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Teacher Retention and COVID-19: Did the Pandemic Complicate Matters? The Case of NYC Public Schools.

Charles Ogundimu
Pace University, cogundimu@pace.edu

Introduction

Since the COVID-19 pandemic hit our shores in 2020, it has undoubtedly increased employee turnover throughout the United States. While the private sector continues to struggle with stubbornly high turnover rates, public education as a whole, appears to remain relatively stable. For instance, in April 2022, quits increased in real estate and rental and leasing by 37,000 (Bureau of Labor Statistics, 2022). The question is: Can this be generalized across public education systems? The primary goal of this study is to attempt to answer this question by examining the extent to which earlier projections of teacher turnover predict present quit and separation patterns in public education, with a particular focus on the NYC public school system. My study focuses on NYC and relies on data from the NYC Department of Education as well as publicly available data sources for its systematic review.

Study Purpose

Recent data (April 2022) from the Bureau of Labor Statistics suggest that while the private sector continues to experience considerable contraction in employment, this pattern does not appear to be replicated in the public education domain, which seems to show relative employment stability (see Appendixes 1 and 2). But does this reported stability in public education employment being experienced across the board, especially in urban areas like NYC? The purpose of this study is to examine the extent to which the Bureau of Labor Statistics numbers correspond with the realities in a major public urban school system such as NYC. I also intend to investigate the predictions of a previous study vis-à-vis current status of teacher labor markets in NYC. Specifically, I plan to analyze the quit patterns of traditional and non-traditional teachers with a view to answering the question of whether or not non-traditional teachers are more likely to remain in teaching longer than traditional teachers.

Theoretical Framework

Consistent improvement in student learning is a fundamental goal in education (Ogundimu, 2014). Students who do not experience success in school are more likely to dropout than those who are successful (Rumberger & Lim, 2008; Belfanz & Legters, 2004). Clearly, the social and economic costs of dropping out of high school are not limited to individual alone; the society as a whole bears the brunt (Belfield & Levin, 2007). Everyone is affected, even when we may/may not know it. On the other hand, it has been established that quality teaching (by quality teachers) can positively affect student performance (Sanders & Rivers, 1996; Rockoff, 2004). While it is true that one bad teacher can erase up to one year of learning, it has also been demonstrated that one quality teacher can improve student learning significantly, especially at the lower elementary grades (Sanders & Rivers, 1996; Rockoff, 2004). Recruiting, training, and developing a good teacher takes time (Berliner, 2000). On average, low-performing students from low-income communities tend to benefit more from high-quality teachers according to Sanders and Rivers (1996). However, high-quality teachers are scarce and teacher turnover tends to be high. This further complicates the issue (Ogundimu, 2014).

Alternative Teacher Certification programs such as the New York City Teaching Fellows were created to solve the teacher shortage problem and inject the educational system with mid-career/career changers individuals who want to transition into teaching. Other examples include Teach For America (TFA), The New Teacher Project (TNTP), and many others.

Limited research supports the fact that non-traditional teachers, such as those who enter teaching through alternative certification routes tend to have more specialized undergraduate training in mathematics, science, and engineering. They are, therefore, arguably better prepared to teach math and science - areas that are often hard to staff (Boyd, et. al, 2003; Hanushek & Rivkin, 2008). Hence, the expectation is that these teachers, with adequate support, may be able to meaningfully improve student performance due to their specialized backgrounds. Logically, finding ways to hire, train, and retain them could potentially be beneficial to all stakeholders (Ogundimu, 2014). However, the COVID-19 pandemic has injected a new dynamic to understanding if and how this can be done. Hence, in this study, the rationale to reexamine previously established findings about the teacher labor markets for traditional and nontraditional teachers vis-à-vis the impact of the COVID-19 pandemic.

Research Questions

For this study, I intend to answer the following research questions:

1. Do non-traditional teachers (TFs) have a higher retention rate than traditional teachers?
2. Compared to traditional teachers (NTF), when are non-traditional teachers (TFs) at the greatest risk of quitting?
3. In what ways, if any, has the COVID-19 pandemic affected teacher retention?

Methodology

In this study, I used both general descriptive statistics and survival analysis, more specifically, the Cox proportional hazards (PH) model to analyze and compare the retention rates of NYC teachers who were hired via the NYC Teaching Fellows Program and traditional teachers (or Non-Teaching Fellows – NTFs). I chose these methods because instead of asking whether or not teachers quit (which we know they do), I wanted to be able to answer the more illuminating question of **when are TFs and NTFs at the greatest risk of quitting?** Knowing when teachers are **at the greatest risk of quitting** not only answers the questions of whether or not they quit, it also tells us **by how much** (Willett & Singer, 1991, cited in Ogundimu, 2014)**.** I also used systematic review of current teacher labor markets research literature to collate and compare the impact of the pandemic on teacher retention in the NYC public school system.

Because survival analysis is relatively more robust and predicts more precisely, it is generally preferred when investigating time-to-event or event history (Murnane, et al., 1988; Willett & Singer, 1993). There are other advantages, namely, affording the researcher the information to describe and compare temporary patterns of time-to-event amongst and within groups and develop statistical models of the risks of occurrence over time (Kleinbaum & Klein, 2005; Willett & Singer, 1991). The Cox PH model is also preferred because it uses more information, such as **survival times**, and **censoring**, that other models like logistic regression overlooks. Censoring refers to what happens when individuals have not yet experienced the event in question (quitting) as of the time that data collection ended. Those individuals – i.e., the ones who have not quit at the end of data collection (2010) are said to be **censored** and are factored into the analysis in the Cox PH model (Ogundimu, 2014).

Its general form is given as[1]:

[1] Kleinbaum & Klein (2005)

$$h(t, \mathbf{X}) = h_0(t)\, e^{\sum_{i=1}^{p} \beta_i X_i}$$

where,

$h(t, \mathbf{X})$ = hazard at time t for a TF exhibiting a set of predictor variables represented by $\mathbf{X}$

$\mathbf{X}$ = a vector of explanatory variables modeled to predict a TF's hazard

$h_0(t)$ = Baseline hazard function; it is the hazard for the particular TFs when all explanatory variable values are equal to zero (This model can be linearized by dividing both sides of the equation by $h_0(t)$ and then taking the natural logarithm of both sides)[2] When there are no predictor variables in the model, the Cox model condenses to the baseline hazard. Hence, before including any independent or predictor variables, such as sex, ethnicity, or age, $h_0(t)$ is considered the "baseline" form of the hazard function. It is an **unspecified** function; hence the Cox PH model is often referred to as a **semiparametric** model. (Kleinbaum & Klein, 2005).

$e^{\sum_{i=1}^{p} \beta_i X_i}$ = the exponential expression "*e*" raised to the linear sum of $\beta_i X_i$; where the sum is over the "*p*" predictor variables[3]

$\beta_i \ldots \beta_p$ = are the coefficients of the predictor variables described below.

$X_i \ldots X_p$ = are predictor variables: TFs(Women), school type (early childhood, elementary, junior high, high, K-12, secondary), subject taught/license area, ethnicity, and age.

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[2] http://www.statsoft.com/textbook/survival-failure-time-analysis/#rcox

[3] Kleinbaum & Klein (2005), p.94.

We must recall that the fundamental survival analysis being modeled here is the Cox Proportional Hazards (PH) model:

$$h(t, \mathbf{X}) = h_0(t)e^{\beta(Fellow)} \tag{1}$$

where,

$h(t, \mathbf{X})$ = hazard at time t for a TF exhibiting a set of predictor variables represented by **X**

$\mathbf{X}$ = a vector of explanatory variables modeled to predict a TF's hazard

$h_0(t)$ = Baseline hazard function; it is the hazard for the particular TFs when all explanatory variable values are equal to zero (This model can be linearized by dividing both sides of the equation by $h_0(t)$ and then taking the natural logarithm of both sides)[4] When there are no predictor variables in the model, the Cox model condenses to the baseline hazard. Hence, before including any independent or predictor variables, such as sex, ethnicity, or age, $h_0(t)$ is considered the "baseline" form of the hazard function. It is an **unspecified** function; hence the Cox PH model is often referred to as a **semiparametric** model. (Kleinbaum & Klein, 2005).

$\sum^{p} \beta_i X_i$ = the exponential expression "e" raised to the linear sum of $\beta_i X_i$; where

[4] http://www.statsoft.com/textbook/survival-failure-time-analysis/#rcox

$e^{i=1}$ the sum is over the "p" predictor variables[5]

Results and Conclusions[6]

Research Question 1: Do non-traditional teachers (TFs) have a higher retention rate than traditional teachers?

The evidence in this analysis does not support the notion that TFs have a higher retention rate than NTFs (see Figure 1). Both groups demonstrated similar quit patterns, especially in the first two years (see Figure 2). It appears that both TFs and NTFs of the early cohort years of 2003 and 2004 showed very similar quit rates in the first two years with the TFs showing discernibly higher rates than NTFs in year two (see Figure 2). By year three, for practically all the cohorts for which data were analyzed, quit rates for both TFs and NTFs have overtaken retention rates. But again, it appears that TFs' quit rates exceeded NTFs' by up to 17 percentage points in some instances (see Figure 1).

Research Question 2: Compared to traditional teachers (NTF), when are non-traditional teachers (TFs) at the greatest risk of quitting?

The evidence in this data suggests that relative to NTFs, **TFs are at the greatest risk of quitting at the end of their first, second, and third years of teaching.** This is evident in the PLSE (see Figures 1 and 4) where we see the largest drop or rate of change in the survival probability function in the aggregate curve structure in years one, two, and three, tapering off in years four and beyond. **The evidence suggests that year-2 represents the largest change in the overall survival estimates for the combined cohort groups**. Incidentally, year-two also happens to be the time when TFs are expected to have completed their subsidized master's degree in education. It is important to point out that there is evidence to support the fact that TFs (and NTFs) can quit at just about anytime from the time they are hired. Part of my essential question is in *when* they are at the *greatest risk of quitting*. I was able to answer this question accurately through the use of the PLSE of the Cox PH model because the predicted survival probabilities matched the actual retention patterns of both TFs and NTFs.

[5] Kleinbaum & Klein (2005), p.94.

[6] Many parts of these results were adapted from my dissertation study. See Ogundimu, C. (2014).

Table 1: Hazard Ratios and Percent of Teaching Fellows Still Teaching After 5, 4, 3, and 2 Years by Cohort

	2003	**2004**
Total	27,014	20,110
Non-Teaching Fellows	24,792	18,222
Teaching Fellows	2,222	1,888
TFs as a Percent of Total	**8.23%**	**9.39%**
Teaching Fellows' Hazard Ratio	1.442	1.379
P-Value	<.0001	<.0001
Percent Still Teaching After 5 Years – Cohorts 2003, 2004	11.07 (NTF = 33.1)	24.05 (NTF = 39.67)

Figure 1: Cohort **2003:** Product-Limit Survival Probability Estimates

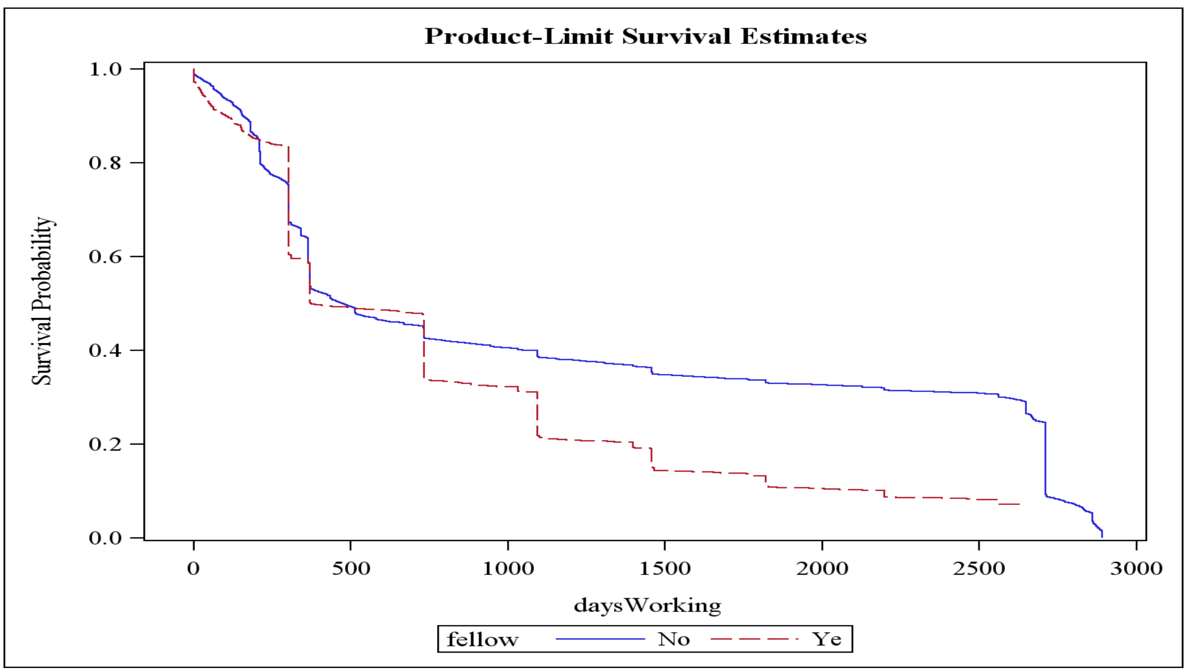


Figure 2: Cohort **2003** – Year 1

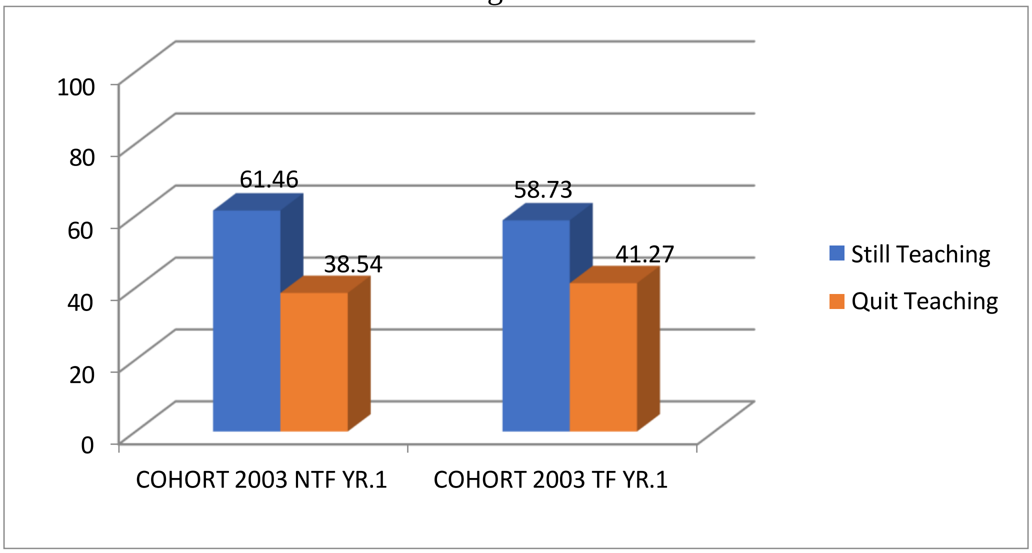


Figure 3: Cohort **2003** – Year 2

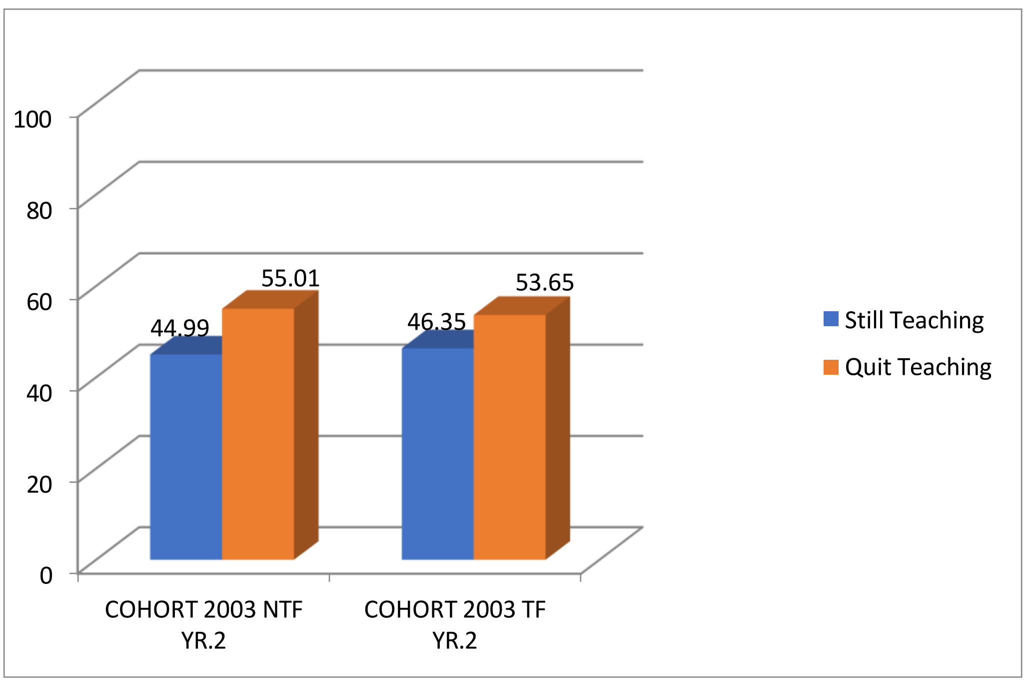


Figure 4: Cohort **2004**: Product-Limit Survival Probability Estimates

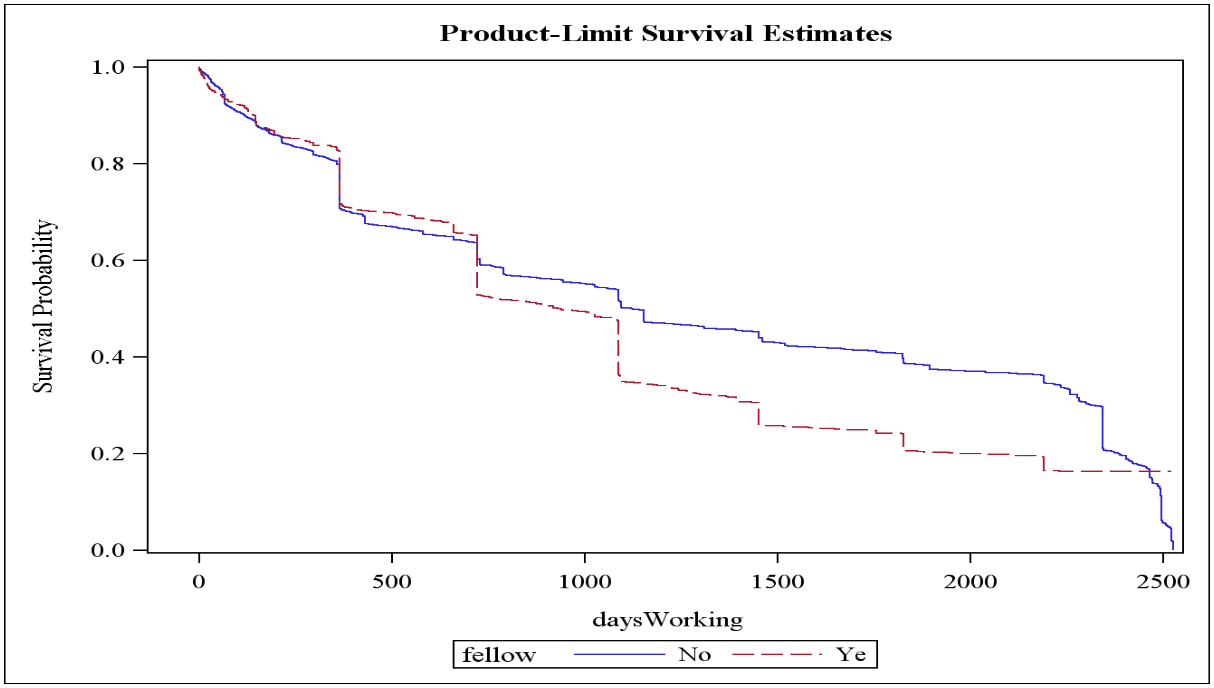


Figure 5: Cohort **2004** – Year 1

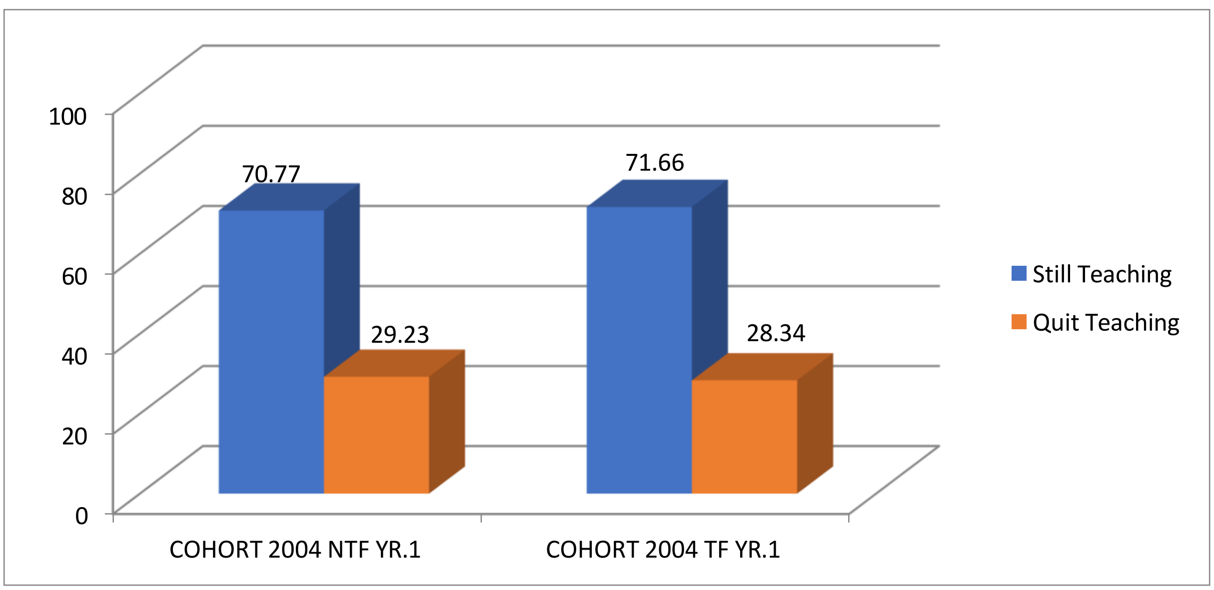
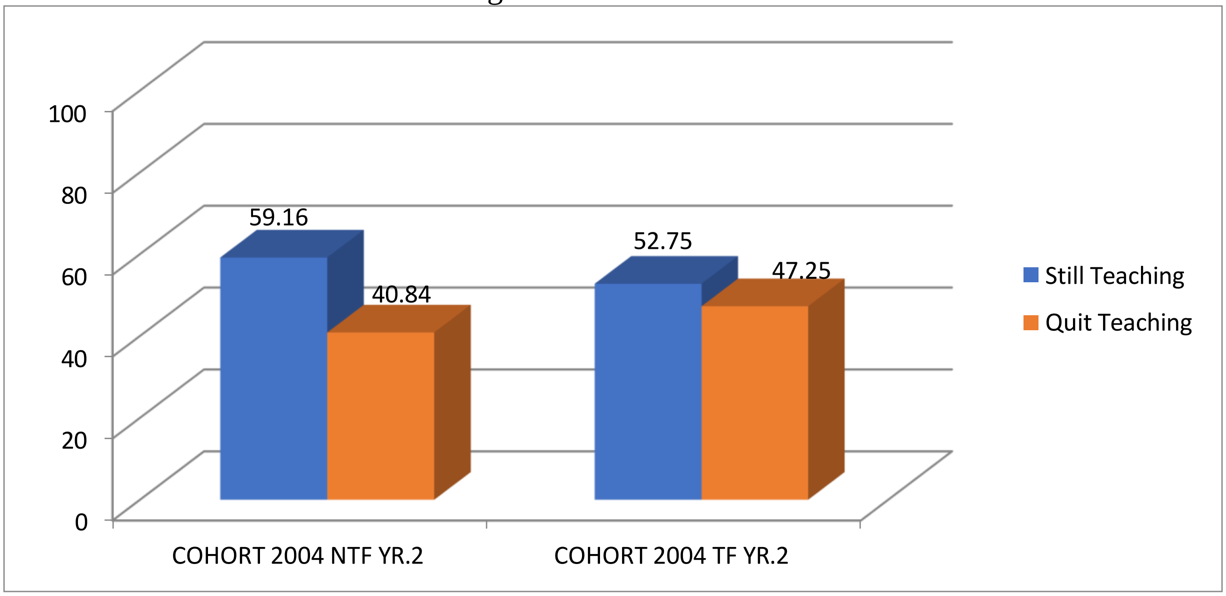


Figure 6: Cohort **2004** – Year 2



<u>Research Question 3</u>: In what ways, if any, has the COVID-19 pandemic affected teacher retention?

Table 2: Teacher Turnover/Attrition 2016-2021

School Year	% Of Teachers Separated
2016-2017	**6.5%**
2017-2018	**6.1%**
2018-2019	**6.0%**
2019-2020	**4.2%**
2020-2021	**5.8%**

The above data was recently released by the NYCDOE in reference to questions on teacher turnover/attrition rates for five years since the 2021-2022 school year. It appears that fewer teachers actually quit in 2019-2020, the school year that COVID-19 pandemic started, and 2020-2021, the following year. This is a surprising development because of its counter-intuitiveness. Generally, many thought that the attrition rate would be astronomical due to the pandemic, but it appears that the reverse was actually the case. On the other hand, one rationale could be the uncertainty brought on by onset of COVID-19. Uncertainty, especially in times of the types of health concerns generated by the pandemic, can potentially induce a rethinking of priorities. caused people to delay quitting. This phenomenon needs further exploration.

Critical Assessment of Conclusions and Educational Implications for Further Research

A persistent question relates to whether or not the NYCTF program has had any measurable impact on the teacher recruitment landscape in NYC public schools. The short answer is yes. The reason is that the program was established to solve two intertwined problems:

i. to curb the endemic teacher shortage problem in NYC schools in the late 1990s;
ii. to respond to regulatory changes at the State level to tighten teacher certification (Pabon, 2011).

Given the evidence to date, it is difficult to argue that the program has not had an impact on either or both of these two critical teacher retention issues. Since it began in 2000, its purpose was to attract, hire, train and retain nontraditional applicants to staff hard-to-staff schools (Stein, 2002). These schools were hard-to-staff because of persistent anemic attendance, and invariably poor graduation rates. Many of the original schools that were catalysts for the formation of the TFP are no longer in existence today because of major systemic restructuring at the NYCDOE that called for the dismantling or in very few cases, downsizing of large high schools into smaller ones as well as closures and phase-outs of persistently lowest performing schools. Through it all, the TFP appears to be a mainstay of teacher recruitment into the NYC school system. Today, the NYCDOE depends on the TFP for up to 30 percent of its beginning teachers (Boyd, et al., 2012) and spends between $20,000 and 30,000 to train one TF. They constitute about 12 percent of the teaching force in NYC (NYCTeachingFellows.org). To this end, it is reasonable to argue that it has noticeably affected the dynamics of teacher recruitment in NYC public schools.

More research is needed to follow up on the impact of the pandemic on long-term teacher retention. A longitudinal study that looks at the extent to which the unexpected lower rates of teacher attrition in NYC prevail post-pandemic will be one important area. Long-term impact of post-pandemic teacher retention dynamics on alternative traditional teachers can illuminate our current understanding of teacher retention.

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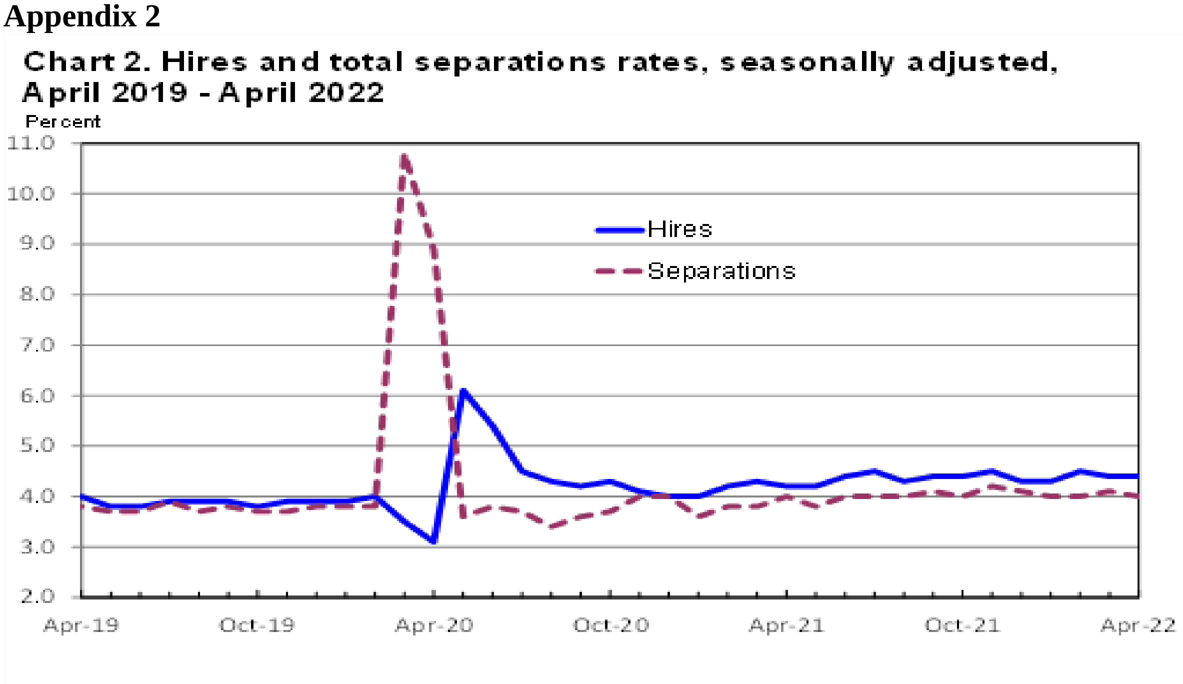
Appendix 1

Source: Adapted from: The Bureau of Labor Statistics

Appendix 2



Source: Adapted from: The Bureau of Labor Statistics

Appendix 3

Table 3: Cohort 2003: Survival Analysis Models

Estimates of maximum likelihood analysis, including parameter estimates, standard errors, and hazard ratios from survival analysis modeling of cohort 2003.

	1* **	**2*** **	**3*** **
N	27,006	19,400	19,311
Predictor	**Baseline**		
TF	**0.36619**	**-0.09974**	**-0.10482**
	(0.02334)	(0.02381)	(0.02385)
	1.442	0.905	0.900
Sex		-0.21006	-0.21070
		(0.01692)	(0.01697)
		0.811	0.810
Ethnicity			
Asian			**0.21713**
			(0.03431)
			1.243
Black			**0.06014**
			(0.01916)
			1.062
Hispanic			**-0.03629**
			(0.02287)
			0.964

Table 3 - Cohort 2003: Survival Analysis Models (continued)

	4* **	**5*** **	**6*** **
N	19,278	18,057	14,590
TF	-0.08635	**-0.09357**	-0.08616
	(0.02468)	(0.02749)	(0.02972)
	0.917	0.911	0.917
Sex	-0.20702	-0.08701	0.00543
	(0.01704)	(0.01811)	(0.02104)
	0.813	0.917	1.005
Ethnicity			
Asian	**0.21973**	**0.12524**	0.05711
	(0.03432)	(0.03577)	(0.04090)
	1.246	1.133	1.059
Black	**0.05529**	**0.04080**	**0.05722**
	(0.01927)	(0.01989)	(0.02295)
	1.057	1.042	1.059
Hispanic	**-0.03714**	**-0.06898**	-0.05151
	(0.02290)	(0.02404)	(0.02725)
	0.964	0.933	0.950
AgeThen	0.00191	**-0.0003712**	**-0.00425**
	(0.0006419)	(0.0007079)	(0.0008040)
	1.002	1.000	0.996
Subject			
CB		**-0.24522**	-0.10952
		(0.02928)	(0.03431)
		0.783	0.896
ESL		**0.36769**	**0.34464**
		(0.05619)	(0.06306)
		1.444	1.411
English		0.47025	0.26314
		(0.03636)	(0.04286)
		1.600	1.301
Foreign L.		0.67400	0.36102
		(0.06401)	(0.07160)
		1.962	1.435
Mathematics		0.51788	0.36226
		(0.03709)	(0.04321)
		1.678	1.437

Table 3 - Cohort 2003: Survival Analysis Models (continued)

	4***	5***	6***
Predictor			
Other		0.25114 (0.02720) 1.285	0.17413 (0.03191) 1.190
Science		**0.53197** (0.04297) 1.702	**0.26011** (0.04949) 1.297
Soc. St.		0.39666 (0.04314) 1.487	0.13254 (0.05030) 1.142
SchoolType			
Early Childhood			-0.55089 (0.11380) 0.576
Elementary			-0.69327 (0.05160) 0.500
High School			0.22697 (0.04965) 1.255
JHS			-0.74573 (0.05127) 0.474
K-12			-0.90994 (0.07225) 0.403
K-8			-0.72213 (0.05668) 0.486

Table 3 - Cohort 2003: Survival Analysis Models (continued)

		7***	8***	9***
N		14,590	14,590	14,590
Predictor				
TF		**0.31139**	**0.33353**	0.17652
		(0.10662)	(0.10818)	(0.13193)
Sex		0.00256	0.00367	0.00422
		(0.02105)	(0.02105)	(0.02107)
		1.003	1.004	1.004
Ethnicity				
	Asian	0.05378	0.04392	0.03791
		(0.04091)	(0.04502)	(0.04511)
		1.055		
	Black	**0.05625**	**0.07792**	**0.07772**
		(0.02295)	(0.02410)	(0.02411)
		1.058		
	Hispanic	-0.05003	**-0.04391**	**-0.04392**
		(0.02726)	(0.02864)	(0.02866)
		0.951		
Age		**-0.00336**	**-0.00342**	**-0.00358**
		(0.0008360)	(0.0008368)	(0.0008398)
Subject				
	CB	-0.11065	-0.11066	**-0.14739**
		(0.03428)	(0.03429)	(0.03717)
		0.895	0.895	
	ESL	**0.34089**	**0.34189**	**0.34069**
		(0.06305)	(0.06308)	(0.06738)
		1.406	1.408	
	English	0.25721	0.25308	0.22416
		(0.04286)	(0.04290)	(0.04719)
		1.293	1.288	
	Foreign L.	0.35481	0.35111	0.32707
		(0.07160)	(0.07164)	(0.07389)
		1.426	1.421	
	Mathematics	0.35817	0.35413	0.35716
		(0.04323)	(0.04327)	(0.04913)
		1.431	1.425	

Table 3 - Cohort 2003: Survival Analysis Models (continued)

	7	**8**	**9**
Other	0.16644 (0.03194) 1.181	0.16450 (0.03195) 1.179	0.13657 (0.03411)
Science	**0.25400** (0.0.04950) 1.289	**0.24919** (0.04953) 1.283	0.22466 (0.05321)
Soc. St.	0.12854 (0.05030) 1.137	0.12654 (0.05030) 1.135	0.07801 (0.05405)
SchoolType			
Early Childhood	-0.54976 (0.11380) 0.577	-0.55123 (0.11384) 0.576	-0.54747 (0.11388) 0.578
Elementary	-0.69424 (0.05161) 0.499	-0.69394 (0.05161) 0.500	-0.69087 (0.05164) 0.501
High School	0.22706 (0.04965) 1.255	0.22854 (0.04965) 1.257	0.23453 (0.04974) 1.264
JHS	-0.74459 (0.05127) 0.475	-0.74212 (0.05128) 0.476	-0.73391 (0.05135) 0.480
K-12	-0.90792 (0.07227) 0.403	-0.91014 (0.07229) 0.402	-0.90404 (0.07233) 0.405
K-8	-0.72392 (0.05669) 0.485	-0.72342 (0.05670) 0.485	-0.71775 (0.05675) 0.488
Age*Fellow	-0.01157 (0.00302)	-0.01108 (0.00301)	-0.00997 (0.00307)
Ethnicity*Fellow (Asian)		0.04949 (0.10721)	0.06956 (0.10780)

Table 3 - Cohort 2003: Survival Analysis Models (continued)

	7	8	9
Ethnicity*Fellow (Black)		-0.22344 (0.07948)	-0.23311 (0.07996)
Ethnicity*Fellow (Hispanic)		-0.05468 (0.09209)	-0.07380 (0.09332)
Subject*Fellow (CB)			**0.22122** (0.08614)
Subject*Fellow (ESL)			-0.07706 (0.19340)
Subject*Fellow (English)			**0.13219** (0.10391)
Subject*Fellow (Foreign Language)			**0.07563** (0.33063)
Subject*Fellow (Mathematics)			0.01682 (0.09592)
Subject*Fellow (Other)			0.25901 (0.12020)
Subject*Fellow (Science)			0.10724 (0.13749)
Subject*Fellow (Social Studies)			0.32650 (0.14167)

Appendix 4

Table 4: Cohort 2004: Survival Analysis Models

Estimates of maximum likelihood analysis, including parameter estimates, standard errors, and hazard ratios from survival analysis modeling of cohort 2004.

	1* **	**2*** **	**3*** **
N	20,110	18,290	18,139
Predictor	**Baseline**		
TF	**0.32131**	**0.22669**	**0.21676**
	(0.02673)	(0.03107)	(0.03127)
	1.379	1.254	1.242
Sex		0.07561	0.07076
		(0.01860)	(0.01868)
		1.079	1.073
Ethnicity			
Asian			**0.07622**
			(0.03782)
			1.079
Black			**0.12843**
			(0.02336)
			1.137
Hispanic			**0.05242**
			(0.02804)
			1.054

Table 4 - Cohort 2004: Survival Analysis Models (continued)

	4***	**5*****	**6*****
N	18,125	17,274	14,926
TF	0.04139	**0.02788**	0.00788
	(0.03297)	(0.03602)	(0.03870)
	1.042	1.028	1.008
Sex	0.04403	0.04938	0.03952
	(0.01878)	(0.02031)	(0.02303)
	1.045	1.051	1.040
Ethnicity			
Asian	**0.03535**	**0.01673**	-0.08349
	(0.03793)	(0.03998)	(0.04531)
	1.036	1.017	0.920
Black	**0.15097**	**0.17060**	**0.09489**
	(0.02341)	(0.02404)	(0.02738)
	1.163	1.186	1.100
Hispanic	**0.03297**	**0.03553**	-0.01490
	(0.02807)	(0.02950)	(0.03251)
	1.034	1.036	0.985
Age	-0.01178	**-0.01172**	**-0.01113**
	(0.0007234)	(0.0007846)	(0.0008679)
	0.988	0.988	0.989
Subject			
CB		**-0.02946**	-0.17115
		(0.03198)	(0.03825)
		0.971	0.843
ESL		**0.10984**	**0.05993**
		(0.06013)	(0.06718)
		1.116	1.062
English		0.18579	0.19062
		(0.03938)	(0.04611)
		1.204	1.210
Foreign L.		-0.01827	0.03333
		(0.06392)	(0.07128)
		0.982	1.034
Mathematics		0.11988	0.13978
		(0.04028)	(0.04703)
		1.127	1.150

Table 4 – Cohort 2004: Survival Analysis Models (continued)

	4***	5***	6***
Predictor			
Other		0.10474 (0.02957) 1.110	0.04854 (0.03446) 1.050
Science		**0.09725** (0.04638) 1.102	**0.11122** (0.05372) 1.118
Soc. St.		-0.17446 (0.04640) 0.840	-0.20662 (0.05439) 0.813
School Type			
Early Childhood			0.06812 (0.16388) 1.070
Elementary			0.00481 (0.05845) 1.005
High School			-0.27793 (0.05523) 0.757
JHS			-0.0007393 (0.05890) 0.999
K-12			-0.30955 (0.07684) 0.734
K-8			0.05939 (0.06457) 1.061

Table 4 - Cohort 2004: Survival Analysis Models (continued)

		7*** 14,926	**8***** 14,926	**9***** 14,926
N		14,926	14,926	14,926
Predictor				
TF		**-0.09560** (0.15319)	**-0.06489** (0.15529)	-0.19209 (0.16919)
Sex		0.04009 (0.0305) 1.041	0.04142 (0.02306) 1.042	0.04126 (0.02308) 1.042
Ethnicity				
	Asian	-0.08386 (0.04531) 0.920	-0.11242 (0.04817)	-0.11488 (0.04831)
	Black	**0.09477** (0.02738) 1.099	**0.11351** (0.02873)	**0.11197** (0.02873)
	Hispanic	-0.01484 (0.03251) 0.985	**0.0007218** (0.03421)	**0.00350** (0.03422)
Age		**-0.01125** (0.0008840)	**-0.01131** (0.0008848)	**-0.01137** (0.0008864)
Subject				
	CB	-0.17124 (0.03826) 0.843	-0.17421 (0.03826) 0.840	**-0.19555** (0.04058)
	ESL	**0.05977** (0.06717) 1.062	**0.05983** (0.06716) 1.062	**0.0001646** (0.07310)
	English	0.19144 (0.04612) 1.211	0.18964 (0.04612) 1.209	0.15526 (0.05037)
	Foreign L.	0.03404 (0.07129) 1.035	0.03060 (0.07132) 1.031	-0.02320 (0.07451)
	Mathematics	0.13971 (0.04703) 1.150	0.13657 (0.04705) 1.146	0.15498 (0.05209)

Table 4 - Cohort 2004: Survival Analysis Models (continued)

	7	**8**	**9**
Other	0.04916 (0.03447) 1.050	0.04643 (0.03447) 1.048	0.02559 (0.03646)
Science	**0.11167** (0.05372) 1.118	**0.10791** (0.05373) 1.114	0.07626 (0.05743)
Soc. St.	-0.20639 (0.05439) 0.814	-0.20652 (0.05440) 0.813	-0.23143 (0.05641)
School Type			
Early Childhood	0.06931 (0.16389) 1.072	0.07692 (0.16395) 1.080	0.08489 (0.16407) 1.089
Elementary	0.00473 (0.05845) 1.005	0.00408 (0.05846) 1.004	0.00953 (0.05853) 1.010
High School	-0.27749 (0.05523) 0.758	-0.27871 (0.05524) 0.757	-0.27134 (0.05532) 0.762
JHS	-0.00140 (0.05891) 0.999	-0.00233 (0.05891) 0.998	0.00759 (0.05900) 1.008
K-12	-0.30987 (0.07685) 0.734	-0.31092 (0.07684) 0.733	-0.30647 (0.07691) 0.736
K-8	0.05932 (0.06457) 1.061	0.05807 (0.06458) 1.060	0.06355 (0.06467) 1.066
Age*Fellow	0.00304 (0.00435)	0.00332 (0.00434)	0.00458 (0.00437)
Ethnicity*Fellow (Asian)		0.26326 (0.13947)	0.25998 (0.14047)

Table 4 - Cohort 2004: Survival Analysis Models (continued)

	7	8	9
Ethnicity*Fellow (Black)		-0.19018 (0.09365)	-0.18299 (0.09425)
Ethnicity*Fellow (Hispanic)		-0.15677 (0.10751)	-0.20572 (0.11205)
Subject*Fellow (CB)			**0.13588** (0.11255)
Subject*Fellow (ESL)			0.38890 (0.18109)
Subject*Fellow (English)			**0.17956** (0.11471)
Subject*Fellow (Foreign Language)			**0.70605** (0.25592)
Subject*Fellow (Mathematics)			-0.09865 (0.11068)
Subject*Fellow (Other)			0.21656 (0.16957)
Subject*Fellow (Science)			0.19776 (0.15473)
Subject*Fellow (Social Studies)			0.22617 (0.25621)