"Late to the Game": A single point-in-time, and cumulative effect of late registration on students' academic success

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'At Risk' - a (non statistical) Fixed vs. Dynamic Profiling of Students Entering CC

- CC are using numerous metrics to profile 'at-risk' students, and allocate services to fit students' needs.
- The Limitations:
  - (a) Most profiling activities take place <u>prior</u> to students' enrollment, and are mainly derived from a limited set of demographic, academic and financial qualities.
  - (b) Colleges underutilize* dynamic profile information regarding students' behavior <u>once at the college</u>, and rarely re-profile 'at-risk' groups using behavioral indicators.

*[*a common exception is when students enter "academic probation".]*

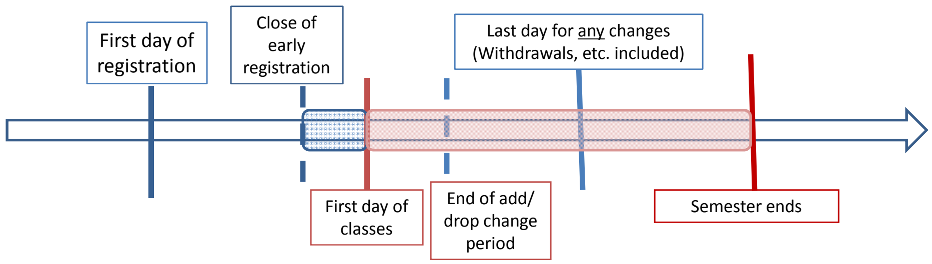
‘At Risk’ - a (non statistical) Fixed vs. Dynamic Profiling of Students Entering CC (II)

- The Challenge:
  - (a) Recognize students needing support services.
  - (b) Correctly allocating services to students who need them.
  - (c) Match student need with the correct services.
  - (d) Maximize the utilization of dynamic information collected regarding student patterns once at the college.
- Potential Dynamic Indicators of ‘At-Risk’ Status:
  - (a) Students who delay their course registrations to college (“Late to the game”)
  - (b) Students who ‘cruise’ or ‘swirl’, and do not make progress towards a degree.
  - (c) Students who constantly change their class schedule.
  - (d) Students who jeopardize their financial aid package due to a single schedule change.

Study Objectives

- Demonstrate that colleges can use their information systems to recognize delayed registration, as an ‘at risk’ pattern.
- Demonstrate that students dynamic behavior can be used to evaluate future performances.
- Adding to the previous studies, demonstrate that there is a ‘late’ effect, and that it:
  - remains over time,
  - may be cumulative,
  - remains in place after controlling for common covariates,
  - Is robust controlling for time-dependent variation

The concept of 'delayed registration'



- Individual colleges handle registration differently, but there are commonalities.
- Solid lines represent common stages in the registration process across virtually all colleges. Most colleges also establish additional dates ('*dotted' lines*).
- Many studies referred to late registration as any activity conducted post ' registration season' (even if the student already registered for the semester).
- In this study, delayed registration is defined as having the student conducting their FIRST registration activity on or after the first day of classes. This definition is more conservative than previously used.

Delayed Registration: Previous Literature (I)

- Despite the prevalence of late registration practices practiced at the majority of open-enrollment colleges, few rigorous studies have been conducted to determine the effect of late registration on postsecondary student outcomes.
- Perkins (2002) reports that earlier studies [i.e. Chilton (1964),Parks (1974) Mannan &Preusz (1976)] suffered from limitation of previous data systems, and lack of national comparisons.
- Most studies have emerged when colleges deployed modern information systems (beginning in the 1980's).

Delayed Registration (II): Previous Findings

Research results were mixed, but mostly negative:

- Late registration associated with lower grades relative to the average class grade (i.e. Ford et al., 2008; Neighbors, 1996; Safer, 2009; Smith et al., 2002; Summers, 2000), and lower GPA in absolute terms (i.e. Roueche & Roueche, 1994a; Sova, 1986, Hiller: 2005)

- Late registrants were less likely to complete their courses, (i.e. Roueche & Roueche, 1994a; Sova, 1986, Hiller: 2005)

- Late registrants were less likely retain for consecutive terms (i.e. Summers:2000, Smith et. al 2002, Freer-Weiss: 2004, Johnson: 2006).

The Previous Literature (III): Challenges and drawbacks

- The magnitude of late registration effect varied, and so did the ability to control for alternative covariates.
- The population, study-period, and the definition of characteristics defining a late registrant varied widely.
- The method use to control for variation usually did not control for time-dependent variation and for random errors over time.

- Overall, the majority of studies were challenged by:
  - a single semester/point-in-time examination.
  - *relatively* small samples (though recent studies used larger samples)
  - confined to a single campus, or even single major, with no reference point for comparison,
  - Limited control for *covariates.*
  - Lack of control for students changing over time, limited control for time-dependent variables.

Employing growth-curve models: Current Study(I)

- Growth-curve models were used to analyze the effect of late registration as a behavioral indicator.
- This study uses a sample of more than 3,000 students entering an urban, 2-year community college.
- Records were derived for students entering the college in 2004, and followed through 2009.
- The time-frame was selected to allow for longitudinal evaluation, and to maintain an equivalent cohort to BPS 2004:09. Urban CC account for more than two thirds of all CC students nationwide.
- Student level qualities were derived for each semester. Any changes in these over time are controlled for.

Employing growth-curve models: Data Structure(II)

- Conceptual illustration:

ID	Semester	AGE	Late Registration	Cumulative delay	Semester GPA	Semester Credits	Cumulative Credits	Hispanic?	…
1234	1	29.56	0	0	.	0	0	0	
1234	2	30.06	1	1	3.784	5	5	0	
1234	3	30.56	0	1	3.623	4	9	0	
2345	1	46.36	1	1	3.426	3	3	1	
2345	2	46.86	1	2	3.555	6	9	1	

- The student record is derived for each semester.
- By including the full student profile (trajectory), one can control for observed characteristics, as well as systematic differences in student performance unaccounted for by other predictors

Analysis Structure (I)

Growth curve models are organized as follows:

$$Y_{it} = X_{it}\beta + Z_{it}\delta_i + \varepsilon_{it}$$

With

$$\delta_i \sim N(0,G), \quad \varepsilon_{it} \sim N(0,R)$$

The δ capture systematic, *between* individual differences and the ε capture all *within* subject, unexplained differences. In typical models, these terms are univariate, independent of each other, with constant variance. In our models,

$$G = \begin{pmatrix} \sigma^2_{\delta_0} & 0 \\ 0 & \sigma^2_{\delta_T} \end{pmatrix}, \quad R = \sigma^2_{\varepsilon}$$

Analysis Structure (II)

The X terms are potentially time-dependent predictors, Z is captures and individual-specific level and linear trend, by setting it as follows: Z =(1,time) for a single subject in our models.

The subject-specific effects $\delta=(\delta_0, \delta_T)'$ model the correlation structure within subject (one would expect individuals to maintain approximately the same level and trend, net of any other predictors/trends, across their enrollment)

One cannot pool time periods, and thus use all of the information available, without imposing some control for between subject differences as we have done. *In other words, OLS applied to longitudinal data violates the independence assumption*.

These subject-level controls ensure a form of robustness, as well, since time-constant differences between subjects are controlled (we explored fixed effects, rather than random effects model forms and the findings are robust to these two approaches to heterogeneity controls)

Analysis Structure (III): Misc. Tech.

•The models were fit using restricted maximum likelihood estimation in Stata v11.2 with the xtmixed procedure.

•Due to 'time-dependent' constraints (presentation time), today's review would address term GPA and cumulative GPA as central outcomes.

•The effect of late registration presented applies to other academic outcomes as well, i.e. credits earned.

Model 1 and model 2: lateness effect

Model 1:

$$TGPA_{it} = b_0 + b_1 t + b_2 Sem1_{it} + b_3 Sem7to12_{it} + \delta_{0i} + \delta_{Ti} t + \varepsilon_{it}$$

We controlled for first semester and semester in years 4-6 because the baseline pattern was non-linear. First terms tended to be higher GPA; later terms also showed some difference as a whole.

Model 2:

$$\begin{aligned} TGPA_{it} &= b_0 + b_1 t + b_2 Sem1_{it} + b_3 Sem7to12_{it} \\ &+ b_4 Late_{it} + b_5 Late_{it} \times Sem7to12_{it} + \delta_{0i} + \delta_{Ti} t + \varepsilon_{it} \end{aligned}$$

This model allows the late registration effect to differ in the early and later semesters, a pattern we noted as we explored the functional form of the model for robustness.

Model 1 and model 2: lateness effect

	Model 1	Model 2
Block Zero:		
Constant	**2.183**	**2.191**
Time	-0.003	0.000
First Semester	**0.256**	**0.281**
Semester Enrolled is in year IV-VI	**0.111**	0.103
Block 1: Delayed Registration		
Late Registration		**-0.280**
Lateness in year IV-VI		0.083

- Notice the higher GPA in the first term (+.26).
- Notice the effect of delayed registration is significant and suggests a drop of -0.28 in the student GPA for the semester with the delay.
- Delayed registration in later semester *was not* significantly different from the effect in early semesters in this limited model. This may changes as further controls are added to the model.

Model 3: Adding demographics

	Model 1	Model 2	Model 3
Block Zero:			
Constant	**2.183**	**2.191**	**1.882**
Time	-0.003	0.000	0.001
First Semester	**0.256**	**0.281**	**0.268**
Semester Enrolled is in year IV-VI	**0.111**	0.103	0.099
Block 1: Delayed Registration			
Late Registration		**-0.280**	**-0.270**
Lateness in year IV-VI		0.083	0.073
Block 2: Demographics			
Asian			0.055
Hispanics			**-0.472**
African American			**-0.582**
Other Minorities			**-0.334**
Males			**-0.202**
Age at Entrance			**0.030**

- The analysis controls for the common demographics reported in the literature. It suggests that minority students (with the exclusion of Asians) would perform at a lower rate and so would male students.
- While controlling for the demographic covariates, the effect of late registration remains significant and accounts for a decline of 0.27 in the student GPA.

Model 4: Adding academic qualities

`	Model 1	Model 2	Model 3	Model 4
Block Zero:				
Constant	**2.183**	**2.191**	**1.882**	**1.988**
Time	-0.003	0.000	0.001	**-0.023**
First Semester	**0.256**	**0.281**	**0.268**	**0.293**
Semester Enrolled is in year IV-VI	**0.111**	0.103	0.099	0.135
Block 1: Delayed Registration				
Late Registration		**-0.280**	**-0.270**	**-0.253**
Lateness in year IV-VI		0.083	0.073	0.169
Block 2: Demographics				
Asian			0.055	0.004
Hispanics			**-0.472**	**-0.432**
African American			**-0.582**	**-0.541**
Other Minorities			**-0.334**	**-0.324**
Males			**-0.202**	**-0.201**
Age at Entrance			**0.030**	**0.030**
Block 3: Academics				
GED Recipient				0.175
Remedial Reading				0.082
Remedial Math				**-0.199**
Remedial Writing				**-0.104**
Total Credits to date				**0.005**
Part Time				**-0.165**

•The effect of student delayed registration upholds. Delayed registration leads to lowering student GPA by 0.25 points.
•Students who require remedial math, writing or enroll part time at a given semester, are likely to earn lower GPA.

Model 5: Addressing financial constraints

	Model 1	Model 2	Model 3	Model 4	Model 5
Block Zero:					
Constant	**2.183**	**2.191**	**1.882**	**1.988**	**1.991**
time	-0.003	0.000	0.001	**-0.023**	-0.019
First Semester	**0.256**	**0.281**	**0.268**	**0.293**	**0.288**
Semester Enrolled is in year IV-VI	**0.111**	0.103	0.099	0.135	**0.134**
Block 1: Delayed Registration					
Late Registration		**-0.280**	**-0.270**	**-0.253**	**-0.246**
Lateness in year IV-VI		0.083	0.073	0.169	0.180
Block 2: Demographics					
Asian			0.055	0.004	0.001
Hispanics			**-0.472**	**-0.432**	**-0.389**
African American			**-0.582**	**-0.541**	**-0.505**
Other Minorities			**-0.334**	**-0.324**	**-0.303**
Males			**-0.202**	**-0.201**	**-0.209**
Age at Entrance			**0.030**	**0.030**	**0.028**
Block 3: Academics					
GED Recipient				0.175	0.181
Remedial Reading				0.082	**0.089**
Remedial Math				**-0.199**	**-0.185**
Remedial Writing				**-0.104**	**-0.094**
Total Credits to date				**0.005**	**0.005**
Part Time				**-0.165**	**-0.173**
Block 4: Finance					
Paid tuition off pocket					**0.062**
Paid tuition through aid					**0.128**
Pell recipient					**-0.233**
TAP recipient					-0.017

•Paying tuition off-pocket and paying tuition through financial aid reflect on the students' financial status. Receiving aid and paying off-pocket both increase student commitment to college (and GPA). However, Pell recipients are likely to earn lower grade.
•Holding all covariates, delayed registration effect is sig.

Model 6: Other explanations- stopout*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Block Zero:						
Constant	**2.183**	**2.191**	**1.882**	**1.988**	**1.991**	**2.003**
Time	-0.003	0.000	0.001	**-0.023**	-0.019	**-0.030**
First Semester	**0.256**	**0.281**	**0.268**	**0.293**	**0.288**	**0.287**
Semester Enrolled is in year IV-VI	**0.111**	0.103	0.099	0.135	**0.134**	**0.135**
Block 1: Delayed Registration						
Late Registration		**-0.280**	**-0.270**	**-0.253**	**-0.246**	**-0.248**
Lateness in year IV-VI		0.083	0.073	0.169	0.180	0.193
Block 2: Demographics						
Asian			0.055	0.004	0.001	0.001
Hispanics			**-0.472**	**-0.432**	**-0.389**	**-0.390**
African American			**-0.582**	**-0.541**	**-0.505**	**-0.506**
Other Minorities			**-0.334**	**-0.324**	**-0.303**	**-0.309**
Males			**-0.202**	**-0.201**	**-0.209**	**-0.209**
Age at Entrance			**0.030**	**0.030**	**0.028**	**0.028**
Block 3: Academics						
GED Recipient				0.175	0.181	0.172
Remedial Reading				0.082	**0.089**	**0.090**
Remedial Math				**-0.199**	**-0.185**	**-0.185**
Remedial Writing				**-0.104**	**-0.094**	**-0.096**
Total Credits to date				**0.005**	**0.005**	**0.006**
Part Time				**-0.165**	**-0.173**	**-0.176**
Block 4: Finance						
Paid tuition off pocket					**0.062**	**0.063**
Paid tuition through aid					**0.128**	**0.130**
Pell recipient					**-0.233**	**-0.232**
TAP recipient					-0.017	-0.015
Block 5: Stopout						
Returned from stopout						**0.184**

- It is possible that delayed registration may reflect a positive outcome, i.e. returning to college from a stopout. The study examined that possibility as well. The effect of students' return from stopout is positive.
- Yet, delayed registration remains a significant negative indicator to students' success.

Examining the variances

Model	$\sigma_{\delta 0}$	$\sigma_{\delta t}$	σ_{ε}
1	0.913	0.101	0.822
2	0.900	0.100	0.823
3	0.819	0.098	0.826
4	0.764	0.088	0.833
5	0.753	0.087	0.834
6	0.753	0.088	0.833

- The reading of the variance components for each model provides more information.
- The variance components [$\sigma\delta_0$ and $\sigma\delta_t$] are assumed to be independent from each other.
- The variance [of the random intercepts] decreases, as blocks were added to the model. It is reasonable, as some of the variation is captured by 'improving' the model (that is- adding covariates).
- Any other variations are considered random noise [SD(residual)].
- At the same time, the relative strength of 'delayed registration' remained strong (in terms of both raw and standardized Z scores).

Applications to Research

- The analysis demonstrates that existing college's IT structures can be useful in employing growth model curves.
- Growth curve models may be used to better control for individual (student)-level errors over time.
- Unlike a OLS/regression analysis, studies using longitudinal data can control for students change over time and reevaluate their 'risk' at a higher confidence.

Applications to Practice

- Many scholars and policymakers strongly recommended an elimination of late registration (i.e. Ignash, 1997; Boylan,Bonham & White, 1999); Roueche and Roueche, 1999; Lucy-Allen, Merisotis, & Redmond, 2002; McClenney ,2004…)
- This study does not take a position with regards to the policy decision. Rather, we demonstrate that the effect of delayed registration can be properly measured and evaluated over time.
- Policymakers have several options to address delayed registration. This study allows to conduct an informed decision, and employ dynamic recognition of 'at-risk' students.
- Policymakers may further expand the evaluation by addressing additional time-dependent indicators of students progress.