Competitive Crowding and Risk Taking in a Tournament: Evidence from NASCAR Racing

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This article uses National Association for Stock Car Auto Racing (NASCAR) races to examine how competitive crowding affects the risk-taking conduct of actors in a tournament. We develop three claims: (1) crowding from below, which measures the number of competitors capable of surpassing a given actor in a tournament-based contest, predisposes that actor to take risks; (2) as a determinant of risky conduct, crowding from below has a stronger influence than crowding from above, which captures the opportunity to advance in rank; and (3) the effect of crowding from below is strongest after the rank ordering of the actors in a tournament becomes relatively stable, which focuses contestants' attention on proximately ranked competitors. Using panel data on NASCAR's Winston Cup Series from 1990 through 2003, we model the probability that a driver crashes his car in a race. Findings show that drivers crash their vehicles with greater frequency when their positions are increasingly at risk of displacement by their nearby, lower-ranked counterparts; the effect of crowding from below exceeds that of crowding from above; and the effect of crowding by lower-ranked contestants is greatest when there is relatively little race-to-race change in the rank ordering of drivers.●

Organization theorists have long worked toward understanding the social structural causes, and the many consequences, of competition. The most extensive work on the subject recently has been in organizational ecology, which has developed a model of competition centered on the concept of the niche (Carroll and Hannan, 2000). Network theorists have also examined the social structural configurations that engender competition (White, 1981; Burt, 1992) and the effects of competition on individual (Burt, 1987) and organizational conduct (Stuart, 1998). In fact, these two areas of research have intersected in recent years, as researchers have developed network-based measures to represent empirically the ecological construct of the niche (McPherson, 1983; DiMaggio, 1986; Burt, 1992; Baum and Singh, 1994; Podolny, Stuart, and Hannan, 1996; Sørensen, 1999).

Although many empirical studies have related competitive crowding in positions to actors' performance, the preponderance of this work has considered lateral, rather than hierarchical differentiation between competitors: economic actors make choices to participate in particular arenas, and competitive intensity is assumed to be a function of the resultant density of actors in these areas. Thus the competition between actors is an inverse function of the differentiation between them in some type of resource space, such as a labor market (Sørensen, 1999), a supplier-buyer network (Burt, 1982), a geographic area (Baum and Haveman, 1997; Sorenson and Audia, 2000), a technology space (Podolny, Stuart, and Hannan, 1996), or a product features space (Dobrev, Kim, and Hannan, 2001). Crowding among rivals when competitions are hierarchically differentiated, as they are in tournaments, looks quite different.

A tournament (Lazear and Rosen, 1981) is a classic means of structuring competition with two features that distinguish it from other resource spaces. First, rivals in tournaments

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receive resources or rewards as a function of their relative ranking in a performance hierarchy rather than on the basis of their absolute performance. The highest-ranked competitor garners the most; the lowest-ranked earns the least. Second, competition in a tournament is typically zero-sum: a lower-ranked rival's significant advancement on the continuous metric(s) on which the ranking is established necessarily results in an adjacent, higher-ranked actor's loss. Tournaments thus tightly link position with performance, forcing contestants to react to one another's attempts to advance. There are compelling reasons why actors' behavior in tournaments deserves further study.

Tournaments are used extensively to organize competition—a reality belied by the scant attention devoted to the phenomenon in the management literature. Whether the emphasis is on individuals in organizations or on organizations themselves, tournament-like structures abound in market contexts. A few of the myriad examples in which individuals compete in tournament-type contests include executives striving for large shares of bonus pools (Gibbons and Murphy, 1990; Eriksson, 1999) and for the job of chief executive officer (Bognanno, 2001), entry-level workers competing for promotions (Rosenbaum, 1984), authors vying for positions on best-seller lists (Frank, 1985), and athletes competing in sporting events (Maloney and McCormick, 2000). At the market level as well, tournament-like contests are nearly ubiquitous, including management schools striving for the top positions in the *Business Week* rankings, investment banks competing for the top spots in league tables and tombstones (Podolny, 1993), and firms contending for corporate and government contracts (Taylor, 1995; Fullerton and McAfee, 1999). More generally, the core features of tournament systems—the ranking of actors by relative performance, the pairing of rewards and ranks, and, when performance data are transparent, rivals' attempts to outstrip each other in rank before the contest closes—operate to varying extents in virtually all status hierarchies (Chase, 1980; Bothner, Stuart, and White, 2004). Despite the pervasiveness of tournament-like forms of organization in market contexts, however, we know more about the tournaments themselves than about the conduct-related consequences of actors' positions in these tournaments, in particular, the risks they are willing to take to advance in the hierarchy. The purpose of our paper is to understand the positional antecedents of that risky behavior better.

Extant theories of competition in organizational sociology have the potential to shed light on the competitive dynamics in tournaments because of two similarities in the structural features of markets and tournaments. First, structural approaches conceptualize positions as external to actors. One can therefore characterize the positions in a competitive domain apart from the actors that inhabit them, potentially allowing researchers to identify positional effects net of individual attributes, in both economic markets and tournaments. Second, structural approaches cast positions in relative terms, so that competitive intensity (among other positional attributes) depends on the structure of relationships among the positions the system in question comprises. In tournaments, positions are relative by construction: any given position is defined only in juxtaposition to the others that make up the system. The level of crowding around an actor's position in a tournament is a measure of the competitive intensity experienced by the position's occupant, and actors who occupy crowded ranks in a tournament are more likely to undertake risky behavior. Because the likelihood that a position's occupant will fall victim to a slip in rank rises with the number of competitors concentrated just below that rank's incumbent (crowding from below), crowding just below an actor may lead that incumbent to take greater risks to defend his or her rank, and the promised resources to which it corresponds.

Two other features of tournaments may also have effects on risk taking. First, the movements of the actors in tournaments are vertical: competitors can only move up or down. This fact brings into focus the potentially asymmetric effects of crowding in the rankings above and below an actor's position, because individuals' desires for upward mobility may not equal their distaste for downward mobility. When the ordering of the actors in a tournament is mutable, and cardinal performance data determine ordinal standings, then the level of crowding just below a rank reflects the risk that the occupant of that rank will lose his or her status to a competitor. Conversely, when an individual's position is close to many others situated above him or her in the rankings (crowding from above), the position's occupant is likely to sense the opportunity to surpass multiple others and thereby advance in rank. Because individuals' distaste for moving down may exceed their desires to move up, however, we anticipate that encroachment from competitors ranked further back will affect the propensity to take risks more strongly than will the opportunity to pass competitors who are ranked further ahead.

Second, the effects on risk taking of crowding from below are likely to be contingent on the level of permanence in the correspondence between actors and ranks. As a stable rank ordering forms, competitors may start to acknowledge their current position in the contest and to question chances of recapturing a rank forfeited to a rival. Consequently, crowding by inferiors would matter most after the constitutive elements of the tournament-based hierarchy lock into place, and hence the ordering of contestants is perceived by those competing for positions to be reasonably fixed. With greater state dependence in ranks, and the corresponding perception that recapturing a position is less likely, competitive crowding then confronts contestants as a consequential local process, or "social fact" (Durkheim, 1950; Berger and Luckmann, 1966) that commands their attention and induces adjustments in conduct.

The empirical setting for our analysis of competitive crowding and risk taking is the National Association for Stock Car Auto Racing (NASCAR). Using panel data on NASCAR's Winston Cup Series, a season-long tournament composed of professional athletes competing in weekly races, we model the probability that a driver will crash his car in a given race. Consequently, although we believe that the findings of our analyses carry implications for individual as well as corporate actors, our unit of analysis is the individual NASCAR driver. Our assumption is that a crash is more likely if a driver attempts risky maneuvers on the track. Thus the rate of crashing, which is observable, is treated as a proxy for the unobservable tendency of a competitor to take risks.

COMPETITIVE CROWDING AND RISK TAKING IN TOURNAMENTS

There are large literatures in psychology and economics on the antecedents of risk taking (e.g., Lyng, 1990, and Lopes, 1994, offer reviews of different areas of the psychology literature; Hvide, 2003, discusses risk taking in tournaments). Psychologists have examined the personality traits associated with individuals' proclivity to take risks, ranging from achievement motivation to low self-control, as well as situational factors that appear to prompt individuals to take risks. Economists, by contrast, have focused on exogenous factors that affect the costs individuals incur when they engage in risky behavior. For instance, insurance policies and safety regulations are thought to protect individuals from absorbing the full costs of risky behavior and thus (perhaps paradoxically to the non-economist) to promote chancy actions.

Work in economics has examined how an actor's ranking in the performance distribution of a tournament influences his or her inclination to take risks. According to these studies, tournaments sort rivals into different ranks according to their unequal abilities, and the differential rewards attached to these ranks in turn affect rivals' risk preferences. Weaker competitors located near the bottom of performance-based hierarchies are assumed to be the most risk prone (Rosen, 1988). With little to lose from downward mobility, they opt for risky strategies to raise their expected rewards. Using a formal model of a two-player tournament, Bronars (1987) showed that the lower-ranked actor was more risk prone than his superior as the contest came to a close. Similarly, in an empirical study, Knoeber and Thurman (1994) found that less able producers selected riskier strategies than their more skilled, higher-ranked counterparts. Chevalier and Ellison (1997) offered a more nuanced portrayal of the risk-related effects of rank: while finding risk aversion among mutual funds that were outperforming the market, they also found "gambling" both in lower ranks and in very high ranks. The latter result may reflect successful competitors' efforts to garner a spot on annual lists of the best-performing funds.

Several earlier investigations have thus demonstrated that rank influences risk taking, but our knowledge of the consequences of crowding around a given rank on the proclivity to take risks is minimal. After adjusting for a chosen competitor's rank, an important question is whether risk taking is uniquely influenced by the clustering of other competitors around his or her ordinal position in the tournament. The time-varying level of crowding faced by a given competitor may be as important as his or her rank as a determinant of risky conduct. Crowding is an important phenomenon because, in many tournaments, final ordinal rankings (and thus rewards) are derived from cardinal measures of performance that rivals watch carefully as a contest unfolds. Thus in tournaments in which rivals' performances are publicly observable, shifts in the rankings themselves are only one piece of relevant information. Until the final ordinal rankings are posted and prizes are distributed, the clustering (or dearth) of rivals around particular positions will also have an effect on their occupants' actions. Emphasizing crowding around ranks, as opposed to the ranks themselves, highlights the effects of ecological processes that are overlooked when researchers only take into account competitors' standings. Focusing on the ecological antecedents of risk taking in a tournament may therefore shed further light on the precise mechanisms underlying actors' conduct in a commonly utilized system of organizing competition.

The idea that competitive crowding has adverse consequences for individuals' career chances has long been central to sociological research on labor markets. Several scholars have noted the deleterious consequences experienced by occupants of work roles that are crowded by others contending for their valued positions. Work from a demographic perspective (e.g., McCain, O'Reilly, and Pfeffer, 1983; Stewman and Konda, 1983; Stewman, 1988), for instance, has underscored the disadvantages attached to residing in large, densely populated cohorts, such as fiercer competition for senior-level jobs and correspondingly weaker chances for promotion. Under conditions of high crowding, mobility rates decrease as individuals' career paths run into size-induced bottlenecks (Reed, 1978). Similarly, other investigations have brought into focus the inauspicious effects of crowding on individuals' ability to realize the gains of otherwise promising opportunities, such as vacancies (Skvoretz, 1984) or occasions for brokerage (Burt, 1997). Additionally, human capital theorists have noted that women frequently enter occupations requiring general skills that are robust to temporary exits from the labor market. The result of this process is the crowding or oversupply of workers in such roles and a consequent drop in the wages attached to such jobs (Bergmann, 1986; Barnett, Baron, and Stuart, 2000).

Correspondingly, much recent research at the organizational level also verifies the supposition that the rivalry, and thus the mortality chances, faced by a firm depends on the extent of its proximity to numerous others along one or more relevant resource dimensions. The idea that competitive intensity is localized by size is one example of this type of work in organization theory (Hannan and Freeman, 1977; Baum and Mezias, 1992). Comparably sized firms in the same industry are thought to install similar structures, pursue similar strategies, and thus compete head to head. Size therefore maps onto the pockets of resources on which firms depend, so that crowding on a size gradient tends to lower life chances. Empirical studies have found that size-localized competition reduces the performance of firms in populations of credit unions (Amburgey, Dacin, and Kelly, 1994), banks (Hannan, Ranger-Moore, and Banaszak-Hall, 1990), and insurance companies.

A related area of research, and one that inspires the approach we have adopted, operationalizes competitive crowding in terms of the level of structural equivalence between members of a population of actors in a network of resource flows (DiMaggio, 1986; Burt, 1992; Bothner, 2003). For example, Podolny, Stuart, and Hannan (1996) showed that semiconductor firms with many structurally equivalent competitors in a network comprising all patented semiconductor technologies experienced low rates of revenue growth. Sørensen (1999) focused on different factor inputs but reached a similar conclusion: when competing television firms hired executives from the same firms (i.e., they were structural equivalents in the market for executive labor), their growth rates fell.

From this brief review of the literature on competitive crowding, it is clear that the thrust of the existing work has been to document the consequences of crowding for individual attainment or for organizational life chances. Unless actors are incapable of responding to an onslaught of competitors, however, it is probable that those experiencing significant competitive crowding will adjust their conduct with the intention of averting an otherwise likely loss in financial resources or social standing. Thus in most market contexts, an intermediate step in the link between crowding and performance is a modification in actors' conduct. Yet despite the many earlier investigations that directly relate competitive crowding to individual or firm performance, relatively few scholars have observed (or modeled) the effects of crowding on actors' conduct, either among individuals or organizations.

A few exceptions include research on individuals' inclinations to take risks in auctions and in tournaments. Earlier studies suggest that risky bids that result in overpayment are more likely in auctions with a lot of bidders (Kagel, 1995). Using a game theoretic model of selection tournaments, such as contests for promotion or membership on a team, Hvide and Kristiansen's (2003) investigation also suggests that risk taking is more likely when there are more individuals competing in the system. Other approaches have traced risk taking to competition among organizations, especially financial institutions. Using a model of spatial competition, Dam and Sanchez-Pages (2004) found that under low market concentration (and thus acute rivalry), banks take greater risks. Bolt and Tieman (2004) also found that greater rivalry in the banking industry led its incumbents into risky conduct. To the limited extent that the existing literature has considered the behavioral outcomes associated with competitive crowding, it suggests that occupying positions in tournaments that are crowded from below will precipitate risky action intended to avoid loss of position. We therefore predict:

Hypothesis 1: An increase in the competitive crowding below an actor's position in a tournament induces the position's occupant to take risks.

Because ranks are vertically ordered and upward mobility is preferable to downward, we can also compare the effects of the crowding on either side of a given rank. When a position is crowded from below, its occupant senses the pressure of many advancing subordinates and keenly perceives the risk of losing his or her current status to a rival. Conversely, when a focal actor's position draws near to those of multiple higher-ranked competitors, the position's occupant perceives the opportunity to surpass competitors and advance in rank. Thus an increase in crowding from below implies a higher risk of positional loss, and an increase in crowding from above connotes an improved opportunity to advance in status. The level of crowding from below is thus associated with the risk of loss and the degree of crowding from above with the opportunity for gain.

Structural measures of the opportunity for gain are known to affect actors' investments of effort to move ahead. This is true, for instance, in labor markets. Building from White's (1970) analysis of vacancy chains, Halaby (1988) developed a model of job search tied to workers' perceptions of the opportunity for jobs that would compensate them more than the positions they currently hold. In the model, the perception of opportunity causes worker mobility. Similarly, students of collective action have focused on the structure of opportunity as a factor influencing the likelihood of insurgency (see McAdam, 1982: 36–59): at times when more established actors appear "vulnerable" to the goals of marginal actors (Eisinger, 1973: 28), efforts to mobilize collectively are more likely to occur. Both areas of work address the effect of the perception of opportunities to advance on actors' motivation. With greater opportunities for advancement, the returns to risk taking should rise, leading to more risky actions.

Although many studies document how the perception of opportunity elicits effort, crowding from below (encroachment) should exert a stronger influence on actors' conduct than does crowding from above (opportunity) for two reasons. The first is consistent with work on structural equivalence and relative deprivation. Burt (1982) argued that deprivation is concentrated between structurally equivalent people and that the feeling of relative deprivation is most acute precisely when a peer who was just behind a focal actor has moved ahead of him or her. Thus Burt's work localizes comparisons on the basis of proximity of social positions and underscores the distress experienced by an individual who is being surpassed by a peer. Second, the distress of losing a position to an inferior exceeds the pleasure of gaining the position of a superior. In work in psychology on prospect theory, Kahneman and Tversky (1984) described an asymmetry in actors' valuation of goods, known as loss aversion: they observed that the disutility individuals experience when losing an object of value typically exceeds the positive utility they enjoy from acquiring the same object. Kahneman and Tversky's work indicates that valuations of gains and losses are made with regard to a reference point and that a loss from the reference point is perceived to be more discomforting than are the benefits of a corresponding gain. In keeping with this stream of research, if an actor's current position in a tournament is taken to be his or her reference point, the displeasure of losing one's rank to a competitor should exceed the pleasure experienced by displacing a superior. Consequently, we hypothesize:

Hypothesis 2: Crowding from below an actor's position in a tournament has a stronger positive effect on risky conduct than does crowding from above.

Finally, the relationship between crowding from below and risk taking should be strongest after a stable set of positions has materialized. Typically, research on the consequences of social structure—whether of institutional arrangements or the properties of an actor's network—takes structure as given. In other words, in studies of attainment and other outcomes, earlier investigations have typically assumed that social structural covariates are equally influential across varying states of the evolution of the social structure. Very little empirical research illuminates when a rank ordering (or social structure more generally) is sufficiently established for its local properties to have consequential effects on future outcomes.

In a dynamic tournament such as a foot race (Maloney and McCormick, 2000) or a promotion contest (Rosenbaum, 1984), in which actors sort into stable positions gradually, the degree of temporal consistency in ranks should increase the extent to which contestants orient themselves to the encroachments of nearby, lower-ranked competitors. For instance, in a tournament in which the rank ordering is so unpredictable that it shifts randomly between iterations of the contest, players will not orient themselves to their current positions, and properties of actors' local positions in the rank structure would be expected to have little or no bearing on behavior. As the tournament moves away from the extreme of random resorting of contestants to ranks (i.e., as rank stability begins to emerge), properties of local positions should become significant in shaping contestants' behavior, for two interrelated reasons. First, as the rank structure stabilizes, contestants are more likely to accept their rank in the contest as a state to be defended and thus narrow their attention to the encroachments of nearby rivals, rather than monitor the entire field. Second, the certainty with which contestants believe they can recover from downward mobility by regaining lost positions clearly declines with rank stability. Whereas a lot of turnover creates an awareness of the chance to recover, a crystallized set of ranks would lead individual incumbents of a tournament to infer that regaining a rank lost to a rival is improbable. A contestant's assessment of the prospects of recouping a position should therefore decrease with the aggregate level of rank stability in the system.

Consequently, in dynamic tournaments, if we assume that contestants view the overall, period-to-period permanence in ranks as an indicator of their inability to reacquire a lost position, then rank stability will amplify the effect of crowding from below on the level of risk taking. In a highly stable structure, the displeasure associated with a loss in rank will be especially high. Thus we expect the effect of crowding from below to rise as a relatively stable structure of ranks takes shape:

Hypothesis 3: Crowding by lower-ranked competitors has a greater effect on risk taking in tournaments as the rank ordering of competitors grows more stable.

METHOD

The National Association for Stock Car Auto Racing

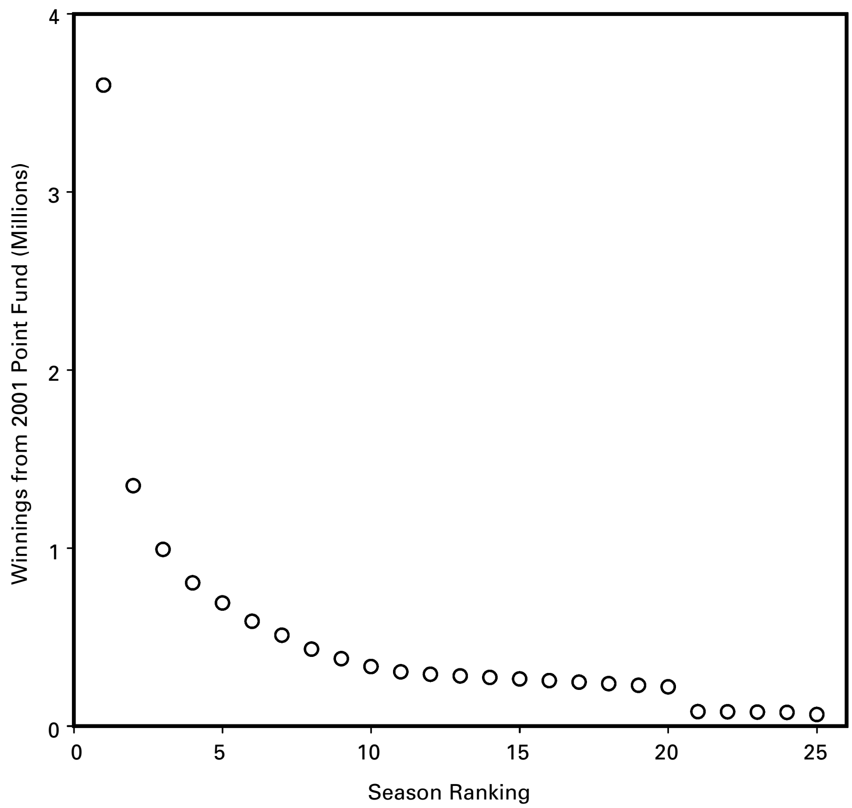
To test our predictions, we examined how competitive crowding affects the probability that drivers in the National Association for Stock Car Auto Racing's Winston Cup Series will crash their vehicles in each race in the 1990 to 2003 NASCAR seasons. Two considerations drove the choice of this research site. First, as we describe below, an evolving rank structure unfolds throughout each NASCAR season, enabling observers and contestants to clearly delineate the crowdedness of each driver's position in the tournament's hierarchy. Second, although there are a number of causes of accidents, the risk of crashing certainly depends in part on drivers' risky maneuvers on the track. Thus NASCAR enables us to develop empirical measures of competitive crowding and risky conduct.

Incentives and ranks. NASCAR's Winston Cup Series is a season-long collection of races, the number having risen almost linearly with time from 29 races in the 1992 season to 36 races in the 2001 season, each typically with 43 drivers. The overall series winner is the driver with the most points at the end of the season. Points are allocated as a function of one's finishing position in each race. In effect, the Winston Cup is a set of discrete tournaments (individual races) that jointly constitute a larger, season-level tournament. Throughout the season, each driver's accumulated points collected over all previous races is the main performance metric and the basis for public rankings after each event.

Like most athletic contests, NASCAR uses a tournament structure to motivate drivers. One of the variables tournament designers can manipulate to affect contestants' incentives is the payoff schedule. The extent to which rewards move nonlinearly across ranks is a central choice variable and one that significantly affects contestants' incentives. At one extreme, the winner takes all; at the other, prizes are a linear function of ordinal finishing positions. Economic models suggest that the optimal shape of the reward function largely depends on the cost of advancing one rank in the system. When a contestant's marginal cost of advancing rises rapidly with his or her rank in the system, rewards should increase by a proportionate amount to elicit appropriate levels of effort (von Allmen, 2001).

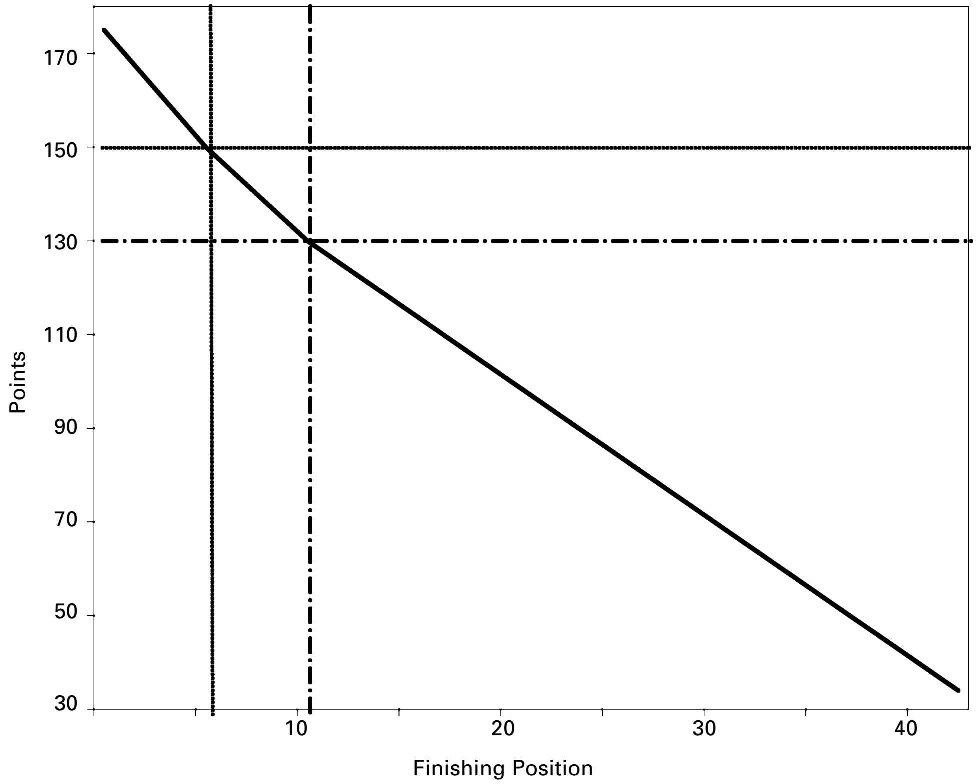
Much like the convex functions typically used in professional golf, executive labor markets, and other systems in which the reward for winning is much greater than that for finishing in second (and lower) places in the tournament, NASCAR uses a non-linear season-level payoff schedule to motivate its drivers. At the completion of the last (36th) race in the season, all drivers are ranked in order of the number of Winston Cup Series points they have accumulated throughout the season. NASCAR then allocates cash prizes according to a highly nonlinear (convex) payoff schedule in the season-long tournament. In other words, the top-ranked driver, who wins the Winston Cup Series, collects a very large share of the final purse. The convex payoff schedule for the overall Winston Cup, which is typical of the reward schedule in tournaments when they are used in sports and in firms, is shown in figure 1. This figure depicts the relationship between prize money and the ordinal rank of each driver's point fund.

Figure 1. The nonlinear reward schedule for the 2001 Winston Cup season.



Conversely, although smaller cash rewards for finishing position in each race also fall rapidly with the order in which drivers finish, NASCAR's race-day points schedule is nearly linear. In each NASCAR race, drivers receive points toward their season-level ranking and prize money based on their finishing position in the contest. In each of the 36 races in the season, the winner of the contest collects 175 points, and the occupant of the forty-third position receives 34 points. One other source of points than finishing position is bonuses. Leading at least one lap in a race yields 5 bonus points, and the leader of the most laps in a race is awarded 10 bonus points. Thus, 185 is the maximum number of points a driver can earn in each event (175 points for winning the race, plus 10 bonus points for leading the most laps). The purpose of bonus points is to induce intense driving for the entirety of each race. The plot in figure 2 shows how points vary with race-day performance. Unlike the convex monetary reward schedule for the season shown in figure 1, the points schedule for each race is piecewise linear. The top five drivers are separated by five points, the next five by four points, and all of the rest by three points. Using a piecewise linear rather than a convex payoff schedule at the level of the race is consistent with NASCAR's efforts to curtail the number of acci-

Figure 2. The linear reward schedule for a typical NASCAR race.



dents per year and to preserve the balance of competition among drivers (von Allmen, 2001).

Restating our predictions in the NASCAR context, our central hypothesis is that occupants of positions that are crowded from below in the Winston Cup season-long rank structure will have higher hazards of crashing. In other words, a focal driver is most likely to crash when, at the start of a given race, there are numerous drivers who could potentially pass him, at the conclusion of that race, in the season-cumulating distribution of points. When a driver faces a reasonable probability of loss in rank, he is likely to become more risk prone on the track. Under the threat of positional loss, his driving may bring him too close to other vehicles, into debris on the track, or onto the "apron," the flat paved area inside the track. When a car is partially on the apron and partially on the upward sloping part of the track, a larger-than-usual (triangular) space for air under the car opens up. With more air under the car, down force and traction are reduced, and the car may slide across the track, toward the audience, and into the wall. Additionally, when faced with the threat of being eclipsed in rank, drivers may fail to engage properly in what is known in the parlance of the sport as "tire conservation," instead allowing their tires to lose traction and thus raising the hazard of "kissing the wall" in turns and crashing.[1] Crowding from below should have a stronger effect on the accident rate than will crowding from above, and the strongest effect of crowding from below should occur when the rank ordering of drivers in the Winston Cup Series

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Personal communication, 2006, from Charles B. Sigler, NASCAR Observer and Certified ASE (Automotive Service Excellence) Mechanic.

becomes relatively stable, so that drivers focus their attention on the rivals in their immediate neighborhood. We have also presented a formalization of these hypotheses in the Appendix.

Measuring Crowding and Rank Change

We used data on drivers' time-varying positions in the Winston Cup (season-long) total points distribution to devise measures of competitive crowding. We proceeded in the spirit of recent work in organizational ecology, in which direct competition is seen as a local process, so that each rival competes only with the members of the total population who occupy its "neighborhood" or region (see Hannan and Freeman, 1977; Baum and Mezias, 1992; Lomi and Larsen, 2001: 277–280; Greve, 2002; Bothner, 2005), and the number of rivals in a region is typically used to measure competitive intensity. We devised a measure of crowding by lower-ranked competitors as follows: for each driver before the start of each race, we computed pairwise distances between that driver's points and those of his competitors in that race $P_{it-1} - P_{jt-1}$, where i indexes the focal driver, j his competitors, and t the race in a Winston Cup season.[2] Using the information given by NASCAR's points schedule, we then defined for each race the "striking distance," S_t, as the difference between the points accruing to the driver who finishes last and the maximum number of points any driver can collect. This difference in points usually equals 151 when 43 drivers enter the contest, although it varies as a function of the number of drivers entering on a given day; with more than 43 drivers, the minimum number of points falls below 34, expanding the difference. With this information, we then tallied the number of lower-ranked drivers j in striking distance of i, which we term *crowding from below* (CB_{it}):

$$CB_{it} = \sum_{j=1}^{J} D_{ji},\ D_{ji} = 1 \text{ if } 0 \leq P_{it-1} - P_{jt-1} < S_t,\ D_{ji} = 0 \text{ otherwise} \qquad (1)$$

Consequently, CB_{it} captures the number of lower-ranked drivers capable of passing driver i in the points distribution in race t. Contestant j is theoretically able to surpass i if i places last, and j receives the maximum number of points. This information is transparent to driver i before race t and therefore serves as an appropriate metric of the risk of loss in rank.

Similarly, *crowding from above,* CA_{it}, which reorders the terms yielding the difference in points, P_{it-1} and P_{jt-1}, is computed as follows:

$$CA_{it} = \sum_{j=1}^{J} D_{ji},\ D_{ji} = 1 \text{ if } 0 \leq P_{jt-1} - P_{it-1} < S_t,\ D_{ji} = 0 \text{ otherwise} \qquad (2)$$

This measure captures the count of higher-ranked drivers whom i could surpass if i received the maximum number of points, and they finished last, in other words, the opportunity of driver i to surpass rivals ranked higher in the points distribution. Using these two measures allows us to consider the potentially asymmetric consequences of encroachment

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Although our dataset is a 14-year panel, for ease of presentation we have not added a season-level subscript to the formulas. Additionally, because our measures of crowding necessarily equal the total number of drivers before the end of the first race of the season, when all contestants have zero points, subsequent models that enter measures of crowding only consider the probability of crashing in race 2 and after.

(crowding from below) versus opportunity (crowding from above). For example, at the start of the 25th race in the 2002 season, Kyle Petty had accumulated 2375 Winston Cup Series points, ranking 23rd in the points distribution. With 43 drivers racing that day, S_t, the striking distance, equaled 151 points, meaning Petty was crowded from below by drivers beneath or at his rank who held more than 2224 points. This subset consisted of Elliott Sadler, Bobby Hamilton, and Jimmy Spencer, who had 2273, 2251, and 2242 points, respectively. Because Ward Burton had 2214 points by the start of this race—just shy of the needed 2225 point threshold—Burton did not figure in the count of those crowding Petty from below, which equaled 3. By counting the drivers inside a 151-point range, we assume that Petty orients locally to those drivers who might outstrip him by the close of the current contest. Were additional drivers—such as Burton and others with fewer points—to close in on Petty's rank, our expectation is that Petty would take greater risks to preserve his rank from loss and thus face a higher hazard of crashing.

Similarly, the set of drivers above Petty, and yet holding fewer than 2526 points, included Robby Gordon, Dave Blaney, Jeff Green, Kevin Harvick, and Terry Labonte (with 2413, 2423, 2476, 2480, and 2493 points, respectively), bringing Petty's score on crowding from above to 5. Were this score to rise by virtue of other higher-ranked drivers falling below a threshold such that they could be caught by Petty in points, we also expect that Petty's proclivity to take risks, and thus the chances of crashing his vehicle, will escalate.

Rank change. To assess our third hypothesis that the effect of crowding from below is greatest when the race-to-race turnover in ranks is lowest, we devised an additional, race-level measure, which we term rank change. We collected the ranks of each driver in the Winston Cup series points distribution at the start of the prior race and at the end of the prior race and then identified the number of drivers who underwent a transition in rank. We therefore defined *rank change (RC)* as follows, where K denotes the number of active drivers in race t-1, defined as those seeking a qualifying position at t-1; R_{kt-2} equals the rank of driver k at the start of race t-1; and R_{kt-1} denotes the rank of k at the end of race t-1.

$$RC_{t-1} = \sum_{k=1}^{K} \delta_{kt-1}, \quad \delta_{kt-1} = 1 \text{ if } |R_{kt-2} - R_{kt-1}| > 0, \ \delta_{kt-1} = 0 \text{ otherwise} \quad (3)$$

Using this measure, which counts the number of nonzero differences in starting and finishing ranks across drivers seeking to qualify in the prior race, we were able to examine the possibility that crowding from below is most consequential as an antecedent of chancy conduct as the tournament's rank structure locks into place and drivers begin to orient to the encroachments on their position in the contest. To capture the number of rank changes occurring in race 1, which we in turn use to predict the accident rate in race 2, we assigned to each driver the rank of 1 at the start of the opening race. Unless drivers are tied for first place immediately after the season opener, rank change at that juncture equals the number of drivers competing for a spot in the first race minus one (for the driver holding the most Winston Cup Series points).

Estimation and Controls

To test the hypotheses, we began by estimating models of the following form:

$$\ln[\mu_{it} / (1 - \mu_{it})] = \sigma_i + \mathbf{X}_{it-1}\boldsymbol{\beta} + \mathbf{Z}_t\boldsymbol{\gamma} + \theta_1 CB_{it} + \theta_2 CA_{it} + \boldsymbol{\tau}_t \qquad (4)$$

where μ_{it} is the i-th driver's probability of crashing in race t. Our unit of observation is therefore the driver, who is at risk of crashing in each race of a 14-season panel that extends from 1990 to 2003. Using data from published sources (e.g., NASCAR, 2004) and NASCAR-related Web sites, we assigned a 1 to a driver's entry in the event vector if that driver did not finish the race because of an accident, and 0 otherwise. This outcome is one of many destination states. NASCAR's publications typically identify a driver as having finished the race (denoted by "running") but also clarify reasons other than an accident for not finishing (usually related to equipment failure).

We add fixed effects to adjust for innate, driver-specific tendencies to crash, which are represented by σ_i. Scholarly work emphasizing innate tendencies as antecedents of risk taking traces back to discussions of personality types, such as achievement motivation and stress seeking. Correspondingly, researchers have recently tied risky behavior empirically to several stable traits, such as "sensation seeking" (Rolison and Scherman, 2003) and low self-control, an underlying factor shown to result in automobile accidents (Gottfredson and Hirschi, 1990). In our empirical setting, allowing the intercepts to vary by drivers is important in light of well-known variations in individuals' ability, temperament, and posture toward risk. Among NASCAR fans, some drivers are known for dangerous tactics, while others, such as Mark Martin, have reputations for disciplined, careful driving. Using a fixed effects specification constrains the estimates to reflect the consequences of within-driver changes in covariate values on the odds of crashing.

The matrix $\mathbf{X}_{it-1}$ contains time-varying covariates measured at the driver level. Table 1 reports a matrix of correlations and descriptive statistics for all variables included in our models. Starting in the second row of table 1, we enter a count of the focal driver's *prior accidents* in the current season. Without fixed effects, we would expect this occurrence dependence term (Heckman and Borjas, 1980) to have a positive effect on the probability of an accident, as it would reflect otherwise occluded variation in the tendency to crash (see Otten and van der Pligt, 1992, for evidence of state dependence in risk taking). With fixed effects, we expect the opposite. Because accidents carry physical, psychic, and economic tolls, once we control for drivers' time-invariant temperaments, we expect them to exhibit caution after recent crashes.[3]

3
Accidents may also adversely affect a driver's sponsors. To sponsors, cars are "200 mile per hour billboards" (Ronfeldt, 2001) that provide a return on investment insofar as they yield exposure beyond what sponsors could otherwise purchase in standard advertising channels. Sponsors therefore rarely suffer accidents gladly. Unless a spectacular accident brings a sponsor's decal repeatedly into view in highlight clips from the race, an accident cuts exposure short for the day because the vehicle no longer appears in the telecast of the race.

Table 1

Descriptive Statistics and Correlations for Variables in the Analysis (N = 18,617)

Variable	Mean	S.D.	Min.	Max.	1	2	3	4	5	6	7	8	9
1. Accident	.087	.282	0	1									
2. Prior accidents	1.091	1.308	0	9	.035								
3. Prior did not finish	1.378	1.592	0	14	.017	.290							
4. Multicar team	.237	.426	0	1	–.039	–.004	–.118						
5. Owner's rank	20.589	12.712	1	50	.095	.091	.109	–.607					
6. Pole position	21.238	12.067	1	44	.035	.023	.014	–.159	.370				
7. Points rank	20.568	12.384	1	44	.100	.135	.116	–.275	.834	.398			
8. Experience in 1,000 miles	81.465	66.797	0	283.402	–.071	–.038	.000	.193	–.259	–.072	–.299		
9. Age	37.833	7.161	10.758	65.422	–.016	–.044	.027	–.068	.073	.098	.049	.612	
10. Race number	16.770	9.501	1	36	.011	.478	.438	.049	.019	.015	.016	.043	.006
11. Race length	394.950	108.477	124.95	600	.044	–.018	–.016	–.011	.027	.023	.024	–.015	–.001
12. Track length	1.526	.707	.526	2.66	.004	–.028	–.028	.011	.035	.034	.033	–.010	.004
13. Crowding from below	6.355	8.634	0	42	–.034	–.295	–.323	.072	–.253	–.085	–.293	.066	–.028
14. Crowding from above	6.355	8.654	0	42	–.013	–.233	–.267	–.034	.109	.049	.172	–.030	–.007
15. Finishing position below	24.437	10.108	1	44	.038	.066	.074	–.139	.481	.238	.559	–.161	.051
16. Finishing position above	17.675	9.874	0	44	.030	.088	.014	–.092	.291	.179	.377	–.085	.024
17. Performance below	88.839	27.874	0	139.783	–.068	–.003	–.043	.183	–.557	–.264	–.644	.234	–.047
18. Performance above	110.391	29.409	0	175	–.038	–.029	.014	.112	–.301	–.177	–.385	.112	–.019
19. Rate below by rank	.077	.042	0	.45	–.001	.014	–.011	–.038	–.010	.007	.023	.020	–.010
20. Rate below by pole position	.065	.047	0	.4	–.021	–.080	–.110	.012	–.141	–.057	–.125	.052	–.016
21. Conditional rate below	.077	.055	0	1	–.002	.002	.010	–.051	.054	.041	.084	–.003	.012
22. Rank change	24.765	8.978	5	49	–.019	–.362	–.440	.068	.023	.023	.023	.021	–.003

Variable	10	11	12	13	14	15	16	17	18	19	20	21
11. Race length	–.043											
12. Track length	–.027	.389										
13. Crowding from below	–.623	.039	–.112									
14. Crowding from above	–.618	.038	–.111	.445								
15. Finishing position below	.103	.015	–.001	–.226	–.029							
16. Finishing position above	–.075	.032	.060	.000	.208	.122						
17. Performance below	–.059	–.011	.008	.248	.017	–.752	–.145					
18. Performance above	.138	–.013	–.053	–.023	–.244	–.117	–.764	.185				
19. Rate below by rank	–.214	.030	.005	.231	.242	–.358	.128	.382	–.115			
20. Rate below by pole position	–.332	.029	.016	.389	.345	–.310	.109	.342	–.109	.555		
21. Conditional rate below	–.182	.034	.002	.180	.233	–.242	.121	.229	–.116	.787	.453	
22. Rank change	–.790	.091	.004	.614	.610	–.040	.092	.054	–.110	.178	.277	.144

We also adjusted for the number of prior occasions on which a driver *did not finish (DNF)* a race in the current season for reasons other than a crash. The primary causes of DNFs are mechanical problems, which force drivers to exit a competition in progress. Examples include alternator, ignition, and piston failures, as well as problems with steering, suspension, and transmission. We included this covariate because drivers who frequently experience mechanical problems may race under the supervision of less able crew chiefs and mechanics or may regularly push the limits of their equipment and may therefore also be more prone to accidents.

To account for the possible effects of membership on NASCAR teams, we included two additional covariates: *multicar team* and *owner's rank*. First, to adjust for the potential advantages of collaboration during the race, we entered the indicator variable, multicar team, which was set equal to 1 if a driver was accompanied by at least one team member in the race. A "team" exists if more than one contestant is driving for the same owner in a race. We place quotation marks around the term "team" because, although team members do share data to prepare for a race, they compete once they are on the track. It is understood that each member of a team races for himself. While most drivers do race alone, in over 20 percent of the observations, a driver benefits from the presence of at least one other team member competing in the same race. In the last fifteen years, owners have occasionally entered more than one car per race, in part to achieve economies of scale in data collection. When a driver competes as a member of a multicar team, he is typically privy to more site-specific information, such as the tire compound that is optimal for the racetrack. With more team members, drivers also have access to additional spotters, who monitor the race from the grandstands and communicate with drivers by radio. For instance, Terry Labonte's spotter will also convey data to Jeff Gordon, his team member, and vice versa. Gordon is then more likely to know about spinouts or debris on the track, which in turn decreases his probability of crashing.

Second, we computed a proxy for the resources enjoyed by a focal driver's owner. Following Cyert and March's (1963) insight that slack insulates organizations from problems, drivers racing for owners with more resources should face less pressure to enhance their standing in the tournament and therefore take fewer risks. Under the assumption that higher-ranked owners possess more resources than their less-well-positioned peers, we ranked all owners at the start of each race by the sum of the Winston Cup Series points garnered by those driving for them. We then included for each driver a measure of his owner's ranking in the season-unfolding points distribution. Our expectation is that drivers whose owners are ranked further back, and are thus less resource-rich, sense a greater burden to advance in the tournament and thus crash their vehicles with greater frequency.

We also adjusted for each driver's *pole position.* The pole is the order in which drivers start the race. A driver's pole position is determined by his performance in a qualifying round, which often occurs on the Friday before a Sunday race. The driver with the best qualifying time starts the race at the front of the queue, on the inside of the track. Next to him, on the outside of the track, is the driver whose pole position equals 2. Thus, before the race begins, 43 drivers fill slots in 21 rows, with the last driver alone in back. To ensure that popular drivers have the opportunity to compete even if they post poor qualifying times, NASCAR reserves the last seven slots in the pole for each race, called "provisionals," to allocate to drivers on the basis of owner points. This way, Sterling Marlin, Geoff Bodine, and other fan favorites can race even if they have poor qualifying times. We included pole position as a covariate ranging from 1 to 43 to account for the possible effects of being at the back of the queue, where drivers may take more risks to advance their position during the race.

We measured performance by converting the total points accumulated over the current season by each driver competing in the race into a vector of ranks. We estimated the effect of rank on the hazard of crashing *(points rank)* by including a full set of dummy variables. Using a dummy for each rank has the advantage of accounting for possible nonlinearities in the effects of standing in the tournament caused by discontinuities in the payoffs associated with particular ranks in the season-long reward schedule. Additionally, by fitting the effects of rank with a full set of indicators, we adjusted for the particular and asymmetric mix of potential losses and gains attached to each position in the tournament. As a general trend, our expectation is that as a driver falls further back in rank, his hazard of crashing will rise.

Two final covariates at the driver level are *experience* and *age.* We measured experience as the total number of miles driver i completed in Winston Cup Series races before the start of race t over the course of his career, divided by 1,000. We expected experience and age both to lower the hazard of crashing. With additional miles on the circuit come better skills, and following many earlier studies that have tied risk taking to youth (Kweon and Kockelman, 2001), our expectation was that older NASCAR contestants would crash their vehicles less frequently.

Among the race-level covariates contained in the matrix Z_t, we also entered *race number,* which ranges from 1 to 36, and *race number squared.* We included the second-order term to account for the possibility that the incidence of risk taking on the track varies nonlinearly over the stages of the contest. Specifically, we anticipated that the probability of crashing follows an inverted U-shaped pattern across the number of races, for two reasons: first, drivers may be most willing to fully test the limits of their technology or "set-up" in the middle of the season, after they have gained initial acquaintance with their equipment; and second, the midpoint of the NASCAR season is also when drivers endure the hottest temperatures on the track, making it harder to gain traction and thus raising the hazard of crashing.[4]

Z_t contains two additional covariates operating at the race level: the length of the race *(race length)* and the distance around the track *(track length),* both in miles. A longer race will increase the hazard of crashing because a driver has more opportunity to crash (and is more fatigued) in a 600-mile race than in a 125-mile race. By contrast, a longer track will decrease the hazard of a crash. First, there is less space for error on shorter tracks, which force drivers close together, tightly coupling their maneuvers and thus render accidents more likely. Like the tightly coupled, complexly interacting elements of other high-risk systems (Perrow, 1984), NASCAR drivers are especially accident prone on shorter tracks, in which minor errors may concatenate into significant crashes. Fatigue is the second factor. On shorter tracks, which look more like a circle than an elongated oval, there is more centripetal force because drivers are always in a turn. Greater exposure to heat and carbon monoxide, resulting from the narrow space between cars, also wears drivers down (Walker, Dawson, and Ackland, 2001). Third, shorter tracks allow for far less cooperation and so pit drivers more intensely against each other in direct competition (Ronfeldt, 2001: 2). It is only on the longer tracks that transitory structures of collaboration regularly emerge, in which drivers achieve higher speeds in packs by "drafting." Without occasions to cooper-

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Personal communication, 2006, from Charles B. Sigler, NASCAR Observer and Certified ASE (Automotive Service Excellence) Mechanic.

ate, we expect drivers to take more risks and thus crash more often on shorter tracks.

Finally, as denoted by $\boldsymbol{\tau}_t$, we also adjusted in two ways for various forms of temporal heterogeneity. First, we entered year dummies for the seasons in our analysis, from 1990 to 2003, which absorb the effects of year-to-year changes in technology that may enhance or decrease the likelihood of an accident. Then, in a subsequent specification, we entered a dummy variable for each of the over 400 races in our panel. The race-level indicators adjust conservatively for wind speed, temperature, track conditions, the dispersion of the points distribution, the size of the race-day purse, the magnitude of race-day prize differentials (Becker and Huselid, 1992), and all other similar factors that might influence the odds of crashing. Similarly, race dummies account for all regulatory changes and safety rules that may affect the likelihood of accidents (e.g., Peltzman, 1975). Recent work on this topic suggests that safety regulations yield greater risk taking in auto racing (Sobel and Nesbit, 2004) and mountain climbing (Clark and Lee, 1997). Using race fixed effects enabled us to separate the consequences of crowding from those of NASCAR's regulatory environment.

RESULTS

Table 2 presents results of nine logistic regression models predicting the probability of crashing. Model 1 contains only the controls described in the preceding section and does not include dummy variables for drivers. First, although the effects of the count of prior mechanical failures and of our multicar-team indicator fall short of statistical significance at the .05 level, many of the coefficients are in the direction we anticipated, and the effect of the number of prior accidents is statistically discernible. With each prior accident over the course of the season, the odds of crashing rise by about 5 percent, reflecting the importance of adjusting for otherwise unobserved variation in drivers' innate tendencies to crash. Additionally, the odds of crashing rise by 1.5 percent for each drop in the rank of a driver's owner [exp(.0149) = 1.015]. This effect is consistent with the fact that when drivers race under a more competent, resource-rich owner, they are less likely to crash.

Although the effect of pole position differs insignificantly from zero, the pattern of effects of rank in the tournament (not shown but available upon request) concurs with our expectation that drivers undergo accidents with greater frequency when located further back from the top of the hierarchy. Using 43 dummy variables to account for drivers' ordinal positions allowed us to address the possibility that the propensity to crash is associated with different incentives attached to various locations in the set of ranks. Although the probability of crashing against rank fit as a spline contains peaks and troughs, it is nonetheless clear that, on average, a given driver will crash more frequently when he is positioned toward the bottom of the hierarchy than when he is near the top. We see this pattern of results as evidence of risk-taking behavior among drivers who lag behind the rest of the field and have little to fear in terms of positional loss, physical

Table 2

Logit Models Predicting the Probability of an Accident*

Control variable	1	2	3	4	5	6	6- 1	7	8
Prior accidents	.0508•	.0537•	.0512•	–.0617•	–.0391	–.0411	–.0420	–.0429	–.0634•
	(.0241)	(.0241)	(.0242)	(.0274)	(.0289)	(.0288)	(.0288)	(.0291)	(.0275)
Prior did not finish	.0180	.0191	.0172	.0334	.0384	.0372	.0372	.0398	.0363
	(.0203)	(.0203)	(.0204)	(.0227)	(.0244)	(.0242)	(.0242)	(.0244)	(.0228)
Multicar team	.1316	.1354	.1322	–.0635	–.1020	–.1080	–.1080	–.0918	–.0359
	(.1350)	(.1350)	(.1351)	(.1653)	(.1721)	(.1719)	(.1718)	(.1724)	(.1655)
Owner's rank	.0149•	.0150•	.0147•	.0068	.0052	.0048	.0047	.0055	.0080
	(.0070)	(.0070)	(.0070)	(.0082)	(.0086)	(.0086)	(.0086)	(.0086)	(.0083)
Pole position	–.0014	–.0016	–.0018	–.0003	.0009	.0011	.0010	.0010	–.0003
	(.0025)	(.0025)	(.0025)	(.0027)	(.0027)	(.0027)	(.0027)	(.0027)	(.0027)
Points rank (dummies)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Experience in 1,000 miles	–.0031••	–.0030••	–.0030••	.0048	.0069	.0068	.0069	.0072	.0053
	(.0006)	(.0006)	(.0006)	(.0035)	(.0038)	(.0038)	(.0038)	(.0038)	(.0036)
Age	.0084	.0081	.0078	–2.3811	–.0080	–.0065	–.0082	–.0032	–.9588
	(.0050)	(.0050)	(.0050)	(2.2056)	(.0410)	(.0409)	(.0410)	(.0414)	(2.2696)
Race number	.0516••	.0750••	.0582••	.1437•					.0824
	(.0143)	(.0175)	(.0218)	(.0723)					(.0758)
Race number squared	–.0015••	–.0020••	–.0016••	–.0023••					–.0016•
	(.0004)	(.0004)	(.0005)	(.0007)					(.0007)
Race length	.0019••	.0019••	.0019••	.0020••					.0020••
	(.0003)	(.0003)	(.0003)	(.0003)					(.0003)
Track length	–.1740••	–.1758••	–.1760••	–.1996••					–.2019••
	(.0478)	(.0479)	(.0478)	(.0494)					(.0495)
Year dummies	Yes	Yes	Yes	Yes	No	No	No	No	Yes
Driver dummies	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Race dummies	No	No	No	No	Yes	Yes	Yes	Yes	No
Predictors									
Crowding from below		.0203•	.0181•	.0190•	.0340••			.0333••	.0900••
		(.0084)	(.0085)	(.0091)	(.0120)			(.0122)	(.0349)
Crowding from above			–.0102	–.0071	.0067			.0057	–.0062
			(.0080)	(.0086)	(.0113)			(.0115)	(.0087)
Finishing position below						–.0120••	–.0120••		
						(.0037)	(.0037)		
Finishing position above						–.0031	–.0031		
						(.0032)	(.0032)		
Simulated finishing position							–.0072		
							(.0042)		
Performance above								–.0005	.0000
								(.0011)	(.0010)
Performance below								.0007	.0012
								(.0019)	(.0018)
Rate below by rank								2.1046	1.5137
								(1.2311)	(1.1158)
Rate below by pole position								.1272	–.0799
								(.7968)	(.7724)
Conditional rate below								–1.6774	–1.5051
								(.9098)	(.8131)
Rank change									–.0063
									(.0076)
Crowding from below × Rank change									–.0018•
									(.0009)
Constant	–4.2776••	–4.5575••	–4.3816••	127.9569	–4.2375	–2.0018	–2.5909	–4.5749•	49.8158
	(.3716)	(.3909)	(.4129)	(121.432)	(2.2159)	(1.8462)	(2.0216)	(2.2653)	(124.943)
N	17846	17846	17846	17655	15454	15454	15454	15454	17655
Chi-square	396.31	401.99	403.66	649.06	1221.37	1223.96	1226.87	1226.22	662.96

• $p < .05$; •• $p < .01$.

* Standard errors are in parentheses. Year dummies are not reported.

harm notwithstanding. More generally, this pattern of effects concurs with earlier research showing that risky conduct is especially likely at the margins of competitive systems, where contestants must cover great distances to secure a viable position (e.g., Bowman, 1982).

Our final two driver-level covariates, experience and age, have opposite effects when they enter the model jointly. Experience—the number of Winston Cup Series miles (divided by 1,000) a driver has accumulated during his career before the current race—strongly and negatively affects the hazard. With each standard deviation increase in mileage, the odds drop by 19 percent. Conversely, once experience is held constant, age positively (although insignificantly) affects the rate. We suspect that, without fixed effects, the effect of age may reflect between-driver variation in the time of entry into the sport, with later entrants receiving better training and thus crashing less frequently.

Model 1 shows that in the matrix of race-level covariates, race number, race length, and track length have the effects we expected. The significant coefficients on race number and race number squared show that the accident rate moves nonlinearly over the course of the season, reaching a maximum midway through the season at about the 17th race [$.0516 / (2 \times .0015) = 17.2$]. Additionally, a standard deviation increase in race length (about 100 miles) raises the odds of an accident by nearly 23 percent. More intriguing is the finding that a standard deviation decrement in track length raises the odds of crashing by about 13 percent. With other factors kept constant, accidents are more likely on shorter tracks, where drivers have little room for error, are worn down by centripetal force, face higher heat and carbon monoxide levels, and have few opportunities to form the drafting lines that ephemerally hold competitive impulses at bay.

Model 2 adds to our baseline specification the measure of crowding from below depicted in equation (1) to test our first hypothesis. This model reports a significant positive effect of crowding from below. This result supports our first hypothesis that drivers take greater risks when their ranks are increasingly likely to be assumed by other, lower-ranked competitors. With each standard deviation increase in the count of lower-ranked rivals in position to outstrip a chosen driver in a given race, the odds of crashing go up by 19 percent. As a driver's lower-performing rivals encroach on his rank, his tendency to crash correspondingly rises. This effect fits with our general expectation that when an actor faces the threat of positional loss, risky conduct follows in response. In NASCAR, drivers are particularly keyed to the threat of such losses largely because of the public discussion among fans, pundits, and drivers that surrounds changes in rank.

Model 3 establishes that the effect of crowding from below substantially exceeds that of crowding from above. The coefficient on crowding from above falls short of statistical significance, while the effect of crowding from below remains robust even as our measure of crowding from above is added, and the estimated coefficients and standard errors of crowding from below remain quite similar across models 2 and 3.

A test of the difference in coefficients, θ_1 and θ_2 from equation 4, provides formal support for hypothesis 2. The difference between the two coefficients significantly exceeds zero at the .01 level of confidence ($p < .0035$, one-tailed test). More broadly, the virtue of performance data in a sharply defined hierarchy is the chance they afford to split the distribution for each actor, devise separate metrics of clustering around each rank, and then identify the differential consequences of crowding by others in either direction. This approach demonstrates that the density of those positioned behind a focal actor in a tournament matters more than the number of those in higher ranks as an antecedent of risky conduct.

Robustness Checks

We took a number of steps to assess the robustness of the primary finding, that crowding from below positively influences the rate of accidents. First, we guarded against the possibility that crowding from below correlates with unobserved driver ability by including in model 4 a separate dummy variable for each driver. In this model, which adjusts for all time-invariant individual characteristics, several parameters undergo shifts, although crowding from below stays strongly significant.[5] Specifically, neither experience nor age retains its significance, and the effect of the count of prior accidents turns negative. This reversal in the consequence of our occurrence dependence term is sensible in a within-driver model. With every additional accident that a driver endures in a season, that driver's distaste for risk taking is likely to grow. Using the estimate in model 4, each additional prior accident reduces the odds of crashing by 6 percent. Additionally, the effect of crowding from below remains strong.[6]

Second, in model 5, we added a fixed effect for each of the over four hundred races in the panel. Using this specification allowed us to sweep out the effects of factors beyond drivers' control, such as track conditions, weather, safety regulations, the average level of crowding faced by drivers on the field, nearness to the end of the season, and related outcomes. In model 5, which necessarily excludes measures of race length, track length, race number, and year dummies, whose effects cannot be identified independent of the race dummies, the coefficient on crowding from below remains strongly positive. Consequently, the effects of the clustering of rivals around drivers' ranks are not the result of aggregate-level processes affecting both levels of crowding and proclivities to take risks. Instead, crowding from below uniquely elevates the odds of crashing.

Third, if our theory of crowding is correct, the sequence of action within a current race should have a meaningful effect on the probability that a driver crashes. Unfortunately, the data available to us do not provide information about the happenings in any given race: we know only the order in which drivers finished, the number of points drivers received, and for those who failed to cross the finish line, whether they

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The reported fixed effects models include actual dummy variables for each driver. Greene (2004) provided theoretical and simulation-based results on bias in maximum likelihood fixed-effects models, showing that the bias of logit coefficients approaches zero as the number of observations per group increases from 2 to 20. In model 4 in our analysis, the average group size, number of observations per driver, is 121.8. This average group size substantially exceeds Greene's tested group sizes of up to 20. Consequently, our results are very unlikely to be affected by the incidental parameters problem. Nonetheless, we assessed this possibility by estimating a version of model 4 that used a conditional fixed effects estimator, rather than entering dummy variables for each driver. Using this estimator, our effects were virtually identical: the coefficient on crowding from below was .0186 (2.06 t-test; $p < .039$) and the coefficient on crowding from above was –.0072 (–.85 t-test; $p < .396$).

6
We also estimated a version of model 4 in which we replaced crowding from above with distance in points from the nearest passable superior, on the assumption that drivers may only orient to the most proximate rival above. With the covariate in the model, crowding from below remained strongly significant, while the effect of this new measure was insignificant (–1.71 t-test).

crashed or experienced a mechanical failure. If we assume that drivers' positions midway through the race are reasonably correlated with their finishing position, however, then we can use the finishing positions of a focal driver's proximate rivals to create covariates that proxy the relative position of that driver during the current race. Our theory suggests that a focal driver should crash with greater incidence when his lower-ranked competitors (those who could potentially leapfrog him) are performing well in the current race and that this effect should be greater than the effect of the current-race performance of the drivers ranked just above the focal driver. Consequently, we developed two additional covariates—*finishing position below* and *finishing position above*—that measure, respectively, the average current-race finishing position of those drivers that crowd driver i from below and the average finishing position of those that crowd i from above, where, as before, crowding is defined by locations in the points distribution at the start of the current race.[7] Letting f_{jt} denote the finishing position of driver j in race t, our measure of *finishing position below (FPB)* is defined as follows:

$$FPB_{it} = \frac{\sum_{j \in CB_{it}} f_{jt}}{CB_{it}} \tag{5}$$

where CB_{it} records the number from equation (1) of all lower-ranked drivers capable of passing driver i. Correspondingly, we calculated *finishing position above (FPA)* as follows, where the only change is that we computed the average finishing position of higher-ranked drivers in striking distance of driver i:

$$FPA_{it} = \frac{\sum_{j \in CA_{it}} f_{jt}}{CA_{it}} \tag{6}$$

Using these covariates in place of our crowding measures in model 6 allowed us to assess further our expectation that encroachment by lower-ranked drivers matters more than the locations of higher-ranked drivers as an antecedent of risky conduct. Model 6 shows that the coefficients on FPB_{it} and FPA_{it} are both negative. With finishing positions ranging from 1 to 44, the directions of the effects suggest that the focal driver is more (or less) likely to crash, the better (or worse) his peers perform during the given race. Furthermore, because the magnitude of the parameter capturing the effect of FPB_{it}, finishing position below, statistically exceeds that of its counterpart FPA_{it} at the .05 level of confidence ($p < .0297$, one-tailed test), we can conclude with greater confidence that drivers are more attentive to the possibility of losing ground to lower-ranked contestants than they are to the standings of those further ahead of them in the race. We nevertheless performed several additional robustness checks to address alternative explanations of our findings.

7
One concern with these covariates is that when the focal driver crashes, the rest of the field will automatically improve in rank because he performs poorly. In turn, this will mechanically create a positive relationship between the finishing position of competitors and the probability that the focal driver crashes. There are a number of ways to remove this spurious correlation. In model 6-1, we have included one additional covariate, *simulated finishing position,* which is defined as the average finishing position of n randomly selected drivers, where, for driver i in race t, n represents the number of drivers who are crowding i from below.

First, although driver dummies adjust for intrinsic ability levels, they cannot control for those of competitors who are positioned nearby in the rankings. Without controls for the quality levels of those crowding the focal driver from above and below, the possibility remains that the stronger effect of crowding from below results only from drivers' tendency to discount their chances of surpassing higher-ranked (and presumably more able) rivals. Taking average performance historically as a proxy for ability, we therefore constructed two additional adjustments: *performance above* and *performance below,* which capture, respectively, the average points per race accumulated over the career of each contestant crowding driver i from above and the average points per race collected over the career of each contestant crowding i from below. We collected the set of drivers k who crowd driver i from above in each race t, and then computed a time-varying average points per race for those drivers, or *performance above (PA):*

$$PA_{it} = \frac{\sum_{k \in CA_{it}} p_{kt-1}}{CA_{it}} \tag{7}$$

where p_{kt-1} is driver k's average points per race before race t. We obtained p_{kt-1} by dividing driver k's career total Winston Cup Series points by the count of all races in which he participated before race t. CA_{it} again equals the number from equation (2) of all higher-ranked drivers at risk of being passed by driver i. We thus calculated a double average, computing the expected points per race across all drivers k crowding i from above. Correspondingly, our measure of *performance below (PB)* takes the following form:

$$PB_{it} = \frac{\sum_{k \in CB_{it}} p_{kt-1}}{CB_{it}} \tag{8}$$

where the difference between equations (7) and (8) is that we now consider the career-level performances of those proximate drivers j crowding i from below. Using these measures jointly accounts for the fact that those ahead of the focal driver may be better athletes while those beneath him are likely to possess relatively less skill.

Second, although NASCAR's formal rules and norms circumscribe the extent to which drivers can commit acts of sabotage on the track, an alternative causal story worth assessing is that crowded ranks are surrounded by risk-prone inferiors and that these lower-ranked drivers j, eager for driver i's standing, induce the accidents that i undergoes. Under this scenario, the effects we have reported would be spurious. To address this possibility from various angles, we devised three additional measures.

First, given that drivers vary in their risk-taking propensities as a function of their rank in the tournament, we began with a covariate, *rate below by rank (RBR),* which takes into account inferiors' tendencies to take risks as a function of their positions in the contest by assigning the largest weights to the worst-ranked rivals. This approach is consistent with the possibility that intrinsic propensities to crash are shaped by location in the tournament, most significantly affecting the actions of drivers nearest to the bottom of the hierarchy. Thus we collected the set of drivers in each race who crowd driver i from below and then calculated a time-varying weighted average accident rate for those drivers. Letting a_{jt-1} equal the number of races in which driver j crashed his vehicle, divided by the count of all Winston Cup Series races driver j entered from the onset of his career before race t, a measure of lower-ranked drivers' intrinsic tendency to crash is as follows:

$$RBR_{it} = \sum_{j \in CB_{it}} r_{jt} a_{jt-1} \qquad (9)$$

where CB_{it} equals the density of all lower-ranked drivers from equation (1) capable of passing driver i,

$$r_{jt} = R_{jt} \Big/ \sum_{j \in CB_{it}} R_{jt}$$

and R_{jt} is the rank of j at the start of race t. We thus applied rank-based weights r_{jt} to the average accident rates a_{jt-1} of all drivers j that crowd i from below. Using this measure allowed us to disentangle the effects of driver i's perception of the possibility of loss in rank from the ranked-weighted, risk-seeking proclivities of his encroaching competitors.

Second, we controlled for the extent to which lower-ranked, accident-prone drivers surround the focal driver spatially at the start of each race with a covariate, *rate below by pole position.* This measure allocates weights to the career-level accident rates of those crowding driver i from below according to their proximity in NASCAR's starting line-up, or "pole." Again allowing a_{jt-1} to denote the count of races in which driver j crashed his car, divided by the number of all Winston Cup Series races j entered from the start of his career through race t-1, we computed *rate below by pole position (RBPP)* as follows:

$$RBPP_{it} = \sum_{j \in CB_{it}} pp_{jt} a_{jt-1} \qquad (10)$$

where pp_{jt} denotes the nearness of drivers j and i in the pole. We obtained the weights pp_{jt} in several steps, following Burt (1987). To generate a simple distance measure, we began by computing the absolute difference in pole positions between i and all other actors j crowding i from below. Next, we converted these distances to proximity scores by subtracting each from the maximum distance in the set. Then, so that weights pp_{jt} sum to unity, we divided each proximity score by the sum of the proximity scores. With the measure in equation (10), we could emphasize the accident propensities of those encroaching on the focal driver as a function of their initial spatial proximity on the track.

Third, we developed a measure that took into account the degree to which those encroaching on the focal driver have crashed historically as members of a set together with other drivers also capable of advancing in rank. Although a weighted average accident rate for the crowd below may be quite high, not all of its incumbents are necessarily equally likely to crash when they occupy a group of those poised to advance. Conversely, those drivers who have undergone accidents in such circumstances historically may be especially likely to amplify the focal driver's hazard of crashing in the current race. Given that those drivers may be most motivated to take risks and affect the fate of the focal driver on the track, we developed a metric for their earlier conduct when they were collectively in contention for a higher rank. Using data on drivers' accident history and prior levels of proximity to others, we devised the measure, *conditional rate below (CRB):*

$$CRB_{it} = \frac{\sum_{j \in CB_{it}} A_{jt-1}}{CB_{it}} \qquad (11)$$

where A_{jt-1} is what we term the *conditional accident rate* for driver j. We computed A_{jt-1} first by counting the number of races in which j crashed his vehicle under two conditions: (1) j was close enough in Winston Cup Series points to surpass a higher-ranked driver; (2) there was at least one other driver facing the same opportunity as driver j. To complete the calculation of A_{jt-1}, we divided the count of these crashes by the total number of races during j's career in which the second condition was met. A_{jt-1} therefore captures j's intrinsic propensity to take risks as a member of a pack composed of at least one other driver in contention for a higher rank. As the propensity for those crowding the focal driver from below increases, the focal driver's hazard of crashing may correspondingly rise.

The estimates reported in model 7 show that while the effects of our measures of nearby higher- and lower-ranked drivers' ability levels—performance above and performance below—are close to zero, our measure of rate below by rank is stronger, although statistically indiscernible. Similarly, the additional measures we devised as robustness checks—rate below by pole position and conditional rate below—also fall short of statistical significance. Most important, our main measure of interest, crowding from below, retains its significance with these added controls.

Having evaluated the robustness of our primary result, we could assess our third hypothesis, which was that the effect of crowding from below is most consequential after the rank structure has achieved stability and its incumbents orient locally to their positions within it, rather than compete with the entire field. To do so, in model 8, we retained our measures of crowding from equations (1) and (2), dropped the race-level fixed effects, which would otherwise span the effect of the rank change covariate described in equation (3), and added the product of crowding from below and rank change.

The coefficient on the interaction term supports our third hypothesis. The negative effect of crowding from below by rank change indicates that the impact of crowding from below is greatest when the level of race-day turnover in ranks is at a minimum. Using the parameters from model 8, a standard-deviation increase in crowding from below leads to a 70 percent increase in the hazard of crashing when rank change is at a standard deviation below its mean value; by contrast, the same shift only leads to a 29 percent increase in the rate when the rank change covariate is a standard deviation above its mean value. Consequently, our results indicate that crowding from below exerts a contingent effect. It has its strongest effect on the propensity to crash when a high degree of stability in rank has materialized. This finding is consistent with the premise that contestants perceive the opportunity to recapture a lost position as less likely when there is minimal race-to-race churn in the rankings.

DISCUSSION AND CONCLUSION

We sought to clarify the social-structural sources of risky conduct in a tournament, and our results have demonstrated that crowding by lower-ranked rivals around a focal driver's position elevates his hazard of crashing in NASCAR. We also confirmed that crowding by inferiors has a greater effect than crowding by superiors and that crowding by inferiors exerts its strongest effect when contestants' positions in the hierarchy of ranks are relatively stable. In addition to the empirical evidence we have presented, one of our primary contributions has been to show that the conduct of actors in a tournament is shaped not only by their relative positions but also by the level of crowding around those positions. Thus by combining insights from work on tournaments in organizational economics with conceptions of localized competitive dynamics in organizational sociology, we have sought to advance our understanding of how tournaments work. We have also demonstrated that competitive processes within tournaments can be better understood when the analyst is explicit about the direction in which competitive crowding exists. To fail to decouple the directional effects of crowding is to conflate encroachment and opportunity from the standpoint of affected actors. Additionally, by showing that the impact of crowding by inferiors rises with permanence in ranks, we have drawn attention to the importance of considering the stability of a collection of ranks, or of a performance distribution more generally, as a factor changing the effects of localized processes on contestants' conduct.

Finally, in the formal model developed in the Appendix, we found that the inclusion of a confidence parameter was necessary to predict a positive effect of crowding from above on the hazard of crashing. Going beyond the theory developed here, our formalization uncovered the possibility that the focal driver must react with significant overconfidence to the opportunity to outstrip higher-ranked and presumably more able rivals if crowding from above is to affect the accident rate positively. Although it is not implausible to assume that aspirations induced by the chance to surpass superiors create overconfidence in race car drivers, we did not observe an effect of crowding from above in our models. This may reflect the fact the Winston Cup Series was not designed as an elimination tournament, in which the set of competitors is progressively winnowed to a single winner as the series unfolds. NASCAR has instead typically fielded the same number of drivers in each race. Were the Winston Cup devised to eliminate drivers, however, then selection occurring over the course of the season might gradually induce a population of survivors marked by overconfidence, producing a significant effect of crowding from above. Consequently, examining the effects in other kinds of tournaments of the measures we have devised may offer new perspectives on the links between competitive crowding and the propensity to take risks.

Correspondingly, one limitation of the findings may be that NASCAR is an idiosyncratic context and that the findings we report may not generalize to other competitive arenas. Needless to say, no other organization operates according to the rules and incentive schemes NASCAR has implemented. Many competitive systems also do not make the rankings of contestants publicly available, which may lead to differences in interpretations about the ordering of contestants. And in other arenas, there may well be disagreement among evaluators and rivals about the main criteria by which rivals are to be judged and ranked. Such differences are especially likely whenever evaluators are free to bring their subjective inclinations to bear on their rankings of contestants (Goode, 1978: 153–154). Additionally, in some tournament-like systems, positional changes are quite infrequent. In such domains, many actors enjoy considerable role security (Phillips and Zuckerman, 2001) and rarely respond meaningfully to the advances of lower-status contestants.

To mitigate concerns about generalizability, all we can do at present is to emphasize the prevalence of the conditions that give rise to the hypothesized effects: the theoretical framework assumes that actors are competing for positions in a formal or informal tournament, that they are aware of one another's positions, and that changes in rank do occur. When the tournament is informal and the positions of contestants are ambiguous to outsiders, our findings may be more applicable if there is a tightly connected network through which the perceptions of key evaluators disseminate, but the conditions that are assumed for the argument to have relevance are reasonably common. There are tournaments and tournament-like structures at multiple levels, including those among shop-floor workers (Maciariello, 1999), plant managers, and senior executives (Lambert, Larcker, and Weigelt, 1989), between firms ranked by profitability, market share (Hannan et al., 1998), and status (Podolny, 2005), and even among cities competing in selection tournaments to stage the Olympic Games. Such tournaments offer valuable opportunities to cast further light on the effects of the dynamics of competitive crowding. Although refinements and extensions may be necessary for some empirical settings—for instance, the opportunities to recover a position taken by an inferior in a status-based tournament may be quite sparse, given the inherent stickiness of status as a social property—a number of contexts exist in which our results might be replicated and extended. There are two main criteria necessary for identifying them. First, a tournament-like ranking system is necessary, in which it is possible to measure time-varying levels of crowding from below and above, as we have done using NASCAR's Winston Cup Series. Second, a proxy for risk taking analogous to our use of accidents is required, which could be any observable action taken to avert a threat and that may in turn prove costly to the agent. Two possible research sites that meet these criteria are the corporate law firm and the investment banking industry.

The corporate law firm is an especially promising empirical site because of the precise data it maintains. Almost immediately after newly minted attorneys begin work at large firms, they start sorting into a tournament-like hierarchy based on several interrelated factors. As junior and senior associates progress in the race for partnership, they assume positions in a ranking based on these metrics: client feedback, the number and importance of the deals on which they work, the size of their merit bonuses (which often become widely known internally), the status of the partners under whom they work, and, increasingly as they near the partnership decision, their ability to bring in new clients. Within an internally competitive law firm, in which peer monitoring is pervasive and knowledge of levels on these metrics diffuse widely, associates have a clear sense of where they stand in the overall performance distribution. Using this information, they can also make accurate assessments of the numbers of those capable of surpassing them, and of those they can eclipse, in the near future. When there are more rivals poised to outstrip a focal associate, the crowding faced by that associate by definition has gone up, and consequently, his or her job security and likelihood of achieving partnership have declined. The results of our analysis suggest that risk taking will be more likely under this type of competitive crowding. To replicate our results, one promising measure of risky conduct would be whether an associate crosses a very high threshold in the number of billable hours (Landers, Rebitzer, and Taylor, 1996). Just as we expected crowding to raise the hazard of crashing in a Winston Cup Series race, here the related result is the threatened associate exceeding the number of billable hours generally understood as sustainable. Similar to risky maneuvers on the NASCAR track, accumulating more than, say, 140 hours per week also entails potential costs to the actor, which may manifest in adverse effects on long-run productivity and quality of life. In this empirical domain, it would be equally possible to adjudicate between the effects of encroachment by inferiors and the opportunity to pass others further ahead and, with access to semi-annual performance reviews, to test for interactions across the level of temporal stability in the ranking of associates. Like NASCAR, the law firm offers a productive research site because of the opportunity it affords to define crowding in a tournament-based contest and the existence of an appropriate measure of risky conduct.

In light of earlier studies showing that executives, not unlike NASCAR drivers, are also risk-prone when faced with the possibility of loss (e.g., Kahneman and Lovallo, 1994), the implications of our analysis could also be examined productively at the organizational level. In particular, the intensity with which banks fight for positions in league tables would make investment banking a compelling research setting. Like NASCAR's weekly rankings of drivers, league tables rank investment banks by their activity in particular kinds of deals. There are separate, quarterly league tables for mergers and acquisitions, initial public offerings, syndicated loans, and other types of transactions, which are often broken out by geography. Investment banks closely monitor their rankings on these tables, carefully watching the trajectories of proximate rivals. As in other systems with widely publicized rankings, when one firm surpasses another, the incumbent's reputation is contested. Anxious to defend and advance their standings, some investment banks have until recently (when they were faced with more scrutiny) sought to repackage the same deals to inflate their market share. Over the long run, it may be possible to trace other, more subtle activities to measures of crowding in league tables. Any fraudulent act that leads to sanctioning by the Securities and Exchange Commission or New York Stock Exchange would serve as a viable analogue to accidents. Another outcome worth modeling would be lending at very low (or even negative) margins, in order to build a relationship and in turn land more lucrative mergers and acquisitions and equities business. In this way, the same measures of crowding from below and crowding from above devised in this article could be put to use in a study of risky conduct among investment banks.

Car crashes in a NASCAR race can have serious consequences for individuals involved in the contest—drivers, owners, sponsors, and sometimes spectators—but the consequences of competitive crowding in other tournaments and tournament-like settings involve costs for organizations and society as well that have yet to be identified and explored. There is much new work to be done.

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APPENDIX: Formal Depiction of Hypotheses

This appendix clarifies the premises underlying our hypotheses in more formal terms. Our objective is deliberately focused. We proceed in the spirit of recent work in organizational sociology whose goal is to express with greater precision mechanisms previously posited or implied in the course of verbal theory construction (Hannan, Pólos, and Carroll, 2004). We described the institutional features of NASCAR previously, so we make reference to our empirical site and refer to the typical Winston Cup Series driver in what follows.

Initial Premises

We start from the premise that the typical driver faces a piecewise subjective value function $V_L(x)$ and $V_G(x)$, where V denotes the subjective disutility or utility corresponding to an expected loss or gain in rank. Specifically, in the domain of losses, where $x < 0$:

$$V_L(x) = -\log_\beta(1 - x) \tag{A1}$$

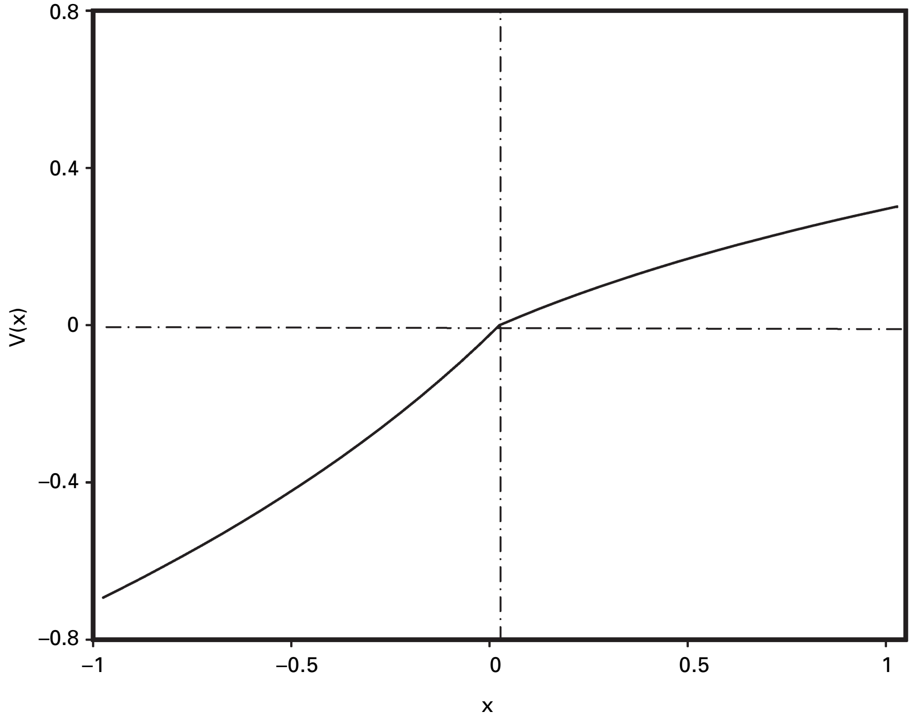
and in the domain of gains, where $x > 0$:

$$V_G(x) = \log_\alpha(1 + x) \tag{A2}$$

Consistent with a model of human nature in which "losses loom larger than gains" (Kahneman and Tversky, 1979: 279), we posit $1 < \beta < \alpha$. For illustration, in the graph in figure A.1, we use the natural log in equation (A1) and the common log in equation (A2), thus setting $\beta = e$ and $\alpha = 10$.

Using this formulation as our point of departure, we can now state several additional assumptions. Starting with the domain of losses ($x < 0$), we posit that the level of risk taking (and thus the probability of crashing in a NASCAR race) rises with the *difference* between the disutility expected for taking risks, V_{LIR}, and the disutility expected for playing it safe, V_{LIS}. That is, driver i will engage in risky conduct to the degree that a risky strategy brings about less expected disutility than a playing-it-safe strategy. Stated differently, if

Figure A.1. A piecewise subjective value function.



$V_{LIR} – V_{LIS}$ denotes the relevant difference and r designates the level of risk-taking, then this simple specification follows:

$$r \propto [\ V_{LIR} – V_{LIS}\ ] \tag{A3}$$

Additionally, we assume that V_{LIS} is a function of the number of drivers crowding driver i from below—CB_{it}, as depicted in equation (1)—divided by the maximum possible count, which is 43. We use the term $cb_{it} = CB_{it} / 43$ for ease of illustration. The linearly transformed term cb_{it} is thus just the rescaled value of crowding from below, taking values between zero (no encroachment) and unity (maximum crowding).

We assume further that the expected disutility for playing it safe V_{LIS} rises with cb_{it}. This follows immediately both from the composition of equation (A1) and from the premise that the odds of a loss in rank rise with the count of the drivers poised to pass driver i in race t. Performance in any given race is partly stochastic. Thus, even if drivers' current positions correctly represent ability, there is still a greater chance that the focal driver will be passed by a lower-ranked rival, the more of those there are poised to eclipse him. We therefore write V_{LIS} as:

$$V_{LIS} = V_L(–cb_{it}) \tag{A4}$$

With $\beta = e$ in equation (A1), V_{LIS} thus equals zero when cb_{it} equals zero and becomes maximally negative when cb_{it} equals one. In this formulation, the forecasted pain of loss equals zero when there is no one positioned to eclipse the focal driver, and it reaches a maximum when that driver faces the greatest chances of dropping in rank. Although it would be straightforward to add a constant or an error term to (A4) and to related equations, we maintain the existing formulation for simplicity.

Under the simplest formulation, one might write V_{LIR}, our measure of the expected disutility given risk taking, as an unweighted average, which implies that drivers believe that enduring a loss and retaining the present rank are equally probable. That is, if drivers put equal weights on the probability of the forfeiture and the defense of the current rank, one might write V_{LIR} as follows:

$$V_{LIR} = [V_L\ (-1)\ V_L(0)] \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} \tag{A5}$$

where both multipliers or weights in the column vector **w** equal .5.

Equation (A5) fails to recognize the dynamics of competitive crowding, however. Taking this ecological process into account, we maintain instead that cb_{it} influences drivers' expectations of probable outcomes under a risk-taking strategy. Specifically, we let the multipliers in **w** vary with the extent to which driver i faces the likelihood of being passed by inferiors. Under the supposition that the chances of a loss again rise, with more crowding from below, we write the elements in **w** as:

$$w \equiv \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} = \begin{bmatrix} \tan^{-1}(cb_{it}) \\ 1 - \tan^{-1}(cb_{it}) \end{bmatrix} \tag{A6}$$

Since $V_L(0)$ equals zero, we can restate equation (A5) as follows:

$$V_{LIR} = \tan^{-1}(cb_{it})V_L(-1) \tag{A7}$$

or, because $V_L(-1)$ is known from equation (A1), as:

$$V_{LIR} = \tan^{-1}(cb_{it})\ [\ -\log_{\beta}(2)\ ] \tag{A8}$$

The arctangent function implies a simple mapping of actors' postures toward risk taking and the possibility of loss. Recall that $cb_{it} \in [0,1]$. When $cb_{it} = 0$, V_{LIR}, the expected disutility under risk taking, also equals zero (if a driver takes risky actions on the track, it is impossible for him to forfeit his rank if no one is in striking distance). And as $cb_{it} \rightarrow 1$, the focal driver, as in equation (A4), believes that a loss, and thus the outcome $V_L(-1)$, is more likely than the preservation of the current rank. Specifically, when $cb_{it} \rightarrow 1$, $w_1 \rightarrow .785$ and $w_2 \rightarrow .215$, so that the relative effect in **w** shifts from w_2 to w_1 as cb_{it} increases. Also, the relatively gentle convexity resulting from the arctangent transformation mirrors a plausible conception of drivers as optimistic about the consequences of their risky actions on the track.

The Effect of Crowding from below

Using the preceding equations, we can now restate our first hypothesis, which was that the hazard of crashing rises with the level of crowding from below. We begin by recalling from equation (A3) our assumption that the level of risk taking r is proportional to the difference between the disutility expected for taking risks, V_{LIR}, and the (more pronounced) disutility expected for playing it safe, V_{LIS}. Of central importance is the question of whether this assumption translates empirically into a positive effect of crowding from below on the accident rate, as asserted in our first hypothesis, and which may be re-expressed as:

$$\mu_{it} \propto \theta_1 CB_{it};\ \theta_1 > 0 \tag{A9}$$

where μ_{it} is the probability that driver i crashes his vehicle in race t and CB_{it} tallies the number of drivers crowding the focal driver from below in the chosen race. Treating the rate of crashing μ_{it} as a proxy for the degree of risk taking r, the specification in (A9) then becomes:

$$r \propto \theta_1 CB_{it};\ \theta_1 > 0 \tag{A10}$$

Additionally, if it can be shown that CB_{it} from (A9) is positively correlated with $V_{LIR} - V_{LIS}$ from (A3), it then follows that crowding from below raises the accident rate. A positive correlation exists if the following inequality holds for all cb_{it}:

$$\frac{\partial[V_{LIR} - V_{LIS}]}{\partial cb_{it}} > 0 \tag{A11}$$

Using equations (A8) and (A4), the inequality in (A11) reduces to:

$$\frac{-\log_{\beta}(2)}{1 + cb^2_{it}} + \frac{1}{\ln(\beta)(1 + cb_{it})} > 0 \tag{A12}$$

or, using a change of base

$$\log_b(x) = \frac{\ln(x)}{\ln(b)}$$

and recalling that we set β in equation (A1) equal to Euler's number:

$$\frac{-\ln(2)}{1 + cb^2_{it}} + \frac{1}{1 + cb_{it}} > 0 \tag{A13}$$

Inspection of the left hand side of (A13) as a function of $cb_{it} \in [0,1]$ offers confirmation. For instance, if $cb_{it} = 0$, then the LHS equals .307. And for $cb_{it} = 1$, it equals .153. With the inequality in (A11) holding for all values of cb_{it}, we see that our first hypothesis is consonant with the premises we have stated.

The Effect of Crowding from above

We predicted in our theory discussion that crowding from above would raise the accident rate. With the expected returns to risk taking rising in the count of passable superiors, drivers should take greater risks when presented with more opportunity to advance. We clarify the specific conditions that must hold for crowding by superiors to amplify the accident rate, which differ from those under which crowding by inferiors raises the rate.

In the domain of gains (x > 0), our primary assumption is that the level of risk taking rises with the difference between the utility expected for taking risks, V_{GIR}, and the utility anticipated for playing it safe, V_{GIS}. That is, driver i will pursue risky maneuvers on the track to the extent that this strategy yields more expected utility than playing it safe. That is, if $V_{GIR} - V_{GIS}$ captures the difference in expected utility, and r again refers to the degree of risk taking, then a second term can enter the proportionality in (A3), giving us:

$$r \propto [V_{LIR} - V_{LIS}] + [V_{GIR} - V_{GIS}] \tag{A14}$$

Competitive Crowding

Just as we posited that V_{LIS} is a function of the number of drivers crowding driver i from below, we maintain that its counterpart, V_{GIS}, depends on the number of competitors crowding i from above. We use the term $ca_{it} = CA_{it} / 43$ to denote crowding from above in what follows. Thus, the linearly rescaled term ca_{it} assumes values ranging from zero (no opportunity to pass others) to unity (maximum opportunity).

We assert as well that the expected utility for playing it safe, V_{GIS}, is a positive function of ca_{it}. This follows from equation (A2) and from the premise that the chances of gaining in rank (and thus the pleasure V_G accruing from such an improvement) increase with the number of drivers i can eclipse in race t. This again reflects the partly stochastic nature of performance in any given race; even by playing it safe, given that at least some superiors likely will not do well on the track that day, the chances of advancement for the focal driver rise with the density of those ahead of him who are in striking distance. A simplifying assumption here is that, consistent with the view that actors in a tournament are boundedly rational, in determining the riskiness of his maneuvers on the track, a driver attends to the crowding around his position but does not determine his strategy in light of deductions about how the crowding elsewhere in the rank structure shapes other drivers' postures toward risky behavior. We therefore write V_{GIS} as:

$$V_{GIS} = V_G(ca_{it}) \tag{A15}$$

With $\alpha = 10$ in equation (A2), V_{GIS} thus equals zero when ca_{it} equals zero and reaches its maximum when ca_{it} equals unity. Thus, the forecasted value of gain for playing it safe is zero when the focal driver is incapable of surpassing anyone and reaches its maximum when that driver faces the greatest chances of advancing.

For our measure of the expected utility given risk taking, V_{GIR}, mirroring our prior discussion that started with equation (A5), we assume that, in evaluating the gains space, the focal driver again attaches multipliers to the two possible outcomes. Thus, as a first approximation, we write V_{GIR} as follows:

$$V_{GIR} = [V_G(1)\ V_G(0)]\begin{bmatrix} m_1 \\ m_2 \end{bmatrix} \tag{A16}$$

where the column vector of multipliers **m** is defined as:

$$\mathbf{m} \equiv \begin{bmatrix} m_1 \\ m_2 \end{bmatrix} = \begin{bmatrix} \tan^{-1}(ca_{it}) \\ 1 - \tan^{-1}(ca_{it}) \end{bmatrix} \tag{A17}$$

Using the arctangent transformation in equation (A17), as we did in (A6), has at least two advantages. First, as we show subsequently in this appendix, it permits us to make explicit comparisons between the effects of crowding from below and crowding from above. Second, as before, this transformation corresponds to the fact that, rather than mentally underscoring possible events equally, drivers allocate weights to outcomes as a function of the crowding around their rank.

Thus, recalling that $ca_{it} \in [0,1]$, when $ca_{it} = 0$, then V_{GIR}, the anticipated utility under risk taking, also equals zero (if a driver takes risky actions on the track it is impossible for him to advance in rank if no one is in striking distance). And as $ca_{it} \rightarrow 1$, the focal driver believes that a gain, and thus the outcome $V_G(1)$, is more likely than staying at the current rank. More precisely, as $ca_{it} \rightarrow 1$, then $m_1 \rightarrow .785$ and $m_2 \rightarrow .215$, so that the relative effect in **m** tilts from m_2 to m_1 as ca_{it} rises.

Although we consider our use of weights a reasonable strategy for conceptualizing the dynamics of competitive crowding as they relate to drivers' judgments about race-day outcomes, we nonetheless extend our specification of V_{GIR} to incorporate a parameter capturing the driver's reaction to the fact that he faces the opportunity to surpass drivers who are higher ranked.

The drivers crowding him from above by definition enjoy higher status, and they potentially possess more innate ability as well. This structural reality brings us to two behavioral possibilities. On the one hand, a driver may be less optimistic about his chances for advancement, given his perception of superiors' stronger capabilities. Under that scenario, the multiplier m_1 would be discounted. On the other hand, aspirations triggered by opportunities to outstrip competitors (cf. Burt, 1982; Barnett and Hansen, 1996; Barnett and Sorenson, 2002) may instead elicit temporary feelings of overconfidence. Under this alternative scenario, the multiplier m_1 would be amplified.

Given these possibilities, we retain the basic structure of (A16) and (A17), but multiply the term m_1 by the parameter σ. We refer to this as a "confidence parameter." Specifically, for $\sigma < 1$, driver i acknowledges the higher ranking of his proximate superiors in the tournament but discounts his capacity to succeed them through risk taking accordingly. Conversely, when $\sigma > 1$, i still acknowledges their higher positioning but, affected by the opportunity to pass them, grows overly optimistic instead. Thus, we rewrite (A16) as follows:

$$V_{GIR} = [V_G(1)\ V_G(0)] \begin{bmatrix} \sigma m_1 \\ m_2 \end{bmatrix} \tag{A18}$$

With $V_G(0) = 0$, and collecting $V_G(1)$ from equation (A2), we can restate equation (A18) as:

$$V_{GIR} = \sigma \tan^{-1}(ca_{it})[\log_\alpha(2)] \tag{A19}$$

Additionally, the deviation of σ from unity is easily interpretable. When $\sigma < 1$, $1 - \sigma$ mirrors the degree of diffidence with respect to superiors in the tournament. And if $\sigma > 1$, $\sigma - 1$ reflects the level of competitively induced overconfidence.

With these specifications in place, we can now derive the conditions under which crowding from above elevates the hazard of crashing, when the following inequality holds for all ca_{it}:

$$\frac{\partial[V_{GIR} - V_{GIS}]}{\partial ca_{it}} > 0 \tag{A20}$$

This is because we posited earlier in (A14) that the level of risk taking r is proportional to $V_{GIR} - V_{GIS}$ and that μ_{it} is a proxy for r. Accordingly, the following proportionality—stating that crowding from above amplifies the probability that driver i will crash his vehicle in race t—only holds when (A20) holds:

$$\mu_{it} \propto \theta_2 CA_{it};\ \theta_2 > 0 \tag{A21}$$

When then is the inequality in (A20) satisfied? Using equations (A19) and (A15), and collecting terms, the inequality in (A20) may be re-expressed as follows:

$$\frac{\sigma \log_\alpha(2)}{1 + ca_{it}^2} + \frac{-1}{\ln(\alpha)(1 + ca_{it})} > 0 \tag{A22}$$

Setting $ca_{it} = 1$ as a limiting case, and using a change of base, (A22) simplifies to:

Competitive Crowding

$$\sigma > \frac{1}{\ln(2)} \tag{A23}$$

where the right-hand side of (A23) can be approximated by 1.44. Under this threshold, the returns to risk taking—that is, the gap between V_{GIR} and V_{GIS}—no longer monotonically rise with ca_{it}. Offering an insight beyond our main argument in the text, which we derived from earlier research, this result suggests that the typical driver must generate a non-trivial degree of overconfidence in the face of crowding from above for it to affect the hazard of crashing positively.

Comparing the Effects of Crowding from below and Crowding from above

Using the equations derived in previous sections, we can now express what must hold for the realization of our second hypothesis, namely, that crowding from below an actor's position in a tournament has a stronger positive effect on risky conduct than does crowding from above. Stated in the language of our empirical context, this hypothesis corresponds to the following specification:

$$\mu_{it} \propto \theta_1 CB_{it} + \theta_2 CA_{it};\ \theta_1 > \theta_2 \tag{A24}$$

Additionally, it follows from the foregoing discussion that $\theta_1 > \theta_2$ when the left-hand side of (A11) exceeds the left hand side of (A20) for $cb_{it} = ca_{it}$, that is, when:

$$\left.\frac{\partial[V_{LIR} - V_{LIS}]}{\partial cb_{it}}\right|_{cb_{it} = ca_{it}} > \left.\frac{\partial[V_{GIR} - V_{GIS}]}{\partial ca_{it}}\right|_{cb_{it} = ca_{it}} \tag{A25}$$

Collecting results from (A12) and (A22), the inequality in (A25) takes the following form:

$$\frac{-\log_\beta(2)}{1 + cb_{it}^2} + \frac{1}{\ln(\beta)(1 + cb_{it})} > \frac{\sigma\log_\alpha(2)}{1 + ca_{it}^2} + \frac{-1}{\ln(\alpha)(1 + ca_{it})} \tag{A26}$$

Setting $cb_{it} = ca_{it} = x$, using a change of base, and rearranging terms, the preceding inequality becomes:

$$\sigma < \frac{-\ln(\alpha)}{\ln(\beta)} + \left[\frac{\ln(\alpha) + \ln(\beta)}{\ln(2)\ln(\beta)}\right]\left[\frac{1 + x^2}{1 + x}\right] \tag{A27}$$

We set $x = \sqrt{2-1}$ as a limiting case, because it minimizes the right-hand side of (A27). With our original values of $\beta = e \equiv 2.718$ and $\alpha = 10$ from equations (A1) and (A2), respectively, we are able to identify an upper bound on σ, the confidence parameter, beneath which the effect of crowding from below exceeds that of crowding from above, specifically:

$$\sigma < 1.645 \tag{A28}$$

Recalling the inequality in (A23), it is within the scope conditions defined by $1.44 < \sigma < 1.645$ that the effect of crowding from above is positive, and the effect of crowding from below still exceeds that of crowding from above.

The Contingent Effect of Crowding from below

We conclude with a brief examination of our third hypothesis—that the effect of crowding from below is greatest as the race-to-race churn in drivers' rankings declines—in light of the premises articulated in this appendix. We developed this hypothesis from the supposition that the disutility of forfeiting a rank should rise with the stability in the ordering of Winston Cup Series drivers. With the acceptance of one's current rank and the sense that there is little probability of recovering a lost position, a drop in relative standing should carry greater disutility for the typical driver. Or, equivalently, the typical driver faces less disutility from being passed when rank change is high. This premise is easily expressed in the context of our formalization; in particular, it corresponds to a specific change to the value function in the domain of losses, $V_L(x)$, shown in equation (A1). Inspection of equation (A1) shows that the level of $V_L(x)$ becomes more negative as β drops toward 1.00, the asymptote on the base for the logarithmic function. More precisely, greater disutility as β declines follows from the first derivative of $V_L(x)$ with respect to x in equation (A1), $\partial V_L(x)/\partial x = [\ln(\beta)(1 - x)]^{-1}$, where $x < 0$. Thus, it is possible to articulate the core of our hypothesis by adding a new parameter to equation (A1). Allowing the base to decline as rank change drops, we have:

$$V_L(x) = -\log_{\beta f(RC_{t-1})}(1 - x) \qquad \text{(A29)}$$

where RC_{t-1} is the measure of rank change discussed in text, and $f'(RC_{t-1}) > 0$. Using this extension, it is then possible to represent the various versions of the value function as shown in our final plot in figure A.2.

With the assumptions brought forward in our modified function in (A29), it is straightforward to show that this translates into the empirical prediction that crowding from below exerts its strongest effect when there is low race-to-race turnover in the Winston Cup Series rankings. Recalling the proportionality in (A3) and the inequality in (A11), the magnitude of the effect of crowding from below on the hazard of crashing is positively associated with the left hand side of the inequality in (A12). That is, returning to the coefficient θ_1 on CB_{it} in (A9) and substituting $\beta \times f(RC_{t-1})$ from (A29) for β brings us to:

$$\theta_1 \propto \frac{-\log_{\beta f(RC_{t-1})}(2)}{1 + cb_{it}^2} + \frac{1}{\ln[\beta \times f(RC_{t-1})](1 + cb_{it})} \qquad \text{(A30)}$$

Using a change of base, setting $cb_{it} = 1$, and omitting a constant multiplier, we conclude with:

$$\theta_1 \propto \frac{1}{\ln[\beta \times f\,(RC_{t-1})]}$$

This conforms with the hypothesis that as rank change declines, the magnitude of the effect of crowding from below on the hazard of crashing rises.

Figure A.2. The value function contingent on the level of rank change.