Modeling Parallel Latent Growth Trajectories with Time-Varying Baselines: A Demonstration Examining the Intersection between Minority-Serving Institution Status and Females' Participation in STEM Majors over Time

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Abstract

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The current paper demonstrates an application of parallel latent growth modeling with time-varying baselines and high missingness levels using extant data on higher education institutions participating in the National Center for Women and Information Technology Extension Services (NCWIT-ES) program between 2006 and 2018. Using this methodology, we test the relationship between the growth trajectory factors for the number of women applying to STEM undergraduate departments (of participating institutions) and the growth trajectory factors for the number of women graduating from STEM undergraduate departments. Further, we also illustrate use of an intersectionality lens in framing the research by including a key institution-level predictor, minority-serving institution (MSI) status, to test whether undergraduate women's involvement in STEM significantly differed for MSI and predominantly white institutions (PWIs). Analysis results showed that the number of women applying to STEM departments at the year their institution joined NCWIT-ES was positively predictive of the number of women graduating from those STEM departments five years later. Moreover, growth in the number of women applicants per year was positively predictive of growth in the number of women graduates five years down the line. Last, year joining NCWIT-ES was positively predictive of higher baseline and greater growth in both applications and graduations, whereas MSI status had less application growth acceleration and was negatively related to graduation baseline and growth factors.

Keywords: parallel latent growth model, time-varying baseline, higher education, STEM, women, minority-serving institutions, intersectionality

Modeling Parallel Latent Growth Trajectories with Time-Varying Baselines:

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Growth modeling methods allow researchers to test hypotheses related to change over time, and can be specified a variety of ways. Repeated measures analysis of variance (RM ANOVA), a univariate general linear modeling method that is a one form of a multilevel model, is perhaps the simplest and easiest approach; however, this methodology requires complete data (no missingness in any variables), ordinary least squares estimation, and has a restrictive assumption of sphericity (that differences among all pairs of time points have homogeneous variances) and as a result, assumes that all individuals have the same trajectory. Multilevel modeling relaxes some of these restrictions: it can handle some missing data on the outcome (when missingness is at random) variable due to its use of maximum likelihood estimation, it can incorporate random slope variance (i.e., allowing individuals to have differing rates of change over time), and further, it can easily include time-varying and time-invariant predictors (e.g., Kwok et al., 2008). Despite the advantages multilevel modeling confers over RM ANOVA, the multilevel modeling approach makes the same implicit assumption that all univariate analyses share: that the variables in the model are measured perfectly. A structural equation modeling (SEM) approach to growth modeling, known as latent growth modeling, however, is a multivariate approach that can allow for different measurement error at each observed time point—in addition to the advantages of multilevel modeling over RM ANOVA. Moreover, the SEM framework also permits researchers to flexibly link sets of growth trajectories together, known as parallel growth modeling (e.g., Muthén, 2004).

The current paper aims to demonstrate an application of parallel latent growth modeling with time-varying baselines and high missingness levels using extant data on higher education institutions participating in the National Center for Women and Information Technology Extension Services (NCWIT-ES) program between 2006 and 2018. Using this methodology, we test the relationship between the growth trajectory factors for the number of women applying to STEM undergraduate departments (of participating institutions) and the growth trajectory factors for the number of women graduating from STEM undergraduate departments. Further, we also illustrate use of an intersectionality lens in framing the research by including a key institution-level predictor, minority-serving institution (MSI) status, to test whether undergraduate women's involvement in STEM significantly differed for MSI and predominantly white institutions (PWIs).

The Undergraduate STEM Education Gender Gap and the NCWIT Program

The metaphor of a 'leaky' STEM pipeline refers to the institutional issues in the STEM education and career pipelines that researchers and practitioners have identified as barriers to achievement for individuals who hold underrepresented identities in STEM fields. These barriers result in a disproportionate number of women, people of color, and individuals with other marginalized identities within STEM to exit the field at various key transition points (e.g., Vitores & Gil-Juárez, 2016). This is one of the reasons women continue to hold a disproportionately low share of STEM undergraduate degrees, particularly in engineering and computing (Fletcher et al., 2020).

Research-based initiatives have been developed to encourage and support women to and through the STEM education and career pipeline. The National Center for Women and Information Technology (NCWIT) is an organization that acts as a leading agent in these efforts.

NCWIT works with key actors in major sectors of the STEM pipeline (K-12 education, higher education, and the workforce) to identify and resolve structural issues that present barriers for women in STEM. In doing this, NCWIT aims to increase the influential and meaningful participation of girls and women in STEM fields, with a particular emphasis on fields related to computing.

One such initiative, at the higher education level, is their ‘Extension Services’ program (NCWIT-ES). The Extension Service program is a NCWIT membership that higher education institutions can join to receive guidance in applying research-based strategies for fostering inclusion in their computing departments. NCWIT-ES consultants work with institutions to enact the following practices (Thompson et al., 2020).

(a) Integrate teaching methods that create inclusive and collaborative environments in early curriculum.

(b) Successfully implement a strategic recruiting plan for creating an enduring pipeline of diverse students with appropriate competencies.

(c) Help students understand how their classes and other experiences (internships, REUs, etc.) contribute to their future identities as computing professionals.

(d) Align assignments and coursework with student interests and career goals.

(e) Foster everyday positive student-student and student-faculty interactions that contribute to a sense of belonging in the departmental community.

(f) Include visible, high-level administrative support and resources for sustained implementation and evaluation.

(g) Ensure that efforts to diversify are positively reinforced within the reward structure for promotion and tenure.

(h) Evaluate efforts to identify what works and what doesn't work and make mid-course corrections to increase success and communicate findings for increased support and replication by others.

As a result of applying these research-based strategies within their STEM departments, NCWIT-ES member institutions hope to observe increased numbers of female students applying, being accepted, enrolling, and graduating from their STEM departments.

An Intersectionality Lens: Women in STEM and Institutional MSI Status

'Intersectionality' was first put forward by critical race theorist Kimberlé Crenshaw (1989, 1991) as a conceptual framework or lens from which to investigate and remedy the ways in which oppression manifests at the intersections of socio-politico-geo-temporal power structure contexts and individuals' intertwined experiences of racism, sexism, and other forms of marginalization (e.g., Bowleg, 2012; Cho et al., 2013; Collins & Bilge, 2020). The primary tools for testing for social inequities quantitatively has included modeling the effects of two or more intersecting subgroups on a given outcome, or testing whether subgroups have different predictor-outcome relations using interaction tests (e.g., Bauer et al., 2021).

In the present study, we use an intersectional lens to frame the research agenda by evaluating the intersection between gender (women applying to and graduating from STEM departments) and the minority-serving status of their institutions. The rationale for doing so is because prior research has shown at students of color receive different supports within STEM programs at MSIs versus PWIs, which may produce better STEM graduation outcomes for historically marginalized students (e.g., Fleming et al., 2013). Thus, when reviewing the efficacy of programs like NCWIT-ES, it is important to apply an intersectional lens in the evaluation process. For NCWIT in particular, we should consider outcomes for women of color as they comprise a very small proportion of the students in engineering and computer science (Mendenhall et al., 2018). Although the current study did not have access to individual-level intersectional information, we employ an intersectional framework by assessing differences in the trajectories for women at MSIs and PWIs. To our knowledge, a large-scale analysis of this particular intersection has yet to be taken up in the scholarly literature.

Current Study

Methodologically, the present study demonstrates the use of parallel latent growth modeling in complex longitudinal data that included time-varying baselines (i.e., when the institution joined NCWIT-ES) and large proportions of missingness. Substantively, in addition to the question of describing the general trajectories women's applications in, and graduations from, STEM departments for NCWIT-ES participating institutions, we also investigate the intersection between individual-level gender (undergraduate women) growth factors and institution-level context (institutional MSI status).

Method

Data Source

Original dataset. The National Center for Women and Information Technology Extension Services (NCWIT-ES) asks member institutions to annually report STEM departmental-level counts of undergraduate women applicants, acceptances, enrollments, and graduates using an online tracking tool. In addition, member institutions are also asked to input any outcome data they have available from years prior to joining NCWIT-ES. The dataset available for the present study included all institutions who joined NCWIT-ES at some point between years 2006 to 2018. However, time points reported by these participating institutions spanned a longer time period (15 consecutive years in total, from 2003 to 2018) because institutions could report on counts prior to the year they joined NCWIT-ES (some up to 14 years prior to joining), and some report up to 10 years after joining. Although the original dataset included 1,724 measurements from 218 STEM departments across 90 institutions, 17 of which were minority-serving, there were extraordinarily high levels of missingness due to the varying years that institutions joined the program as well as the varying lengths of time institutions reported before and after joining.

Analytic dataset. Before selecting the analytic sample, missingness was evaluated. First, the data were centered at a common baseline according to the year the institution joined NCWIT-ES, which led to available measurements ranging from 14 years before joining to up to 10 years after joining (including the baseline, 15 years). Next, only institutions that had some amount of data available on each of the outcomes (applications, acceptances, enrollments, and graduations) were selected, resulting in N = 61 institutions (142 departments in total), 12 of which were MSIs. Third, using aggregate department counts we examined missingness across time to establish the final timeframe to be used in analyses. On average, missingness ranged from 16% to 98% (averaging 66%), and was highest at the tail ends of the time spans. By constraining the analytic sample to span eight years, from -2 years to +5 years from year of joining, missingness levels were reduced (ranging from 16% to 70%, averaging 51%). (We note that any further reductions to the time span would have reduced the number of institutions that could be used in analyses due to the high variation in reporting years.)

Last but not least, because our preliminary analyses showed that two of the four potential outcomes—acceptances and enrollments—had model convergence problems when we analyzed them individually, and further, that both of these two outcomes were less correlated with graduation counts compared with application counts, we focused all analyses on applications and graduations. Table 1 provides institution-level descriptive statistics on the original and analytic samples for comparison. In the combined analytic sample, the average year of joining NCWIT-ES was *M* = 2012.80 (*SD* = 3.99, *Range* = 2006 – 2018) and the average STEM department count was *M* = 2.33 (*SD* = 1.67; *Range* = 1 –9).

Variables

Outcomes. We focused on two outcome variables for this analysis: the number of female applicants and number the female graduates for each institution, at each time point. In our individual growth trajectory models, we center both variables at year joined as the baseline/intercept. In the parallel growth models in which we were interested in testing the relationship between application growth and graduation growth, we centered graduation counts at year joined + 5 years, given the average length of time between applying to an institution and graduating with a 4-year degree.

Predictors. We used time-invariant predictors in each of the growth models, including year that the institution joined NCWIT, the number of STEM departments at the institution, and the MSI status of the institution.

Analysis Plan

Preliminary analyses. Univariate multilevel models with maximum likelihood estimation (to handle missingness as missing at random) were conducted as preliminary checks on the general functional form of growth in these outcomes as well as to check residual distributions for non-normality, particularly given that the outcomes are count data that tend to be right skewed. These analysis results indicated that (a) the best functional form for each outcome was a second-order polynomial (i.e., including an intercept, linear growth, and a quadratic growth representing acceleration in change over time resulted in the best model-fit indices and were significantly better than linear-only models), (b) the residuals of these models were fairly normally distributed, albeit with mild leptokurtosis. When we checked the log-transformed data, the same growth patterns emerged. Hence, we use the “raw” count data in the forthcoming final models.

Preliminary analyses were also conducted to check the correlations among counts over time (disregarding institution membership), which revealed that application counts were more predictive of graduation counts than the other two potential outcomes (acceptance and enrollment counts). Further, when we moved into the multivariate structural equation modeling (SEM) framework, models for these two outcomes (acceptance and enrollment counts) displayed substantial convergence problems (i.e., negative residual variances) without placing further constraints on the model.

Last but not least, given that each of our time points had some serious amount of missing data, especially at the beginning of the time span (-2 years from joining), we focused on a polynomial time coding approach, rather than piecewise. Additionally, because MSI status was unbalanced with only 12 MSIs, and further, because it was correlated with year joining and number of departments, we were not able to test their interactions.

Final Models

SEM approach to growth modeling. In a multivariate SEM framework, the model can be represented as follows.

$$\mathbf{y}_{\boldsymbol{j}} = \boldsymbol{\upsilon} + \boldsymbol{\Lambda}\boldsymbol{\eta}_{\boldsymbol{j}} + \boldsymbol{\varepsilon}_{\boldsymbol{j}} \quad (1)$$

In the model above, the vector of outcomes **y** for institution *j* measured at *t* time points (i = (0,1,2,3…t-1)) are a function of a vector of intercepts $\boldsymbol{\upsilon}$ (t x 1 vector often fixed to **0** to identify the intercept and growth factor means; a t x P matrix of factor loadings $\boldsymbol{\Lambda}$, where P = the number of growth factors (usually constrained to a design matrix layout within which the first column is fixed to **1** and the next column is fixed to **t** (if the first time point is serving as the reference for the intercept, **t** may be coded **t-1**); a p x 1 vector of weights $\boldsymbol{\eta}_j$ constraining each of the individual-specific latent factors (e.g., α_i and β_j with distribution $\boldsymbol{\eta}_j \sim N(\boldsymbol{\mu},\boldsymbol{\Sigma})$); and a t x 1 vector of time point-specific errors $\boldsymbol{\varepsilon}_j$ with distribution $\boldsymbol{\varepsilon}_j \sim N(\mathbf{0},\boldsymbol{\Theta})$. The t x t covariance matrix $\boldsymbol{\Theta}$ is typically fixed to assume local independence for institution j across t time points, conditional on the latent factors $\boldsymbol{\eta}_j$ as follows:

$$\boldsymbol{\Theta} = \begin{bmatrix} \theta_0 & & \\ 0 & \ddots & \\ 0 & 0 & \theta_{t-1} \end{bmatrix}.$$

Importantly, in all SEM, the scales of the latent variables depend on how we relate the observed variables to them, as well as our assumptions about the latent variables themselves (i.e., a latent variable need not be a normal distribution). In SEM growth modeling, however, in order to estimate the latent means and variances (i.e., intercept, linear slope, and quadratic slope factors), we must put in place model constraints: the paths from the intercept to each time point are constrained to 1, and the paths from the slopes to each time point reflect the distance of the measurements. This specification forces the estimation of the mean of the intercept to be the estimated mean at the time point coded 0, the linear slope mean to be the estimated change in the outcomes per one year increase in time, and the quadratic slope mean to the estimated change in the linear growth rate per year increase in time.

Individual growth trajectories. Growth trajectories for each outcome were modeled separately using a 3-factor latent growth model in which the intercept was centered at the year institutions joined NCWIT-ES and for which the intercept and linear slope were allowed to freely vary but the quadratic term was constrained in order to ensure proper model convergence.

The first model (Model 0) did not include predictors. The second model (Model 1) included year joined (standardized), MSI status (effect coded, 1 = MSI, -1= PWI), and department count (standardized) as predictors of each of the three growth factors. Figure 1, Panels A and B, display the path diagram for each outcome, respectively, for Model 1. As discussed, growth models are typically highly constrained (i.e., we set the path values between observed and latent variables), and therefore their fit metrics are generally poorer than other SEM models.

Parallel growth trajectories. A parallel growth model (Model 2) was then specified to reflect the same underlying structural equation model as individual growth models, but with added parameter estimates to link the different outcome trajectory factors together. For example, in our prior Model 1 for a given outcome, we estimated three latent means and variances, one covariance (intercept and linear slope), three predictor relationships for each of the three growth factors, as well as residual error variances for each of the eight time points. Given the relatively small sample size of $N = 61$ institutions, in addition to the missingness on each of the eight time points, in order to estimate the parallel growth model, growth factor means and variances for this model were constrained to the values estimated in the previously specified individual models (i.e., not freely estimated). Importantly, the interest was in how the three growth factors for applications would predict the three growth factors for graduations. Figure 2 displays the path diagram this model (*Mplus* code shown in the Appendix).

Fit indices. For all models, we report model fit indices, including the chi-square test for exact fit, the comparative fit index (CFI; values ≥ 0.95 are desirable), the Tucker-Lewis index (TLI; values ≥ 0.95 are desirable), standardized root mean square residual (SRMR; values ≤ 0.10 are desirable), and the root-mean-square error of approximation (RMSEA; values ≤ 0.05 are desirable) (Hu & Bentler, 1999). This said, we note that highly constrained SEMs such as growth models often have relatively poorer fit metrics than typical SEMs.

Results

Table 1 displays the overall means of the original and analytic sample on the three focal predictors and the two outcomes (across time points). As can be seen, MSIs in the analytic sample have greater overall counts of women applications and lower overall women graduation counts than in the original sample, and PWIs had the reverse.

Zero-order Pearson correlations among the observed predictors and outcomes for the analytic sample are provided in Table 2. As is readily apparent, MSI status was positively correlated with the year of joining the National Center for Women and Information Technology Extension Services (NCWIT-ES) program. In other words, MSIs joined the program later relative to PWIs. In terms of predictor-outcome relations, we see that institutional STEM department count is a predictor that is positively correlated with graduation outcomes at multiple time points (which makes sense; greater numbers of STEM departments can attract and serve greater numbers of students), while MSI and Year Joining NCWIT-ES was more moderately correlated with application and graduation counts, and only significantly so with applications. This said, these observed bivariate correlations do not take into account missing data patterns or the interrelationships among the predictors.

Model Fit

The model fit indices for all of the models are provided in Table 3; as is readily seen, the fit values are not ideal, but this was not unexpected given the model constraints, particularly for the parallel growth model, and even more so due to the high levels of missingness in the data.

Additionally, because of the added constraints to the latent means and variances in estimating the parallel model in particular, the fit was worse.

Individual Growth Model Trajectories

Rather than focusing on model fit indices, for growth models we prefer to emphasize the patterns in the parameter estimates. Examining the first set of columns in Tables 4 and 5 (Model 0), we see that the intercept, linear growth rates, and quadratic growth rates were each significant for both applications and graduations. Interpretation of the parameter estimates for applications indicates that, at year of joining, institutions averaged 205.09 female applications to their STEM departments, and that the linear rate of growth averaged 34.49 applications per year, and that this rate accelerated at 3.57 applications/year^2 (Figure 3, Panel A). For graduations, at year of joining NCWIT-ES, there was a predicted count of 19.23 women graduating at a given institution. The linear growth rate was predicted at 2.64 women per year graduating, and this growth accelerated at a rate of 0.36 graduations/year^2 (Figure 3, Panel B).

In our Model 1, which folded in predictors, we also found consistent patterns (see the second set of columns in Tables 4 and 5 for applications and graduations, respectively). Department count (as a proxy of institution size) was positively predictive of linear growth and growth acceleration in both outcomes (Figure 4, Panel A and B, illustrates model-implied trajectories for applications and graduations by institution STEM department count, respectively). Institution MSI status, on the other hand, was negatively predictive of growth and quadraticity in STEM graduation counts only (not applications). In other words, MSI institutions had lower growth rates, at 1.85 – 2.42 = -0.57 graduations per year, compared to the average growth rate of 1.85 graduations per year, as well as a different change in the graduation rate, at 0.27 – 0.75 = -0.48 change in the graduation rate per year (i.e., deceleration or slowing of growth), compared to the average acceleration of +0.27 change in the graduation rate per year (see Table 5 as well as Figure 5, Panel A and B, show model-implied trajectories for applications and graduations by institution MSI status, respectively). Last but not least, year of joining NCWIT-ES was a significant positive predictor of linear growth and quadraticity for both outcomes (i.e., institutions who joined NCWIT-ES much later (+1 *SD*, around 2017) were predicted to have an application growth rate of 28.86 + 29.53 = 58.39 applications per year compared to the average growth rate of 28.86 for institutions who joined around 2013; see Table 4 for coefficients). In other words, institutions who joined NCWIT-ES later had greater counts of women applying to and graduating from their STEM departments from the start, and their popularity grew over time (Figure 6, Panels A and B depict model-implied trajectories for applications and graduations by institution year of joining, respectively).

Parallel Latent Growth Model Results

Our final model, Model 2, links the two trajectories together to determine the relations between application and graduation counts. Given that the latent growth factor means and variances were constrained and that the pattern of predictor relationships was substantively the same as the individual trajectory models, we focus here on the linkages between the two outcomes (see Table 6, middle set of rows), we found that the number of women applying to STEM departments at the year of joining NCWIT-ES was significantly positively predictive of the number of women graduating from those STEM departments five years later (i.e., for every standard deviation increase in applications at baseline, 0.41 more graduations per year were predicted five years later (recall that the average at baseline was 17.62 graduations; see again Table 5). Similarly, growth in the number of women applicants per year was predictive of growth in the number of women graduating: for each standard deviation increase in institutional application growth, there was a 0.26 graduation/year growth rate increase predicted compared to the average graduation growth rate (recall that the average growth rate was 1.85 graduations/year; see again Table 5). Although we did not find a predictive relationship for the quadratic factor (i.e., that acceleration in the growth in applications was not significantly predictive of acceleration in the growth of graduations), the pattern was in the same direction (i.e., positive).

Discussion

The present study had two aims: first, we sought to demonstrate the use of parallel growth modeling with time-varying baselines and high levels of missingness within a structural equation modeling framework; the second aim was to use an intersectional lens to explore institutional change over time for institutions participating in the National Center for Women and Information Technology Extension Services (NCWIT-ES) program between the years 2006 and 2018. Due to the nature of the data and the relatively small sample size, use of the parallel modeling process required that we constrain the latent variables to values estimated from a previous, individual outcome trajectory model. In other words, a 2-step process was employed to test the relationships between the two sets of growth factors.

Substantively, our findings showed that: (a) application rates were significantly predictive of graduation rates at participating NCWIT-ES institutions; (b) across participating institutions, there was significant growth in women applying to and graduating from STEM departments; (c) that year of joining NCWIT-ES was a key positive predictor in greater outcomes (i.e., institutions that joined later had better outcomes); (d) that minority-serving institutions (MSIs) participating in NCWIT-ES had lower growth rates, on average, in women applications and graduations to their STEM departments than predominantly white institutions (PWIs), even after controlling for department counts (as a proxy for institution size).

Although we cannot draw causal conclusions, the findings may suggest that NCWIT-ES has been improving its program model over time. Institutions that are joining NCWIT-ES in later years are seeing slightly better outcomes than those that joined in earlier years. While this does not suggest a causal relationship it is worth investigating how the program model has shifted over time to better support institutions in setting women applicants up for success and graduating with a STEM degree. Additionally, the results also call attention to the need for MSIs to potentially receive better targeted support that takes the intersectional identities of the student body at MSIs into consideration.

Future Research Directions

Methodologically, our demonstration was limited by the small sample size and sparseness of the data; yet, the two-step approach for dealing with these constraints may be quite useful to researchers using limited data. In addition, we assumed missingness at random as the missingness mechanism; we cannot verify whether this assumption is valid, but given the very different years of joining the program we have no reason to believe there is a systematic mechanism underlying the missingness in these data.

Substantively, the first major limitation in the data (putting aside the sample size and missingness problems) include that causality between NCWIT-ES participation and growth over time cannot be determined due to a lack of a control group with which to compare the NCWIT-ES participating institutions, as well as a lack of time-varying information about program fidelity over time. Nevertheless, the present study's results provide a good first step in evidence supporting NCWIT-ES participation given the positive trajectories we observed.

From an intersectionality perspective, it would have been extremely useful to have information about individual-level intersectional identity data (i.e., counts of women of color vs. men of color), as well as some disaggregation of racial demographics since different groups experience barriers like racism in different ways. In other words, it is possible that MSIs have comparable or better growth rates for Black or Latinx women entering STEM majors than their PWI counterparts; from these data we simply cannot know. Future research can take up these weaknesses by collecting richer data, perhaps by providing greater incentives to participating institutions for reporting information.

Conclusion

Despite the limitations, the present study contributes to the literature on parallel growth modeling methodology by articulating how to handle time-varying baselines (by centering on a common point, such as year joining a program, and including the actual baseline year as a covariate), and further, demonstrating how to use a 2-step approach in estimating a parallel growth model when the sample size (in this case, number of institutions) is relatively small and missingness levels are high. Although the typical structural equation modeling framework was built for large sample data, we show that it is also quite flexible at handling complex data structures for small samples as well.

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Table 1

Comparison of Original and Analytic Sample Summary Characteristics

Characteristic	Original Sample (N = 90)				Analytic Sample (N = 61)			
	MSI (n = 17)		PWI (n = 73)		MSI (n = 12)		PWI (n = 49)	
	M	*(SD)*	*M*	*(SD)*	*M*	*(SD)*	*M*	*(SD)*
STEM Department Count	1.71	(0.99)	2.63	(2.09)	1.67	(0.99)	2.49	(1.77)
Year Joined NCWIT-ES	2015.09	(2.20)	2012.09	(3.70)	2015.20	(1.81)	2012.31	(3.66)
Women Applications (across years)	62.01	(88.11)	87.91	(153.01)	112.20	(105.44)	69.56	(141.48)
Women Graduations (across years)	7.45	(7.44)	9.89	(13.23)	5.94	(6.11)	8.43	(13.23)

Note. MSI = minority-serving institution; PWI = predominantly white institution.

Table 2

Zero-Order Correlations among Variables used in Analyses

Variables	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.
Predictors																			
1. STEM Dept Count	--																		
2. MSI Status (1 = yes)	-.20	--																	
3. Year Joined	.06	**.46**	--																
Outcomes																			
4. Apps Time= -2	.22	.00	**.32**	--															
5. Apps Time= -1	.24	.20	**.42**	**.92**	--														
6. Apps Time= 0	.22	.22	.28	**.89**	**.95**	--													
7. Apps Time= 1	**.52**	.34	.33	**.87**	**.94**	**.96**	--												
8. Apps Time= 2	.38	**.62**	**.47**	**.84**	**.94**	**.97**	**.98**	--											
9. Apps Time= 3	.27	**.70**	**.50**	**.88**	**.92**	**.95**	**.94**	**.96**	--										
10. Apps Time= 4	.19	**.66**	**.69**	**.87**	**.91**	**.92**	**.90**	**.92**	**.98**	--									
11. Apps Time= 5	-.14	--	.28	.39	**.61**	**.73**	**.65**	**.83**	**.89**	**.94**	--								
12. Grad Time= -2	**.53**	-.09	.16	**.61**	**.39**	**.44**	**.47**	.15	.26	.27	-.05	--							
13. Grad Time= -1	**.50**	.01	.15	**.71**	**.51**	**.51**	**.52**	.28	.40	.43	.02	**.96**	--						
14. Grad Time= 0	**.67**	.04	.20	**.69**	**.49**	**.45**	**.52**	.20	.24	.19	-.13	**.96**	**.94**	--					
15. Grad Time= 1	**.67**	-.06	.20	**.66**	**.45**	**.39**	**.51**	.25	.26	.24	.02	**.94**	**.94**	**.96**	--				
16. Grad Time= 2	**.74**	.02	.34	.40	**.45**	.35	**.53**	.31	.35	.33	.25	**.68**	**.66**	**.82**	**.85**	--			
17. Grad Time= 3	**.74**	-.02	.37	.40	**.41**	.34	**.54**	.32	.43	.45	.41	**.75**	**.71**	**.85**	**.89**	**.91**	--		
18. Grad Time= 4	**.54**	--	.24	**.73**	**.70**	**.76**	**.79**	**.64**	**.61**	**.58**	**.46**	**.72**	**.78**	**.87**	**.89**	**.87**	**.95**	--	
19. Grad Time= 5	**.60**	--	.28	**.83**	**.78**	**.80**	**.84**	**.62**	**.59**	**.59**	.44	**.79**	**.85**	**.89**	**.93**	**.88**	**.93**	**.92**	--

Note. N = 61 institutions measured at eight time points (-2, -1, 0, 1, 2, 3, 4, 5); Time coded in years from the baseline (baseline = the year institution joined NCWIT-ES); STEM Dept Ct = number of STEM departments at the institution; MSI = minority-serving institution, dummy coded 1 = yes and 0 = no; Year Join = the year the institution joined NCWIT-ES; App = number of women applying to the institution; Grad = number of women graduating from the institution; Pearson's r reported (boldfaced values = significant at the .05 level, and dashes indicate perfect positive correlation), but note that sample sizes for correlations among time points varies due to missingness.

Table 3

Summary of Model Fit Indices

Model	Number Parameters Estimated	Log-Likelihood Value	Chi-square test			Fit Indices					
			Value	*(df)*	*p*	CFI	TLI	RMSEA	SRMR	BIC	AIC
Latent Growth Model without Predictors (Model 0)											
Applications	14	-1447.20	463.43	28	<.001	.83	.84	.2	.10	2951.95	2922.4
Graduations	14	-886.02	60.44	31	<.001	.93	.94	.13	.12	1825.49	1798.05
Latent Growth Model with Predictors (Model 1)											
Applications	23	-1428.87	580.95	52	<.001	.74	.70	.23	.15	2952.29	2903.73
Graduations	22	-868.36	125.61	46	<.001	.84	.82	.17	.14	1827.16	1780.72
Parallel Latent Growth Model (Model 2)											
Both Applications and Graduations	36	-2305.23	838.74	164	<.001	.54	.53	.26	.26	4758.45	4682.46

Note. N = 61 institutions measured at eight time points (-2, -1, 0, 1, 2, 3, 4, 5); residual variance of the measurement at Time = -2 was constrained to 0 for Model 2 to avoid impermissible negative residuals.

Table 4

Growth Model Unstandardized Results for Number of Women Applying to Participating Institutions at Year Joining NCWIT-ES

Parameters	Model 0: Growth Only				Model 1: With Predictors			
	Coeff	*SE*	*Z*	*p*	*Coeff*	*SE*	*Z*	*p*
Intercept (Count at Year Join)	205.09	30.01	6.83	<.001	211.42	40.50	5.22	<.001
STEM Department Count					52.59	29.25	1.79	.07
MSI Status (1= yes, -1=no)					-11.58	43.83	-0.26	.79
Year Joined NCWIT-ES					102.22	34.35	2.98	<.001
Linear Growth (Count Change per Year)	34.79	7.40	4.70	<.001	28.86	12.07	2.39	.02
STEM Department Count					5.92	7.69	0.77	.44
MSI Status (1= yes, -1=no)					-21.49	13.30	-1.62	.11
Year Joined NCWIT-ES					29.53	10.47	2.82	<.001
Quadratic Growth (Count Change in Linear Growth per Year)	3.57	1.31	2.73	<.001	-4.81	3.93	-1.22	.22
STEM Department Count					-3.62	1.22	-2.98	<.001
MSI Status (1= yes, -1=no)					-14.12	3.74	-3.77	.06
Year Joined NCWIT-ES					5.06	2.69	1.88	<.001

Note. N = 61 institutions measured at eight time points (-2, -1, 0, 1, 2, 3, 4, 5); Time coded in years from the baseline (baseline = the year institution joined NCWIT-ES); metrical predictors (Year Joined and Department Count) are standardized in z-scores and categorical predictor (MSI Status) effect coded. *Coeff* = standardized parameter estimate, *SE* = standard error, *Z* = the quotient of the standardized parameter estimates and the standard errors. Model estimated with maximum likelihood using *Mplus*.

Table 5

Growth Model Unstandardized Results for Number of Women Graduating from Participating Institutions Five Years Post-Entry into NCWIT-ES

Parameter	Model 0: Growth Only				Model 1: With Predictors			
	Coeff	*SE*	*Z*	*p*	*Coeff*	*SE*	*Z*	*p*
Intercept (Count at Year Join)	19.23	2.72	7.07	<.001	17.62	3.17	5.56	<.001
STEM Department Count					10.95	2.38	4.60	<.001
MSI Status (1= yes, -1=no)					-2.58	3.47	-0.75	.46
Year Joined NCWIT-ES					3.66	2.79	1.31	.19
Linear Growth (Count Change per Year)	2.64	0.48	5.56	<.001	1.85	0.78	2.37	.02
STEM Department Count					0.59	0.43	1.37	.17
MSI Status (1= yes, -1=no)					-2.42	0.85	-2.85	<.01
Year Joined NCWIT-ES					1.90	0.73	2.61	<.01
Quadratic Growth (Count Change in Linear Growth per Year)	0.36	0.10	3.50	<.001	0.27	0.32	0.85	.40
STEM Department Count					-0.21	0.10	-2.09	.04
MSI Status (1= yes, -1=no)					-0.75	0.33	-2.26	.02
Year Joined NCWIT-ES					0.63	0.26	2.49	<.01

Note. N = 61 institutions measured at eight time points (-2, -1, 0, 1, 2, 3, 4, 5); Time coded in years from the baseline (baseline = the year institution joined NCWIT-ES); metrical predictors (Year Joined and Department Count) are standardized in z-scores and categorical predictor (MSI Status) effect coded. *Coeff* = standardized parameter estimate, *SE* = standard error, *Z* = the quotient of the standardized parameter estimates and the standard errors. Model estimated with maximum likelihood using *Mplus*.

Table 6

Parallel Growth Model Standardized Results for Participating NCWIT-ES Institutions

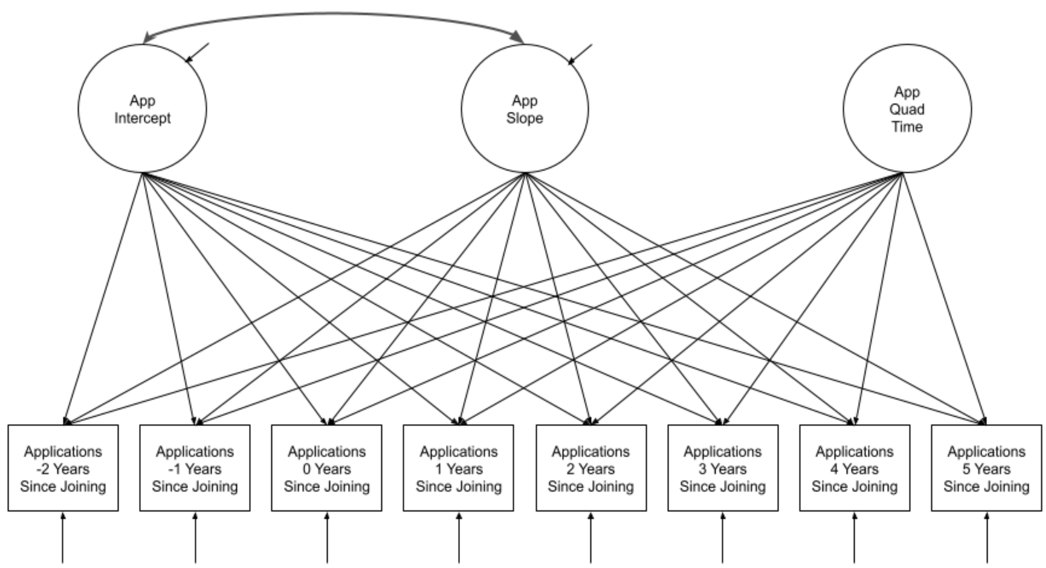
Parameter	*Coeff*	*SE*	*Z*	*p*
App Intercept (Count at Year Join)				
STEM Department Count	0.26	0.12	2.16	.03
MSI Status (1= yes, -1=no)	0.01	0.11	0.13	.90
Year Joined NCWIT-ES	0.32	0.13	2.49	.01
App Linear Growth (Count/Year Change)				
STEM Department Count	0.18	0.14	1.28	.20
MSI Status (1= yes, -1=no)	-0.11	0.14	0.76	.45
Year Joined NCWIT-ES	0.38	0.17	2.29	.03
App Quadratic Growth (Acceleration)				
STEM Department Count	-0.45	0.21	-2.21	.03
MSI Status (1= yes, -1=no)	-0.90	0.16	-5.57	<.001
Year Joined NCWIT-ES	1.03	0.14	7.56	<.001
Grad Intercept (Count at Year Join)				
STEM Department Count	0.19	0.10	1.90	.06
MSI Status (1= yes, -1=no)	-0.54	0.12	-4.62	<.001
Year Joined NCWIT-ES	0.48	0.15	3.31	<.001
Grad Linear Growth (Count/Year Change)				
STEM Department Count	-0.14	0.11	-1.30	.19
MSI Status (1= yes, -1=no)	-0.85	0.12	-7.43	<.001
Year Joined NCWIT-ES	0.80	0.14	5.84	<.001
Grad Quadratic Growth (Acceleration)				
STEM Department Count	-0.36	0.18	-1.98	.05
MSI Status (1= yes, -1=no)	-1.19	0.27	-4.46	<.001
Year Joined NCWIT-ES	1.28	0.23	5.63	<.001
Latent Growth Factor Relationships	*Coeff*	*SE*	*Z*	*P*
App→Grad Intercept	0.41	0.07	5.62	<.001
App→Grad Linear Growth	0.26	0.08	3.33	<.001
App→Grad Quadratic Growth	-0.25	0.19	-1.30	.19
Grad Intercept↔Linear Growth	0.86	0.03	25.50	<.001
Variance Explained (R^2)	*Coeff*	*SE*	*Z*	*P*
Applications Intercept	0.18	0.09	2.03	.04
Applications Linear Growth	0.17	0.11	1.51	.13
Applications Quadratic Growth	--	--	--	--
Graduations Intercept	0.66	0.08	8.47	<.001
Graduations Linear Growth	0.88	0.06	13.98	<.001
Graduations Quadratic Growth	--	--	--	--

Note. N = 61 institutions measured at eight time points (-2, -1, 0, 1, 2, 3, 4, 5); App = Applications; Grad = Graduations; residual variance of the measurement at Time = -2 was constrained to 0 to avoid impermissible negative residuals.Time coded in years from the baseline (baseline = the year institution joined NCWIT-ES); metrical predictors (Year Joined and Department Count) are standardized in z-scores and categorical predictor (MSI Status) effect coded. *Coeff* = standardized parameter estimate, *SE* = standard error, *Z* = the quotient of the standardized parameter estimates and the standard errors. Model estimated with maximum likelihood using *Mplus*.

Figure 1

Path Diagram for Modeling the Number of Women Applying to (Panel A) and Women Graduating from (Panel B) STEM Departments at NCWIT-ES Participating Institutions, 2006-2018

Panel A



Panel B

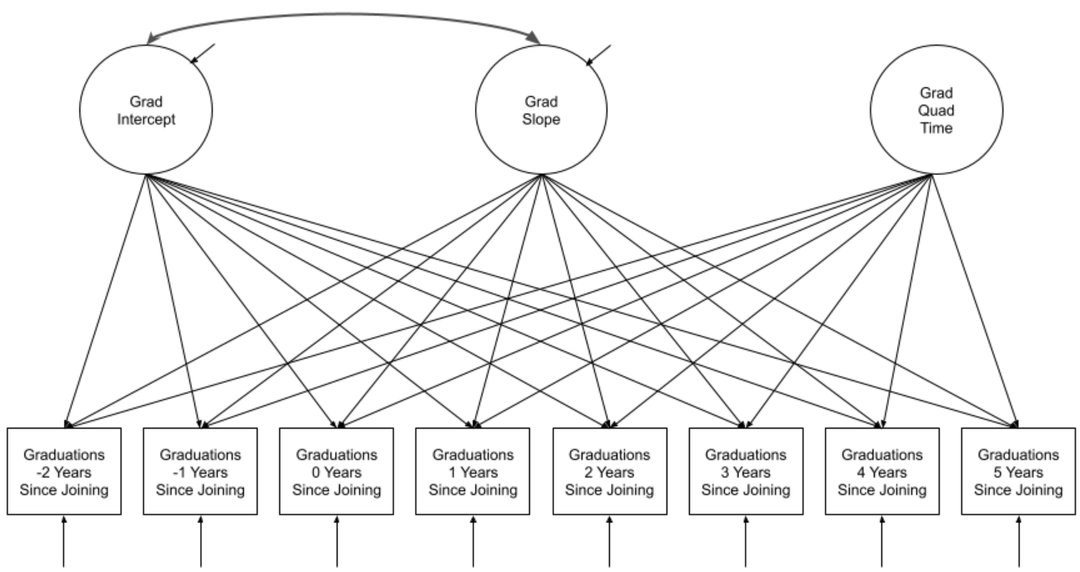


Figure 2

Path Diagram for Parallel Growth Model of the Number of Women Applying to and Graduating from STEM Departments at NCWIT-ES Participating Institutions

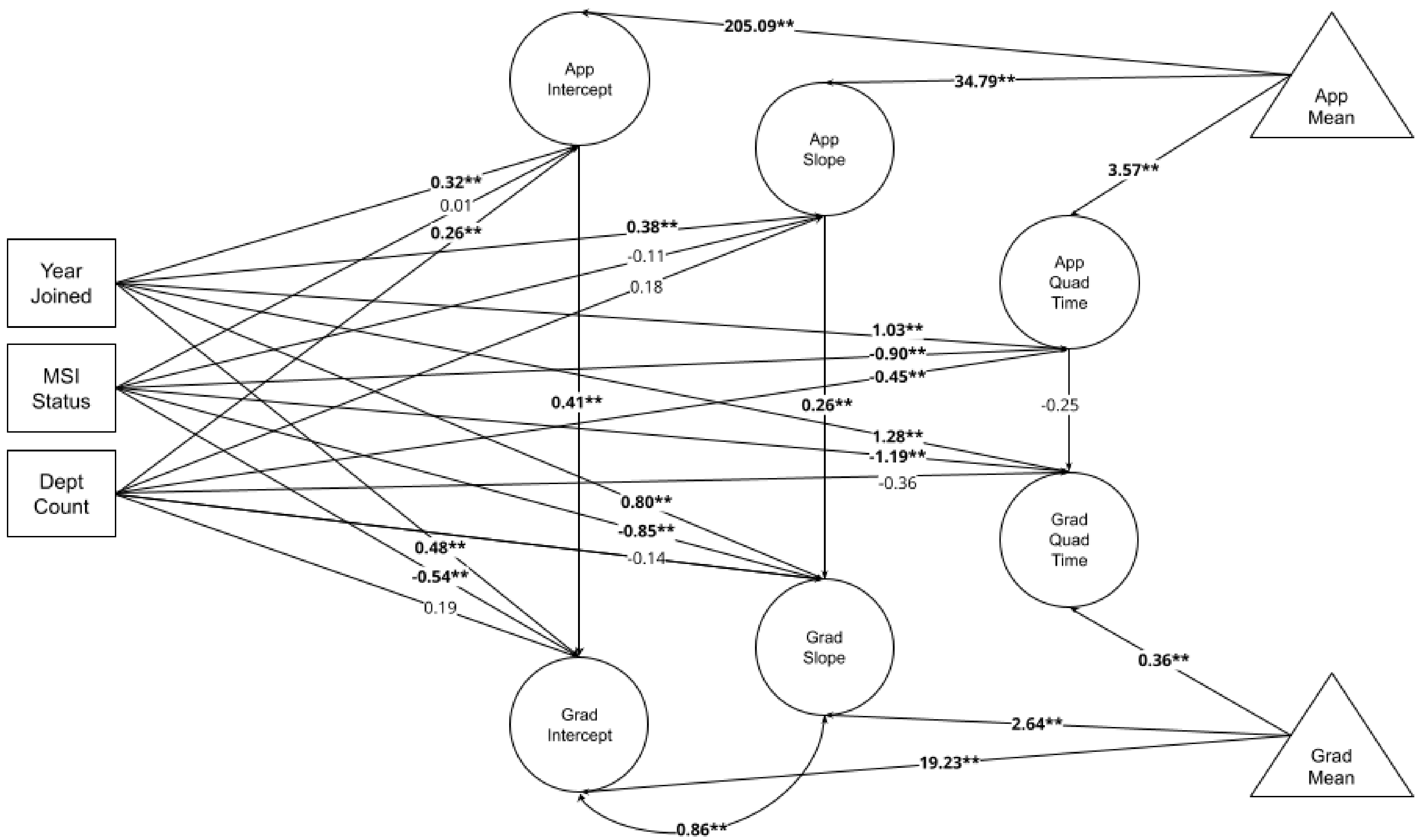
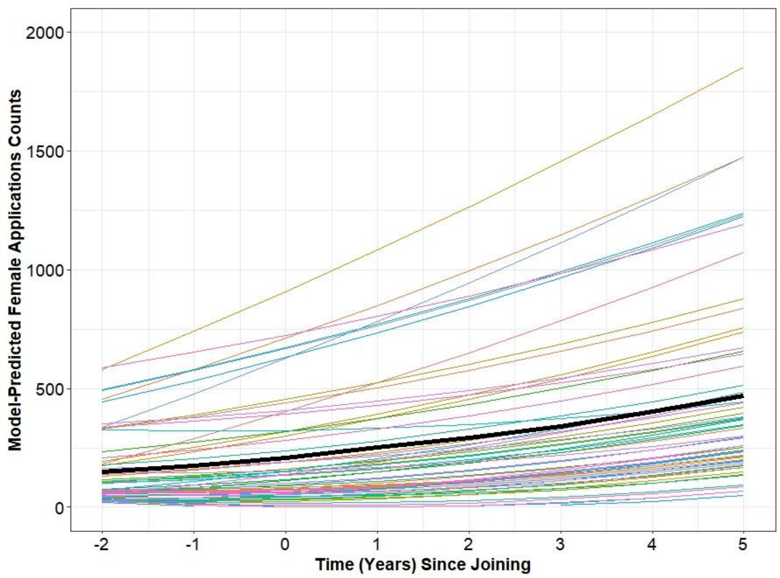


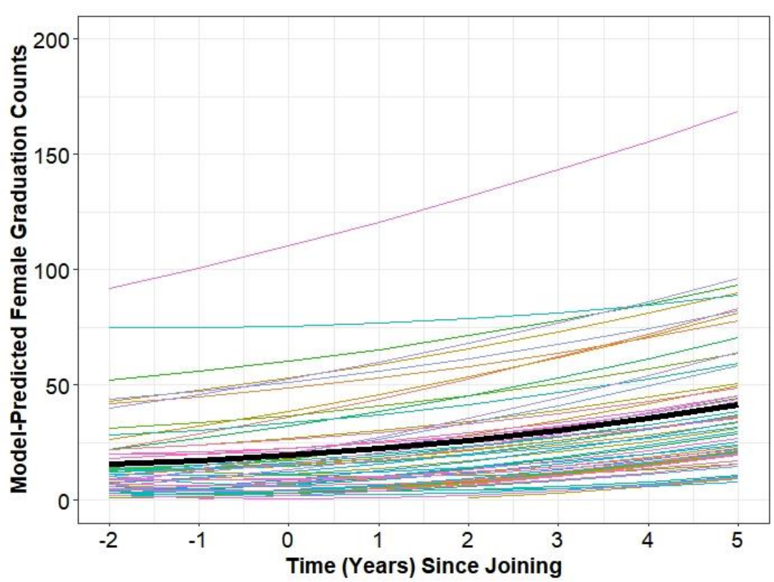
Figure 3

Model-Predicted Trajectories for Women Applying to (Panel A) and Graduating from (Panel B) STEM Departments at NCWIT-ES Participating Institutions, 2006-2018

Panel A



Panel B

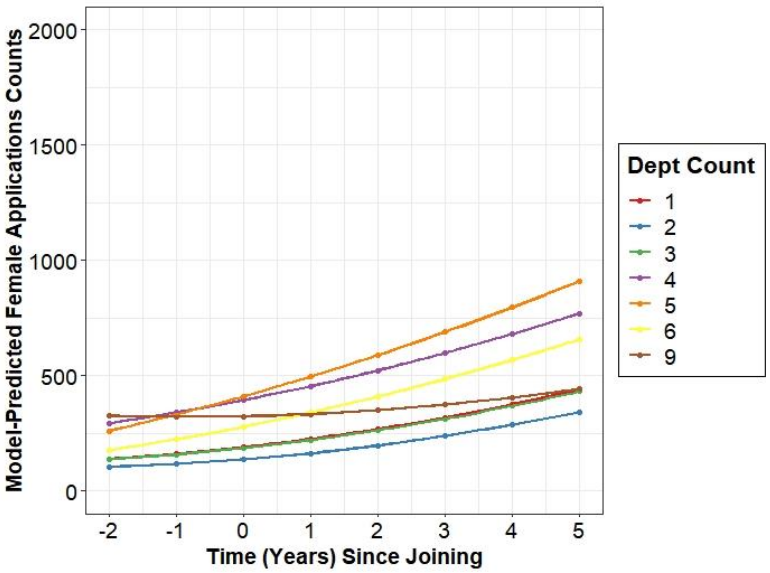


Note. N = 61 institutions. Solid black line represents mean trajectory; lines in color represent individual institutions.

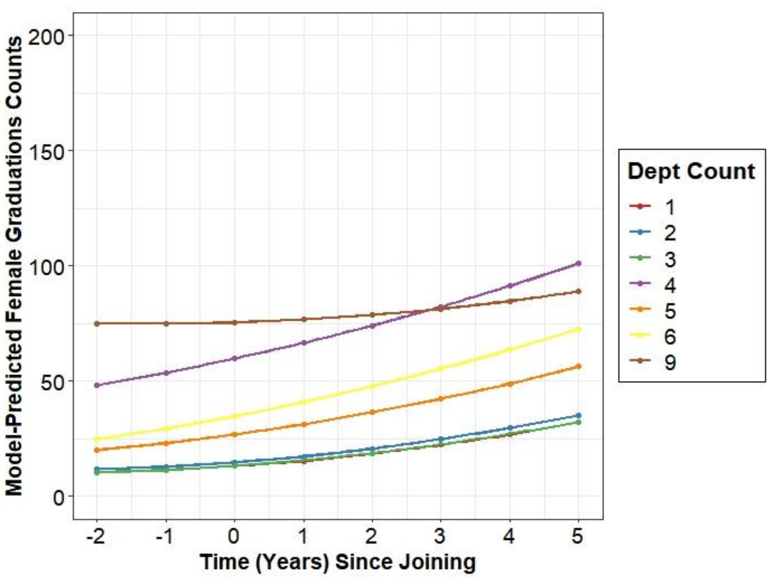
Figure 4

Model-Predicted Trajectories by Department Count for Women Applying to (Panel A) and Graduating from (Panel B) STEM Departments at NCWIT-ES Participating Institutions, 2006-2018

Panel A



Panel B

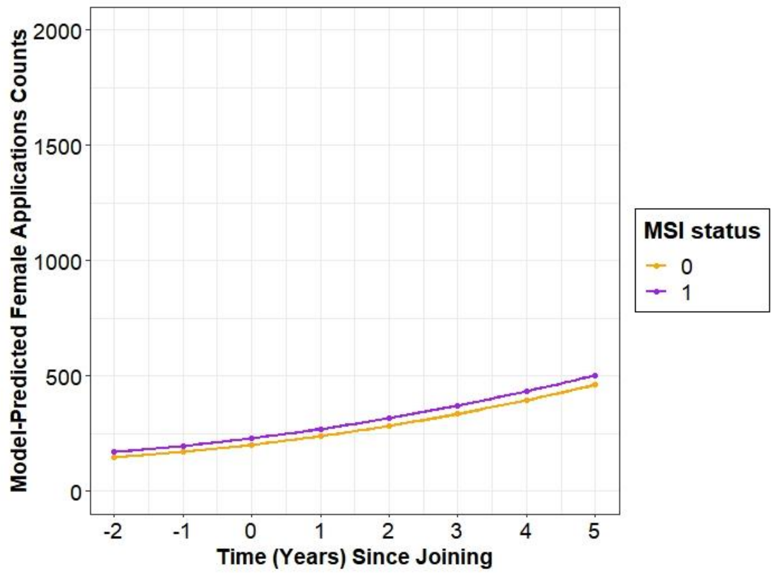


Note. N = 61 institutions.

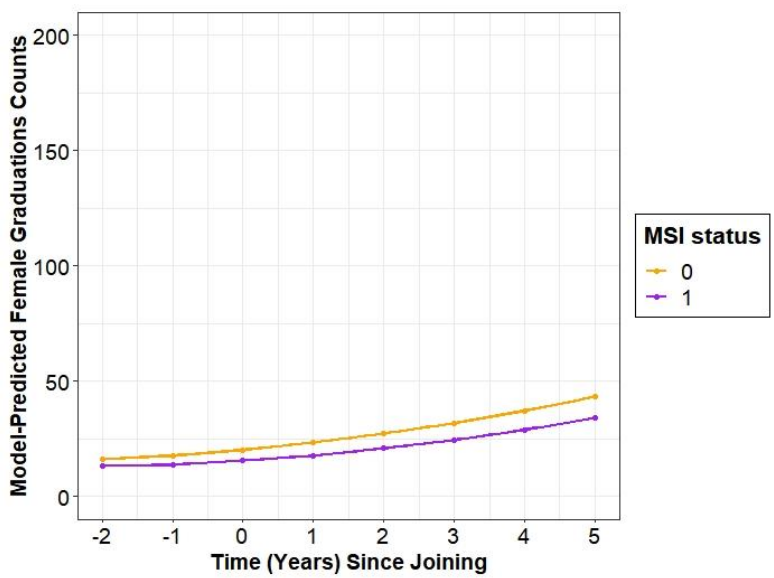
Figure 5

Model-Predicted Trajectories by Institution MSI Status for Women Applying to (Panel A) and Graduating from (Panel B) STEM Departments at NCWIT-ES Participating Institutions, 2006-2018

Panel A



Panel B

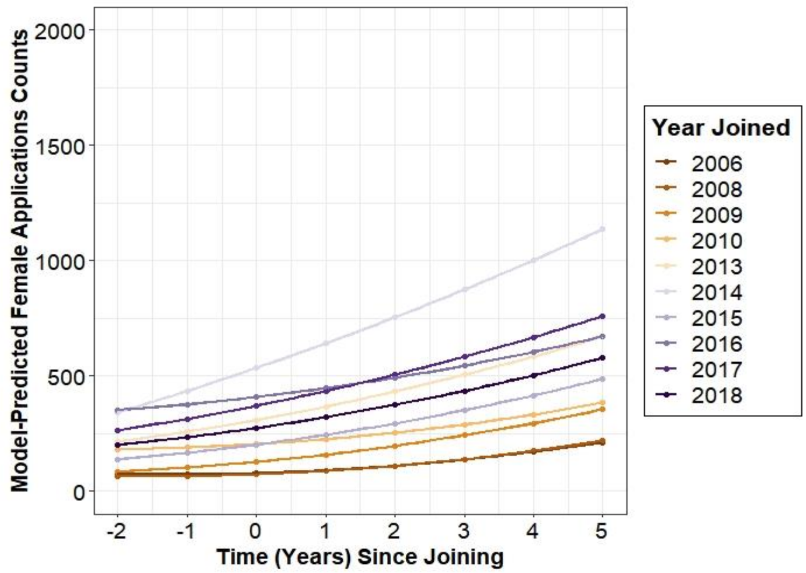


Note. N = 61 institutions. MSI status 1 = minority-serving institution, 0 = predominantly white institution.

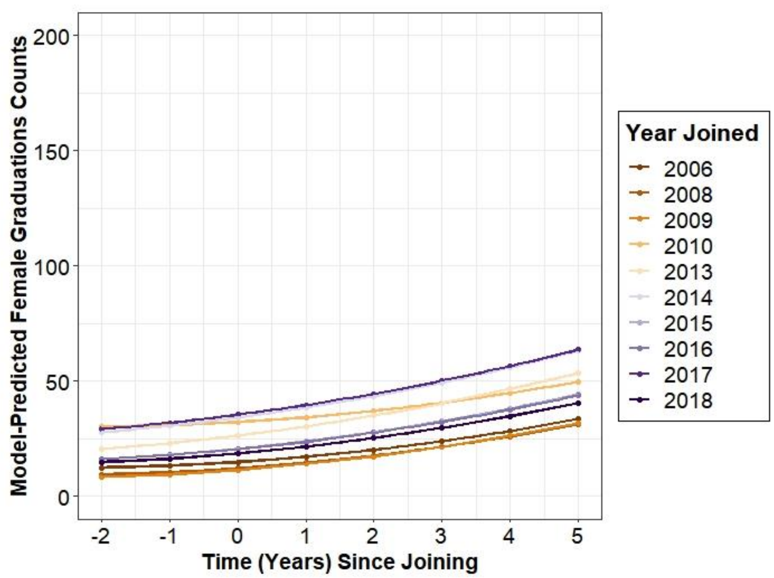
Figure 6

Model-Predicted Trajectories by Department Count for Women Applying to (Panel A) and Graduating from (Panel B) STEM Departments at NCWIT-ES Participating Institutions, 2006-2018

Panel A



Panel B



Note. *N* = 61 institutions.

Appendix

Parallel Growth Model *Mplus* Code

```
TITLE: 2L Parallel Process Growth Model;
DATA: FILE = file.csv;

VARIABLE:
NAMES =
InstID
DeptCt
ZDeptCt
App_11
App_10
App_9
App_8
App_7
App_6
App_5
App_4
App_3
App_2
App_1
App0
App1
App2
App3
App4
App5
App6
App7
App8
App9
App10
Grd_11
Grd_10
Grd_9
Grd_8
Grd_7
Grd_6
Grd_5
Grd_4
Grd_3
Grd_2
Grd_1
Grd0
Grd1
Grd2
Grd3
Grd4
Grd5
Grd6
Grd7
Grd8
Grd9
```

```
Grd10
GrdLag_16
GrdLag_15
GrdLag_14
GrdLag_13
GrdLag_12
GrdLag_11
GrdLag_10
GrdLag_9
GrdLag_8
GrdLag_7
GrdLag_6
GrdLag_5
GrdLag_4
GrdLag_3
GrdLag_2
GrdLag_1
GrdLag0
GrdLag1
GrdLag2
GrdLag3
GrdLag4
GrdLag5
YrJoin
MSIdum
MSIeff
ZYrJoin
;

USEVARIABLES =
App_2
App_1
App0
App1
App2
App3
App4
App5
Grd_2
Grd_1
Grd0
Grd1
Grd2
Grd3
Grd4
Grd5
MSIeff
ZYrJoin
;

IDVARIABLE = InstID;
MISSING ARE ALL (-999);
ANALYSIS:
ITERATIONS=100000;
H1ITERATIONS=100000;
```

```
SAVEDATA:
RESULTS = L2_growth_pp_M2_results.dat;
FILE = PP_m2.dat;
SAVE = FSCORES;
FORMAT = FREE;

MODEL:
i_app s_app q_app |
App_2@-2
App_1@-1
App0@0
App1@1
App2@2
App3@3
App4@4
App5@5;
q_app@0;
App_2@0;
[i_app@205.088];
[s_app@34.791];
[q_app@3.568];
i_app@49515.688;
s_app@2001.672;

i_grd s_grd q_grd |
Grd_2@-6
Grd_1@-5
Grd0@-4
Grd1@-3
Grd2@-2
Grd3@-1
Grd4@0
Grd5@1;
q_grd@0;
Grd_2@0;
[i_grd@19.225];
[s_grd@2.640];
[q_grd@0.359];
i_grd@416.397;
s_grd@7.695;

i_grd ON i_app;
s_grd ON s_app;
q_grd ON q_app;
i_grd s_grd q_grd i_app s_app q_app ON MSIeff ZYrJoin ZDeptCt;
```