Contagion and heterogeneity in new product diffusion: An empirical test

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Abstract

Marketing researchers often assume that innovation diffusion is affected by social contagion. However, there is increasing skepticism about the importance of contagion and, as has long been known, S-shaped diffusion curves can also result from heterogeneity in the propensity to adopt. To gain insight into the role of these two different—though not mutually exclusive—mechanisms, we present substantive conjectures about conditions under which contagion and heterogeneity are more pronounced, and test these conjectures using a meta-analysis of the q/p ratio in applications of the Bass diffusion model. We find that the q/p ratio is positively associated with the Gini index of income inequality in a country, supporting the heterogeneity-in-thresholds interpretation. We also find evidence that q/p varies as predicted by the G/SG diffusion model, but the evidence vanishes once we control for national culture. As to contagion, we find that the q/p ratio varies systematically with the four Hofstede dimensions of national culture, and for three of them in a pattern theoretically consistent with the social contagion interpretation. Furthermore, we find that products with competing standards have a higher q/p ratio, which is again consistent with the social contagion interpretation. Finally, we find effects of national culture only for products without competing standards, suggesting that technological effects and culturally mediated social contagion effects may not operate independently from each other.

Key words: Innovation diffusion, social contagion, income heterogeneity, national culture, meta-analysis.

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1. Introduction

How new products gain market acceptance has long been of great interest to marketers. While there is a fairly long tradition to study how marketing efforts affect diffusion, more recently researchers have started to investigate how diffusion trajectories vary systematically across product categories (e.g., Hahn et al. 1994; Sultan et al. 1990), demographic and macro-economic conditions (e.g., Dekimpe et al. 1998; Talukdar et al. 2002; Van den Bulte 2000), and national cultures (e.g., Gatignon et al. 1989; Jain and Maesincee 1998; Tellis et al. 2003). Identifying sources of systematic variation across diffusion trajectories is not only important to developing descriptive empirical generalizations, but is also relevant to addressing a fundamental theoretical issue in diffusion research: that S-shaped diffusion curves can stem from social contagion as well as from heterogeneity in the intrinsic tendency to adopt.

1.1. Contagion and heterogeneity

1.1.1. Social Contagion

Possibly because of the popularity of the Bass (1969) diffusion model, the contagion explanation for S-shaped diffusion curves has long dominated the marketing science literature. The Bass model specifies the rate at which actors who have not adopted yet do so at time t (or, more precisely, in the time period between t and $t+dt$, where $dt \rightarrow 0$) as $r(t) = p + qF(t)$, where $F(t)$ is the cumulative proportion of adopters in the population, and p and q are constants. Parameter p captures the intrinsic tendency to adopt and parameter q captures social contagion, i.e., the extent to which prior adoptions affect one's tendency to adopt. Since the proportion of the population that adopts at time t can be written as $dF(t)/dt = r(t)\ [\ 1 - F(t)\ ]$, one obtains:

$$dF(t)/dt \;=\; [\,p + q\,F(t)\,]\,[\,1 - F(t)\,] \qquad [1]$$

While this equation clearly conveys the process of social contagion as endogenous feedback (i.e., $F(t)$ affects future changes in $F(t)$), it does not show the shape of the diffusion curve, i.e., how $F(t)$ varies with t. This is better reflected in the solution of the differential equation (1). Assuming that one starts with zero adoptions ($F(0) = 0$), the solution is:

$$F(t) \;=\; [1 - e^{-(p+q)t}] \,/\, [1 + (q/p)\, e^{-(p+q)t}] \qquad [2]$$

The curve is S-shaped when $q > p$, and more pronouncedly so as the ratio of q over p increases. Hence, the q/p ratio succinctly summarizes the shape of the diffusion curve and can be interpreted as a shape parameter (e.g., Chatterjee and Eliashberg 1990). Note that all members of the population have the same intrinsic tendency to adopt (p) and the same tendency to respond to previous adoptions (q). So, the original derivation of the Bass model assumes social contagion in a homogenous population. However, as has long been acknowledged, S-shaped diffusion curves can also result from heterogeneity in the intrinsic tendency to adopt.

1.1.2. Heterogeneity in the intrinsic tendency to adopt

Two types of heterogeneity models can be distinguished, namely threshold models and Bemmaor's (1994) Gamma/shifted Gompertz model. We discuss each in turn.

Threshold models are based on the principle that actors adopt as soon as the utility of the innovation exceeds some critical level or threshold. If the utility increases systematically over time and the thresholds follow some bell-shaped density function, then the cumulative number of adopters, i.e., the diffusion curve, will be S-shaped (Duesenberry 1949). For instance, if the utility increases linearly and the thresholds are normally distributed, the diffusion curve will be the cumulative normal curve (e.g., Dernburg 1958). If the distribution of reservation prices is log-normal and prices decrease exponentially, then the normal diffusion curve results again (e.g., Bonus 1973). Many other combinations of exogenous change pattern and threshold distribution are possible. The main result is that S-shaped diffusion curves, including skewed ones like the lognormal curve (Davies 1979) and the Bass curve (Chatterjee and Eliashberg 1990), can result without any contagion.[1]

Bemmaor's (1994) Gamma/Shifted Gompertz or G/SG model is not based on the idea of thresholds, but it too can result in the Bass model. The G/SG model assumes that each actor's time of adoption is randomly distributed according to a shifted Gompertz distribution with c.d.f.:

$$G(t \mid \eta, b) \;=\; [1 - e^{-bt}] \exp(-\eta e^{-bt}), \qquad [3]$$

where b is a scale parameter that is constant across all actors and $\eta \geq 0$ represents the intrinsic tendency to adopt later rather than sooner (the higher η, the higher the expected adoption time). Next, the model assumes that the intrinsic tendency η varies according to a Gamma distribution. This distribution has two parameters, a shape parameter α and a scale parameter β, determining the mean ($\alpha\beta$) and the variance ($\alpha\beta^2$). Combining the shifted Gompertz model of individual adoption times with the Gamma distribution of heterogeneity across individuals, Bemmaor obtained the following expression for the cumulative distribution function of adoption times:

$$F(t) \;=\; [1 - e^{-bt}] \,/\, [1 + \beta\, e^{-bt}]^{\,\alpha} \qquad [4]$$

This function can generate sigmoid curves. When $\alpha = 1$, it reduces to the Bass model since one can reparametrize equation 4 into equation 2 using $b = p + q$ and $\beta = q/p$.

[1] In these threshold models, changes in the utility need not be purely exogenous to the diffusion process. Examples of endogenous changes are price declines stemming from experience curve effects (Stoneman and Ireland 1983), quality improvements based on feedback from earlier adopters (Jones 1977), and information spillovers from prior adopters. Chatterjee and Eliashberg (1990) develop of a heterogeneous threshold model with uncertainty that, when actors obtain information from prior adopters, can result in the Bass model. Hence, while contagion and threshold heterogeneity are alternative explanations, they are not mutually exclusive.

1.1.3. Theoretical over-determination

The fact that S-shaped diffusion curves can result from both contagion and heterogeneity has long frustrated researchers. Macro-level diffusion models often describe diffusion patterns over time quite well, but given the observational equivalence between many different models, it is unclear what process is being captured in the equations (Gatignon and Robertson 1986; Golder and Tellis 1998; Parker 1994). The problem is even more fundamental: many of the popular models themselves are over-determined. That is, the model equations can be derived mathematically from two very different sets of substantive assumptions and causal mechanisms. Consequently, it is mathematically impossible to unambiguously interpret the model parameters of any single diffusion curve as reflecting social contagion or heterogeneity in the propensity to adopt.[2]

The difficulty in identifying which of these two different—though not mutually exclusive—mechanisms operate(s) in the diffusion of any one innovation has led skeptics like Stoneman (2002) to deem such model parameters to be more informative as data summary devices than as evidence of contagion (or, one should add, heterogeneity). While using model parameters as mere summary devices can lead to substantive insights (e.g., Bayus 1992; Griliches 1957; Van den Bulte 2000), the nature of the process matters for marketing strategy recommendations. For instance, a price penetration strategy can be optimal when contagion exists: a low price can help to get the endogenous feedback process going and the firm can be able to increase its price once

[2] The problem that contagion and heterogeneity, while conceptually quite distinct, lead to similar predictions or even identical models and are hence difficult to distinguish from aggregate-level data is not unique to innovation diffusion research. For instance, the negative binomial distribution (NBD) model can be derived not only from a heterogeneous Poisson process in which the rate is a Gamma random variable, as it is commonly interpreted in marketing, but also from a contagious Poisson process in which the rate depends linearly on the number of prior events (Eggenberger and Pólya 1923). The heterogeneous and contagious processes yield the same theoretical distribution for the number of events occurring in a single time interval. Brand switching is another, but better known, instance where population heterogeneity and social contagion can be hard if not impossible to distinguish from aggregate-level (brand switching) data alone (e.g., Frank 1962).

the feedback momentum is strong enough (e.g., Horsky 1990). When the S-shaped diffusion curve stems only from heterogeneity in reservation prices, in contrast, this rationale for price penetration vanishes and skimming clearly seems the better strategy. Another strategy decision affected by the strength of contagion is whether to enter multiple markets simultaneously or sequentially. The optimality of a sequential or "waterfall" strategy partially depends on the strength of contagion across markets (Kalish et al. 1995). So, knowing not only the shape of diffusion paths but also to what extent diffusion is driven by contagion is important for both theory and practice. Fortunately, that the theoretical over-determination precludes one from causally interpreting the model parameters of any single S-shaped diffusion curve does not mean that nothing can be learned from real world data.

1.2. The present study

The key idea underlying the present study is that, even though fitting the Bass model to any single diffusion data series cannot empirically identify which process is at work, one can still draw inferences from patterns of variation across multiple diffusion paths (compare Taibleson 1974). While contagion and heterogeneity theories can both result in the Bass model and hence fit equally well when assessed against the diffusion path of any single innovation, contagion and heterogeneity have different implications about how the q/p ratio will vary across multiple diffusion paths, such as the diffusion of the same product in different countries. The social contagion interpretation predicts that q/p will be higher in situations where contagion (captured by q) is higher and the average intrinsic tendency to adopt independently from others' behavior (captured by p) is lower. The two heterogeneity interpretations imply that q/p will be higher or lower depending on how the intrinsic tendency to adopt varies in the population. Hence, our research strategy consists in developing substantive conjectures about conditions under which contagion and heterogeneity are more pronounced, and assessing these conjectures using a meta-analysis of the *q*/*p* ratio in applications of the Bass diffusion model to consumer durables.

For heterogeneity, we assume that income is an important dimension, and develop conjectures about the relationship between income heterogeneity and the shape of the diffusion curve as reflected in the *q*/*p* ratio. For social contagion, we capitalize on diffusion theory and broader social theory and develop conjectures about the relationship between Hofstede's (2001) dimensions of national culture and the *q*/*p* ratio. In addition, following work on technologically-induced endogenous feedback (Choi 1997; Katz and Shapiro 1994), we also develop conjectures about the relationship between the presence of competing standards and the *q*/*p* ratio. Through these conjectures, we are able to assess empirically the different types of mechanisms that may result in sigmoid diffusion curves.

Our contribution consists of five findings. First, we find that the Gini index of income inequality, capturing the shape of the income distribution, is positively related to the *q*/*p* ratio capturing the shape of the diffusion curve. This is consistent with income threshold models of diffusion. Second, we find evidence that the *q*/*p* ratio varies as predicted by the G/SG model assuming that η in the latter is inversely related to income. The evidence, however, vanishes once we control for national culture. Third, we find that the *q*/*p* ratio varies systematically with the four Hofstede dimensions of national culture, and for three of them in a pattern theoretically consistent with the social contagion interpretation. Because the different dimensions of national culture are related to different contagion processes, our results also shed some light on the nature of contagion, in particular the role of status concerns, social cohesion, and uncertainty reduction (compare Burt 1987). Specifically, we find evidence consistent with contagion being fueled by both status concerns and social cohesion but inconsistent with contagion as driven by risk avoidance. Our fourth finding is that products with competing standards have a higher q/p ratio, which is again consistent with the social contagion interpretation. Fifth, we find that the presence of competing standards drastically dampens the effects of culture and income inequality. That cultural effects operate only for products without competing standards supports Choi's (1997) argument that social contagion and the fear to adopt a losing technology do not operate independently from each other. So, our study provides fresh empirical evidence on several theoretical issues in diffusion research. More generally, since we analyze variations in diffusion trajectories as a function of the income distribution and national culture across 28 countries, we also provide new substantive insights into international diffusion patterns (e.g., Dekimpe et al. 2000; Kumar and Krishnan 2002; Talukdar et al. 2002; Tellis et al. 2003).

We proceed by first presenting conjectures on how diffusion through social contagion implies variations in the q/p ratio across national cultures and between products with and without competing standards, and on how diffusion driven by heterogeneity implies variations in the same ratio as a function of the shape and scale of the income distribution. We then describe the data, analysis method, and the results. The paper concludes with a discussion of implications and limitations.

2. Hypotheses

Given the theoretical over-determination of the Bass model (and of sigmoid diffusion curves in general), additional theoretical detail must be provided about the contagion and heterogeneity processes for one to obtain refutable hypotheses pertaining to each process separately (Taibleson 1974). One can do so by specifying the type of contagion process, the type of heterogeneity, or contingency factors. Our research strategy therefore consists in testing not the contagion explanation in general but the narrower claim that culture and competing standards affect innovation adoption in a particular way if contagion is indeed a driver. Similarly, we test not the heterogeneity explanation in general but the narrower claim that the income distribution affects adoption timing for consumer durables in a particular way if heterogeneity in the intrinsic tendency to adopt is indeed a driver.[3]

As equation 4 shows, combining the G/SG model with the substantive claim that heterogeneity in income drives diffusion does not provide one with testable implications for p and q, but does so for their ratio q/p. Similarly, income threshold models have an implication not for p and q separately but for the degree of curvature reflected in the q/p ratio. We therefore limit our hypotheses about social contagion to the same ratio which, according to that interpretation, reflects the relative importance of imitative and innovative tendencies.

2.1. Social contagion and national culture

Since their introduction in 1980, Hofstede's (2001) four dimensions of national culture have become important elements in studying consumer behavior across countries. Several researchers have recognized the value of these dimensions when seeking to explain differences across national cultures in adoption behavior and new product growth (e.g., de Mooij 1998; Jain and Maesincee 1998; Steenkamp et al. 1999; Tellis et al. 2003). Building on prior research and introducing some additional arguments from sociology, we conjecture how the q/p ratio should vary across these four dimensions if social contagion is a driver of diffusion. Different social contagion mechanisms can be related to the different Hofstede dimensions. More in particular, the hypothesis relating the dimension "individualism" to the q/p ratio is based on social cohesion and that relating "uncertainty avoidance" to q/p is based on social learning, two mechanisms that

[3] One may argue that both the social contagion and the heterogeneity interpretations predict that the income distribution affects diffusion. However, as we will discuss, the social contagion interpretation leads to different conjectures than the heterogeneity interpretation.

are quite standard in the marketing diffusion literature. For the hypotheses on "power distance" and "masculinity," in contrast, we build on arguments of social status that have received more attention in the sociology than in the marketing literature on innovation diffusion (e.g., Burt 1987; Simmel 1971).

2.1.1. Individualism

This is the extent to which "the ties between individuals are loose" and is opposed to collectivism, which is the extent to which "people from birth onwards are integrated into strong, cohesive in-groups" (Hofstede 2001, p. 255). Since individualist cultures deemphasize conformity to social norms and group behavior (e.g., Bond and Smith 1996), they expectedly have lower q values. Also, since individualist cultures value novelty and variety more (Roth 1995) and use mass media more extensively than collectivist cultures do (de Mooij 1998; Hofstede 2001), they have expectedly higher p values. In sum, the social contagion interpretation of the Bass model implies:

H1: The q/p ratio is negatively associated with individualism.

Two prior studies provide some indirect support for this conjecture. In a study of six consumer durables in fourteen European countries, Jain and Maisencee (1998) reported a negative association between individualism and q, but it was significant (at 95% confidence) for only three of the six products. In a survey of over 3000 consumers in eleven European countries, Steenkamp et al. (1999) found a positive association between the country's individualism and its citizens' consumer innovativeness, an individual-level construct (measured using a 10-item scale) similar to the intrinsic tendency to adopt captured by the population-level parameter p.

2.1.2. Uncertainty avoidance

This is "the extent to which the members of a culture feel threatened by uncertain or unknown situations" (Hofstede 2001, p. 161). While social learning under risk aversion is only one of several reasons why social contagion may occur (e.g., Van den Bulte and Lilien 2001), it is often mentioned as an interpretation of the effect captured by q (e.g., Horsky 1990; Kalish 1985). To the extent that diffusion is driven by social learning, one would expect high q values in high uncertainty avoidance countries. Also, one would expect a lower intrinsic tendency to adopt innovations, and hence a lower p, because consumers in such countries are more averse to what is different and new (Hofstede 2001). In short, to the extent that diffusion is driven by social contagion and that the latter arises from social learning, the following conjecture should hold:

H2: The q/p ratio is positively associated with uncertainty avoidance.

Studies by Jain and Maesincee (1998), Steenkamp et al. (1999), and Tellis et al. (2003) provide some indirect support for this conjecture. The first found evidence of a negative relation between p and uncertainty avoidance but only for three of the six products investigated. The second found a negative association between the country's uncertainty avoidance and its citizens' consumer innovativeness. The third found that new products took off faster in countries with low uncertainty avoidance, but the effect was sensitive to changes in the model specification.

2.1.3. Power distance

This third dimension is "the extent to which the less powerful members of [a culture] expect and accept that power is distributed unequally" (Hofstede 2001, p. 98). More broadly, power distance captures how members of a culture deal with status differences. "Cultures high in power distance tend to emphasize the importance of prestige and wealth in shaping boundaries or vertical relationships … In high power distance cultures […] social consciousness is high and [people] are motivated by the need to conform with those in their class or in classes to which they aspire" (Roth 1995, p. 165). In other words, high power distance cultures are more status-conscious.[4] This has direct implications for differences in the extent of social contagion, since competition for status can be an important reason for contagion (Burt 1987; Simmel 1971), as can recognition of status (Tarde 1903).

People buy and use products not only for functional purposes but also to construct a social identity and to communicate it to each other (Baudrillard 1981; Douglas and Isherwood 1979). As a result, product use and ownership often confirms the existence and supports the reproduction of social status differences (Barthes 1957; Bourdieu 1984). The extent to which such inequality is expected and accepted, then, affects how important it is to adopt the "right" innovations at the "right" time. On the one hand, one must not adopt too early such that one does not appear presumptuous about one's place in society. This implies a low intrinsic tendency to adopt (p) in high power distance cultures. On the other hand, consumers will seek to emulate the consumption behavior of their acknowledged superiors (Tarde 1903) and aspiration groups (Simmel 1971) and will also quickly pick up the innovations adopted by their direct peers if they fear that such adoptions might undo the present status ordering (Burt 1987). This implies a high contagion effect (q). Hence, to the extent that diffusion is driven by social contagion and that the latter arises from status considerations, the following conjecture should hold:

H3: The q/p ratio is positively associated with power distance.

Apart from an early intimation by Tarde (1903, p. 198) that "[t]he common people have always been inclined to copy kings and courts and upper classes according to the measure in

[4] Note that power distance and income inequality are very different concepts. First, power distance is the extent to which people are sensitive to differences in social status, not the extent to which such differences are large or small. Second, even in highly developed market economies, social status is defined not only by wealth but also by occupation and education. In some cultures, bloodlines and race are also important determinants of one's status. Still, though conceptually distinct, power distance and income inequality are likely to covary. Social inequalities are likely to be greater in cultures that accept them, and income and wealth tend to correlate with social status. Hence, while the cultural trait power distance is conceptually distinct from income heterogeneity, their effects expectedly must be analyzed jointly to avoid omitted variable bias.

which they have submitted to their rule," we are not aware of prior work advancing a similar conjecture. Jain and Maesincee (1998) did not investigate the association of power distance with Bass model parameters, Steenkamp et al. (1999) stated that it cannot be related to consumer innovativeness, and Tellis et al. (2003) reported having found neither theoretical support nor empirical evidence linking it to the take-off time of new products. While, as we have shown, one can use sociological theory to conjecture a relation between power distance and diffusion trajectories, the existence of such a relation remains to be investigated.

2.1.4. Masculinity

This fourth and final dimension is the extent to which "social gender roles are clearly distinct: men are supposed to be assertive, tough, and focused on material success; women are supposed to be more modest, tender, and concerned with the quality of life." Femininity is the extent to which "social gender roles overlap: both men and women are supposed to be modest, tender, and concerned with the quality of life" (Hofstede 2001, p. 297). Importantly for consumer behavior, more masculine cultures put more emphasis on wealth, material success, and achievement (de Mooij 1998; Steenkamp et al. 1999). Hence, both display of status in general and display of material possessions and achievement in particular should be more prevalent in masculine than in feminine cultures. As with power distance, this implies a positive association between masculinity and q. However, as Steenkamp et al. (1999) and Tellis et al. (2003) note, the greater importance that masculine cultures give to material possessions suggests a higher intrinsic tendency to adopt innovations. This implies a positive association between masculinity and p (unlike power distance). So, the net effect of q/p is unclear *a priori*. Empirical evidence that the typical diffusion curve is sigmoid even in wealthy countries like the U.S.A., when interpreted in terms of social contagion, suggests that the association with q is stronger than that with p. So, to the extent that diffusion is driven by social contagion and that the latter arises from competition for status, the following conjecture should hold:

H4: The q/p ratio is positively associated with masculinity.

We are not aware of prior research advancing a similar conjecture. Jain and Maesincee (1998) did not investigate the association between p or q and masculinity. Whereas Gatignon et al. (1989) and Talukdar et al. (2002) conjectured about relationships between Bass model parameters and the female labor participation rate (they found none), our conjecture hinges not on whether women work or not but on the prevalence of values of wealth, material success, and achievement. Steenkamp et al. (1999) found a positive association with consumer innovativeness akin to p, but did not investigate the q/p ratio. Tellis et al. (2003), finally, did not find support for a positive relation between masculinity and faster take-off.

2.2. Social contagion and competing standards

When multiple competing standards exist early in the life of a new product, even innovative consumers may postpone adoption until the uncertainty about what standard will dominate has been resolved (Choi 1997; Katz and Shapiro 1994). Such wait-and-see behavior or "excess inertia" should result in a more pronounced S-shape in the diffusion curve and a higher q/p ratio, both because of a lower intrinsic tendency to adopt (p) and a higher level of endogenous feedback (q). As several authors have noted, the presence of competing standards and the related issue of the provision of complements have an important supply-side element that is absent from purely demand-side social contagion stemming from information transfer, normative pressures, and competitive and status concerns (e.g., Stoneman 2002). To acknowledge and assess this alternative explanation for variation in the q/p ratio, we posit:

H5: The q/p ratio is higher for products with competing standards.

Van den Bulte (2000) provided some evidence that the diffusion path of product categories with competing standards has a more pronounced S-shape, but his analysis used the logistic model featuring q only. We are not aware of prior evidence pertaining to q/p directly.

The deterrent effect of competing standards on early adoption, we expect, varies across cultures. Products with competing standards exacerbate the uncertainty faced by early adopters, suggesting a lower p and a higher q. This effect of increased uncertainty on the q/p ratio will expectedly be more pronounced in uncertainty avoiding cultures. The presence of multiple standards is expectedly also a stronger deterrent to early adoption in individualistic than in collectivist cultures. In the latter, consumers are more likely to coordinate their purchases with their direct peers, hence reducing the fear of being left with a technological orphan. Coordination at the local level of the social network reduces the benefits of waiting until the overall market has decided which standard wins. The presence of multiple standards, we expect, is also less likely to slow down initial adoption in highly status-conscious cultures, i.e. power-distant and masculine cultures. The more important the symbolic as compared to the functional reasons to buy a new product, the less consumers care about the risk of ending up with a technological orphan providing little functional value. At the extreme, ending up with the minority technology may even be interpreted as evidence that one is indeed different from the majority of consumers (an attribution long exploited in advertising campaigns for Apple computers). To acknowledge and assess such moderating effects, we posit:

H6: The effect of competing standards on q/p is larger in (a) individualistic and (b) uncertainty avoidant cultures and smaller in (c) power distant and (d) masculine cultures.

Jain and Maisencee (1998) reported a negative association between individualism and q, but only for clothes dryers, dishwashers and microwave ovens, and not for home computers, color

TVs and VCRs. They also found a negative relation between uncertainty avoidance and p, but only for the latter set of products. While Jain and Maesincee did not interpret these findings in terms of competing standards, they are consistent with H6a and H6b.

2.3. Income heterogeneity

The generic threshold model and the G/SG model do not specify the causal determinants of the propensity to adopt. However, economic theory and prior research offer a candidate for the case of consumer durables, namely income (e.g., Bonus 1973; Chatterjee and Eliashberg 1990; Dernburg 1958; Russell 1980). We similarly assume that the heterogeneity in the propensity to adopt stems from income heterogeneity.

The two types of heterogeneity models lead to very distinct hypotheses on the effect of income distribution on the q/p ratio. Threshold models imply that the shape of the diffusion curve will be determined mostly by the <u>shape</u> of the threshold distribution. The G/SG model, in contrast, implies that the parameter related to q/p is not the shape but the <u>scale</u> parameter of the heterogeneity distribution. We detail each in turn below.

2.3.1. Threshold models

Diffusion models based on income thresholds imply that the diffusion curve is determined mostly by the shape of the income distribution. Most prior studies focus on price declines and assume that one's income determines one's reservation price. Under these conditions, one can make the general claim that the diffusion curves "will be flatter in countries … in which income is more evenly distributed" (Russell 1980, p. S73). The most commonly used measure of income inequality that succinctly captures the shape of the income distribution is the Gini concentration index or Gini coefficient. Hence, if diffusion operates as described by threshold models and the shape of the threshold distribution reflects the shape of the income distribution, then the following should hold:

H7: The q/p ratio is positively associated with the Gini coefficient of income inequality.

This prediction is unique to the income heterogeneity interpretation and can not be derived from the contagion interpretation. Working along the lines of the latter, Talukdar et al. (2002) posited a negative (rather than positive) association between income inequality and q. Reasoning that contagion requires personal interaction, that personal interaction is lower in heterogeneous populations, that income is a social dimension affecting interaction frequency, and that income inequality is captured by the Gini coefficient, they posited a negative association between the Gini coefficient and q. Since they did not make any claims about p, their conjecture implies a negative association with q/p. They actually observed a positive association between q and the Gini coefficient. Though the effect was significant at 90% confidence only, it is less in line with the social contagion than with the heterogeneity interpretation of diffusion processes.

Since we are not aware of any prior direct support for H7, and since the exact shape of the diffusion curve depends on both the income distribution and the pattern of price change, we provide a synthetic example based on empirical generalizations about both elements. Income distributions typically have longer tails to the right than the left (skewed to the right) and can be described using the Gamma or the inverse Gamma distribution (e.g., Kloek and van Dijk 1978; McDonald 1984). Figure 1 shows two distribution densities of reservation prices θ_i. Both are Gamma and have the same scale parameter $\beta = 6$. The distributions vary in their shape parameter: one has $\alpha = 2$ and the other has $\alpha = 4$. The corresponding Gini coefficients are 0.375 and 0.273, reasonable values for national income distributions.[5] A consumer i adopts as soon as the price falls below her reservation price, $\theta_i > p(t)$. As a result, the proportion of the population

[5] For the Gamma distribution, the Gini coefficient C is a function of the shape parameter only: $C = \Gamma(\alpha + ½) / [\sqrt{\pi}\ \Gamma(\alpha + 1)]$ (Johnson et al. 1994).

that has adopted by time t, $F(t)$, equals 1- $F_\theta(p(t))$, where F_θ is the c.d.f. of the threshold distribution. Since the price of innovations tends to decrease in real terms in an approximately exponential fashion (e.g., Agarwal and Bayus 2002), we assume that the price path is given by $p(t) = 45\ e^{-.1t}$. This results in the two diffusion curves shown in Figure 2. Clearly, the diffusion curve corresponding to the higher Gini value (more inequality) is less skewed to the right and will hence have a higher q/p ratio than the other curve. (Fitting the Bass model to each curve and forcing the ceiling to 1 to avoid censoring bias, the estimated q/p ratios are 20 and 6.)

2.3.2. G/SG model

The G/SG model implies that the q/p ratio of the diffusion curve will vary with the scale parameter β of the heterogeneity distribution of the adoption tendency η. Since high values of η lead to late rather than early adoption, it cannot be interpreted as income, but can be interpreted as its reciprocal.[6] Since the G/SG model assumes η to be Gamma(α, β) distributed with mean $\alpha\beta$ and variance $\alpha\beta^2$, this implies income to be Inverse Gamma distributed with mean $[\beta(\alpha - 1)]^{-1}$ and variance $[\beta^2(\alpha - 1)^2(\alpha - 2)]^{-1}$, an assumption that is reasonable (e.g., Kloek and van Dijk 1978).[7]

Hence, if diffusion operates as described by the G/SG model and η is reciprocal to income, then the following should hold:

H8: The q/p ratio is positively associated with the scale of the reciprocal of income, assuming income is Inverse Gamma distributed.

As eq. (4) shows, the G/SG model reduces exactly to the Bass model only if $\alpha = 1$. Income distributions, however, typically have $\alpha > 1$. Fortunately, the assumption that $\alpha = 1$ is not critical

[6] We thank Albert Bemmaor for this suggestion.

[7] Unlike what one might perhaps expect intuitively, the Inverse Gamma distribution can be bell shaped and skewed like the Gamma. Actually, there is a direct relationship between their pdf's. If $\eta \sim$ Gamma(α,β) with pdf $g(\eta)$ and $\eta = 1/y$, such that $y \sim$ IG(α,β) with pdf $ig(y)$, then $ig(y) = g(\eta)\eta^2$.

Figure 1. Gamma threshold distributions with high and low Gini coefficient

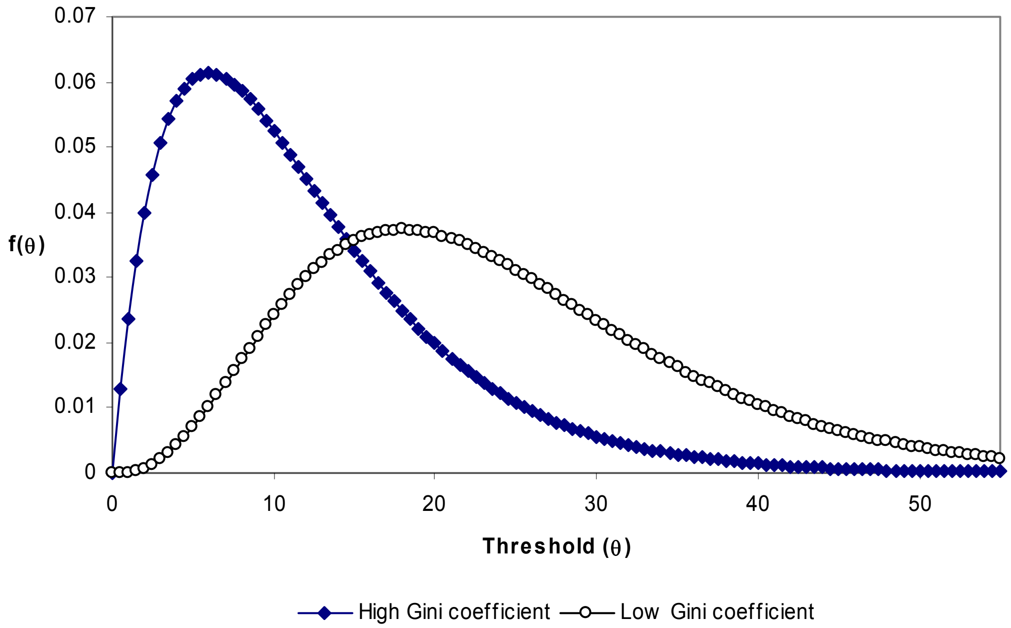
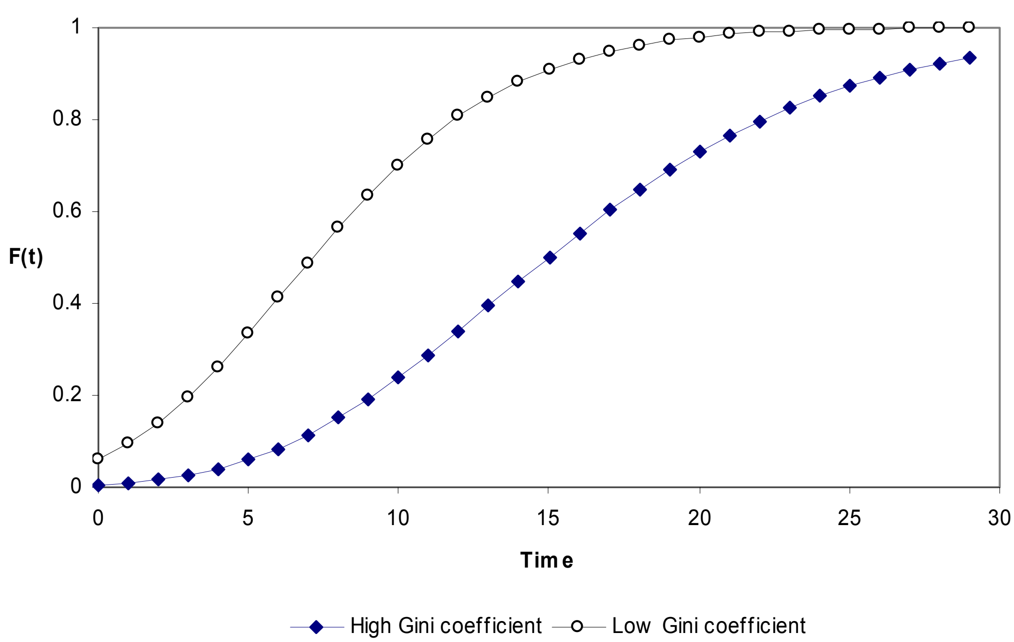


Figure 2. Corresponding diffusion curves, assuming price declines exponentially ($p(t) = 45\ e^{-.1t}$)



to test H8: estimates of q/p obtained from estimated a traditional Bass model tend to approximate β even when the true data generating process is G/SG with $\alpha > 1$ (see Appendix).

Even though the scale of the reciprocal of income is highly negatively correlated with average income, the directional prediction in H8 can not be derived from the contagion interpretation unambiguously. Some work in the latter tradition has posited that wealthier countries may exhibit a higher average tendency to adopt. It is not clear *a priori*, however, whether average income affects diffusion by increasing the size of the adopter population (m or "market ceiling" in the Bass model), the tendency to adopt early regardless of others' behavior (p), or both. That average income would boost p is hence conceivable, but is not a strong prediction flowing from the social contagion interpretation.[8] Moreover, since the importance of social status considerations in the adoption of innovations captured in q is expected to increase with average income (e.g., Becker and Murphy 2000), social contagion may also make that q increases with average income. In short, whereas the G/SG model implies that q/p is inversely related to average income, social contagion makes no such clear directional prediction.

2.4. Heterogeneity and competing standards

To the extent that the presence of competing standards results in excess inertia, it will dampen the extent to which the diffusion curve reflects the shape of the income distribution. Similarly, to the extent that the presence of competing standards results in excess inertia and endogenous feedback, the G/SG model and its predictions will not hold for products with competing standards. Hence we posit:

H9: The effect of competing standards on q/p dampens the effect of (a) the Gini coefficient and (b) the scale of the reciprocal of income, assuming income is Inverse Gamma distributed.

[8] Studies by Dekimpe et al. (1998) and Talukdar et al. (2002) report evidence that m increases with average income, but do not provide evidence that p does.

4. Methods

4.1. Research design

To test our hypotheses, we use a meta-analysis of published q/p ratios of consumer durables. Meta-analysis, the statistical analysis of results from previous individual studies, is a way to document robust patterns that generalize across a variety of data collection designs, estimation methods, and products and adopter populations. While meta-analysis is often used to synthesize prior research (e.g., Sultan et al. 1990), it can also be used to test hypotheses of theoretical interest (e.g., Geyskens et al. 1999; Miller and Pollock 1994). We limit our study to consumer products because the income heterogeneity hypotheses do not apply to businesses and other organizations. We limit our study to durables because their non-negligible price makes them a more relevant domain to test heterogeneity and contagion hypotheses: income thresholds are likely to matter, products are more likely to convey status, and adoption is more likely to present financial risk.

4.2. Literature search and inclusion criteria

We limited the search for applications of the Bass model to published research reports. We performed a forward citation search in the *Social Science Citation Index* computerized database, retrieving all articles published between January 1969 and May 2000 citing the Bass (1969) paper. We also performed subject searches in the *ABI Inform* and *EconLit* databases for the same period using the keywords “Bass & diffusion,” “Bass & new product,” “product diffusion,” and “new product growth.” Further, we manually checked early volumes of *Marketing Letters* and the *International Journal of Research in Marketing* excluded from the *SSCI*, checked three edited book volumes (Mahajan and Wind 1986; Wind et al. 1981; Mahajan et al. 2000), and checked our file drawers for additional publications reporting Bass model estimates.

For a study to be included, it had to report estimates for the basic Bass model, possibly extended with control variables, applied to new consumer durables. Both *p* and *q* had to be estimated and $\hat{p}$ and $\hat{q}$ had to be reported in the original form or sufficient information had to be provided for one to retrieve the original parameters' estimates via some transformation.

This procedure resulted in 746 sets of estimates pertaining to 75 different consumer durables in 77 countries and reported in 54 publications. For 44 of those countries, representing 694 observations, Hofstede culture scores are available. Since both the mean and Gini value of income vary over time, calculating income heterogeneity requires that the publication identify the start and end year of the data series used for estimation and that data be available to calculate both average income and Gini for that period and that country. This reduced the sample size to 302. Finally, we deleted observations for which *p* or *q* was smaller than zero or larger than 1. Our final data set contains 293 observations pertaining to 52 different consumer durables in 28 countries and reported in 46 publications.

4.3. Variables

4.3.1. Dependent variable. To reduce skew, we use $\ln(\hat{q}\ /\ \hat{p})$ as our dependent variable. It has only moderate skew (-.68) and kurtosis (5.38) compared to the normal (0 and 3).

4.3.2. National culture. We use Hofstede's (2001) national culture scores UAI, IDV, PDI and MAS based on data collected in the early 1970s. This period corresponds to the average start year of the data series used to estimate the *p* and *q* values included in our sample.

4.3.3. Competing standards. To account for the presence of competing standards, we use a dummy variable coding scheme. The variable COMPSTAND equals 1 for PCs (N = 3), VCRs (N

= 57), and cellular telephones (N = 43) and equals 0 for other products. The decision to code cellular telephones as a category with competing standards can be questioned (Van den Bulte 2000), especially for non-US countries where cellular telephony services may have been offered by state monopolies using only a single technology. So, to assess robustness, we also created a separate CELLTEL dummy variable. The mean effects of cellular telephones are not different from those of other products with competing standards (see below).

4.3.4. Income heterogeneity. Many measures of income inequality exist, the most commonly used being the Gini concentration index or Gini coefficient, C. Another very popular index of income inequality is the Gini's mean differences, GMD, which is the expected value of the absolute difference between the incomes of two independently drawn people or households. An important difference between the two measures is that the first is a measure of relative inequality such that scaling all incomes in a country proportionally does not affect the value of the index. The latter is a measure of absolute inequality and does not change when all incomes in a country are increased by the same amount. For variables that do not assume negative values, both measures are closely related, since multiplying the relative index by twice the mean value μ leads to the absolute index (Johnson et al. 1994):

$$GMD = 2C\mu \qquad [5]$$

Because the Gini coefficient C is an index of relative inequality, it is not affected by the scale factor of the distribution. For distributions with separate shape and scale parameters, this means that it is a function of the shape parameter only. This is problematic for testing hypothesis H8, since it pertains to the scale rather than the shape of the heterogeneity distribution. However, a more complex relationship exists that allows us to relate the scale parameter β to available macro-economic data on the mean and Gini of national income distributions. Recall that H8, based on combining the G/SG model structure with income heterogeneity, assumes that income is Inverse Gamma distributed with mean $\mu = [\beta(\alpha - 1)]^{-1}$ and standard deviation $\sigma = [\beta(\alpha - 1)(\alpha - 2)^{1/2}]^{-1}$, where α and β are the parameters of the G/SG diffusion model. This implies $\sigma/\mu = (\alpha - 2)^{-1/2}$. Since many moderately skewed distribution have $\sigma \approx GMD$ (Hosking and Wallis 1997, p. 35), eq. (5) implies $2C \approx (\alpha - 2)^{-1/2}$, and hence $(2C)^{-2} + 1 \approx \alpha - 1$. Combining this expression with the formula for the mean $\mu = [\beta(\alpha - 1)]^{-1}$ results in the expression $\beta \approx [\mu \{(2C)^{-2} + 1\}]^{-1}$, where μ is the average income and C the Gini coefficient of the income distribution.

We measure average income using the real gross domestic product per capita expressed in 1996 international prices reported in the Penn World Table (Mark 6.1) published by the Center for International Comparisons at the University of Pennsylvania (Summers and Heston 1991). All expenditures in this database are denominated in a common currency based on purchase power parities rather than exchange rates, so valid comparisons can be made across countries and over time. Since the Penn World Table covers the period 1950-2000 only, our main data set contains only p and q estimates from data series starting in 1950 or later.

We use the Gini coefficients calculated by Deininger and Squire (1996) and published by the World Bank. Since we use a per capita measure of income, we use Gini values computed using personal rather than household income to maintain consistency. When multiple values are available for a country, we linearly interpolate between the years. Outside the interval, we use the value observed in the nearest year.

Since both mean income and the Gini coefficient can vary over time, we use the average Gini and the average mean income observed over the period used for estimating p and q. Since we use the logarithm of $\hat{q} / \hat{p}$ as our dependent variable, we similarly transform our income heterogeneity scale metric $[\mu\{(2C)^{-2}+1\}]^{-1}$, creating the variable LNSCALE. We also take the log of the Gini coefficient, creating the variable LNGINI.

4.3.5. Control variables. Before computing the dependent variable $\ln(\hat{q}/\hat{p})$, we recoded 8 zero values of $\hat{p}$ and 4 zero values of $\hat{q}$ to 0.01. We therefore add control dummy variables, PNULL and QNULL, that take the value 1 when such recoding occurred and 0 otherwise.

We also add two dummy variables capturing heterogeneity in the products. The first is BRAND, capturing whether the original data series pertained to the entire product category or to the product of particular manufacturer (N = 4). One might expect the growth trajectory of the latter to have a less pronounced S-shape. Second, following Van den Bulte (2000), we created a variable INFRA that takes the value 1 for one-to-many broadcasting products requiring large investments in infrastructure (black and white TV, cable TV, color TV, and radio; N = 66). Unlike Van den Bulte (2000) in his study limited to the U.S.A., we do not code cellular telephones as requiring large infrastructure investments because in many developing countries cellular telephony is used as a means to avoid the even larger investments in fixed-line equipment. Treating cell phones as a separate category does not affect the results (see below).

STARTC is the year in which the data series starts, centered around the sample mean (1972.8). This variable captures both genuine changes in the average q/p ratio over time across products and countries (compare Sultan et al. 1990) and the bias stemming from different levels of left-truncation across different analyses of the same product in the same country (Dekimpe et al. 1998). As a result, no interpretation will be offered.

We include several variables to control for variation in the $\hat{q}/\hat{p}$ ratio possibly induced by differences in how the estimates were obtained (e.g., Putsis and Srinivasan 2000).

First, we allow for different estimation techniques to lead to different results (Sultan et al. 1990). Using non-linear least squares as the baseline, we coded three dummy variables: ESTOLS for OLS, ESTMLE for maximum likelihood, and ESTOTH for others like Dekimpe et al.'s (1998) staged procedure. One would not expect effects for ESTOLS and ESTMLE (Putsis and Srinivasan 2000), but it is possible that authors resort to other techniques when these more traditional approaches do not lead to satisfactory results (e.g., convergence problems).

Second, we coded whether the model was formulated in discrete or continuous time (CONTTIME). This takes into account that the discrete-time specification may result in a bias.

Third, we control for the number of observations used in the estimation. We do so by using two variables. WINDOW10 captures the number of years covered by the data series, in tens of years. LNFREQ is the natural logarithm of the data frequency (1 for annual, 4 for quarterly (N = 12), 12 for monthly (N = 10)). Research documenting systematic increases in $\hat{p}$ and decreases in $\hat{q}$ as one extends the data series suggests a negative relation between $\hat{q} / \hat{p}$ and WINDOW10. If this effect stems from ill-conditioning, as Van den Bulte and Lilien (1997) claim, then one should also observe a negative association between $\hat{q} / \hat{p}$ and LNFREQ. However, LNFREQ may also capture time-aggregation bias, in which case the recent results by Non et al. (2003) imply a positive association.

A fourth issue is the frequent use of data other than actual adoptions or penetration rates, which leads to contamination by replacement and additional purchases. As Putsis and Srinivasan (2000, p. 280) note, "shortly after the introduction this is likely to be only a minor problem, although we have no empirical evidence documenting the degree—or lack—of any bias that may result." However, as they note, the problem is likely to be exacerbated the more years are covered in the data series (see also Parker and Neelamegham 1997). So, we create a NONADOP dummy taking value 1 when either sales (N = 196) or production (N = 6) data were used and taking value 0 when adoption or penetration data were used (N = 91), as well as an interaction term NONADOP*WINDOW10.

Fifth, we coded three dummies to capture to what extent $\hat{q} / \hat{p}$ is associated with whether the Bass model allowed p, q or m (the ceiling parameter) to vary as a function of covariates (P_CONTROL, Q_CONTROL, M_CONTROL). Finally, we also control for whether m was allowed to vary over time as a proportion of the total population M, i.e., $m(t) = \lambda M(t)$, by dummy variable PROPCEILING. The arithmetic of discrete-time empirical hazard rates (e.g., Allison 1984) implies that failing to control for growth in the ceiling (and hence the "population at risk") is likely to underestimate the hazard rate early on and overestimate how much the hazard rate increases over time. Hence, one would expect both M_CONTROL and PROPCEILING to be associated with a higher $\hat{p}$, a lower $\hat{q}$, and thus a lower $\hat{q} / \hat{p}$.[9]

4.4. Descriptive statistics

The 293 observations pertain to 52 different consumer durables in 28 countries. Color television accounts for 60 observations (20%), VCRs for 57 (19%), cellular telephone for 43 (15%), and microwave ovens for 16 (5%). The US account for 210 observations (72%), Asia for 36 (12%), Europe for 33 (11%), and Latin America for 14 (5%). For $\hat{p}$, the mean is 0.027, the median is 0.012 and the 10%-90% range is 0.001 – 0.083. For $\hat{q}$, the mean is 0.419, the median is 0.420 and the 10%-90% range is 0.128 – 0.690. The means are quite close to those reported in the meta-analysis by Sultan et al. (1990).

[9] When extending his theoretical model with market growth, Davies (1979, p. 81) similarly obtains that the rate of growth in the size of the population is inversely related to the steepness of the diffusion curve. This leads to the same prediction about the *q*/*p* ratio.

Table 1 reports descriptive statistics for the variables of substantive interest. Some correlations are high. To better assess the danger of harmful collinearity, we performed a conditioning analysis of all variables included in the analysis. Only when both LNSCALE and national culture variables entered jointly did both the condition number and two or more variance decomposition proportions exceed the commonly accepted cut-offs for potentially harmful collinearity (30 and 0.8, respectively). Otherwise, the relatively large sample size seems to protect us from harmful collinearity in spite of some high bivariate correlations reported in Table1.

Table 1. Descriptive statistics of variables of substantive interest

	Mean	SD	Min	Max	Correlations 1	2	3	4	5	6	7
1. ln(q/p)	3.42	2.13	-7.93	10.96							
2. IDV	79.63	22.83	6	91	-0.24						
3. UAI	50.69	13.26	23	112	0.26	-0.71					
4. PDI	43.54	12.64	11	104	0.13	-0.69	0.43				
5. MAS	58.50	12.85	8	95	-0.01	0.42	-0.12	-0.16			
6. LNGINI	-1.02	0.13	-1.16	-0.49	0.20	-0.75	0.69	0.56	-0.47		
7. LNSCALE	-10.66	0.75	-11.37	-8.14	0.15	-0.85	0.43	0.78	-0.37	0.59	
8. COMPSTAND	0.35	0.48	0	1	0.34	-0.29	0.27	0.04	-0.27	0.35	0.00

4.5. Statistical model

Since we have repeated observations for the same products and the same countries and the observations are not independent, we use a multilevel model allowing for random effects in both the intercept and slopes across both countries and products. Using subscript i to denote a product, j to denote a country, k to denote a replication, and s to identify a covariate, the model structure we use to explain variations in the observed $\ln(\hat{q} / \hat{p})_{ijk}$ is:

$$\ln(\hat{q} / \hat{p})_{ijk} = \gamma_{0ij} + \Sigma_s \gamma_{sij} x_{sijk} + \varepsilon_{ijk} \quad (s: 1, \ldots, S), \quad \text{where} \qquad [9]$$

$$\gamma_{sij} = \gamma_s + U_{si} + U_{sj} \quad (s: 0, \ldots, S),$$

$$\varepsilon_{ijk} \sim N(0, \sigma^2),\ U_{si} \sim N(0, \tau_s^2), \text{ and } U_{sj} \sim N(0, \upsilon_s^2).$$

Since the panel is very unbalanced with many product-country combinations having no or a very few observations, we impose a variance components structure, Cov (U_{si}, $U_{s'i}$) = 0 and Cov (U_{sj}, $U_{s'j}$) = 0. We estimate the model using residual maximum likelihood or REML, as is common for hierarchical linear models. We use the BIC to identify the simplest yet statistically defensible error structure.[10] We use *t*-tests to assess whether the γ_s parameter estimates are significantly different from zero. Note that the model allows for a random effect when the mean effect γ_s is forced to zero. When performing robustness checks pertaining to treating cellular telephones as a separate category, we found that allowing for a random country effect for cellular telephones better captured the error correlation structure than doing so for all products with competing standards. So, we will report models allowing for such random effects even when the CELLTEL dummy does not enter as a regressor ($\gamma_{celltel} = 0$).

5. Results

Table 2 reports the fixed or mean slope effects (γ_s) of three models. All include the control variables and the competing standards dummy, but differ in the set of other covariates of theoretical interest. Model 1 includes only the culture variables. Model 2 includes only the income distribution variables. Model 3, finally, includes all covariates.

Since COMPSTAND is binary 0-1, the linear effects of IDV, UAI, PDI, MAS, LNGINI and LNSCALE pertain to products without competing standards, and their interaction with COMPSTAND capture whether these linear effects are different from those for products with

[10] We also used a more traditional specification with random effects at the level of the individual product-country combination. BIC comparisons indicated this specification to be inferior to one with crossed random effects for product and country separately.

Table 2. Effects of culture, heterogeneity and competing standards on ln(*q*/*p*)

Independent variables	Model 1: National culture [a]		Model 2: Income heterogeneity [b]		Model 3: Full model [c]	
	γ	t	γ	t	γ	t
Intercept	4.401***	8.11	4.052***	5.99	4.665***	7.64
IDV	-0.101***	-3.84			-0.109*	-1.79
UAI	-0.023	-1.47			-0.137***	-2.88
PDI	-0.008	-0.28			0.100**	2.00
MAS	0.233***	4.38			0.277***	5.35
LNGINI			2.707**	2.29	12.593***	3.90
LNSCALE			1.793***	6.97	-1.667	-1.04
COMPSTAND	1.694**	2.07	2.527*	1.71	3.089***	3.67
COMPSTAND x IDV	0.115***	4.17			0.124**	1.97
COMPSTAND x UAI	0.041**	2.08			0.157***	3.13
COMPSTAND x PDI	-0.002	-0.07			-0.097*	-1.83
COMPSTAND x MAS	-0.244**	-2.53			-0.292***	-3.25
COMPSTAND x LNGINI			-5.414***	-2.78	-16.094***	-4.37
COMPSTAND x LNSCALE			-1.694***	-3.82	2.184	1.25
INFRA	-1.464**	-2.49	-1.532	-0.98	-1.000	-1.52
BRAND	-10.037***	-8.66	-4.035**	-2.41	-9.815***	-8.28
STARTC	-0.066**	-2.40	-0.097**	-2.57	-0.111**	-2.58
WINDOW10	-0.973***	-2.87	-0.891**	-2.39	-1.351***	-3.15
LNFREQ	-0.236**	-2.06	-0.285**	-2.48	-0.269**	-2.39
NONADOP	-1.489**	-2.52	-1.229**	-2.28	-1.767***	-2.85
NONADOP x WINDOW10	1.098***	2.76	0.850**	2.05	1.286***	3.08
ESTOLS	0.124	0.19	-0.262	-0.96	-0.133	-0.43
ESTMLE	0.707**	2.03	0.771**	2.46	0.510	1.59
ESTOTH	1.450***	3.15	1.394***	3.13	1.404***	3.01
CONTTIME	0.643**	2.29	0.485**	1.90	0.673**	2.38
P_control	-0.304	-0.87	-0.419	-1.21	-0.228	-0.66
Q_control	-0.685	-1.66	-0.582	-1.43	-0.683*	-1.69
M_control	-0.670**	-1.98	-0.600**	-1.77	-0.617*	-1.85
PROPCEILING	-1.237***	-3.98	-1.021***	-2.96	-1.286***	-4.10
PNULL	-0.245	-0.61	-0.183	-0.46	-0.071	-0.17
QNULL	-3.897***	-5.21	-3.787***	-4.68	-3.770***	-5.01
-2 Res LL [d]	990.5		970.6		969.3	

* $p \leq 0.10$; ** $p \leq 0.05$, *** $p \leq 0.01$.

[a] Coefficients with random effects across countries are ESTOLS (Var (U) = 1.32), ESTOTH (2.60) and CELLTEL (1.23). Coefficients with random effects across products are MAS (0.01), STARTC (0.01), NONADOP (0.74), WINDOW10 (0.91), and PROPCEILING (0.85).
[b] Coefficients with random effects across countries are ESTOTH (Var (U) = 2.49) and CELLTEL (1.42). Coefficients with random effects across products are the intercept (6.57), STARTC (0.02), WINDOW10 (1.42), and PROPCEILING (1.07).
[c] Coefficients with random effects across countries are ESTOTH (Var (U) = 2.56) and CELLTEL (1.44). Coefficients with random effects across products are MAS (0.01), STARTC (0.02), NONADOP (0.79), WINDOW10 (1.01), and PROPCEILING (0.90).
[d] Because the residual likelihood function corrects for the number of fixed effects (i.e., γ coefficients), one cannot compare the likelihoods across models with different sets of explanatory variables, even if nested. Hence, likelihood ratio tests can not be conducted.

competing standards. Since we mean-centered the culture and income variables before estimation, the linear effect of COMPSTAND can be interpreted as a main effect.

Model 1 gives only partial support to the cultural hypotheses: UAI and PDI do not show the posited effect and PDI does not have the expected interaction with COMPSTAND. Model 2 shows the expected effects for both LNGINI and LNSCALE. Model 3, incorporating all posited effects and expectedly free of omitted variable bias, finds support for all hypotheses except two: UAI has a negative rather than a positive effect (though this is moderated by the presence of competing standards) and LNSCALE has no effect at all. The effect of LNGINI, an elasticity of 12.6, seems quite large but is not excessive taking into the difference in range between the explanatory and the dependent variable.[11] Before discussing the findings in greater detail, we report on some robustness checks.

5.1. Robustness checks

To check the robustness of the results in Table 2, we performed four additional analyses reported here only briefly. First, to check the sensitivity to our coding of cellular telephones, we extended the full model with a CELLTEL dummy and with its interaction terms with each of the cultural dimensions. None of the new coefficients was significant ($p > 0.10$) and the other coefficients barely changed. Second, using the natural log of the culture variables does not make the results more consistent with social contagion. In Model 3, for instance, the effect of UAI remains negative and highly significant and the negative effect of IDV remains significant at 90% confidence only. Third, as a check against collinearity artifacts involving LNSCALE and the culture variables, we re-estimated Model 3 without LNSCALE. This reduced the coefficient

[11] The LNGINI coefficients capture the simple effect when COMPSTAND = 0. Additional tests indicate that the simple effect of LNGINI when COMPSTAND = 1 in Models 2 and 3 is negative (-2.7 and -3.5, respectively) but significant only at 90% confidence.

of IDV from -.109 to -.053 but increased the confidence level from 92.5% to 95.2%. It also reduced the coefficient of PDI from 0.100 to 0.061 (both significant at 5%). Other coefficients and confidence levels barely changed. This high level of stability indicates that the null effect of LNSCALE in the full model cannot simply be dismissed as an artifact stemming from harmful ill-conditioning of the model-data structure (Myers 1990). Finally, we expanded our data set with 107 observations having 1949 as start date of the data series, i.e. one year before the Penn World Table data on mean income start. Given that we average income over the entire length of the data series, we judge that imputing the 1950 mean income values for the 1949 values would create only a very low level of measurement error in the covariates. Doing so allows us to add 107 observations, all from the US, bringing the total sample size to 400. This addition increases the number of products from 52 to 62, though most observations pertain to clothes dryers (N = 46) and room air conditioners (N = 42). Re-estimating all models on this expanded data set led to remarkably similar coefficients and identical hypothesis test results, the only difference being that the gain in statistical power nudged some effects from the 90% to the 95% confidence level (e.g., IDV and COMPSTAND*PDI in Model 3).

5.2. Results of theoretical interest

The effects of the control variables are fairly robust across specifications, so we will discuss them after the results of theoretical interest. Five key results emerge from the analysis taking into account national culture, income heterogeneity, and the presence of competing standards. First, we find support for most of the culture hypotheses and, hence, for the social contagion interpretation of the Bass model—at least for categories without competing standards. Second, our results shed some light on the nature of the social contagion process. Consistent with social cohesion accounts for why social contagion might occur, we find that less individualistic and more collectivistic cultures tend to have a higher q/p ratio. Also, we find that cultures with high power distance and masculine values have a higher q/p ratio. This is consistent with a long tradition in sociological theory positing that competition for status can be, and often is, an important source of social contagion in innovation diffusion (e.g., Burt 1987; Simmel 1971). Surprisingly, we find that cultures with high uncertainty avoidance tend to have lower rather than higher q/p ratios. This is inconsistent with the often-espoused but poorly documented interpretation that q captures the effect of a risk mitigation strategy by later adopters. However, we do find evidence that uncertainty avoiding cultures have higher q/p ratios for products with competing standards. Since such products exhibit arguably high levels of uncertainty and risk, this finding is consistent with the contagion-as-uncertainty-mitigation mechanism.[12]

Third, we find that the q/p ratio varies positively with the Gini index of income inequality. This is consistent with the interpretation of S-shaped diffusion curves as stemming from heterogeneity in adoption thresholds related to income, rather than only from social contagion. Fourth, we also find evidence, consistent with the G/SG model, that the q/p ratio varies positively with the scale of the heterogeneity if η is interpreted as the reciprocal of income. The evidence, however, is not very strong: the effect disappears once one controls for differences in national culture.

Fifth and finally, we find not only that the presence of competing standards has a large main effect on the q/p ratio but also that it interacts with both culture and the Gini index of income heterogeneity. While the results are consistent with our hypotheses on how culture moderates the

[12] It is conceivable that the significantly negative effect of UAI on q/p is an artifact operating via the set of potential adopters captured in the adoption ceiling m. In highly uncertainty avoidant countries, many consumers may prefer to avoid innovations altogether. As a result, the set of potential adopters consists primarily of very innovative consumers, resulting in a low q/p. While post-hoc, this "approach-avoidance" type explanation is consistent with the finding that uncertainty avoidant cultures use fewer insurance products, presumedly because consumers prefer to avoid thinking about uncertainty altogether (de Mooij 1998).

risk of adopting a losing technology, an alternative interpretation is that cultural effects are swamped by technology considerations. The latter interpretation follows from both Models 1 and 3, where the interaction term between COMPSTAND and each cultural dimension is about equally large as that dimension's main effect, but with the reverse sign. The relative size of the linear and interaction coefficients of LNGINI in Model 3 suggests that the presence of competing standards swamps how the shape of the income distribution is reflected in the shape of the diffusion curve.

5.3. Results of methodological interest

Even though our research design and analysis were not optimized to identify methodological effects causing estimates to diverge from their true value, the results involving some of the control variables are relevant to current methodological issues in diffusion modeling.

The negative effect of WINDOW10 indicates that longer time series are associated with lower $\hat{q}\ /\ \hat{p}$ values. The estimated effect sizes are quite sizable. Increasing the number of observations from 10 to 20 is associated with an expected decline in the $\hat{q}\ /\ \hat{p}$ ratio ranging from about 60% (1-exp(-0.9)) in Model 2 to about 75% (1-exp(-1.4)) in Model 3.

The negative association between LNFREQ and $\hat{q}\ /\ \hat{p}$ is consistent with Van den Bulte and Lilien's (1997) claim that the systematic changes in $\hat{q}$ and $\hat{p}$ that occur as one adds later data points can stem from ill-conditioning. Keeping constant the number of years covered, increasing the data frequency increases the number of data points, which improves conditioning.

The significant effects of NONADOP and its interaction term with WINDOW10 confirm the increasing concerns that using sales rather than adoption or penetration data might systematically affect parameter estimates. Our results indicate that, while in short data sets it tends to depress the $\hat{q}\ /\ \hat{p}$ ratio, in long data sets it tends to inflate the ratio. The relative size of two coefficients indicates that, in our sample, the switchover occurs at about 14 data points. This is only a sample mean, though, and the effects probably vary across product categories—e.g., as a function of the replacement cycle. Lilien et al. (2000), for instance, found very little difference between using sales and penetration data for air conditioners and clothes dryers for 13 years, whereas findings by Parker and Neelamegham (1997) suggest that major problems can occur with as little as 10 data points.

We find no statistically significant differences among the three main estimation techniques (NLS, OLS and MLE) that are consistent among the three models in Table 2. While we do find that using other techniques is associated with a higher $\hat{q} / \hat{p}$ ratio, this might simply reflect that researchers resort to such alternatives when standard techniques fail to converge or to produce reasonable estimates.

As to extending the Bass model with marketing and other control variables to capture temporal variations in p, q or m, we find that controlling for changes in p does not affect the $\hat{q} / \hat{p}$ ratio. The effects of controlling for changes in q are quite marginal, and those of controlling for changes in m are robust and significant at 90% confidence. Expressing the ceiling as a proportion of a time-varying total population tends to depress $\hat{q} / \hat{p}$ considerably, as shown by the larger negative coefficient and the higher confidence level of PROPCEILING. This result is consistent with the idea that not controlling for growth in the population at risk creates an upward bias in the slope of the hazard rate.

6. Discussion

6.1. Implications for diffusion theory

Our results provide empirical support for the role of population heterogeneity in the aggregate-level diffusion path of consumer innovations. That population heterogeneity without contagion could in principle generate a Bass-type diffusion curve has long been known. Our results imply that this can no longer be bracketed as merely an interesting but empirically vacuous analytical result. Specifically, the substantive proposition that income heterogeneity produces diffusion patterns consistent with the Bass model survives an attempt at refutation across a large number of products and countries. More generally, our results add to a body of empirical evidence casting doubt on the dominant role of social contagion in the diffusion of innovations. While a small number of discussions in marketing have raised this possibility (Gatignon and Robertson 1986; Parker 1994), there has long been a want of evidence (Stoneman 2002). Our results from data covering a large set of consumer products and countries over a wide time window corroborate findings from more narrowly focused studies that social contagion need not be the sole or even main mechanism driving the diffusion of innovations (e.g., Kraatz and Zajac 1996; Van den Bulte and Lilien 2001).

While our results regarding income heterogeneity cast doubt on the sole dominance of contagion, our results regarding culture and competing standards indicate that social contagion is indeed at work. In addition, our study also sheds some light on the nature of the contagion process. Specifically, our results involving national culture indicate that the cross-national variation in the extent of contagion is better explained by status considerations than by uncertainty mitigation. The idea of emulation driven by status concerns has a very long tradition in sociology, but has not yet been put to use in diffusion modeling by marketers. Our results suggest that diffusion research might benefit from explicitly taking into account status considerations as one of the mechanisms underlying social contagion.

Our meta-analytic results are of particular relevance to international diffusion research. Not only do they provide strong support to the general claim that culture affects diffusion and sales growth, but they also show that all four of Hofstede's cultural dimensions matter. Prior research in international new product growth and consumer innovativeness has mostly used a subset of cultural traits (Gatignon et al. 1989; Jain and Maesincee 1998; Steenkamp et al. 1999; Tellis et al. 2003). The dimension of power distance, in particular, has been ignored. This stems, we believe, from prior research's theoretical focus on communication among socially cohesive actors. Classic sociological theory (e.g., Simmel 1971) and more recent social network theory (Burt 1987), however, provide arguments to also include status considerations, and cultural dimensions associated with them, in marketing diffusion theory and research.

We found clear evidence that the presence of competing standards is associated with more strongly S-shaped diffusion patterns. This corroborates earlier analytical (Choi 1997) and empirical results (Van den Bulte 2000). Interestingly, we also find interaction effects between the presence of competing standards and cultural dimensions associated with status considerations, social cohesion, and social learning. While the results are consistent with our expectations on how culture may moderate fears of getting stuck with a losing product technology, they may also indicate that cultural effects are swamped by technology considerations. Since products with competing standards always have strong technological network effects, our findings should also be of interest to research on how network effects affect new product growth. Technological network effects and culturally mediated social contagion effects need not operate independently from each other (compare Choi 1997).

6.2. Implications for empirical diffusion modeling

The findings regarding the methodological control variables confirm three concerns in the current marketing diffusion literature. First, they corroborate indirectly earlier simulation and small-sample results that short data series tend to have a lower $\hat{p}$ and a higher $\hat{q}$, even when the

Bass model is the true data generating model (Bemmaor and Lee 2002; Van den Bulte and Lilien 1997). While the reverse can happen when the data exhibit more right skew than the Bass model can account for (Bemmaor and Lee 2002), our results show that this reverse pattern is the exception rather than the rule for consumer durables. The finding that using data with a higher frequency is associated with a lower $\hat{q} / \hat{p}$ is also consistent with Van den Bulte and Lilien's (1997) claim that systematic change in $\hat{q}$ and $\hat{p}$ stem from ill-conditioning. The implication is obvious: short data series with few observations should be avoided.

Our findings also confirm concerns that studies using sales data tend to arrive at different parameter estimates than studies using adoption or penetration data (Putsis and Srinivasan 2000). The size and direction of the deviation tends to be a function of the length of the data series. The implication for future research is again obvious: unless the replacement cycle is very long and households buy only a single unit, sales data should be avoided when estimating models of diffusion (i.e., first-time purchase). Trying to avoid data contamination by using shorter data series is not a proper solution since it raises other problems, as just noted.

Finally, our findings also suggest expressing the ceiling as a proportion of the time-varying population or allowing for other changes in the market ceiling over time (e.g., Bayus 1992; Horsky 1990) tends to result in a lower $\hat{q} / \hat{p}$ ratio. This is consistent with the idea that not controlling for growth in the population at risk creates an upward bias in the slope of the hazard rate. Even when no data are available beyond the size of the total population, using this information may help one avoid spurious evidence of contagion.

The three implications just presented apply to any application of the Bass model to stand-alone data series. Our finding that income heterogeneity and national culture are associated with the q/p ratio also has an important implication for multinational diffusion studies of cross-country spill-over effects (see Dekimpe et al. 2000 for a review). Since income inequality and culture tend to be spatially autocorrelated (i.e., more similar across nearby countries than across distant countries) and since not controlling for country-specific attributes that are spatially autocorrelated can lead to spurious spill-over effects (e.g., Arbia 1989), studies of inter-country contagion should control not only for basic economic variables (e.g., Putsis et al. 1997) but also for national culture.[13]

6.3. Limitations

By necessity, our study does not test the role of heterogeneity in general but the narrower—and hence refutable—claim of income heterogeneity as a driver of adoption timing under both the threshold model and G/SG structures. Similarly, it does not test the role of contagion in general but the narrower claim that culture and competing standards affect the *q*/*p* ratio under the contagion interpretation of the Bass model. Given the over-determination of the Bass model, heterogeneity and contagion cannot be distinguished without recourse to observables that are external to the diffusion data series and that can be interpreted in terms of a more specific theory under study (Taibleson 1974). That is, one must add theoretical detail about the process at work that can lead to refutable hypotheses by specifying the type of heterogeneity, the type of contagion process, and contingency factors. Future research may seek to empirically assess each interpretation using different substantive theories and observable variables than the ones we used. Whether or not such investigations come to different conclusions than those we arrived at, they are bound to enrich our understanding of what drives diffusion.

The present study is a meta-analysis of previously published estimates. While it provides us

[13] This is also suggested by a recent study by Kumar and Krishnan (2002). They did not control for national culture when estimating their cross-country contagion model, and found that the extent of contagion between two countries was significantly associated with how similar the countries were on Hofstede's national culture dimensions.

with a wide variety of products and countries, a meta-analysis as ours could fruitfully be complemented by primary studies that allow for a more focused assessment of the income heterogeneity arguments. Specifically, we did not use information on the path of price declines when testing the heterogeneity-in-thresholds argument. An alternative research strategy would be to build a data base of diffusion time series and price level time series for multiple products in one or more countries, estimate the shape of the income distribution, formulate the expected diffusion curve for each product as a function of prices and the income distribution, and assess how well this performs compared to more standard diffusion models adding a price component to a contagion model. Such a study would expectedly have lower external validity than ours but would incorporate information on the path of price declines.

As to the G/SG model, when constructing our variable operationalizing the scale parameter β, we assumed that the Gini mean difference is a good approximation of the coefficient of variation. For countries with large inequality and hence very skewed income distribution, however, the approximation may not be very good. Also, the q/p estimates we used were obtained assuming a Bass model where α is forced to equal 1. This assumption, while defensible for our research purposes (see Appendix), very probably increased the error variance between the genuine β expressed as a function of mean income and our dependent variable. This additional error variance will have rendered our test of the predictions of the G/SG model more conservative. Future research that estimates α freely might therefore find more supportive evidence regarding the scale parameter β than our study did. Moreover, it will also allow one to test hypotheses relating the G/SG shape parameter α to relative income inequality.

We designed our study to test alternative—though not mutually exclusive—substantive theories, while controlling for possible methods effects in the estimates of p and q. The methodological findings warrant further investigation using a data-analysis design optimized to detect method-induced effects. Such a study would ideally focus on variance across multiple "replicate estimates" for the same innovations in the same country, rather than on the variance across innovations and across countries which is more relevant to the substantive research question addressed in the present study. A more in-depth analysis of method-induced variation therefore falls outside the scope of the present study.

6.4. Conclusion

Heterogeneity, social contagion, and supply-side considerations like product differentiation, competing standards, and the provision of complements lie at the core of current diffusion theory and research (Stoneman 2002). Our meta-analysis indicates that income inequality, cultural differences related to social structure, and competing standards all matter, and mostly in ways consistent with both heterogeneity and contagion arguments. As with the "nature vs. nurture" debate, the most reasonable answer does not lie at either extreme.

Appendix

When $\alpha > 1$, Bemmaor's G/SG model is not identical to the Bass model, and β need not exactly equal q/p. This is likely under the assumption that the distribution of the adoption propensity η reflects the income distribution, since in most countries household and personal income is better described using a Gamma or Inverse Gamma distribution with $\alpha > 1$. In our data set, the Gini coefficients range between 0.314 and 0.615. Assuming for computational convenience a Gamma income distribution, the corresponding α values range from 2.97 to 0.56. The mean Gini is 0.34, implying a Gamma income distribution with $\alpha = 2.5$. Only 9 out of 293 observations have a Gini larger than 50% implying an income distribution with $\alpha < 1$.

This raises the following question: Is the $\hat{q} / \hat{p}$ ratio a useful estimate of β when $\hat{q}$ and $\hat{p}$ are obtained from a standard Bass model but the true data generating process is G/SG with $\alpha >$ 1? Given the prevalence of left-censoring in diffusion studies, the answer is yes. Since allowing for values of α greater than 1 shifts the G/SG diffusion curve towards the right on the time-axis without affecting the curve's shape very much (Bemmaor and Lee 2002), and since most studies using the Bass model do not use the actually launch time but the start of the available data series to set the year at which t =0 (Parker 1994), assuming α =1 even when α >1 does not affect the estimated q/p ratio much. We illustrate this with a small numerical exercise.

We simulated six data series of the Gamma/Shifted Gompertz model, all with p constant at 0.03 and q at 0.38 (Sultan et al. 1990), and hence $b = 0.41$ and $\beta = 12.667$, but with $\alpha = 1$, 2.5, 5, 10, 20 and 40, respectively. Plots confirmed that increasing α shifts the G/SG diffusion curve towards the right on the time-axis but barely affects the curve's shape. We subsequently estimated a standard Bass model (i.e., with $\alpha = 1$) to the data series with $\alpha > 1$ using non-linear least squares. To reflect common practice in empirical diffusion studies using the Bass model, we treated the first period where sizable penetration is observed as the launch time. As cut-off, we used 1.5% penetration. We fit two different operationalizations of the Bass model. Fitting a continuous-time Bass c.d.f. to the cumulative G/SG data led to very good fits with all R^2's in excess of 0.99. More importantly, while $\hat{q}$ was somewhat biased upwards, the $\hat{q} / \hat{p}$ ratio did not diverge very much, certainly compared to random estimation error and previously documented biases, from the true value of β in the data generating process (Table A1). We also fit a discrete-time Bass model which does not use any information (or assumption) about the launch time to the non-cumulative G/SG data. This also resulted in very good model fit, with all R^2's in excess of 0.89. The estimated q/p ratios were very close to the true values. The better recovery of β in the discrete-time operationalization may occur because that operationalization does not require making any assumption about the (unknown) true launch time.

Table A. Estimating a Bass model to left-censored G/SG data with α > 1 does not affect the estimated *q*/*p* ratio much.

Cumulative data, Continuous-time model

α	$\hat{p}$	$\hat{q}$	$\hat{q} / \hat{p}$	Percentage error
2.5	0.0289	0.4323	14.98	+18%
5	0.0269	0.4669	17.35	+37%
10	0.0284	0.4809	16.91	+33%
20	0.0325	0.4806	14.77	+17%
40	0.0388	0.4718	12.17	-4%

Non-cumulative data, Discrete-time model

α	$\hat{p}$	$\hat{q}$	$\hat{q} / \hat{p}$	Percentage error
2.5	0.0297	0.4192	14.12	+11%
5	0.0335	0.4385	13.09	+3%
10	0.0369	0.4464	12.09	-5%
20	0.0402	0.4471	11.12	-12%
40	0.0436	0.4441	10.18	-20%

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