS closures across the Unites States (Consoletti, 2011).

Enrollment Characteristics of Charter Schools

Charter school advocates state that TCS provide innovative options for parents, allow for educational innovation, and are not constrained by school district boundaries and student assignment practices that create racially segregated schooling patterns that exist in many neighborhood school systems (Finn, Manno, & Vanourek, 2000). They also claim that TCS provide options for low socioeconomic students (Finn et al., 2000). However, compared to TPS, TCS tend to disproportionately serve minority, lower achieving and impoverished students. Multiple studies indicated that TCS tend to enroll more minority students than TPS (Carnoy, Jacobsen, Mishel & Rothstein, 2005; Cobb & Glass, 1999; Eckes & Rapp, 2005; Green, 2001; Mickelson, Bottia &

Southworth, 2008; Paino, Boylan, & Renzulli, 2017; Rapp & Eckes, 2007; Whitehurst, Reeves & Rodrigue, 2016). Rapp and Eckes (2007) examined the enrollment characteristics of TCS in 32 states who served more than 1,000 students and found that two-thirds of the TCS they examined enrolled greater proportions of minority students than TPS. However, TCS that only serve gifted students tend to disproportionately enroll White students (Mickelson et al., 2008).

One reason for the racial segregation in TCS is that there is a pattern of TCS locating near, but not directly inside, areas that are predominantly Black. Gulosino and d'Entremont (2011) found that greater percentages of Black students are enrolled in TCS than who live in the area surrounding the TCS. Additionally, they stated that this segregation is due to the clustering of TCS in areas near predominantly Black neighborhoods, areas that encircle the neighborhoods of potential students (Gulosino & d'Entremont, 2011). Using average nearest neighbor analysis, Gilblom and Sang (2019) found that TCS in Cuyahoga Metropolitan School District (CMSD) in Cleveland, Ohio, cluster more tightly on the east side of Cleveland in predominantly Black and lower income neighborhoods than TPS. However, while TCS cluster in the east side of Cleveland, they position themselves in census tracts adjacent to predominantly Black neighborhoods. As a result, these TCS have enrollment characteristics that are more racially and socioeconomically mixed than TPS located in predominantly Black neighborhoods (Gilblom & Sang, 2019). This positioning may indicate that TCS strategically situate themselves outside of census tracts with high proportions of poor, Black individuals to access a steady stream of poor, Black students with less mobility while simultaneously attracting high-ability students of favorable backgrounds who are open to trying a new public school option, specifically students from TPS who require fewer resources to educate and who will most likely enhance the school's performance (Gilblom & Sang, 2019). Similar studies produced evidence of TCS purposely avoiding areas with higher proportions of Black and disadvantaged students (d'Entremont, 2012; LaFleur, 2016; Lubienski, Gulosino, & Weitzel 2009; Saultz & Yaluma, 2017).

Other studies indicated that school district choice policies can lead to greater segregation in schools. Whitehurst (2017) found that school districts that permit parents to enroll their children in the school of their choice have schools that are more segregated than would be the case if school assignment were based entirely on zip code. Some studies suggest that parents tend to select schools with enrollment characteristics that reflect their own race and socioeconomic status (Booker, Zimmer & Buddin, 2005; Garcia, 2008; Mickelson et al., 2008; Renzulli & Evans, 2005).

The Effects of TCS and TPS Closure on Students

Research on the effects of closing TPS and TCS, either elementary or high schools, is growing, but still sparse. Several studies examined the effect of school closure on displaced students and results vary (Brummet, 2014; Carlson & Lavertu, 2016; de la Torre & Gwynne, 2009; Engberg, Gill, Zamarro, & Zimmer, 2012; Kemple, 2015). Studies of closing low-performing schools showed no improvements in test scores, on average, for the students who were displaced (Brummet, 2014; de la Torre & Gwynne, 2009). This finding may be because most displaced students transferred to schools that were modestly higher achieving than their previous school and those few students who enrolled in much higher achieving schools experienced test score gains (Brummet, 2014; de la Torre & Gwynne, 2009; Engberg et al., 2012).

Existing research also suggests that low-income and minority students face greater adverse effects from closures (CREDO, 2017b; Paino et al., 2017). Consequences of TCS closures may vary by race (CREDO, 2017b; Paino et al., 2017) and are dependent on other factors, including the local availability of higher performing schools (Bross, Harris & Liu, 2016; Carlson & Lavertu, 2016; CREDO, 2017b; Glazerman & Dotter, 2016). TCS, in many localities, serve higher percentages of minority students, and research is emerging to look at the varied effects of TCS closures on students by racial group (CREDO, 2017b; Paino et al., 2017).

Carlson and Lavertu (2016) used a regression discontinuity design to examine the effects of the mandatory charter school closure law in Ohio, which states that TCS with lower than expected annual gains must be closed by their authorizer, on student math and reading scores. Using data from the Ohio Department of Education (ODE), the researchers analyzed data from 6,000 individual students across 36 TCS that were at risk of closure due to their gain index scores. They found that students who were enrolled in at-risk TCS experienced statistically significant math and reading score gains three years later, apparently because these students attended a higher performing school (Carlson & Lavertu, 2016). They found a positive effect in reading and math scores for the students who were displaced by school closures and enrolled in another school or who left their "at risk" schools even though their schools had not closed.

Paino, Renzulli, Boylan and Bradley (2014) conducted a mixed-methods analysis that explored how "macro" and "micro-level processes" that affect TCS closure in North Carolina (p. 500). Using event history analysis, Paino et al. (2014) found that a poor financial condition increased the likelihood that a TCS would close, while market and bureaucratic accountability has less of an effect. They found that nearly 63% of closures were due to financial reasons followed by 29% for mismanagement. However, although many closed due to financial issues, most of those schools were underperforming when compared to other TCS. Paino et al. (2014) found that reading scores, but not math scores, are significant predictors of closures. As a reading scores increase, the likelihood that it will close decreases. However, when federal financial per-pupil funding is included in their predictive model, reading achievement is no longer a significant predictor of TCS closure (Paino et al., 2014). Paino et al. (2014) suggest, "North Carolina investigates and revokes charters due to "finances" as a formal explanation, but perhaps tries to isolate academically poor charter schools in order to "weed out" those that are ineffectual" (p. 30). They state that it may be easier to investigate a TCS for financial mismanagement than academic and bureaucratic problems and this finding "in some ways contradicts the general perception that the success and accountability of a charter school is primarily measured in terms of academic outcomes" (Paino et al., 2014, p. 31).

Using quantitative analysis and critical race theory, Paino et al. (2017) examined the relationship between race and TCS closure. As TCS tend to enroll larger proportions of Black students, Paino et al. (2017) argued that Black students may be disproportionately disadvantaged by TCS closures. Using district-level data from the Common Core of Data (CCD), state academic performance data and TCS demographic data from the Center for Education Reform, Paino et al. (2017) conducted an event history analysis and find that TCS across the United States that enroll larger percentages of Black students are more likely to close even when considering other factors that predict closure, including the age and size of the school. TCS that are older and that have greater enrollments are less likely to close. Conversely, academic achievement was not a significant predictor of closure, even among TCS with greater percentages of Black students (Paino et al., 2017).

CREDO (2017b) examined the effects of traditional and TCS closures on students. Using longitudinal data from state departments of education in 26 states, they find that low-income and minority students are more likely to be affected by closure, that closures were more concentrated in urban areas, and they are more likely to occur in elementary schools. Low-performing TPS and TCS with a larger share of Black and Hispanic students were more likely to close than similarly performing schools with a smaller proportions of disadvantaged minority students (CREDO, 2017b). Additionally, fewer than half of displaced students from closed TCS and TPS enrolled in higher performing schools, but more displaced TCS students enrolled in higher performing schools than displaced TPS students (CREDO, 2017b).

A few studies found positive effects involving phase-outs rather than immediate closures, an option that is less disruptive for students, especially for high school students (Kemple, 2015; Bross et al., 2016). Kemple (2015) examined data from 29 high school closures in New York City that occurred as a "phase-out process" in which students were permitted to stay in their schools until graduation or to transfer before the school closed. He found that there were no adverse effects on the academic performance of students who remained in schools that would eventually be closed and that students who left attended higher-performing schools and experienced modest improvements in attendance, progress towards graduation, and graduation rates.

In an ethnographic study of a Midwestern high school primarily serving African American students, Ayala and Galletta (2012) documented the ways in which school closings are often disconnected from the community since they result from the local and state level in relation to federal school accountability policies. While restructuring and turnaround initiatives are framed as solutions for poor, dysfunctional, low-performing schools, Ayala and Galletta (2012) argue that these initiatives neither acknowledge the strengths inherent in local communities, nor do they represent the desire of the community. Frequently, district decisions to employ school closure as a solution has produced community opposition. Although a community may acknowledge the need for school improvement, Ayala and Galletta (2012) stated that closure "squelches a process of working out institutional problems and engaging in conflict toward productive change" (p. 152). As they write, "What gets erased is often not inequality but the history of resistance and struggles for change (Trouillot, 1995), aspects of the reform process that can be volatile yet contribute to meaningful change" (Ayala & Galletta, 2012, p. 154). However underresourced and troublesome many of the failing schools were, "their closing denies communities a public institution and space that holds the capacity for rebuilding and redefining oneself" (Ayala & Galletta, 2012, p. 152). Therefore, closure as a method of educational reform may do lasting damage to a community that was not in favor of the closure in the first place.

The Ohio Context

Charter School Legislation and Development in Ohio

Aided by charter-friendly legislation, TCS have quickly spread throughout Ohio's "Big 8" Urban Counties (OBEUC), the largest urban counties in the state, over the past twenty years. Between 1999 and 2013, the growth rate of Ohio's TCS was double the national rate (Squire, Robson, & Smarick, 2014). Since the pilot TCS program was established in June 1997, by House Bill 215 in Lucas County, Ohio has supported the development of TCS, or community schools as they are referred to in the Ohio Revised Code, as an alternative to TPS.

Ohio has two types of TCS: conversion schools and startup schools. Conversion schools occur when all or part of an existing facility converts into a community school (Ohio Department of Education, 2017). Conversion schools are independent of the district, managed by a sponsor and are permitted to operate in any Ohio public school district (Ohio Department of Education, 2017). Start-up TCS are permitted to operate only in districts identified by the state as "challenged" or in Academic Emergency or Academic Watch status. Therefore, startups are permitted to operate in each of Ohio's eight largest urban districts (Akron, Canton, Cincinnati, Cleveland, Columbus, Dayton, Toledo and Youngstown); districts with low student achievement; districts that receive grades of D's or F's on the Performance Index on the Ohio School Report Cards (which reports student performance on state tests) and F's on report card measures that report knowledge growth in math and reading; and in the lowest 5% of districts in Ohio's Performance Index score rankings (Ohio Department of Education, 2017). No caps exist on the number of TCS permitted operate in these "challenged" areas. However, in 2011 with the passing of House Bill 153, sponsors are permitted to sponsor up to 100 new start-up community schools (Ohio Department of Education, 2017).

Charter School Expansion in Ohio's "Big 8 Urban" Counties

At first, TCS locations were limited to "challenged" districts, which included districts in Lucas County and the other seven largest urban districts in Ohio, but House Bill 282, passed in 1999, expanded "challenged" districts to include Ohio Urban 21 districts and those districts designated as "Academic Emergency" (Ohio Department of Education, 2017). Two years later, with the passage of House Bill 364, TCS were permitted to open in "Academic Watch" districts (Ohio Department of Education, 2017). In the 2016–2017 school year, over 117,000 students enrolled in 362 TCS, about 7% of the total public school enrollment in Ohio (Ohio Department of Education, 2017). About 70% of Ohio's TCS students were enrolled in site-based schools during the 2016–2017 school year and the remaining students attended E-schools (Ohio Department of Education, 2017).

According to the Ohio Department of Education (2018), 266 TCS operated in Ohio during the 2015–2016 school year. The largest concentrations of TCS exist in OBEUC, counties with school districts that serve high numbers of economically disadvantaged students. The number of TCS that existed in each of these urban counties was: Cuyahoga County (79), Franklin County (74), Hamilton County (23), Lucas County (34), Mahoning County (9), Montgomery County (29), Stark County (5) and Summit County (14). In the 2015–2016 school year, TCS in OBEUC enrolled 50,328 Black students, 35,138 White students, and 48,317 students received a free or reduced lunch.

Ohio's Automatic Closure Law

Ohio's automatic closure law became effective in 2008 and was revised in 2011. Under Ohio Revised Code 3314.023, TCS that serve children in grades four through eight (but no grade above 9) face automatic closure if they have the academic emergency designation in two of the three most recent years and in at least two of the three most recent school years, the school has less than one year of academic growth in either reading or math. (Lawriter Ohio Laws and Rules, 2019). This provision only applies to grades four and eight because Ohio's standardized testing measures academic progress only in those grades and only in reading and math. The requirements of the automatic closure law in place for the 2007–2008 school year required TCS serving grades K-3 or 10-12 to close if they had received the "academic emergency" designation in four consecutive school years (Lawriter Ohio Laws and Rules, 2019). Ohio began identifying TCS for closure during summer 2008 based on performance from the 2008 school year. TCS were permitted to remain open for an additional year after receiving notification of closure, although they are permitted to close immediately if they chose. The state notified 23 TCS between 2008 and 2012 that they were required to close under the law for failing to meet minimum performance standards. Between 2000 and 2018, 293 TCS closed (Ohio Department of Education, 2018).

In 2015, House Bill 2 was passed which requires ODE to annually rate all sponsors beginning with the 2015–2016 school year. This bill also revokes sponsorship authority for sponsors rated "ineffective" for three consecutive years or rated "poor" (Ohio Department of Education, 2017). HB 2 also allows sponsors to terminate or not renew a school's contract even if the school does not meet the standards of poor academic performance that trigger automatic closure of the school, but it excludes schools that primarily serve students with disabilities from the academic performance component used to grade sponsors (Ohio Department of Education, 2017).

CREDO (2019c) examined the effect of HB 2 on Ohio's overall TCS performance since CREDO's (2009a) study that examined national TCS performance, including those located in Ohio, for the 2007–2008 school year. Using Ohio state standardized achievement test scores between the 2013–2014 and the 2016–2017 school years, CREDO (2019c) found "little to no progress in Ohio

TCS performance" (p. 44). While students attending TCS have reading scores similar to TPS students, TCS students still fall behind in math, a shortcoming equal to "los[ing] 41 days of learning in a school year" (CREDO, 2019c, p. 42). However, stronger performances exist for Black TCS students, including those in poverty, who attend elementary, middle schools and TCS operated by management organizations (CREDO, 2019c). Additionally, they found that many Ohio TCS have higher learning gains than TPS for the same students (CREDO, 2019c). But, CREDO (2019c) argues that more focus on TCS with substantially lower student achievement gains and those with below-the-state-average achievement is needed. Overall, CREDO (2019c) states that HB 2 emphasized the quality of TCS rather than quantity, since the number of new TCS openings decreased after its passing, and they suggest that further studies examine the impact of HB 2 and student learning outcomes as time progresses.

Reasons for Charter School Closure in Ohio

ODE periodically posts a spreadsheet that lists closed TCS and their respective reasons for closure in the Community School page of the ODE website, which can be found here: http://education.ohio.gov/Topics/Community-Schools. This spreadsheet contains a list of closed TCS with dates and the reasons for closure are formatted in free form, unstructured text, which obscures the specific reasons for closure. While this spreadsheet contains text about why a TCS closed, it lacks distinct, fixed categories with accompanying clear explanations that detail each TCS closure. Additionally, this irregular formatting may also result in several reasons for closure without a distinct indication of the primary closure reason, if there is one.

After analysis of the 293 TCS that closed between 2000 and 2018 in ODE's closure spreadsheet, we determined that one primary reason for closure is financial viability, which was identified in 106 (36.2%) of the TCS closures. The second highest listed reason of closure is academic performance, accounting for 55 (18.8%) of all closures. Contact nonrenewal or expiration is the third highest listed reason with 39 associated closures (13.3%) and merging with another school is fourth with 23 closures (7.8%). These reasons for closure were not included in our survival analysis due to the irregularity of the data. However, we compare these reasons for closure with the results of our analysis.

Summary

The evidence from these studies suggests that TCS closure produces mixed results and disproportionately affects disadvantaged minority students. While one study indicated that students in Ohio who were displaced by TCS closures and enrolled in another school had significant math and reading score gains three years later, another study found that fewer than half of displaced students from closed TCS and TPS enrolled in higher performing schools (Carlson & Lavertu, 2016; CREDO, 2017b). Additionally, there is evidence suggesting that Ohio TCS performance is stagnant, even after HB 2 was passed (CREDO, 2019c). Existing research also indicates that low-income and minority students face greater obstacles from closures (CREDO, 2017b; Paino et al., 2017).

But, few studies examine the predictive factors of TCS closure. Several studies found that TCS across the nation that enroll more Black students are more likely to close even when considering other factors that predict closure (CREDO, 2017b; Paino et al., 2017). Similarly, low-performing TPS and TCS with higher Black and Hispanic enrollments are more likely to close than similarly performing schools with a smaller proportions of disadvantaged minority students (CREDO, 2017b). Additionally, Paino et al. (2014) found that reading scores, but not math scores, are significant predictors of closures. However, when federal financial per-pupil funding is included in their predictive model, reading achievement is no longer a significant predictor of TCS closure (Paino et al., 2014).

Missing from the TCS closure literature are additional studies that examine predictive factors of closure, specifically in Ohio. It is vital to learn more about which student bodies and TCS face higher risks for closure so that policymakers and educators can improve conditions and outcomes at these schools. It is also important to find more evidence about the relationships among performance, age, early adopter status and the likelihood of closure, as the research is sparse and inconclusive.

Methodology

The purpose of our research is to determine which student bodies and TCS characteristics contribute to the likelihood of TCS closure. Using a methodology similar to the study conducted by Paino et al. (2017) that examined predictors of TCS closure across the United States, we conduct a survival analysis of TCS closure in Ohio's "Big 8" Urban Counties (OBEUC). Utilizing life tables and binary logistic regression, we conduct a discrete-time survival analysis to examine the effects of specific academic performance measures, TCS age and early adopter status, and the socioeconomic and racial characteristics of the student body on the likelihood that a TCS will close.

Survival Analysis

Survival analysis, or event history analysis, allows researchers to answer questions by using data about the number, timing and sequence of changes in the dependent variable (Box-Steffensmeier & Jones, 1997). It also explores patterns and causes of change (Yamaguchi, 1991). Survival analysis refers to statistical methods developed to model dichotomous outcomes in longitudinal data, or the timing of events. Survival analysis has three identifying characteristics. Zhao (2018) notes that two characteristics are a time variable and an event happening at a certain time. Events terminate an episode and cause the subject to change from one state to another, such as death, graduating from college or entering the workforce, and can happen during the study's period of observation or beyond it (Allison, 1982). If the study's observation period is terminated without the event taking place, it is regarded as "censored".

The third characteristic of survival analysis is the presence of explanatory or predictor variables (Allison, 2014; Rodriguez, 2010). Explanatory variables, such as income, may change over time which makes accurate measuring and inclusion in a model challenging if traditional statistical methods are employed (Allison, 2014). Due to these characteristics and their subsequent challenges, survival analysis does not consist of a single analytical method. Instead, it is a collection of competing and complementing methods (Allison, 2014).

Many disciplines are interested in the relationship between time and the occurrence of a specific event. While drawing on similar statistical foundation, each discipline refers to survival analysis with a different term and with a slightly different approach. Researchers in the field of economics conduct duration analysis or duration modeling to study topics such as unemployment, crop adoption, and employee turnover (Beyene & Kassie, 2015; de Una-Alvarez & Otero-Giraldez, 2003; Dolton & von der Klauw, 1995; Holmas, 2002). Analyzing data on the failure of machines and their components, engineers perform reliability analysis to identify component reliability or failure rates in software, structures, and electronics (Bucher & Bourgund, 1990; Lyu, 1996; Zong-xiang, 2005). Event history analysis is the term used by sociologists who studied racial rioting in the 1960s, social integration and longevity, and policy (Berry & Berry, 2018; Moen, Dempster-McClain & Williams Jr., 1989; Myers, 1997). Health researchers, such as oncologist, biostatisticians, and epidemiologists, use the traditional term survival analysis in their study of disease onset, death, and medical interventions (Christiansen & Jensen, 2007; Mittelman, Farris, & Shulman, 1996; Stice, Killen, Hayward & Taylor, 1998). In this study, rather than analyzing the lifespans of cancer survivors, we analyze the lifespans of TCS to determine if student achievement, enrollment and TCS characteristics and school age predict TCS closure in the eight largest urban counties in Ohio.

Variables in this Study

As discussed above, survival analysis has three components: a time variable, an event of interest, and the presence of explanatory or predictor variables. The following section lists the variables used in this study for each of these components (Table 1).

Time Variable (Variable SchoolAge in Table 1). The time variable used in this study is the age of the school, which was measured from the first year in which the school had an enrollment larger than zero until one of the following options occurred: (a) the school closure event or (b) the school year 2015, at which time the school was considered censored. Time was measured in one-year intervals.

Generally, time-scales can be classified as continuous or discrete. Continuous-time estimation estimates an occurrence of an event using a precise time unit, such as a minute, hour, or day (Allison, 1982). Discrete-time survival analysis estimates the risk of occurrence (or hazard) in a large time metric, such as a quarter-year, half-year, or year marks (Kim, Chang & Park, 2018). In discrete-time survival analysis, the risk is also referred to as a hazard, which "is defined by the conditional probability the event will occur…in [a] time period, assuming that the event has not occurred…up to that time" (Kim, Chang, & Park, 2018, p. 515).

Allison (1982) presents two circumstances when discrete-time models are appropriate for analyzing event histories: 1) When an event occurs only at discrete points in time, e.g., graduation only occurs at the end of the 12th grade school year, and 2) When events can occur at any point in time, but data reports only a particular interval of time in which the event occurred, e.g., a school can close during the school year, but the data report the closure at the end of the school year. To analyze the effects of enrollment characteristics on TCS closure, we used a discrete-time survival (or hazard) model, which estimates the risk of occurrence, or chance, of the target event (closure) in a time unit (year). We chose a discrete-time hazard model rather than a continuous model because ODE reports public school data at the year mark.

This model has several attributes that are suitable for the study. First, survival models consider the timing and the occurrence (or nonoccurrence) of closure. Second, discrete-time survival analysis models right-censored data and accounts for the fact that some TCS will not close during the observation period. Third, survival model permits for the inclusion of time dependent covariates and time by independent variable interactions. These interactions allow for the examination of whether the effect of covariates change over time, such as whether the effect of higher White student enrollment on school closure changed as TCS age. Finally, the model allows for a discrete specification of time, which is the age of the TCS. In this data, school closure was measured at yearly intervals along a time scale. Therefore, we do not know the exact date time of a school's closure; we only know that it occurred within a yearly interval that is reported by ODE and NCES.

Event of Interest (Outcome variable). The event of interest in this study is school closure (Variable ClosureYN in Table 1). The closure variable that has two possible categorical outcomes that indicates when a school in our sample closed. This is a time-varying variable that is equal to 1 in the year that a school closed and 0 when that school is open. For example, if a TCS opened in 2004 and closed in 2010, then the dependent variable will be coded as 1 only in 2010, the year that it closed, and 0 in each year it was open.

A TCS is considered closed if ODE reported it as closed. ODE maintains a spreadsheet available on their website that lists each TCS that is closed, why the closure occurred, when it closed and other information related to the closure. We verified that each TCS listed as closed on this spreadsheet was, in fact, closed. We also analyzed our sample to ensure that there were no additional TCS that were closed but were not listed on the spreadsheet. We cross-checked the TCS reported as closed on the ODE website with the data downloaded from NCES and found that both data sources listed the same number of closures.

Explanatory/Predictor Variables (Independent variables). Our independent variables provide context for each charter school's risk of closure in a given year and they include racial demographics, academic performance, and other organizational and environmental characteristics associated with the school. Our covariates are similar to the variables utilized in Paino et al. (2017).

Table 1
List of Variables with Descriptions

Variable	Variable Description
SchoolAge	Age of the TCS, measured in years from the first year in which enrollment > 0 until one of two outcomes: (a) school closure, or (b) school censored
ClosureYN	Last year in which school had enrollment >0 =1 All other years = 0
EarlyAdopter	School opened between 1998 and 2004 =1 School opened in 2005 or later = 0
TFRL_pct	% of students who receive free or reduced lunch
SchoolRacialComp	Racial composition of school. 1 = Integrated school 2 = Over 75% Black students 3 = Over 75% White students
PI_Score	Average PI scores for the school for that school year
ReadAvg	% of students at or above the proficient level in reading
MathAvg	% of students at or above the proficient level in math

Early Adopter (Variable EarlyAdopter) – TCS are classified as an early adopter if they opened in or between 1998 and 2004. This variable was created to account for differences in TCS closure by policies that may have affected TCS that opened in the earlier period of our study, as discussed by Paino, Boylan and Renzulli (2017).

Free and Reduced Lunch (Variable TFRL_pct) – We reported the percentage of students who are eligible for free or reduced lunch in a given year at each TCS.

Racial Demographics (Variable SchoolRacialComp) – The racial composition of each TCS in a given year is categorized by a categorical variable: 1) Integrated enrollment (the racial composition of the school is less than 75% Black or White), 2) Predominantly Black enrollment (75% or greater of total enrollment is Black), and 3) Predominantly White enrollment (75% or greater of total enrollment is White).

Academic Achievement – We use three measures for academic achievement for each academic year: 1) Performance Index scores (variable PI_Score), 2) the percentage of students who scored at or above the performance level considered proficient in reading on Ohio's state tests (variable ReadAvg), and 3) the percentage of students who scored at or above the performance level considered proficient in math (variable MathAvg). Performance Index is part of the achievement component on the Ohio School Report Cards. It is a calculation that measures every student's performance on the Ohio Achievement Assessments for each public school. Schools that enroll higher performing students receive more points towards its Performance Index.

Average scores in reading and in math and PI scores were available for all years starting in the 2003–2004 school year. The grade levels for the percentage of students who scored at or above the performance level considered proficient in math and in reading varied by year, but in general were reported for grades 3-11.

Average scores in reading and in math were calculated as school-level measures in which the percentage proficient were averaged across all grade levels served by the school, as described by Paino et al. (2017). For example, if a school served grades K-6, and average scores in reading or in math were reported in a certain year only for grades 3, 4, and 6, these scores were averaged to create the score for the school in reading or in math. We used these school-level calculations to create consistent measurements for reading and for math because our study covers a broad span of time that begins with the emergence of TCS in OBEUC through 2016 and school rating policy changed throughout the years, including the use of value-added calculations to warrant TCS closure. As the purpose of our study is to examine the relationships between student achievement and TCS closure and not to analyze Ohio's automatic closure policy outcomes, we created this measure so that we can evaluate this relationship consistently throughout time and among the variety of school levels in our sample. TCS for which data were missing had their achievement data imputed, as described in the missing data section.

Binary Logistic Regression

Binary logistic regression is one of the most commonly used tools for discrete data analysis. It is used to obtain odds ratios when there are multiple independent variables (Allison, 1982; Cox, 1972; Singer & Willett, 1993). Binary logistic regression allows a researcher to explore relationships among the probability of event occurrence and covariates of interest. All predictor variables are tested in one block to assess their predictive ability while controlling for the effects of other predictors in the model. The logistic regression analysis was conducted by the logistic procedure in SPSS version 25 (IBM Corp, 2017) and we determined statistical significance at a level of $p < .05$ or less. The charts were created using the Survminer package (Kassambara & Kosinski, 2018) in R (R Core Team, 2013). As the literature regarding predictors of TCS closure is scarce, several models were tested. Table 2 identifies these models.

Table 2
Binary Logistic Models Tested in this Study

Variable	School Age	SchoolRacial Comp	Early Adopter	TFRL_pct	PI_Score	ReadAvg	MathAvg
Model 1 (full model)	X	X	X	X	X	X	X
Model 2	X						
Model 3	X	X					
Model 4	X		X				
Model 5	X	X	X				
Model 6	X	X	X	X			
Model 7	X				X		

Table 2
Binary Logistic Models Tested in this Study

Variable	School Age	SchoolRacial Comp	Early Adopter	TFRL_pct	PI_Score	ReadAvg	MathAvg
Model 8	X					X	
Model 9	X						X
Model 10	X					X	X
Model 11	X				X	X	X

Life Tables

Prior to conducting the binary logistic regression, we built life tables to gain basic knowledge about the life spans of TCS in OBEUC. A life table "tracks the event histories (the 'lives' of a sample of individuals from the beginning of time (when no one has experienced the target event) through the end of data collection" (Singer & Willett, 2003, p. 326). Life tables start with a group of subjects who are exposed to an event. Over time, the group becomes smaller as they experience the event or are censored, meaning they are withdrawn from the event because the observation period has ended. Life tables subdivide the period of observation into smaller time intervals and then the probability of the event happening during each of the intervals is estimated (Hebel & McCarter, 2012; Singer & Willett, 2003). After these probabilities are estimated, they are used to estimate the overall probability of the event happening at different points in time (Hebel & McCarter, 2012; Singer & Willett, 2003).

The estimated hazard rate is the conditional probability that a subject will experience a particular event in a particular time period, given that the subject has not yet experienced it (Singer & Willett, 2003). Hazard is the "risk of event occurrence in each discrete time period among those people eligible to experience the event," who are those present within the risk set (Singer & Willett, 2003, p. 330). The estimated survival function, "provides maximum likelihood estimates of the probability that an individual randomly selected from the population will 'survive' – not experience the event – through each successive time period" (Singer & Willett, 2003, p. 336). In other words, the survival function is the declining percentage of subjects who have 'survived' through each of the time intervals while the hazard rate is a percentage representing the chance of 'not surviving' or dying.

The hazard rate and survival function can be plotted against time on the X axis, forming graphs of the rates over time, with the hazard rate or survival rate marked on the Y axis. Hazard plots illustrate "possible patterns of failure" (Simes & Zelen, 1985). A hazard curve that goes from a low X,Y value to high X,Y value (meaning, going up) signifies an increasing hazard rate. In this case, as time passes, the likelihood of the event of interest occurring increases. Conversely, a hazard curve that decreases over time suggests that the likelihood of event of interest happening over time is reduced. Lastly, a flat hazard curve means that the likelihood of the event of interest happening is the same over time. Survival plots are read as the inverse of hazard plots, meaning that a sharp downwards slope in comparison to increasing time demonstrates an increase in occurrence of the event of interest (Coldman & Elwood, 1979).

In this study, we use life tables to track the lives of TCS to analyze closures. The hazard rate is the percent chance of a TCS closing, given they have not closed, at the start of each year interval. The survival function is the cumulative percent of all TCS that 'survived' and did not close at the end of each year interval. Using the cumulative survival functions and hazard rates, we constructed respective graphs to visually present the patterns of TCS closures over time for each categorical variable in this study: 1) the three-level racial demographic variable, 2) early adopter status and 3) TCS age. As suggested for longitudinal data (Singer & Willett, 2003), graphing the estimated hazard and survival probabilities permits greater ease when examining and interpreting each function. We also tested for statistical difference between the survival curves for the racial demographic variable and early adopter status using the log-rank test. Log rank tests are used to test the null hypothesis that there is no difference between the survival curves each comparison group, which means that the probability of an event occurring at any time point is the same for each comparison group (Kleinbaum & Klein, 2012). Calculated like a chi-square statistic, it is a nonparametric test used for simple comparisons that calculates the difference between the observed and expected number of closures in each comparison group (Kleinbaum & Klein, 2012).

Median survival times were reported for the racial composition and the early adopter status variables. Median survival time is reported in survival analysis because it identifies the time in which the survivor function is equal to .50, meaning that one-half of the schools in the variable closed and one-half did not close (Singer & Willett, 1993). Mean survival time is usually not reported in survival analysis because it is defined only if all subjects have experienced the event of interest, in this case, TCS closure (Moore, Gentleman, Hornik, & Parmigiani, 2016). Since only some of the TCS closed, mean survival time cannot be calculated for this study.

The life tables were created using SPSS version 25 (IBM Corp, 2017). The survival plots were created using the Survminer package (Kassambara & Kosinski, 2018) in R (R Core Team, 2013).

Data Sources

Our analysis incorporates data from the Common Core of Data (CCD) available from the U.S. Department of Education's National Center for Educational Statistics (NCES) for school years between 1998–1999 and 2015–2016. The CCD data contained school location, age, and enrollment characteristics, including race and the percentage of students eligible for a free or reduced lunch. Additionally, CCD data classified each school as a charter (TCS) or a non-charter school (TPS) and if the school was considered a regular, special education, vocational or an alternative school.

CCD data were combined with data from ODE. ODE data provided information on the year of closure and student achievement, which included PI scores and the percentage of students attending the school who scored at or above the level considered proficient in math and reading.

Sample

The sample included 3,204 TCS school years (424 TCS) in OBEUC from the arrival of TCS in 1998 to 2015. Ohio TCS included in this sample are classified as 'regular' schools, meaning they are not classified as special education, vocational or other/alternative public schools. TCS located outside of OBEUC, TCS that opened after the 2015–2016 school year, or TCS that operated as a regular school for a few years before transitioning to a special education school are not included in this sample.

Data Structuring

We combined the ODE and CCD data in SPSS using the Information Retrieval Number (IRN). The data set for the binary logistic regression analysis included a record for each year from the opening of the TCS and until the TCS closure or the school year 2015–2016, which is the last year of our study. The life tables data set included one record per TCS, either for the 2015–2016 school year if the school was in operation at that year or for the year in which it was closed.

Missing Data

Data screening methods were taken to ensure the completeness of the data set. The mice package (van Buuren & Groothuis-Oudshoorn, 2018) in R used to identify missing data, which revealed that some variables (percentage of students receiving free or reduced lunch, PI scores, reading achievement and math achievement) had missing data. For the free or reduced lunch variable, the dataset was first split by survey year using the Split File function in SPSS, and then missing data were imputed in SPSS by using the series mean methods under the Replace Missing Values function. The combination for splitting by survey year and the series mean method calculated a series mean separately for each survey year.

For the PI scores and reading and math student achievement variables, a two-step imputation method was employed. First, the prior knowledge method was used (Tabachnick & Fidell, 1996). The last reported scores for reading and math for each grade in each TCS and PI scores were entered for all years of missing data for TCS that reported that information. The second step used the series mean method, in which missing values are replaced with the mean for the series. In our study, a different series mean was calculated for each year (meaning that 2006 will have a different series mean than 2009, for example). Therefore, each TCS had an average math and average reading score for each year that was used in the analysis. The Split File function was turned off after data imputation was completed to ensure the survival analysis is conducted correctly. There was no multicollinearity among the independent variables.

Results

The total sample included 424 TCS located inside of OBEUC that opened between the 1998–1999 and 2015–2016 school years. The database contained 3,204 school years, meaning that the database contains enrollment and achievement data for each school year for each TCS in the sample between 1999 and 2015, including the years the TCS were open and the last year before the school was closed and had no enrollment. Table 3 presents descriptive data for the overall data set.

Table 3
Descriptive Statistics for the Sample

	N	Minimum	Maximum	Mean	Std. Dev.
Age of school/years since school opened	3204	0	17	4.67	3.91
Performance Index score	2367	.00	116.70	64.76	27.17
% of students at or above proficient level in reading	2067	.00	100.00	59.02	20.96
% of students at or above proficient level in math	2065	.00	100.00	47.51	22.38
% of students that receive free or reduced lunch	2783	.00	100.00	62.0.	38.19
Racially integrated schools (Showing % of Black enrollment)	1162	0	74.92	43.33	20.66
Enrollment 75% or more Black	1730	75.00	100.00	91.28	7.25
Enrollment 75% or more White	295	75.00	100.00	85.22	7.15

Figure 1 illustrates the count of TCS that opened and closed in OBEUC between 1999 and 2015. TCS began closing in the 1999-2000 school year, one year after they were permitted to open. In the 2000–2001 school year, closure increased (6 closures) and gradually decreased until 2005 when a second spike occurred (18 closures) and then declined (5 TCS closed) in the 2006–2007 school year. Closure continued to increase in 2007 (14), 2008 (15 closures) and 2009 (17 closures). Closures between 2011 and 2015 remained relatively constant between 12 to 16 closures each year. The highest number of newly opened TCS occurred in the 2013–2014 school year (56). The number of operating TCS in OBEUC steadily increased between 1999 and 2015, reaching over 100 TCS in 2002 and over 200 TCS in 2007.

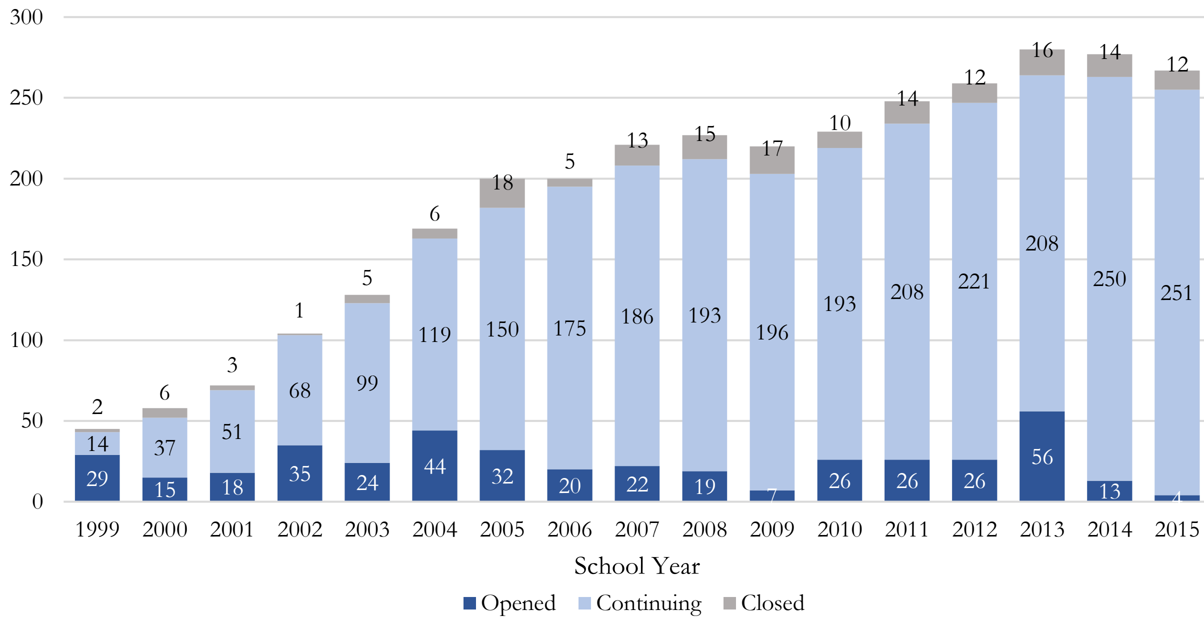

Figure 1: Number of TCS by Operational Status and School Year

Life Tables

Figure 2 illustrates the survival function for TCS from their first year of operation (year 0) to their 17th year. The survival function shows, for this entire sample, a cumulative decline in the proportion of TCS surviving at the end of each year began during year 0 (94%), the year in which the TCS opened. The median survival time for TCS to remain open before closing is 12 years (marked as a dotted black line in Figure 2). This illustration shows the proportion of TCS in the sample at each year of operation still at risk of closure and it reveals no striking point in time at which TCS began closing. Closure stabilizes at 45% during year 13, indicating that 45% of the entire sample remained open and avoided closure within the observed time period.

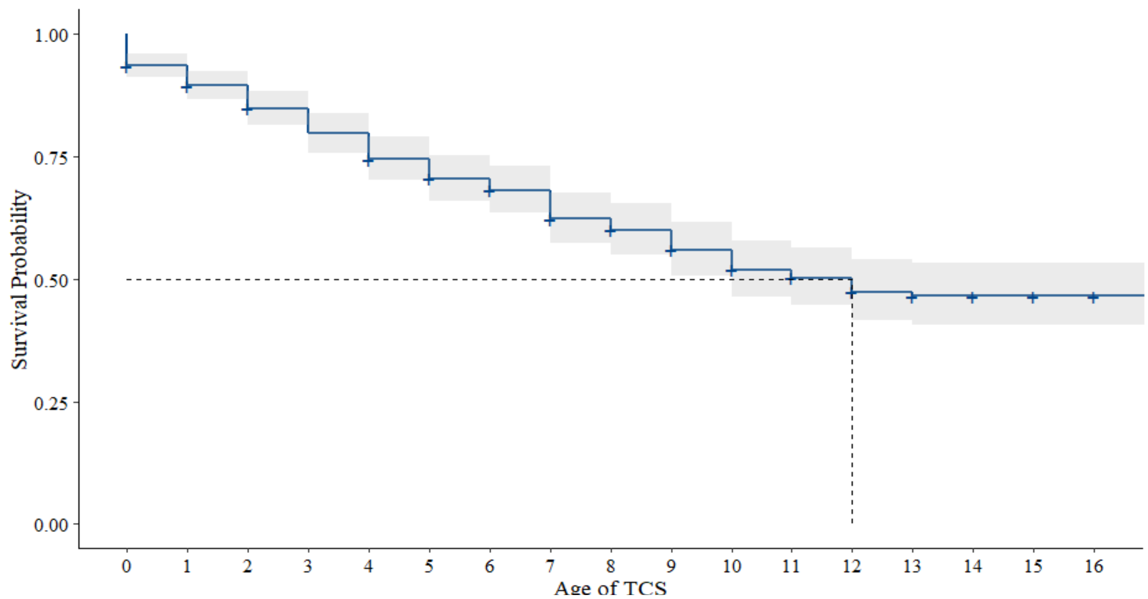

Figure 2. Survival Probability by Age of TCS

Figure 3 illustrates the estimated hazard probability for TCS from their first year of operation (year 0) to their 17th year. Based on the life table model, analysis revealed that TCS in their seventh year experience their highest risk of closure at 9%. After the 2% chance of closure in year 13, the risk of closure falls to 0, indicating that TCS that are 14 years or older are not at risk of closing.

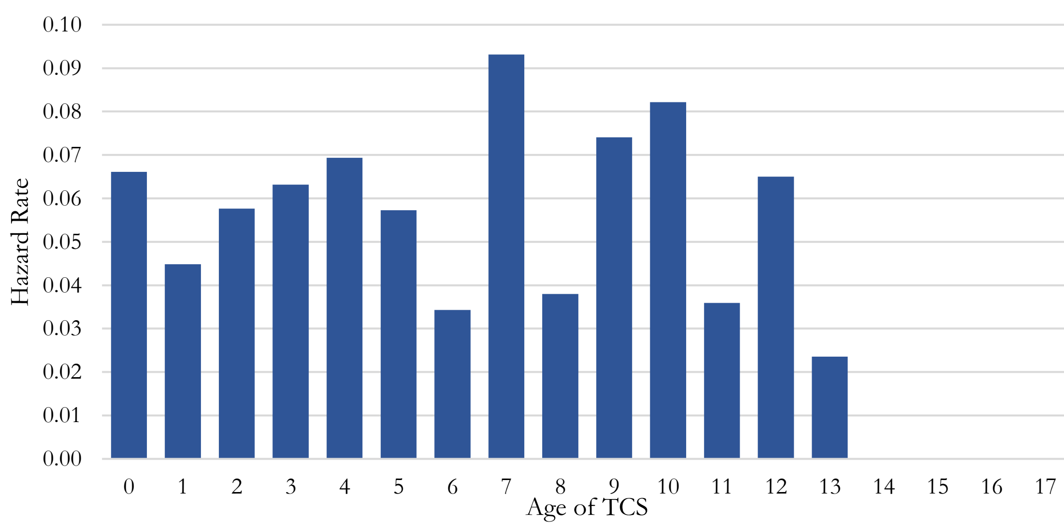

Figure 3. TCS Hazard Rate by age of school

Figure 4 illustrates the survival functions for TCS by racial enrollment and age from their first year of operation until their 17th year. The difference between the survival curves was statistically significant $\chi2$ (2, N = 424) = 19.7, p <.01, indicating that probability of survival varies significantly depending on the racial composition of the TCS. The median survival times, or life expectancy, for TCS with over 75% Black enrollment is 9 years and for TCS with over 75% White enrollment is 4 years. There is no median survival time available for racially integrated schools because the survival probability for racially integrated schools doesn't reach and fall below 0.5. This figure suggests that TCS with integrated enrollments have the greatest chance of survival, or of remaining open, while TCS with Black or White enrollments over 75% or greater are less likely to survive. TCS with White enrollments of 75% or greater are least likely to survive between years 2 and 5, but the risk falls to zero after year 5. While it is normal for the survival curve's confidence intervals to expand as time passes due to closure events and censoring, the width of the 75% or more White enrollment schools indicates that very few of these schools remain open in an already small sample.

The survival function for TCS with racially integrated enrollments shows a cumulative decline in the proportion of TCS surviving at the end of each year (Figure 4). From the 12-year mark through year 17, 64% of all TCS with racially integrated enrollments in the sample avoided closure. Of the 145 TCS in the sample, 25 closed by their 5th year and 33 closed by their 10th year. Overall, 36 racially integrated TCS closed, accounting for 23% of the racially integrated TCS category. The estimated survival function for TCS with predominantly Black enrollments shows a cumulative decline in the proportion of TCS surviving at the end of each year. In years 13 through 17, 35% of all TCS with predominantly Black enrollments in the sample remained open. There are 249 TCS with Black enrollment of 75% or more, 46 of these schools (18.07%) closed before their third year of operations, and more than 100 closed by their ninth year. Of the schools with over 75% Black enrollment, almost half (46.18%, N = 115) closed during this study's period of examination. The survival function for TCS with White enrollment of over 75% shows a cumulative decline in the proportion of TCS surviving at the end of each year. Between years 5 and 15, 37% of all TCS with

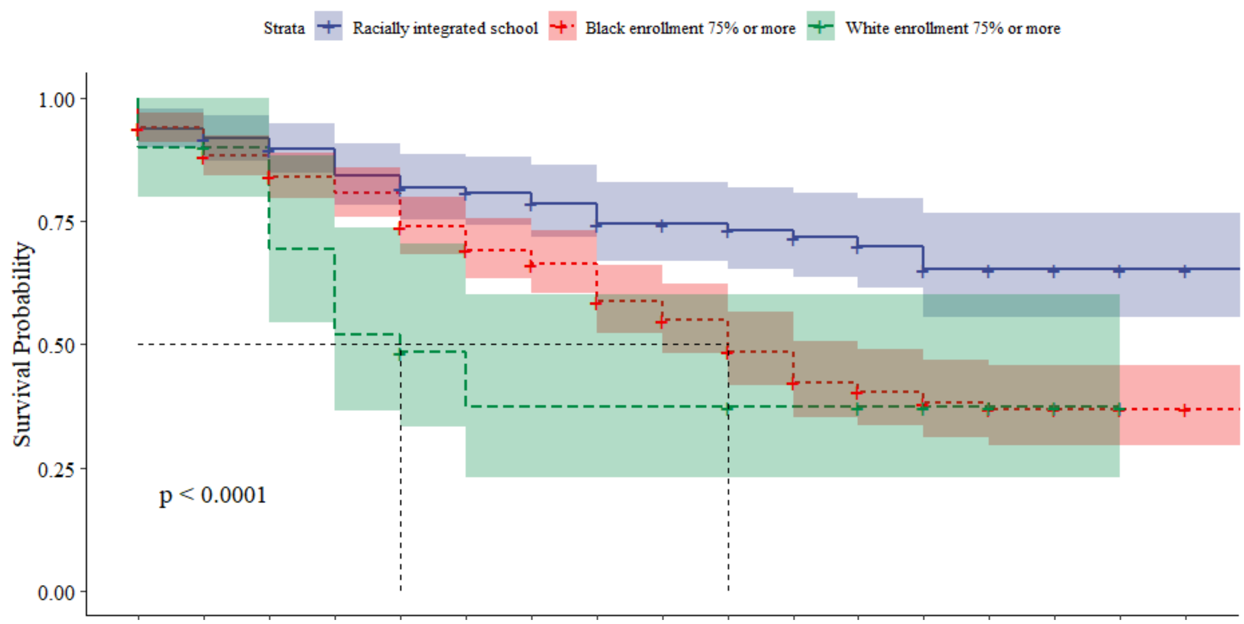

Figure 4. Survival Probability by Racial Enrollment Characteristics

predominantly White enrollment remained open. Of the 30 predominantly White schools in this sample, 18 closed, with half closing by their fourth year of operation.

Figure 5 shows the hazard rates of TCS by racial enrollment, with the ages of the schools shown on the X-axis and hazard (proportion of TCS at risk) shown on the Y-axis. For TCS with racially integrated enrollments, the highest rate of closure (8%) occurs during year 12, after which the risk declines to 0 in years 13 through 17. TCS with Black enrollment over 75% experience higher risks of closure during years 7 (13%), year 9 (13%), and year 10 (15%), after which the risk of closure declines to 4% in year 13 and zero for years 14-17. TCS with White enrollment of over 75% experience very high risks of closure in their early years of operation. During year 0, TCS have an 11% risk of closure. They experience a 26% risk of closure in years 2 and 5 and 29% in year 3. However, the risk of closure falls to zero from year 6 forward.

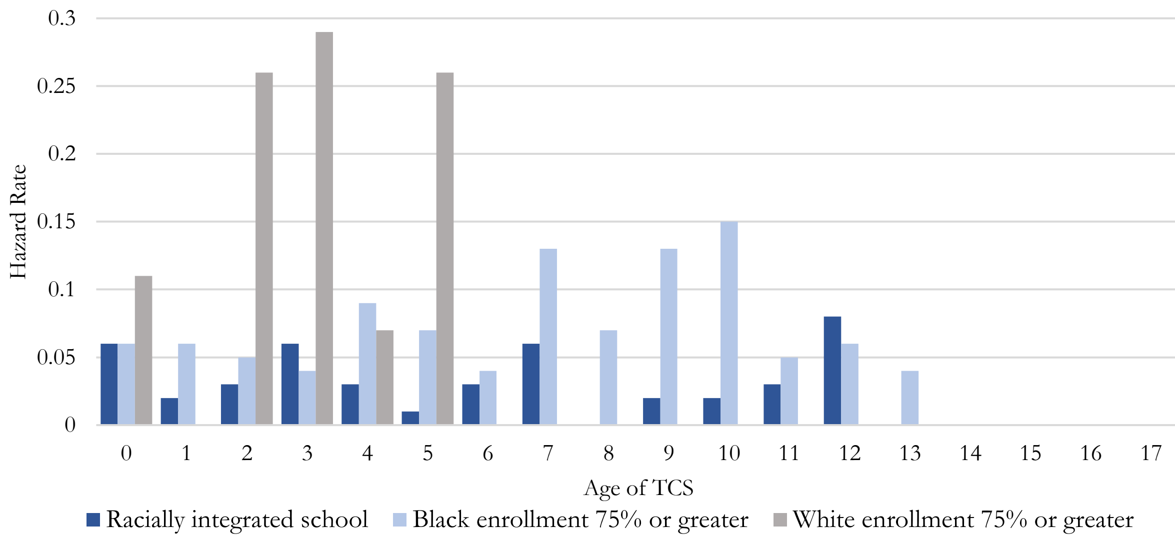

Figure 5. *Hazard Rate by Racial Enrollment*

Figure 6 shows the survival probability for TCS by age and early adopter status. Schools that are early adopters have a median survival time of 12 years. The estimated survival function for early

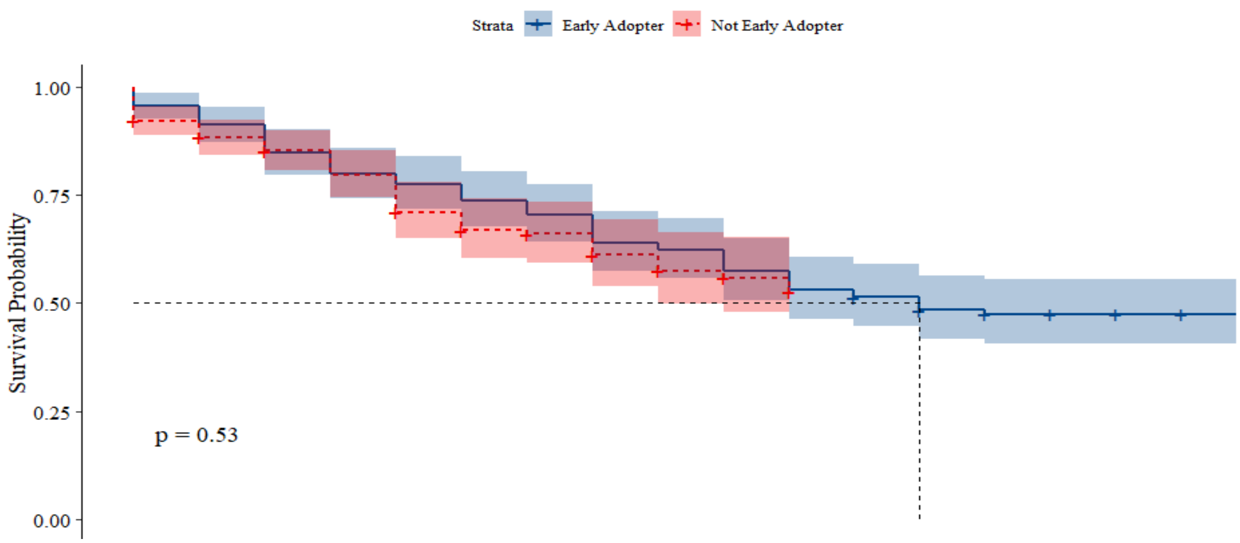

Figure 6. Survival Probability by Early Adopter Status

adopter TCS indicates a gradual, cumulative decline in the proportion of TCS surviving at the end of each year. By years 13 through year 17, 47% of early adopters in the sample have remained open. The estimated survival function for non-early adopter TCS indicates a gradual, cumulative decline in the proportion of TCS surviving at the end of each year. The difference between the survival curves of early adopters and non-early adopters was not statistically significant $\chi 2$ (1, N = 424) = 0.4, p =.53.

Figure 7 presents the hazard rate for TCS by age and early adopter status. The highest risk of closure for early adopters (10%) occurs during year 7, after which the risk of closure declines to 3% in year 8 and rises to 8% in years 9 and 10 (Figure 7). Non-early adopter TCS experience an increased rate of closure of 8% in year 0 followed by a decline to 4% and 7% in years 1-3. Years 4 and 10 have the highest risk of closure (12%). There are no non-early adopter TCS in the sample over the age of 10 years. Overall, this figure indicates that non-early adopters experience higher spikes of risks of closure than early-adopters.

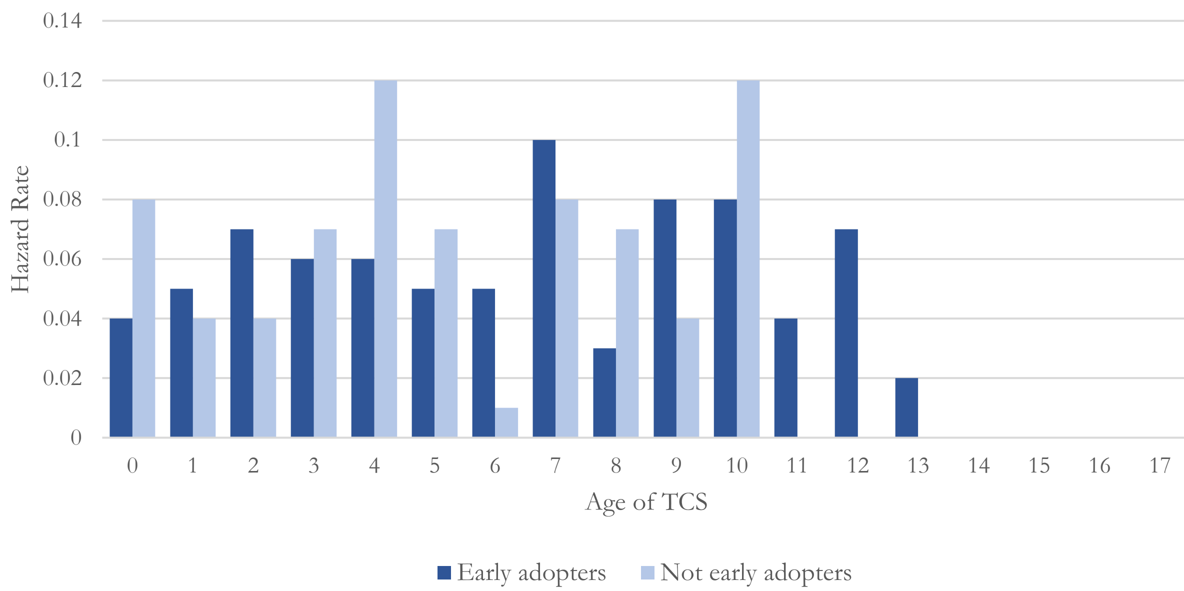

Figure 7. Hazard Rate by Early Adopter Status

Binary Logistic Regression

A binary logistic regression was performed to ascertain the effects of the age of a TCS, percentage of students at or above the proficient level in math and reading, Performance Index scores, the percentage of students who are eligible for a free or reduced lunch, early adopter status, and the racial enrollment categories (integrated enrollment, Black enrollment 75% or greater, White enrollment 75% or greater) on the likelihood that a TCS will close. Age of school was included in all models as it is the time variable for this survival analysis study. Models 2–6 examined the predictive probability of variables that illustrate school characteristics: racial composition, early adopter status, and percentage of students who receive free or reduced lunch. Models 7–11 examined the impact of student performance characteristics on TCS closure.

Table 4 presents the results of the logistic regression for model 1. A test of the full model with all predictor variables against a constant-only model was statistically significant, $\chi 2(8) = 40.31$, $p < .001$, indicating that this set of predictors has a good degree of fit with the data and reliably distinguished between open TCS and closed TCS. The Hosmer-Lemeshow test produced a significant result, which is understandable for this large data set (Hosmer, Hosmer, Le Cassie, &

Lemeshow, 1997; Wuensch, 2016). The model explained 3.7% (Nagelkerke R^2) of the variance in closure and correctly classified 94.7% of cases. The -2 Log Likelihood for this model was 1283.097.

Employing a 0.5 criterion of statistical significance, only the racial composition variable was a predictor of TCS closure (integrated body $p < .001$; Black enrollment of 75% or more β = .3792, $p < .001$; and White enrollment 75% or more β = .913, $p = .004$). Compared to integrated enrollments at TCS, TCS with Black enrollments of 75% or greater are 2.08 times as likely to close (108.0% increase in the chance of closure) and TCS with White enrollments of 75% or greater are 2.491 times as likely to close (149.1% increase in the chance of closure). The age of the TCS, early adopter status, percentage of students receiving free or reduced lunch, percentage of students at or above the level considered proficient in reading or in math, and PI scores are nonsignificant and do not improve the model.

Table 4
Logistic Regressions Analysis of TCS Closure As A Function Of All Predictive Variables (Model 1)

				95% Confidence Intervals for Odds Ratio	
Variables	B	Wald	Odds Ratio	Upper	Lower
SchoolAge	.005	.041	1.005	.960	1.052
SchoolRacialComp (Integrated enrollment - reference group)		15.898			
SchoolRacialComp (75% Black)	.732	13.613	2.080***	1.410	3.068
SchoolRacialComp (75% White)	.913	13.613	2.491**	1.348	4.604
EarlyAdopter (late adopter – reference group)	.204	1.282	1.226	.862	1.743
TFRL_pct	-.002	.900	.998	.993	1.002
PI_Score	.002	.103	1.002	.989	1.016
ReadAvg	-.009	1.613	.991	.976	1.005
MathAvg	-.010	1.911	.990	.976	1.004
Constant	-2.585	35.551	.075		

* $p < .05$. ** $p < .01$. *** $p < .001$.

Table 5 presents the results of the logistic regression for models 2-6. Model 2, which included only the age of the TCS and the intercept, was not statistically significant $\chi2(1) = 1.496$, $p = .221$. The model explained 0.1% of the variance (Nagelkerke R^2) and correctly classified 94.7% of the cases. Adding the racial composition variable (Model 3) produced a significant model $\chi2(3) = 21.224$, $p < .001$, and increased the Nagelkerke R^2 to 2%. Compared to TCS with integrated racial enrollment, TCS with 75% or more Black enrollment are 2.25 times as likely to close (124.8% increase in chance of closure, β = .810, $p < .001$), whereas TCS with 75% or more White enrollment are 2.04 times as likely to close as TCS with integrated racial enrollment (103.9% increase, β = .713, $p = .016$). The age of the TCS was not significant in this model.

Table 5

School Characteristics Models (Models 2-6)

	Model 2		Model 3		Model 4		Model 5		Model 6	
Variables	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI
SchoolAge	0.98	0.936-1.016	0.975	.937-1.018	0.98	.937-1.023	0.982	.940-1.027	0.983	.940-1.028
SchoolRacialComp (75% Black)			2.248 ***	1.534-3.294			2.253***	1.537-3.301	2.27***	1.542-3.342
SchoolRacialComp (75% White)			2.039 **	1.140-3646			2.094**	1.166-3.761	2.056**	1.127-3.754
EarlyAdopter (late adopter)					1.11	.792-1.543	1.136	.810-1.592	1.137	.811-1.595
TFRL_pct									0.999	.995-1.004
-2 Log likelihood	1321.912		1302.184		1321.563		1301.64		1301.575	
χ2	$\chi 2(1) = 1.496$, p = .221		χ 2(3) = 21.224, $p < .001$		$\chi 2(2) = 1.844$, $p = .398$		$\chi 2(4) = 21.768$, $p < .001$		$\chi 2(5) = 21.833$, $p = .001$	
Hosmer-Lemeshow	$\chi 2(8) = 10.564$, $p = .228$		$\chi 2(8) = 21.048$, $p = .007$		$\chi 2(8) = 9.437$, $p = .307$		$\chi 2(8) = 6.546$, $p = .586$		$\chi 2(8) = 9.857$, $p = .275$	
Nagelkerke R^2	0.001		0.02		0.002		0.02		0.02	

* $p < .05$. ** $p < .01$. *** $p < .001$.

In model 4 we tested the age of the TCS and early adopter status as predictors of TCS closure. The model was not significant $\chi2(2) = 1.844$, $p = .398$ and produced a low Nagelkerke R^2 score (.002). Adding the racial composition variable into the model (model 5) produced again a statistically significant model $\chi2(4) = 21.768$, $p < .001$. The model did not increase the level at which the variance in closure was explained (Nagelkerke $R^2 = 2\%$). The percentage of correctly classified cases was 94.7% and the Hosmer-Lemeshow Test produced a non-significant chi-square, indicating that the data fit the model well. In this model, racial composition was a significant predictor of closure, but age of the TCS and early adopter status were not. The odds ratio for enrollment racial composition was similar to model 3. For model 6, the percentage of students who receive free or reduced lunch was added. The chi-square test was statistically significant $\chi2(5) = 21.833$, $p = .001$, and the Hosmer-Lemeshow test was not significant. Nagelkerke R^2 remained the same at 2%. Like model 5, only the racial composition of enrollment was a significant predictor of closure and at similar rates to model 5 and model 3. The age of the TCS, early adopter status, and percentage of students who receive free or reduced lunch were not significant predictors.

All student achievement models (models 7–11, presented in Table 6) were statistically significant, and correctly classified 94.7% of the cases, yet none produced a non-significant Hosmer-Lemeshow test. Model 7 included age of the TCS and PI scores. PI scores were a significant predictor of TCS closure ($\beta = -.010$, $p = .021$), indicating that with every point increase in PI scores, the likelihood of TCS closure drops by 1%. Likewise, models 8 and 9, which included the percentage of students at or above the level considered proficient in reading and math, respectively, indicated that with each point increase in those scores a TCS is 2% less likely to close ($\beta = -.016$, $p < .001$).

Both average scores in reading and math were included in Model 10, along with age of school, to estimate probability to TCS closure. This model was statistically significant $\chi2(3) = 20.762$, $p < .001$ and explained 1.9% of the variance in closure (Nagelkerke R^2). Average scores in reading and math were not significant predictors of closure, even when PI scores were included in model 11 ($\chi2(4) = 21.057$, $p < .001$).

Table 6

Student Achievement Models (models 7-11)

	Model 7		Model 8		Model 9		Model 10		Model 11	
Variables	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI
SchoolAge	0.987	.946-1.029	0.998	.948-1.029	0.994	.953-1.036	0.992	.951-1.034	0.99	.950-1.033
PI_Score	0.99*	.981-.998							1.004	.990-1.017
ReadAvg			.984***	.977-.991			0.991	.978-1.004	0.99	.977-1.004
MathAvg					.984***	.977-.992	0.992	.978-1.004	0.99	.377-1.004
-2 Log likelihood	1316.721		1304.222		1304.39		1302.645		1302.351	
$\chi 2$	χ 2(2) = 6.687, p = .035		χ 2(2) = 19.185, p < *.001*		χ 2(2) = 19.018, p < *.001*		χ2(3) = 20.762, p < *.001*		χ 2(4) = 21.057, p < *.001*	
Hosmer-Lemeshow	χ 2(8) = 54.063, p < *.001*		χ 2(8) = 53.599, p = .007		χ 2(8) = 27.313, p = .001		χ 2(8) = 23.630, p = .003		χ 2(8) = 38.434, p < *.001*	
Nagelkerke R^2	0.006		0.018		0.017		0.019		0.019	

* p < .05. ** p < .01. *** p < .001.

Discussion

In the longitudinal examination of TCS closure in OBEUC, our analysis indicates that, of the partial models, the only statistically significant findings are racial composition of school enrollment. Both in life tables/survival curves and in BLR, racial composition was the only significant variable. The full model (Table 4) with all variables produced the highest Nagelkerke R^2 (3.7%), which means that none of the partial models improved the fit of the model. In this model, we found that compared to integrated enrollment at TCS and regardless of other factors that may influence closure, including academic achievement factors and TCS characteristics, TCS that serve greater proportions of Black students are more likely to close.

While TCS in Ohio are limited to failings school districts in an effort to help low performing, minority populations achieve academic success through alternative school options, our findings indicate that TCS in OBEUC with higher proportions of Black students, even after controlling for other factors that predict closure, are more likely to close and already disadvantaged students may be forced to transition between schools after enrolling in a TCS. TCS with Black enrollments of 75% or greater are 2.08 times as likely to close (108.0% increase in the chance of closure). This finding supports results from studies conducted by Paino et al. (2017) who found that TCS across the nation that enroll larger percentages of Black students are more likely to close even when considering other factors that predict closure, including the age and size of the school and CREDO (2017b) that found TCS with a larger share of Black and Hispanic students were more likely to close than similarly performing schools with a smaller proportions of disadvantaged minority students, which is particularly troublesome, given that TCS in Ohio are limited to operating in underperforming districts, areas in which low income households and predominantly Black individuals reside and who have experienced TPS closure. This lack of a connection between performance and TCS closure calls into question the political rhetoric that TCS closure is evidence that the accountability function of school choice policy is working. Our findings suggest that the most vulnerable populations in OBEUC are exposed to unstable educational institutions that are not providing the innovation and improved outcomes on which TCS are predicated.

The life table findings for the racial enrollment categories (Figure 4) indicated that TCS with integrated enrollments are more likely to remain open over time. Similarly, the binary logistic regression indicated that TCS in OBEUC with integrated enrollments are less likely to close compared to TCS in OBEUC with predominantly White or Black enrollments. Additionally, we found that TCS with White enrollments of 75% or greater are 2.491 times as likely to close (149.1% increase in the chance of closure) than TCS with integrated student enrollments. The survival functions in Figure 4 indicate that predominantly White TCS experience a higher risk of closure during their first four years than do integrated TCS or predominantly Black TCS. This surprising finding is not supported by existing TCS literature, but they could be influenced by geographic location.

One possible reason that TCS with integrated enrollments are less likely to close may be due to geographic location. Several studies indicated that many TCS position themselves near, but not directly inside, areas that are predominantly Black and purposely avoid areas with high proportions of Black and disadvantaged students (d'Entremont, 2012; Gilblom & Sang, 2019; Gulosino & d'Entremont, 2011; LaFleur, 2016; Lubienski et al., 2009; Saultz & Yaluma, 2017). By locating in areas that border predominantly Black neighborhoods, TCS may attract a more diverse student body that comes from both the predominantly Black neighborhoods and the adjacent White community. Our analysis suggests that these more integrated TCS may have a higher likelihood of survival than nonintegrated TCS. However, future research that examines why predominantly White TCS in

OBEUC experience higher rates of closure in their early years or that examines the geographic locations of closures may help explain higher rates of closure for predominantly White TCS.

We also found that average scores in reading or in math and PI scores are nonsignificant, a finding similar to Paino et al. (2017) who found that academic achievement was not a significant predictor of closure, even among TCS with greater percentages of Black students. This finding differs from Paino et al. (2014) who found that reading scores, but not math scores, are significant predictors of closures. While ODE attributes about 19% of school closures to academic performance and TCS advocates claim that closure is an indication that the accountability function within school choice policies is working, we were unable to find evidence that student performance is linked to TCS closure in OBEUC. Although TCS exist because of TPS poor performance and are meant to increase student achievement, and Ohio's law mandate closure based on TCS low performance, our study found no relationship between student achievement and TCS closure.

In our study, the age of school, early adopter status and percentage of students receiving free or reduced lunch do not improve the model. While existing research suggests that low-income students face greater adverse effects from closures (CREDO, 2017b; Paino et al., 2017), we did not find that enrollments with more students who qualify for free or reduced lunch face a higher risk of closure. The nonsignificance of early adopter status is also an interesting finding. It was hypothesized that TCS that opened in the early years may have faced an increased risk for closure, especially due to the state audit conducted in 2002 that led to greater oversight of TCS by the State Board of Education and comprehensive revisions to the state's TCS law. But, we found no connection between early adopters and closure. Additionally, age was not a significant predictor of closure. However, the survival function and hazard rate for age of school (Figures 2 and 3) indicate that TCS that are 14 years or older are not at risk of closing.

Conclusion

Our analysis reveals a complicated picture of TCS in OBEUC. While ODE reports that poor academic performance is the second most cited reason for TCS closure, we were unable to find evidence that student performance predicts TCS closure. However, we found that compared to TCS with integrated enrollments, TCS that are predominantly Black or predominantly White have higher risk for closure, while controlling for all other variables. It is important for policy to consider how and why TCS close, when we found no connection between student performance and closure. Although TCS closures are framed as evidence that the academic accountability function is working, the lack of this relationship indicates that there are other factors at work.

This study does not investigate TCS that were vocational, special education or other/alternative. Also, this study did not examine how the profit status (CMO vs EMO) of a TCS affects closure or the relationships between finances and closure, nor did it analyze the effect of the different closure policies enacted during our study's time period. Future research that examines connections between student performance, finances, and closure may help uncover these relationships. Analysis of closure policies such as value-added scores or other annual measurable objectives will help reveal the effect these policies have on TCS closure. Additionally, studies that examine closure policies by school grades will contribute to the closure literature considering that specific policies, such as value-added scores, are only calculated in the fourth and eighth grade. Research that investigates TCS closure in smaller geographies, incorporates reported reasons for closure into predictive models and integrates qualitative research methods, such as Paino et al. (2014), may contribute to the TCS closure literature. Additionally, transparent and clear data reporting by ODE in terms of reasons for closure may facilitate this research and contribute to an overall understanding of why some charter schools close in OBEUC. Despite these important caveats, this study offers valuable insights into the factors that underlie TCS closure in OBEUC. It also provides a starting point for future research that examines the impact of school choice policy in urban areas and the relationships among accountability, TCS closure and students.

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