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Modeling College WithdrawalDecisions

Timothy J. Pleskac& Jessica Keeney
Michigan State University

Stephanie M. Merritt
University of Missouri – St. Louis

Neal Schmitt
Michigan State University

Frederick L. Oswald
Rice University

Timothy J. Pleskac, Ph.D.
Department of Psychology
282A Psychology Building
Michigan State University
East Lansing, MI, 48824-1116
Phone: 517.353.8918 / Fax: 517.4322476
Email: pleskact@msu.edu

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Abstract

Many students during their college careersconsiderwithdrawing from their respective college or university. Understanding why some students decide to withdraw yetothers persist has implications for both the well being of students as well as for institutes of higher education. The present study integrates theories of voluntary employee turnover from organizational psychology and signal detection theory from the cognitive sciences to account for students' decisions to withdraw from college and transfer to another university. A major theory of voluntary employee turnoversuggests that a precipitating event or *shock* (e.g., increase in tuition) leads students to consider withdrawing. We use signal detection theory to index how sensitive students are to potential shocks that differ in their nature and severity, and test hypotheses about the underlying decision process students use to make adecision about withdrawing. A Gaussian equal-variance signal detection model provides the best account of college withdrawal decisions. The theoretical implicationsof this model in terms of understanding and predicting student withdrawal decisions and voluntary employee turnover decisions are discussed.

Keywords: college withdrawal, signal detection theory, shocks, turnover, quit

Modeling college withdrawaldecisions

An unavoidable fact in higher education is that some students persist in obtaining a degree, while others withdraw. The National Center for Education Statistics reported that, in 2007, only 57% of the bachelor's or equivalent degree-seekers who began college in 2001 had graduated from that same college. Thisoverall completion rate is qualified by a number of dimensions. Females have a greater completion rate than males (60% versus 54%). Completion rates also differby race and ethnicity, with Asian/Pacific Islanders having the highest rate and American Indian/Alaskan natives the lowest (66% and 40%, respectively; Knapp, Kelly-Reid, &Ginder, 2009). Understanding why some students persist at their chosen institution and others decide to withdrawhas important implications for a range of institutional processes includingstudent admissiondecisions, colleges' intervention efforts for at-risk students, directions for federal funding, and maintenance of a rigorous athletic program (Hagedorn, 2005).

Most descriptive level explanations of student retention are structural in nature. They focuson how academic, social-psychological, and environmental factors predictintermediate attitudes such as different levels of satisfaction and perceptions of poor fit with the university setting(Aitken, 1982; Braxton & Lee, 2005; Bean, 1985; Tinto, 1975). An alternative approach, one we take in this paper, is to focus on the underlying properties of a student's decision to voluntarily withdraw. To do so, we integrate two mutually informative but distincttheoretical frameworks: (a) theories of voluntary employee turnover from organizational psychology and (b) signal detection theory from the cognitive sciences. This integration provides an explanation of micro-level phenomena. These phenomena include what events initiate the decision process as well as testing various hypotheses about the properties of the underlying decision process. The integration also speaks to macro-level phenomena like the changes in withdrawal rates across academic years. We begin by reviewing the literature on voluntary employee turnover.

Voluntary Employee Turnover

The decision to withdraw from a university is in many ways analogous to an employee's decision to quit a job. Both involve a decision – often made at the individual level – to leave a larger organization and in many cases involve individuals considering a transferto another institution (similar in nature or perhaps entirely different). Both decisions directly affect the culture of an organization and its ability to survive (cf. Simon, 1947). The two decisions, however, are not perfect analogs. For example, students are also consumers of a product. Thus, a student withdrawing from a university may in fact be more consistent with a customer remaining loyal to a particular brand or company. However, despite the possible disparities between the two conceptual models (employees quitting or customers leaving), March and Simon (1958) havein fact suggested that both decisions might draw on the same general underlying process of deciding to quit (p. 127).

Focusing on an employee deciding to quit, March and Simon (1958) conceptualized the process in terms of the utility individuals place on staying with or leaving their organization. More specifically, in the model,an employee's utility was both a function of the desire to stay and also the perceived ease of movement from the organization. Operationalizing desirability in terms of employee satisfaction and ease of movement in terms of the number of job alternatives, this framework has been successful in identifying several moderators of turnover decisions (Hom, Caranikas-Walker, Prussia, &Griffeth, 1992; March & Simon, 1958; Mobley, 1977; Porter & Steers, 1973).

A critical aspect missing from March and Simon's (1958) turnover framework are the external events that lead employees down the path of deciding whether or not to quit. Lee, Mitchell and colleagues contend that for many turnover decisions, precipitating events or *shocks* lead individuals to consider quitting (Harman, Lee, Mitchell, Felps, & Owens, 2007; Holtom, Mitchell, Lee, &Inderrieden, 2005; Lee, Mitchell, Wise, & Fireman, 1996; Lee & Mitchell, 1994). The unfolding model, in turn, describes how shocks are used in deciding to quit (Holtom et al., 2005; Lee & Mitchell, 1994; Lee et al., 1996). The model draws largely upon image theory (Beach & Mitchell, 1998). The basic idea of the model is that there is not one clear-cut path that can lead to a decision to withdraw from an organization.Different paths can lead to an employee quitting a job or, in our case,to a student withdrawing from the university (see Table 1). Some paths occur after a student experiences a shock. Path 1 depicts a course where the decision to withdraw is basically automatic. In this case, a shock triggers a preexisting script thatdirects the person to leave with little deliberation. Paths 2 and 3, in comparison, involve an employeeconductingwhat is called a *compatibility test*in image theory. In response to a shock, an individual compares his or her present surroundings with personal standards defined by values, expectations, and/or goals (Beach & Mitchell, 1998). This comparison process can put an employee into either a state of fit or misfit. Whenemployeesarein a state of misfit then they are more likely to withdraw. Finally, according to the unfolding model, some withdrawal decisions happen in the absence of a shock and are the result of a build-up of dissatisfaction (Paths 4a and Paths 4b).

The unfolding framework is broad and describes a large proportion of the different possible types of voluntary employee decisions to quit (Holtom, et al., 2005; Lee, Mitchell, Holtom, McDaniel, & Hill, 1999; Lee et al., 1996). Although its comprehensiveness is in some ways an asset, the full model is difficult to test. Most tests of the model have relied upon exit interviews of employees who have already quit, providing a post-hoc explanation of the events that triggered their thoughts of quitting (e.g., Lee et al., 1996; Lee et al., 1999). Little work has been done to identify what events might be considered shocks. To address these gaps in the literature, we draw uponsignal detection theory, which provides both a theoretically meaningful means to measure sensitivity to shocks and a parsimonious method to test some of the underlying properties of the decision to quit.

Signal Detection Theory

Signal detection theory is applicable to any situation in which a decision is made under conditions of uncertainty(Green &Swets, 1966; Tanner &Swets, 1954). Modern day tutorials and applications within psychology can be found in Macmillan and Creelman (2005) or Wickens (2002). Applying the model to college withdrawal decisions and the influence of shocks, there are four different types of observable outcomes based on whether or not students experience a shock and whether they decide to withdraw or stay (see Table 2). Some decisions to withdraw occur following a shock (Outcome I). These decisions would be called *hits* in most signal detection theory applications.Other decisions to withdraw occur when a student does not experience a shock (Outcome III). These decisions would typically be called *false alarms* under signal detection theory. In comparison, a decision to stay might also occur following a shock (Outcome II) or not (Outcome IV). Conditionalizing on the presence or absence of a shock the rates of Outcome II and Outcome IV can be found if the rates of Outcomes I and III are known, respectively.

A signal detection account of college withdrawals and turnover in general is not at odds with the unfolding model. We can map the decision paths of the unfolding model(Table 1) onto the possible outcomes of signal detection theory (Table 2). However, we can also see the mapping is a many-to-one mapping. Paths 1, 2, and 3, for example, only occur after a shock and thus map onto Outcomes I and II in Table 2. This many-to-one mapping implies that there is not a straightforward way to use signal detection theory to identify the different pathsstudents took to reach their decision. Instead,we use signal detection theoryas a tool to examine several properties about the underlying decision process to withdraw from a university.

Our first question concerned students' sensitivity to different potentially shocking events. One advantage of signal detection theory models is that they provide natural measures of sensitivity. In traditional laboratory applications of signal detection theory, sensitivity refers to observers' discrimination between a signal and background noise. In the context of student withdrawal, sensitivity refers to the discrimination between shocks and background or "everyday" events. To arrive at a measure of sensitivity, the proportion of individuals withdrawing after experiencing a shocking event, $p(withdraw \mid shock)$ (or Outcome I in Table 2) is compared to the proportion withdrawing who did not experience a shock, $p(withdraw \mid everyday\ events)$ (or Outcome III in Table 2). In other words, higher sensitivity reflects higher turnover rates for those who experience the shock relative to turnover rates of those who do not experience the shock. To illustrate how the difference between the two rates forms the basis of our sensitivity measure, we will use the Gaussian signal detection model.

The basic Gaussian signal detection model assumes that when deciding whether to withdraw from an institution, students form an internal level of evidence$x$. In the model, without experiencing a shock,the distribution of evidenceis normally distributed with a mean of 0 and with a standard deviation $s_{everyday}$. Likewise after a shock, the distribution of evidence is normally distributed with a mean of d' and a standard deviation of s_{shock}. Thus, shocking events as well as everyday events give rise to variable levels of evidence. A Gaussian signal detection model is illustrated in Panel A of Figure 1.

To make a decision, students compare this internal level of evidencewith a response criterion*k* (solid black line in Panel A of Figure 1). This criterion represents a threshold of evidencethat must be exceeded in order to justify leaving. That is, if the internal level of evidence*x*is greater than the criterion *k*, then the student withdraws from the university.Thus, the response criterion *k* indexes different biasesthat students have due to, for example, the costs and benefits associated with withdrawing or persisting. As *k* gets smaller (*k* moves to the dotted lines marked a and b in Panel A of Figure 1) the more biased a student becomes to withdraw, regardless of the precipitating events. If we specify the values of *d*', s_{normal}, s_{shock}, and a value for *k* (e.g., at the bolded criterion labeled as *c* in Figure 1), we can use the model to calculate the predicted probabilities of the different outcomes in Table 2. Note that to account for rating data, where a student rates on a scale from 1 to 5 their intent to withdraw (the response mode of our study), the Gaussian model uses four response criteria as shown in Figure 1 and assumes that students map a rating according to where their evidence falls relative to the response criteria.

We can see in this model a good measure of sensitivity would be *d*' or the average difference between the evidenceproduced from shocking events as compared to everyday events. In fact, if we assume that standard deviations are equal to one ($s_{normal} = s_{shock} = 1$), then we can algebraically estimate *d'* using the observed proportion of students withdrawing after experiencing a shock (Outcome I) and those withdrawing after experiencing everyday events (Outcome III),

$$d' = z\,[\,p(withdraw \mid shock)\,] - z\,[\,p(withdraw \mid everyday\ events)\,] \qquad (1)$$

The function *z*is the *z*-score transformation of the observed proportion assuming a standard normal distribution.

One desirable attribute of*d'* as a measure of sensitivity is thatit is independent of the intensity of a shock that a student must feel in order to form withdrawal intentions (the size of the criterion *k*). To illustrate its independence, we have plotted Receiver Operator Characteristic (ROC) curves in Panel B of Figure 1. The probability of withdrawing given an experience of everyday events is on the *x*-axisand the probability of withdrawing given an experience of a shocking eventis on the *y*-axis. Each curve represents a different hypothetical level of sensitivity to shocks. Looking at the ROC curve for *d*' = 1, one can see that even if a choice criterion is at the different locations in Panel A (*a*, *b*, *c*, or *d*), these points will still fall on the same ROC curve. Increasing sensitivity (*d*') moves the ROC curve to the upper left and decreases move the curve to the lower right.

A weaknessof *d*' is that it is specific to the equal-variance Gaussian model. A measure of sensitivity that is relatively model free is the area under the ROC curve, *A*(Green &Swets, 1966; Pollack & Hsieh, 1969).The area measure increases from *A* = .5 at no sensitivity (i.e., the underlying distributions perfectly overlap) to*A* = 1.0 for maximum sensitivity (i.e., there is no overlap in the underlying distributions) The ROC curve in Panel B of Figure 1 displays the area under the ROC for different levels of *d'* in the equal-variance Gaussian signal detection model. To address our question of sensitivity to different shocks we first used the area under the ROC statistic, *A*, to assess how sensitive college students across ten U.S. colleges and universities were to 21 potentially shocking events. This, however, raises the question as to whether the Gaussian signal detection theory model is the best model of the decision process or if other detection models would better describe the decision process. To address this second question, we conducted a model comparison analysis thatcan help us make firmer statements of how well the Gaussian model describes the data compared to other competing detection models.

Model Comparison and Underlying Properties of the Decision Process

Gaussian model. The Gaussian signal detection model tests the idea that a shock (or lack thereof) produces some graded/continuous internal level of evidence and the decision is based on whether a criterion level of evidence is observed. Furthermore, in the model the evidence is normally distributed. The Gaussian model has been successful in accounting for a number of decision processes across cognitive psychology from recognition memory (Ratcliff et al., 1992) to other higher-order decisions (Wallsten, Bender, & Li, 1999) as well as in applied settings including lie detection (Ben-Shakhar, Lieblich, Bar-Hillel, 1982), clinical assessment (McFall& Treat, 1999), and stress assessment in cardiac patients (Young, Ignaszewski, Fofonoff, &Kaan, 2007).

The properties of the Gaussian model also appear to be consistent with image theory's compatibility test (Beach & Mitchell, 1998). Recall the compatibility test is used in path's 2 and 3 in the unfolding model where an individual compares his or her present surroundings with personal standards defined by values, expectations, and/or goals to determine if leaving is an appropriate option (Table 1). In image theory, these personal standards are called images and the compatibility test examines if the environment is consistent with these images or if there is a violation. According to image theory (Beach &Michell, 1998), "Each violation is all-or-none. The decision rule is that if the weighted sum of the violations exceeds some absolute rejection threshold" (p. 15). In other words, within the unfolding model the decision to leave is based on a graded level of evidence and using the central limit theorem as the number of violations increases the distribution of the sum of the violations will be approximately normally distributed.

*Threshold models.*Within signal detection theory, an alternative hypothesis is that of discrete internal evidence states. In this case, a shock might put a student in a state of uncertainty, a state of certainty that he or she will leave (conviction), or a state of certainty that he or she will quit (assurance). Returning to the unfolding model, this would be akin to the compatibility test *not weighting or summing*, but only registering a violation.Finite state or threshold models in signal detection theoryinstantiate this discrete-state assumption and have proven helpful in understanding aspects of memory (Batchelder&Riefer, 1990; Bayen, Murnane, &Erdfelder, 1996) as well as in psychological assessment (Batchelder, 1998; Riefer, Knapp, Batchelder, Bamber, & Manifold, 2002). Thus, comparing the fit of threshold models to the Gaussian models can help investigate the basic underlying architecture of the decision to quit.

A useful threshold-model that captures the basic idea of the unfolding model is a three-state model shown in Figure 2 (cf. Wickens, 2002). The model has three discrete evidence states labeled as assurance, uncertainty, and conviction. The three-state model in Figure 2 also illustrates how response ratings of intent to withdraw (the structure of our data) were incorporated within this class of models.According to the model, after students experience a shock there is a probability α the student enters an evidence state of conviction. Once a student enters this state of conviction, then with probability of 1.0 he or she withdraws or in terms of intent "Strongly Agrees" with the statement that he or she intends to withdraw. This is analogous to the unfolding model's Path 1 where once a student experiences a shock he or she leaves without deliberation. Alternatively, after experiencing a shock with probability 1 – α the student can enter a state of uncertainty. In terms of the unfolding model, this would be the state of misfit where an individual's surroundings do not match his or her goals, values, or expectations. From this state the student decides what the best course of action would be. In our case, as Figure 2 illustrates, this is the state from which different levels of ratings can emerge so that with probability γ_i rating *i* is given under the constraint that $\Sigma\gamma_i = 1$. If we were modeling a simple binary decision to stay or withdraw, then with probability γ the student would stay and with probability $1 - \gamma$ the student would withdraw.

If a student experiences a normal event,then with probability $1 - \beta$ he or she also enters a state of uncertainty. This we suggest is analogous to Paths 4a and 4b in the unfolding model (see Table 1). Alternatively after experiencing normal events the student with probability β enters(or stays in) a state of assurance. If the student is in a state of assurancethen the he or she will stay with probability 1.0 or in terms of a rating the student “Strongly Disagrees” with the statement that he or she intends to withdraw.

As the discussion of the three-state model illustrates, besides helping test the assumption of whether the internal state produced from a shock is continuous or discrete, the three-state model can potentially help test hypotheses about the possible paths that are needed to account for the data. For example, if after fitting the model the probability of entering a state of conviction is approximately zero ($\alpha \approx 0$) then we would arrive at what is called a low-threshold model, implying that a third state (the conviction state) is not necessary to account for the data on hand. This would also imply that perhaps Path 1 in the unfolding model is not necessary to account for intent to withdraw. Alternatively if $\beta \approx 0$ then the assurancestate is not needed and we arrive at another common threshold model called a high-threshold model(Blackwell, 1963). This model also has a psychological interpretation implying there is no decision path that results in a student certainly staying.

Summary

In summary, we have adapted a signal detection framework to account for the decision to withdraw from a university or college and transfer to another. Next, we use the model to measure the strength of student responses to a variety of different events that might be considered shocks. We also tested whether a Gaussian signal detection model or threshold model better accounts for the underlying decision process. To address these questions, we used data collected from one wave of a longitudinal study of student performance across ten U.S. colleges and universities. Our analysis focused on the intentions of students to withdraw and transfer to another college or university. This focus was due in part to the more frequent endorsement by respondents to transfer (as compared to simply dropping out or withdrawing to enter the workforce). More generally, though, transfer decisions make up a larger proportion of withdrawals,reflecting an increasing trend toward unstable student enrollment due to “institution switching” (Herzog, 2005). We were interested in particular events that might prompt a student to change institutions. The first year of attendance poses an especially high risk of flight; hence, we concentrated our research sample and analyses on intent to transfer after the freshman year of college. We describe the data and the methods used to collect it next.

Method

Sample

The data were collected in the context of a longitudinal study aimed at developing and testing alternative predictors of student performance. The longitudinal study took place in four different waves. During the first wave a total of 2,771 freshman students at ten colleges and universities across the United States participated in the study during their freshman orientation on a voluntary basis. Students were deliberately sampled from participating universities that were diverse in terms of region of the country; one was in the Southwest, two were historically

Black colleges in the Southeast, five were Big Ten Midwestern universities, one was in the Southeast, and one was a highly selective private Midwestern school. The numbers of participants in each of the original set of schools ranged from 139 to 464.

The measures for the present analyses were collected in the second wave near the end of students' first semester of college. A total of 2,631 students from the original sample agreed to be contacted for future participation; 1,234 responded to the survey in the fall (47%); and 1,158 provided enough responses to be included in our analyses and comprised our final sample. Responses were made on an online survey. As compensation for their time, participants were given a $20 gift certificate to a major retailer and were entered into a drawing for a $100 cash prize.

The average age of the sample was just over 18 years and 66% of the sample was female. Ninety-four percent were U.S. citizens, and 94% indicated that English was their native language. Sixty-five percent reported being Caucasian, 10% African American, 12% Asian, 6% Hispanic, and 5% other ethnicities (2% did not respond).[1] Participants were diverse in terms of intended major with over five colleges represented (e.g., business, engineering),each major comprising no more than 20% of the sample.

Materials

Intentions to dropout/transfer.We asked students three questions regarding their intent to withdraw from their current university. First, they reported whether they intended to be enrolled at their school 6 months from the time of the survey. Second, they indicated whether they intended to transfer to a different school at or before the end of the academic year. Last, they rated their intentions to leave school and get a job at or before the end of the academic year. All responses were made on a 5-point scale (1 = *Strongly disagree* to 5 = *Strongly agree*). As previously mentioned, we focused our analyses primarily on the intent to withdraw and transfer to a different school (i.e., the second question). This item was more frequently endorsed than either of the other withdrawal items (over two-fold).

We chose to measure intentions as they are the best predictors of behavior, with prediction improving the closer together the measurements are taken (Fishbein&Ajzen, 1975). Employee turnover models almost invariably place intentions as the most proximal measure to the actual turnover decision (e.g., Mobley, Griffeth, Hand, &Meglino, 1979), and meta-analyses have shown that quit intentions are the single best predictor of employee turnover (Griffeth, Hom, &Gaertner, 2000; Hom et al., 1992). This is also consistent with literature on college withdrawal (Bean, 1980, 1982). Bean (2005) stated that “in every study of residential students I have participated in, the intent to leave (or stay) variable was the best predictor of actual student departure from college” (p. 218). Therefore, in all of our analyses we assume that with respect to students’ decision process, intent to withdraw should be a direct predecessor to actual withdrawal with most other factors influencing withdrawal through intentions. Lastly, the use of rated intent is consistent with the use of confidence ratings in testing signal detection models in cognitive psychology (Macmillan &Creelman, 2005; Wickens, 2002).

Withdrawal deliberations. In addition to assessing intent to withdraw and transfer, we also measured students’ turnover deliberations (e.g., “I am considering transferring to another school”) on a rating scale (1 = Strongly disagree to 5 = Strongly agree). Several models of employee turnover (see Maertz& Campion, 1998) including the unfolding model (Lee & Mitchell, 1994; Lee et al., 1996) specify deliberations as one precursor to intent to withdraw and eventual withdrawal.

Shocks.In a later portion of the survey, participants indicated whether or not each of the 21 events listed in Table 3 “happened to me”during college. We generated the list of shocks based on our own experiences and observations of college life as well as from two additional sources. First, a focus group (*n* = 11) was conducted with undergraduate students who were asked to identify sudden, major events that might make students withdrawor consider withdrawing. Second, an undergraduate director in charge of student petitions to dropout was interviewed in order to derive additional themes or issues regarding reasons for student withdrawal. The final list comprised 21 events of a shocking nature. Sample items include “Lost financial aid” and “Death or illness of a family member.” The full set of items is listed in Table 3. Only item 3 (pregnancy) was gender specific in that it read “became pregnant” and participants indicated whether it “happened to me”. Consequently, we only used female responses for this item; all other analyses in Table 3 collapse across genders. In the survey, selfreports of experiencing (or not experiencing) a shocking event were collectedwell after rated intent to transfer, with a large number of unrelated intervening items being asked. This was done to minimize possible biases and/or item priming effects (Podsakoff, MacKenzie, Lee, &Podsakoff, 2003).

Results

The results section is organized as follows. To address our first question regarding the sensitivity of students to different shocks, we estimated ROC curves for each potential shock and calculated the area under the ROC curve. Next we used maximum likelihood methods (described later) to fit different detection models to the data to identify a particular model that can best characterize the decision process to withdraw from a university.Finally, after identifying the best fitting model,we use a more powerful but model-specific measure of sensitivity to re-examine our original question of sensitivity to potentially shocking events.

ROC Analyses of Sensitivity to Potentially Shocking Events

As a first step, we estimated ROC curves for each event using our respondents' ratings on their intent to withdraw and transfer to a new college or university. The basic data structure is a 2 (shock or not) x 5 (rated intent to leave) contingency table conditional on each shock. To estimate empirical ROC curves from the data, we used methods developed in signal detection theory to form ROC curves from confidence ratings (Macmillan &Creelman, 2005; Wickens, 2002). The basic idea is that each rating is considered a choice at a different level of the response criteria (*a*, *b*, *c*, or *d* in Panel A of Figure 1). The frequency of students withdrawing, for example, at the criterion for the intent rating of 4 is the cumulative frequency of ratings at or below 4. This was done for both the group of participants reporting a particular shock (e.g., tuition increase) and the group not reporting a particular shock. Using this method for each shock we calculated four different estimates of withdrawal rates conditional on experiencing a shocking event and an everyday event. These estimates then were used to form an empirical ROC curve. Thus, in the end, assuming homogeneity across subjects, we had 21 empirical ROC curves.

Table 3 lists the area under the ROC, *A*, for each of the 21 shocking events. Recall that for events that are not very shocking *A* will be approximately .5 and as the effect of the shock increases the area will grow larger than .5. The shocks that produced*A*s significantly different from .5 are bolded.[2]Only three of the 21events were significantly different from .5: (a) if a student was recruited by another job or institution; (b) if a student reported being clinically depressed; and (c) if a student experienced a large increase in tuition and/or living expenses.[3] There were also several shocks that had a comparable effect in terms of *A*, but were not significant. This we suspect is due in part to differing levels of base rates across the shocks. The sample size and base rates for each shock are listed in Table 3. For example, there were only 5 reported pregnancies out of 732 (0.7%) female responses.

Out of a concern that we were merely capitalizing on chance, we sought further evidence that the ROC analyses can help identify shocking events in terms of students withdrawing from a particular college and transferring to another institution. One set of results that imply the ROC analyses are revealing meaningful relationships are respondents' self –reported *deliberation* to transfer to another school. A consistent finding in voluntary employee turnover research is that the intention to quit is the closest antecedent to actual turnover, whereas an individual's reported thoughts of quitting (i.e., withdrawal cognitions) occur earlier in the decision process (Hom et al., 1992; Mobley, 1977; Mobley et al., 1979; Mobley, Horner, & Hollingsworth, 1978). Thus, we expected that students' deliberative thoughts to transfer should be more proximal to the shocking event and as a result should show greater sensitivity to the event.

Table 4lists the results of the estimated ROC curves for students' reported deliberations to transfer to another school. Notice that the ROC analysis with reported deliberations identified the same three shocks as having *A*s significantly different from .5 as did the analysis of the intent to transfer response.We interpret this as converging evidence that students are particularly sensitive to these three shocks. Consistent with the hypothesis that deliberation is more proximal to the shocking event, the ROC analysis with the deliberation response identified six additional shocks for which *A* was significantly different from .5 (see Table 4). Furthermore, *A* was larger when using deliberation as opposed to intention to transfer for most of the shocks (14/21; $p <$ .05).

The empirical ROC curves are shown in Figure 3for the three shocks that had significant *A*s using the response of intent to transfer. The figures highlight two observations. The first observation is that, as the area *A* estimates indicate, the ROC curves do not exemplify the high levels of sensitivities typically found in other signal detection analyses (e.g., *d*' > 1 or *A*> .76), such as in recognition memory (e.g., Ratcliff et al., 1992) or psychophysical studies (e.g., Macmillan &Creelman, 1990). One explanation for these weaker effects is the fact that most signal detection analyses are conducted with laboratory data collected under very controlled settings. Our data, in contrast, were collected in the field,where the outcome likely has multiple determinants that constitute "noise" in ROC analyses (e.g., we may not have listed an important shock, participants may have inaccurately reported their experience of a shock, and/or there is substantial inter-participant noise in rating one's intent to withdraw). A second (and related) explanation is that the shock could have occurred at any point during the respondent's first semester at school. Thus, because the survey was completed at the end of the first semester, the distancebetween the shock and their rated intention to transfer may have dampened our assessment of the sensitivity of individuals to a shock. A second observation is that theROC curves of the individual shocks plotted in Figure 3 fall in the lower left quadrant. In other words, the estimated conditional withdrawal rates (*p(withdrawal|shock)* and *p(withdrawal|everyday event)* fall below .5 for all three shocks. This makes model comparisons at the individual shock level difficult because most models make similar predictions in this quadrant.

Detection Model Comparison

There are, however, a number of benefits in identifyingthe best fitting detection model including increasing statistical power of our sensitivity analyses and acquiring a better understanding of the underlying decision process. In light of these benefits, we conducted a model comparison to provide some insight into the best fitting detection model. To increase the power of our model comparisons, we collapsed acrossthe three shocks identified with the area under the ROC curves as significant (clinically depressed; recruited by other job/institution; change in tuition/financial status) and treated any individual who reported at least one of these events as experiencing a shock. All other individuals were coded as not experiencing a shock. This produced n = 1,119 usable cases (39 failed to provide responses on these three items or intent to transfer) of which 29.7% reported experiencing at least one of the three shocks. Out of these individuals, 85.3% experienced 1 of the three shocks; 13.9% reported experiencing 2 of the three shocks; and .9% reported experiencing all three shocks. The ROC curve for this collapsed variable is plotted in panel D of Figure 3. The area under the ROC is A = .57 (.02), p< .01.

We fit six different models to the response proportions and two baseline statistical models using maximum likelihood methods. A description of the specific models is given in Table 5. The different detection models test different hypotheses about the underlying decision process. For example, the Gaussian models assume a continuous level of unobservable evidence, whereas the threshold models posit discrete unobservable states. Within each of those sets of models, we can constrain the model parameters to test even more specifichypotheses. The Gaussian equal variance model tests the hypothesis that the distribution variances for everyday and shocking events are equal. Similarly, the low threshold model tests the hypothesis that a low threshold process, where $\alpha = 0$ in the three-state model (i.e., automatic quitting does not occur), best characterizes the decision process to withdraw and transfer to a new institution.

The first baseline model is a saturated baseline model that assumes no decision process and simply uses the empirical response proportions conditional on experiencing a shock or not to calculate the likelihood of the data. The model is saturated – the number of free parameters equals the degrees of freedom (df= 8). As a result, the saturated model can perfectly reproduce the data. This baseline model allows statistical differences to occur between shocks, but does not posit an underlying decision process. The second baseline model listed at the bottom row of Table 5 also assumes no decision process, but uses the marginal response proportions collapsed across experiencing a shock and not experiencing a shock to calculate the likelihood of the data. It, thus, has four free parameters and basically assumes no effect of shock. Assuming a decision process underlies the intent to withdraw, the detection models should do better than both of these models.

The models were fit using maximum likelihood methods where the likelihood function for all the models is based on a multinomial distribution.[4]We used the Bayesian Information Criterion (BIC; Kass&Raftery, 1995; Raftery, 1995; Schwarz, 1978; Wasserman, 2000) to make our model comparisons. The BIC is calculated for each model according to the following expression

$$BIC = -2ML_i + j_i log(n). \tag{2}$$

Where ML_i is the maximum log-likelihood of model i, j is the number parameters in the model, and n is the number of observations. The model with the smallest BIC is selected as the best fitting model.[5] The number of parameters in the expression serves as a handicap for model complexity, where models with more parameters tend to overfit the data and therefore the BIC ishandicapped more. As a rule of thumb, based on the BIC's Bayesian roots, a BIC difference of 2 or less is interpreted as weak evidence, 2 to 6 as positive evidence, 6 to 10 as strong evidence, and greater than 10 as very strong evidence, for the particular model (Raftery, 1995; Wagenmakers, 2007).

The last column in Table 5 lists the BIC value for each model. Several observations can be made based on the BIC values. The first observation is that except for the high threshold model, all the detection models give a better fit than either of the two statistical baseline models. This implies that a model of the decision process adds some explanatory power beyond simply a statistical description. Another observation is that the low-threshold model ($\alpha = 0$) is the best fitting model of the threshold models. This is informative especially for the unfolding model. This implies that the unfolding model's Path 1 where once a person experiences a shock it is automatic that he or she will leavemaynot be necessary to account for the data. Finally, according to the model comparisons with BIC, across all models the Gaussian equal variance model is the best fitting model.

As a final model comparison method, we can also examine the fits of the models to the data. We have plotted the fits of the Gaussian equal variance model and the low threshold model to the ROC curves of the individual shocks as well as the collapsed shock variable in Figure 3.Visually, they show the fits for both models are similar. However, for clinical depression and the collapsed shock variable, the Gaussian equal variance model better describes the data. Taking the visual inspection of the fits together with the BIC index of fit, we conclude that the model that best describes the data is the Gaussian equal variance model. This result, in turn, implies that a more precise process account for the decision to withdraw or quit is not in terms of discrete states, but in terms of a continuous level of evidence.Because of the good fit of the Gaussian equal-variance model, we re-examined our original question regarding which shocks most affect students' rated intent to withdraw and transfer to another university.

d' Analyses of Sensitivity to Potentially Shocking Events

The nonparametric measures of the area under the ROC and empirically estimated ROC’sthat we previously used together underestimate the “true” area under true ROC curves (see Donaldson & Good, 1996; Macmillan &Creelman, 2005). A model-based analysis of shock sensitivity is potentially a more powerful approach. The maximum log-likelihood estimates of *d*’ obtained from fitting the Gaussian equal variance model to the response proportions for the intent to quit from each shock are listed in the right-hand side of Table 3.[6]Indeed, this re-analysis of sensitivity confirmed the significance of the three previously-identified shocks(recruited by other job/institution; became clinically depressed; and a large increase in tuition/living costs), and also found four additional shocks to be significant(unexpected bad grade; roommate conflicts; became ill; unable to enter intended major at school) for which the *d*’ was significantly different from 0. Note again that some events displayed a relatively large effect size compared to others (pregnancy, lost financial aid, became addicted to a substance), but were not significant, likely due to a low base rate of these events occurring (well under 10%).

Discussion

This study integrated theoretical frameworks of employee turnover with signal detection theory to better understand students’ decisions to withdraw from their current university and transfer to another institution. Using a dataset collected across 10 U.S. universities and colleges, the analysis identified seven events that could be considered significant predictors of intent to turnover. Three shocks that students were particularly sensitive to were (a) being recruited by another job/institution; (b) suffering from clinical depression; and (c) experiencing changes in tuition or financial status. A model comparison analysis also revealed that an equal variance Gaussian function best represents rated intent to withdraw from their current university and transfer to another institution. In the remaining sections of this discussion we will review the theoretical implications of these results in terms of understanding what events are particularly shocking to college students as well as the consequences of the equal variance Gaussian model and the predictions it makes.

What Do the Shocks Tell Us?

Signal detection theory (Green &Swets, 1966)offered a theoretically meaningful method to measure how sensitive students were to different potentially shocking events. The ability to identify what events are shocking has implications for the nature and timing of useful student interventions. For example, learning that students are particularly sensitive to being recruited by other jobs / institutions impliesinstitutionsmay want to adjust their recruitment strategiesso that they do not end after a student enrolls, but continue after enrollment. Such a recruitment strategy could potentially serve two roles: (a) make students feel sought after even after they arrive at the institution; and (b) better identify factors (e.g., jobs) that can keep students at a particular institution.

While one should always be cautious in interpreting null results, the analysis is also potentially informative in terms of what shocks do not have a large impact on the decision to withdraw and transfer. Across our analyses (whether we used the area under the ROC, *d*', intent to transfer or deliberating about transferring) there were a number of events which consistently had little to no effect: theft, assault, death or illness of a family member, conflict with a faculty member, a family member who lost job,losing ajob that was needed to pay tuition, and becoming engaged.Knowing what events are not shocking suggests, for example, that an institution seeking to help students deal with these traumatic events would be best served in helping them cope with the event at hand as compared to addressing whether or not they intend to withdraw.

NewPredictions from aSignal Detection Model of Quit Decisions

New predictions at multiple levels of analysis also emerge from the signal detection model of college withdrawal decisions. For example, while shocks are hypothesized to influence the internal levels of evidence, signal detection theory provides – via the decision criterion – a way to index factors that influence the bias students might have towards withdrawing.For example, if we assume that the costs of withdrawing increase as students progress in college, then one would hypothesize that their decision criterion would increase so that independent of the level of the shock the amount of evidence one must feel to decide to withdraw gets higher as tenure at school increases. A realization of this hypothesis within the equal variance Gaussian model can produce an intuitive quantitative prediction: college withdrawal rates decline at a diminishing rate as tenure increases (see left-hand panel of Figure 4).[7, 8]

To examine the same tenure-at-school question with threshold models we used the probability γ a student stays if they are in an uncertain state. Recall in these models for binary decisions there is a probability γ that the student will stay and a probability $1 - \gamma$ that the student will withdraw from the uncertain state. This parameter γ is similar to the Gaussian decision criterion *k*parameter. Using the better-fitting low threshold model ($\alpha = 0$ in Figure 2), we can then model the effect of increasing grade level as increasing the probability γ that the student stays when he or she enters the uncertain state. Doing so reveals that the low-threshold model(and most other finite state models) predict a linearly decreasing withdrawal rate (see right hand side of Figure 4).[9]In contrast, intuition (Pantages&Creedon, 1978) and past data (Kohen, Nestle, & Karmas, 1978) suggest – like the Gaussian equal variance prediction – withdrawal rates decrease at a diminishing rate as grade level increases.

Although our own data are limited in terms of looking at withdrawal rates across grade levels, data from one large Midwestern institution in our dataset is consistent with this predicted pattern where withdrawal rates were 15.5% after year 1, 9.2% after year 2, and 5.4% after year 3.[10]This curvilinear relationship is not limited to student withdrawals. Employee turnover rates also decrease at an increasing rate as employee tenure increases (Hom, Roberson, & Ellis, 2008). Thus, theGaussian model provides a quantitativeaccount of a macro-level phenomenon that appears consistent with the micro-processes of student withdrawal and employee turnover decisions.

The signal detection model also opens up a range of similar multi-level analyses that allow comparisons between college withdrawal decisions and employee turnover. For example, while males have larger withdrawal rates than females (46 vs40%) from four-year colleges (Knapp et al., 2009),this pattern reverses in the workplace. Hom et al. (2008), for example, report that female managers and executives quit at a rate of 4.88% whereas their male counterparts quit at a rate of 3.20%. Obviously there are some shocks that may be specific to gender (e.g., pregnancy), which might account for the reversal between college and the workplace.For the shocks that are not gender specific, the Gaussian model offers three non-exclusiveexplanations for this pattern reversal: changes in sensitivity (*d*'), changes in bias or response criterion (*k*), and/or changes in base rates of shocking events. In our college sample,we found little difference between genders in terms of sensitivity. Using our collapsed shock variable, males had a sensitivity of d'= 0.38 (SE = 0.10) while females had d' = 0.37 (SE = 0.08). In terms of base rates, if anything, females (30.2%, SE = 2.3)were more likely to report more shocks than males (27.6% , SE = 2.3). These results thensuggest the explanatory factor for the gender reversal between withdrawing from college and quitting a job rests with the response criterion and the associated changes in bias across the two domains. In other words, males may be more biased than females to withdraw from college due to perhaps disproportional costs of withdrawing from (and benefits of staying at)the university. But, in the workplace this bias reverses. This is an interesting shock by group interaction and deserves future attention.

Relation to Past Turnover Frameworks

As our new predictions outlined, our signal detection model of college withdrawals also gives a new perspective to voluntary employee turnover decisions. Only future empirical work will tell if generalizations of the signal detection model to employee turnover decisions aresupported. We do not think though that this new view supplants past turnover frameworks. Rather it in many ways supplements both March and Simon's (1958) more rational view of employee turnover as well as Lee and Mitchell and colleague's (Harman et al., 2007; Lee & Mitchell, 1994; Lee et al., 1996) more process oriented unfolding model. For example, according to March and Simon's (1958) the two factors that influence the utility a person puts on leaving an institution are the desirability of stating and the ease of movement. Signal detection theory suggests one way these two factors are realized within the decision process: desirability impacts sensitivity and ease of movement impacts the criterion.

In terms of the unfolding model, in many ways, the various signal detection models used in the analysis allowed us to test different aspects of the model (Harman et al., 2007; Lee & Mitchell, 1994; Lee et al., 1996). This is an important step because while the unfolding model gives a more complex and potentially more complete picture of withdrawal and turnover decisions, the model itself is difficult to test in its entirety. For example, the data used in this study had at most eight degrees of freedom (four degrees of freedom for responses from individuals not experiencing a shock and four from individuals experiencing a shock). We suspect that if the unfolding model were formalized, it would be difficult to give it fewer than eight free parameters to account for the data on hand. Thus, the model would be saturated in terms of accounting for the eight degrees of freedom within the data.

From this perspective, the signal detection framework provides a number of new ways to test hypotheses about the underlying decision process. Our analysis with the threshold model revealed, for example, that in terms of the unfolding model the relatively automatic withdrawal specified in Path 1 is not necessary to account for many typical college withdrawal decisions. This is because the maximum likelihood estimate of α was approximately 0 and the high-threshold model gave a particularly poor account of the data. In comparison, Lee et al. (1996) found via exit interviews with nurses leaving their job that 14% of them reported taking Path 1 as compared to 14% taking path 2; 32% taking path 3; and 41% taking paths 4a and 4b. The change in response mode may account for the divergence between the present dataset based on intent to withdraw and the exit interviews used with nurses. Alternatively, nurses might have well scripted exit plans. Nevertheless, we think this ability of the threshold models to test which paths students or employees take to voluntarily quit demonstrates an asset of the signal detection framework to efficiently identify the paths without expensive exit interviews. Future work should focus on the validity and reliability of this framework.

Our model comparison also showed that a Gaussian equal variance model provides a better account of the withdrawal intentions than any of the threshold models. This preliminary result directly supports the assumed properties of the compatibility test in the unfolding model and more generally image theory where individuals are assumed to integrate the number of image violations and then use that sample as evidence of whether leaving the university is a reasonable option (Beach & Mitchell, 1998; Lee & Mitchell, 1994). An alternative formulation not all together at odds with the unfolding model is where the student calculates some measure of fit akin to a similarity calculation such as in multidimensional scaling procedure (Shepard, 1988; Torgerson, 1965). Thisfit could serve as a proxy for this internal level of evidence and, in turn, serve as a foundation for a more detailed account of the processesimplicated in the unfolding model. A similar idea exists in formal cognitive models of categorization (Nosofsky, 1986). Such an adaptation is beyond the scope of this article, but a more precise and testable process model of quit decisions is certainly needed.

Limitations and Future work

One limitationof the signal detection model is that although it parameterizes the level of a shocking event, it does not identify the aspects of particular events that make them shocking. There are a number of possible reasons why, for instance, clinical depression affectsthe intent to transfer to another university (e.g., astudent feeling the university setting is the source of his/herdepression or, alternatively, advisors recommending some time away from the university). A more precise process model would potentially reveal the attributes associated with each of these events that lead to an intent to transfer and ultimately withdrawing from a particular college. This process model of withdrawal decisions could also speak to the plausibility of assumptions like the equal variance assumption. While this assumption is helpful in that it leads to a parsimonious model that makes calculating measures of sensitivity simple and straightforward (Equation 1), it may prove to be incorrect in future studies. If we imagine that the experience of a shocking event is akin to adding a noisy signal to everyday noisy background events (everyday events), then clearly the assumption of equal variance between shocking events and normal events is false. Indeed such an unequal variance finding is consistently found in studies of recognition memory (Nelson, 2003; Ratcliff et al., 1992).

Methodologically, our large dataset with students across the United States provided an informative first step in providing a better understanding of college withdrawals. The survey methodology had a number of advantages. One advantage is that it gave us enough power to examine how sensitive students' withdrawal intentions were to some fairly infrequent shocking events. It also afforded us the possibility to compare students who experienced a shock and students who did not. Without this methodology, a comparison between these two types of students is difficult as students who experience a shock would be, as the theory goes, withdrawing from their university.At the same time, there are limitations to this survey approach. One is that we collected information on intentions and shocks within the same session. Although we did everything possible to minimize bias and priming (e.g., asking intentions to withdraw first then asking a substantial number of unrelated questions before asking about shocks), these are still concerns. Our finding would be complemented by future studies based on exit interviews, which would allow comparisons between students who have actually chosen to withdraw and those who havenot. These interviews would also give us more insight into the time course between experiencing a shock and deciding to withdraw.

Conclusion

In this article, we integrated theories of voluntary employee turnover from organizational psychology and signal detection theory from the cognitive sciences to account for students' intentions to withdraw from college and transfer to another university. In general, the model contributes to the growing field of the computational modeling of behavior in organizations (Ilgen&Hulin, 2000). This integration provides a means to assess the impact of particular events (i.e., shocks) on withdrawal decisions while simultaneously integrating previous theory. The framework also revealed new insights for modeling withdrawal decisions, suggesting the

Gaussian equal variance model provides the best account.It also made new testable predictions regarding the effect of tenure and gender on the decision to quit school and work. The model is of both applied and basic interest. From an applied perspective, the model provides a means to measure what events students are particularly sensitive to in leading them to withdraw from the university. Thus, for example, the model can be used to help inform institutional strategic plans to help curb withdrawal rates. From the perspective of understanding the basic decision process, the model helps connect these more everyday decisions of withdrawing to a larger experimental literature examining judgment and decision processes in the lab (see for example Erev, 1998; Ferrell &McGoey, 1980; Pleskac, 2007; Treat, McFall, Viken, &Kruschke, 2001; Wallsten et al., 1999; Wallsten&González-Vallejo, 1994). Thus, the model can help serve as a bridge to help cognitive scientists scale up their models of relatively simplistic decisions that take place in the lab to account for more complex everyday decisions.

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Author Note

Timothy J. Pleskac, Jessica Keeney, Neal Schmitt, Department of Psychology, Michigan State University. Stephanie Merritt, Department of Psychology, University of Missouri-St. Louis. Frederick L. Oswald, Department of Psychology, Rice University. This material is based on work supported by the College Board. We thank RuchiSinha, Abigail Quinn, and Mark Zorzie for their input during the development of this project. We are indebted to Marcy Schafer for her careful editing of the manuscript.

Footnotes

[1]Although two historically black colleges were included in our sample response rates were lower at these institutions.

[2]Area was calculated using the trapezoidal rule and the standard error was calculated using nonparametric methods based on the multinomial distribution (Pollack & Hsieh, 1969).

[3]Identical results were obtained using the Goodman-Kruskal gamma coefficient (Goodman &Kruskal, 1954). The gamma coefficient makes even fewer assumptions than the area under the ROC when used as a measure of sensitivity in signal detection analyses (Nelson, 1986; 1987).

[4]The detection models were fit to the response proportions using Matlab®'s constrained nonlinear optimization routine based on a quasi-Newton approximation of the Hessian function.

[5]When comparing two models (M_1 and M_2), if we assume that the prior distributions over the parameters conform to certain reasonable noninformative priors and that the likelihood of the two models are equally likely then the posterior probability of M_1 given the data can be found. For more detail see Raftery (1995) and Wagenmakers (2007).

[6]Standard errors were estimated from numerical estimates of the Hessian matrix obtained from the optimization routine.For large sample sizes, taking the inverse of the element at*i*-th diagonal position of the Hessian matrix and multiplying it by -1 provides an estimate of the variance of the *i*-th parameter. If we take the square root of this element,then we have a numerical estimate of the standard error of this parameter.

[7]The hypothetical withdrawal rate for the Gaussian equal variance model was calculating assuming a base rate of .10 and then calculating the predicted withdrawal rate, $p(withdraw) = p(shock)*p(withdraw|shock) + (1 – p(shock))*p(withdraw \mid everyday\ events)$. In the Gaussian

model this was done with d' = .5 and criterion values of k = .7, 1.2, 1.7, 2.2 for years 1, 2, 3, and 4 respectively.

[8]The Gaussian equal variance model actually predicts a sigmoid relationship over the entire set of criterion values. However, if we assume withdrawal rates are generally below .5 – as empirical data suggest (see Hendrickson et al., 2004) – then for most values of d' the slope of withdrawal rates diminishes as criterion values increase.

[9]The hypothetical predictions for the low threshold model in Figure 46 were calculated setting β = .3 and γ = .3, .21, .12, .03 for grade levels 1, 2, 3, and 4, respectively.

[10]These withdrawal rates are based on actual enrollment reports. The other universities in our sample only provided GPA data, which proved to be a fairly unreliable measure of withdrawal.

Table 1

Illustration of Lee and Mitchell's (1994) Unfolding Model

	Initiating Event	→	Cognitive/emotional process	→	Search behavior	→	Quit Decision
Path 1	Shock	→	Prompts quitting script enactment	→	None	→	Automatic
Path 2	Shock	→	Prompts comparison of current situation to individual's values, expectations, and goals.	→	None	→	Fairly automatic
Path 3	Shock	→	Prompts comparison of current situation to individual's values, expectations, and goals.	→	Search for alternatives	→	Deliberate
Path 4a	No shock	→	Accumulating dissatisfaction	→	None	→	Fairly automatic
Path 4b	No shock	→	Accumulating dissatisfaction	→	Search for alternatives	→	Deliberate

Adapted from Harman et al. (2007) Table 1.

Table 2

The Different Outcomes Possible for College Withdrawal Decisions

		Decision	
		Withdraw	Stay
External Event	Shock	Outcome I	Outcome II
	No shock	Outcome III	Outcome IV

Table 3

ROC Analyses of the Twenty-one Possible Shocking Events Using Students' Rated Intent to Withdraw and Transfer

Shock	*N*	*Base Rate*	*A*(*SE*)	*95 % Confidence Interval*	*d'*(*SE*)	*95% Confidence Interval*
1. Theft	1144	10.9%	.49 (.03)	.44 < *A* < .54	0.00 (0.34)	-0.67 < d' < 0.67
2. Assault	1128	2.8%	.48 (.05)	.38 < *A* < .58	0.00 (1.01)	-1.99 < d' < 1.99
3. Pregnant	732	0.7%	.61 (.12)	.37 < *A* < .85	0.35 (0.45)	-0.54< d' < 1.24
4. Recruited by other job/institution	**1140**	**9.9%**	**.57* (.03)**	**.51 < *A* < .63**	**0.39* (0.11)**	**0.17 < d' < 0.61**
5. Unexpected bad grade	1134	58.6%	.53 (.02)	.49 < *A* < .56	0.13* (0.05)	0.04 < d' < 0.22
6. Roommate conflicts	1112	43.0%	.53 (.02)	.49 < *A* < .56	0.15* (0.06)	0.05 < d' < 0.26
7. Lost financial aid	1134	6.1%	.56 (.04)	.48 < *A* < .63	0.28 (0.14)	-0.01 < d' < 0.56
8. Became ill	1144	52.7%	.52 (.02)	.49 < *A* < .56	0.12*(0.05)	0.02 < d' < 0.22
9. Death or illness of family member	1131	18.4%	.50 (.02)	.46 < *A* < .55	0.01 (0.08)	-0.16 < d' < 0.17
10. Became clinically depressed	**1134**	**10.6%**	**.59* (.03)**	**.54 < *A* < .65**	**0.45* (0.10)**	**0.25 < d' < 0.66**
11. Close friend/significant other left school	1138	9.0%	.53 (.03)	.47 < *A* < .59	0.19 (0.12)	-0.05 < d' < 0.43
12. Became addicted to a substance	1137	3.1%	.57 (.05)	.47 < *A* < .68	0.34 (0.19)	-0.04 < d' < 0.72

13. Conflict with a faculty member	1139	8.1%	.50 (.03)	.44 < *A* < *.57*	0.05 (0.13)	-0.2 < d' < 0.29
14. Came into a large sum of money	1139	5.7%	.52 (.04)	.45 < *A* < *.59*	0.11 (0.15)	-0.18 < d' < 0.41
15. Family member lost job, family in need of financial help	1138	13.2%	.48 (.03)	.43 < *A* < *.53*	0.00 (0.26)	-0.51 < d' < 0.51
16. Lost job that was needed to pay tuition	1140	2.3%	.51 (.06)	.40 < *A* < *.62*	0.07 (0.24)	-0.39 < d' < 0.54
17. Large increase in tuition/living costs	**1139**	**13.3%**	**.55* (.03)**	**.50 < *A* < *.60***	**0.22* (0.10)**	**0.04 < d' < 0.41**
18. Experienced a significant injury	1132	5.5%	.55 (.04)	.47 < *A* < *.63*	0.24 (0.15)	-0.05 < d' < 0.53
19. Became engage or married, or entered a civil union	1134	1.7%	.41 (.06)	.30 < *A* < *.53*	0.00 (0.77)	-1.52 < d' < 1.52
20. Received a job offer	1120	15.9%	.52 (.02)	.48 < *A* < *.57*	0.13 (0.09)	-0.04 < d' < 0.31
21. Was unable to enter intended major at school	1138	3.7%	.57 (.05)	.48 < *A* < *.66*	0.36* (0.18)	0.01 < d' < 0.71

Only female response were used for item 3 (whether a person experienced a pregnancy or not).* = p< .05 Bolded items identify shocks for which A was significantly different from .5.

Table 4

ROC Analyses of the 21 Possible Shocking Events Using Students' Rated Deliberation to Withdraw and Transfer

Shock	*A (SE)*	*95 % Confidence Interval*
1. Theft	.50 (.03)	.45 < *A* < *.56*
2. Assault	.56 (.06)	.45 < *A* < *.67*
3. Pregnant	**.74*(.07)**	**.60< *A* < *.88***
4. Recruited by other job/institution	**.58* (.03)**	**.52 < *A* < *.64***
5. Unexpected bad grade	**.55* (.02)**	**.51 < *A* < *.58***
6. Roommate conflicts	**.54* (.02)**	**.51 < *A* < *.58***
7. Lost financial aid	**.57* (.04)**	**.50 < *A* < *.64***
8. Became ill	.53 (.02)	.50 < *A* < *.56*
9. Death or illness of family member	.50 (.02)	.45 < *A* < *.54*
10. Became clinically depressed	**.61* (.03)**	**.56 < *A* < *.67***
11. Close friend/significant other left school	**.57* (.03)**	**.51 < *A* < *.63***
12. Became addicted to a substance	.54 (.05)	.45 < *A* < *.63*
13. Conflict with a faculty member	.55 (.03)	.48 < *A* < *.61*
14. Came into a large sum of money	.51 (.04)	.44 < *A* < *.58*
15. Family member lost job, family in need of financial help	.52 (.03)	.47 < *A* < *.57*
16. Lost job that was needed to pay tuition	.52 (.06)	.41 < *A* < *.64*
17. Large increase in tuition/living costs	**.56* (.03)**	**.51 < *A* < *.60***
18. Experienced a significant injury	.50 (.04)	.42 < *A* < *.58*

19. Became engage or married, or entered a civil union	.53 (.07)	.39 < *A* < .*67*
20. Received a job offer	.53 (.02)	.49 < *A* < .*58*
21. Was unable to enter intended major at school	**.60* (.05)**	**.50 < *A* < .*69***

Only female response were used for item 3 (whether a person experienced a pregnancy or not).

* = p< .05   Bolded items identify shocks for which A was significantly different from .5.

Table 5

Summary of Detection Models and Indices of Goodness of Fit

Model	Hypothesis	Parameter Constraints	No. Free Par.	BIC
Saturated Baseline	No decision process. But different response proportions when responding to a shock or not.		8	2,150.49
Gauss	A shock gives rise to a continuous unobservable level of evidence which is normally distributed	Free: d'; s_{shock}; $k_{1,2,3,4}$	6	2,137.88
Gauss Equal Variance	A shock gives rise to a continuous unobservable level of evidence. The evidence is normally distributed and variances of normal and shocking event distributions are equal.	Free: d'; $k_{1,2,3,4}$ Fixed: $s_{normal} = s_{shock} = 1$	5	2,131.31
Gauss No Sensitivity	A shock gives rise to a continuous unobservable level of evidence. Evidence is normally distributed. The means of the distributions are the same, but the variances differ.	Free: s_{shock}; $k_{1,2,3,4}$ Fixed: $d' = 0$	5	2,139.77
Three State Threshold	There are three internal states (conviction, uncertainty, assurance). Our assumption is that	Free: α; β; $\gamma_{1,2,3,4}$	6	2,142.16

	only if one is in an uncertain state does the person respond with intermediate ratings.			
Low Threshold	There are two internal states (uncertainty and assurance). A shock puts a student into a state of uncertainty. If a student does not experience a shock then they are in an uncertain state with prob. β; otherwise they are in a state of assurance.	Free: α; β; $\gamma_{1,2,3,4}$ Fixed: α = 0	5	2,136.81
High Threshold	There are two internal states (uncertainty and conviction). A shock puts a student into a state of conviction with prob. α; otherwise they are uncertain. If a student does not experience a shock then they are in an uncertain state.	Free: α; $\gamma_{1,2,3,4}$ Fixed: β = 0	5	2,148.15
Constrained baseline model	No decision process. The likelihood is the marginal response proportions.		4	2,145.58

Figure Captions

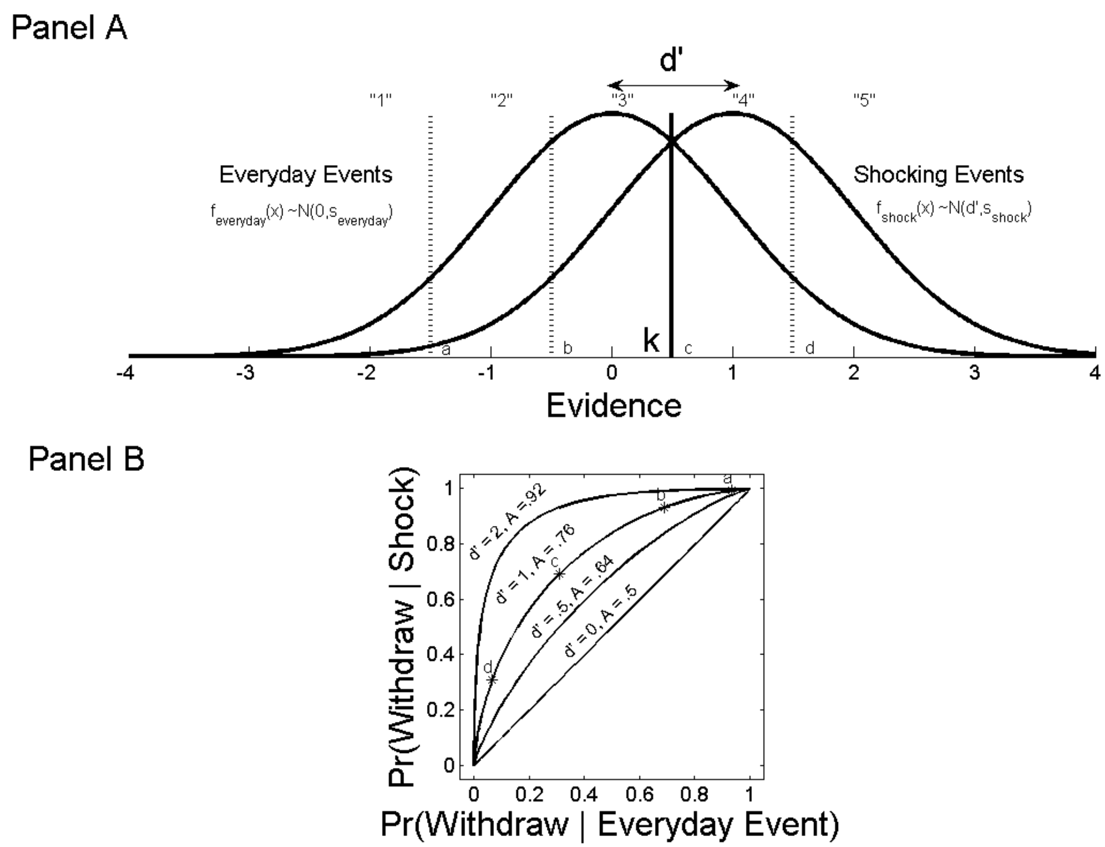
Figure 1. The Gaussian equal variance model of college withdrawal decisions.

Figure 2. A three-state model of college withdrawal decisions.

Figure 3. The ROC curves for the three individual shocks identified with the area under the curve analyses.

Figure 4. Hypothetical withdrawal rate functions for the Gaussian equal variance and the low threshold models calibrated to approximate plausible withdrawal rates.

Figure 1.The Gaussian Equal Variance Model of College Withdrawal Decisions.



Panel A illustrates the model and its associated parameters. The model assumes that at the time of a decision an individual forms an internal level of evidence. The evidence has two different distributions depending if the student has experienced a shocking event ($N(d', s_{shock})$) or an everyday event ($N(0, s_{everyday})$). If the internal feeling is greater than a criterion *k* then the student withdraws otherwise they stay. The model separates between the sensitivity of an individual to a shocking event indexed by *d'* and the contextual factors present at the time of the decision indexed by the criterion *k*. Panel B illustrates four different Receiver Operator Characteristic (ROC) functions each with a different level of sensitivity. To account for rating data, where a student rates on a scale from 1 to 5 their intent to withdraw (the response mode of our study), the Gaussian model uses four response criteria as shown in Panel A and assumes a student maps a rating (1, 2, 3, 4 or 5) according to where their evidence falls relative to those criteria.

Figure 2.A Three-state Model of College Withdrawal Decisions.

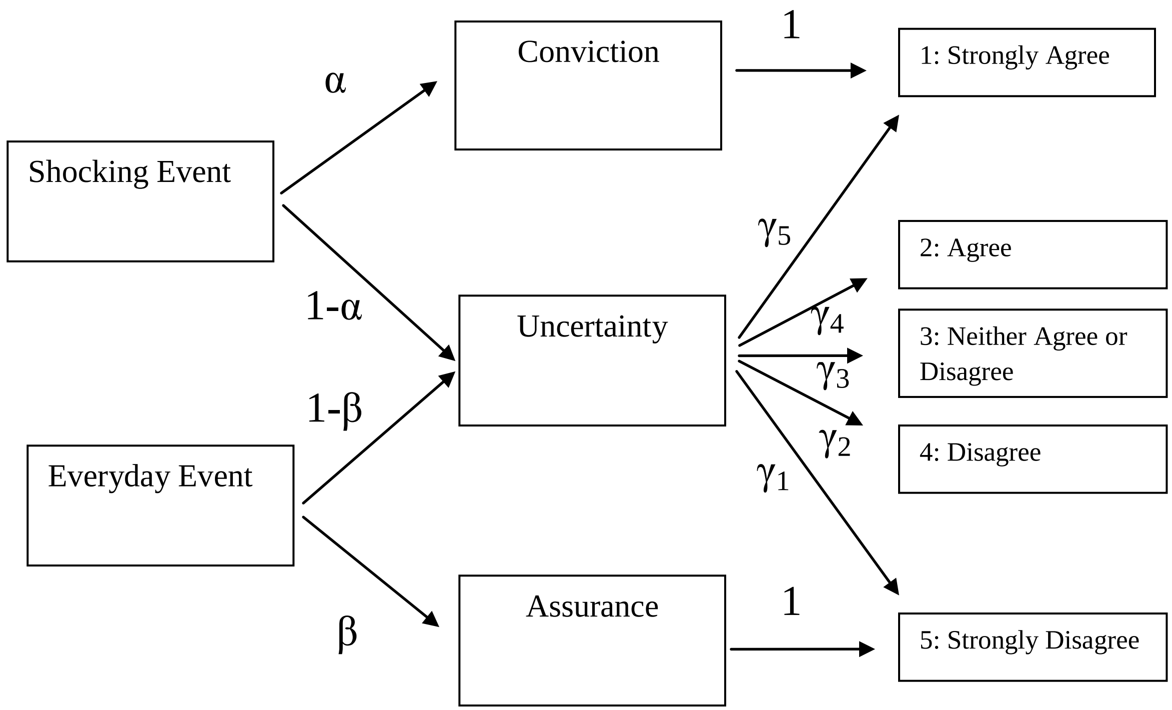
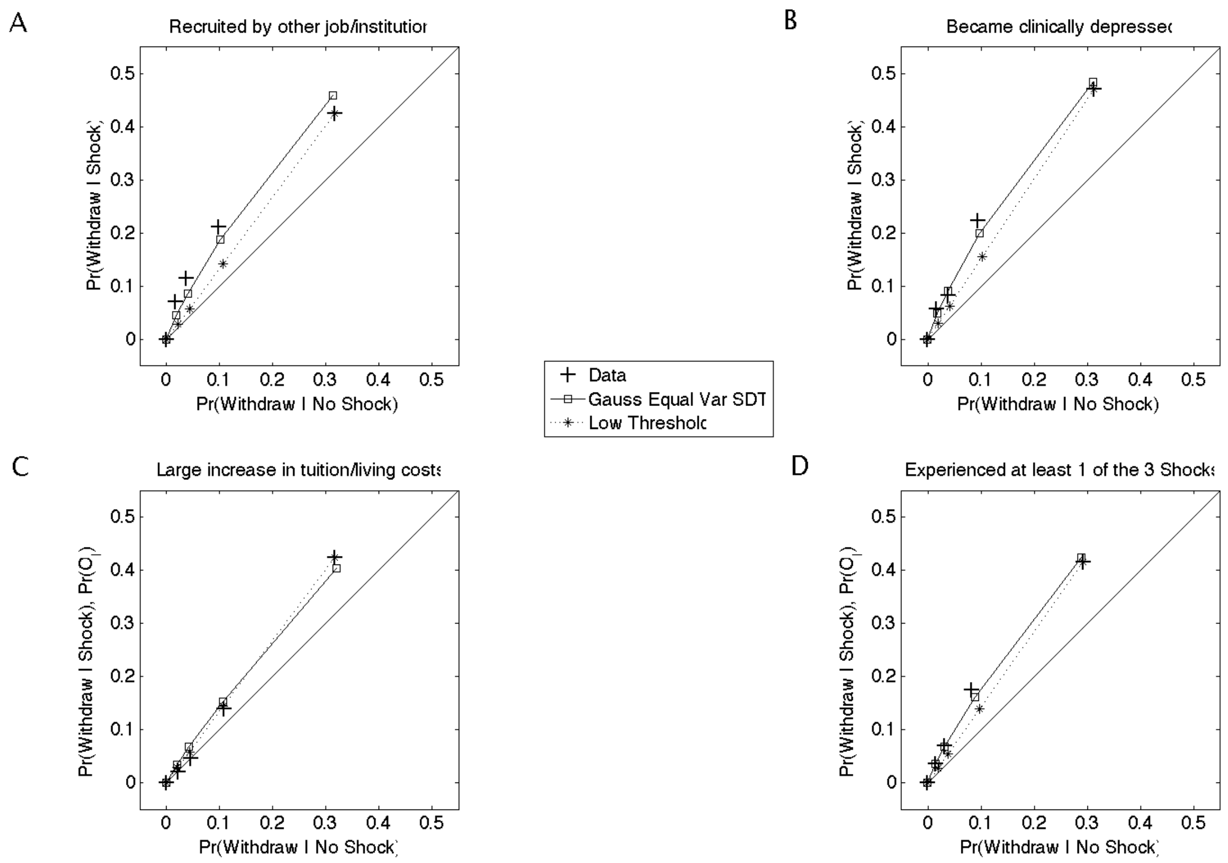
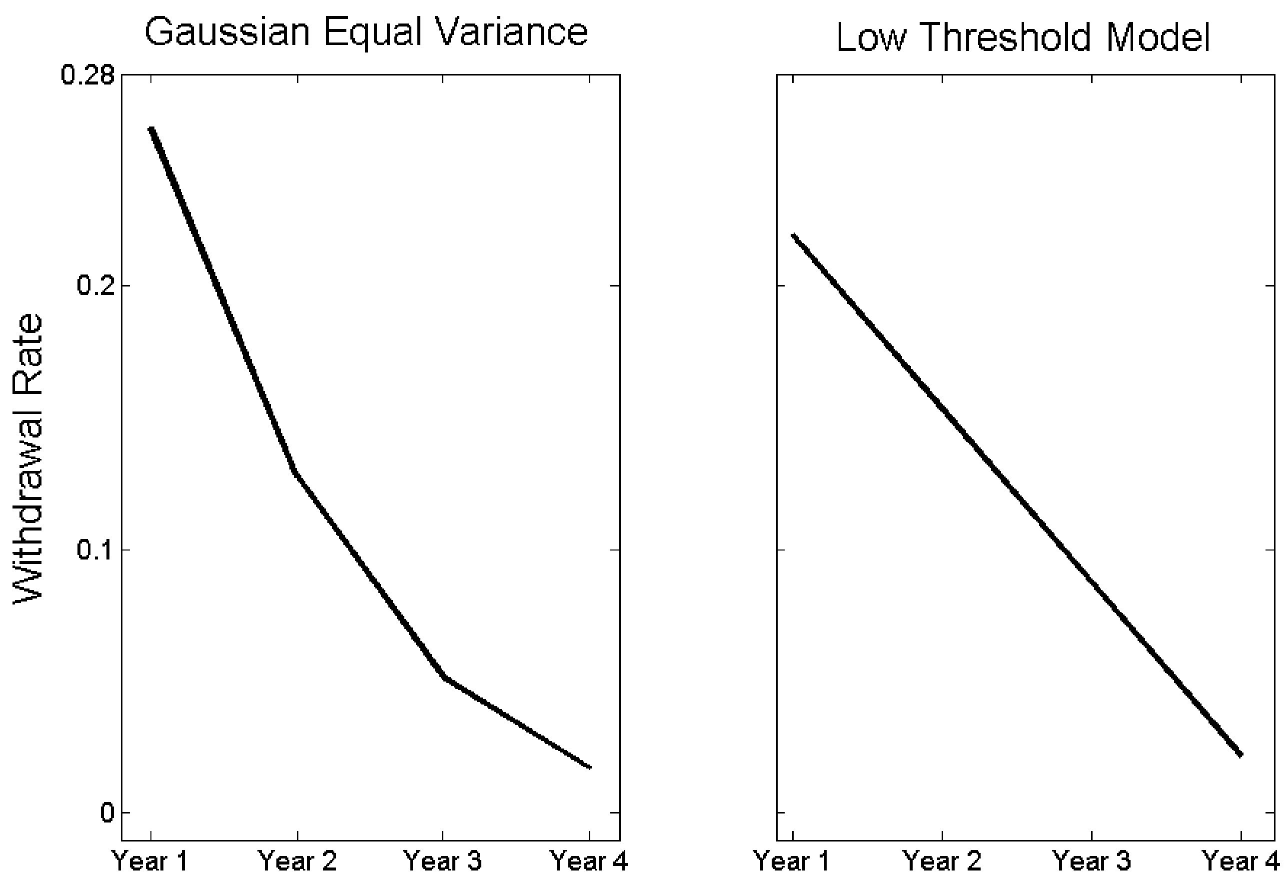


Figure 3. The ROC Curves for the Three Individual Shocks Identified with the Area Under the Curve Analyses and the Collapsed Shock Variable.



The fourth ROC (Panel D) was calculated by collapsing across all three of the other shocks and was used to identify the best fitting detection model. The functions were calculated using students' rated intent of withdrawing and transferring to another institution.

Figure 4.Hypothetical Withdrawal Rate Functions for the Gaussian Equal Variance and the Low Threshold Models Calibrated to Approximate Plausible Withdrawal Rates.



If we assume as tenure at college increases the bias to stay increases (via k in the Gaussian and γ in the threshold model), then both the Gaussian equal variance and low threshold model predicta decline in withdrawal rates. The Gaussian equal variance model correctly predicts the decline decreases at a diminishing rate over time.