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# Movement without mobility: Adolescent status hierarchies and the contextual limits of cumulative advantage

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**Abstract**
This paper develops a theory of interpersonal status hierarchies that builds on and challenges traditional models of cumulative advantage. Cumulative advantage models predict stability in interpersonal status hierarchies, where status is defined by asymmetries in social relationships. According to strict cumulative advantage, initial status differences are exaggerated over time, making upward or downward mobility unlikely. We argue that interpersonal status hierarchies are instead quite fluid, with individuals regularly moving up or down the hierarchy. Individual status gains do not, however, disrupt the status order as the upwardly mobile are often pulled back to their original positions. This drag of the past generates the same long run status outcomes as cumulative advantage models, but through very different means: sustained upward mobility is rare because the upwardly mobile fail to maintain their status gains, and not because initial gains are impossible. More generally, the effect of the past limits sustained mobility in most, but not all, status hierarchies, and we expect sustained mobility where ties are stable and the expectations for reciprocity are low. We test our model using longitudinal data on adolescents, finding strong support for the theory. We end the paper with a reflexive discussion about measurement error, hypothesis testing, and "messy" longitudinal network data.

**Keywords:** Status, Hierarchy, Mobility, Network dynamics, Adolescent networks

## 1. Introduction

How is status mobility possible? Traditional sociological theories of status (e.g. Berger et al., 1974; Cook and Emerson, 1978; Gould, 2002) generally characterize mobility as the exception to the rule, citing cumulative advantage, or what Merton (1968) famously referred to as the "Matthew Effect", as the cause of enduring status inequalities (for a recent example see Rossman et al., 2010).[1] "Strict" cumulative advantage models can take a variety of functional forms (see DiPrete and Eirich, 2006 for a review) but generally describe the benefits, or returns, to holding a privileged position: where individuals with initial advantages—whether by virtue of their own talents or serendipity—garner subsequent advantages, and are thus unlikely to lose status.[2] Low status actors, meanwhile, are unlikely to gain it. In some contexts, high status actors are also in position to alter the "rules of the game" in their favor, further cementing the advantage of the upper echelon (Bourdieu, 2004). High status actors are especially advantaged when merit is difficult to distinguish from status, such as in interpersonal status hierarchies. Cumulative advantage generates a rigid hierarchy in such settings, where mobility is extremely unlikely, yet enduring in the rare event it does occur.

Here we reverse these propositions, arguing that social mobility in interpersonal hierarchies is actually quite common, but not often lasting. Moves up or down the status hierarchy are frequent, but fleeting, as the past strongly drags the mobile back to their original positions. Our model thus arrives at the same long-term pattern of stratification as the strict cumulative advantage model—where sustained mobility is unlikely—but through very different means. In contrast to cumulative advantage models, which predict growing inequality, or

1. The Matthew Effect refers to high status individuals receiving more credit or prestige than their accomplishments would otherwise warrant, or as Merton (1968, p. 58) put it, "accruing greater increments of recognition for particular scientific contributions to scientists of considerable repute and the withholding of such recognition from scientists who have not yet made their mark." For empirical examples outside of the scientific domain, Rossman et al. (2010) find that high status film actors are more likely to find subsequent success, and Martin (2009) shows that youth dominance hierarchies quickly become fixed, and that dominant youths are challenged even less often than would be expected.
2. DiPrete and Eirich (2006) show that the "Blau-Duncan" form of cumulative advantage, which attempts to explain *group*-level inequality through direct and indirect effects, does not necessarily lead to growing inequality over time—though in practice, most empirical applications seem to find growing inequality. Because our focus is on individual actors, unless stated otherwise, we focus on "strict" cumulative advantage mechanisms.

at minimum a stable status ranking, our actors make fleeting moves up and down the hierarchy before returning to their original positions. The long-term solidity of most status hierarchies belies, in our view, a great deal of movement between time points, and is achieved only through the stabilizing influence of the past. Status hierarchies are thus fluid rather than fixed, but they are also slippery.

Some status hierarchies are less slippery than others, however, providing the upwardly mobile with sufficient traction to maintain their status gains. Rather than treat sustained mobility as an anomaly, we systematically extend our theory to the contextual level, explaining why sustained mobility happens in some settings but not in others. We identify two properties of networks that facilitate lasting mobility: sustained mobility is possible in networks where ties, once made, tend to endure and where the expectations for reciprocity are low. In such settings, the upwardly mobile are unfettered from the past, free to enjoy their newly won status.

We begin the paper by discussing the centrality of cumulative advantage in sociological theory. We then move to our own theory and explain why status hierarchies are often characterized by movement without sustained mobility. We also explain why the "drag" of the past is weak, and thus sustained mobility possible, in some, but not most, contexts. We test our theory using longitudinal data on adolescents, showing in multiple contexts that the past matters, dragging aspiring social climbers back to their original positions.

Unlike most studies of network dynamics, we test our theory while recognizing the messy nature of longitudinal network data. Any study that is dependent on the reporting of particular ties to particular people is subject to sources of measurement error: individuals may report ties inaccurately or inconsistently, making it difficult to distinguish between true change and change to due error. We develop a simulation procedure to test the validity of our results. We believe this is a useful exercise. In our case, we can be confident that the results are real, but this may not be true of all studies, and one can only be sure by taking the problem of measurement error seriously.

## 2. Theory

### 2.1. *Status as asymmetry*

To describe the process of status change we must first define status. There are many different conceptualizations (see Martin, 2009 for a review), but most center on the idea that high status people are socially desirable and receive deference (Gould, 2002; Martin, 2009 ; Rossman et al., 2010). Gould operationalizes status in network terms, where high status individuals receive many nominations (or "gestures of approval" p. 1147). Research in both the status characteristics/expectations states (e.g. Cohen and Roper, 1972; Ridgeway, 1978; Ridgeway, 1982) and social network traditions (Bukowski and Newcomb, 1984; Moody, 1999; Moody et al., 2011; Bothner et al., 2010a; Bothner et al., 2010b) have similarly defined status as a function of social relationships—higher status actors receive more friendship nominations (relative to lower status actors), give advice that is followed, talk more in meetings, and so on.

Asymmetric relationships are particularly useful markers of status as they imply both social desirability *and* deference. Receiving a nomination without the expectation of reciprocity establishes interpersonal leverage, and we are unlikely to see asymmetries favor lightly regarded individuals. Higher status individuals receive many nominations relative to their outdegree—in other words, ego is high status if the demand for ego's time/attention/friendship is much greater than ego's rate of reciprocity. Symmetric relationships are of great value (e.g. because they provide social support, facilitate socialization, etc.), but they establish status distinctions, or signals of deference, to a lesser extent than asymmetric nominations. An individual thus moves up the status hierarchy by gaining social leverage, or distinctions, over a large number of people. [3] The questions are how often upwardly mobility happens and how often the upwardly mobile maintain their status gains. Below, we contrast our own answers to these questions with those based on classic cumulative advantage. Though the answers are quite different, the overall outcome—long-term stability of status hierarchies—is often the same.

### 2.2. *Cumulative advantage and its limits*

Merton's (1968) study of scientific careers spurred initial interest in cumulative advantage processes, where initial advantages—created by talent or chance—lead to subsequent advantages, thus increasing the gap between the top and the bottom over time.[4] Cumulative advantage ideas were subsequently formalized (Zuckerman and Merton, 1971; Cole and Cole, 1973; Allison et al., 1982) and applied widely as an explanation for persistent or growing inequality in political, organizational, educational, economic, and even cultural (Salganik et al., 2006) realms (see DiPrete and Eirich, 2006; Bothner et al., 2010a; Bothner et al., 2010b).

"Strict" cumulative advantage models assume that future accumulation depends on the current level of accumulation.[5] In the strongest form (for growing inequality), the rate of return itself varies by the level of current accumulation; thus, the wealthy not only have more money to invest, and thus higher absolute returns, they also receive better interest rates. In scientific settings, more talented or luckier scientists enjoy ever increasing advantages over their less talented or unlucky colleagues: even when their contributions are equivalent, they are evaluated in light of past accomplishments (DiPrete and Eirich, 2006). Strict cumulative advantage also lies at the root of preferential attachment models, where new entries into a network preferentially choose people with many nominations (Barabási and Albert, 1999; Newman, 2001; Albert and Barabási, 2002).

Cumulative advantage will operate strongly when projections of future quality or merit are driven by perceptions of current quality – thus scientists with prestigious publications win grants and websites with many links receive more visibility. When quality is difficult to discern, observers must rely on current perception as a benchmark, a measure that will disproportionably reward people in advantaged positions. Thus, current status directly leads to higher future status. Yet even in a more "objective" world, individuals receive education, training, and resources based on their past performance. These resources lead to an increase in productivity, amplifying the initial advantage in perceived quality (Merton, 1988). These feedback loops make it possible for small initial differences between individuals to grow into very large differences in outcomes.

3. Our measure also differs from a patronage based definition, where actors in fragile positions are likely to lose status precipitously if one or more of their patrons loses status or stops their endorsement (Bothner et al., 2010a and Bothner et al., 2010b). Ours can be viewed as a more "democratic" conception: one cannot achieve high status by receiving many votes from a few people, but must instead receive single vote from a large number of people.

4. We thus assume that the cumulative advantage process is "positive" so that the parameter describing the relationship between past and current accumulation is greater than 0. The full range of past events, or "shocks", thus affects the current level of accumulation. See Footnote 2 in DiPrete and Eirich (2006) for more details.

5. We ignore, for space considerations, simple cumulative advantage models which specify a time dependence but no explicit relationship between future and current accumulation.

Though they are central to many theories of inequality, rigorous longitudinal tests of cumulative advantage are "more the exception than the rule" (DiPrete and Eirich, 2006, p. 272). Instead, the mere presence of inequality in the cross section is sometimes taken as evidence of cumulative advantage, despite the possibility of alternative explanations, as we outline below. For example, extremely unequal "superstar" markets are generated when rewards are based on relative, not absolute, performance (Rosen, 1981; Frank and Cook, 1995), but such inequality does not necessarily imply a cumulative advantage process.

Many studies have, however, recognized the subtlety (and variety) of cumulative advantage mechanisms, noting that few settings devolve into the winner-take-all monopolies predicted by the simplest version of the theory (Merton, 1968). Instead, factors such as redistributive policies (Merton, 1968), incomplete information (Collins, 2000), normative constraints (Luhmann, 1987), and the diffusion of status from elites to their associates (Bothner et al., 2010a; Bothner et al., 2010b) all prevent winner-take-all outcomes.

In the case of interpersonal status hierarchies, Gould (2002) offers a clear explanation for the asymptotic growth in inequality, arguing that actors must balance the desire for high status alters against the desire for reciprocity (Gould, 2002). If people cared little for reciprocity, they would simply send ties to those who received the most ties, eventually creating a "star" network, where one actor receives all ties. Thus, for Gould, it is desire for reciprocity alone that prevents the hierarchy from turning into a winner-take-all system of maximum inequality.

In short, constrained cumulative advantage models expect no winner-take-all systems but still predict growing inequalities and long run stability in the status hierarchy. There is little room for mobility in such a model unless there are clear measures of exogenous quality distinct from status. The rare upward moves that do occur should be lasting, however, as the upwardly mobile take advantage of their positions to consolidate their gains.

We argue that a strict cumulative advantage model is a useful, but ultimately incomplete, way to approach status mobility: incomplete, as the model cannot naturally account for movement in a system; useful, as the basic elements of the model can be refashioned to explain the causes and consequences of status mobility. We begin by describing the micro dynamics of status change, explaining why there are "Mark Effects", where initial gains in status are made by previous losers, not winners, of status contests. We then describe why this initial mobility is often fleeting. We frame our discussion in terms of upward mobility, but we note that any explanation of upward mobility has reverse implications for downward mobility.

### 2.3. *Mark effects and the drag of the past in the reproduction of status hierarchies*

Individuals in our model often gain and lose status from period to period (although the moves are generally temporary). Status movement is possible, in part, because tie formation and dissolution are stochastic processes driven by multiple considerations, only one of which is status. The desire for novelty, the need for companionship, and the bitterness over past disputes may lead people to make friends with the 'wrong' people and abandon ties to the 'right' ones. Thus, a certain amount of dynamism inheres in interpersonal hierarchies, and some friendship choices may seem illogical from a status perspective (e.g. befriending an isolate).

Status considerations are, of course, still important for relationship decisions, and we incorporate the two conflicting demands in Gould's (2002) model into our own explanation of status mobility: (a) the desire for reciprocity and (b) the desire for high status alters. In Gould's model, the desire for reciprocity prevents the cumulative advantage process from devolving into a winner-take-all hierarchy. On one extreme, if the desire for reciprocity greatly outweighs the desire for high status alters, then ties are likely to be withdrawn if they are not reciprocated, resulting in less status differentiation and greater equality.[6] In these compressed settings where relatively few ties differentiate the top from the bottom, changes in ties—which occur for many reasons besides status considerations, including conflict, drifts, changed activities, and new romances and friendships—have more dramatic effects on status. Status effects could, in contrast, be quite strong. Despite the drive toward reciprocity (Hallinan, 1978; Lubbers and Snijders, 2007), many adolescent ties are asymmetric. For example, in the widely-used Add Health study, the overall reciprocity rate is just 37% (Ueno, 2005).[7] If there is any desire for high status alters, then they should be more likely than low status actors to gain and maintain asymmetric ties over time (as they already receive the esteem of their peers – Gould, 2002).[8]

The question is whether the reciprocity demands are high enough to compress the hierarchy and make shifts in the status order possible. There are several reasons to believe that reciprocity demands outweigh the desire for high status alters in interpersonal status hierarchies; not the least of which is that many relationships—especially friendship—are premised on companionship and mutual positive affect. If *A* tolerates dramatic asymmetry in her personal relationship with *B*, *B* is more likely to carelessly neglect and possibly abuse *A*'s feelings. More to the point of status, *A*'s tolerance signals her lower social rank to others. If, however, *A* breaks the connection, the social distinction becomes less clear. Furthermore, such breakups are not easy for high status actors to prevent. Since status is based on positive affect (which cannot be coerced), they have few enforcement mechanisms at their disposal. These factors imply a general tendency for unreciprocated ties to be withdrawn or to become mutual, consistent with empirical research (Doreian et al., 1996; Schaefer et al., 2010).

We thus have a system where higher status actors have a hard time maintaining their asymmetric nominations. They have many ties to juggle and reciprocity outweighs the status effects.[9] Additionally, if the preference for high status alters is relatively weak, high status actors' advantage in gaining new ties will not fully compensate for their losses. Meanwhile, those with lower status are able to gain new ties, albeit at a lower rate, without losing many (since they can invest heavily

6. One might argue, akin to the parable about the one-eyed king in the land of the blind, that a network with one asymmetric tie is less equal than one with many (since in the former, one person will receive 100% of the asymmetric ties). However, we suggest that for inequality to be meaningful, the absolute differences between the highest status person and the lowest must be substantial.

7. Even for "best" friend nominations of the same gender, reciprocity is less than 50% (Strauss and Pollack, 2003). Other studies have found that between one-fifth and one-third of adolescents have no reciprocated friendships and that the majority of friendship nominations are unreciprocated (Parker and Asher, 1993, Cascairo et al., 1999 and Vitaro et al., 2000). Most rates are, however, subject to fixed degree, potentially leading to undercounts of reciprocity.

8. Higher status people may also be incapable of fully reciprocating every social offer they receive due to limited time and resources (Mayhew, 1980 and Roberts et al., 2009).

9. This is true even if they have lower probabilities of tie loss. For example, assume an upper status person has 6 nominations and a .2 probability of losing a given tie over time. Also assume that there is a lower status person with 2 ties and a .3 probability of losing a given tie. Thus the high status person has an advantage in keeping ties over time. On average, the high status person loses 1.2 ties while the low status person loses .6 ties, meaning the two converge over time despite the advantage of the high status person. The high status person keeps .8 of their ties while the low status person keeps .7 of their ties over time.

in their few ties). Thus, rather than adding increasingly more ties over time, as in preferential attachment models, we expect people with higher status to *lose* status in subsequent time points, both in relative and absolute terms. [10]

The model does not directly predict the cycles of status found in adolescent ethnographies (Eder, 1985; Kinney, 1993), but the loss of status at the top does imply that mobility is possible: the more the status hierarchy is compressed, the more likely that idiosyncratic changes will alter the status rankings. The shrinking inequality and status mobility predicted by our model are difficult to reconcile, however, with the widespread perception that social status is relatively stable and mobility the exception (Bukowski and Newcomb, 1984; Eder and Kinney, 1995). We suggest that movements up and down the hierarchy are possible but fleeting as the drag of the past is severe, effectively moving the mobile back toward their previous position. Those below their long run status position are likely to enjoy a net gain in ties, while those above it are likely to experience a net loss, producing a general regression toward individual equilibrium points. Our view is therefore similar to that of Franzoi et al. (1994) who describe status trajectories as having "movement yet nonmovement" and we find this language and interpretation quite appealing. Substantial individual-level movement (and even types of trajectories, Moody et al., 2011) is compatible with long-term stability of the status hierarchy if movers tend to revert to prior positions.

Much of our expectations regarding the past are based on a simple proposition that new ties are less stable than old ties. Here, stability refers to the likelihood of an existing tie dissolving, not the likelihood of new ties forming. Intuitively, new relationships involve a great deal of uncertainty: two people may become friends without knowing if this is a good pairing. Empirical research has shown that new ties are less stable than old, more established relationships (Hallinan and Williams, 1987; Burt, 2000). If new ties are more fragile than old ones, the upwardly mobile should be more likely to drop in status in subsequent periods: for their status rests disproportionately on new ties. By contrast, individuals with stable status, as well as the downwardly mobile, are more likely to retain status in subsequent periods (as they rely less on new ties).

The upwardly mobile also lose ties because the expectations of reciprocity are tied up in the certainty of the receiver's status: less certainty about the upwardly mobile's high status position results in higher expectations of reciprocity and, consequently, less stable nominations. Essentially, if the sender cannot be sure the receiver is going to remain high status, then she is less likely to tolerate asymmetry (as asymmetries are not tolerated from status inferiors or equals). The higher expectations of reciprocity also make it difficult to gain ties. The upwardly mobile face greater demands and must spend more time and energy maintaining their current relationships.[11] This leaves less time and energy for interacting with new sets of people, which could, potentially, have led to future nominations. The downwardly mobile will, in contrast, find it easier to add ties relative to status peers and may regain their lost position (as they have higher past status and thus lower expectations of reciprocity than status peers).

Our model is thus comprised of two countervailing tendencies. Lower status individuals often gain status in subsequent time periods, but find it difficult to maintain their newfound status, as they gain fewer ties and lose more ties over time. If the drag of the past (time 1) is strong relative to the effect of present status (time 2), a past reputation of high status is likely to cushion, or possibly reverse, the predicted fall of high status actors, while those of lowly origins are likely to fall farther than their consistently high status peers. A picture of stability thus emerges in the face of period to period movement, where the stratification order is maintained and the initially high status win in the long run.

### *2.4. Contextual variation*

We have so far presented a model where initial mobility is diminished or reversed by the effect of the past, rendering status gains fleeting and lasting mobility unlikely. Our model thus arrives at the same long run pattern of inequality as the strict (constrained) cumulative advantage models, although by very different means. Unlike cumulative advantage models, however, we describe how and, more importantly, where, lasting mobility is possible. Specifically, we argue that the effect of the past, and thus the possibility of lasting mobility, depends crucially on network stability and reciprocity, the macro realizations of our micro mechanisms (Smith, 2012). We begin with a discussion of tie stability and then move to reciprocity.

We have argued that upwardly mobile people rely heavily on new ties and that new ties are less stable than more established relationships, making it difficult to maintain status gains. We suggest, however, that the differences between old and new ties will be less consequential when ties, in general, are more stable. The stability of new and old ties should converge (or be closer) in stable settings as the forces supporting stability make new ties effectively old in a shorter amount of time.[12] The upwardly mobile are then more likely to hold on to their status when ties are more stable: for they are penalized less for their reliance on newer ties. Formally, we define tie stability as the proportion of ties (both symmetric and asymmetric) that last from one period to next. The expected loss in status (T2 to T3) that follows a status gain (T1 to T2) should decrease as the stability of ties in the network increases (given status at T2).[13]

Past position is less important in stable settings, but should, in contrast, matter more in contexts with higher reciprocity. Following Gould (2002), we assume a tradeoff exists between reciprocation and nominating a high status alter. If reciprocity is expected and not received, the differentials in status between sender and receiver must be higher to balance the relationship. Reciprocity here serves as a proxy for the level of asymmetry tolerated in relationships. The effect of receiver status on asymmetric tie stability and formation is thus larger in higher reciprocity settings (as the level of tolerated asymmetry is lower). Upwardly mobile people will have a more difficult time maintaining their social rise in higher reciprocity settings. They have less certain status, and higher reciprocity expectations, than consistently high status people and status matters more for keeping and gaining asymmetric nominations.[14] Thus past position will matter more where reciprocity rates are higher.

We offer a summary of our main expectations before empirically testing our theory of status change, arguing that: (a) higher status people have a lower likelihood of losing

10. Of course, it is not possible for the highest status person in a network to gain status in relative terms, and therefore they have nowhere to go but down. However, cumulative advantage models suggest that such people should continue to make absolute status gains, and so should have an increasingly easy time maintaining their position at the top. Thus, it is meaningful when they fail to do so.
11. See a similar idea in the work on negative social capital (Portes and Sensenbrenner, 1993).
12. For example, structured, repetitive interaction may make all ties more stable while simultaneously making new ties old ties faster: the higher rate, or frequency, of contact means new ties spend less time in the uncertain phase of development, when breaking off the relationship is more likely.
13. This is not tautological since network stability refers to the network average. It is possible for new ties to be less stable than old ones even in highly stable networks, just as it is possible that new ties will be equally stable as old ties in low tie stability settings.
14. The downwardly mobile will, in contrast, find it easier to regain their lost position: they face lower expectations of reciprocity and there is room in the hierarchy to move up (as the upwardly mobile are losing status).

ties and higher likelihood of gaining ties, but that the benefits of status are overwhelmed by the demand for reciprocity; and (b) for this reason, higher status actors often suffer status losses, rather than gains; (c) that the higher the gain in status between T1 and T2, the lower status at T3, given status at T2; (d), that the underlying mechanisms structuring this drag are differential tie stability and expectations of reciprocity; and more specifically, (e), that the past drags more strongly on current transitions when tie stability is lower and reciprocity is higher.

## 3. Data and methods

Our longitudinal, multilevel network data come from the Context of Adolescent Substance Use Study (see Ennett et al., 2006; Ennett et al., 2008). The study was originally commissioned to study adolescent networks, social context and substance use, although we are primarily interested in the network variables. The survey included three school districts in North Carolina and began in the spring of 2002. A saturated sample of students answered surveys every sixth month until the spring of 2004 (for most schools).[15] There are 5 waves of full data but we only make use of the first three to avoid boundary problems associated with the transition from middle school to high school. The network nominations were restricted to grades while students were in middle school (coinciding with the first three waves of data) but expanded to the entire school upon entry to high school (waves 4 and 5). The networks are thus not directly comparable across the five waves and we use the first three to maintain consistent boundaries.

The initial cohorts were in sixth, seventh and eighth grade. The sample includes about an equal number of males and females and an equal number of whites and non-whites (52% white, 37% black, 4% Hispanic, 7% other). The data are not representative of the population of adolescents, but the study has the advantages of being relatively large ($N$ = 4244 in wave I) and including longitudinal network data over a sizable number of settings and time points. Our dataset includes 24 separate contexts of varying size and network properties, where each "context" corresponds to a unique grade/school combination. [16] The average size of the grades/schools is 251, with a minimum of 44 and a maximum of 511.

## 4. Measures

### *4.1. Dependent variable*

We construct our status measure from friendship nomination data. Students were asked to nominate up to five friends from a complete student roster. Using that network information, we measure status as the rate of indegree (or nominations) of an individual, net of their outdegree and the expected rate of reciprocity in that network. This captures how many nominations an individual receives conditioned on the number of (expected) reciprocated relationships.

We first estimate a p1 model for each network (Holland and Leinhardt, 1981). The model predicts a tie as a function of volume (edges), reciprocity (mutuality), and outdegree (sender), indegree (receiver) effects for each individual. There is one receiver and sender term for each individual in the network. We then take the coefficients on the receiver effects as the measure of status. Formally:

$$p(X = x) = \frac{\exp\left(\theta \sum_{i,j} x_{ij} + \sum_j x_{+j}\beta_j + \sum_i x_{i+}\alpha_i + \rho \sum_{i,j} x_{ij}x_{ji}\right)}{\kappa(\theta, \beta, \alpha, \rho)}$$

where $X$ is a random network on $n$ nodes; $x$ is the observed network; $\theta$, $\beta$, $\alpha$, $\rho$ capture effects for edges, out-degree, in-degree and reciprocity respectively; and $\kappa(\theta, \beta, \alpha, \rho)$ is the normalizing constant.

The basic idea is to estimate indegree conditioned on outdegree, or how often they nominate others, as well as the rate of reciprocity in the network. Indegree forms the base of the measure but this is discounted by the expected number of reciprocated ties. Higher status individuals will receive many nominations relative to the number given out, and are thus able to form relationships even if they do not reciprocate. Someone who is nominated 4 times and gives out 1 tie has higher status than someone who receives 4 nominations and gives out 3 ties. Someone with 4 nominations and 3 out-going ties will still have higher status than someone with 0 or 1 nominations and low outdegree (for example).

As an alternative, we could use the simple counts of asymmetric nominations as the measure of status. Here, we would determine if each nomination per person is asymmetric, where the focal respondent does not return a received nomination. We would then sum up the number of asymmetric nominations for every respondent. The results are very similar between the model based and count based measures of status, but there are substantive reasons to use the model based approach. First, the count approach equates an isolate with no ties and someone with 5 symmetric nominations and no asymmetric nominations. This is a rather harsh penalty for reciprocation as it affords no status value to symmetric ties. Symmetric ties do, however, serve as a metric of social desirability. We do not believe that the isolate and the person with 5 symmetric ties should have the same social standing, and the model based approach explicitly reflects this belief (by giving higher status to the person with 5 symmetric ties). Second, the model based approach estimates status scores net of total volume and reciprocity rates across networks. Thus, the status measures are conditioned on the specific network context. Finally, the model based approach offers a continuous measure of status, which is more highly differentiated than the simple count measure (where many people across and within contexts would have the same status, despite having different profiles of indegree and outdegree).

### 4.2. Independent variables

Our main individual level control variables capture signals of attractiveness, or high status, in adolescence. They include GPA, athletic participation, and substance use (Suitor et al., 2001).[17] We use drinking behavior to measure substance use, where drinking equals 1 if the student has had a drink in the last 3 months and 0 otherwise. We measure GPA, athletic participation and drinking at different waves to see if changes in "quality", or signals of high status, correspond to changes in status.[18] We also include a control variable that measures how important popularity is to each student. People who value popularity, will, following a strategic actor model, do things to gain status. Importance of popularity ranges from 0 to 3, where 0 equals

15. The response rate was 88.4%, 81.3%, 80.9%, 79.1% and 76.0% for the first five waves of the study.

16. We exclude the two smallest schools (around 10 people with full data) and one school where a box of surveys was lost in the second wave. The school had approximately 35% of the surveys lost and 50% missing data overall.

17. GPA ranges from 1 to 4 where 4 indicates academic success. Athletic participation is an indicator variable, 1 for participates in sports and 0 for no participation.

18. We measure change in sports participation as a four category factor: "no change-never in sports", "joined sports", "dropped sports", "no change-always in sports". We use "no change-never in sports" as the comparison group. We have a parallel four category variable for drinking.

**Table 1.** Summary statistics.

| Variable | Min | Max | Mean | SD | N |
|---|---|---|---|---|---|
| Adolescent data: cross section | | | | | |
| Status Time 1 | −4.909 | 2.705 | −.334 | 1.221 | 3834 |
| Status Time 2 | −4.437 | 3.142 | −.367 | 1.173 | 3834 |
| Status Time 3 | −4.682 | 2.663 | −.418 | 1.162 | 3834 |
| Status T1–T3 | −4.909 | 3.142 | −.373 | 1.186 | 3834 |
| Asymmetric Nominations Time 1 | .000 | 11.000 | 1.580 | 1.692 | 3834 |
| Asymmetric Nominations Time 2 | .000 | 14.000 | 1.601 | 1.752 | 3834 |
| Asymmetric Nominations Time 3 | .000 | 15.000 | 1.527 | 1.699 | 3834 |
| Asymmetric Nominations T1–T3 | .000 | 15.000 | 1.569 | 1.715 | 3834 |
| GPA T1 | 1.000 | 4.000 | 2.910 | .795 | 3834 |
| Sports Participation T1 | .000 | 1.000 | .622 | .485 | 3834 |
| Black | .000 | 1.000 | .348 | .476 | 3834 |
| Hispanic | .000 | 1.000 | .040 | .195 | 3834 |
| Other | .000 | 1.000 | .062 | .242 | 3834 |
| White | .000 | 1.000 | .550 | .497 | 3834 |
| Male | .000 | 1.000 | .478 | .500 | 3834 |
| Importance of Popularity T1 | .000 | 3.000 | 1.784 | 1.022 | 3834 |
| Drinking Behavior T1 | .000 | 1.000 | .127 | .333 | 3834 |
| Number of club affiliations T1 | .000 | 5.000 | 1.278 | 1.324 | 3834 |
| Adolescent data: longitudinal variables | | | | | |
| Number of Ties Lost T2–T3 | .000 | 9.000 | 1.420 | 1.409 | 3834 |
| Number of Ties Added T2–T3 | .000 | 9.000 | 1.446 | 1.441 | 3834 |
| Number of Ties Net T2–T3 | −8.000 | 9.000 | −.026 | 1.795 | 3834 |
| Status Change T2 to T3 | −4.506 | 4.183 | −.033 | 1.198 | 3834 |
| Status Change T1 to T2 | −4.386 | 4.978 | −.051 | 1.082 | 3834 |
| GPA Change T2 to T3 | −3.000 | 3.000 | −.028 | .661 | 3834 |
| Never in sports T2–T3 | −1.000 | 1.000 | −.085 | .435 | 3834 |
| Joined Sports T2–T3 | .000 | 1.000 | .288 | .453 | 3834 |
| Dropped Sports T2–T3 | .000 | 1.000 | .056 | .230 | 3834 |
| Always in sports T2–T3 | .000 | 1.000 | .141 | .348 | 3834 |
| Importance of Popularity T2 | .000 | 1.000 | .515 | .500 | 3834 |
| Number of Affiliation Change 2–3 | .000 | 3.000 | 1.668 | 1.057 | 3834 |
| Never Drinking T2–T3 | −5.000 | 5.000 | −.135 | 1.225 | 3834 |
| Start Drinking T2–T3 | .000 | 1.000 | .716 | .451 | 3834 |
| Stop Drinking T2–T3 | .000 | 1.000 | .099 | .298 | 3834 |
| Always Drinking T2–T3 | .000 | 1.000 | .068 | .251 | 3834 |
| Symmetric Ties T2 | .000 | 1.000 | .118 | .322 | 3834 |
| Adolescent data: multilevel variables | | | | | |
| Log of Size | 4.159 | 6.236 | 5.438 | .557 | 24 |
| Tie Stability | .306 | .578 | .409 | .056 | 24 |
| Reciprocity | .249 | .379 | .296 | .042 | 24 |

not at all important and 3 equals very important, and should be positively correlated with changes in status.

We also include a control variable for the number of extra-curricular activities (excluding sports) in each wave. Finally, we include the number of reciprocated nominations as a control variable. Individuals with many symmetric ties are socially active, making it more likely that individuals outside their social circle will nominate them in the future. The results are very similar when the number of reciprocated nominations is not included in the model.

At the network level, we measure the reciprocity rate as the fraction of non-null dyads (so at least one tie exists between $i$ and $j$) which are symmetric (so $i$ nominates $j$ and $j$ nominates $i$). We take the average over the three time points as the measure of real interest. Tie stability is measured as the proportion of nominations, either symmetric or asymmetric, that exist at time $T$ that still exist at time $T + 1$. [19] We take the average over the 3 waves as the measure of interest.

## 5. Models

We begin the analysis with simple descriptive tables of status mobility over time. This shows how much movement there is from period to period and how much past position matters for current transitions. We then tease out the underlying mechanisms underlying these status movements. We predict the gain and loss of ties at the dyadic level. The models predict the gain and loss of ties conditioned on whether the tie is reciprocated or not. The question is whether an individual can gain and maintain ties even though they do not reciprocate. We create a dyadic level dataset and use two multilevel logistic regression models. The first models the probability of a tie remaining at wave 3; the second models the probability of a new tie forming at wave 3 (the dependent variable equals 1 if a new tie forms and 0 otherwise). The cases in the first regression are pairs of adolescents with a tie in period 2. The cases in the second regression are pairs of adolescents without a tie in period 2.

These models have the same basic form as the newly developed STERGMs (Krivitsky and Handcock, 2013), the dynamic extension of traditional ERG models. STERGMs produce separate estimates for the formation and dissolution of ties, as does our model. This is analogous to comparing the pseudo-maximum likelihood estimates produced from dyadic independent cross sectional models to ERGM MLE estimates. We opt for the dynamic dyadic independent models as our theory is not contingent on higher order dependencies, such as transitivity or other triadic terms, and the coefficients should be estimated sufficiently with these simpler models. Additionally, the dyadic independent models make it easier to summarize the coefficients over multiple networks, as the coefficients can

19. The results are quite similar if we define stability by the maintenance of only asymmetric ties. The asymmetric only measure is, however, more definitionally tied to the dependent variable and thus a less ideal choice.

be estimated using all networks at once (as opposed to estimating separate models for each and then summarizing the coefficients afterwards).

For the first set of regressions, we model the probability of a tie remaining at wave 3 as a function of tie presence in time 1 and receiver status in time 1 and time 2 (i.e. the status of the person being nominated). A tie is present if it is asymmetric in time 1 and not present otherwise.[20] Individuals with an asymmetric tie in time 1 should be more likely to maintain a tie currently, given whether they currently reciprocate or not—as there was asymmetry originally in the relationship. We also include controls for homophily effects (race, gender, and GPA), sender status in time 2 and outdegree of sender in time 2. Formally:

$$\begin{aligned}
&logit(Y_{ik}[TieKeptT2\quad toT3]) = b0 + Y_{ki}T3 + b1(AsymmetricT1)\\
&+ b2(StatusofRecieverT2) + b3(StatusofRecieverT1)\\
&+ b4(StatusofSenderT2) + b5(MatchRace) + b6(MatchSex)\\
&+ b7(AbsoluteGPADifference) + b8(OutdegreeofSenderT2)\\
&+ b_j(Fixedeffectsforeachnetwork)
\end{aligned}$$

We offer a parallel model for the second set of dyadic regressions, where we model the probability of a new tie forming. The key independent variables are time 1 status and time 2 status for person $k$, the second person in each dyad, or the potential receiver of the tie in time 3. Here we test if individuals with higher status in time 1 are more likely to receive new nominations between time 2 and time 3, given the existence/non-existence of a reciprocated tie. We include the same controls as above.

$$\begin{aligned}
&logit(Y_{ik}[TieGainedT2\quad toT3]) = b0 + Y_{ki}T3 + b1(AsymmetricT1)\\
&+ b2(StatusofRecieverT2) + b3(StatusofRecieverT1)\\
&+ b4(StatusofSenderT2) + b5(MatchRace) + b6(MatchSex)\\
&+ b7(AbsoluteGPADifference) + b8(OutdegreeofSenderT2)\\
&+ b_j(Fixedeffectsforeachnetwork)
\end{aligned}$$

Significance test are likely to be generous in dyadic independent models and we perform a permutation test, the Quadratic Assignment Procedure (QAP), to test the significance levels of the coefficients (Krackhardt, 1987). QAP compares the observed coefficients to the coefficients found under simulated datasets, where we randomly permute the rows and columns of each network. We test whether a coefficient is larger (for positive values) or smaller (for negative values) than coefficients found under random datasets with the same type of dependence structure. We allow the intercept to vary, making the model a fixed effects multilevel logistic QAP regression (see also Martin, 2005).

We then move from the dyadic level to the node level, looking at the aggregation of these dyadic mechanisms. We ask how individual level status changes from period to period and how this varies across contexts. We model the change in status from period 2 to period 3 as a function of status change from period 1 to period 2. We include second period status, change in GPA, drinking behavior, number of club affiliations and athletic participation in subsequent models. We also include controls for the importance of popularity and the number of reciprocated ties in time 2. Fixed demographic characteristics (race, gender) are not included as no change is possible. We use a linear mixed model as the dependent variable, change in status, is approximately normal and the data have a nested structure. Our final model examines the relative strength of past status transitions on current transitions. We again predict status change from time 2 to time 3 as a function of status change from time 1 to time 2, second period status, and the individual level controls. Here, the coefficient on status change from period 1 to period 2 is allowed to vary across networks. At the second level (networks), we model the effect of past transitions as a function of reciprocity and tie stability. Formally, the model may be written as:

$$\begin{aligned}
&Y_i(StatusT3 - StatusT2) = b0_j + b1_j(StatusT2 - StatusT1)\\
&+b2(StatusT2) + b3(GPAT3 - GPAT2) + b4(JoinSportsT2\quad toT3)\\
&+ b5(DropSportsT2\quad toT3) + b6(AlwaysinSportsT2\quad toT3)\\
&+ b7(ImportanceofPopularityT2) + b8(NumberofClubsT3\\
&- NumberofClubsT2) + b9(StartDrinkingT2\quad toT3)\\
&+ b10(StopDrinkingT2\quad toT3) + b11(StayDrinkingT2\quad toT3)
\end{aligned}$$

$$\begin{aligned}
&b0_j = a00 + a01(TieStability) + a02(Reciprocity) + \varepsilon_{0j}\\
&b1_j = a10 + a11(TieStability) + a12(Reciprocity) + \varepsilon_{1j}
\end{aligned}$$

where $j$ corresponds to the network.

## 6. Results

Table 1 presents a snapshot of our key variables. We begin by examining the distribution of status in the cross section. The mean number of asymmetric nomination varies from 1.6 in time 1 to 1.527 in time 2. Many children have no asymmetric nominations, ranging from 28% to 30% over the three waves. Around 15% of the students (this also varies by wave) receive over 4 asymmetric nominations. The average top person receives approximately 9 nominations but this varies greatly by context. In some schools the maximum asymmetric indegree is as high as 15 while in others it is as low as 5. In short, students unequally receive nominations from their fellow students.

The next question is how strongly the status system is reproduced from period to period. We summarize the level of period to period movement in Table 2. The mobility tables measure the proportion of students moving from one status category to another over time. Status is measured in relative terms, capturing the proportion of status inferiors for each student. The status categories range from low to high, defined by intervals of .2.

Individuals make significant period to period shifts in Table 2. For example, approximately 15% of low status students in time 2 are middle/high status or higher in time 3, while 30% are middle status or higher. Similarly, about 30% of the high status students in time 2 are middle status or lower in time 3. And, more generally, low and high status individuals have about a 50% chance of remaining in their current status quintile from one period to next. This suggests that individuals have a good chance of being in different status position over time, although they do not move randomly across the status hierarchy (confirmed using a simple Chi-square test).

Table 3 offers a more nuanced look at the status movement across the three time periods. Like in Table 2, the table captures the probability of moving between status quintiles. Here, however, the transition probabilities between time 2 and time 3 are conditioned on the time 1 status of the adolescent. Thus, we ask where individuals move between time 2 and time 3 given where they started in time 1. If the time 1 position did not matter at all for current transitions, then the sub tables in Table 3 would all be identical and would simply replicate Table 2.

20. The results are quite similar if you define presence by asymmetric and symmetric ties.

**Table 2.** Distribution of future status category by current status category.

| | | Wave 2 status | | | | | |
|---|---|---|---|---|---|---|---|
| | | **Low status** | **Low/Middle** | **Middle** | **Middle/High** | **High status** | **Total** |
| Wave 1 status | Low status | 44.9% | 25.3% | 15.3% | 10.6% | 3.9% | 100.0% |
| | Low/Middle | 24.9% | 24.9% | 25.5% | 16.7% | 7.9% | 100.0% |
| | Middle | 19.3% | 22.4% | 22.8% | 21.9% | 13.8% | 100.0% |
| | Middle/High | 9.2% | 16.9% | 21.2% | 27.4% | 25.3% | 100.0% |
| | High status | 2.5% | 10.2% | 14.3% | 23.4% | 49.6% | 100.0% |
| | | **Wave 3 status** | | | | | |
| | | **Low status** | **Low/Middle** | **Middle** | **Middle/High** | **High status** | **Total** |
| Wave 2 status | Low status | 47.0% | 27.5% | 14.7% | 8.5% | 2.4% | 100.0% |
| | Low/Middle | 25.7% | 29.3% | 23.9% | 14.7% | 6.4% | 100.0% |
| | Middle | 17.8% | 21.2% | 25.3% | 23.0% | 12.8% | 100.0% |
| | Middle/High | 7.3% | 15.8% | 22.7% | 29.9% | 24.3% | 100.0% |
| | High status | 2.5% | 6.2% | 12.8% | 23.7% | 54.8% | 100.0% |

Low status, status in lowest 20th percentile in network; Low/Middle, status between 20 and 40 percentiles in network; Middle, status between 40 and 60 percentiles in network; Middle/High, status between 60 and 80 percentiles in network; High Status, status in top 20th percentile in network.

**Table 3.** Distribution of time 3 status category by time 1 and time 2 status category.

| | | Wave 3 status | | | | | |
|---|---|---|---|---|---|---|---|
| **Low status in time 1** | | **Low status** | **Low/Middle** | **Middle** | **Middle/High** | **High status** | **% of total** |
| Wave 2 status | Low status | 56.7% | 25.8% | 9.6% | 5.7% | 2.3% | 9.0% |
| | Low/Middle | 42.3% | 29.4% | 15.5% | 11.9% | 1.0% | 5.0% |
| | Middle | 37.6% | 30.9% | 20.8% | 8.7% | 2.0% | 3.8% |
| | Middle/High | 37.5% | 26.4% | 20.8% | 12.5% | 2.8% | 1.8% |
| | High status | 30.0% | 15.0% | 25.0% | 10.0% | 20.0% | .5% |
| | | **Wave 3 status** | | | | | |
| **Low/Middle status in time 1** | | **Low status** | **Low/Middle** | **Middle** | **Middle/High** | **High status** | **% of total** |
| Wave 2 status | Low status | 35.2% | 32.7% | 18.6% | 9.5% | 4.0% | 5.1% |
| | Low/Middle | 30.4% | 27.3% | 24.2% | 13.4% | 4.6% | 5.0% |
| | Middle | 21.3% | 33.9% | 24.7% | 14.4% | 5.7% | 4.4% |
| | Middle/High | 15.2% | 30.3% | 26.5% | 20.5% | 7.6% | 3.4% |
| | High status | 18.5% | 13.6% | 29.6% | 22.2% | 16.0% | 2.1% |
| | | **Wave 3 status** | | | | | |
| **Middle status in time 1** | | **Low status** | **Low/Middle** | **Middle** | **Middle/High** | **High status** | **% of total** |
| Wave 2 status | Low status | 26.4% | 26.4% | 28.1% | 13.2% | 5.8% | 3.1.% |
| | Low/Middle | 18.2% | 27.8% | 22.7% | 22.7% | 8.6% | 5.1.% |
| | Middle | 10.3% | 13.3% | 28.5% | 30.9% | 17.0% | 4.5% |
| | Middle/High | 9.2% | 16.9% | 21.2% | 27.4% | 25.3% | 4.2% |
| | High status | 14.0% | 13.2% | 21.1% | 28.1% | 23.7% | 2.9% |
| | | **Wave 3 status** | | | | | |
| **Middle/High status in time 1** | | **Low status** | **Low/Middle** | **Middle** | **Middle/High** | **High status** | **% of total** |
| Wave 2 status | Low status | 8.3% | 21.4% | 26.2% | 26.2% | 17.9% | 2.1% |
| | Low/Middle | 8.5% | 13.8% | 27.7% | 28.5% | 21.5% | 3.3% |
| | Middle | 10.1% | 14.9% | 27.4% | 29.2% | 18.5% | 4.3% |
| | Middle/High | 6.2% | 15.7% | 19.5% | 33.8% | 24.8% | 5.4% |
| | High status | 4.8% | 15.6% | 17.2% | 29.0% | 33.3% | 4.8% |
| | | **Wave 3 status** | | | | | |
| **High status in time 1** | | **Low status** | **Low/Middle** | **Middle** | **Middle/High** | **High status** | **% of total** |
| Wave 2 status | Low status | 6.5% | 9.7% | 29.0% | 16.1% | 38.7% | .8% |
| | Low/Middle | 6.5% | 11.3% | 17.7% | 33.9% | 30.6% | 1.6% |
| | Middle | 1.9% | 11.2% | 19.6% | 28.0% | 39.3% | 2.7% |
| | Middle/High | 3.5% | 7.6% | 15.7% | 26.3% | 47.0% | 5.1% |
| | High status | 1.3% | 3.0% | 7.6% | 20.0% | 68.1% | 10.1% |

Low status, status in lowest 20th percentile in network; Low/Middle, status between 20 and 40 percentiles in network; Middle, status between 40 and 60 percentiles in network; Middle/High, status between 60 and 80 percentiles in network; High Status, status in top 20th percentile in network.

**Table 4.** Multilevel logistic dyadic regression with QAP adjustment: tie kept and gained from time 2 to time 3.

| Variables | Tie Kept T2-T3[a] | | | Tie Gained T2-T3[b,c] | | |
|---|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
| Intercept | −0.601*** | −0.705*** | −1.291*** | −5.031*** | −5.781*** | −7.446*** |
| Tie*ji* Exists in Time 3 | 1.881*** | 1.926*** | 1.889*** | 4.708*** | 4.987*** | 4.453*** |
| Asymmetric Time 1 | .640*** | .523*** | 3.166*** | | 2.454*** | |
| Time 2 Status of Receiver | | .116*** | .136*** | | .479*** | .477*** |
| Time 1 Status of Receiver | | .127*** | .078*** | | .16*** | .078*** |
| Time 2 Status of Sender | | −.051** | −.031 | | −.205*** | −.194*** |
| Match Race | | .235*** | | | .867*** | |
| Match Sex | | .556*** | | | 1.258*** | |
| GPA Difference | | −.093 | | | −.236*** | |
| Out-degree of Sender | | −.044 | | | .109*** | |
| *N* (Dyads) | 10,465 | 10,465 | 10,465 | 724,162 | 724,162 | 724,162 |
| Deviance | 12,508.938 | 12,532.240 | 12,344.779 | 75,256.573 | 75,390.044 | 68,909.971 |
| AIC | 12,558.938 | 12,586.240 | 12,408.779 | 75,262.573 | 75,400.044 | 68,929.971 |
| BIC | 12,740.333 | 12,782.150 | 12,640.964 | 75,297.051 | 75,457.508 | 69,044.898 |

*p*-values are calculated using non-parametric, permutations tests. We randomly permute the rows and columns of each network 1000 times, randomly attaching the independent variables to the dyads in the school/grade. We then use the randomly permuted data to calculate the coefficients in Models 1, 2 and 3 for each iteration. The observed coefficients are statistically significant at the 5% level if the observed coefficient is larger (for positive coefficients) or smaller (for negative coefficients) than 95% of the randomly generated coefficients.

a. Models only include cases where a tie existed in time 2.

b. Models only include cases where a tie did not exist in time 2.

c. The "receivers" in these models correspond to the second person, *j*, in each dyad, or the potential receiver of the tie in time 3.

** $p < .01$ (one tailed test).

*** $p < .001$ (one tailed test).

It is clear that initial status matters for current transitions. For example, we can look at individuals who started at the bottom of the status hierarchy in time 1 (the top panel in Table 3). They are, across the board, most likely to be in the lowest status quintile in time 3, despite the time 2 position. Even the middle/high and high status individuals are most likely to fall back to their original position. This represents an unlikely trajectory (only 2% of the total population), but it is still the case that when low status people rise to the top, they have a good chance of falling back to the bottom.

More generally, those with lower starting status position in time 1 occupy lower status positions in time 3, given status in time 2. For example, the probability of remaining in the lowest quintile between time 2 and time 3 goes from .57 to .35 to .26 to .8 to .065 as time 1 status moves from low to high. Or, from the top of the distribution, those in the top quintile in time 1 and time 2 have an almost 90% chance of being in the top two quintiles in time 3, while that number is only 30% for a strongly upwardly mobile person. This is not to say that time 2 status is unimportant. Those with higher status in time 2 are the least likely to be in the low status position in time 3, given time 1 location. The overall picture, however, is still one where those in the bottom spot in time 1 are likely to be in the bottom or adjacent status position in time 3, even if they occupy a high status position in time 2.

Taken together, Table 2 and Table 3 offer a mixed picture of the status system: there is considerable movement from period to period but individuals are likely to move back to their original status position after a move up the hierarchy. Much of the period to period movement is thus individuals losing gained status or returning to a lost position of the past.

### *6.1. Underlying mechanisms*

We have so far established that there is movement from period to period but little lasting mobility. We now ask why status gains are possible but often met with moves back down the hierarchy, confirming our underlying propositions: first, expectations of reciprocity depend on current status; second, new ties are less stable than old ties; and third, expectations of reciprocity are dependent on previous status, given current status. The results of the dyadic logistic regression are presented in Table 4. The first set of regressions predicts which ties remain from period 2 to period 3. The second set of regressions predicts the formation of new nominations.

We first explain why mobility is possible, focusing on the time 2 status effects in Model 2 and Model 5 of Table 4. Individuals with higher status in time 2 are more likely to retain an existing tie, net of reciprocating, but the effect is not overwhelming. For example, in Model 2, the probability of keeping a tie is .38 for someone with 1.5 status in time 2 and .44 for someone with a status value of 4 (an increase of 2 standard deviations in status, assuming both have 0 status in time 1). Higher status actors are thus only somewhat advantaged in keeping ties, leading to a large absolute loss of nominations. Individuals with higher status are also more likely to gain ties over time, but this advantage is not enough to outweigh the loss of asymmetric nominations.

We examine the drag of the past propositions in Model 3 and Model 6. Beginning with tie stability in Model 3, a tie is more likely to remain from time 2 to time 3, given current reciprocity, if that tie existed and was asymmetric in time 1.[21,22] A tie that was asymmetric in time 1 is 1.69 times more likely to remain (given current reciprocity) than a tie that was not asymmetric in time 1. Upwardly mobile individuals differentially rely on new ties for their status and thus have a difficult time retaining their newly found position.

Initial status also plays an important role in structuring the stability of ties. A tie is more likely to remain if the receiver of the tie has higher status in time 1. A tie is about 1.9 times more likely to remain when the receiver is of high status in time 1 (moving from status of 0, the mean, to a status of 4, the maximum). The demands for reciprocity are higher for people with lower initial status and maintaining asymmetric nominations, and thus status, is more difficult. The effect is similar for tie gain: individuals are more likely to offer a new nomination to

21. The results are similar if we include symmetric ties in our measure of time 1 tie existence.

22. The results are given current reciprocity. This implies two possibilities. In both cases, person A likes person B in time 1, but person B does not return the sentiment. In the first case, person B may start to like person A by time 3, creating a reciprocated tie. In the second case, person B does not create a reciprocated tie in time 3, despite the initial liking from person A in time 1. In both cases the initial asymmetric tie is more likely to stay than a tie that did not exist in time 1.

**Table 5.** HLM for change in status time 2 to time 3.

| Variables | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| Intercept | −.066 | −.182*** | −.423*** | −.448 |
| | (.037) | (.034) | (.053) | (.295) |
| Status Change T1–T2 | −.355*** | −.198*** | −.184*** | −.199 |
| | (.013) | (.014) | (.018) | (.132) |
| Status T2 | | −.337*** | −.412*** | −.411*** |
| | | (.014) | (.017) | (.012) |
| GPA Change T2–T3 | | | .004 | .003 |
| | | | (.023) | (.023) |
| Join Sports T2–T3 | | | −.020 | −.021 |
| | | | (.069) | (.069) |
| Drop Sports T2–T3 | | | −.011 | −.012 |
| | | | (.048) | (.048) |
| Always in Sports T1–T3 | | | .052 | .052 |
| | | | (.036) | (.036) |
| Importance of Popularity T2 | | | .013 | .014 |
| | | | (.014) | (.014) |
| Number of Affiliations Change T2–T3 | | | .015 | .015 |
| | | | (.012) | (.012) |
| Start Drinking T2–T3 | | | .084 | .079 |
| | | | (.051) | (.051) |
| Stop Drinking T2–T3 | | | .062 | .066 |
| | | | (.060) | (.060) |
| Stay Drinking T2–T3 | | | .040 | .042 |
| | | | (.047) | (.047) |
| Reciprocated Ties T2 | | | .116*** | .116*** |
| | | | (.015) | (.015) |
| Tie Stability | | | | .337 |
| | | | | (.793) |
| Status Change × Tie Stability | | | | .917** |
| | | | | (.319) |
| Reciprocity | | | | −.389 |
| | | | | (1.019) |
| Status Change × Reciprocity | | | | −1.201** |
| | | | | (.414) |
| Number of Networks | 24 | 24 | 24 | 24 |
| N | 3834 | 3855 | 3834 | 3834 |
| Deviance | 10,787.995 | 10,282.742 | 10,214.726 | 10,202.689 |
| AIC | 10,795.995 | 10,292.742 | 10,244.726 | 10,244.689 |
| BIC | 10,821.002 | 10,324.001 | 10,338.5 | 10,375.974 |

Standard errors in parentheses.
** $p < .01$ (two tailed test) ; *** $p < .001$ (two tailed test)

those with higher status in time 1, given reciprocity at time 3. Individuals with lower status in time 1 have less time/energy to foster new ties, as they face higher expectations of reciprocity, and are thus less likely to receive new nominations. Overall, the dyadic logistic models show that the past drags on current transitions because new ties are less stable than old ones and the expectations of reciprocity are higher for initially low status people.

### *6.2. Multilevel models of status change*

We now place the process of status change into particular contexts, describing how different trajectories of status are likely/possible across settings. The key is that the micro mechanisms described in Table 4 are amplified or deflated depending on the larger context in which status gains and losses occur, leading to larger or greater drags of the past after initial status gains (McFarland et al., 2014).

We begin with a simple continuous model of status gain and loss. Table 5 presents a linear mixed model predicting status change between time 2 and time 3 as a function of previous status change. Status moves between period 1 and period 2 are negatively correlated with status moves between period 2 and period 3. Someone moving up in status is likely to move back down. Someone moving down in status is likely to move back up. The negative correlation between previous and current status change holds even if we control for current status and changes in individual characteristics (see Models 2–4). Thus, like in Table 3, upward mobility is often fleeting as status gains in the previous period are met with status losses in the current period (given current status).

Model 4 describes how our micro processes play out in different contexts and how this shapes the potential for sustained upward mobility. We allow the coefficient on status change between time 1 and time 2 to vary across networks, predicting the variation as a function of tie stability and reciprocity (at the network, or second, level).[23] As in Models 1–3, status gains between time 1 and time 2 are met with status losses between time 2 and time 3. The strength of this relationship, however, varies systematically with the level of tie stability and reciprocity. The drag of the past, or the effect of status transitions between T1 and T2, is lower in schools where ties are more stable. The case for reciprocity is reversed. The reciprocity interaction coefficients in Table 5 are negative, as expected, and significant. Thus,

23. We ran parallel models where each student was assigned tie stability and reciprocity values purged of individual level effects. We first removed a student from the network and then recalculated tie stability and reciprocity on the reduced network, assigning those network level measures to the removed student. This procedure was repeated for each student in the network. In these models, the ties, and therefore status trajectory, of an individual could not affect their tie stability and reciprocity values. The substantive results for these models are identical to the findings presented here.

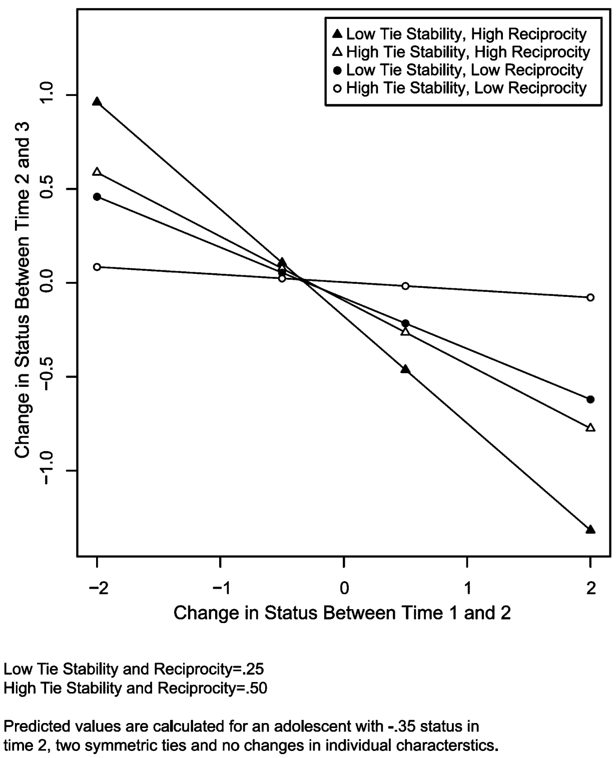


**Figure 1.** Change in status between time 2 and 3 by tie stability and reciprocity.

schools with higher reciprocity have stronger effects of the past, as the expectations of reciprocity are stronger.[24]

We present a stylized set of results for tie stability and reciprocity in Figure 1. The lines represent the effect of past status transitions on current status change in different contexts. We offer four possible settings. The first line represents a low tie stability, high reciprocity network; the second represents a high tie stability, high reciprocity network; the third is a low tie stability, low reciprocity network; and the last line represents a high tie stability, low reciprocity network.[25] The extreme cases occur when tie stability and reciprocity differ, as they affect the drag of the past in the opposite manner. When reciprocity is high and tie stability is low then the effect of the past is quite strong, while it is almost non-existent in a system with low reciprocity and high tie stability. A status move of 2 is met with an expected status loss of 1.2 in the low reciprocity, high tie stability setting, but only a loss of .08 in the high reciprocity, low tie stability network. The effect of the past is somewhere between these two extremes in networks with similar reciprocity/tie stability values (which is the most likely case as reciprocity and tie stability tend to be positively correlated).

Or consider two hypothetical cases: person A goes from 1.5 status to 2 between time 1 and time 2 while person B goes from 2.5 to 2.[26] They both have the same status in time 2, but one is upwardly mobile while the other has recently lost status. The difference in expected status between the two cases in time 3 is .57 in the high reciprocity, low tie stability setting but only .04 in the low reciprocity, high tie stability setting. Thus in one setting, the difference almost returns to the original

**Table 6.** Multilevel logistic dyadic regression, comparing measurement error coefficients to observed coefficients: tie gained from time 2 to time 3.

| Variables | 95% confidence interval: measurement error coefficients | Observed coefficient |
|---|---|---|
| Asymmetric Time 1 | (.092, .450) | 2.249 |
| Time 2 Status of Receiver | (−.026, .034) | .316 |
| Time 1 Status of Receiver | (−.028, .026) | .098 |
| Time 2 Status of Sender | (−.378, −.355) | −.089 |
| Match Race | (−.048, .034) | 1.017 |
| Match Sex | (−.055, .040) | 1.218 |
| GPA Difference | (−.086, .112) | −.229 |
| Out-degree of Sender | (.359, .377) | .047 |

status difference (1), despite having the same status at time 2 (2), while in another setting the status differences would be almost non-existent in time 3, despite having different staring points in time 1 (2.5 versus 1.5).

In short, mobile students are dragged back toward their initial positions in the low tie stability, high reciprocity setting, thus reproducing the rank order present at time 1. The past plays a much less discernible role in the high tie stability setting. The upwardly mobile rely on new, unstable ties and have higher expectations of reciprocity. They thus have a better chance of retaining their status when new ties are less unstable relative to old ties and the expectations of reciprocity are low.[27]

## 7. Testing network hypotheses in the face of measurement error

Overall, the results are encouraging: our propositions about status change are supported, as are our contextual level hypotheses. Thus far, we have tested our hypotheses while bypassing all questions of data quality: we have assumed that adolescents offer and rescind ties in a systematic manner and that our measure of status change is valid. This follows the majority of network studies. It is possible, however, that these assumptions are rather generous. The data may be prone to the whims of adolescents, simple errors in reporting, and other unsystematic, random tendencies in the reporting of friendships (as well as incomplete coverage of the network – Smith and Moody, 2013).

It is important to see if our results, which assume the nominations are real, could have resulted from measurement error in the data. We would not expect all of the data to be false, of course, but our results could be compromised even if parts of the data are error filled. For example, we can safely assume that reciprocated relationships are real—as two people acknowledge the existence of the social tie (for example, $i$ is about 100 times more likely to form a new tie with $j$ if $j$ already nominates $i$). Asymmetric ties are more uncertain. Individuals may write down the names of their real, reciprocated friends and then anyone else they can remember on the spot (perhaps people they saw in the hall or in class). Similarly, people may circle the wrong name by mistake. It would not be surprising that such nominations are not reciprocated, as the other person is unlikely to make the same mistake. If this is true, then asymmetries do not represent differences in status, as we have assumed, but rather mistakes in the data. We would be unable to differentiate between true changes and changes due to random error, casting some doubt on the initial results.

24. We would, however, hesitate to push this finding too far as the range of reciprocity across schools is limited, (.249–.379), meaning the inference is restricted to a small part of the entire range of possible reciprocity values.
25. We define "low" and "high" by the extreme values found in the data (technically a bit above or below the extreme values). Both reciprocity and tie stability are on the same scale, and we thus use the same low and high values for both tie stability and reciprocity. This ensures that the effects do not seem larger just because the empirical ranges were wider for tie stability. We use .25 as the low value and .5 for the high value for both reciprocity and tie stability.
26. Assume they both started to drink, were always in sports, had two symmetric ties and valued popularity.
27. We may be concerned that this analysis is misleading if no status gains are possible in stable settings. We suggest that such concerns are misplaced as initial status moves are possible in our high tie stability settings.

**Table 7.** HLM for change in status time 2 to time 3, comparing measurement error coefficients to observed coefficients.

| | Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|
| Variables | 95% CI: measurement error coefficients | Observed coefficient | 95% CI: measurement error coefficients | Observed coefficient | 95% CI: measurement error coefficients | Observed coefficient |
| Intercept | (−.001, .001) | −.066 | (−.015, .146) | −.182 | (−.015, .146) | −.448 |
| Status Change T1–T2 | (−.531, −.473) | −.355 | (−.300, −.227) | −.198 | (−.502, .053) | −.199 |
| Status T2 | | | (−.528, −.445) | −.337 | (−.556, −.474) | −.411 |
| GPA Change T2–T3 | | | | | (−.042, .045) | .003 |
| Join Sports T2–T3 | | | | | (−.104, .161) | −.021 |
| Drop Sports T2–T3 | | | | | (−.074, .106) | −.012 |
| Always in Sports T1–T3 | | | | | (−.043, .052) | .052 |
| Importance of Popularity T2 | | | | | (−.029, .010) | .014 |
| Number of Affiliations Change T2–T3 | | | | | (−.020, .018) | .015 |
| Start Drinking T2–T3 | | | | | (−.065, .099) | .079 |
| Stop Drinking T2–T3 | | | | | (−.069, .127) | .066 |
| Stay Drinking T2–T3 | | | | | (−.077, .098) | .042 |
| Reciprocated Ties T2 | | | | | (.068, .101) | .116 |
| Tie Stability | | | | | (−.576, −.018) | .337 |
| Status Change × Tie Stability | | | | | (−.716, .527) | .917 |
| Reciprocity | | | | | (−.552, .121) | −.389 |
| Status Change × Reciprocity | | | | | (−1.079, .971) | −1.201 |

Given these concerns, we have included an additional analysis checking the validity of the results.[28] The test is based on a simple question: could we have found the same results if all changes in the nominations were due to measurement error? We begin by generating networks consistent with this null hypothesis. The networks are constant except for changes due to measurement error. We begin with the observed networks in time 1. The reciprocated ties are treated as real. The asymmetric nominations are treated as random guesses on the part of the respondent. The reciprocated ties are held constant: reciprocated ties present in time 1 are still present in time 2 and time 3 (so no "real" change occurs). The asymmetric nominations in time 1 are randomly reassigned to other people in the network. Thus, if person 1 sent out 3 asymmetric ties in time 1, then we randomly select 3 people in the network and assign nominations from person 1 to those randomly selected people. We do this for every person in the network who sent asymmetric ties in time 1. These generated networks are then used to calculate the status scores. This process is repeated three times to mirror the three waves of empirical data (so three networks are generated, all starting from the time 1 network). Any changes in status are due to measurement error.

We then rerun the original analysis, using the measurement error status scores instead of the observed data. The models are specified as before, except for some small changes to the dyadic models. Here, we only consider changes in the asymmetric ties, as, by definition, no reciprocated ties are lost or gained over time. Similarly, we only present the results for gaining ties. Few asymmetric ties are kept from period to period in the measurement error data, making it impossible to properly estimate the model for keeping ties.[29] For example, in the empirical data 8% of the asymmetric ties last over the 3 periods, while only .05% last in the random error data. We repeat the entire process 100 times to capture variation in the measurement error results.

## 8. Measurement error results

The results, on the whole, are encouraging: the key findings in the paper cannot be generated by measurement error alone. Table 6 presents the dyadic model results. The table includes the measurement error results as well as the estimates for the observed data. It is clear that the presence of a tie in time 1 has a much stronger effect in the observed data than in the measurement error data. Similarly, the status effects are essentially non-existent in the measurement error model but are strong and positive in the observed data.

The contextual level results tell a similar story, where it is once again clear that the observed results could not have been generated by random measurement error. Table 7 presents the multilevel models. Model 1 presents the unconditioned model, predicting status change between time 2 and time 3 as a function of status change between time 1 and time 2. The first column presents the measurement error results. Those who received new asymmetric ties between time 1 and time 2, and thus gained status, are unlikely to get lucky again and receive asymmetric ties in time 3. Thus, by measurement error alone, those who gain status between time 1 and time 2 tend to lose status between time 2 and time 3. It is clear that the observed coefficient is larger (or absolutely smaller) than that generated by measurement error. This means that individuals who move up between time 1 and time 2 move down between time 2 and time 3, but at a slower rate than that expected by measurement error alone. Some of the gained ties are real and are thus kept period to period (unlike in the measurement error data).

Model 3 presents the full model. The key coefficients are the school-level predictors: the interaction between status change and tie stability and the interaction between status change and reciprocity. The 95% confidence interval for the interaction between tie stability and status change is (−.716, .527) in the measurement error model, while the observed value is .917. Similarly, the confidence interval for the interaction between reciprocity and status change is (−1.079, .971), while the true value is −1.201. The empirical values are thus well outside the range expected under random measurement error.

It is important to note that the status change coefficient is less robust to measurement error in Model 3. The coefficient captures the baseline effect of previous status change on current status change for a network with low tie stability and low reciprocity. Here, the empirical value falls within the range produced by the random measurement error process. The empirical value is −.199, while the 95% CI is (−.502, .053,). This means that *in some networks* measurement error can generate the basic negative correlation between movement in one period and movement in the next; this cannot be the case in most networks, however, as the overall correlation cannot be generated by measurement error alone (see Model 1).

28. We would like to thank an anonymous reviewer for this suggestion.

29. The data are based on the random assignment of asymmetric ties, and it is unlikely to see a person nominated by the same person twice in a row. The estimates are very unstable given the small number of ties kept from period to period.

**Table 8.** OLS for change in status time 2 to time 3: comparing measurement error status change coefficients to observed coefficients in high to low tie stability contexts.

| Tie stability of network | 95% CI for status change T1–T2, unconditioned measurement error model | Observed coefficient |
|---|---|---|
| High (value = .463) | (−.576, −.420) | −.202 |
| Medium High (value = .436) | (−.616, −.392) | −.286 |
| Medium (value = .393) | (−.682, −.391) | −.344 |
| Medium Low (value = .363) | (−.584, −.346) | −.509 |
| Low (value = .306) | (−.633, −.367) | −.682 |

The values correspond to the coefficient for status change T1–T2. The models include an intercept but are unconditioned on any other terms. We do not report the intercept in the table. The models are run on 5 example networks, running from high to low stability. The models are run separately for each network.

We explore these contextual differences more directly in Table 8. Table 8 presents the results for 5 example networks, running from high to low tie stability. We run separate regression models for each network. Here, there are no contextual interactions and the model predicts status change between time 2 and time 3 as a function of status change between time 1 and time 2 (and the intercept, not reported in the table). It is like Model 1 in Table 7, but there are separate results for each network. The results mirror those of Table 7. First, the drag of the past is stronger in low tie stability settings than in high tie stability settings, and this finding is not replicated in the measurement error results. Second, the observed coefficient on status change between time 1 and time 2 is outside the measurement error bounds in four out of five cases. It is only in the medium-low tie stability network that the observed coefficient is consistent with the measurement error results (with an observed coefficient of −.509 and a measurement error confidence interval of (−.584, −.346)). Thus, most of the networks have status movement that is inconsistent with measurement error. We can then be confident in our basic findings.

Overall, the results are real and robust. The dyadic results clearly show that individuals gain ties in a systematic manner: people give ties to high status actors and do not randomly pick among the people they see. Measurement error can generate the negative relationship between status change in one period and status change in the next in a few settings, but not most. Similarly, our contextual level results could not have been generated by measurement error. Thus, our basic findings would be the same even if we ignored the few settings that are indistinguishable from measurement error.

Still, we cannot ignore the fact that status change is indistinguishable from measurement error in some settings. This does not upset the findings of this paper, but it does offer a cautionary tale, and we encourage future work to seriously consider the problem of measurement error in dynamic network data.

## 9. Discussion and conclusion

This paper has examined the stability of status hierarchies by building on, and ultimately diverging from, traditional cumulative advantage models. Strict cumulative advantage models suggest that inequality increases over time, making status rankings stable and mobility unlikely. We argue, in contrast, that status hierarchies exhibit considerable period to period change. Higher status people may be socially attractive (Gould, 2002), but their attractiveness is overwhelmed by the demand for reciprocity, leading many unreciprocated ties to disappear and raising the possibility of upward mobility – as the gap between the upper and lower strata decreases. The rosy scenario of reduced status inequality, is, however, spoiled by the drag of the past: newcomers to the top of the hierarchy often fall farther than status peers, while those who had previously lost status are buoyed by past reputation. Mobile actors are therefore pulled back to their original position and the status system exhibits long term stability in the face of period to period movement. We thus arrive at the same long term pattern of stratification as cumulative advantage theories, where sustained mobility is unlikely, but from very different paths.

We also diverge from cumulative advantage approaches by systematically explaining how, and more importantly, where, sustained mobility is possible. We argue that the upwardly mobile are more likely to retain their status gains when relationships are durable and reciprocity is not universally demanded. Such settings raise the prospects for lasting mobility. We found, using data on adolescents that our theory was largely supported.

We have so far developed and tested a theory of status mobility that assumes status is important, but it is worth briefly considering *how* status matters. It is clear that status matters a great deal when it cannot be distinguished from quality: careers, scientific and otherwise, are built on status and reputation. Status is not, however, merely a means to win resources, but is an end to itself. The majority of adolescents in our study felt that "being popular" was somewhat or very important, and status valuation predicts subsequent aggression and other risk behaviors ( Faris and Ennett, 2012; Sijtsema et al., 2009). Park and Burgess (1921, p. 30; quoted in Bothner et al., 2010a and Bothner et al., 2010b) observed that "men work for wages…they will die to preserve their status."

Given the value that individuals place on status, it is important to consider the role of individual action in status hierarchy dynamics. We have so far treated strategic action, where actor want status and act to attain it, as a variable to control away. Valuing popularity and changing 'quality' did not predict changes in status, nor did they affect our results. Compared to our model, changes in individual characteristics may matter more, however, in settings where quality is more easily distinguished from status. For example, a tennis player's status within her team may largely be a function of her court performance. Yet, even here other factors may come into play, and we might yet expect past interactions to drag on future status changes.

We have dealt less directly with starker strategic action, where individuals purposely join or leave settings. It is worth noting, first and foremost, that many contexts are difficult or costly to enter or exit (e.g. workplaces) and the desire to move may be inconsequential. Additionally, actors are unlikely to change settings based solely on status considerations, and, even if they do, they are likely to make their entrances blindly, and to exit only after having failed. The choice to enter or exit a setting is therefore unlikely to substantially influence our model. Future work could, however, add to the fullness of our theory by incorporating self selection into the model.

We also encourage network scholars to address the problem of measurement error. Longitudinal network data may be prone to misreporting, making it difficult to differentiate true change from error. Our simulation offers a simple way to incorporate measurement error into an analysis, and we look forward to future studies developing more sophisticated approaches.

Our theory also has a number of more specific implications for ongoing lines of research. For example, social psychological research on task groups (Berger et al., 1974; Berger et al., 1980; Gibson, 2003) might consider the interaction between sequence, or action order, and context: where initial actions are more important for long term outcomes in settings where status moves are difficult to maintain. Similarly, status expectations (Berger et al., 1972) will be more consequential, or harder to overcome, in task groups where the network features make sustained status movement unlikely.

We also hope that our theory adds to the literature on cumulative advantage processes. DiPrete and Eirich (2006) argued that future studies should be more precise in specifying the cumulative advantage mechanisms at work. One could, in part, answer that call by describing the maintenance of inequality along the lines presented here. For example, the literature on cumulative advantage and school tracking (Kerckhoff, 1993; Kerckhoff and Glennie, 1999) could distinguish between strong cumulative advantage settings and settings where educational gains occur but are hard to maintain, perhaps as a result of "summer setbacks" (Entwisle and Alexander, 1992). Of course, we may find that cumulative advantage is overwhelmingly strong in other substantive settings: our argument simply points to the possibility of period to period movement in ultimately stable status hierarchies. The theory thus challenges, however modestly, the monopoly of cumulative advantage, offering a different answer, or perhaps a different question, to the puzzle of enduring inequality.

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