Marketing Science Institute Working Paper Series 2012
Report No. 12-106

The Social Status of Innovators, Imitators, and Influentials in New Product Adoption: It's Not Just about High versus Low

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Report Summary

Marketers seek to leverage social influence among customers to accelerate the penetration of new products and technologies. To do so effectively, they need to identify and target (1) innovators, who adopt early and can speed up the product's early penetration and generate quick positive cash flow; (2) influentials, who can accelerate the product's penetration and boost the ROI on marketing investments; and (3) imitators, who are especially susceptible to social influence and so require less marketing inducement once their peers have adopted.

In this report, authors Yansong Hu and Christophe Van den Bulte examine the impact of social status on who is an innovator, influential, or imitator. Their findings provide deeper insight into the mechanisms through which contagion operates, and improve managers' ability to identify customers likely to adopt early and to influence others into adopting.

Much current research assumes that the higher an individual's status, the sooner he or she adopts, the more he or she influences others, and the less he or she is susceptible to influence by others. Leveraging insights from social psychology and sociology, Hu and Van den Bulte propose and test the notion that, for innovations that have the potential to boost one's social rank, the tendency to adopt and the susceptibility to contagion are higher for individuals of *middle status* than for individuals of either low or high status. They also examine how various dimensions of status and use experience make early adopters especially contagious and hence influential.

They conduct their investigation in the context of commercial kits used in genetic engineering. This research setting has two advantages. First, social status was likely to matter considerably for this new product's acceptance by scientists. Second, the setting provided two clean metrics of social status: centrality in the network of co-authorship ties, and citation counts.

Hu and Van den Bulte find that middle-status, rather than high-status, individuals are most likely to adopt early. Similarly, middle-status, rather than low-status, individuals are most susceptible to contagion. These findings, the authors note, may apply only to new products and technologies with the potential to boost one's social rank.

They also find that high-status adopters are more influential or "contagious" not simply because they are connected to more people but also because they exert more influence *within* each of their ties. The amount of experience using the product boosted the adopters' within-tie contagiousness as well.

For managers keen to leverage social influence dynamics, the findings imply that new product launch campaigns should not focus exclusively on customers with the highest status or centrality in the network. While high-status individuals are the most influential once converted into adopters, middle-status customers are actually easier to convert into adopters, both independently and through social influence. Thus, astute marketers will want to find the optimal balance between focusing on high- and middle-status prospects.

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Acknowledgments
The authors thank research fellows and assistants at the School of Life Sciences of University of Warwick and at the Conway Institute of Biomedical and Biomolecular Research of University College Dublin for their advice and help with collecting and coding the data. The authors also benefited from discussions with Ran Kivetz and Oded Netzer, and from comments by Jonah Berger, Stephen Brammer, Lloyd Harris, Gary Lilien, Renana Peres, Ezra Zuckerman, participants in the 2012 University of Iowa Marketing Symposium, and seminar participants at the University of Texas at Dallas and Warwick Business School. This study was supported by research development funding from Warwick Business School. Part of the research was conducted while Van den Bulte was a Chazen Visiting Scholar at Columbia University.

Introduction

Marketers have become very keen on leveraging social influence among customers. Social contagion in new product adoption, the phenomenon that adopting a new product or technology is affected by the extent to which peers are already using that innovation, is a specific form of such influence that has received much attention lately. The conditions are ready for the research frontier to move from investigating whether contagion is at work to providing insights into why it occurs and how it can best be exploited (Aral 2011; Godes 2011; Peres et al. 2010).

Practitioners planning to leverage social influence when launching a new product or service would like to know the answer to four key questions. First, who will be the innovators? Targeting customers who adopt early and regardless of what others do can speed up the product's early penetration and generate quick positive cash flow. Second, are there sound reasons to expect sizable contagion or word of mouth effects and through what mechanisms would such influence operate: creating awareness, reducing risk, exerting normative pressure, …? Third, who will be the influentials? Targeting and converting these customers early will accelerate the product's penetration and boost the ROI on marketing investments. Fourth, who will be the imitators they influence? Customers who are especially susceptible to social influence and so need only a little extra marketing push can be attractive targets for one's initial efforts.

When answering those questions, marketers should consider customers' social status. Understanding how social status affects the sources' influence or contagiousness and the recipients' susceptibility to such influence provides deeper insight into the mechanisms through which contagion operates (Van den Bulte 2010; Van den Bulte and Stremersch 2004). It also improves the ability to identify customers likely to adopt early and to influence others into adopting (Iyengar et al. 2011).

Much of the current theory and recent research on how status affects the tendency to adopt early, to influence others, and to be influenced by others is about monotonic effects: The higher the status, the sooner one adopts, the more one influences others, and the less one is susceptible to influence by others (e.g., Goldenberg et al. 2009; Hinz et al. 2011; Iyengar et al. 2011).

We introduce the notion that, for innovations that have the potential to boost one's social rank, people's current status affects both the tendency to adopt and the susceptibility to contagion in a non-monotonic fashion: higher for middle-status than for low- and high-status. We develop this notion from classic insights in social psychology and sociology about middle-status anxiety and conformity (e.g., Homans 1961; Mills 1951). These concepts have gained renewed appreciation in the last decade (de Botton 2004; Phillips and Zuckerman 2001) but have not been related to how status moderates the susceptibility to social contagion in the adoption of new products and technologies. In addition to non-monotonic effects on the propensity to adopt early and to be susceptible to social contagion, we also study how various dimensions of status and use experience affects the within-tie influence or contagiousness of prior adopters, an issue of debate in recent research (Godes and Mayzlin 2009; Iyengar et al. 2011).

We investigate these questions in the context of the adoption of commercial kits used in genetic engineering. This research setting offers important methodological benefits when studying the role of status in adoption and contagion dynamics. First, social status is quite important to scientists (e.g., Cole and Cole 1973) and is likely to matter considerably in the adoption of the new product we study because it offered the potential for greater research productivity and impact—the gateway to higher scientific status—but was not considered quite legitimate at first (Davies and Pugsley 1990; Jordan and Lynch 1998). Second, the research context provides us with not one but two metrics of social status that vary over time and are measured quite precisely: Centrality in the network of co-authorship ties among all members of the relevant population, and citation counts.

We study the adoption dynamics using an individual-level hazard model implemented within a nested case-control design. The latter avoids the need to construct covariates for the entire population of potential adopters while at the same time avoiding truncation biases (Van den Bulte and Iyengar 2011) and achieving statistical efficiency.

We find evidence that status affects (i) how early or late one adopts regardless of social influence, (ii) how susceptible one is to social influence operating through social ties, and (iii) how influential one's own behavior is in triggering adoption by others. All three effects go beyond the standard notions that high-status individuals are influential or influenceable merely because they are social hubs connected to many others. Also, the inverse-U patterns in (i) and (ii) are consistent with middle-status anxiety and conformity.

Our work extends current insights on how status affects new product adoption in four ways. First, we propose and document that it is not high-status but middle-status individuals who are most likely to adopt early—at least for innovations that have the potential to boost one's social rank. Second, we propose and document that for such innovations it is not low-status but middle-status individuals who are most susceptible to contagion. Third, we show that high-status adopters are more influential or “contagious” not simply because they are connected to more people but also because they exert more influence *within* each of their ties. Finally, this study not only documents the importance of *both* the status and experience of prior adopters in driving social contagion, but also suggests that these two source characteristics operate through different mechanisms.

These findings have implications for diffusion theory and research, including identifying why contagion takes place. They also imply that new product launch campaigns might not want to focus exclusively on customers with the highest status or centrality in the network. Though the latter are the most influential once converted into adopters, middle-status customers can actually be more easily converted into adopters, both independently and through social influence.

Status: Definition and Current Insights

Status defined and contrasted

Status is a position within a social structure in which individuals are evaluated based on social esteem and respect (Turner 1988). Status is different from power, class, and reputation.

Status based on differences in esteem and respect is related to yet distinct from power, i.e., the ability to influence others. Though status is a source of power and perceived influence can be a source of status, the concepts are distinct (Ridgeway and Correll 2006). Status is an evaluative hierarchy of relative standing in which one person is more respected and deferred to than another, but not necessarily more powerful or influential (Berger et al. 1972).

Status and class are also related yet distinct concepts. Both pertain to social stratification, but class is based on economic wealth whereas status is based on esteem and respect (Turner 1988). The two need not go hand-in-hand, as illustrated by the contempt for nouveaux riches, by the respect for impoverished intellectuals, nobility, and monks, and by the variation of status within economic classes (Cole and Cole 1973; Lamont 1992).

Status and reputation are related yet distinct concepts as well (e.g., Podolny 2005). One important difference is that the notion of relative rank ordering is essential to status but not reputation. Whereas status pertains by definition to relative vertical differentiation, reputation may also pertain to an absolute quality level or to relative horizontal differentiation. A second key difference is that a person's or product's reputation is based on their prior performance observed directly or indirectly through social learning, whereas status can be based not only on perceived or inferred competence or performance but also on unearned ascription along hereditary, racial, or other group membership (e.g., Gould 2002; Rossman et al. 2010).

Finally, the relation between status and network centrality merits consideration. The former pertains to rank of social esteem and respect, i.e., some form of public valuation, whereas the latter pertains to a position of importance in a network. Though the number of network ties or "degree centrality" is often used to measure status, the two concepts converge only if the ties in the network capture a relationship of esteem or appreciation. So, centrality in a network of close collaboration or advice seeking reflects status, whereas centrality in a network of buy/sell ties of search goods without any uncertainty does not.

Status of both prior and potential adopters (sources and recipients of influence) may affect several facets of social contagion and new product diffusion processes. We review the current insights.

Status competition as a mechanism of social contagion

Building or maintaining status through emulating superiors and equals is one of the reasons positive social contagion occurs (Burt 1987). Conversely, maintaining status by differentiating one's behavior from that of socially inferior types is a likely mechanism of negative contagion (e.g., Joshi et al. 2009; Simmel 1904). Building and maintaining status also can be a powerful motivation for providing free advice and information both offline and online (e.g., Lampel and Bhalla 2007) and so can facilitate social contagion through social learning.

Status of prior adopters enhancing contagion

Even when status is not the reason for imitation, high-status adopters may be more contagious than low-status peers because of differences in attention, authority, ability to educate and persuade through expertise or mere status signaling, normative legitimacy, and reward power or coercion.

One reason why high-status individuals are more contagious is that they attract more *attention* (Cole and Cole 1973; Merton 1968) and so their adoptions are more likely to be noticed. This moderator effect may operate through impersonal media or weak social ties, but not through strong ties where potential adopters are likely to be aware of all their contacts' adoption regardless of status.

Differential contagiousness may also operate through persuasion based on mere *authority*. When making decisions under uncertainty, people tend to give more credence to the opinions of high-status individuals (Berger et al. 1972; Storer 1966).

High-status individuals may also be more persuasive not because of their status per se but because they have deeper expertise and experience and so can present more *compelling arguments and explanations* about the relative advantage of the innovation or how to use it (Goldenberg et al. 2006; Iyengar et al. 2011). An example is the role that Freeman Dyson at the Institute for Advanced Study in Princeton played in the early diffusion of Feynman diagrams in theoretical physics by educating Institute visitors in the intricacies of this new technique (Kaiser 2005). Adopter status may also inform and persuade simply by acting as a *signal for unobserved quality* of the innovation (Podolny 2005).

High-status individuals tend to be more contagious when the *normative legitimacy* of the innovation is in question (e.g., Haveman 1993). High-status adopters legitimate the innovation, especially if high status is paired with high charisma or institutional legitimacy and not based purely on instrumental sources of power.

Differential contagiousness of high-status adopters, finally, may also be based on *reward and coercive power* rather than actual status or esteem (Magee and Galinsky 2008). To the extent that high-status individuals control resources needed by potential adopters (e.g., money, access to equipment, recommendations, prospects for promotion) and that they welcome the use of an innovation they adopted themselves, potential adopters will be more inclined to imitate high-status than low-status adopters. In cases of extreme power imbalance, high-status individuals may simply impose their will and coerce adoption. Conversely, high-status individuals may also prevent the use of innovations they disapprove of, as illustrated by the success of the Samurai in getting fire weapons banned from Japan in the early Tokugawa shogunate (Perrin 1979).

Each of the mechanisms described here implies that high-status individuals wield above-average influence not simply by influencing more people by virtue of being more central in a web of social connections, but by exerting above average influence on each person they are connected to. Prior adopters with high status are expected to be more influential not only because of their greater number of ties but also because they are more contagious *within* each tie.

Status of potential adopters affecting contagion susceptibility

Not only the status of prior adopters but also that of potential adopters matters. A recent study of the adoption of a new drug by physicians found that those who fancied themselves to be opinion leaders were less sensitive to the prescription behavior of their fellow physicians. In contrast, those who were recognized through peer nominations as sociometric leaders with whom fellow physicians discuss medical issues or to whom they refer patients to, were not differentially sensitive to contagion (Iyengar et al. 2011). These findings, we expect, apply to many high-risk innovations in settings where self-perceived status correlates highly with confidence in one's assessment of risks and benefits, but true high-status experts recognize they can learn from others' input. For other innovations and settings, however, differences in social status may engender differences in threats to professional stature or economic benefits (e.g., Becker 1970). As discussed in the next section, theory and research in sociology and psychology suggest the existence of an inverse-U relation between status and susceptibility to contagion, at least for products that adopters believe can boost their status.

Status of potential adopters motivating or facilitating early adoption.

High status tends to be associated with early adoption. This may happen for several reasons. One is that high-status individuals are more knowledgeable, more confident, and less concerned about making a costly mistake (Iyengar et al. 2011). Another is that they tend to be central in the relevant social networks and hence tend to be exposed to more information even early on (Goldenberg et al. 2009). Yet another explanation is that, even though the association between social and economic status is far from perfect (Lamont 1992), high-status individuals tend to have more economic resources and so can more easily afford to adopt quickly. As discussed next, the notion of middle-status anxiety implies not a positive but an inverse-U relation between status and the tendency to adopt early.

Middle-status Anxiety and Middle-status Conformity

The current insights on the role of status in new product adoption and contagion involve monotonic effects. In contrast, we advance the notion that people most likely to adopt an innovation early and most likely to be susceptible to social contagion are those in the middle strata of social status. The rationale is that it is those people who experience the most status anxiety. This makes them especially prone to quickly adopt an innovation, at least one that has the potential to help them maintain or improve their social standing. Status anxiety can also make people in the middle strata of social status especially prone to imitate others' adoption of such new products and technologies. These claims pertain to social status purely, under the usual *ceteris paribus* condition making abstraction of differences in wealth and other factors possibly correlated with status and enabling the adoption of new products and technologies.

Middle-status anxiety and the propensity to adopt early

Status anxiety is a concern induced by the uncertainty about how much others esteem us and will do so in the future. This anxiety is most pronounced in settings where status matters considerably and the status ordering is ambiguous, unstable, or in flux (Gould 2003). Social theory posits that status anxiety is typically the highest among middle-status individuals (de Botton 2004; Mills 1951; Newman 1999). One reason is fluidity: they experience both a threat from a below and an opportunity to advance from above. Low-status and high-status individuals, in contrast, experience only one of those sources of potential flux in their position. Another reason is ambiguity: making a rank assessment between oneself and another is less straightforward for individuals located in the middle of the distribution. The third reason is the goal gradient: the nearer one is to the goal, the harder one works to achieve it. Hence, assuming that high status is a goal, middle-status individuals will work harder to maintain and improve their ranking than low-status individuals who are further away from the goal or prize. They will also work harder than high-status individuals who not only already have the prize (so the goal-gradient is zero) but also typically feel most secure in their standing (e.g., Harvey and Consalvi 1960; Kivetz et al. 2006; Menzel 1960).

This middle-status anxiety thesis provides an explanation for the commonly accepted notion that consumers' concern to "keep up with the Joneses" (maintain status through consumption) is most pronounced (i) among upwardly or downwardly mobile middle-class consumers who (ii) live in market-based societies that (iii) experience important social changes (e.g., de Botton 2004; Mills 1951). More generally, the middle-status anxiety thesis is that middle-status individuals will be the most keen to adopt innovations that may improve adopters' status.

Middle-status conformity and the susceptibility to contagion

The middle-status conformity hypothesis is an equally venerable insight from sociology and social psychology. The logic is quite similar, but pertains specifically to the tendency to conform to others' opinions (Dittes and Kelley 1956; Harvey and Consalvi 1960; Homans 1961; Phillips and Zuckerman 2001). Status is the outcome of a group's or other collective's differentiated perception of an individual, and leads to particular expectations regarding his or her behavior (Hollander 1958). Of particular interest is that higher status permits "greater latitude in the manifestation of behaviors which would be seen to be nonconformist for the other [lower-status] members of the group" (Hollander 1958, p. 120). In short, the degree to which an individual may deviate from the common expectancies of the group is greater for high-status individuals, as documented in several studies (e.g., Blau 1960; Hollander 1958; Kelley and Shapiro 1954). Hollander (1958) adds the important qualifier that the degree to which the individual is "visible" may also alter the effects of not conforming. As documented by Dittes and Kelley (1956) and Harvey and Consalvi (1960), being a marginal, barely visible member of the group may negatively affect one's motivation to conform to the group. Combining both considerations, how status enhances both the motivation to conform and the latitude to deviate with impunity, suggests an inverse-U relation. As Harvey and Conslavi (1960, pp. 182-183) proposed, "… the very remoteness of the lowest status man from the top position might result in his being less motivated to move up the status ladder and consequently less sensitive to group pressures … The second ranking person could prove to be the member on whom the goal of the top position exercises greatest motivational pull … The leader's behavior should be less affected by striving for the top position than that of either of the other two status members by virtue of having attained that goal. … If his position is secure, the leader can perhaps afford to deviate further from the behavior of the other members."

In short, the middle-status conformity argument is that (i) lower-status individuals see relatively little potential upside from conforming and no downside, (ii) high-status individuals see little upside from conforming and, when the position is secure, little downside from not conforming, with the results that (iii) it is individuals of middle-status who are most prone to conform. Applied to new product diffusion, the middle-status conformity hypothesis is that of an inverse-U relation between status and susceptibility to contagion, at least under specific conditions.

Scope conditions

Middle-status anxiety and conformity predict non-monotonic relations between status on the one hand and the tendency to adopt early and the susceptibility to social contagion on the other hand. These non-monotonic patterns are not predicted by basic diffusion theory or even recent diffusion research, so it is important to delineate scope conditions under which the middle-status logic applies and the non-monotonic patterns are expected to hold (Phillips and Zuckerman 2001).

The first condition is that conformity is indeed a concern motivating one not to adopt immediately and leading the adoption decision to be susceptible to social contagion. This will be the case whenever the innovation is not fully legitimate, adoption is visible, and potential adopters care about legitimacy. The second condition is that the innovation is sufficiently attractive to justify adoption if legitimacy were not a concern.

The third condition is that middle-status individuals are more motivated than low-status individuals to adopt early and to conform to others' adoptions. Goal-gradient theory implies that the condition is met when status is a goal and potential adopters expect that adopting the innovation enables them to improve their status, setting apart legitimacy considerations. The fourth condition is that middle-status individuals are more motivated than high-status individuals to adopt early and to conform to others' adoptions. This condition will be met whenever high-status feel sufficiently secure in their position, for instance because of Matthew effects providing protection at the high end of the status spectrum (Merton 1968) or because non-conformity by high-status individuals in fact enhances their status (Berkowitz and Macaulay 1961).

A fifth condition is that there is single dominant reference group for everyone, so there is agreement on both legitimacy and status ordering. This condition precludes the existence of "sub-communities" or "sub-cultures" each having their own norms of legitimacy and their own assessment of the esteem to be bestowed on various individuals (Berger and Heath 2008; Üstüner and Holt 2010). Of course, middle-status conformity may still operate within each those sub-cultures.

Besides these theoretical scope conditions, there is also a key methodological condition that must be met in empirical research: The effects of status must be assessed while controlling, either through the research design or statistically, for the effect of other relevant stratifying variables, like economic resources, access to information, and ability. Separating status effects pertaining to motivation from other effects pertaining to opportunity or ability is a challenge that has plagued several studies investigating non-monotonic status effects (Cancian 1967, 1979; Faris and Felmlee 2011; Han 1994).

Research Setting

To better understand the nuanced role of status in new product diffusion, we study the adoption by life scientists of commercial kits to perform site-directed mutagenesis (SDM), a form of genetic engineering. Since status and diffusion researchers emphasize the importance of institutional details for proper theoretical inference (e.g., Phillips and Zuckerman 2001; Van den Bulte and Lilien 2001), we discuss how our research setting allows for an informative assessment of the middle-status anxiety and conformity hypotheses.

Fit to the theoretical scope conditions

The adoption of commercial SDM kits meets the theoretical scope conditions for an informative assessment of the middle-status anxiety and conformity hypotheses. SDM researchers, like all scientists, seek to improve their peers' esteem of them and their work. Status is gained mostly through research achievements (Latour and Woolgar 1986), and there are no sub-cultures in which people can easily alter status orderings by redefining what constitutes good taste or good research. Achievements are reflected in commonly verifiable publications in prestigious journals, and status is quite publicly visible through citation counts and honorific awards (e.g., Cole and Cole 1973). SDM kits hold the promise of enabling their adopters to successfully complete their research in less time, which is important in fast-cycle biomedical research to improve one's status (Fujimura 1996; Jordan and Lynch 1992). Initially, however, SDM kits were considered somewhat illegitimate by many (Hengen 1994; Weiner and Slatko 2008), and their adoption was quite visible to collaborators, colleagues, and any reader of one's working papers and publications. That middle-status scientists would care more about their status than low-status scientists is quite consistent with the general goal-gradient principle, whereas well-documented Matthew effects (e.g., Merton 1968) provide security to scientists with the highest status. Additional background information on the relevance of status in science and on SDM kits is provided in the Appendix.

Ease of measuring status

Studying new product adoption by scientists allows us to measure social networks and status within these networks with unusual clarity (e.g., Jones et al. 2008; Leahey 2007; Newman 2001). In addition, the research context provides us with the opportunity to use not one but two metrics of social status that vary over time and can measured quite unambiguously: Centrality in the network of co-authorship ties among all members of the relevant population, and citation counts (Cole and Cole 1973).

Absence of other relevant stratifying variables

The adoption of SDM kits not only meets the theoretical scope conditions for middle-status anxiety and conformity, but also allows one to assess status effects without confounding them with the effects of other relevant stratifying variables, like access to information, ability, and economic resources. The existence and characteristics of these kits was common knowledge across all status levels. Their main benefits are convenience and reproducibility, and so do not vary across status levels. Hence, there is no systematic relation between scientists' status and their ability to use or benefit from the kits that may confound the analysis. The same holds for status and economic resources. Using kits involves a greater cash expenditure than buying the components separately and following publicly available protocols. However, kits reduce the amount of training and trial-and-error tinkering necessary to run a procedure, and provide reliably high yields. Also, maintaining quality control of the reagents, matching components, labeling, and finding detailed manuals and solutions to unexpected problems all require time and labor, which—many feel—outweigh the difference in purchase costs between using kits and fully "DIY" mutagenesis. Through all these cost reductions, kits increase the number of experiments that can be done with a given budget. So, unless their lab is extremely cash constrained, the appeal of commercial kits is unrelated to scientists' economic resources.

Methods and Data

We study the adoption of commercial SDM kits by life scientists from 1988 when the first kits appeared on the market until 1997 by which time they had become rather commonplace. We define the population at risk as academic scientists who use SDM in their research. We identify them using MEDLINE (Medical Literature Analysis and Retrieval System Online) compiled by the U.S. National Library of Medicine and maintained by the National Institutes of Health. This bibliographic database of life sciences and biomedical information covers approximately 5,000 journals and other publications pertaining to health and biomedicine, including biology and biochemistry. We identify each scientist with at least two publications using SDM between 1988 and 1997 as a potential adopter of SDM kits. We identified 24,310 scientific and technical papers involving SDM authored by 8,259 academic scientists meeting this criterion, of whom 1,030 used commercial SDM kits at least once in a publication between 1988 and 1997. So, the "population at risk" of potential adopters is $N = 8{,}259$ and the penetration at the end of the observation window is 12.5%.[1]

We measure adoption as the use of SDM kits in a publication, and analyze how status and contagion affect the time of adoption using hazard models. Since we observe all the life scientists who have used SDM in their publications, we know the entire population of potential adopters.[2] The author data recorded in scientific publications allows us to construct a rich set of covariates without facing unit non-response problems common to survey research.

Since we include a large set of covariates and the population at risk counts more than 8,000 individuals, coding all variables for each and every potential adopter would be extremely demanding. However, limiting the analysis only to the 1,030 adopters would generate serious biases (Van den Bulte and Iyengar 2011). Using a stratified sample ensuring that the relative proportion of adopters and non-adopters in the data set corresponds to that in the population avoids those biases, but requires the deletion of many adopters and hence is statistically quite inefficient.

We resolve these competing considerations of coding effort, bias, and statistical efficiency through a nested case-control design. Widely used in epidemiology, this design controls for unmeasured confounders, improves the precision of the estimates, and does so with substantial

[1] We exclude a small number of scientists specializing in computer modeling, assuming that they will never use a kit for an experiment and so are not part of the "population at risk" for adopting a commercial SDM kit.
[2] Though we observe adoption through publications the great majority of which are co-authored, it is appropriate to use individual researchers and not the lab they work in as the unit of analysis. Research teams in molecular biology are only of moderate size and nothing like the sometimes massive teams in high energy physics (Knorr Cetina 1999; Newman 2001). The median number of authors per paper in our data is 4, and the 5% - 95% range is 1-9, so every author is likely to be involved in the decision to use commercial kits or not. Also, even junior researchers like doctoral students and postdocs often have considerable freedom in defining the specific problems they pursue and choosing the modalities used in doing so (Knorr Cetina 1999; Latour and Woolgar 1986).

savings in cost and time (Armenian 2009; Essebag et al. 2003). The core idea is to combine response-based sampling with an appropriate statistical model, adapted specifically to hazard modeling.

Nested case-control design

The design involves three main steps prior to estimation: (1) Defining and selecting cases (adopters), (2) Defining the population at risk and the risk set of controls for each type or nest of adopter, and (3) randomly selecting controls from each risk set.

Step 1 consists of identifying the 1,030 cases using MEDLINE, as described previously. Step 2 involves defining a risk set for each case, from which the controls are selected. We identified the total population at risk of 8,259 academic scientists also using MEDLINE. Next, we define, for each adopter, a risk set of controls consisting of all members of the population who still had not adopted by the time (calendar year) the focal adopter did.[3] In addition, we restrict each adopter's risk set to researchers who matched the adopter on two time-invariant characteristics. The first is the country where the institution is located with which the scientist is affiliated (or the first listed in case of multiple affiliations). The second is whether the scientist is (i) a specialist in SDM who has published papers on SDM technology modifications or improvements, (ii) a molecular biologist, or (iii) other. As a result, each adopter is matched with a risk set of all other scientists with the same scientific profile and country of affiliation who had not adopted yet when the adopter did.

In Step 3, we randomly select 5 controls from each adopter's risk set. A higher control-to-case ratio generates little gain in statistical efficiency (Donkers et al. 2003; Gail et al. 1976; Ury 1975). As recommended in the literature (e.g., Essebag et al. 2003), we sample the controls randomly from the risk sets with the requirement that the controls do not adopt in the same year as the case. So, controls may include scientists who are never observed to adopt between 1988 and 1997 or who are observed to adopt later than the case does. Also, the selection within a given year is without replacement. So, it is possible for the same scientist to be a control for multiple cases (adopters), but only if these cases do not adopt in the same year.

[3] Since not everyone published their first SDM paper in the same year within the 1988-1997 window, not everyone became at risk of adopting SDM kits at the same time. Hence, matching on calendar time implies that the members of the risk set need not have been at risk of adopting as long as the case was at the time the latter adopted. In a case-control design, cases and controls need *not* be members of the same "birth cohort" (e.g., Langholz 2005). Our model includes cohort dummies, so the baseline hazard (duration dependency) is allowed to vary non-parametrically.

We estimate a grouped-time Cox proportional odds model adjusted for the case-control design (e.g., Langholz 2005; Lee and Wang 2003). Estimation simply amounts to estimating, across all case-control sets, a conditional multinomial logit model for the probability that, of each sextet consisting of a case adopting in a particular year and its five non-adopting controls, it is indeed the case who adopts. All effects that are common across the case and its controls are conditioned out. This includes the effect—even time-varying—of variables used for matching and of variables that vary over time but not across individuals, like category-level legitimacy, advertising, price level, and product quality of the innovation.

An alternative is to estimate, across all members of all case-control sets, a traditional unconditional binary logit model for the hazard of adoption. Because the number of controls matched to each case remains constant over time, neither the conditional or unconditional case-control model generates the truncation biases documented by Van den Bulte and Iyengar (2011). As readers familiar with the consequences of choice-based sampling when estimating logit choice models may intuit, the unconditional model provides inconsistent estimates of the time-varying intercepts used to represent the Cox non-parametric baseline hazard (e.g., Langholz 2005; Lee and Wang 2003; Prentice and Breslow 1978). More importantly, the unconditional model should include all the matching variables as covariates, and allow them to moderate the effects of variables that vary over time but not across individuals. The conditional model is clearly more efficient to control for sources of variation that are not of substantive interest.

Status measures

We use two measures of status. The first is the scientists' degree centrality in the network of scientific collaboration involving SDM. Degree centrality is the standard measure of status in social network research. A scientist's status in year t is measured as the number of co-authors in year t-1 on any of the 24,310 scientific and technical papers involving SDM we identified. Such archival data on "affiliation networks" where ties are based on joint involvement in activities or common membership in groups have three advantages over self-reported ties (Goldenberg et al. 2010; Newman 2001): (i) unit or item non-response is not a problem so complete data can be collected over large networks; (ii) the measurement is often much more reliable than with self-reports; (iii) affiliation data are often available longitudinally, so the network can be measured over multiple points in time rather than only once—typically retrospectively. Of course, all these benefits pertaining to measurement are irrelevant unless the ties are substantively relevant for the phenomenon at hand (Trusov et al. 2010; Van den Bulte 2010). Our data meet this requirement as well. Collaborating with other scientists and publishing the results jointly represents a very intensive type of communication (Crane 1972; Stokes and Hartley 1989).[4] Such intense interaction is often necessary for transferring mastery of complex research techniques (e.g., Collins 1985; Kaiser 2005) and is an important conduit for normative influence about what constitutes a proper research procedure (e.g., Latour and Woolgar 1986).

Our research setting provides us with the opportunity to use a second measure of status. Specifically, we use the natural logarithm of the (non-cumulative) number of citations in year t-1 to a scientist's work reported by the ISI Web of Science as the second measure of his or her status in year t.[5] Citations are meant to recognize that one's own work has been informed or otherwise influenced by the work one cites. Though some citations refer to papers that are being criticized rather than endorsed, and though some authors might use citations strategically to position their work within particular research traditions or to generate sympathy from peers who they believe may referee their work, these negative and strategic citations also are acts of recognition or even deference, and so do not detract from the validity of citation counts as a measure of status (Baldi 1998; Cole and Cole 1973). The same holds for the fact that citations may be used as rhetorical devices rather than records of influence (Gilbert 1977; Latour 1987). Even when used for persuasion, the fact that a specific reference is used rather than another reflects those references' relative status.

The number of citations scientists receive has been shown to be a good indicator of the amount of recognition that their work has received and hence of their status (e.g., Cole and Cole 1973; Gaston 1978). There are other, more formal types of recognition, including prestigious awards (e.g., Nobel and MacArthur), memberships in honorific societies (e.g., Royal Society), and appointments at prestigious university departments and institutes. However, these identify only the very elite. The attention one's research receives from the scientific community, as reflected in citations, provides a more fine-grained measure over the entire range of status. This

[4] Extremely large research collaborations involving many co-authors may be an exception to this association between co-authorship and intense interaction. This phenomenon is rare in biomedical research (Knorr Cetina 1999; Newman 2001), and not a concern in our study. The median number of authors per paper in our data is 4, and only 3.8% of the papers count more than 10 authors.

[5] Since 103 of the 6,180 observations (1,030 cases and 5,150 controls) had zero citations in the prior year, we increase the number of citations by one before taking the log.

may be why, according to some, such attention operates as a greater incentive for scientists than formal types of recognition which only the most elite scholars receive (e.g., Waterman 1966).

The Pearson correlation between our two measures of status is 0.71. This is high enough to indicate satisfactory convergent validity, and low enough to interpret the analysis using one metric as a true robustness check for the analysis using the other metric.

Contagion variables

We construct various contagion variables. The amount of social influence that individual i experiences from his or her peers j at time t through conduit k and moderated by source characteristic c is represented as:

$$\beta_{kc}\ \Sigma_j\ w_{ijk}(t)\ y_j(t\text{-}1)\ x_{cj}(t\text{-}1),$$

where β_{kc} is a parameter to be estimated, $w_{ijk}(t)$ is binary indicator for whether i and j were connected through conduit k at time t, $y_j(t\text{-}1)$ is binary indicator for whether j had ever used commercial SDM kits by t-1, and $x_{cj}(t\text{-}1)$ is either 1 or a mean-centered characteristic of the peers.

We investigate three conduits: direct collaborative ties (co-authorship), being a member of the same department, and being a member of the same university or institute, all in the *prior* year. We focus on the first conduit and use the second and third only as controls, since prior research indicates that joint involvement in research projects is a more influential conduit than shared departmental affiliation (e.g., Rawlings and McFarland 2011).

We investigate how four "source" characteristics of prior adopters *j* moderate the influence exerted on the adopter-recipient i. The first is *usage volume* (Iyengar et al. 2011), measured as the number of papers using SDM kits published in the prior year. The second is *usage diversity* (Shih and Venkatesh 2004), measured as the number of domains in which the peer had used SDM kits from 1988 to the prior year. SDM is applied in three domains, identified by the type of organism: micro-organisms, plant or animal organisms, and human organisms. Adopters with experience in applying SDM kits in more than one domain may be more influential, since they have broader experience and possibly also a stronger conviction about the appropriateness of the kits.[6] The third and fourth source characteristics are related to status rather than experience with

[6] Two judges, one having a PhD in biochemistry, coded, categorized, and counted the usage domain of each SDM kit application by each user. The reliability of the coding was assessed by presenting a sample of 50 applications to

SDM kits. The third is the source's *status* operationalized as either network degree centrality or citation count so that it matches the measure of the potential adopter's status. The fourth characteristic is the *prestige of the source's institution*, operationalized as score from 30 to 0 with the top-ranked institution receiving 30 points, the next 29 points, and so on until the 30th-ranked receiving 1 point and all institutions outside the Top 30 receiving zero points.[7]

Control variables

We include several control variables besides the period, country, and specialty effects already accounted for through the nested case-control matching. The first set captures characteristics of the paper and team of authors. *Number of co-authors* is self-explanatory. The indicator *Non-specialist co-author* takes the value 1 if any of the co-authors is not a SDM specialist (who may therefore favor using a commercial SDM kit). *Number of funding sources* acknowledged in the paper is again self-explanatory.

The next set of control variables pertain to characteristics of the focal scientist. *Past use of other kits* is a dummy indicating whether the scientist had used kits for purposes other than SDM before year t, which may reflect a positive attitude towards using commercial kits. *Number of SDM papers for purpose 1* or *purpose 2* is the total number of papers published by the scientist in year *t* on either studying protein function (Purpose 1) or producing final protein products (Purpose 2). The sum of those two counts is the total number of SDM publications by scientist *i* in year *t* and so would be an obvious offset variable, but we distinguish between the two since kits are more appropriate for the first type of SDM application. *Prior faculty adoptions at PhD institution* is the number of faculty at a scientist's PhD-granting institution who adopted SDM kits before the scientist graduated. The variable is time-invariant, and is zero for anyone who received their PhD before 1988. We control for *Academic Age*, operationalized as the number of years since the scientist earned his or her PhD, to avoid confounding status with mere work experience. We also include *Cohort* dummies for the first year that the scientist published an SDM paper within our 10-year observation window. Including such non-parametric controls for

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seven additional judges who were Masters or PhDs in biochemistry. The overall inter-judge agreement was 95% which resulted in a Perreault index of .96 (Perreault and Leigh 1989) and a PRL of 1 (Rust and Cooil 1994).

[7] We used U.S. News & World Report rankings for the world's best universities in Life Sciences and Biomedicine, supplemented when necessary by the rankings from the Times and the Academic Ranking of World Universities. For institutions for which no information was available for 1988-1997, we use the first available ranking after 1997.

birth cohort in a conditional logit case-control hazard model corresponds to including a flexible baseline hazard in a traditional hazard model (because age = period - cohort).

Finally, we also control for whether the institution that the scientist was affiliated with was an *Applied vs. basic research institution* (1 for applied; 0 for basic) and for the Top 30 *Ranking of own institution* (see above for details). We allow the effects of these two variables to differ before and after 1993, roughly the mid-point in our observation window and the year that Michael Smith received the Nobel Prize in Chemistry for developing SDM.

Findings

Table 1 (following References) presents the results of various models with status measured as degree centrality. Covariates moderating social contagion are always mean-centered, so coefficients of non-moderated contagion correspond to average or "main" effects.

Main analysis

Model 0 includes only the control variables. Though their effect sizes vary somewhat after adding variables of theoretical interest, the signs and significance levels are quite robust across Models 0 through 5. The number of co-authors does not affect adoption, but working with others who do not specialize in SDM does increase the odds of adopting a commercial kit. Research supported by multiple sources of funding is associated with early adoption as well. Researchers are more likely to adopt commercial kits quickly if they have used other commercial kits before, publish extensively on studying protein function but little on producing final protein products, are young, and have received their PhD at a school where several faculty had used SDM kits before they graduated. Working at an institution focusing on applied versus basic research was associated with early adoption, especially before 1993. So did working at a highly ranked institution.

Extending Model 0 with the linear and quadratic effects of status (Model 1) significantly improves model fit (Δ -2LL =117.88, $p < .01$). Status has an inverse-U effect on the tendency to adopt early, consistent with the middle-status anxiety hypothesis. As shown in Figure 1a (following References), the effect of status on the tendency to adopt early reaches its maximum when degree equals 9. This corresponds to the 88^{th} percentile of the status distribution. So, for the 12% of individuals with the highest status (more than 700 people in our sample), the adoption propensity is expected to decrease rather than increase as one moves up the hierarchy. Individuals with degree of 18 or higher, the top 3%, are less likely to adopt than someone with no connections whatsoever (degree zero).

Model 2 extends the analysis with contagion from past co-authors and allows the susceptibility to such contagion to vary non-monotonically with status. This further improves model fit (Δ -2LL = 10.54, $p < .05$). Status has an inverse-U effect on contagion susceptibility, consistent with the middle-status conformity hypothesis. As shown in Figure 1a, the effect of status on susceptibility to contagion reaches its maximum when degree equals 7. This corresponds to the 87th percentile in the degree distribution. Contagion is expected to be negative for scientists with a degree of 15 or higher, the top 7.5% of the status hierarchy.

Model 3 extends the analysis by assessing whether the influence of past co-authors increases with their usage level, usage diversity, status, and institutional status. Each of those source effects is allowed to vary non-monotonically as a function of the potential adopter's status. These joint source and recipient contagion effects improve model fit quite drastically (Δ -2LL = 625.24, $p < .01$). There is an interesting pattern in the findings. Keeping the status of the potential adopter at the population average, each of the four source characteristics matter ($p < 0.01$). Also, the effect of the two variables pertaining to *sources' experience* with SDM kits (usage level and diversity) is most pronounced among potential adopters of middle status. In contrast, the effect of the two variables pertaining to *sources' status* does not vary significantly across low-, middle-, or high-status potential adopters. In short, (i) on average, potential adopters are sensitive to *both* the experience and the status of prior adopters they have collaborated with; (ii) people of middle-status are especially sensitive to the contagion sources' experience; but (iii) low-, middle-, or high-status people are equally sensitive to the contagion sources' status.

Model 4 shows that the middle-status anxiety finding is not due to a confound with some "mid-career" or "middle-age" effect, and Model 5 shows that shared departmental and university affiliation are not important conduits of contagion once closer collaboration ties are controlled for. Of the 18 covariates pertaining to contagion through common departmental or university affiliation introduced in Model 5, only two have a significant effect. Prior adoption by high-status colleagues within one's own department increases the odds of adoption. Also, the behavior of colleagues within one's own department is less contagious in top-ranked institutions than in institutions of lower rank. This may occur because in top-ranked institutions, everyone considers themselves to be of above-average stature. Apart from these two traces of status-related contagion, there is no evidence of contagion operating through mere departmental or university affiliation or collocation.

Even though only those two covariates have a significant effect at 95% confidence, adding all 18 covariates improves the model fit significantly (Δ -2LL = 70.24, $p < .01$) and affects the size of several of the control variables (applied versus basic research orientation of the institution; the number of SDM publications; and the number of funding sources). The effects of contagion through active collaboration, in contrast, are barely affected. This pattern suggests that the influence of departmental and institutional ties is more closely intertwined with mere contextual effects than with the effect of true collaborative network ties.

Robustness checks

Table 2 (following References) contains the results of key interest from the same Models 1-4, except that status is now measured using citation counts rather than network centrality. The results are strikingly robust across the two analyses, including the key findings of middle-status anxiety and conformity. Results for Model 5, not reported to save space, are robust as well.

As shown in Figure 1b (following References), there are again clear inverse-U effects of status. After converting the measure from the logged to the actual number of prior citations, the effect on the tendency to adopt early reaches its maximum for scientists with 9 citations. This corresponds to the 16th percentile of the citation distribution. Individuals with 620 citations or more, the top 2-3%, are less likely to adopt than someone with no citations whatsoever (ceteris paribus). The effect of status on the susceptibility to social contagion is the highest for scientists with 25 citations. This corresponds to the 25th percentile of the citation distribution. Individuals in the top 2-3% are less susceptible to social influence than someone with no citations. So, the analyses support the notions of middle-status anxiety and conformity for both measures of status. Both analyses suggest that individuals at the very 2%-3% top of the status hierarchy are less likely to adopt or imitate their close collaborators than those at the very bottom of the hierarchy. Only the intermediate percentiles of the degree and citation distributions for which the adoption propensity and contagion susceptibility are the highest vary across the two measures of status.

A possible concern about the interpretation of middle-status effects stems from the special situation faced by very young scientists. One the one hand, researchers who are just embarking on their career tend to have few achievements and hence low status, but may actually be very eager to build their status. Hence, the "I am low status so I care less about status" argument used to derive the middle-status anxiety and conformity hypotheses may be less applicable to them. This would work against our hypotheses. On the other hand, very young researchers who are still completing their postdoc training might to a sizable extent simply be following, by coercion or by choice, the research procedures set out by their senior advisors and lab directors. If so, this might provide an alternative explanation for why the effects at the two extremes of the status distribution are similar.

These concerns are easily put to rest. Scientists who earned their PhD less than 5 years ago accounted for only 7.5% of the population at risk in 1988 and only 7% in 1997. Also, as shown in Tables 1 and 2, the middle-status anxiety and conformity effects are robust to the inclusion of linear and quadratic Academic Age effects. Finally, we re-estimated all models in Table 1 including only those observations for which both the case and all its controls had earned their PhD at least 5 years ago. The results pertaining to middle-status anxiety and conformity were robust.

We estimated two other variants of Models 1-5 in Table 1 as additional robustness checks. The same substantive conclusions about middle-status anxiety and conformity are obtained when status is operationalized as the number of citations to SDM papers specifically. Using this alternative measure, however, produces worse model fits than using network centrality or total citation count. One likely reason is that the higher frequency of zero counts makes it a coarser measure of status. The substantive findings pertaining to middle-status anxiety and conformity are also robust to operationalizing contagion in terms of the fraction rather than the number of past co-authors who have adopted.

Discussion

Status is a central concept in diffusion theory and research. Most work, both classic and recent, focuses on monotonic effects (e.g., Becker 1970; Iyengar et al. 2011; Simmel 1904; Van den Bulte and Joshi 2007). The present study, informed by long-established sociological theory and research hitherto unexploited by diffusion researchers, investigates the presence of non-monotonic effects of status in new product adoption.

Analyzing the diffusion of a high-tech product and using two different operationalizations of status, one generic (degree centrality in a network) and one specific top our research setting (citations to prior publications), we present evidence that status affects (i) how early or late one adopts regardless of social influence, (ii) how susceptible one is to social influence operating through social ties, and (iii) how influential one's own behavior is in triggering adoption by others. All three effects go beyond the notions that high-status individuals are influential or influenceable merely because they are social hubs connected to many others (Goldenberg et al. 2009; Hinz et al. 2011; Watts and Dodds 2007). Also, we document inverse-U patterns in (i) and (ii).

Implications for diffusion theory and research

Status matters. Our findings support the notion that social status itself, rather than merely its economic and educational correlates, affect new product adoption and contagion dynamics. The convention of labeling consumption expressing social class positions as "status consumption" obfuscates the distinction between social class based on economic wealth and social status based on esteem and respect (Üstüner and Holt 2010). Even prior research attuned to the distinction has often struggled with separating the effects of status in diffusion from those of economic resources, education, access to information, and technical ability (e.g., Cancian 1979; Han 1994). Our findings, in contrast, cannot be explained as being driven by such differences because they are of no relevance in the adoption of SDM kits by life scientists and cannot explain the non-monotonic effects we observe.

Middle-status anxiety. Consistent with classic sociological arguments about middle-status anxiety, we find that status affects the propensity to adopt early in a non-monotonic, inverse-U fashion. An important scope condition for this pattern, we expect, is that we focused on a product that adopters expected would help them be more productive researchers and so attain higher status. For innovations that do not offer the potential for status advancement, and especially for innovations with a high risk of status loss like those studied by Phillips and Zuckerman (2001), status anxiety implies not an inverse-U but a U-shaped relation between status and early adoption. The notion that status anxiety affects who adopts early (ceteris paribus) has implications for targeting and seeding, as we discuss below.

Middle-status conformity. Status also impacts the susceptibility to social contagion in a non-monotonic, inverse-U fashion. This is consistent with the classic notion of middle-status conformity. This facet of our study complements the recent study by Iyengar et al. (2011) documenting that self-reported opinion leaders were less susceptible to social influence, whereas sociometric leaders were not more or less susceptible. It is conceivable that this prior study did not detect a linear effect of network degree centrality on susceptibility to contagion because the true effect was non-monotonic pattern and, on average, nil. More likely, however, is that the physicians studied by Iyengar et al. had little reason to expect that adopting the drug would boost their status, so a necessary condition for middle-status conformity to operate did not hold in that setting.

Identifying the nature of the contagion mechanism. The research frontier in diffusion and contagion research is moving towards providing sharper insights into the mechanisms driving adoption and contagion (Aral 2011; Godes 2011; Van den Bulte 2010). Moderator effects provide a venue to more sharply identify the nature of the mechanisms at work (Iyengar et al. 2012).

Much work in marketing conceives of social contagion as an informational process driven by spreading awareness, social learning about the product's advantages and disadvantages, or installed base effects. Our findings do not dispute this depiction, but suggest it is incomplete. The inverse-U patterns we document are consistent with adoption and contagion being driven by legitimation or competition for status, rather than other contagion mechanisms. Our research setting is one where the product was likely to be known to all and where all potential adopters had the economic and human capital to adopt immediately if they so desired. The inverse-U pattern between status and adoption propensity therefore suggests that middle-status individuals adopt early because of the motivation induced by status anxiety, rather than because of improving opportunity or ability through information dissemination. Similarly, the non-monotonic pattern between status and susceptibility to contagion is consistent with people adoption in order to improve their status, rather adopting because of changes in the opportunity or ability to start using the new product.

Identifying the most influential customers. Our study investigated not only the non-monotonic effects of the *potential adopters'* status but also whether contagion was moderated by the *prior adopters'* status and experience with the new product. Differential source influence within ties being driven by user experience versus status has been the topic of some recent debate, with all parties agreeing that the answer likely depends on the nature of the contagion process (Godes 2011; Godes and Mayzlin 2009; Iyengar et al. 2011). The richness and size of our data allow us not only to operationalize both types of source effects separately using two metrics for each, but also to include all effects jointly in the model. We find that both experience and status matter, but in a somewhat different fashion: (i) on average, potential adopters are sensitive to *both* the experience and the status of prior adopters they have collaborated with; (ii) people of middle-status are especially sensitive to the contagion sources' experience; but (iii) low-, middle-, or high-status people are equally sensitive to the contagion sources' status.

The presence of different moderator effects suggests that the sources' experience and status affect potential adopters through different mechanisms. The most likely explanation is that experience more compellingly conveys the new product's functional benefits whereas status more compellingly conveys its legitimacy. This would account for the finding that those most sensitive to source experience are middle-status scientists who are likely to be most keen to improve their status through research output. It would also account for the finding that the effect of source status does not vary with recipient status (Iyengar et al. 2012). The distinctions and interplay between expertise, experience, and status warrant more research (e.g., Goldenberg et al. 2006).

Implications beyond new product diffusion

Consumers use products and brands to build, signal, and maintain social status. This has attracted much attention, but research to date has ignored non-monotonic patterns consistent with middle-status anxiety and conformity. Future research may benefit from moving beyond linear contrasts among subjects representing only a narrow range of the status spectrum (Berger and Ward 2010; Han et al. 2010; Ordabayeva and Chandon 2011; Üstüner and Holt 2010).

Building, signaling, and maintaining social status is one of the reasons why customers engage in brand communities and share user-generated content in public forums. Being sensitive to status anxiety and conformity motives may improve marketers' understanding of such forms of customer engagement and of the market monitoring value of the data they generate. Stewart (2005), for instance, documents that in an online community where status is determined in part by peer recognition for having made a valuable contribution, members of the second-highest status were the most active in giving such tokens of recognition. Are other forms of behavior in such forums, like discussions and product ratings, also subject to non-monotonic status effects rather than only monotonic effects documented recently (Moe and Schweidel 2012; Shen et al. 2012)?

Middle-status considerations can also affect product line and segment entry decisions in professional services and credence goods industries (Phillips and Zuckerman 2001; Podolny 2005). Many such markets have not only a generally agreed upon stratification but even publicly visible rankings. This includes not only universities and business schools, investment banks, audit companies, law firms, and strategy consulting firms for which both rankings and network data are available, but also many medical, legal, financial advice, and real estate services geared towards local consumers and for which city-specific magazines publish "Best of" lists.

Implications for practice

Many marketers and consultants struggle with identifying customers with above-average social influence, and some have even suggested that trying to identify such "influentials" or "opinion leaders" is futile. The difficulty of identifying opinion leaders using demographic and psychographic variables has led some to question the relevance of the construct itself (Thompson 2008; Watts and Dodds 2007). Our findings suggest there is no need to throw out the baby with the bathwater.

Many practitioners will find comfort in our finding that network centrality—a standard measure of status and opinion leadership—is systematically associated with time of adoption, contagiousness within ties, and susceptibility to such influence. The ineffectiveness of demographics and psychographics to identify influentials and susceptibles is likely due to inept measures rather than useless concepts and marketing frameworks.

Assuming that "more is always better" may also have contributed to the lack of success in prior studies and field applications. Looking for a linear effect when the true pattern is non-monotonic may have led some to erroneously conclude that a concept or metric is of little value. When the product has the potential to improve status, those most likely to adopt early will not be those at the top of the hierarchy and those most susceptible to contagion will not be those at the bottom. Instead, they will be those in the middle. Hence, our findings have implications for whom to target for gaining market traction quickly and leveraging the power of WOM. Focusing one’s marketing efforts exclusively on those at the high end of the sociometric degree distribution or status hierarchy need not be the most effective strategy when the product offers the opportunity to boost one’s status and customers in the middle are more likely to adopt both independently and through contagion. Because middle-status customers are easier to convert, astute marketers mindful of the benefits from not only “leveraging the influential customers” but also “targeting the switchable customers” (Gensch 1984; Slywotzky and Shapiro 1993) will want to find the optimal balance between focusing on high- and middle-status prospects.

Appendix

This Appendix provides more information on how the research setting meets the theoretical scope conditions of middle-status anxiety and conformity effects.

The importance of social status to scientists

Status is both an end in itself and a means to other ends in many areas of consumer behavior (Heffetz and Frank 2011), but especially so in our research setting. As Cole and Cole note (1973, pp. 45-46), “Recognition by peers is probably the chief motivating force in modern science.” This is echoed by many other students of science (e.g., Gaston 1973; Hagstrom 1965; Latour 1987; Merton 1973). Peer recognition is part of a “cycle of credibility” (Latour and Woolgar 1986) in which recognition helps one gain access to research funding, equipment and junior collaborators, which in turn affects one’s ability to generate high quality data, which in turn help one win key arguments or make new contributions, which cycle back into peer recognition. Status also translates into higher salaries for academic researchers, over and above the effect of their research productivity (Leahey 2007).

Site-directed mutagenesis (SDM) kits

Site-directed mutagenesis is a molecular biology and biochemistry technique in which a genetic mutation is created at a defined site in a DNA molecule by changing the sequence of the four bases: adenine (A), cytosine (C), guanine (G), and thymine (T). Since genetic information is encoded by means of the sequence of bases in DNA, SDM allows one to create mutants. The technique was pioneered by Michael Smith for which he was awarded the 1993 Nobel Prize in Chemistry, together with Kary Mullis who developed the polymerase chain reaction (PCR), a technique with many applications, SDM being one of them.

Like many other molecular biology techniques, SDM is a complex multi-step procedure involving bacterial strains or other cell material, various reagents (chemicals), and various pieces of equipment for mixing, heating and cooling, and diagnosing. The many steps are carefully described in detailed protocols running over multiple pages. There is often a very delicate interplay among the various reagents and among the reagents and procedural steps (varying number and sequence of steps, temperatures, latency periods, etc.), so even minor deviations can lead to failure.

Commercial SDM kits are a solution to these problems. They provide researchers with a proven set of reagents and procedural steps described in detailed manuals. Vendors typically also provide technical support. Commercial SDM kits appeared on the market in 1988. Table A1 (following References) lists several vendors of SDM kits. Each kit allows one to perform several reactions. Stratagene's QuikChange kit, for example, retailed for $385 in 1997 and allowed for 25 reactions.

Status advantages and risks of SDM kits

Commercial SDM kits allow scientists to be more productive and so improve their status. However, especially in their early years, using such kits was not considered a fully legitimate by some. So, there was both a promise of functional benefits and status advancement, but also a danger of normative illegitimacy and status loss.

Commercial SDM kits help overcome several challenges that life scientists face in their work (Jordan and Lynch 1992): (i) Achieving reliability and efficacy, and hence scalability; (ii) Determining whether one person's method of performing the procedure is the same as another's; (iii) Accounting for discrepant results; (iv) Formulating procedures in publications; (v) Convincing others of the validity of one's method; and (vi) Explaining to novices how to use the technique. Standardized tools and kits help overcome these challenges because they (i) reduce the number of factors that researchers must consider when conducting their experimental tasks, (ii) make the procedure easily portable to and replicable by researchers at other locations, and (iii) translate the messy and complex bench work into codes that are easy to convey to other researchers (Fujimura 1996). By providing commonly applied, uniform, and stable materials and routines in a single package, commercial SDM kits known and accessible to all make it easier to assess one's own or others' research results and, ultimately, to get one's work accepted as a contribution to knowledge that others can build on. In addition, the fact that kits are branded enables researchers to convey their procedures succinctly (Table A2, following References)).

SDM kits sold by commercial companies also present prospective users with disadvantages, making them not quite legitimate in the eyes of many scientists. One concern is that vendors sometimes hide some of the components under the term "proprietary reagent." This secrecy precludes any flexibility on the part of the user, which requires knowledge of all the components to make subtle adjustments to the procedure (Hengen 1994). This loss of control over experimental procedures is a major impediment among purists.

A second concern stems from the professional pride derived from building one's technique from raw ingredients and the value put on skillful *bricolage* at the workbench. Scientists and lab technicians have been known to resist kits as they erode the value of their skill and give lab managers greater opportunities to control their work (Jordan and Lynch 1998). Academic mentors sometimes worry that students' training is shallower when they perform experiments using commercial kits instead of assembling their own materials, reagents and protocols (Hengen 1994; Weiner and Slatko 2008).

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Table 1. Results with status measured as degree centrality

	Model 0	Model 1	Model 2	Model 3	Model 4	Model 5
-2LL	1058.28	940.40	929.86	304.62	298.46	228.22
Number of Coauthors	-.09	-.10	-.11	-.12	-.14	-.13
	(.07)	(.07)	(.08)	(.09)	(.09)	(.11)
Non-specialist Coauthor	2.16**	1.90**	1.91**	1.91**	1.93**	1.96**
	(.13)	(.14)	(.15)	(.28)	(.29)	(.24)
Number of Funding Sources	.72**	.73**	.74**	.48**	.46**	.31**
	(.05)	(.06)	(.06)	(.11)	(.11)	(.09)
Past Use of Other Kits	2.25**	2.29**	2.24**	2.28**	2.27**	2.31**
	(.14)	(.15)	(.16)	(.30)	(.21)	(.22)
Number of SDM Papers for Purpose 1	.91**	.87**	.86**	.66**	.63**	.52**
	(.14)	(.11)	(.10)	(.09)	(.07)	(.05)
Number of SDM Papers for Purpose 2	-.71**	-.68**	-.66**	-.48**	-.45**	-.38**
	(.16)	(.12)	(.11)	(.08)	(.07)	(.06)
Faculty Adoptions at PhD Institution	.33**	.36**	.37**	.29**	.28**	.31**
	(.02)	(.02)	(.03)	(.05)	(.05)	(.07)
Academic Age	-.07*	-.07*	-.09*	-.09*	-.08*	-.07*
	(.03)	(.03)	(.04)	(.04)	(.03)	(.03)
Academic Age^2	.01	.01	.01	.01	.01	.02
	(.01)	(.02)	(.05)	(.03)	(.03)	(.05)
Applied vs. Basic Institution	2.80**	2.58**	2.57**	1.10**	1.23**	.87**
	(.26)	(.29)	(.29)	(.31)	(.31)	(.21)
Applied vs. Basic Institution × Post 1993	-1.22**	-1.05**	-.96**	-.63**	-.73**	-.41**
	(.32)	(.25)	(.23)	(.12)	(.15)	(.13)
Ranking of Own Institution	.28**	.27**	.27**	.26**	.25**	.28**
	(.09)	(.08)	(.07)	(.06)	(.03)	(.03)
Ranking of Own Institution × Post 1993	-.07**	-.06**	-.05**	-.03**	-.02**	-.03**
	(.007)	(.006)	(.006)	(.008)	(.006)	(.006)
Own Status		.11**	.10**	.10**	.09**	.09**
		(.02)	(.02)	(.02)	(.01)	(.01)
Own Status^2		-.012**	-.011**	-.011**	-.010**	-.010**
		(.001)	(.001)	(.002)	(.002)	(.001)
Coauthor Adoptions			.23**	.22**	.21**	.20**
			(.03)	(.04)	(.03)	(.02)
Coauthor Adoptions × Own Status			.06**	.09**	.08**	.08**
			(.02)	(.01)	(.01)	(.02)
Coauthor Adoptions × Own Status^2			-.013**	-.012**	-.012**	-.011**
			(.001)	(.001)	(.001)	(.001)
Usage-weighted Coauthor Adoptions				.34**	.34**	.36**
				(.05)	(.05)	(.08)
Diversity-weighted Coauthor Adoptions				.40**	.39**	.41**
				(.06)	(.06)	(.08)
Status-weighted Coauthor Adoptions				.21**	.21**	.22**
				(.05)	(.05)	(.06)

Institution Rank-weighted Coauthor Adoptions	.16**	.17**	.13**
	(.05)	(.06)	(.04)
Usage-weighted Coauthor Adoptions × Own Status	.12**	.11**	.10**
	(.04)	(.03)	(.03)
Usage-weighted Coauthor Adoptions × Own Status^2	-.015**	-.015**	-.014**
	(.001)	(.001)	(.001)
Diversity-weighted Coauthor Adoptions × Own Status	.12**	.11**	.09**
	(.02)	(.02)	(.02)
Diversity-weighted Coauthor Adoptions × Own Status^2	-.016**	-.015**	-.014**
	(.003)	(.003)	(.003)
Institution Rank-weighted Coauthor Adoptions × Own Status	.09	.08	.07
	(.07)	(.07)	(.06)
Institution Rank-weighted Coauthor Adoptions × Own Status^2	-.009	-.008	-.006
	(.009)	(.009)	(.007)
Status-weighted Coauthor Adoptions × Own Status	.13	.13	.15
	(.12)	(.12)	(.12)
Status-weighted Coauthor Adoptions × Own Status^2	-.008	-.007	-.007
	(.008)	(.009)	(.008)
Coauthor Adoptions × Academic Age		.08	.11
		(.12)	(.14)
Coauthor Adoptions × Academic Age^2		-.003	-.004
		(.007)	(.008)
Coworker Adoptions at Department Level			.01
			(.11)
Coworker Adoptions at Department Level × Own Status			.01
			(.13)
Coworker Adoptions at Department Level × Own Status^2			-.001
			(.009)
Usage-weighted Coworker Adoptions at Department Level			.08
			(.06)
Diversity-weighted Coworker Adoptions at Department Level			.01
			(.06)
Institution Rank-weighted Coworker Adoptions at Department Level			-.18*
			(.09)
Status-weighted Coworker Adoptions at Department Level			.08*
			(.04)
Usage-weighted Coworker Adoptions at Department Level × Own Status			.01
			(.01)
Usage-weighted Coworker Adoptions at Department Level × Own Status^2			-.001
			(.018)
Diversity-weighted Coworker Adoptions at Department Level × Own Status			-.01
			(.02)
Diversity-weighted Coworker Adoptions at Department Level × Own Status^2			.001
			(.008)
Institution Rank-weighted Coworker Adoptions at Department Level × Own Status			.04
			(.05)
Institution Rank-weighted Coworker Adoptions at Department Level × Own Status^2			-.002
			(.024)

Status-weighted Coworker Adoptions at Department Level × Own Status	.02
	(.17)
Status-weighted Coworker Adoptions at Department Level × Own Status^2	-.001
	(.004)
Coworker Adoptions at University Level	.03
	(.36)
Coworker Adoptions at University Level × Own Status	.01
	(.06)
Coworker Adoptions at University Level × Own Status^2	-.003
	(.016)

Standard errors in parentheses. * $p \leq .05$, ** $p \leq .01$. All models include 10 cohort dummies, indicating the year of the author's first SDM publication in the 1988-1997 window.

Table 2. Key results with status measured as citations count

	Model 1	Model 2	Model 3	Model 4
-2LL	932.11	905.12	322.36	313.58
Own Status	.26**	.26**	.25**	.25**
	(.09)	(.08)	(.06)	(.06)
Own Status^2	-.07**	-.07**	-.07**	-.07**
	(.02)	(.02)	(.02)	(.02)
Coauthor Adoptions		.51**	.51**	.50**
		(.11)	(.10)	(.10)
Coauthor Adoptions × Own Status		.19**	.18**	.17**
		(.03)	(.03)	(.03)
Coauthor Adoptions × Own Status^2		-.04**	-.04**	-.04**
		(.01)	(.01)	(.01)
Usage-weighted Coauthor Adoptions			.34**	.34**
			(.05)	(.05)
Diversity-weighted Coauthor Adoptions			.40**	.38**
			(.06)	(.06)
Status-weighted Coauthor Adoptions			.32**	.30**
			(.05)	(.05)
Institution Rank-weighted Coauthor Adoptions			.18**	.17**
			(.06)	(.05)
Usage-weighted Coauthor Adoptions × Own Status			.10**	.09**
			(.03)	(.03)
Usage-weighted Coauthor Adoptions × Own Status^2			-.01**	-.01**
			(.00)	(.00)
Diversity-weighted Coauthor Adoptions × Own Status			.14**	.15**
			(.04)	(.04)
Diversity-weighted Coauthor Adoptions × Own Status^2			-.01**	-.01**
			(.00)	(.00)
Institution Rank-weighted Coauthor Adoptions × Own Status			.09	.08
			(.09)	(.13)
Institution Rank-weighted Coauthor Adoptions × Own Status^2			-.01	-.00
			(.01)	(.01)
Status-weighted Coauthor Adoptions × Own Status			.08	.09
			(.12)	(.13)
Status-weighted Coauthor Adoptions × Own Status^2			-.00	-.00
			(.02)	(.02
Coauthor Adoptions × Academic Age				.05
				(.16)
Coauthor Adoptions × Academic Age^2				-.01
				(.02)

To save space, Models 0 and 5 are not reported, nor are the effects of control variables. Standard errors in parentheses. * $p \leq .05$, ** $p \leq .01$. All models include 10 cohort dummies, indicating the year of the author's first SDM publication in the 1988-1997 window, as well as all the control variables included in Model 0 in Table 1.

Table A1. Some SDM Vendors and Kits

Vendors	Kits
Amersham (now part of GE Healthcare)	Sculptor
Biorad	MutaGene
Clontech (now part of Takara Bio)	Transformer
5 Prime → 3 Prime	Morph
Intron	Muta-Direct
Life Technologies	GeneTailor
New England Bio Labs	Code 20; Phusion
Pharmacia Biotech	Unique Site Elimination (USE)
Promega	Altered Sites
Quantum Biotechnologies	Quant-Essential
Stratagene (now part of Agilent Technologies)	Chameleon; DoubleTake; ExSite; QuikChange
Takara	Mutan
United States Biochemical	T7-Gen

Table A2. Examples of the use of SDM kits
(Excerpts from the methods section of two scientific papers)

"Site-directed SRA mutants (SDMs) were generated by using synthetic oligonucleotides (sequences are shown in Fig. 4A) and either the GeneEditor in vitro Site-Directed Mutagenesis System (Promega) or the QuikChange Site-Directed Mutagenesis Kit (Stratagene) following the manufacturers' protocols."

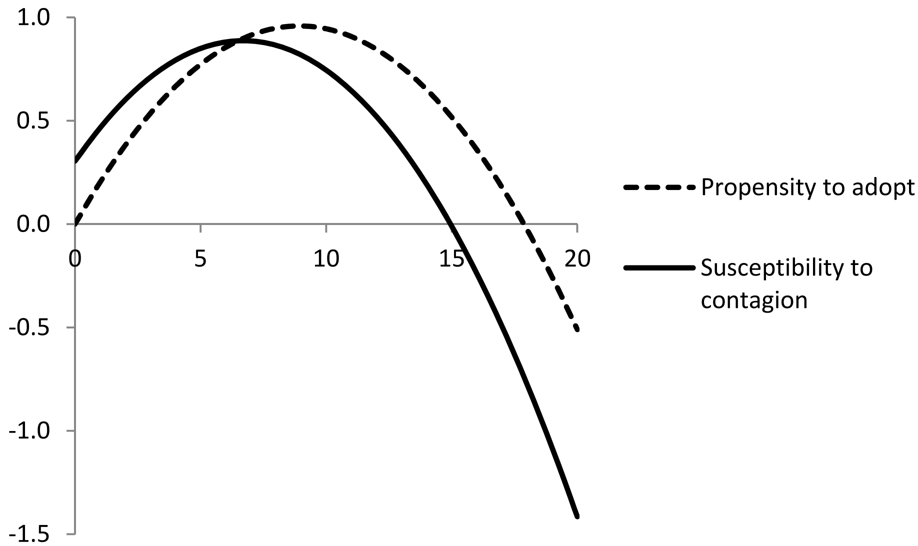
> R.B. Lanz, B. Razani, A.D. Goldberg, B.W. O'Malley. 2002. Distinct RNA motifs are important for coactivation of steroid hormone receptors by steroid receptor RNA activator (SRA). *Proc. Natl. Acad. ScienceUSA* **99** 16081-16086.

"The C terminus of maltose-binding protein was fused to the N terminus of the second nucleotide-binding domain of rat SUR1 (residues Lys-1319 to Lys-1581) by using the pMal-c2 vector system (New England Biolabs) and expressed as a fusion protein, abbreviated here as NBD2. Site-directed mutagenesis was carried out according to the manufacturer's instructions (QuikChange SDM kit; Stratagene) and confirmed by sequencing."

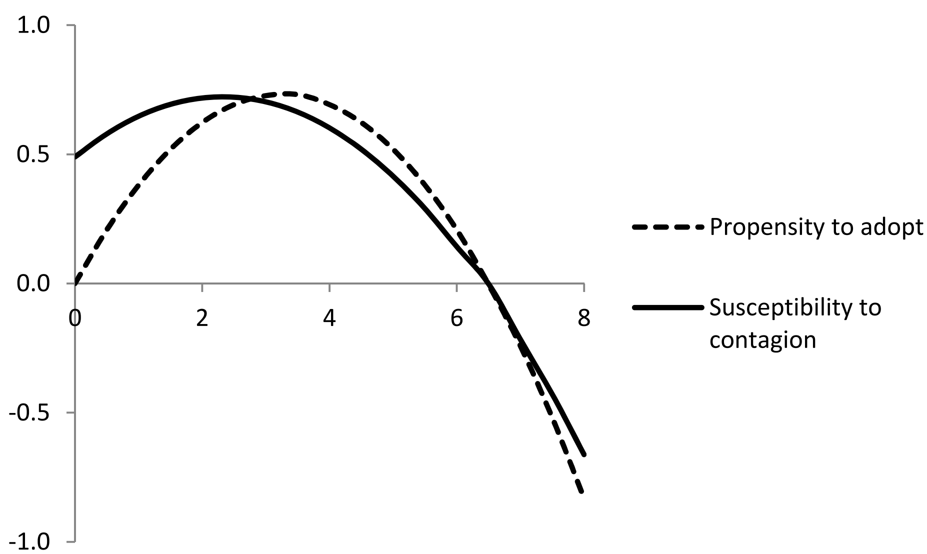
> H. de Wet, M.G. Rees, K. Shimomura, Journal of Aittoniemi, A.-M. Patch, S.E. Flanagan, S. Ellard, A.T. Hattersley, M.S. P. Sansom, F.M. Ashcroft. 2007. Increased ATPase activity produced by mutations at arginine-1380 in nucleotide-binding domain 2 of ABCC8 causes neonatal diabetes. *Proc. Natl. Acad. Science USA* **104** 18988-18992.

Figure 1. How the propensity to adopt and the susceptibility to contagion vary with status

1a. Status operationalized as network degree centrality



1b. Status operationalized as the logarithm of citation count



Note: The dashed lines show how the log-odds of adoption varies with status in Model 1 (Tables 1 and 2) re-estimated without mean-centering . The full lines show how the effect of coauthor adoptions on the log-odds of adoption varies with status in Model 2 (Tables 1 and 2) re-estimated without mean-centering.