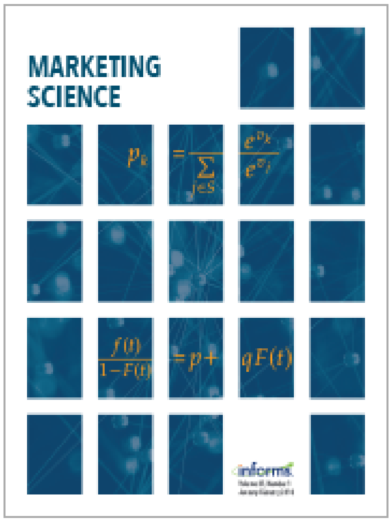

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Nonmonotonic Status Effects in New Product Adoption

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We investigate how the tendency to adopt a new product independently of social influence, the recipients' susceptibility to such influence, and the sources' strength of influence vary with social status. Leveraging insights from social psychology and sociology about middle-status anxiety and conformity, we propose that for products that potential adopters expect to boost their status, both the tendency to adopt independently from others and the susceptibility to contagion is higher for middle-status than for low- and high-status customers. Applying a nested case-control design to the adoption of commercial kits used in genetic engineering, we find evidence that status affects (i) how early or late one adopts regardless of social influence, (ii) how susceptible one is to such influence operating through social ties, and (iii) how influential one's own behavior is in triggering adoption by others. The inverse-U patterns in (i) and (ii) are consistent with middle-status anxiety and conformity. The findings have implications for how to use status to better understand adoption and contagion mechanisms, and for targeting customers when launching new products.

Keywords: hazard model; nested case-control design; new product adoption; social contagion; social networks; social status
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1. 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 is affected by the extent to which peers are already using it, is a form of 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 why it occurs (Aral 2011, Godes 2011, Peres et al. 2010). 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).

Yet, status motivations have not been studied much in diffusion research (Rogers 2003, p. 231). Theory and research in marketing on how status in general and status as an esteemed source of information and influence in particular relate to adoption behavior has so far considered only monotonic effects: the higher the status, the sooner one adopts, the more one influences others, and the less susceptible one is to others' influence (e.g., Iyengar et al. 2011).[1]

We introduce the notion that, for innovations that have the potential to boost one's social status, people's current status affects both the tendency to adopt and the susceptibility to contagion in a nonmonotonic fashion: more so for middle-status than for low status 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, Marwick 2013, Phillips and Zuckerman 2001) but have not been related to how status moderates the susceptibility to social contagion in the adoption of new products. In addition to nonmonotonic effects on the propensity to adopt early and the susceptibility to social contagion, we also study

[1] The asymmetric influence and pure-type two-segment diffusion models of Van den Bulte and Joshi (2007) are a partial exception. They are consistent with a situation where middle-status consumers are more susceptible to social influence than both low- and high-status consumers (Van den Bulte and Joshi 2007, pp. 403–404). However, the models do not focus on status per se, and neither does the empirical analysis reported by the authors.

how 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 commercial kits used in genetic engineering. This research setting offers important methodological benefits. First, social status is quite important to scientists (e.g., Cole and Cole 1973, pp. 45–46) 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 setting 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 coauthorship ties 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 one adopts regardless of social influence, (ii) how susceptible one is to social influence, and (iii) how influential one's own behavior is in triggering adoption by others. Inverse-U patterns in (i) and (ii) are consistent with middle-status anxiety and conformity. Hence, the three effects go beyond the notions that individuals are influential or influenceable merely because they are social hubs connected to many others.

Our work extends current insights on status and 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 status. 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, our evidence not only documents the importance of *both* the status and experience of prior adopters in driving social contagion, but also suggests that these two characteristics operate through different mechanisms.

These findings provide new insights into why contagion takes place. They may also help to improve targeting decisions when launching new products.

2. 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, p. 5). Status can be thought of as prestige, and many authors have at times used the two terms as synonyms (e.g., Gardner and Moore 1950, p. 22; Goode 1978, p. 4; Hagstrom 1965, pp. 84, 168, and 192; Leahey 2004, p. 523; Scott 1996, p. 100). Shils (1968) does so as well (p. 120) but prefers the term "deference-position" to convey more emphatically that "status is not a substantial property of the person... but is in fact an element in a relationship between the person deferred to and the deferent person. Deference towards another person is an attitude which is manifested in behaviour" (p. 116). Podolny and Lynn (2009, pp. 547–548) similarly define status in terms of being the recipient of "accumulated acts of deference." Consistently with Shils's emphasis that status is relational and manifested in behavior, they note that the deference on which status is based is "something awarded by others." In short, status has three defining elements: it is a *position* in a social structure based on *esteem* that is bestowed by *others*.

Next, we differentiate status from power, class, reputation, and ability (including expertise). We also note that metrics of network centrality can be used to measure status, provided that the ties in the network capture a relationship of esteem.

Status, based on differences in esteem, is related to yet distinct from power, the ability to influence others. Status is a source of power, and perceived influence can be a source of status. Yet, the concepts are distinct, and each has many other causes and consequences (Berger et al. 1972, Ridgeway and Correll 2006).

Status and class are also related yet distinct. 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 and the respect for impoverished intellectuals, nobility, and monks, and as documented by the variation of status within economic classes (Cole and Cole 1973, p. 45; Lamont 1992) and the rather weak association between occupational status and income (Chan and Goldthorpe 2007).

Status and reputation are related yet distinct as well (e.g., Podolny 2005). First, 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 absolute quality level or to relative horizontal differentiation. Second, people's or products' reputations are based on their prior performance, whereas status can stem not only from perceived competence or performance but also from unearned ascription based on gender, ethnic, racial, or other group membership (e.g., Gould 2002, Rossman et al. 2010).

Status is also distinct from ability and its various facets like expertise (e.g., Cohen and Zhou 1991, Sauder et al. 2012). Hence, using labels like "informational status" to refer to the "amount of skill or knowledge possessed" obfuscates rather than illuminates, as Runciman (1968, p. 33) notes. First, status is based on the esteem bestowed by others, whereas ability is intrinsic rather than relational. Second, the esteem is manifested in others' behavior whereas ability need not be. Finally, even though local esteem may be driven by a perception of competence among immediate colleagues (Owen-Smith 2001), "the link between status and expertise is tenuous" in general, as Leahey notes (2004, p. 533). Students of science, for instance, have long noted that scientific talent is only one of many factors that tend to produce status differentiation (Cole and Cole 1973, p. 68). One reason is that ability is only one of many determinants of research performance, with other important factors being luck, perseverance, and resources like the right laboratory equipment and cell tissues (e.g., Latour and Woolgar 1986). Another reason is that performance (volume and quality of research achievements) does not map perfectly into status, even though the scientific ethos tries to make that link as strong as possible (Azoulay et al. 2014, Leahey 2007, Merton 1968).[2]

Finally, the relation between status and network centrality merits consideration. The former is based on social esteem and respect, i.e., some form of public valuation, whereas the latter pertains to a position of importance in a network. Though network centrality is often used to measure status (Sauder et al. 2012), metrics of network centrality are valid measures of status only if the ties in the network capture a relationship of esteem and respect. So, centrality in networks of purely transactional buy/sell ties with little to no trust—the attribution of ability, honesty, or benevolence—does not capture status. But it does in networks of collaboration among scientists or investment banks (e.g., Podolny 2005) or in networks of patient referral or advice seeking among physicians (e.g., Iyengar et al. 2011, Menchik and Meltzer 2010).

3. 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 the 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 argument involves a double premise and two claims:

Premise. *Middle-status individuals (i) are more concerned about their status than others are ("middle-status anxiety") and (ii) have a higher tendency to conform to social-normative influence ("middle-status conformity").*

Claim 1. *For a product that is expected to help maintain or increase status, middle-status individuals have the highest propensity to adopt early.*

Claim 2. *For a product that is expected to help maintain or increase status but is also subject to social-normative contagion, middle-status individuals have the highest susceptibility to social contagion.*

Claim 1 posits an inverse-U relation between status and adoption propensity, whereas Claim 2 posits such a relation between status and susceptibility to contagion. Both claims pertain to social status purely, under the usual *ceteris paribus* condition making abstraction of differences in wealth, ability, and other factors that may be correlated with status and may enable the adoption of new products and technologies. We now present the argument in greater detail.

3.1. Middle-Status Anxiety and the Propensity to Adopt Early

Status anxiety is the concern induced by the uncertainty about how much others esteem us now and will do so in the future (e.g., Gardner and Moore 1950, Homans 1962). 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 likely reason is fluidity: they experience both a threat to lose and an opportunity to gain status. Low-status and high-status individuals, in contrast, experience only one of those sources of potential flux in their position. Another likely 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 likely reason is the goal gradient: the nearer one is to the goal, the harder one works to achieve it (Harvey and Consalvi 1960, Kivetz et al. 2006). 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 strive harder to maintain or improve their status than high-status individuals who not only already have achieved the desired state (so the goal gradient is zero) but also typically feel most secure in their standing.[3]

[2] The link between performance and status can be moderate even when purely objective data on performance is available, as documented in Erickson and Nosanchuk's (1984) study of bridge players.

[3] The consistency between middle-status conformity and the goal gradient is noted by Harvey and Consalvi (1960, pp. 182 and 186). Several studies document cumulative advantages in science, such that maintaining high status is easier than attaining it (e.g., Allison et al. 1982). Erickson and Nosanchuk (1984) find that better-known bridge players get a higher status boost for the same objective level

Middle-status anxiety provides an explanation for the commonly accepted notion that consumers' concern to "keep up with the Joneses" and maintain status through consumption is most pronounced among upwardly or downwardly mobile middle-class consumers who live in market-based societies that experience important social changes (de Botton 2004, Marwick 2013, Mills 1951).

Middle-status anxiety implies Claim 1: middle-status individuals are the keenest to quickly adopt a product that is expected to help maintain or increase status. Apart from some suggestive evidence in an early study of new drug adoption by Menzel (1957), we are not aware of empirical support for that claim. Phillips and Zuckerman (2001) find evidence of a U rather than an inverse-U relation between status and propensity to adopt early. Though the pattern is the reverse, it is consistent with middle-status anxiety because they studied the adoption of an innovation likely to harm rather than boost status. Similarly, outside the realm of innovation, Yim (2012) finds that middle-status departments are the least likely to hire their own Ph.D. graduates as faculty, a form of academic inbreeding typically frowned upon.[4]

3.2. 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 consists of relating middle-status anxiety 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 others' perception of an individual and leads to particular expectations regarding his or her behavior (Hollander 1958). Of particular note 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, as long as the transgression is not tantamount to betraying the core interests of the group, the degree to which an individual may deviate from the common normative expectancies of the group is greater for high-status individuals, as documented in several studies (e.g., Alvarez 1968, Blau 1960, Erickson and Nosanchuk 1984, Hollander 1958, Kelley and Shapiro 1954, Leahey 2004, Phillips et al. 2013). 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), Menzel (1960), and Harvey and Consalvi (1960), being a marginal, barely visible member of the group can negatively affect one's motivation to conform to the group or community.

Combining both considerations, how status enhances the motivation to conform as well as the latitude to deviate with impunity, suggests an inverse-U relation. As Harvey and Consalvi (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 lower-status individuals see relatively little upside from conforming and no downside from not conforming; high-status individuals see little upside from conforming and, when the position is secure, little downside from not conforming, with the results that it is individuals of middle-status who are most prone to conform.

Applied to new product diffusion, middle-status conformity implies Claim 2: for a product that is expected to help maintain or improve status but is also subject to social-normative contagion, middle-status individuals will have the highest susceptibility to social contagion. We are not aware of any prior empirical support for that claim.

3.3. Scope Conditions

The nonmonotonic patterns predicted based on middle-status anxiety and conformity are not part of standard diffusion theory. So, it is important to delineate scope conditions under which the middle-status logic applies and the nonmonotonic patterns are expected to hold (Phillips and Zuckerman 2001).

The first condition is that conformity to social norms 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,

of performance. For recent evidence of very low turnover at the very top end of the hierarchy of fame, a concept distinct from but related to status, see van de Rijt et al. (2013). All these findings are consistent with, though do not directly document, a flatter goal gradient in status attainment at the very high end of the status distribution: since attaining high status is harder than maintaining it, one would expect middle-status people to exert more effort than high-status people.

[4] More puzzlingly, Jensen (2010) finds that Danish middle-status actors were more likely than low- and high-status actors to feature in potentially illegitimate movies combining comedy with pornography in the 1970s. However, some features of the research setting make it less than ideal to study status effects: (i) these sex comedies were attempts to appeal to a large public, making low-status actors less likely to be selected by producers, and (ii) high-status actors likely had commercially less risky projects open to them.

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 people expect that adoption will increase their status, setting aside 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 people 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 nonconformity by high-status individuals in fact enhances their status (Bellezza et al. 2014, Berkowitz and Macaulay 1961).

A fifth condition is that there is a single dominant reference group for everyone, so there is agreement on both legitimacy and status ordering. This condition precludes the existence of subcommunities or subcultures 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 subcultures.

Besides these theoretical scope conditions, there is also a methodological condition that must be met in empirical research (Phillips and Zuckerman 2001): 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 nonmonotonic status effects (Cancian 1967, 1979; Faris and Felmlee 2011; Han 1994).

4. Research Setting

We study the adoption by life scientists of commercial kits to perform site-directed mutagenesis (SDM), a form of genetic engineering. Given the importance of the institutional setting for proper theoretical inference in status and diffusion research (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.

4.1. Fit to the Theoretical Scope Conditions

Like all scientists, SDM researchers seek to improve their peers' esteem of them and their work. Status is gained mostly through research achievements (Hagstrom 1965, Latour and Woolgar 1986), and there are no subcultures 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 publicly visible through citation counts and honorific awards (e.g., Cole and Cole 1973, pp. 46–60). 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. Since researchers "tend to select methods that will make [their] work acceptable to [their] colleagues" and "[c]onformity with methodological standards is necessary if social recognition is to be given for contributions" (Hagstrom 1965, pp. 17–18), dubious legitimacy is likely to have affected adoption of SDM kits. That middle-status scientists would care more about their status than low-status scientists is quite consistent with the general goal-gradient principle, whereas Matthew effects (e.g., Allison et al. 1982, Merton 1968) provide security to scientists with the highest status. The Web appendix (available as supplemental material at http://dx.doi.org/10.1287/mksc.2014.0857) provides additional background information on the relevance of status in science and on SDM kits, including concerns about their legitimacy.

4.2. Ease of Measuring Status

Studying scientists allows us to measure social networks and status with unusual clarity (e.g., Jones et al. 2008, Leahey 2007, Newman 2001). It also allows us to use not one but two metrics of social status that vary over time and can be measured quite unambiguously: centrality in the network of coauthorship ties among all members of the relevant population, and citation counts (Cole and Cole 1973, pp. 23–24, 58–60; Goode 1978, p. 153; Sauder et al. 2012). We do not use honorific awards because they tend to be given only to the most prestigious scholars (e.g., Waterman 1966). Since they do not cover the entire range of status, they cannot be used to study nonmonotonic status effects. Also, it is very difficult to rank awards from different countries.

4.3. 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 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. 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, outweighs the difference in purchase costs between using kits and fully "do it yourself" mutagenesis. Through all these cost reductions, kits increase the number of experiments that can be done with a given budget. Unless their lab is extremely cash constrained, the appeal of commercial kits is unrelated to scientists' economic resources.

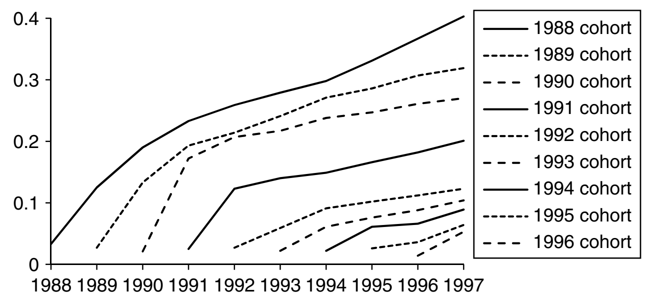
5. Methods and Data

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 1996 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. Thus, the "population at risk" of potential adopters is $N = 8{,}259$.[5]

The number of people publishing their first paper within our window grew over time as the field developed. The cohort sizes from 1988 to 1996 are 305, 332, 429, 763, 985, 1,063, 1,898, 1,278, and 1,206. The growth is quite steady, except for a bump in 1994, the year after Michael Smith received the Nobel Prize in Chemistry for developing SDM.

[5] 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.

Figure 1 Cumulative Adoption Rates by Cohort (1988–1997)



Of the 8,259 scientists, 1,030 (12.5%) used commercial SDM kits at least once in a publication between 1988 and 1997. Figure 1 reports the cumulative adoption rates by cohort. The 10-year rate of the 1988 cohort is 40% and the nine-year rate of the 1989 cohort is 32%. The adoption is still increasing in all cohorts in 1997. Though the average penetration at the end of the observation window is only 12.5%, this stems from the presence of large cohorts observed for only a short time span, rather than from the new product having fizzled out or from only a small subset of scientists being at risk of ever adopting.

We analyze how status and contagion affect the time of adoption using hazard modeling. Since we observe all of the life scientists who have used SDM in their publications, we know the entire population of potential adopters. Adoption in our study means being involved in a publication, typically coauthored, using a commercial SDM kit rather than simply purchasing such a kit. Contributing to such a publication implies that one agrees with the use of such a kit in a research report visible to other biomedical researchers and on which one's name appears, so status considerations should be at work.[6] The author data recorded in scientific publications allows us to construct a rich set of covariates without facing unit nonresponse problems common to survey research.

Since we include a large set of covariates, many of which vary over time, and since the population at

[6] Status effects might be easier to detect in adoption processes where the individual is solely responsible for adoption rather than only as part of a small collective. Though we observe adoption through publications, the great majority of which are coauthored, it is appropriate to use individual researchers and not the laboratory 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 four, and the 5%–95% range is one–nine, so every author is likely to be involved in the decision to use commercial kits or not. Also, confounding status with power effects is unlikely in our research context since 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).

risk counts more than 8,000 individuals, coding all variables for each and every potential adopter over time would be extremely demanding. It would require collecting and coding data on 28,001 scientist-year observations up to adoption. 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 nonadopters 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 savings in cost and time (Armenian 2009, Essebag et al. 2003). In our case, it requires fully coding 6,180 instead of 28,001 observations, a significant reduction since the data collection and coding effort still took about 6,000 man-hours. The core idea is to combine response-based sampling with an appropriate statistical model, adapted specifically to hazard modeling.

5.1. 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 define, for each adopter, a risk set of controls consisting of all SDM scientists who still had not adopted at the time (calendar year) the focal adopter did.[7] 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 scientist's institution is located (or the first institution 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 when the adopter did.

In step 3, we randomly select five 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 not observed to adopt or who are observed to adopt later than the case does. Also, the selection within a given year is without replacement. As a result, 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.

We estimate a discrete-time Cox proportional odds model adjusted for the case-control design (e.g., Breslow 1996, Langholz 2005, Lee and Wang 2003). This 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 nonadopting 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 the 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 estimating logit models in choice-based samples may intuit, the unconditional model provides inconsistent estimates of the time-varying intercepts used to represent the Cox nonparametric baseline hazard (e.g., Langholz 2005, Lee and Wang 2003, Prentice and Breslow 1978). More importantly, the unconditional model should include all of 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. The appendix presents the likelihood functions for the full-population hazard model and for the conditional case-control models with and without matching.

5.2. Status Measures

We use two time-varying measures of status. The first is the degree centrality in the network of scientific

[7] Since not everyone had 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 nonparametrically.

collaboration involving SDM. In directed networks involving deference or appreciation like advice seeking or favor seeking, the number of incoming ties or in-degree centrality is a popular measure of status (e.g., Knoke and Burt 1983; Lu et al. 2013; Menchik and Meltzer 2010; Prell 2012, p. 99; Sauder et al. 2012; Sgourev 2011; Wasserman and Faust 1994, p. 202). In undirected networks consisting of ties requiring both parties to mutually approve of one another, like collaboration among scientists or alliances among firms, degree is the same as in-degree and so reflects the extent to which one is esteemed by others, i.e., one's status (e.g., Burt 2010, pp. 33–35; Stuart et al. 1999). Another reason for using degree centrality as a measure of status in our study is that two graph-theoretic measures assuming that one's status is a function of the status of one's contacts, Katz's (1953) prestige measure and PageRank centrality without arbitrary additive constant, are both identical to degree centrality in networks with undirected ties (Jackson 2008, pp. 40–41; Newman 2010, pp. 177–178).[8]

We measure a scientist's degree in year t as the number of coauthors in year $t-1$ on any of the 24,310 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 nonresponse is not a problem so complete data can be collected over large networks; (ii) the measurement is often more reliable than with self-reports; and (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 of 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).[9] 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 a second measure of status. Specifically, we use the natural logarithm of the (noncumulative) number of citations in year $t-1$ to a scientist's work reported by the Institute for Scientific Information Web of Science, excluding self-citations, as the second measure of his or her status in year t.[10] 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, p. 25). 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 is a good indicator of the amount of recognition that their work has received and hence of their status (e.g., Cole and Cole 1973, pp. 99–106; 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 may be why, according to some scholars, such attention operates as a greater incentive for scientists than formal recognition that only the most elite scholars receive (e.g., Waterman 1966).

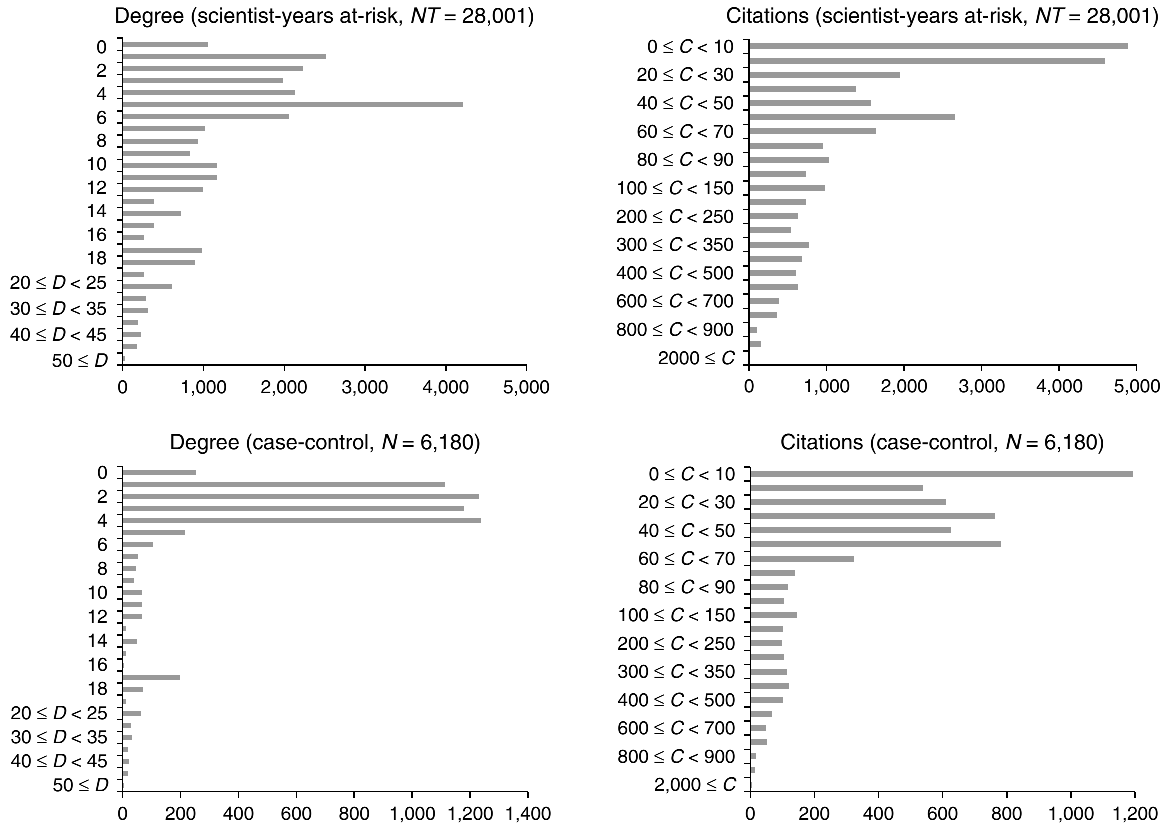
Figure 2 shows histograms for degree and citations in both the full scientist-year at-risk data ($NT = 28{,}001$) and the case-control data ($N = 6{,}180$). The Pearson correlation between the two measures is 0.56 in the

[8] Some researchers have used eigenvector and Bonacich beta-centrality rather than degree centrality as graph-theoretic measures of status (Sauder et al. 2012). These two measures, however, cannot be computed validly in networks consisting of multiple disconnected subgraphs or "components" (Bonacich 2007, Poulin et al. 2000, Wei et al. 2011). The collaboration networks we study feature multiple components. Computing eigenvector and Bonacich beta-centrality scores for each component separately is possible, but the scores are not comparable across components and hence cannot be used together as a single measure of status in a statistical analysis. Limiting the analysis to the largest component is not an attractive option either, since it accounts for only a small fraction of the overall network, e.g., less than 10% in 1996.

[9] Extremely large research collaborations involving many coauthors may be an exception to this association between coauthorship 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 four, and only 3.8% of the papers count more than 10 authors.

[10] Since 122 of the 6,180 case-control observations (2.0%) and 592 of the 28,001 at-risk scientist-year observations (2.1%) had zero citations in the prior year, we increase the number of citations by one before taking the log.

Figure 2 Histograms of Status Measures: Degree and Citations



full-population scientist-years at-risk data and 0.55 in the case-control data. The Spearman rank correlations are 0.66 and 0.65, respectively. These values are high enough to be consistent with the presence of a common underlying construct, and low enough to interpret the analysis using one metric as a true robustness check for the analysis using the other metric.

5.3. Contagion Variables

We construct several 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

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

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

We investigate three conduits: direct collaborative ties (coauthorship), 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 (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: microorganisms, 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.[11] The third and fourth source characteristics

[11] Two judges, a life scientist with a Ph.D. in biochemistry, and a marketing scientist with a Ph.D. in marketing and over 10 professional certificates 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 seven additional judges who were Masters or Ph.D.s in biochemistry. The overall interjudge agreement was 95%, which resulted in a Perreault index of 0.96 (Perreault and Leigh 1989) and a Proportional Reduction in Loss of 1 (Rust and Cooil 1994).

are related to status rather than experience with 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 a 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 one point and all institutions outside the top 30 receiving zero points.[12]

5.4. 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 the team of authors. The *number of coauthors* is self-explanatory. The indicator *nonspecialist coauthor* takes the value 1 if any of the coauthors is not an SDM specialist (who may therefore favor using a commercial SDM kit). The *number of funding sources* acknowledged in the paper is again self-explanatory.

The next set of control variables pertains 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 likely reflects a positive attitude toward 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 and could also be interpreted as a measure of research performance affecting one's reputation, but we distinguish between the two because kits are more appropriate for the first type of SDM application. *Prior faculty adoption at Ph.D. institution* is the number of faculty at a scientist's Ph.D.-granting institution who adopted SDM kits before the scientist graduated. The variable is time invariant, and is zero for anyone who received their Ph.D. before 1988. We control for *academic age*, operationalized as the number of years since the scientist earned his or her Ph.D., 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 nonparametric controls for 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 versus basic research institution* (1 for applied; 0 for basic)[13] 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 midpoint in our observation window and the year that Michael Smith received the Nobel Prize in Chemistry for developing SDM.

6. Findings

We present analyses without control variables for the full population, followed by analyses including control variables for the case-control subset.

6.1. Model-Free Analysis

Table 1 reports, for each cohort over time, the empirical hazard rate, i.e., the probability that people adopt in a given year provided that they have not done so yet. For the first seven of nine cohorts, the hazard first increases, then decreases, and stops trending. The pattern is especially pronounced for the first four cohorts (Figure 3).

These patterns are consistent with a process where one group has a higher susceptibility to contagion than another group, and hence with middle-status conformity (Blossfeld et al. 1989, p. 93; Van den Bulte and Joshi 2007). The evidence is only suggestive, however.

More compelling evidence of adoption consistent with middle-status anxiety and conformity is presented in Figure 4. Each of the four plots reports how the empirical hazard for low-, middle-, and high-status scientists varies with the exposure to prior adopters. We first organized all scientists at risk of adopting in any calendar year into one of 30 bins created by crossing three levels of status (bottom 20%, middle 60%, top 20%) against the 10 deciles of the coauthor contagion variable. Each of the 30 dots in a plot shows the fraction of adopters in each bin. The plots in the top row pertain to the 1988–1991 cohorts, those in the bottom row to the later cohorts. The plots on the left use citations as measure of status, those on the right use degree centrality.

[12] We used U.S. News and World Report rankings for the world's best universities in Life Sciences and Biomedicine, supplemented when necessary by the rankings from the Times Higher Education World University Rankings 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.

[13] We define basic research institutions as those directed toward developing big-picture understanding and enhancing general knowledge about biochemistry and molecular biology. Such institutions include departments of chemistry and biochemistry, and life science research centers where scientists work to enhance the understanding on the structure of genes. In contrast, applied research institutions aim at meeting a specific need with particular consideration for commercial application such as developing commercial drugs. Applied institutions include such organizations as a Fermentation Research Institute, departments of pharmacology, and departments or divisions of clinical chemistry.

Table 1 Empirical Hazard Rates by Cohort

	Year									
Cohort	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997
1988	0.033	0.095	0.074	0.053	0.034	0.027	0.026	0.047	0.054	0.057
1989		0.027	0.109	0.069	0.026	0.034	0.040	0.021	0.029	0.017
1990			0.021	0.154	0.042	0.013	0.027	0.012	0.019	0.012
1991				0.025	0.101	0.019	0.010	0.020	0.019	0.023
1992					0.027	0.033	0.034	0.012	0.011	0.012
1993						0.022	0.040	0.016	0.013	0.018
1994							0.022	0.040	0.005	0.025
1995								0.026	0.010	0.029
1996									0.014	0.040

The pattern in the plots in the top row, for the early cohorts, is striking. The hazard of middle-status scientists is higher than that for the others and this is due mostly to a higher slope though there is also some evidence that the hazard is higher at low levels of peer exposure. In short, there is strong evidence that middle-status scientists are more susceptible to contagion and moderate evidence that they are more prone to adopt regardless of contagion.

The plots in the bottom row, for the later cohorts, have the same key features: a higher hazard on average, a higher hazard even at low levels of peer exposure, and a higher responsiveness to peer exposure. However, the patterns are not as pronounced as for the earlier cohorts. To the extent that the use of SDM kits had become more legitimate by 1992, this contrast is consistent with middle-status anxiety and conformity.[14]

6.2. Statistical Hazard Models Without Control Variables

Before moving to the main analysis using nested case-control hazard modeling with control variables, we present some hazard model results with dummies for each decile of status but without control variables. Doing so for the full population with a traditional hazard model requires us to calculate the status and contagion variables for 28,001 rather than only 6,180 observations, but avoids the coding of many control variables. Such an analysis may be deemed informative if one sets aside concerns about omitted variable bias.

To maintain the proportional odds property of the multinomial logit model used in the nested case-control analysis, we use a discrete-time hazard model with logit link function (e.g., Iyengar et al. 2011, Van den Bulte and Lilien 2001). Making the latter fully comparable to the matched case-control model, however, would further require adding $10 \times 32 \times 3 = 960$ year-by-country-by-specialty dummies to the model, and as many additional parameters to estimate (Prentice and Breslow 1978, p. 157). This model not only is inefficient but also resulted in a nonconcave likelihood function. Therefore, instead, we estimate three models: (i) a traditional discrete-time hazard model with logit link function, (ii) a case-control hazard model without matching on country and specialty, and (iii) our nested case-control hazard model with matching. Comparing the results for models (i) and (ii) shows to what extent the case-control approach leads to different point estimates and inflated standard errors compared to the traditional full-population approach. Comparing the results for models (ii) and (iii) shows to what extent controlling for otherwise unaccounted time-by-country-by-specialty affects the model estimates. Note, since model (i) uses a binary logit specification and models (ii) and (iii) use a multinomial logit specification, all slope coefficients can be interpreted as the change in log odds of adoption associated with a one-unit increase in the covariate holding all other covariates constant (e.g., Hosmer and Lemeshow 2000, pp. 224–226). Hence, one can meaningfully use the coefficients to compare effect sizes across model specifications.

[14] Note, though, that legitimacy is more likely to increase with calendar time (regardless of cohort) than with cohort (regardless of calendar time). The model-free analysis does not disentangle these two time dimensions.

Figure 3 Empirical Hazard Rates for 1988–1991 Cohorts

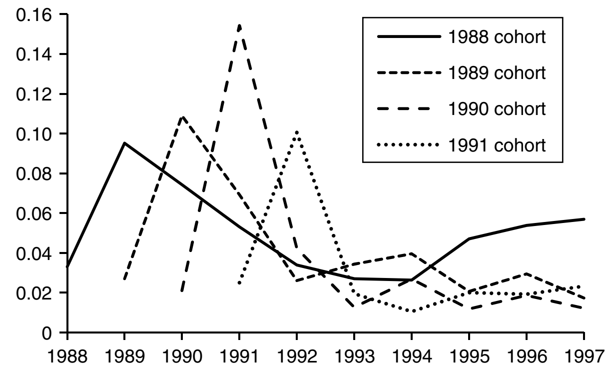
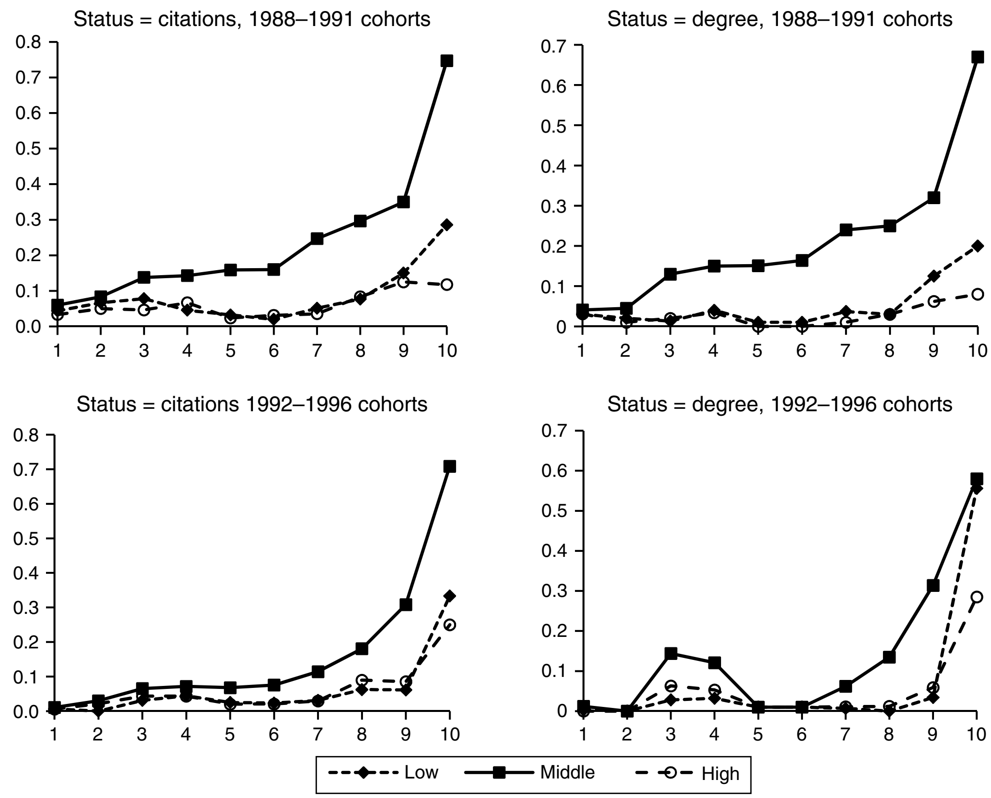


Table 2(A) shows the results when status is measured as degree centrality. All three models show clear nonmonotonic patterns in both the propensity to adopt and the susceptibility to contagion. The point estimates (log odds) in the traditional hazard model and the nonmatched case-control hazard model are extremely similar. The estimated standard errors are larger in the case-control model, due to the reduced number of observations, but the differences are quite small. These two patterns are in complete agreement with what is to be expected based on the statistical properties of case-control models. The efficiency gained from not having to collect and code data on all members of the population at risk at any time does not come at the cost of bias or significant loss of statistical efficiency.

Contrasting the point estimates in the case-control models with and without matching leads to two insights. First, controlling for unobserved heterogeneity across countries and specialties leads to larger estimated effect sizes. To the extent that such heterogeneity

Figure 4 Empirical Hazard Rates by Low/Middle/High Status and by Decile of Peer Exposure



Notes. The three lines in each plot correspond to low, middle, or high status. The points on the horizontal axis are deciles of the peer exposure variables (coauthor adoptions).

matters but is uncorrelated with the included covariates, accounting for it reduces the true error variance and hence boosts the estimates in logit models identified only up to an arbitrary scaling of the error variance. The second insight is that controlling for unobserved country and specialty characteristics through matching decreases the contagion effect in the first status decile and makes it insignificantly different from zero. This is consistent with prior evidence that failing to control for common contextual influences and other correlated unobservables can bias contagion effects upward (e.g., Aral et al. 2009, Van den Bulte and Lilien 2001).

Finally, all three models lead to the same conclusion on when status effects are the largest. Both the tendency to adopt independently and the susceptibility to contagion are the highest in the seventh decile of the degree distribution.

All patterns in Table 2(A) are robust to including year dummies in the full-population model to make it more consistent with the case-control models in which years are already conditioned out, and robust to including age dummies in all models reflecting the flexible baseline hazard of a proper discrete-time proportional odds Cox hazard model (not shown here).

Table 2(B) shows the results when status is measured through citations rather than degree centrality. Once again, all three models show clear nonmonotonic patterns in both the propensity to adopt and the susceptibility to contagion. Also, all three indicate that both status effects are the largest in the fourth and fifth deciles of the citations distribution. Just as in Table 2(A), the full-population model leads to very similar point estimates and standard errors as the case-control model without matching. Also, controlling for common country and specialty characteristics through matching again decreases the contagion estimate in the first status decile, though it remains significantly different from zero this time.

6.3. Main Analysis with Degree Centrality

Table 3 presents the results of various nested case-control models with control variables and status measured as degree centrality. Covariates moderating social contagion are always mean centered, so coefficients of nonmoderated contagion correspond to average or "main" effects.

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 coauthors has no effect, but working with others who do not specialize in SDM does increase

Table 2(A) Adoption Propensity and Contagion Susceptibility by Status Decile in Full-Population and Case-Control Hazard Models Without Covariates: Status Measured as Degree Centrality

	Full population model		Case-control models: Nonmatched		Case-control models: Matched	
	Coef.	S.e.	Coef.	S.e.	Coef.	S.e.
Intercept	−4.847**	0.348	—		—	
Status decile 2	0.370**	0.110	0.389**	0.118	2.220*	1.061
Status decile 3	0.641**	0.240	0.651**	0.241	2.253*	1.030
Status decile 4	1.529**	0.429	1.653**	0.435	2.324*	1.038
Status decile 5	1.580**	0.442	1.707**	0.472	3.065**	1.038
Status decile 6	1.680**	0.418	1.834**	0.427	3.070**	1.057
Status decile 7	2.596**	0.382	2.741**	0.418	4.725**	1.044
Status decile 8	1.085*	0.511	1.180*	0.542	2.878**	1.031
Status decile 9	1.016*	0.481	1.137*	0.492	2.812**	1.083
Status decile 10	0.349*	0.149	0.302*	0.144	2.389*	1.047
Contagion	0.457**	0.090	0.441**	0.110	−0.415	0.459
Status decile 2 × Cont.	0.080**	0.012	0.109**	0.022	0.602**	0.169
Status decile 3 × Cont.	0.220**	0.079	0.177*	0.072	0.638**	0.156
Status decile 4 × Cont.	0.286**	0.113	0.206*	0.092	0.680**	0.161
Status decile 5 × Cont.	0.386**	0.116	0.358**	0.127	0.758**	0.150
Status decile 6 × Cont.	0.537**	0.104	0.505**	0.133	0.795**	0.151
Status decile 7 × Cont.	0.865**	0.114	0.971**	0.167	1.293**	0.212
Status decile 8 × Cont.	0.223**	0.050	0.247**	0.067	0.870**	0.155
Status decile 9 × Cont.	0.086**	0.032	0.128**	0.047	0.651**	0.174
Status decile 10 × Cont.	−0.519**	0.150	−0.588**	0.140	0.446**	0.163
−2LL	3,554.13		2,210.21		1,831.50	
NT (scientist-years)	28,001		6,180		6,180	
N (scientists)	8,259		6,180		6,180	

*$p \leq 0.05$; **$p \leq 0.01$.

Table 2(B) Adoption Propensity and Contagion Susceptibility by Status Decile in Full-Population and Case-Control Hazard Models Without Covariates: Status Measured as Citations

	Full population model		Case-control models: Nonmatched		Case-control models: Matched	
	Coef.	S.e.	Coef.	S.e.	Coef.	S.e.
Intercept	−4.985**	0.358	—		—	
Status decile 2	0.275*	0.122	0.302*	0.132	0.242*	0.102
Status decile 3	0.576*	0.253	0.603*	0.261	0.391**	0.081
Status decile 4	1.230**	0.371	1.229**	0.372	0.483**	0.172
Status decile 5	0.945*	0.461	0.956*	0.466	0.264**	0.102
Status decile 6	0.864**	0.257	0.879**	0.261	0.124**	0.032
Status decile 7	0.675**	0.256	0.696**	0.263	0.089**	0.031
Status decile 8	0.063**	0.019	0.073**	0.021	0.028**	0.011
Status decile 9	−0.156**	0.061	−0.179**	0.071	−0.201**	0.062
Status decile 10	−0.158**	0.049	−0.187**	0.058	−0.367**	0.092
Contagion	0.481**	0.095	0.471**	0.101	0.226**	0.029
Status decile 2 × Cont.	−0.234*	0.102	−0.229*	0.109	−0.132**	0.048
Status decile 3 × Cont.	0.171**	0.041	0.198**	0.049	0.284**	0.091
Status decile 4 × Cont.	0.525**	0.157	0.567**	0.171	0.532**	0.182
Status decile 5 × Cont.	0.976**	0.218	0.967**	0.212	0.755**	0.193
Status decile 6 × Cont.	0.246**	0.095	0.281**	0.098	0.451*	0.194
Status decile 7 × Cont.	0.215*	0.101	0.213*	0.099	0.351*	0.165
Status decile 8 × Cont.	0.147*	0.069	0.169*	0.072	0.235*	0.099
Status decile 9 × Cont.	0.135**	0.042	0.157**	0.048	0.229**	0.087
Status decile 10 × Cont.	−0.568**	0.192	−0.579**	0.193	−0.127*	0.051
−2LL	3,563.25		2,221.76		1,807.58	
NT (scientist-years)	28,001		6,180		6,180	
N (scientists)	8,259		6,180		6,180	

*$p \leq 0.05$; **$p \leq 0.01$.

the odds of adopting quickly. Research supported by multiple sources of funding is associated with early adoption as well. Researchers are more likely to adopt 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 received their Ph.D. at a school where several faculty members had used SDM kits before they graduated. Working at an institution focusing on applied versus basic research is associated with early adoption, especially before 1993. So does working at a highly ranked institution.

Extending model 0 with the linear and quadratic effects of status (model 1) significantly improves model fit ($\Delta - 2\text{LL} = 117.88$, $p < 0.01$). Status has an inverse-U effect on the tendency to adopt early, consistent with the middle-status anxiety hypothesis.

Model 2 extends the analysis with contagion from past coauthors and allows the susceptibility to such contagion to vary nonmonotonically with status. This further improves model fit ($\Delta - 2\text{LL} = 10.54$, $p < 0.05$). Status has an inverse-U effect on contagion susceptibility, consistent with the middle-status conformity hypothesis.

Model 3 extends the analysis by assessing whether the influence of past coauthors increases with their usage level, usage diversity, status, and institutional status. Each of those source effects is allowed to vary nonmonotonically as a function of the potential adopter's status. These joint source and recipient contagion effects improve model fit quite markedly ($\Delta - 2\text{LL} = 625.24$, $p < 0.01$). There is an interesting pattern in the findings. Keeping the status of the potential adopter at the average, each of the four source characteristics matters

Table 3 Main Results with Status Measured as Degree Centrality

	Model 0	Model 1	Model 2	Model 3	Model 4	Model 5
−2LL	1,058.28	940.40	929.86	304.62	298.46	228.22
Number of coauthors	−0.09 (0.07)	−0.10 (0.07)	−0.11 (0.08)	−0.12 (0.09)	−0.14 (0.09)	−0.13 (0.11)
Nonspecialist coauthor	2.16** (0.13)	1.90** (0.14)	1.91** (0.15)	1.91** (0.28)	1.93** (0.29)	1.96** (0.24)
Number of funding sources	0.72** (0.05)	0.73** (0.06)	0.74** (0.06)	0.48** (0.11)	0.46** (0.11)	0.31** (0.09)
Past use of other kits	2.25** (0.14)	2.29** (0.15)	2.24** (0.16)	2.28** (0.30)	2.27** (0.21)	2.31** (0.22)
Number of SDM papers for purpose 1	0.91** (0.14)	0.87** (0.11)	0.86** (0.10)	0.66** (0.09)	0.63** (0.07)	0.52** (0.05)
Number of SDM papers for purpose 2	−0.71** (0.16)	−0.68** (0.12)	−0.66** (0.11)	−0.48** (0.08)	−0.45** (0.07)	−0.38** (0.06)
Faculty adoptions at Ph.D. institution	0.33** (0.02)	0.36** (0.02)	0.37** (0.03)	0.29** (0.05)	0.28** (0.05)	0.31** (0.07)
Academic age	−0.07* (0.03)	−0.07* (0.03)	−0.09* (0.04)	−0.09* (0.04)	−0.08* (0.03)	−0.07* (0.03)
Academic age^2	0.01 (0.01)	0.01 (0.02)	0.01 (0.05)	0.01 (0.03)	0.01 (0.03)	0.02 (0.05)
Applied vs. basic institution	2.80** (0.26)	2.58** (0.29)	2.57** (0.29)	1.10** (0.31)	1.23** (0.31)	0.87** (0.21)
Applied vs. basic institution × Post 1993	−1.22** (0.32)	−1.05** (0.25)	−0.96** (0.23)	−0.63** (0.12)	−0.73** (0.15)	−0.41** (0.13)
Ranking of own institution	0.28** (0.09)	0.27** (0.08)	0.27** (0.07)	0.26** (0.06)	0.25** (0.03)	0.28** (0.03)
Ranking of own institution × Post 1993	−0.07** (0.007)	−0.06** (0.006)	−0.05** (0.006)	−0.03** (0.008)	−0.02** (0.006)	−0.03** (0.006)
Own status		0.11** (0.02)	0.10** (0.02)	0.10** (0.02)	0.09** (0.01)	0.09** (0.01)
Own status^2		−0.012** (0.001)	−0.011** (0.001)	−0.011** (0.002)	−0.010** (0.002)	−0.010** (0.001)
Coauthor adoptions			0.23** (0.03)	0.22** (0.04)	0.21** (0.03)	0.20** (0.02)
Coauthor adoptions × Own status			0.06** (0.02)	0.09** (0.01)	0.08** (0.01)	0.08** (0.02)
Coauthor adoptions × Own status^2			−0.013** (0.001)	−0.012** (0.001)	−0.012** (0.001)	−0.011** (0.001)
Usage-weighted coauthor adoptions				0.34** (0.05)	0.34** (0.05)	0.36** (0.08)
Diversity-weighted coauthor adoptions				0.40** (0.06)	0.39** (0.06)	0.41** (0.08)
Status-weighted coauthor adoptions				0.21** (0.05)	0.21** (0.05)	0.22** (0.06)
Institution rank-weighted coauthor adoptions				0.16** (0.05)	0.17** (0.06)	0.13** (0.04)
Usage-weighted coauthor adoptions × Own status				0.12** (0.04)	0.11** (0.03)	0.10** (0.03)
Usage-weighted coauthor adoptions × Own status^2				−0.015** (0.001)	−0.015** (0.001)	−0.014** (0.001)
Diversity-weighted coauthor adoptions × Own status				0.12** (0.02)	0.11** (0.02)	0.09** (0.02)
Diversity-weighted coauthor adoptions × Own status^2				−0.016** (0.003)	−0.015** (0.003)	−0.014** (0.003)
Institution rank-weighted coauthor adoptions × Own status				0.09 (0.07)	0.08 (0.07)	0.07 (0.06)
Institution rank-weighted coauthor adoptions × Own status^2				−0.009 (0.009)	−0.008 (0.009)	−0.006 (0.007)

Table 3 (Continued)

	Model 0	Model 1	Model 2	Model 3	Model 4	Model 5
Status-weighted coauthor adoptions × Own status				0.13 (0.12)	0.13 (0.12)	0.15 (0.12)
Status-weighted coauthor adoptions × Own status^2				−0.008 (0.008)	−0.007 (0.009)	−0.007 (0.008)
Coauthor adoptions × Academic age					0.08 (0.12)	0.11 (0.14)
Coauthor adoptions × Academic age^2					−0.003 (0.007)	−0.004 (0.008)
Coworker adoptions at department level						0.01 (0.11)
Coworker adoptions at department level × Own status						0.01 (0.13)
Coworker adoptions at department level × Own status^2						−0.001 (0.009)
Usage-weighted coworker adoptions at department level						0.08 (0.06)
Diversity-weighted coworker adoptions at department level						0.01 (0.06)
Institution rank-weighted coworker adoptions at department level						−0.18* (0.09)
Status-weighted coworker adoptions at department level						0.08* (0.04)
Usage-weighted coworker adoptions at department level × Own status						0.01 (0.01)
Usage-weighted coworker adoptions at department level × Own status^2						−0.001 (0.018)
Diversity-weighted coworker adoptions at department level × Own status						−0.01 (0.02)
Diversity-weighted coworker adoptions at department level × Own status^2						0.001 (0.008)
Institution rank-weighted coworker adoptions at department level × Own status						0.04 (0.05)
Institution rank-weighted coworker adoptions at department level × Own status^2						−0.002 (0.024)
Status-weighted coworker adoptions at department level × Own status						0.02 (0.17)
Status-weighted coworker adoptions at department level × Own status^2						−0.001 (0.004)
Coworker adoptions at university level						0.03 (0.36)
Coworker adoptions at university level × Own status						0.01 (0.06)
Coworker adoptions at university level × Own status^2						−0.003 (0.016)

Notes. Standard errors in parentheses. All models include 9 cohort dummies, indicating the year of the author's first SDM publication in the 1988–1997 window.
$^{*}p \le 0.05$; $^{**}p \le 0.01$.

($p < 0.01$). 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 with potential adopters' status. 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; and (iii) low-, middle-, or high-status people are equally sensitive to the contagion sources' status.

Model 4 shows that the middle-status conformity finding is not due to a confound with some "mid-career" or "middle-age" effect. Hence, to the extent that research ability and expertise first rise and then decline with age, this does not provide an alternative account for the nonmonotonic status in the data.

Model 5 shows that shared departmental and university affiliations 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 affiliations 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 peer influence 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 ($\Delta - 2\text{LL} = 70.24$, $p < 0.01$) 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.

6.4. Main Analysis with Citations

Table 4 contains the results of key interest from the same models 1–4 as in Table 3, except that status is now measured using citation counts rather than network centrality. The results are strikingly robust across the two analyses. Results for model 5, not reported to save space, are robust as well. So, regardless of whether status is measured using network centrality or citations, the data indicates clear nonmonotonic status effects on adoption propensity and contagion susceptibility.

6.5. Robustness Checks

One concern about the nonmonotonic results in Tables 3 and 4 is that they rely on a quadratic functional form. We therefore repeated the analyses by replacing status and status-squared in model 2 in Tables 3 and 4 by dummies indicating which status decile the scientists belonged to. This is the same as extending the matched case-control models reported in Tables 2(A) and 2(B) with the control variables from model 0 in Tables 3 and 4. Figure 5 plots the estimates of the status effects and their ± 1.96 s.e. range, using the first decile as baseline. All plots show a clear nonmonotonic pattern.

Two concerns about the interpretation of middle-status effects arise from the special situation faced by very young scientists. On one hand, researchers who are just embarking on their career tend to have few achievements and hence low status, but they may actually be very eager to build their status. Hence, the "I am low status so I care less about status" assumption leading to the middle-status anxiety and conformity hypotheses may be less applicable to them. This would work against our hypotheses. On the other hand, junior researchers who are still completing their training might to some extent be following, by coercion or by choice, the research procedures set out by their senior

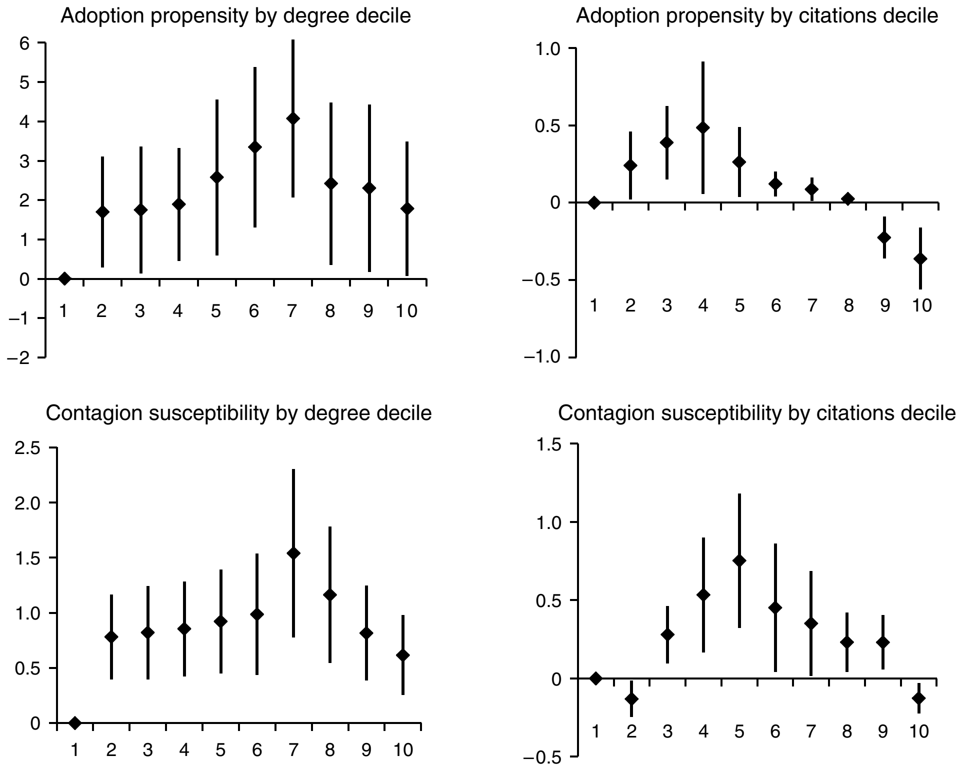
Table 4 Key Results with Status Measured Using Citations Count

	Model 1	Model 2	Model 3	Model 4
−2LL	932.73	904.61	322.87	315.36
Own status	0.23**	0.21**	0.20**	0.20**
	(0.07)	(0.08)	(0.05)	(0.06)
Own status^2	−0.06**	−0.05**	−0.05**	−0.05**
	(0.02)	(0.02)	(0.02)	(0.02)
Count of coauthor transitions		0.43**	0.41**	0.40**
		(0.10)	(0.10)	(0.10)
Count of coauthor transitions × Own status		0.14**	0.13**	0.12**
		(0.02)	(0.02)	(0.02)
Count of coauthor transitions × Own status^2		−0.03**	−0.03**	−0.03**
		(0.01)	(0.01)	(0.01)
Usage-weighted coauthor transitions			0.33**	0.32**
			(0.05)	(0.05)
Diversity-weighted coauthor transitions			0.41**	0.36**
			(0.07)	(0.05)
Status-weighted coauthor transitions			0.35**	0.32**
			(0.09)	(0.08)
Institution rank-weighted coauthor transitions			0.16**	0.15**
			(0.04)	(0.05)
Usage-weighted coauthor transitions × Own status			0.11**	0.08**
			(0.03)	(0.02)
Usage-weighted coauthor transitions × Own status^2			−0.01**	−0.01**
			(0.00)	(0.00)
Diversity-weighted coauthor transitions × Own status			0.13**	0.12**
			(0.03)	(0.03)
Diversity-weighted coauthor transitions × Own status^2			−0.01**	−0.01**
			(0.00)	(0.00)
Institution rank-weighted coauthor transitions × Own status			0.09	0.07
			(0.11)	(0.18)
Institution rank-weighted coauthor transitions × Own status^2			−0.01	−0.01
			(0.03)	(0.01)
Status-weighted coauthor transitions × Own status			0.05	0.08
			(0.17)	(0.14)
Status-weighted coauthor transitions × Own status^2			−0.01	−0.00
			(0.05)	(0.03)
Count of coauthor transitions × Academic age				0.06
				(0.17)
Count of coauthor transitions × Academic age^2				−0.01
				(0.02)

Notes. To save space, models 0 and 5 are not reported, nor are the effects of control variables. Standard errors in parentheses. All models include 9 cohort dummies, indicating the year of the author's first SDM publication in the 1988–1997 window, as well as all of the control variables included in model 0 in Table 3.

$^*p \le 0.05$; $^{**}p \le 0.01$.

Figure 5 Adoption Propensity and Contagion Susceptibility by Status Decile, in Case-Control Hazard Models with Covariates



Notes. For adoption propensity, the dots report the log odds of adopting for someone in the status decile compared to someone in the first decile. For contagion susceptibility, the dots report the log odds of adopting associated with a one-unit increase in the number of coauthor adoptions for someone in the status decile compared to someone in the first decile. The lines report the ± 1.96 s.e. interval.

advisors and lab directors. If so, this would amount to a confound between power and status mechanisms and would provide an alternative explanation as to why the effects are similar at the two extremes of the status distribution.

Both concerns are easily put to rest. Scientists who earned their Ph.D. less than five years ago accounted for only 7.5% of the population at risk in 1988 and only 7% in 1997. Also, as shown in Tables 3 and 4, the middle-status anxiety and conformity effects are robust to the inclusion of linear and quadratic academic age effects. Finally, we reestimated all models in Table 3 including only the observations for which both the case and all of its controls had earned their Ph.D. at least five years ago. The results pertaining to middle-status anxiety and conformity were robust.

We estimated two other variants of models 1–5 in Table 3 as additional robustness checks. The same conclusions about middle-status anxiety and conformity were obtained when operationalizing status 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 coauthors who have adopted.

6.6. Additional Analyses

Though the theory does not require that people are correct in believing that adopting commercial SDM kits will boost their future status, such evidence might be viewed as strengthening our account of adoption behavior. We assess this using data on the 637 scientists in the 1988 and 1989 cohorts allowing us to perform within-scientist cross-temporal analysis of changes in status over nine years or more. We regress the natural logarithm of degree and of citations on a binary indicator for having adopted commercial SDM kits in the past. In such a semi-log model, exponentiating the regression coefficient b ($[\exp(b) - 1] \times 100\%$) gives the percentage increase in status associated with having adopted. We use annual dummies to control for common temporal variations, and either person fixed effects to control for time-invariant unobserved heterogeneity or the lagged dependent variable to control for state dependency and heterogeneity. Having adopted is associated with a 20%–67% boost in status (Table 5).

The model-free analysis in Figure 4 suggests that middle-status effects may be more pronounced early

Table 5 Change in Status Associated with Having Adopted

	DV = Ln(Degree + 1)		DV = Ln(Citations + 1)	
Having adopted in the past	0.51 (0.04)	0.35 (0.03)	0.36 (0.06)	0.18 (0.04)
Lagged DV	—	0.22 (0.02)	—	0.69 (0.01)
Scientist fixed effects	Yes	No	Yes	No
Year fixed effects	Yes	Yes	Yes	Yes
Total R^2	0.09	0.14	0.12	0.58
Within-scientist R^2	0.10	—	0.30	—

Notes. N (scientists) = 637. NT (scientist-years) = 4,851. Standard errors in parentheses. All reported coefficients $p < 0.001$. We do not estimate models with both person fixed effects and the lagged DV since these are subject to the initial condition problem (Wooldridge 2002, pp. 412–413).

on than later. To directly test such systematic change, we reestimated models 2 and 3 in Tables 3 and 4, but allowing the effects of main theoretical interest to vary over time. Specifically, we organized the observations in three groups: (i) early cohort/early period, (ii) early cohort/late period, and (iii) late cohort/late period, where cohorts and years up to 1991 are early and those from 1992 onward are late. Table 6 reports the results on the contagion and status effects of these models, using the early cohort/early period group as the baseline.

The conclusion is the same for models 2 and 3 as base specification, and for degree and citations as measure of status: the early cohorts are less susceptible to contagion after 1992 than before. The difference in effect size is only small, however. Also, none of the other effects are significantly different early versus late. This indicates that the contagion and status considerations did not weaken markedly in our data window, though early cohorts did become somewhat less susceptible to contagion. The latter would be consistent with the kits becoming increasingly legitimized among those who had been active in the field before it experienced a boom as well as Michael Smith receiving the Nobel Prize for developing SDM.

7. Alternative Explanations

Our findings likely reflect genuine associations between status and contagion on one hand and adoption behavior on the other. Though some alternative explanations are conceivable, they are not very credible given our research setting, data, and analysis.

7.1. Endogenous Tie Formation

One concern may be that the contagion coefficients capture not the effect of coauthors on adoption behavior but that of adoption behavior on the choice of who to collaborate with. Such endogenous tie formation requires that the decision to coauthor with particular peers is affected by the extent to which these prospective coauthors (are expected to) use commercial SDM kits. Two features of the data and the results indicate that such endogenous tie formation is not a credible

Table 6 Contagion and Status Effects Before and After 1992

Measure of status	Degree				Ln(Citations + 1)			
Controls as in	Model 2		Model 3		Model 2		Model 3	
	Coeff.	S.e.	Coeff.	S.e.	Coeff.	S.e.	Coeff.	S.e.
Base = Coh. < 92, Yr < 92								
Own status	0.062*	0.031	0.023*	0.012	0.255**	0.095	0.433*	0.213
Own status^2	−0.010**	0.002	−0.002*	0.001	−0.185**	0.063	−0.282*	0.124
Contagion	0.286**	0.101	0.130*	0.067	0.423*	0.187	0.436*	0.207
Contagion × Own status	0.021*	0.010	0.055**	0.020	0.133*	0.054	0.128**	0.044
Contagion × Own status^2	−0.003*	0.001	−0.002*	0.001	−0.064**	0.024	−0.058*	0.026
Contrast = Coh. < 92, Yr ≥ 92								
Own status	0.046	0.036	0.011	0.073	0.136	0.126	0.083	0.317
Own status^2	0.000	0.003	−0.010	0.006	−0.018	0.059	−0.136	0.213
Contagion	−0.010*	0.004	−0.006*	0.003	−0.013*	0.007	−0.042*	0.020
Contagion × Own status	0.003	0.022	0.106	0.060	0.010	0.067	0.027	0.253
Contagion × Own status^2	0.000	0.002	−0.007	0.009	−0.005	0.057	0.005	0.076
Contrast = Coh. ≥ 92, Yr ≥ 92								
Own status	0.061	0.041	0.121	0.085	0.315	0.211	0.283	0.267
Own status^2	0.003	0.003	−0.005	0.006	−0.015	0.062	−0.082	0.263
Contagion	0.210	0.124	0.953	0.812	0.224	0.193	0.636	0.434
Contagion × Own status	−0.011	0.023	0.144	0.093	−0.053	0.074	0.355	0.297
Contagion × Own status^2	0.001	0.002	−0.005	0.003	−0.004	0.049	−0.054	0.095
−2LL	909.92		284.69		889.13		308.64	
Prob. LR test (10 df) vs. base	0.03		0.03		0.03		0.04	
N (scientists)	6,180		6,180		6,180		6,180	

*$p \leq 0.05$; **$p \leq 0.01$.

rival explanation. First, and more importantly, those researchers who are most likely to adopt are those in the middle strata of degree centrality and citations and hence are *not* those most sought after to collaborate with, i.e., those with high degree centrality (Figure 4; Tables 3 and 4). Second, it is not clear how endogenous tie formation can explain the patterns in our data without invoking middle-status anxiety. Specifically, it is not clear how endogenous tie formation can imply that the propensity to adopt independently and the susceptibility to contagion are higher for middle-status than for low- or high-status researchers, unless it is for their above-average eagerness to advance their status by adopting productivity-boosting commercial kits or by building coauthorship ties to peers who are productive researchers because they use commercial kits.

7.2. Reflection

Reflection arises when the peer behavior used to explain the actions of a focal researcher is actually caused by that very same researcher. This is not a credible threat, since we operationalize contagion in terms of lagged rather than current peer behavior and anyone at risk of adoption has by definition not adopted before and hence not triggered their peers to adopt through contagion (e.g., Iyengar et al. 2013). Also, reflection cannot explain the nonmonotonic status effects in the propensity to adopt independently, and we are not aware of a scenario in which it might explain nonmonotonic status effects in the susceptibility to contagion.

7.3. Correlated Unobservables

Our matched case-control design controls for any time-by-country-by-specialty effect. As a result, our findings cannot be confounded with the effects of contextual variables common to researchers in the same country or specialty, like marketing effort or the general sentiment toward using commercial kits. Since controlling for contagion at the university or department level does not affect our substantive findings (models 2–4 versus model 5 in Table 3), confounds with shared unobservables at that level of granularity are implausible. Finally, since all models in Tables 3 and 4 control for the individuals' prior use of commercial kits, it is hard to give much credence to the notion that the association between status and contagion on one hand and adoption behavior on the other are an artifact stemming from the tendency of researchers to collaborate with peers with a similar but unobserved attitude toward using commercial kits.

7.4. Truncation Bias

Our analyses are not limited to only those who adopted, but use proper case-control hazard modeling (e.g., Langholz 2005, Prentice and Breslow 1978). Therefore, our contagion estimates do not suffer from upward truncation bias (Van den Bulte and Iyengar 2011).

7.5. Expertise Effects

Yet another concern may be that what we posit as associations of adoption with status effects are actually associations with expertise. The argument would be that (i) low-expertise individuals do not understand the innovation enough, (ii) high-expertise individuals do not evaluate it well, and (iii) only in the middle range of expertise does an appropriate appreciation of the innovation occur. There are several reasons why this is not a compelling alternative account for our findings. First and foremost, premise (i) does not match our setting. The main appeal of commercial SDM kits was their ease of use. By providing a proven set of reagents and procedural steps described in detailed manuals, they made it easy even for relatively novice life scientists to conduct SDM successfully and efficiently. The premise that low-expertise researchers would somehow be unable to understand a simple, continuous innovation like commercial SDM kits is empirically unfounded and, more generally, conflicts with empirical findings in consumer research (Moreau et al. 2001). That premise makes the expertise-based explanation of little to no relevance to our research setting, and makes it a noncredible alternative account for our findings. Second, although premise (i) is consistent with a low propensity for novices to adopt independently—at least for complex products and discontinuous innovations (Moreau et al. 2001)—it is difficult to reconcile with a low susceptibility to contagion. One would expect low-expertise individuals who feel that they do not understand a new product well enough to be *more* rather than less susceptible to contagion through social learning (Iyengar et al. 2011). Therefore, differences in expertise are not a viable explanation for the nonmonotonic pattern in susceptibility to contagion in our data (e.g., Figure 4). Finally, and least importantly, we are not aware of prior research documenting claim (iii) about middle-expertise effects, whereas prior support does exist for middle-status effects.

8. Discussion

Status is a central concept in diffusion theory and research. Both classic and recent work focuses on monotonic effects (e.g., Iyengar et al. 2011, Simmel 1904). The present study, informed by sociological insights hitherto unexploited by diffusion researchers, investigates the presence of nonmonotonic status effects in new product adoption.

Analyzing the diffusion of a high-tech product and using two different measures of status, one generic (degree centrality in a network) and one specific to the 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, and (iii) how influential one's own behavior is in triggering adoption by others. Also, we document inverse-U patterns in (i) and (ii). All three effects go beyond the notions that 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).

8.1. 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, affects 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 as opposed to social status based on esteem and respect (Üstüner and Holt 2010). Even when attuned to the distinction, prior research has often struggled with separating the effects of status from those of economic resources, education, access to information, and 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 to the adoption of SDM kits by life scientists.

Middle-status anxiety. Consistent with sociological insights about middle-status anxiety, we find that status affects the propensity to adopt early in a nonmonotonic, 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 nonmonotonic, inverse-U fashion. This is consistent with middle-status conformity. This facet of our work complements the recent studies by Lee et al. (2010) and Iyengar et al. (2011) reporting that people with high in-degree centrality were not more or less susceptible to social influence. It is possible that these studies did not detect a linear association between in-degree centrality and susceptibility because the true relation was nonmonotonic and, on average, nil. More likely, however, is that a necessary condition for middle-status conformity to operate did not hold in those studies. The physicians studied by Iyengar et al. (2011) had little reason to expect that adopting the drug early versus late within a 17-month window would boost their status. Status need not have been very salient to the respondents in the Lee et al. (2010) study either.

Identifying the nature of the contagion mechanism. The frontier in adoption and contagion research is moving from merely documenting contagion (e.g., Bell and Song 2007) toward seeking 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. 2013, Van den Bulte and Stremersch 2004).

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 and 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 nonmonotonic pattern between status and susceptibility to contagion is consistent with people adopting in order to improve their status while being concerned about legitimacy, rather than 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 nonmonotonic 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 allows us not only to operationalize both 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 manner: (i) on average, potential adopters are sensitive to *both* the experience and the status of prior adopters; (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 persuasively conveys the new product's functional benefits, whereas status compellingly conveys its legitimacy. This would account for the finding that those most sensitive to source experience are middle-status scientists likely to be most keen to improve their status through research output. The finding that the effect of source status does not vary with recipient status is a bit more puzzling. The distinctions and interplay between expertise, experience, and status warrant more research (e.g., Goldenberg et al. 2006).

Trial versus repeat. Contagion can affect both trial and repeat behavior (Iyengar et al. 2013). It is not obvious, however, whether middle-status effects would be stronger or weaker in repeat than in trial. On one hand, some research suggests that legitimacy starts to loom larger once concerns about the functional value of an innovation start to dissipate with use (Kennedy and Fiss 2009, Tolbert and Zucker 1983, Westphal et al. 1997). The basic mechanism purportedly at work is similar to that in Maslow's hierarchy of needs: social integration becomes more important once basic functional needs are met. On the other hand, one would expect concerns about legitimacy to ease as the innovation becomes accepted practice. Both processes may be at work, but at different time scales, such that legitimacy concerns first increase as attention shifts from functional performance to normative legitimacy (Iyengar et al. 2013) and then decrease as the innovation becomes legitimized (Table 6). Whether this is indeed so and whether middle-status effects exhibit a similar dynamic is of substantial theoretical interest.

8.2. 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 nonmonotonic patterns consistent with middle-status anxiety and conformity. Future research would benefit from moving beyond linear contrasts among subjects and narrow ranges of the status spectrum (Bellezza et al. 2014, Berger and Ward 2010, Han et al. 2010, Ordabayeva and Chandon 2011, Üstüner and Holt 2010).

Gaining and maintaining 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 customer engagement and of the market monitoring data it generates. 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 group were the most active in giving such tokens of recognition. Are other behaviors in such forums, like discussions and product ratings, also subject to nonmonotonic status effects rather than only monotonic effects documented recently (Moe and Schweidel 2012, Shen et al. 2012, Toubia and Stephen 2013)?

Middle-status considerations can also affect product line and market entry decisions in professional services and credence goods industries (Phillips and Zuckerman 2001, Podolny 2005). Organizations operating in markets having not only a generally agreed upon stratification but even publicly visible rankings include 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, and real estate services geared toward local consumers and for which city-specific magazines publish "best of" lists.

8.3. Implications for Practice

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 them using demographics and psychographics has led some to question the relevance of opinion leadership (Thompson 2008, Watts and Dodds 2007). Our findings suggest that there is no need to throw out the baby with the bathwater.

Practitioners can find comfort in our finding that network centrality—a standard measure of status and opinion leadership that is increasingly easy to collect data on—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 nonmonotonic may have led some to erroneously conclude that the concept of opinion leadership and its metrics are of little value.

Our findings also have implications for whom to target with the objective of gaining market traction quickly and leveraging the power of contagion. 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. Focusing one's marketing efforts exclusively on the most influential or contagious customers 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. Astute marketers launching such a new product will be mindful to not only leverage the high-status customers who are the most "influential" but also target the middle-status customers who are the most "switchable" toward the new product (Gensch 1984, Slywotzky and Shapiro 1993). Hence, optimal targeting when launching a status-enhancing product subject to contagion is likely to consist of a mix of high- and middle-status prospects. Empirical tests of this claim would be valuable.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mksc.2014.0857.

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Appendix

Full-population hazard model

Let the data set consist of observations on $i = 1, \ldots, N$ individuals. Let a_i be the year in which individual i starts publishing and starts being at risk of adopting. Let t_i be the year in which i adopts or the last year in which i is observed publishing in the data window. In discrete time, the hazard of adoption can be expressed in terms of a binary dependent variable model, where the adoption indicator variable y_{it} is set to 0 if i has not adopted by the end of year t and is set to 1 if he has. Using a logit specification, we have the following:

$$P_{it} = P(y_{it} = 1 \mid y_{it-1} = 0) = \frac{\exp(\alpha + X_{it}\beta)}{1 + \exp(\alpha + X_{it}\beta)}, \qquad (1)$$

where X_{it} is a row vector of variables, α is an intercept, and β is a column vector of parameters to be estimated. The log-likelihood for the adoptions and nonadoptions in the data can then be expressed as the log-likelihood for a logit panel data model with y_{it} as the dependent variable:

$$LL = \sum_{i=1}^{N} \sum_{t=a_i}^{t_i} \left[y_{it} \ln P_{it} + (1 - y_{it}) \ln(1 - P_{it}) \right]. \qquad (2)$$

Case-control hazard models

Let $k = 1, \ldots, K$ be the cases, i.e., the individuals who adopt within the data window ($K \ll N$). Let t_k be the year in which k adopts. Let Ω_{zk} be a set of six individuals consisting of the case k and its five controls, all of whom are at risk of adopting at time t_k, under control selection scheme z. For $z = 1$, the controls are chosen randomly; for $z = 2$, the controls are matched with k on time-invariant characteristics. Let $P^z_{kt_k}$ be the conditional probability that, among the members of the set Ω_{zk}, it is the case rather than any of the controls who adopts. Also, let X_{jt_k} be a row vector of variables and let δ_z be a column vector of parameters to be estimated; $P^z_{kt_k}$ is modeled using a conditional logit specification:

$$P^z_{kt_k} = \frac{\exp(X_{kt_k}\delta_z)}{\sum_{j\in\Omega_{zk}} \exp(X_{jt_k}\delta_z)}. \qquad (3)$$

The conditional log-likelihood for the adoptions and nonadoptions in the case-control data set then equals

$$LL^z = \sum_{k=1}^{K} \ln P^z_{kt_k} = \sum_{k=1}^{K} \ln \frac{\exp(X_{kt_k}\delta_z)}{\sum_{j\in\Omega_{zk}} \exp(X_{jt_k}\delta_z)}. \qquad (4)$$

The case-control models are conditional logit models with the usual identification constraints. They have no intercept and the δ_z parameters are identified only up to the scale of the unaccounted random shocks. To the extent that the latter is smaller with matching than without matching, the estimates of δ_1 and δ_2 will differ accordingly.

Interpretation of parameters

The coefficients in β and δ_z capture the effects of covariates on the log odds of adoption, and so have the same interpretation. The IIA property of the conditional logit model implies that sampling on the dependent variable in the case-control design does not create a bias in the slope coefficients. As a result, the estimated coefficients in β in a full-population binary hazard logit model are asymptotically identical to the estimated coefficients in δ_1 in a case-control conditional logit model without matching. In practice, little efficiency is gained from using more than five controls per case.

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