Network-Related Personality and the Agency Question: Multirole Evidence from a Virtual World[1]

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The more consistent a person's network across roles and the more relevant that consistency is for achievement, the more important agency is for understanding network effects on achievement. With network, experience, and achievement data on persons playing multiple characters in a virtual world, evidence is presented to support two conclusions: (1) About a third of network structure is consistent within persons across roles: that is, those who in one role build networks rich in access to structural holes will build similar networks in other roles; builders of closed networks also tend to build that network across roles. (2) Network consistency across roles contributes almost nothing to predicting achievement, which is instead determined by experience and the network specific to the role. The two conclusions are robust across substantively significant differences in the mix of roles combined in a multirole network (too many roles, difficult combination of roles, or roles played to overlapping audiences).

The concept of managers bridging the structural holes in networks has been useful in improving our ability to say why certain people achieve more than

others, but agency continues to play an uncertain, and suspected large, role in the network effect on achievement. This article is about testing for agency in the network association with achievement and the analytical opportunity provided by multirole networks in virtual worlds.

The gist of the network story is that information becomes homogeneous, tacit, and therefore sticky within clusters of densely connected people such that clusters disconnect, buffered from one another by the structural holes between them, which gives information breadth, timing, and arbitrage advantages to people whose networks span the structural holes. The advantaged people, often termed "network brokers," are rewarded socially and materially for their work decoding and encoding information across the structural holes. The story is anchored in an association established in the 1950s between opinion and social clusters (e.g., Festinger, Schachter, and Back 1950; Katz and Lazarsfeld 1955; Coleman, Katz, and Menzel 1957), from which network concepts emerged in the 1970s on the advantages of bridge connections across clusters: Granovetter (1973, 1983) on weak ties when they are bridges; Freeman (1977, 1979) on network centrality as a function of connecting disconnected people; Cook and Emerson (1978) and Cook et al. (1983) on the advantage of centrality from having alternative exchange partners; Burt (1980) on the advantage of disconnected contacts, later discussed as access to structural holes (Burt 1992); and Lin, Ensel, and Vaughn (1981) on the advantage of distant, prestigious contacts, later elaborated in terms of having contacts in statuses diverse and prominent (Lin 2002). Application of these models to predict achievement differences in representative cross sections of managers began in earnest in the 1980s and 1990s, encouraged by earlier images of boundary-spanning personnel (Aldrich and Herker 1977; Tushman 1977; with Brass [1984] a key transition showing the empirical importance of the more general network concept). Numerous research projects since then show that network brokers (relative to peers) are paid more, receive more positive evaluations and recognition, and get promoted more quickly to senior positions (see Burt [2005] and Burt, Kilduff, and Tasselli [2013] for review and contingencies and Aral and Van Alstyne [2011] for an exceptional analysis of network structure as a proxy for information in predicting achievement).

The preceding paragraph reads as though achievement springs directly from network structure. There is no mention of individual differences except as people differ in their network. But, of course, networks do not act. Net-

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works are merely the residue of people spending time together. Networks of connections with certain people and not others can facilitate or inhibit action, but people are the source of action. Common sense is sufficient to wonder about the role of agency. Certain kinds of people could be prone to building networks that bridge structural holes, and those kinds of people could be prone to high achievement. The agency question is often raised: How much does the network association with achievement depend on the person at the center of the network? Though often raised, the question has received too little attention to allow a general response. The neglect has been noted from diverse perspectives (Emirbayer and Goodwin 1994; Kilduff and Krackhardt 1994; Ibarra, Kilduff, and Tsai 2005; Baum and Rowley 2008; Kilduff and Brass 2010; Sasovova et al. 2010; Singh, Hansen, and Podolny 2010).

This is where multirole networks become a welcome complication. How that is so is the substance of the next section, which concludes with two research tests for agency. The data to be analyzed are introduced in the second section. The data are unusual in organization and management research, but construct validity has been established such that it seems imprudent not to take advantage of the unique analytical opportunity the data provide. The third section contains summary results on the two hypotheses, and the fourth section shows that the results are robust across substantively significant differences in the roles combined in a multirole network.

AGENCY IN THE NETWORK EFFECT

Agency has not been ignored in current research so much as it has been assumed away or held constant.

Assume It Away

Formal models of networks have been used to explore theoretical questions such as what would happen if everyone focused on bridging structural holes (Ryall and Sorenson 2007; Buskens and van de Rijt 2008) or if contacts exercised monopoly power, eroding the returns to bridging structural holes (Reagans and Zuckerman 2008). In these models, the agency question is often resolved by assuming that people act on all network opportunities (subject to a budget constraint of limited time or resources). Agency can be ignored because it is coincident with opportunity. To know who acts on opportunity, you need to know only who has opportunity.

The assumption can seem less strident when embedded in data. Imagine that the network around a person is affected by personal preference. People adapt to the network around them. They also learn, editing the network to personal taste. People are motivated to act on advantage provided by the network to which they have adapted and contributed. Motivation need

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not be measured directly because it is already measured by metrics on the opportunities built into a person's network (Burt 1992, pp. 34–36; 2005, pp. 47–50). The result is the same as assuming agency away.

Empirical research supports the assumption and calls it into question. The two points are illustrated in figure 1 with graphs of achievement across increasingly closed networks for a couple thousand observations in diverse business functions in Asia, Europe, and North America. Figure 1*a* displays data averaged within intervals on the horizontal axis. Figure 1*b* displays the data before averaging. In both graphs, people vary on the vertical axis by *Z*-score achievement (compensation, evaluation, promotion) adjusted for variables in company human resource archives, so zero is the level of achievement typical for a manager's peers (same organization, location, job rank, experience, etc.), with respect to which the manager can be higher (positive *Z*-score) or lower (negative *Z*-score). The horizontal axis is a summary network index, network constraint (discussed below), which measures the extent to which a manager's network is small and dense such that it provides no access to structural holes. Network brokers are to the left in each graph (low network constraint, rich access to structural holes). People in closed networks are to the right (high network constraint, low access to structural holes). The aggregate data in figure 1*a* show a nonlinear, downward-sloping association in which network brokers (relative to their peers) are paid more, receive more positive evaluations and recognition, and get promoted more quickly to senior positions. There is variation around the regression line, but it is clear that achievement adjusted for individual differences is higher for network brokers. The robust achievement-network association invites formal, theoretical attention, ignoring as random error variation from the regression line.

The aggregate data in figure 1*a* obscure the fact that achievement differences between individual network brokers are substantial, with many brokers showing no more achievement than people in the most closed networks. The suspicion has long existed (Burt 1992, p. 37). The empirical fact is displayed in figure 1*b* by statistically significant heteroscedasticity and a triangular data distribution, wider over network brokers, across achievement differences wider before individuals are aggregated into averages (vertical axis from -3.0 to 7.0 in fig. 1*b*, -2.0 to 2.5 in fig. 1*a*). The primary characteristic of the figure 1*b* data distribution is not the absence of low achievement in broker networks so much as the absence of high achievement in closed networks. A formal-model strategy more consistent with the data would be to shift focus from broker advantage to the disadvantages of closed networks.

Hold It Constant

Some people are better educated, have more experience, work at central locations in an organization, or hold positions that give them more authority,

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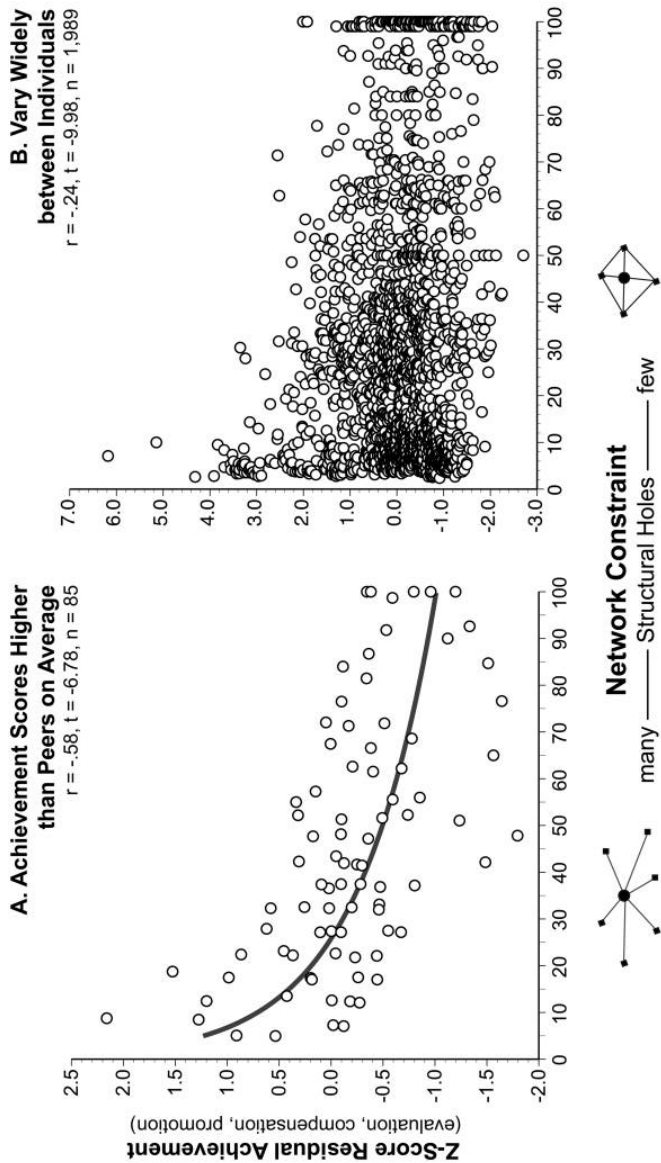
Fig. 1.—Individual differences in returns to brokerage. Graph *a* shows achievement decreasing with less access to structural holes. Circles are *Z*-score residual achievement for 1,986 observations averaged within five-point intervals of network constraint in each of six management populations (analysts, bankers, and managers in Asia, Europe, and North America; heteroscedasticity is negligible, $\chi^2 = 2.97$, 1 *df*, $P \sim .08$; Burt 2010, p. 26; cf. Burt 2005, p. 56). Bold line is the vertical axis predicted by the natural logarithm of network constraint. Graph *b* shows the raw data averaged in graph *a*. Vertical axis is wider to accommodate wider achievement differences. Heteroscedasticity is high given wide achievement differences be-tween brokers ($\chi^2 = 269.5$, 1 *df*, $P < .001$), but returns to brokerage remain statistically significant when adjusted for heteroscedasticity (Huber–White, $t = -8.49$).

any of which could make one person more likely than another to see and act on network opportunities. Such differences are recorded in human resource archives, so the differences can be held constant in network predictions. In figure 1, for example, manager achievement on the vertical axis is measured against the average achievement of peers, that is to say, the achievement of managers in the same job rank, same business function, with the same education, same years of experience, and so on.

Beyond such controls, there is a growing body of work in which the research design illustrated in figure 1 is extended to include behavioral and cognitive variables typically not in human resource archives. Personality has long been studied as a correlate of network structure (Kilduff and Tsai 2003, chap. 4) and interpersonal engagement more generally (Snyder and Deaux 2012), but it is increasingly common to see personality studied as an agency variable in the returns to network advantage. Snyder's (1974; Snyder and Sangestad 1986) concept of "self-monitoring" is central in the work. Self-monitoring distinguishes people by their tendency to adapt speech and behavior to social situations. Empirical measures capture four qualities (Snyder 1974, p. 529; index items in quotes): a concern with being appropriate to the situation (e.g., "At parties and social gatherings, I do not attempt to do or say things that others will like": reverse coding); the ability to control one's presentation to fit the situation (e.g., "I can look anyone in the eye and tell a lie with a straight face [if for a right end]"); use of the ability (e.g., "I may deceive people by being friendly when I really dislike them"); and experience adapting to situational demands (e.g., "In different situations and with different people, I often act like very different persons").

Self-monitoring is particularly interesting because it is a psychological analogue to bridging structural holes. A manager with a network rich in structural holes (which in theory means that he is connected to separate groups with different perspectives, policies, and practice) is likely to have experience presenting himself differently to different groups. A person who spends all his time in a closed network (which in theory means that he is surrounded by people similar to himself) has less experience engaging people who do not share his assumptions and behaviors. Self-monitoring measures the extent to which a person feels that he or she adapts to social situations, and network metrics on access to structural holes measure the person's contact with disconnected social situations that require adaptation. Self-monitoring scores should be higher for network brokers. They are. Mehra, Kilduff, and Brass (2001) show it for employees in a small technology company. Oh and Kilduff (2008) show it for a population of Korean entrepreneurs in Canada. Sasovova et al. (2010) show it for a department of employees in a Dutch hospital and go on to show self-monitors more likely to expand their networks to reach new structural holes.

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Given the correlation between achievement and structural holes and the correlation between self-monitoring and structural holes, achievement should be correlated with self-monitoring. It is. Kilduff and Day (1994) show for a cohort of master of business administration students that high self-monitors were more likely to receive promotions in the five years after graduation. Holding constant network differences between employees in a small technology company, Mehra et al. (2001) show that high self-monitors received more positive evaluations from their supervisors. The summary statement at the moment is that access to structural holes is correlated with self-monitoring, and each variable is associated with achievement when the other is held constant.

Given the results on self-monitoring, there are a great many other personality dimensions likely to be relevant to network advantage. For example, people differ in the extent to which they believe that their actions affect events. Why act on network advantage if your actions have no effect? Example personality measures to consider would include Rotter's locus of control in which high internal control refers to a belief that your actions affect events (e.g., Hansemark [2003] on internal-control men more likely to be entrepreneurs; see Rotter [1966] for the initial statement) or Bandura's concept of self-efficacy in which stronger belief in one's capabilities is associated with greater and more persistent effort (see Wood and Bandura [1989] and Bandura [2001] for a review).

People differ in the extent to which they look for network advantages on which they can act. A familiar story is McClelland's (1961) thesis that early formation of a need to achieve is a personality factor significant for later entrepreneurial behavior. Anderson (2008) shows that managers with a high "need for cognition" are more likely to take advantage of information in their network. More generally, there are the "big five" personality factors correlated with career success (Judge et al. 1999; Ozer and Martínez 2006) though only modestly with network metrics (Klein et al. 2004) and inworld behavior (Yee et al. 2011). Beyond the summary measures are numerous scales in organizational psychology measuring dimensions of personality (see psychwiki.com; Butcher 2009), and there is no barrier to inventing new measures specific to network effects (Burt, Jannotta, and Mahoney 1998).

The list of possible personality measures to control expands with recent work emphasizing the importance of behavior for broker advantage. Powell, Packalen, and Whittington (2012) show that lucrative clusters of biotechnology firms emerged in cities where initial brokers in the local biotech network behaved in an academic fashion of encouraging ideas and independence. Where initial brokers behaved to maintain their central position as brokers, clusters did not develop. Studying the success of a program requiring coordination between doctors and lawyers in community medical

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centers, Kellogg (2012) finds successful implementation in which the doctor-lawyer collaboration is buffered through intermediary brokers. Implementation is comparatively unsuccessful in a community center where the doctors and lawyers had to engage one another directly. In short, behavior matters to broker advantage. What is productive broker behavior in one situation need not be productive in another situation. It can be advantageous to play contacts against one another (Fernandez-Mateo 2007) or connect contacts as a translation buffer to protect each side from the other's irritating specialist jargon (Kellogg 2012), whereas in other situations it is better to facilitate exchange otherwise at risk of misunderstanding (Obstfeld 2005; Lingo and O'Mahony 2010; Leonardi and Bailey 2011) or facilitate the development of broker skills in colleagues (Powell et al. 2012). More generally, there are occupational norms; it would be unseemly for a nun to behave like a salesman or a banker to behave like a construction worker. Behavioral norms can shift, as Stuart and Ding (2006) describe for the shift from academic to more commercial norms in biotechnology, but at any one point in time there are likely to be behavioral norms for successful brokerage. Given behavioral norms for successful brokerage, it follows that behavioral predispositions have implications for success as a network broker.

Single-Role versus Multirole Networks

The research design in the above work is a *single-role* design in the sense that network data and effects are aggregated to the level of a person playing a role. In figure 1, for example, achievement is measured for a person in a management job (e.g., compensation for the job, evaluation of the manager's work in the job, relative speed getting to job rank, etc.), control variables measure the person's background and the nature of her job (e.g., job rank, business function, education, experience), and interactions among the manager and colleagues over a period of time are aggregated into a network describing how the manager does her job (e.g., 360-evaluations of work with colleagues or, more generally, sociometric data asking for key contacts). Kinds of relations can be distinguished for network association with achievement, usually variations on formal versus informal (Podolny and Baron 1997; Mehra et al. 2001; Burt 2005, pp. 50–55; Mizruchi, Sterns, and Fleischer 2011); but interactions of each kind are typically aggregated into summary relations between people.

The single-role design has been, and will continue to be, productive. It fits the kind of person-level data typically available on achievement and networks, and it is an efficient way to study how specific personality traits enhance or erode network effects. For example, the design has been useful for exploring how individual differences in self-monitoring vary with network

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advantage and affect returns to network advantage. Mehra et al. (2001) provide an exemplary analysis. The great strength of the design is its empirical validity relative to assuming agency away. Predisposition toward network advantage is measured directly.

But agency is not about a single personality trait. It is about personality in all its dimensions. How much do individual differences in personality, as they are related to network advantage, affect the network association with achievement? The single-role design cannot provide a general answer to the agency question because there are too many personality measures that could be used to control for personality differences. Research on any one, or any subset of the many, does not provide a general answer to the agency question so much as it provides an answer interesting but specific to the personality variables tested.

A *multirole* design can be helpful. Instead of analyzing data at the level of a person, data are analyzed at the level of the roles played by the person. Multirole networks are an empirical analogue to Merton's (1957) conception of the role-set associated with a status. A single-role network is defined by variables z_{ij} describing the connection between nodes i and j in a person's network. A multirole network is a collection of K networks describing the relations around a person in each of K roles. The network is defined by variables z_{ijk} describing the connection between nodes i and j in the person's performance of role k. The job of professor almost always involves playing the role of teacher, often involves the role of research scientist, and can involve administrative roles. In finer detail, there are distinct roles within the three aggregate ones: The teacher role in a college course is different from the teacher role in a graduate seminar. A person's role in research can vary from project to project depending on the colleagues involved in the project. Administrative roles vary with organization level, from department, to school, to university, to extramural administration. Each role is defined by a network of relations among the people with and for whom the role is played: networks of students, networks of collaborating colleagues, or networks of interdependent administrators. A multirole network is a social system composed of two or more of a person's role-specific networks.

Network Consistency across Roles as an Indicator of Personality

Given N_k, a variable measuring ego's network advantage in role k, average ego's scores N_k across K roles to describe ego's average network advantage in the K roles:

$$\mathbf{P} = \sum_k N_k / K. \tag{1}$$

To the extent that a person knows only one way of engaging people or is comfortable with only one way of engaging people, that one way will man-

ifest again and again in roles the person plays: the average network a person builds will be characteristic of each network the person builds.

Some people are "closure-prone" in preferring a cozy, closed network. Their roles tend to be enacted within a group of densely interconnected people. Trust is likely. Coordination is tight. Ego can just be "one of the guys." People with a preference for the emotional and behavioral characteristics of closed networks can be expected to focus their role performances on a set of closely interconnected contacts: friendship groups tend to be tight-knit, work teams tend to be cohesive, and ego is surrounded by little tolerance for people clearly different from us.

At the other extreme, people with consistently high network metrics for structural holes are "brokerage-prone." Their roles tend to be enacted across people otherwise disconnected in separate groups. Contradictory opinion is likely in their open networks. Coordination costs are high and require constant attention. Ego stands out as a center of attention. People with a strong preference for the emotional and behavioral characteristics of open networks can be expected to broaden role networks to include novel contacts: ego often introduces friends to one another, often coordinates teams across otherwise separate groups, and has a tolerance for people clearly different from himself.

Depending on the network index N_k used in equation (1), the average, $\mathbf{P}$, measures the extent to which a person is closure-prone or brokerage-prone. To simplify, I will refer to $\mathbf{P}$ as ego's "network-relevant" personality, an indicator of ego's propensity toward or away from brokerage. The "how much does personality matter for network advantage" agency question can be answered by predicting role-specific network scores from the average score across roles:

$$N_k = b_n + b_{np}\mathbf{P} + b_{nx}X_k + U_k, \tag{2}$$

where X_k contains control variables for role k, and U_k is the role-specific network index not predicted by ego's average across roles. To the extent that personal preference determines the network advantage measured by N_k, ego's role-specific network scores will equal the average across roles, so ego's average network-relevant personality $\mathbf{P}$ will describe 100% of the variance in her role-specific scores.

Personality is inferred from its effects in equation (2). Network-relevant personality, $\mathbf{P}$, is not a measure of personality. It is the network advantage that can be attributed to personality manifest in consistent network behavior across roles. Consistent network behavior is to be expected if personality determines network behavior (as inconsistent behavior would raise questions about the usefulness of personality as a concept; Funder 2001, pp. 199–200). Generality is the virtue of the multirole design. Whatever dimensions of personality are relevant to the roles ego selects and the way ego per-

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forms those roles, those dimensions are captured in their effects by network consistency across ego's role-specific networks. Equation (2) corresponds to a fixed-effects regression model in which individual differences **P** are removed from the network metric N_k, holding constant the control variables. Comprehensive capture of personal preference as it affects network advantage allows a multirole research design to address agency in a general way.

To be sure, the network associated with a role is affected by the nature of the role. A manager's network is likely to be closed when leading a team of people who often meet face to face. The same manager can have a network bridging structural holes when she leads a team of people who meet only online from their offices scattered around the world. More generally, network consistency across a person's roles has predictable correlates: more consistency is likely for people who spend much of their time in a small number of roles, whose personal preferences typically dominate situational preferences, or who have the luxury of selecting roles consistent with past experience and personal preference. Less consistency is likely for people who spend small portions of their time playing many different roles, who play multiple roles rarely combined, or who play multiple roles to very different audiences. I return to these expected correlates later in the analysis to check that my summary conclusions are robust. For the moment, it is sufficient to say that random error and predictable variation in role performances mean that network-related personality will typically describe less than 100% of network variance. How much less is the empirical question answered by equation (2).

Network-relevant personality can be used to test for agency in the association between achievement and network advantage. Figure 1 shows that achievement is higher, on average, for network brokers, but individuals differ substantially around the average. Agency is a factor in the association to the extent that the achievement differences reflect differences in individuals acting on advantage. Achievement could be unexpectedly low for a person who is rich in access to structural holes but uncomfortable in the role of network broker. Achievement could be unexpectedly high for a person whose brokerage-prone personality facilitates detecting and developing network advantage. To see how much of the average association should be attributed to such individual differences, add network-relevant personality to a model predicting achievement from network advantage:

$$A_k = b_a + b_{ap}\mathbf{P} + b_{ax}X_k + b_{an}N_k + R_k, \qquad (3)$$

where A_k is a measure of ego's achievement in role k, **P** is ego's average network score across roles (eq. [1]), X_k contains control variables for role k, and R_k is a residual term. Given estimates for equation (3), coefficient b_{an} measures the extent to which achievement in role k depends on network advan-

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tage specific to the role, and coefficient b_{ap} measures the extent to which achievement in role k depends on network-relevant personality, the network advantage ego typically builds in the roles she plays.[2] Again, network-relevant personality is not a substitute for measuring personality. For example, Mehra et al. (2001) show that self-monitoring is associated with achievement independent of network advantage. Network-relevant personality in equation (3) captures only individual differences in self-monitoring as they are relevant to network advantage measured by index N_k. However, in capturing all personality differences relevant to N_k, network-relevant personality answers the agency question in a more general way.

DATA

The data needed to estimate personality and network effects in equations (2) and (3) would not be impossible to obtain in the usual research designs, but the data collection would be more difficult than usual. Data are needed on achievement within multiple roles, along with data on role-specific controls and networks relevant to achievement. For example, divide a manager's job into the roles he played on separate projects, say the two largest projects in which he participated last year. To measure achievement on each project you have to ask for evaluations from the manager's supervisor or go into divisional archives for some kind of project data, because project-specific performance data are not in the typical company human resource archives. Data are typically aggregated across the roles a manager plays to provide a summary description of the manager for promotion and compensation decisions. Peer-to-peer data gathered in 360-evaluations aggregate relations across a manager's roles to describe the overall relationship between manager and colleague, again to match the company's compensation and promotion decisions on a manager. To get data on project-specific z_{ijk} relations, you have to ask people to describe their network separately for each project. It is difficult to get managers to complete network matrices for a single-role design. That difficulty is multiplied for multirole networks. Even if you find a senior person willing to fund the work, data quality remains a concern. Guessing about time spent with John versus Mary is one thing; partitioning

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[2] Network-relevant personality is specified as an additive predictor in eq. (3). The equation would be equally consistent with the discussion to this point if personality were written as a multiplier by adding an interaction term $\mathbf{P}N_k$ to the equation. The coefficient for the interaction term would measure the extent to which people with personalities prone to the kind of network advantage measured by $\mathbf{P}$ and N_k earn higher returns to the advantage. I use the simpler additive form in eq. (3) because I do not find interaction effects in the forthcoming analysis (illustrated in fig. 7 below), which is consistent with Mehra et al.'s (2001) analysis showing no interaction effect between brokerage and self-monitoring in predicting achievement. I make no claim that the $\mathbf{P}N_k$ interaction is negligible in other populations; there is merely no need to introduce the complication here.

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time with each into topics is a more difficult, fine-grain bit of remembering. Managers trying to be helpful will answer as best as they can, but the quality of their answers to questions about project-specific connections between pairs of colleagues must be lower than the quality of their answers to the questions currently asked about the typical connection between pairs of colleagues (see Krackhardt [1987] on cognitive networks and Moldoveanu and Baum [2011] on epistemic networks).

Online virtual worlds provide the needed data at high quality and low cost. I use data from EverQuest II (EQ2), a massively multiplayer online environment, analogous to World of Warcraft, in which people play in the role of an avatar engaged with others in quests and combat. EQ2 avatars are discussed as characters. Players develop their character up levels of achievement with higher levels reached by earning experience points for killing creatures, exploring new locations, and completing quests. The data cost and quality problems described above for managers are avoided in EQ2 because the game software records behavior and achievement accurately and unobtrusively at the level of characters, providing data for equations (2) and (3) on each character's activity and achievement, which can be compared for consistency across characters played by the same person.

I obtained the EQ2 data through the Virtual World Exploratorium (Williams et al. 2011), through which reports are available describing the people in EQ2 during the observation period (e.g., Williams, Yee, and Caplan 2008; Shen 2010; Shen and Williams 2011). The data were recorded during a nine-month observation period in 2006, from January 1 to September 11. The data include acts of support between characters and achievements, along with self-reported player age, gender, and geographical location. I follow the convention of using "inworld" to refer to activity by avatars inside the virtual world. The game owner, Sony Online Entertainment, selected the observation period and provided the data. People and characters are identified in the data only by Sony code numbers, so personal identities remained confidential. The virtual world had been operating for two years before the observation period began. The network data for this analysis come from a report on the construct validity of the EQ2 network data (Burt 2011). The data are a server census of 13,968 people playing 44,185 characters active during the observation period: active in the sense that the character advanced to a higher level in the game, sold something to another character, bought something from another character, exchanged items with another character, or was active in collaborative housing or mentoring with another character.

Face Validity

Face validity is an immediate issue. Figure 2 displays the 16 character "races" that were available during the observation period. You enter EQ2

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GOOD: Stout and strong, **Dwarves** are known for bravery and a sense of honor, though not particularly for their intellect. Mentally sharp and morally virtuous, **Froglocks** strive to eliminate villainy and corruption. Courageous **Halflings** are good-natured and friendly, known for their humor. **High Elves** embody nobility and wisdom, but their stoic nature can be mistaken for arrogance. **Wood Elves** are pleasant and friendly, but fierce protectors of the woodlands, battling any who would taint the purity of nature.

EVIL: Sinister, cunning, and dangerous, **Dark Elves** coolly prey on the weak and the ignorant. Calculating and cold, the **Iksar** are a harsh but disciplined people who delight in cruelty and conquest. **Ogres** are aggressive brutes whose physical might is matched only by their hunger for power. **Ratonga** are keenly perceptive and highly intelligent, but tend to be selfish and manipulative. **Trolls** care only about satisfying their hunger for food and lust for battle, making them fearsome and deadly opponents.

NEUTRAL: Hearty and strong, **Barbarians** are loyal companions and unforgiving enemies. **Erudites** eschew their human heritage, seeking arcane knowledge and mystical power. **Gnomes** make up for their small stature with tenacity and ingenuity. Descended from humans and elves, **Half Elves** are known for fierce determination and independence. **Humans** are diverse and adaptable, at once wise, foolish, and brutal. Worshiping spirits of the land, the **Kerra**'s docile manner can mask the fearsome predators that they are.

Fig. 2.—EQ2 characters (during the 2006 observation period; descriptions from EQ2.WIKIA.COM)

by obtaining the inexpensive game software; registering in the game with your age, gender, and geographic location; and then defining a character to play. There is a monthly subscription fee. Different people can play a character in different ways, but characters are broadly defined by the game software to have certain traits and abilities. There were male and female versions of the 16 races in figure 2. Characters were further distinguished by a player-selected "class" (fighter, mage, priest, or scout) and character appearance, but figure 2 is sufficient to communicate the fantasy nature of EQ2. A person could play the role of a lizard "iksar" (known to be people who "delight in cruelty and conquest") or a "gnome," a "troll," or a "froglock" (known for their efforts to "eliminate villainy and corruption" in the community). The networks to be analyzed are composed of social relations between such characters. The virtual-world data could be seen as fixing a data cost or quality problem only to introduce a validity problem.

   At the same time, player demographics are not completely inconsistent with management populations. Williams et al. (2008) use a survey of EQ2 players to debunk stereotypes about online gamers. As might be expected, players were more often male (84.3%), but contrary to expectation, the largest concentration by age was in the 30s, not the teens, or college age. The average player was 31.3 years old, with many in their college years (13.4% less than 23 years old) and many in their middle age or older (15.2% over 40). The sample server was used primarily by U.S. residents (83.0%; next is Canada with 5.6%), but relative to the U.S. population, players came from wealthier backgrounds ($84,715 average household income vs. $58,526 in the U.S. census) and higher levels of education (27.1% of players had bachelor's or graduate degrees vs. 24.0% in the U.S. census).

Construct Validity

Critical validation for using the EQ2 data in equations (2) and (3) comes from a report on the construct validity of social networks in the virtual world. Network structure is associated with trust and achievement in EQ2 just as it is in the real world (Burt 2011). That is to say, first, that trust between characters is more likely in relations embedded in closed networks of mutual friends. Second, achievement is more likely for characters with social networks rich in structural holes, and the association is steeper when avatar behavior is less defined by game software, just as we see in the higher returns to network advantage for managers doing work less defined by the organization, which makes achievement more appealing to colleague interests. It seems that collaborative projects inworld falter without a central person holding things together, just like collaborative projects in the real world. Au (2008, p. 45) opines, "almost invariably at the heart of the collaborative process is a strong avatar with wit and galvanizing energy, keeping

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up the team's cohesion and morale." Au follows with a quote from a leader in the virtual world of Second Life reflecting on her experience: "It was difficult balancing so many strong personalities . . . responding to drama, trying to find compromises when no one wanted to compromise, having to deal with the result of the compromises wherein everyone was unhappy and feeling cheated . . . at one point I was just logging in to be available for people to bitch at" (p. 45). That quote, and others like it (Teigland 2010, p. 12), would not be out of place in the real world coming from the person managing a large project, especially a project that spans more than one functional or corporate organization. High construct validity for the EQ2 data trumps low face validity. It would be imprudent not to take advantage of the unique analytical opportunity the data provide.

However, the data to be analyzed here are a biased sample of the population. For this analysis of multirole networks, I put aside single-role networks, that is, the people who played only one character. The 6,229 excluded people and their characters are a substantial minority of the population: 44.6% of the 13,968 players and 14.1% of the 44,185 characters played. Also, the excluded characters are concentrated in the lower-right corner of the graphs in figure 1 in that the single-role people averaged small, dense networks and relatively low achievement. Excluding a concentration of observations consistent with the predicted low achievement in small, dense networks could leave a weak network association with achievement in the rest of the population.

Figure 3 and table 1 are a quick check on selection bias, a baseline for the analysis, and a vehicle for introducing the data. Given the large population of observations, I focus on the relative strength of test statistics more than absolute magnitude. In table 1, models 1 and 2 predict achievement for all characters in the population. Models 3 and 4 are the same as models 1 and 2, respectively, but exclude the 6,229 characters in single-role networks. Models 5 and 6 are the same as 3 and 4, respectively, but include an additional 5,000 observations by not controlling for player differences in age, gender, and geography. The models are in pairs to check for consistent results across the two network measures.

Judging from figure 3 and table 1, selection bias does not seem to be a problem. Regression results in table 1 are the same with and without single-role networks (compare the pattern of corresponding results in models 1 and 2 vs. models 3 and 4), and all four graphs in figure 3 show character achievement on the vertical axis increasing with access to structural holes. Also, the shapes of the achievement-network associations in figure 3 resemble associations reported for the full population (cf. Burt 2011, fig. 5), as well as those observed in management populations (compare fig. 3d with fig. 1a).

Achievement Dependent Variable and Controls.—For a criterion achievement variable, I use the game level a character achieved by the end of the

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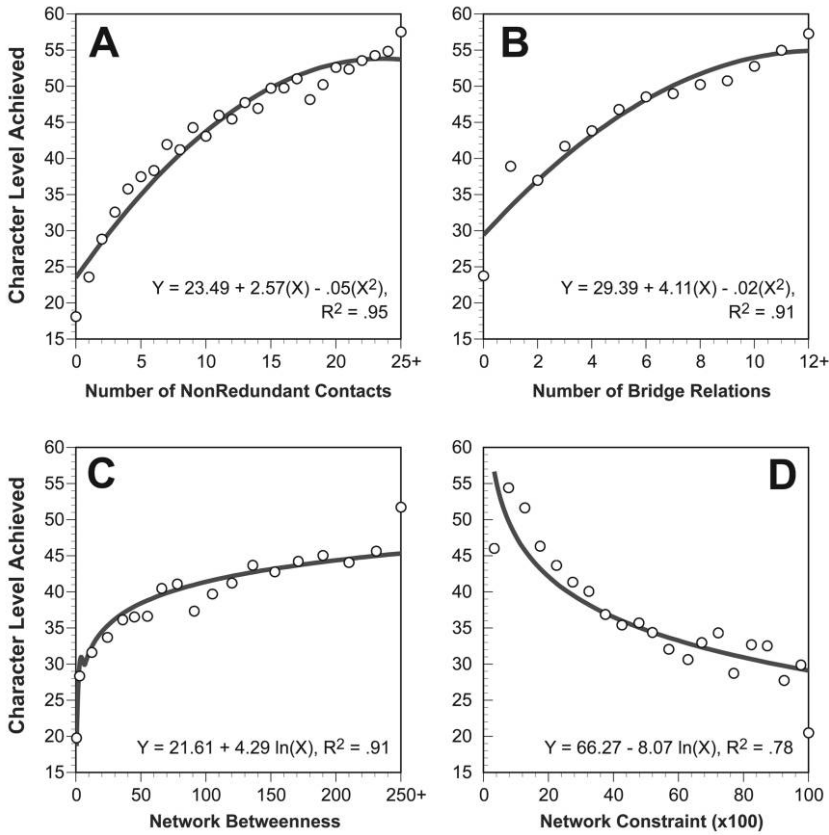
Fig. 3.—Achievement association with network advantage. Statistics are based on aggregate data in the graphs. Data points are averages for intervals of network advantage.

observation period. Williams et al. (2008, pp. 1005–6) report from their survey of EQ2 players that people rate achievement as their most important motivation, and motivation to achieve predicts time inworld better than any other motivations. From his close study of EQ2 players, Yee (2001, pp. 70–72) describes character level as representing manageable steps in task complexity such that the reinforcement of level increases operates like a "virtual Skinner box," encouraging players to spend a little more time to reach that so-close next level (World of Warcraft is similar; Ducheneaut et al. 2006, pp. 23–24).

On average, increasing amounts of time inworld are required to move between higher levels, but it takes more than spending time to move to higher levels. Level is not an outcome fixed by the game software to certain amounts of time inworld or kinds of social networks. Individuals vary widely in the time spent reaching higher levels, and their networks vary widely at each

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TABLE 1
Achievement Association with Network Advantage

	All Characters			Characters in Multirole Networks		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Number of nonredundant contacts	.86 (25)	. . .	.86 (24)	. . .	.98 (26)	. . .
Number squared	−.01 (−12)	. . .	−.01 (−12)	. . .	−.01 (−12)	. . .
Network constraint	. . .	−5.94 (−33)	. . .	−5.90 (−32)	. . .	−6.60 (−36)
Character experience (days inworld)	.11 (19)	.12 (19)	.9 (15)	.09 (15)	.14 (23)	.15 (23)
Proportion player time in this character	.26 (51)	.29 (57)	.30 (55)	.33 (61)	.21 (48)	.24 (53)
Player experience: Days inworld	.04 (18)	.04 (16)	.05 (19)	.05 (18)	.05 (21)	.05 (19)
Number characters played	1.83 (10)	2.33 (12)	.97 (5)	1.27 (6)	1.66 (9)	2.03 (10)
American	−1.73 (−5)	−1.61 (−5)	−1.55 (−5)	−1.39 (−4)	. . .	. . .
Age (decades)	.01 (1)	−.01 (−1)	.01 (1)	−.00 (−0)	. . .	. . .
Female	−3.49 (−12)	−3.72 (−12)	−3.57 (−12)	−3.81 (−12)	. . .	. . .
Intercept	14.53	41.32	15.22	42.06	11.46	41.07
R^2	.64	.61	.65	.62	.62	.58
Observations	21,536	21,536	20,446	20,446	25,610	25,610

Note.—These are ordinary least squares regressions predicting the game level a character achieved by the end of the observation period (t-test statistics are in parentheses). Number of nonredundant contacts is the x axis in fig. 3a. Network constraint is multiplied by 100 for metric and converted to a natural log score to capture the nonlinear association in fig. 3d. Character experience is time measured as 24-hour periods since creation. Player experience is total time a character's player spent in characters active during the observation period and log number of characters the person played during the observation period. Models 1 and 2 are estimated across all characters. Models 3–6 are estimated across characters played by people who played multiple characters. SEs are adjusted up for correlated achievement by characters played by the same person (Stata "cluster" option).

level. There are confirmed instances of "gold farmers," that is, players who develop characters quickly for resale, but the instances are rare (0.43% of characters were banned by Sony as gold-farmer characters [Ahmad et al. 2009], with an equal number of the remaining characters estimated to be the undetected work of gold farmers [Roy et al. 2012]). I use four variables to hold level of experience constant: a player's time inworld, the number of characters in which the player was active, time spent since character creation in the character whose achievement is being predicted, and the player's proportion of time inworld spent in the character. Rows 4–7 in table 1 show achievement increasing with the number of characters a person played (*t*-tests of 6 in model 3, 9 in model 5), the time a player spent inworld (*t*-test of 19 in model 3), and especially time spent in the character whose achievement is being predicted (*t*-tests of 15 and 55 in model 3).

Player age, gender, and regional differences are irrelevant to achievement. The strongest correlate in table 1 is gender, with women less likely to develop their characters to high game levels. Achievement has no association with player age. Closer inspection for age effects among younger and older players separately yielded no strong local associations with age. I also tried controls for character gender and race, but neither improved the prediction (the .65 R^2 for model 3 in table 1 remains .65 with three additional predictors: a dummy variable distinguishing female characters, a dummy variable distinguishing the five "good" characters in fig. 2, and a dummy distinguishing "evil" characters). Given negligible achievement distinctions by player age, gender, and region, I put the distinctions aside, which recovers 5,164 characters lost because of missing demographic data (20,446 characters in models 3 and 4 increase to 25,610 in models 5 and 6).[3]

Missing Data on Retired Characters.—For each character active at the end of the observation period, I know game level and cumulative time spent in the character since its creation. However, a third of the characters active during the observation period were no longer active at the end of the period (12,346 of the 37,956 characters in multirole networks). The no-longer-active characters were "retired." The game software limited players to seven char-

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[3] Player age, gender, and region are self-reported. At least one of the three variables is missing for a third of the players with multirole networks. Players missing data were not much different from other players in the number of characters played but very different in experience and achievement. Missing-data players spent an average total of 19.85 days inworld since they first entered EQ2 vs. 85.58 days spent by other players. The average character played by a missing-data player reached game level 21.20 with a network of 1.77 nonredundant contacts vs. a 33.91 average game level and 5.72 nonredundant contacts for the characters of other players. Even though the missing-data players are returned to the analysis after model 4, their systematic difference from other players makes it useful to see in table 1 that the achievement-network associations estimated without the characters of missing-data players (models 3 and 4) are similar to the associations estimated with the characters included (models 5 and 6).

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acters active at the same time, so the only way a person could be active in more than seven was by retiring old characters and creating new ones. Players with high numbers of characters are people who created a character, played for a while, and then retired the character to create another new one. Most people played fewer than a handful of characters; in fact, the mode for multirole networks is the minimum of two characters. But there are extremes of people playing many characters: one person was active in 82 characters during the observation period. Another was active in 155. The complication is that characters were deleted from the downloaded character data table when they were retired, so final game level and cumulative experience are unknown for retired characters. I know how a retired character collaborated with others during the observation period, but I do not know the character's final game level or cumulative experience. I handle retirements in two ways: I include retired characters in the network measures to accurately represent the networks around nonretired characters, and I created a second set of experience variables with experience imputed for retired characters so I can test my main results for sensitivity to the retired characters.[4] Since I have network measures on the retired characters, I can say that retired characters were relatively peripheral in the virtual world. The retired characters are not as troubling a loss as the same number of socially active characters would have been.[5]

Network Metrics.—Character k's network contains every other character with whom k had a collaborative relationship: z_{ijk} within character k's network varies from zero to one with the strength of housing rights i or j gave to one another, the rights they both have in a mutual friend's house, and the frequency with which i or j helped the other develop (mentoring) or both together helped a mutual friend develop. The z_{ijk} data are taken from the construct validity report on the EQ2 network data (Burt 2011).

An illustrative multirole network is displayed in figure 4. Multirole networks reveal a detailed profile, so to preserve player confidentiality, fig-

[4] I impute time inworld from economic activity during the observation period, which I know for all characters, including those retired. Economic activity is any buying, selling, or trading with other characters or with game vendors. I used economic activity to keep the imputation separate from the social relations analyzed here. Predict time inworld from a count of economic activities for nonretired characters (.64 correlation), and then use the prediction equation to impute time inworld for retired characters from their known economic activities. Sum imputed character time across a player's characters to get the player's imputed time inworld and an imputed proportion of player time spent in each character. Test statistics are larger with the imputed measures of experience since there are more character observations, but none of the conclusions are changed.

[5] More of the retired characters were social isolates (67.9% vs. 14.0% of characters active at the end of the period). On average, a nonisolate retired character's network contained 7.01 contacts, of whom a little less than half were nonredundant (3.08). The corresponding network for a character still active at the end of the observation period contained more contacts (12.62), of whom almost two-thirds were nonredundant (7.73).

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Human Male
Primary Character (56% of time)
10 Contacts
6.4 NonRedundant Contacts
.32 Network Constraint

High Elf
Third Character (18% of time)
13 Contacts
11.2 NonRedundant Contacts
.17 Network Constraint

Human Female
Primary Character (26% of time)
7 Contacts
2.4 NonRedundant Contacts
.47 Network Constraint
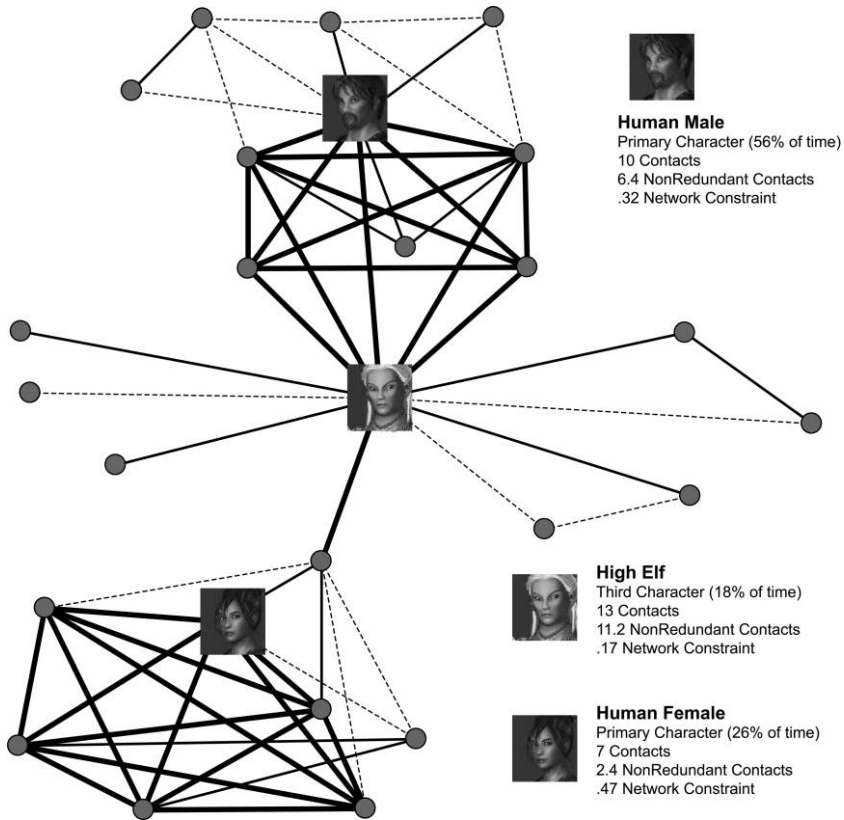
FIG. 4.—Illustrative multirole network. Icons indicate the person's avatars. Dots are other people's avatars. Thicker solid lines indicate stronger social connections.

ure 4 is a composite of roles from multiple players selected to form a typical multirole network. The three characters—each ego in its own network—are a "human male" at the top of figure 4, a "high elf" in the middle of figure 4, and a "human female" at the bottom of figure 4. (With such a majority of male players in EQ2, many female characters were played by male players, 45% of the female characters to be exact.) Lines indicate collaborations. The continuous network data are represented in figure 4 by line weights varying from no connection (no line), to weak connection (thin dashed lines), to strong connection (heaviest bold lines).

   The multirole network in figure 4 shows a network of 10 contacts when the person plays his human male character, a network of 13 contacts when he plays his high elf character, and a network of seven contacts when he plays his human female character. The two male characters are connected within their respective networks through many mutual contacts in a house they

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share (housemates are indicated by the dense cluster between the human male and high elf characters in fig. 4). The human male and human female characters illustrate the network consistency measured by equation (2); the player creates a closed network around himself when he plays a role. The high elf network deviates from the pattern. The high elf is connected to a dense cluster of housemates but in addition has seven contacts outside the house rarely connected to one another. Each disconnect is a structural hole that the high elf character could bridge. The player seems to be using his high elf character to explore and his two human characters as base characters.

Number of nonredundant contacts is my primary measure of access to structural holes. The index is a count of contacts adjusted down for strong connections among the contacts. A large number of nonredundant contacts means that a character had many friends in otherwise disconnected parts of the virtual world, which means that she had rich access to structural holes between the groups from which she drew friends.[6] The larger the number of nonredundant contacts, the more opportunities ego had to broker connections. One nonredundant contact means no access to structural holes. Two means that a character had access to the structural hole between two nonredundant contacts (or two dense clusters of contacts). Four means that a character had access to the six holes between her four nonredundant contacts, and so on. In figure 4, the high elf has 13 contacts largely disconnected from one another. The network contains 11.2 nonredundant contacts. The human male has almost as many contacts, but strong connections among them reduce the network to 6.4 nonredundant contacts.

I use nonredundant contacts as my primary measure because it has a metric intuitive beyond network experts, but I also computed some alternative measures. I get similar results with the alternatives. Table 2 shows how nonredundant contacts covary with some alternatives. Characters are distinguished down the rows of table 2 by their number of nonredundant contacts. I round the quantitative measure of nonredundant friends into categories for the table. The first row contains characters never involved in social relations during the observation period. These isolates were active in some way during the observation period or they would not be in the study population; however, they are isolates in that they did not collaborate with other characters in housing or mentoring relations, neither of which is necessary to achieve high character levels. The second row contains characters

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[6] The index is computed as follows (Burt 1992, pp. 51–54): Begin with contact j in ego i's role-specific network k discounted for the strength of j's relations with ego's other contacts in the network $(1 - \sum_q p_{iqk} m_{jqk}$, where p_{iqk} is the proportional strength of ego's network k relation with contact q, and m_{jqk} is contact j's marginal strength of connection with contact q, $q \neq i, j)$. Sum across ego's contacts j to define the number of nonredundant contacts in network k: $\sum_j (1 - \sum_q p_{iqk} m_{jqk})$.

TABLE 2
STRUCTURAL HOLES IN CHARACTER NETWORKS

NUMBER OF NONREDUNDANT CONTACTS	CHARACTERS	NETWORK SIZE			BRIDGE RELATIONS	NETWORK BETWEENNESS	NETWORK CONSTRAINT
		Min	Mean	Max			
0 (isolate)	11,973	0	.00	0	.00	.00	100.00
	(2,485)						
1	8,349	1	3.26	46	.02	11.60	86.15
	(1,657)						
2	2,980	2	4.62	32	1.22	18.08	64.79
	(435)						
3	1,800	3	6.45	44	1.49	27.99	54.05
	(264)						
4	1,294	4	7.92	48	1.80	39.75	49.05
	(157)						
5	973	5	9.53	46	1.97	55.03	43.89
	(116)						
6	817	6	10.62	51	2.23	66.03	41.93
	(80)						
7–8	1,254	7	12.77	53	2.46	91.71	36.63
	(147)						
9–11	1,292	9	15.78	53	2.93	132.92	32.35
	(128)						
12–16.	1,381	12	22.51	161	3.44	335.91	26.85
	(117)						
17–24.	1,261	18	35.75	168	4.41	1,092.45	21.48
	(96)						
25 or more	1,800	26	62.42	186	6.54	2,471.64	13.01
	(92)						
Total	37,956	0	13.18	186	1.79	299.01	57.12
	(6,229)						

NOTE.—These are means for characters (ego) in multirole networks (excluded single-role characters are in parentheses). Means in the total row exclude isolates. Size is a count of anyone connected to ego. Nonredundant contacts is network size discounted for strong connections between ego's contacts. A bridge is a relationship in which ego and a contact have no mutual contacts. Network betweenness is the number of pairs of contacts between whom ego is the only connection (within ego's network). Network constraint is a concentration index varying from zero to one with the extent to which ego's network time and energy are concentrated in a single cluster of connected contacts.

who had one nonredundant contact. Characters in the second row had at least one contact, but some had many more—up to 46. However, the multiple contacts were strongly connected with one another such that ego ended up with only one nonredundant contact. Down the subsequent rows of table 2, characters are embedded in networks with more and more opportunities to bridge structural holes.

To the right of network size in table 2, a count of bridge relations increases with the number of nonredundant friends. Ego has a bridge relation

to a contact when ego and contact have no mutual friends.[7] Network betweenness is the number of ego's friends between whom ego was the only connection within ego's network.[8] Betweenness is zero in the small networks at the top of table 2. It increases down the rows of the table. Network constraint measures the extent to which ego's network time and energy were concentrated in a single group. Network constraint is high if ego had few contacts (small network), and the contacts were connected to one another directly (dense network) or indirectly through a central, mutual contact (hierarchical network).[9] A score of 100 indicates no access to structural holes (ego had no friends or all of ego's friends were friends with one another). Constraint scores are 100 at the top of table 2 and approach zero for the complex networks toward the bottom of the table.

Figure 3 shows similar achievement associations with the alternative network measures. Initial access to structural holes has a particularly strong association with achievement: connecting beyond an initial group is an important step. Character level increases quickly with the first handful of nonredundant contacts (fig. 3a), with the first one or two bridge relations (fig. 3b), and with the first few points of betweenness counting the number of struc-

[7] The relation from ego to a contact is a bridge relation if they have no mutual friends. That is, ego i's relation to contact j is a bridge if all indirect connections $z_{iqk}z_{qjk}$ are zero for the other contacts q in ego's network. The index in table 2 is simply a count of such relations.
[8] Freeman (1977) proposed network betweenness as a centrality index improving prediction in small groups. The index measures the extent to which none of ego's contacts are connected in a network except through ego. The strength of connection between contacts j and q through ego i is the product $z_{ijk}z_{iqk}$. The total connection between contacts j and q is the sum of direct connection between them, z_{jqk}, plus all indirect connections through ego's other contacts, $\sum_q z_{ijk}z_{iqk}$, $q \neq i, j$. The ratio of the j–q connection through ego, $z_{ijk}z_{iqk}$, divided by the total connection between j and q varies from one (if ego is the only connection between j and k) down toward zero (if ego provides only a small proportion of the total connection). Sum the ratio across all pairs of contacts j and k. The resulting index varies up from zero counting the pairs of ego's contacts for whom ego is the only connection.
[9] Constraint measures the extent to which ego's network is concentrated in a single group (Burt 1992, pp. 54–65; 2010, pp. 294–97). Begin with a measure of the extent to which ego i's relations all connect back to contact j:

$$c_{ij} = \left(p_{ij} + \sum_q p_{iqk}p_{qjk} \right)^2, \quad q \neq i, j,$$

where p_{ij} is the proportion of ego i's network time and energy spent directly with contact j, so contact-specific constraint c_{ij} varies from zero to one with the extent to which ego cannot avoid contact k, either directly (p_{ij}) or indirectly ($\sum_q p_{iqk}p_{qjk}$). Network constraint is the sum of the c_{ij} for each of ego's contacts. The sum is an index that varies from zero to one—for all but very small networks—with the extent to which ego's network time and energy are concentrated in a single group, indicating that ego has no access to structural holes. The index is infinity for social isolates (divide by zero contacts) and can exceed one in maximum-density networks of two contacts. Since such networks provide no access to structural holes, I round their constraint scores to one. I multiply scores by 100 to discuss integer points of constraint in the text.

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tural holes to which ego had access (fig. 3c). At high levels of network advantage, unit increases are associated with smaller increases in character level. Network constraint is a concentration measure, so the nonlinear association with achievement shows up in figure 3d as slow decreases in achievement associated with network disadvantage increasing past an average level.

I focus on the intuitive metric of nonredundant contacts, which has an association with achievement that is characteristic of the first three graphs in figure 3. I also carry network constraint through the analysis because constraint has an association with achievement that is most different from the others in figure 3. I am looking for results consistent across the two different network measures of access to structural holes.

In table 1, the first row shows strong linear achievement associations with the number of nonredundant contacts (t-tests of 24–26). The second row in table 1 shows weaker, but strong, dampening effects from too many nonredundant contacts. As displayed in figure 3a, achievement increases quickly with initial nonredundant contacts, slowly thereafter. As found in previous studies of manager achievement (fig. 1a), linear and dampening effects are combined in the association between achievement and log network constraint in the third row of table 1. Whatever the face validity of the EQ2 achievement and network variables, they display a strong achievement-network association consistent with previous research in management populations.

SUMMARY RESULTS: PERSONALITY EVIDENT BUT IRRELEVANT

Table 3 contains descriptive statistics on the network and experience variables for the characters in multirole networks (these are the characters used to estimate models 5 and 6 in table 1).

Strong Evidence of Personality Shaping Networks

Figure 5 shows how variation in network advantage breaks down into a portion due to a player's network-relevant personality **P** and a residual portion unique to the player's behavior in a specific character. Table 4 contains the equation (2) regression results used to compute the variance pie charts in figure 5.[10]

Players clearly had a network-relevant personality they brought to the characters they played. About a third of the character variance in network advantage can be traced to the average network a player builds (32%–38%

[10] Pie chart slices in fig. 5 are summed contributions to predicted variance in table 4. The proportion of dependent variable variance predicted by a regression equation is the summed products of standardized regression coefficients multiplied by the corresponding

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TABLE 3
DESCRIPTIVE STATISTICS

	Mean	SD	Correlation										
Achieved game level	31.34	19.36	1.00										
Days inworld	78.72	74.77	.30	1.00									
Number of characters	1.65	.59	−.01	.23	1.00								
Days in character	18.01	34.44	.65	.42	−.06	1.00							
% of time in this character	27.92	32.18	.56	−.17	−.35	.55	1.00						
Number of nonredundant contacts	6.65	11.89	.52	.15	.11	.35	.31	1.00					
Number squared	185.45	791.41	.31	.09	.07	.23	.19	.86	1.00				
P number of nonredundant contacts	5.48	5.92	.20	.27	.03	.12	.07	.56	.43	1.00			
P number squared	65.04	173.24	.12	.16	.03	.08	−.02	.48	.44	.88	1.00		
Network constraint.	3.97	.77	−.51	−.22	.17	−.35	−.26	−.76	−.48	−.53	−.41	1.00	
P network constraint	4.19	.41	−.17	−.32	−.07	−.12	.09	−.35	−.21	−.69	−.56	.61	1.00

NOTE.—Statistics are computed across 25,610 characters played by 7,150 people. Days in character is the time spent in the character since its creation (measured in 24-hour days). Days inworld is the sum of days in character across all characters played by the character's player. Number of characters is the log of the number of active characters registered by the character's player during the observation period. % of time in this character is 100 times the ratio of days in character to days inworld. Network constraint is a log score as in table 1. The **P** variables are network indices averaged across a player's characters (eq. [1]; averages are computed before squaring or taking the log).
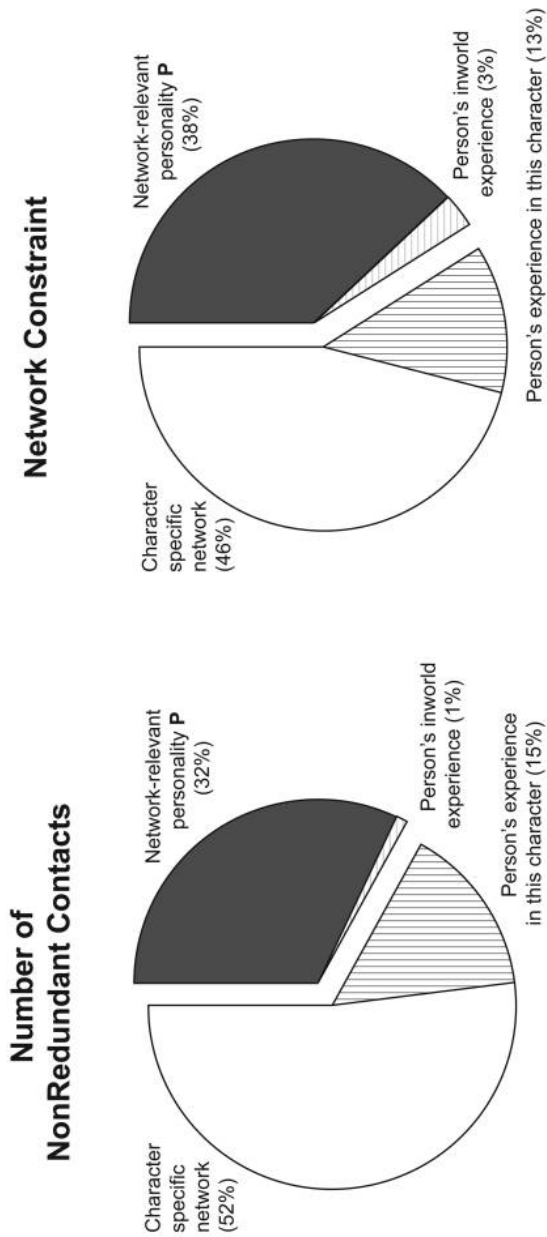
FIG. 5.—What network? People build somewhat similarly open or closed networks in the roles they play (32%–38% of network variance). Based on the regression models in table 4 predicting character network scores used to predict achievement in table 2, each pie shows portions of predicted variance within and across people who played two or more characters (25,610 characters played by 7,150 people).

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TABLE 4
Predict Character Network

	Model 7 Character's Nonredundant Contacts		Model 8 Character's Network Constraint	
	r	β (t)	r	β (t)
Person across characters:				
Average network index for person's				
characters	.556	.632 (61)	.611	.621 (87)
Squared number of nonredundant				
contacts.	.479	−.066 (−5)		
Person's experience:				
Total days inworld	.147	−.069 (−12)	−.223	.028 (6)
Number of characters	.105	.223 (43)	−.169	−.257 (−48)
Person in character:				
Character experience				
(days in this character).	.346	.136 (12)	−.350	−.118 (−13)
% of person's time in this				
character.	.306	.337 (37)	−.258	−.336 (−48)
R^2		.484		.545
Character-specific network				
variance $(1 − R^2)$		.516		.455

Note.—These are correlations and standardized ordinary least squares regression coeffi-cients predicting the column network index for characters. Routine *t*-test statistics are given in parentheses for 25,610 characters played by 7,150 people (with SEs adjusted up for correlation between characters played by the same person using Stata "cluster" option). Means, SDs, and correlations are given in table 3.

of network variance in fig. 5). The percentages are slightly lower if missing experience levels are imputed so that all 37,956 characters are included in the estimation, but the "one-third of variance" conclusion still fits (27% for nonredundant contacts, 38% for network constraint).

   Inworld experience matters but primarily at the character level. Aggre-gate experience across all of a player's characters is largely irrelevant (1%–2% of network variance). What predicts a character's network advantage

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correlations ($R^2 = \sum_x r_{yx} b_{yx}$). For the nonredundant-contacts index in table 4, read the equation down the rows:

$$.484 = .556 \times .632 + .479 \times −.066 + .147 \times −.069 + .105 \times .223 + .346$$
$$\times .136 + .306 \times .337.$$

The sum of the first two terms is .320, which is the 32% of network variance attributed in fig. 5 to network-relevant personality **P**. The sum of the second two terms is .013, which is the 1% of variance attributed in fig. 5 to the person's inworld experience. The sum of the last two terms is .150, which is the 15% of variance attributed in fig. 5 to the person's ex-perience in this character. The residual variance of 1 − .484 is the 52% of network var-iance in fig. 5 left unique to the way this person played this character.

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TABLE 5
PREDICT CHARACTER ACHIEVEMENT

	MODEL 9 NONREDUNDANT CONTACTS AS NETWORK INDEX		MODEL 10 NETWORK CONSTRAINT AS NETWORK INDEX	
	r	β (t)	r	β (t)
Person across characters:				
Average network index for				
person's characters	.204	.022 (1)	−.170	.090 (11)
Squared number of				
nonredundant contacts.	.123	−.086 (−5)		
Person's experience:				
Total days inworld	.301	.191 (21)	.301	.201 (21)
Number of characters	−.006	.039 (7)	−.006	.045 (7)
Person within achieving character:				
Character experience				
(days in this character).	.648	.245 (23)	.648	.256 (23)
% of person's time in this				
character.	.561	.344 (46)	.561	.376 (49)
Character network index.	.523	.628 (26)	−.508	−.324 (−41)
Squared number of				
nonredundant contacts.	.306	−.348 (−12)		
R^2		.626		.586

NOTE.—These are correlations and standardized ordinary least squares regression coeffi-
cients predicting the game level achieved by a character by the end of the observation period.
Routine t-test statistics are given in parentheses for 25,610 characters played by 7,150 people
(with SEs adjusted up for correlated achievement by characters played by the same person us-
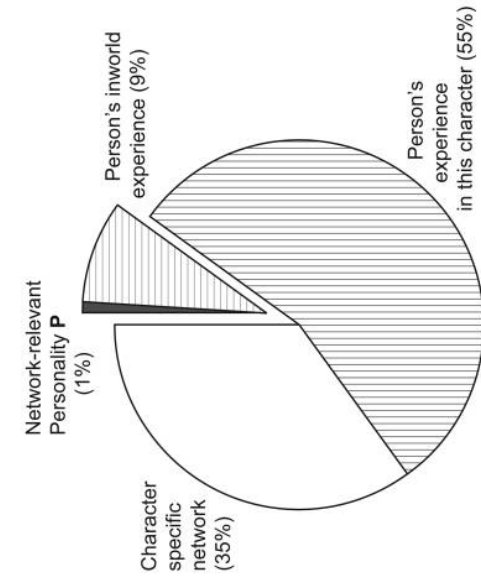ing the Stata "cluster" option). Means, SDs, and correlations are given in table 3.

is the player's experience in that character (13%–15% of variance). As a
player spends more time in a character and that character is a larger propor-
tion of the player's time inworld, the character's network provides more
access to structural holes (more nonredundant contacts and lower network
constraint).

The largest portion of network variance distinguished in figure 5 is the
variance unique to a specific character (46% and 52% of network variance).
The 50% character-specific variance is about the same with missing expe-
rience levels imputed (48% and 44%, respectively, for nonredundant con-
tacts and network constraint).

Little Evidence of Contribution to the Network Association with Achievement

Figure 6 shows how predicted variation in character achievement divides
into a portion due to a player's network-relevant personality, a portion due
to experience, and a portion due to the network around the specific charac-

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Number of
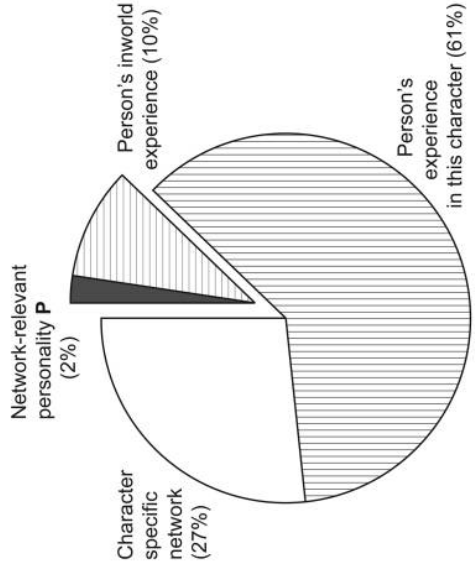# NonRedundant Contacts

Network Constraint

Person's inworld experience (9%)

Network-relevant Personality **P** (1%)

Character specific network (35%)

Person's experience in this character (55%)

Person's inworld experience (10%)

Network-relevant personality **P** (2%)

Character specific network (27%)

Person's experience in this character (61%)

Fɪɢ. 6.—What network effects? The network consistent across a person's roles makes little contribution to predicting achievement. Achievement in a role depends on role-specific experience and the network built up within the role (88%–90% of predicted achievement variance). Based on the regression models in table 5 predicting the game level a character achieved by the end of the observation period, the pies show portions of predicted variance within and across people who played two or more characters (25,610 characters played by 7,150 people). More experience is associated with higher levels of achievement.

ter whose achievement is being predicted. Table 5 contains the equation (3) regression results used to compute the variance pie charts in figure 6.[11]

The results show that network-relevant personality is a minor consideration in character achievement. The *t*-tests for network-relevant personality are among the smallest in table 5, and network-relevant personality contributes only 1%–3% of predicted character achievement in figure 6.[12]

Role-specific factors are the key predictors. The largest *t*-tests in table 5 are in the bottom rows, for predictors measuring a person's activity inside the character whose achievement is being predicted. Achievement increases most closely with experience: again, not so much with the person's aggregate experience (9%–10% in fig. 6) as with the person's experience in the specific character whose achievement is being predicted (55%–60% in fig. 6). Network advantage specific to the character also matters (35% and 27% of predicted achievement variance, respectively, for nonredundant contacts and network constraint). In sum, as a player spends more time in a character and that character is a larger proportion of the player's time inworld, the char-

[11] The pie chart slices in fig. 6 are sums of cross-products as explained in the previous footnote for fig. 5 except for two differences. First, the sums of cross-products are normalized by R^2 to display relative contributions to predicted achievement variance. Second, a person's average network is more correlated with his character networks than either is with achievement, so the average network contribution to R^2 is a negative adjustment to the contribution from the character-specific network. For the heuristic purposes of fig. 6, therefore, I treat the small negative contribution as a small positive and normalize by the increased R^2. For example, cross-products for nonredundant contacts in table 5 are $-.006$ for network-relevant personality (average number of nonredundant contacts in a person's character networks), .057 for the person's inworld experience, .353 for the person's experience in the character whose achievement is being predicted, and .222 for the character-specific network (number of nonredundant contacts in the character's network). The four terms sum to the .626 R^2 in table 5, or to .638 if the small negative adjustment is treated as a small positive contribution. The 35% contribution from character-specific network to predicted achievement variance in fig. 6 is .222 divided by .638. Thus, the two small contributions from network-relevant personality in fig. 6 are slightly overstated, and contributions from other factors are slightly understated.

[12] There is no advantage here to checking for selection bias as was done for fig. 5 because the dependent variable is missing for the retired characters. However, I checked the achievement prediction with a more sophisticated statistical model in which random player effects were estimated within fixed character effects. Using the xtmixed procedure in Stata, I predicted character achievement from character experience and network (bottom three rows of table 5), inferring adjustments for player-level effects from player experience and network-relevant personality (top three rows of table 5). The .628 standardized coefficient in table 5 for the number of nonredundant contacts corresponds to an unstandardized coefficient of 1.022 (.039 SE, $t = 26.11$). Results are similar for the mixed-effects model: 1.020 unstandardized coefficient for character number of nonredundant contacts (.036 SE, $Z = 28.13$) with a negligible adjustment for the player's average network ($Z = 0.30$). The $-.324$ standardized coefficient in table 5 for network constraint corresponds to an unstandardized coefficient of -8.189 (.198 SE, $t = -41.34$). The mixed-effects model yields a -8.341 unstandardized coefficient for character network constraint (.163 SE, $Z = -51.28$) with a negligible adjustment for the player's average network ($Z = 1.09$).
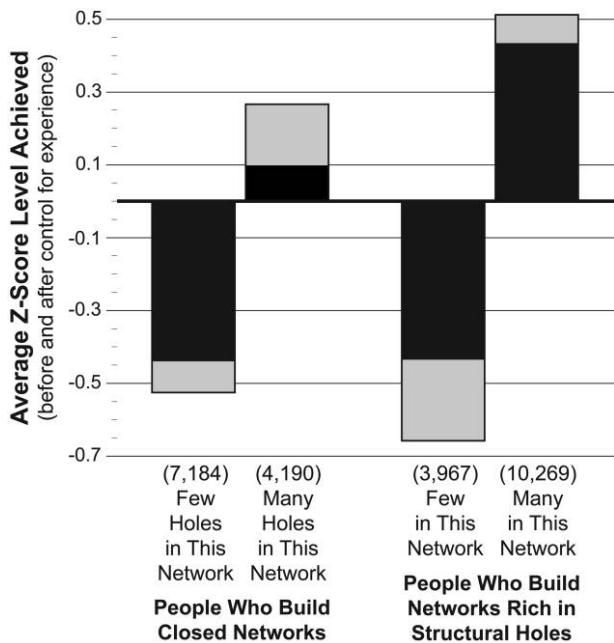
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Fig. 7.—Achievement is not improved by consistency between character network and the person's usual network. Numbers of characters are given in parentheses. Few versus many structural holes are distinguished at the median level of actual network index (*N*) and network-relevant personality (**P**). Network index is the number of nonredundant contacts. Bars indicate average *Z*-score character level. Dark portion of a bar is the mean *Z*-score level when player experience is held constant.

acter's network provides more access to structural holes (more nonredundant contacts and lower network constraint). Role-specific experience and network factors together account for 87%–90% of the predicted variance in character achievement.

There is no direct association between achievement and network-relevant personality, but there could be an indirect association from consistency between character and player networks. A person who prefers open networks might enjoy higher returns to brokerage because he feels comfortable in such a network. A person who prefers closed networks might show lower than expected benefit from a network rich in structural holes because he is not comfortable with or experienced in operating within such a network.

Figure 7 shows negligible indirect association. The vertical axis is *Z*-score achieved character level, before and after experience is held constant. Achievement is compared across columns for characters whose networks match or contradict what is typical for the player. I use median network-relevant personality **P** to divide people into those who typically built closed networks versus those who typically built broker networks. I use median

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network index N to distinguish characters embedded in corresponding closed or broker networks. Categories in figure 7 are defined using the number of nonredundant contacts to measure advantage. I get similarly negligible results when I use network constraint to define the four categories.

Regardless of a player's typical network, character achievement is low if the player built a closed network around the character ($-.53$ and $-.66$ Z-score achievement averages for the first and third bars in fig. 7) and high if the person built an open network (.27 and .51 averages indicated by the second and fourth bars). Similarly with network constraint, closed networks are associated with low achievement regardless of a player's typical network ($-.52$ and $-.66$ Z-score achievement averages, respectively, for players who typically build closed vs. open networks), and open networks are associated with high achievement (respective Z-score achievement averages of .35 and .38). For a more formal test of the differences illustrated in figure 7, regress achieved character level across the four experience controls in table 5, plus the two open-closed network binary variables in figure 7, plus a binary variable equal to one when character and player networks match (first or fourth bar in fig. 7). When nonredundant characters are used as the network metric, 23% of predicted achievement variance is attributed to character network, 2% is attributed to player network, and 1% is attributed to higher achievement when character and player networks are matched. When network constraint is used as the network metric, 20% of predicted achievement variance is attributed to character network, 0.3% is attributed to player network, and 0.2% is attributed to higher achievement when character and player networks are matched. In sum, achievement is below average for characters in closed networks and above average for characters in open networks, regardless of consistency with the player's typical network.[13]

[13] There is a pattern to the results that warrants attention for future research: Experience matters more for achievement when the network around a character does not match the network typical of a player. Bar height in fig. 7 shows average Z-score character level. The dark portion is the average level after experience is held constant. For example, average Z-score achievement for a closed-network person playing an open-network character is .27, which drops to .10 when the four experience variables in table 5 are held constant. In other words, the light portion of each bar is achievement attributed to experience. The bars in which achievement is most due to experience, i.e., the bars with the greatest proportion of light area, are the bars in which character network is mismatched with the player's typical network. For advantage measured by the number of nonredundant contacts, the 55% of predicted achievement variance attributed in fig. 6 to a person's experience playing a character is 50% if character-player networks match vs. 63% if they do not. With advantage measured by network constraint, the 61% in fig. 6 is 58% if character-player networks match versus 68% if they do not. The analysis in the text shows that character-player network consistency is a negligible factor predicting cumulative achievement, but the experience association with achievement in conditions of mismatch implies that the place to study consistency is the learning process rather than the outcome. Do people take longer to learn from their inworld experience when they play a character whose network is incon-

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SUMMARY RESULTS ARE ROBUST

The roles in a multirole network can come together in a variety of ways. Some roles are assigned. Some are sought. Some are stumbled into. Regardless of how a set of roles come together, once they are bundled in a multirole network, there is "strain" on the person playing the multiple roles. Merton's (1957) analysis of role-sets describes mechanisms for managing conflicts between combined roles, and Goode (1960), often arguing parallel to Merton, discussed sources of role strain and its management. Following Merton and Goode, I combine the terms "role strain" and "role conflict" for the purposes here. The term "role strain" is sometimes used to reference conflict between roles associated with one status whereas "role conflict" references conflict between roles associated with different statuses. Role strain would refer to conflict between demands on a professor as teacher versus scholar, whereas role conflict would refer to conflict between demands on a professor as scholar versus wife. The distinction is not necessary here, so I combine the two terms and use "role strain" to reference conflicting demands from the roles in a multirole network. As Goode (1960, p. 483) put it in the original discussion, role strain is "the felt difficulty in fulfilling role obligations."

Role strain is a useful concept for analyzing multirole networks because strain is a contingency factor in the association between network-relevant personality and advantage. I have three examples in EQ2 from which I infer that the summary results just presented are robust.

Role Strain from Too Little Focus

One source of strain is taking on too many roles. A correction is to prioritize roles so that secondary roles can be ignored when their demands conflict with a primary role. Familiar examples are the ambitious person for whom all is secondary to her career, the parent who puts all considerations second to the welfare of his child, or the person of faith who rejects actions visibly inconsistent with his faith. Assuming that all roles generate some conflict with others, I expect to see more evidence of personality across a person's primary roles because that is where a person has more opportunity to display personal preferences.

Figure 8 illustrates the distinction between primary and secondary roles in EQ2. A player's characters are ordered on the horizontal axes by the time the player spent in them. The vertical axes show the percentage of playtime spent in each character. In figure 8a, people on average spent 74.8% of their game time in the character in which they spent the most time. They spent a much lower 17.3% average of their game time in their second character. The

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sistent with the player's typical network (cf. Janicik and Larrick 2005)? This is a research project ideally suited to the real-time data available in virtual worlds.
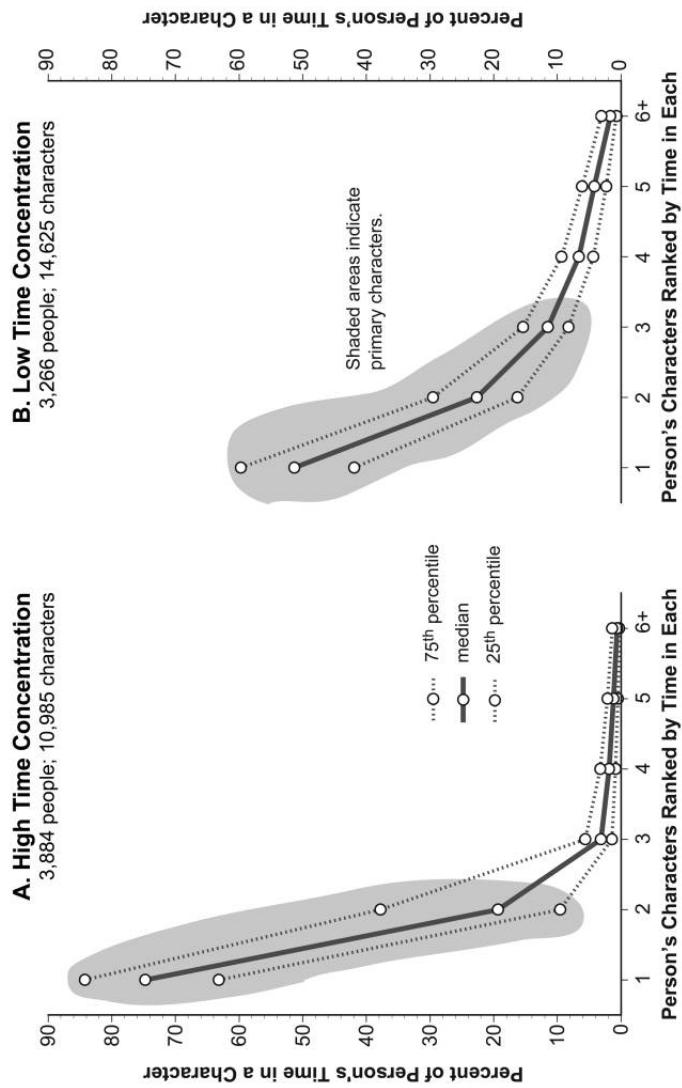
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FIG. 8.—% of a person's time in each character. Each person's characters are ordered by the time spent in each. These graphs include only characters for whom time in character is known. High versus low concentration is distinguished at the median.

bold line through the averages descends quickly in the graph, and the inter-quartile range is tight around the descent.

Figures 8*a* and *b* differ in time concentration. I computed for each player a concentration index by summing the squared proportions of time played in the player's most-often and second-most-often played characters. A person spending 90% of his time in one character and 10% in another would have a concentration score of .82 (.81 + .01). Figure 8*a* describes the distribution of play for people with concentration scores above the median level. Figure 8*b* describes the remaining, low-concentration, people.

Allow a rough operational distinction between primary and secondary characters: Primary are the characters in the shaded areas of figure 8: the two characters most often played by high-concentration players or the three characters most often played by low-concentration players. The distinction ensures that every player has at least two primary characters across which network-related personality can be computed, and figure 8 shows that these primary characters represent about 10% or more of game time for the people playing them (44.7% average proportion per character). All other characters are secondary (3.7% average player game time per character). For each player, I computed two network-relevant personality scores from equation (1), one for their primary characters and another for their secondary characters.

Table 6 shows, as expected, that the characters in which a person concentrated game time—her primary characters—were more likely to display network-relevant personality. The model 7 column in table 6 contains the percentage of variance in a character's number of nonredundant contacts that can be attributed to the player's network-relevant personality. The first row shows the result for all 25,610 characters (corresponding to the 32% in fig. 5). The next two rows show a much higher percentage for primary characters (48%) than for secondary characters (12%). Similarly, the percentage of network constraint variance attributed to network-relevant personality (38% in fig. 5 and the first row of the model 8 column in table 6) is much higher for primary characters (61%) than for secondary characters (24%).[14]

[14] The 48%–61% personality variance in broker metrics for primary roles is not too different from estimates of genetic variance in related network metrics. To the extent that genetics determine networks, people with similar genetic material should have similar network metrics, which is analogous to eq. (2): to the extent that personality determines networks, roles played by the same person should have similar network metrics. Same-sex monozygotic twins (MZ, from one egg) share 100% genetic material. Same-sex dizygotic twins (DZ, from two eggs) share approximately 50% genetic material. Genetically determined variance in network metrics for DZ twins should be half what it is in network metrics for MZ twins. Assuming a fixed ratio of DZ to MZ genetic variance and given covariance between network metrics for a sample of DZ and MZ twins, it is possible to estimate a proportion of network variance attributable to genetics. Fowler, Dawes, and Christakis (2009, p. 1720) analyze friendship networks around twins in the National Longitudinal Study of Adolescent Health (307 pairs of MZ twins, 248 pairs of DZ) to report the following

TABLE 6
Robust Results on Variance Attributed to Network-Relevant Personality

	% Variance in Network around Character (Fig. 5)		% Predicted Variance in Character Achievement (Fig. 6)	
	Nonredundant Contacts (Model 7)	Network Constraint (Model 8)	Nonredundant Contacts (Model 9)	Network Constraint (Model 10)
All characters ($n = 25{,}610$)	32	38	1	2
Role strain, too little focus:				
Person's primary characters				
($n = 15{,}117$)	48	61	4	4
Person's secondary characters				
($n = 10{,}493$)	12	24	1	1
Role strain, difficult combinations:				
Person's characters all same				
gender ($n = 15{,}947$).	34	38	1	2
Gender mix also played by				
others ($n = 6{,}851$)	31	38	2	2
Rare gender mix				
($n = 2{,}812$)	25	37	1	3
Role strain, overlapping				
constituents:				
High % multicharacter				
contacts ($n = 10{,}783$).	34	37	2	3
Low % multicharacter				
contacts ($n = 14{,}827$).	28	29	0	2

Note.—Rows distinguish subsets of characters more or less likely to display network-relevant personality. Network-relevant personality is computed as an average across characters in the same row. The column regression model is estimated for characters in each row as described for tables 4 and 5, from which percentage contributions to variance are computed as described for figs. 5 and 6.

Although network-relevant personality is more visible in the characters played more often by a person, contribution to achievement remains negligible. The model 9 column in table 6 shows the percentage of predicted character achievement variance that can be attributed to a player's network-relevant personality. The contribution is 1% in the first row of table 6 across all 25,610 characters with known time inworld (which is the 1% in fig. 6), and the next two rows in the same column of table 6 show similarly low contributions when results are estimated for primary characters separate from secondary. The same is true for network constraint (last column in the table).

In short, the summary results in figures 5 and 6 are robust across substantively consequential differences in people spreading themselves across

percentages of ego-network variance attributable to genetics: 46% for the number of students citing ego as a friend and 47% for the density of ego's friends citing each other. The broker metrics used here in tables 5 and 6 combine in-degree and density (putting aside Fowler et al.'s network betweenness scores because they include relations beyond ego's network), so it is interesting to see the 46% and 47% genetic variance estimate from Fowler et al. compared to the 48%–61% personality variance estimate for primary roles in table 6.

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multiple roles. More time in a role is associated with more evidence of a player's network-relevant personality, and roles in which a person spends little time show little evidence of network-relevant personality, but more or less makes no difference for the consistently negligible contributions from network-relevant personality to achievement in the role.[15]

Role Strain from Difficult Combinations

The easier it is to play two roles together, the more the person playing them is free to indulge personal preference. Frequency is an empirical indicator of ease. When a role is often played by the same people playing a second role, there is accumulated experience about how to juggle conflicting demands from the two roles and the constituencies to whom each role is played are more accepting of disruptive demands from the other role. For example, the first wave of baby boom mothers entering the labor force experienced more strain between the roles of mother and employee than is experienced today. The first wave had to play each role to constituents inexperienced with, and disinterested in, demands from the other role. The easier it is to play two roles together, the more time and energy the person playing them can spend on performing to his personal preferences. Therefore, I expect more evidence of network-relevant personality from people playing roles that are often combined.

[15] The results on primary roles are corroborated by a spillover design proposed by Duncan, Haller, and Portes (1968). Focus on a person's two most primary roles. The multirole design in the text averages across the two roles. Alternatively, achievement in each role could be regressed across advantage in either role. Achievement in role 1 would be predicted by network advantage in role 1 and network advantage in role 2. The association between role 1 achievement and role 2 advantage measures advantage spillover between roles. Here are the results for the EQ2 data: For role 1, the character in which a person spent the most time, predicted achievement variance (.48 R^2) is 32% attributable to the number of nonredundant contacts in the role 1 network and 62% attributable to experience in role 1 (time in role 1 and percentage of the person's game time in role 1), leaving 6% attributable to the number of nonredundant contacts in role 2. For role 2, the proportions are roughly the same (.52 R^2): 47%, 52%, and 1%, respectively. The proportions are roughly the same for network constraint: 30%, 66%, and 4% in predicting role 1 achievement (.44 R^2) and 39%, 59%, and 3% in predicting role 2 achievement (.46 R^2). In sum, although there is a strong correlation between network advantage in a person's two primary roles (.55 for log network constraint, .42 for number of nonredundant contacts) and there is a strong correlation between a person's achievement in her two primary roles (.48), there is very little spillover advantage between roles (corresponding to the 4% in the second row of table 6). This spillover model becomes awkward with more than two roles, but it is worth mentioning for three reasons: (a) fig. 8 shows that a large proportion of player time is spent in her two primary roles, (b) results with the two-role spillover model clearly corroborate the results in table 6 with primary roles, and (c) the spillover model could be convenient for future research disaggregating the strong correlation between achievement in pairs of primary roles (see Duncan et al. 1968).

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Gender Defines Difficult Combinations in EQ2.—Judging from the relative frequency with which players combined EQ2 roles, gender was the primary source of difficulty. This conclusion comes from seeing the gender pattern the frequency with which people combined the 128 character roles available (128 combinations of 16 races, two genders, and four classes). I constructed a table of 128 rows and columns in which cell *a, b* is the number of people who played both role *a* and role *b*. Figure 9 is a sociogram of the table (NetDraw spring-embedding algorithm; Borgatti 2002). Roles close together were often played by the same people. Lines indicate frequencies. Heavier lines connect roles more often combined. Lines are absent between roles combined by fewer than 10 people. The criterion of 10 could be lower or higher. Setting the criterion at one created too dense a sociogram. At 20, the sociogram pushed too many roles to the periphery as isolates. Each character role in figure 9 is identified by race (1–16 in fig. 2), gender ("f" or "m"), and class ("f" for fighter, "m" for mage, "p" for priest, or "s" for scout). For example, "15ms" identifies the role of human-male-scout. Class indicates abilities: fighters are all-purpose characters. They have good defense and good offense abilities (31% of characters and 31% of player time inworld). Mages can use spells to do a lot of damage from a distance but are easily damaged in close combat (22% of characters, 26% of playtime). Priests are healers (28% of characters, 25% of playtime). Scouts rely on nimble. They can deliver great damage but are able to sustain an attack for only a brief period (20% of characters, 18% of playtime). Two clusters of roles are clearly distinguished in figure 9: a cluster of male roles (white dots) and a cluster of female roles (dark dots). Lines between the clusters show that certain male roles were often combined with certain female roles, but there is clear segregation between male roles to the northwest and female roles to the southeast.

The gender clustering visually apparent in figure 9 is corroborated by summary measures of homophily. People tended to play characters that were consistently one gender or the other, but people showed no preference—on average—in the race or class of the characters they played. The multirole networks contain 45,773 pairs of combined roles, which is the sum of one pair from each of the 1,998 people who played two roles during the observation period, plus three pairs from each of the 1,509 people who played three roles, plus six pairs from each of the 1,105 people who played four roles, and so on. Here is a tabulation of the pairs by gender: 24,096 pairs of male characters, 9,683 male-female pairs, and 11,994 pairs of female characters. Seventy-nine percent of the combined roles were consistent in gender. If pairs were combined independent of gender, holding constant the ratio of female to male characters available, then 54% of the pairs would have been gender consistent (e.g., the number of male pairs expected by random chance, 18,294, is the squared proportion of roles that were male times the number of role pairs). The 79% greater than 54% shows that people played gender-consistent roles
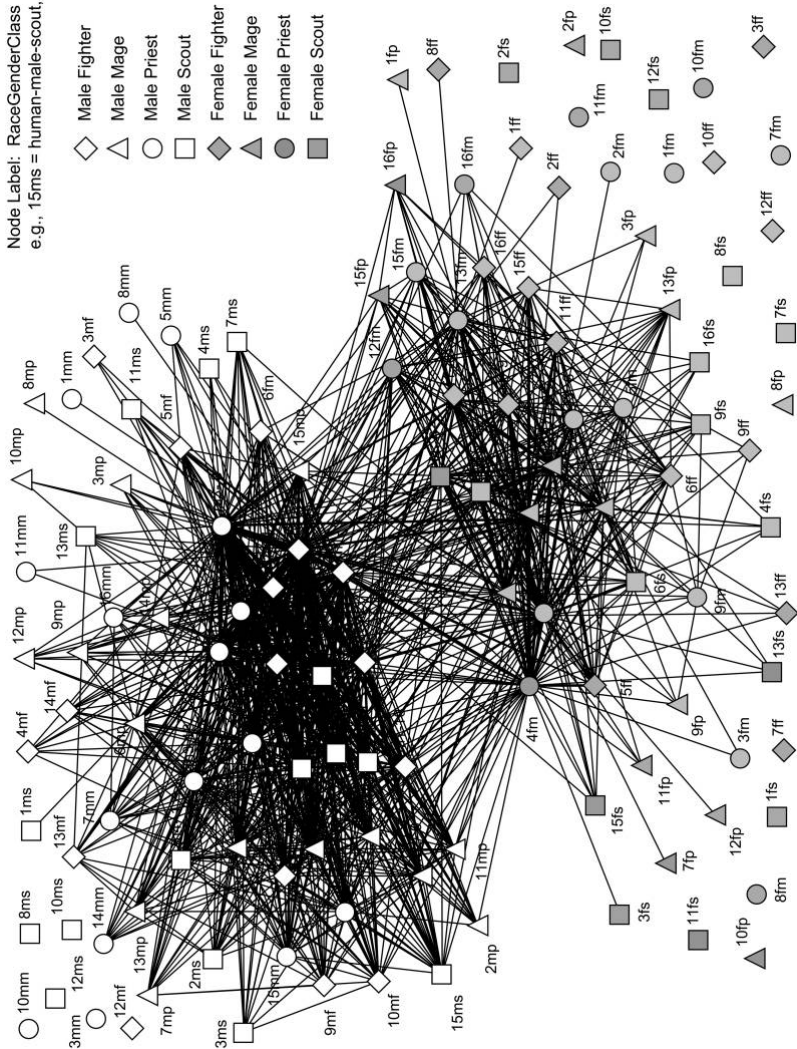
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FIG. 9.—Sociogram of 128 EQ2 roles showing gender segregation

much more often than would be expected by random chance. In contrast, random chance is a good description of the frequency with which people combined character races and classes. Of the 45,773 pairs of combined roles, 21% were the same class (vs. 26% expected by random chance given the relative frequency with which each class was played) and 11% were the same race (vs. 7% expected by random chance given the relative frequency with which each race was played).[16]

Testing for Network-Relevant Personality.—The middle rows in table 6 show that the results in figures 5 and 6 are robust across gender mixtures in a player's characters. Gender mix is not as strong a contingency variable as the distinction between primary and secondary characters, but it covaries in the expected way with network consistency across a person's characters.

The first of the rows contains characters played by people whose characters were all the same gender. Gender role strain is at a minimum for these players. Evidence of network-relevant personality is slightly higher than it is in the whole population, accounting for 34% and 38%, respectively, of character variance in nonredundant contacts and network constraint (vs. 32% and 38% for the whole population in fig. 5).

The second of the middle rows contains characters played by people who played both male and female characters, but the cross-gender combinations were also played by other people. For these gender mixtures, evidence of network-relevant personality is slightly lower than in the whole population (31% and 38%, respectively, for nonredundant contacts and network constraint). In other words, gender mixing need not create disruptive role strain if other people play the same mix.[17]

Role strain emerges more clearly in the rare gender mixtures. The third of the gender rows in table 6 contains characters played by people who combined male and female character roles found in no other player's multirole network. For example, only one person combined a male-froglock-scout with a female-human-fighter. For these rare gender mixtures, network-relevant personality accounts for only 25% of character variance in nonredundant contacts versus 32% for the whole population (network constraint show little difference).

Again, although network-relevant personality is more visible across more compatible roles, contributions to achievement remain negligible. Models 9

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[16] Role counts in the text show no tendencies for players to combine certain races or classes in terms of creating characters, but time spent in roles could matter. For example, a person could create characters at random from each class but spend the bulk of his time in one class of characters. This possibility seems not to be a concern. Average and proportional player time spent in characters shows no homophily effect by gender, race, or class.

[17] I reran the results distinguishing the number of other people playing a gender mix and player time in his gender mixture. Further distinctions yield only slight variations on the results in table 6, so I stop in the text with table 6.

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and 10 of the gender rows in table 6 show low contributions from network-relevant personality to predicted achievement variance.[18]

Role Strain from Overlapping Constituents

Beginning with the initial Merton and Goode articles, a much-discussed way to manage role strain is to segregate the roles, performing one with a constituency separate from the other's. When roles are played to the same people, that is, when the constituents for multiple roles overlap, there is pressure to behave consistently across the roles. Upward and downward mobility, for example, are emotionally simpler when work and parents are in separate cities. Running for political office must have been simpler back when you could share ideas with people in one city, then travel to another city and share ideas that contradicted the earlier ones. All is not negative. Coleman's (1988) concept of social capital depends on role strain. When a student's parents stay in touch with the student's teachers and socialize with the parents of the student's friends, the network closes around the student, making it difficult for the student to engage in destructive behavior with peers without

[18] Figure 9 and the text around it show no tendency for players to specialize in character races or classes, so race and class are not used as role strain criteria in table 6. The lack of pattern in selecting character class is surprising. EQ2 race and gender are largely about a character's appearance. Class is about character behavior and ability, so I expected that personal preferences in network behavior would be revealed in preferences for certain character classes. To be sure about class not affecting the network association with achievement, I reran the table 6 results for each of the four character classes. Since character classes were combined in a random fashion, it would not be a surprise to find that most people played each class at one time or another. The distinctive quality would be never playing a character class. John played priest characters, scout characters, and fighter characters but never played a mage character. Is there something about people like John—who avoided the mage class of character behavior—that affects the robustness tests in table 6? Here are test statistics for the four models in table 6 computed for people who played multiple characters but never one of the characters in the row:

	Model 7	Model 8	Model 9	Model 10
No fighter-class characters ($n = 4,921$)	38	50	1	3
No mage-class characters ($n = 6,112$)	37	48	0	3
No priest-class characters ($n = 7,694$)	36	47	1	3
No scout-class characters ($n = 8,974$)	36	48	0	3

Network-relevant personality here is the average network index for a person's characters excluding the class of characters in the row. Models 7 and 8 show more role consistency here than in table 6, as would be expected since one source of character class variation has been removed. The noteworthy empirical results are as follows: (a) consistency across roles is about the same for each class of characters (about 37% for model 7, 48% for model 8), which means that networks around each class similarly reflect network-relevant personality; and (b) models 9 and 10 show no direct association between achievement and network-relevant personality regardless of character class.

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the parents discovering the bad behavior. Students in closed networks, knowing they will be discovered, are less likely to engage in destructive behavior. Coleman argues that students in such networks are more likely to do well in school and less likely to drop out of school.

Regardless of positive or negative consequences, the strain created by playing multiple roles to the same people can be expected to elicit behavior consistent across the roles. Therefore, I expect more network consistency from a person playing multiple roles with the same contacts.

The bottom two rows in table 6 contain illustrative evidence from EQ2. For each player, I assembled a census of contacts across the networks around each of the player's characters. I excluded from the census any characters that are the player's own. Multinetwork contacts are anyone who is a contact to more than one of the player's characters. The ratio of multinetwork contacts over all contacts measures overlap between the player's character networks. In figure 4, for example, there are 23 contacts (26 nodes minus the three operated by ego), of which five are contacts to more than one of the player's three characters. So the player's contacts are 22% multinetwork. The first of the two rows at the bottom of table 6 contains people whose percentage of multinetwork contacts is above the median.

As expected, there is more evidence of network-relevant personality among people whose characters played to overlapping constituencies. For the people with above-average percentages of multinetwork contacts, 34% of character variance in the number of nonredundant contacts can be attributed to network-relevant personality (37% for network constraint). The percentages decrease to 28% and 29%, respectively, for the people with below-average percentages of multinetwork contacts.

Contributions to achievement continue to be negligible. The last two columns of the bottom two rows in table 6 show low contributions to predicted achievement variance. Again, the summary results in figures 5 and 6 are robust across substantively consequential differences between multirole networks. A player's network-relevant personality is more evident when roles are played to overlapping constituencies but continues to make negligible contribution to achievement.

CONCLUSION

Multirole networks provide a unique way to address the agency question in terms of network consistency across roles. The multirole research design used here has data requirements more demanding than the usual single-role design. It is not suggested as a replacement for the usual design. But where appropriate data are available, the multirole design allows general conclusions, like the two drawn from this analysis: there is clear evidence of people having a network-relevant personality. They tend to recreate the same net-

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work across the roles they play, which accounts for about a third of the variance in network advantage (fig. 5). However, that variance has little to do with achievement. The dominant factors predicting achievement in a role are a person's experience in the role and the network advantage built up in that role (fig. 6). The two conclusions are robust across substantively significant differences in the mix of roles combined in a multirole network (table 6).

The conclusion could be different in other populations. It will be reassuring to see replication. Still, there is reason to generalize from the results presented here. Network-advantage effects in the study population for this analysis are similar to effects observed in management populations (fig. 3). Game play in the EQ2 server analyzed here involves collaboration and competition not unlike work in a large organization. The people playing the game are North Americans above average in education and income, which is not inconsistent with the populations studied in management research. Until contradictory results come in, therefore, my conclusion is that the link between personality and network advantage in general is as described here: much of the variance in network advantage reflects personality, but that portion of advantage variance has little to do with success.

I hasten to qualify the conclusion in two ways and highlight a next step. My first caution is that personality is not challenged as an explanatory variable. There is much more to personality than what is relevant to network advantage. When network and personality predict achievement, three areas of covariance occur: a substantial amount of achievement variance is attributed to the network around a character, a sliver of achievement variance is attributed to network-relevant personality, and some unknown amount of achievement variance can be attributed to dimensions of personality that do not overlap with network advantage. That unknown third area of association between achievement and personality is not measured in equation (2) or (3). The area must be large. Models predicting achievement from network advantage are improved by just adding the self-monitoring dimension of personality (Mehra et al. 2001). Adding all other dimensions of personality would surely increase the achievement variance attributable to personality. The analysis in this article has nothing to say about achievement variance associated with dimensions of personality independent of network advantage.[19]

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[19] Nevertheless, an upper limit can be estimated. Estimating model 9 in table 5 expanded to include all achievement variation attributable to player differences (Stata areg procedure) increases the .626 R^2 for nonredundant contacts up to .835 and increases the .586 R^2 for network constraint in model 10 up to .819. In other words, beyond the variables in table 5, player differences account for another 20.9%–23.3% of the variance in character achievement, which is substantially more than the achievement variance predicted in fig. 6 by player experience and network-relevant personality.

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This is not to say that we are free to indulge in formal models in which benefit is assumed proportional to network-defined advantage. This is my second caution. There is wide variance in the extent to which individuals benefit from bridging structural holes (fig. 1*b*). Some benefit a great deal. Others benefit not at all. The unequal returns can be explained in multiple ways. The explanation addressed in this analysis is personality. In the past, personality differences between people have been argued via the agency question to predispose some people more than others to successful brokerage. The claim is less credible given the results presented here. Whatever the reason, the fact illustrated in figure 1*b* remains: people vary widely in their benefit from access to structural holes. The analysis in this article has not explained the fact, only called into question personality as the explanation.

Time seems a likely explanation. My rough treatment of time is a third and final caution. For comparison with the usual network analysis of manager achievement, I aggregated the EQ2 data over the nine-month observation period to predict achievement at the end of the period from cumulative network structure during the period. The corresponding management prediction would be achievement by the end of a year predicted from cumulative network activity during the year. Figure 6 shows that network-relevant personality does not explain much of the wide achievement differences between people with similar network advantage. The figure also shows that the strongest predictor of character achievement is absolute and proportional time spent in the character (55%–61% of explained variance in fig. 6, with character network the second-strongest predictor at 27%–35%). Strong and robust association between achievement and experience draws attention to the time path on which characters were played and networks built. How much does achievement vary with character sequence, with the gradual evolution of networks expanding to provide more and more access to structural holes, or with developmental cycles of alternating brokerage and closure that cumulate in rich access to structural holes? A next step from this analysis is to see how the network advantage illustrated in figures 1 and 4 is contingent on, or enhanced by, the way the network developed (see, e.g., Padgett and Powell 2012).

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