

# Social Contagion and Income Heterogeneity in New Product Diffusion: A Meta-Analytic Test

Christophe Van den Bulte

The Wharton School, University of Pennsylvania, 3730 Walnut St., Philadelphia, Pennsylvania 19104,  
vdbulte@wharton.upenn.edu

Stefan Stremersch

School of Economics, Erasmus University of Rotterdam, Burg. Oudlaan 50, 3000 DR Rotterdam, The Netherlands, and  
Goizueta Business School, Emory University, 1300 Clifton Road, Atlanta, Georgia 30322-2710,  
stefan\_stremersch@bus.emory.edu

Standard diffusion models capture social contagion only coarsely and do not allow one to operationalize different contagion mechanisms. Moreover, 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. We present hypotheses about conditions under which specific contagion mechanisms and income heterogeneity are more pronounced, and test these hypotheses using a meta-analysis of the  $q/p$  ratio in applications of the Bass diffusion model. The ratio is positively associated with the Gini index of income inequality in a country, supporting the heterogeneity-in-thresholds interpretation. The ratio also varies as predicted by the Gamma-Shifted Gompertz diffusion model, but the evidence vanishes after controlling for national culture. As to contagion, the  $q/p$  ratio varies with the four Hofstede dimensions of national culture—for three of them in a direction consistent with the social contagion interpretation. Furthermore, 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 moderated social contagion effects might not operate independently from each other.

*Key words:* diffusion of innovations; 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. It is commonly accepted that new product diffusion is often driven by social contagion, i.e., that actors' adoptions are a function of their exposure to other actors' knowledge, attitudes, or behaviors concerning the new product. Researchers have offered different theoretical accounts of social contagion, including social learning under uncertainty, social-normative pressures, competitive concerns, and performance network effects (Van den Bulte and Lilien 2001).

Although these contagion mechanisms are conceptually distinct, their expressions in diffusion data of a single innovation are often indistinguishable, making it impossible to identify the exact nature of the contagion at work. So, although diffusion models often describe new product diffusion patterns over time quite well, it is unclear what kind of contagion process, if any, is being captured in the equations. This has long frustrated marketing researchers (Gatignon and Robertson 1986, Golder and Tellis 1998, Parker 1994).

Some have noted an even more fundamental theoretical issue in diffusion research: S-shaped diffu-

sion curves need not stem from social contagion at all but can result from heterogeneity in the intrinsic tendency to adopt. Many of the popular diffusion models can be derived mathematically from both contagion and heterogeneity assumptions (e.g., Bemmaor 1994, Chatterjee and Eliashberg 1990). Consequently, it is impossible to unambiguously interpret the model parameters of any single diffusion curve as reflecting social contagion or heterogeneity in the propensity to adopt.

The difficulty in identifying which of the many possible mechanisms is at work in the diffusion of a single innovation has led skeptics such as Stoneman (2002) to deem diffusion model parameters to be more informative as data summary devices than as evidence of any specific process. Although 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 might be optimal only when contagion exists: A low price can help to get the endogenous feedback process going and the firm can increase its price once the feedback momentum is

strong enough (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 sequentially or simultaneously. The benefits of sequential entry depend in part on the strength of contagion across markets (Kalish et al. 1995). Knowing that contagion is at work is not enough. The nature of the process also matters. Depending on the type of contagion that is at work, advertising and sales calls should convey product information and reduce perceived risk, emphasize social-normative expectations, or play on fear of being outpaced by more innovative competitors. Also, the decision on whom to focus one's early viral marketing efforts will depend on the nature of contagion. For social norms and social learning direct ties are important, and an astute marketer will focus on well-connected actors. This need not be a good choice when contagion is driven by competition for status (Burt 1987). So, it is important to know not only the shape of diffusion paths, but also what contagion process, if any, is at work.

The key idea underlying the present study is that, although fitting the popular Bass (1969) model to any single diffusion data series cannot empirically identify which process is at work, one can draw inferences from patterns of variation across multiple diffusion paths (compare Taibleson 1974). Specifically, while several contagion processes as well as heterogeneity can result in the Bass model and fit the diffusion path of any single innovation equally well, different mechanisms 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.

Our research strategy consists in developing hypotheses about conditions under which different contagion mechanisms and heterogeneity are more pronounced, and testing these hypotheses 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 hypotheses about the relationship between income heterogeneity and the shape of the diffusion curve as reflected in the  $q/p$  ratio. For social contagion, we develop hypotheses about the relationship between Hofstede's (2001) dimensions of national culture and the  $q/p$  ratio. Following work on technologically induced endogenous feedback, we also develop hypotheses about the relationship between the presence of competing standards and the  $q/p$  ratio. Through these hypotheses we are able to assess empirically the different types of mechanisms that might result in sigmoid diffusion curves.

Our contribution consists of six findings. First, 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, the  $q/p$  ratio varies as predicted by Bemmaor's (1994) Gamma-Shifted Gompertz (G/SG) model, assuming that the tendency to postpone adoption is inversely related to income. The evidence, however, vanishes once we control for national culture. Third, several methodological choices affect the estimated  $q/p$  ratio, increasing the risk of spurious evidence of contagion. Fourth, even after controlling for income heterogeneity and method artifacts, the  $q/p$  ratio varies systematically with the four Hofstede dimensions of national culture—for three of them in a direction 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. Specifically, we find evidence consistent with contagion being fueled by both status concerns and social-normative pressures, but inconsistent with contagion being driven by social learning under uncertainty. Fifth, products with competing standards have a higher  $q/p$  ratio, which is again consistent with the social contagion interpretation. Sixth, the presence of competing standards drastically dampens the effects of culture and income inequality. This indicates that social contagion and the fear to adopt a losing technology do not operate independently from each other (Choi 1997).

Our study provides evidence on two fundamental issues in diffusion theory: the nature of contagion and the relevance of income heterogeneity. Because we analyze how diffusion trajectories vary as a function of the income distribution and national culture across 28 countries, we also provide new insights into international diffusion patterns.

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

## 2. Social Contagion

The contagion explanation for S-shaped diffusion curves has long dominated the marketing literature. The Bass (1969) model specifies the rate at which actors who have not adopted yet do so at time  $t$  (more precisely, in the time interval  $[t, t + dt]$  where  $dt \rightarrow 0$ )

as  $r(t) = p + qF(t)$ , where  $F(t)$  is the cumulative proportion of adopters in the population, parameter  $p$  captures the intrinsic tendency to adopt, and parameter  $q$  captures social contagion, be it coarsely. Because the proportion of the population that adopts at time  $t$  can be written as  $dF(t)/dt = r(t)[1 - F(t)]$ , one obtains

$$dF(t)/dt = [p + qF(t)][1 - F(t)]. \quad (1)$$

Whereas this equation clearly conveys social contagion— $F(t)$  affects future changes in  $F(t)$ —how  $F(t)$  varies over time is better reflected in the solution of the differential Equation (1). Assuming that one starts with zero adoptions ( $F(0) = 0$ ), the solution is

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

The curve is S-shaped when  $q > p$ , and more pronouncedly so as the  $q/p$  ratio increases. This ratio summarizes the shape of the curve and can be interpreted as a shape parameter (Chatterjee and Eliashberg 1990).

The model does not specify the nature of the contagion process, such as social learning under uncertainty, social-normative pressures, competitive concerns, or performance network effects. Additional theoretical detail must be provided for one to obtain refutable hypotheses pertaining to each process separately. One can do so by specifying observable contingency factors for each type of contagion. Our research strategy therefore consists in testing, not the contagion explanation in general, but the narrower claim that culture and competing standards affect diffusion in a particular way if contagion is indeed a driver. Because the heterogeneity models we investigate provide testable implications for  $q/p$  but not for  $p$  and  $q$  separately we limit our hypotheses about social contagion to the same ratio which, according to the contagion 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 adoption behavior (Jain and Maesincee 1998, Sundqvist et al. 2004, Steenkamp et al. 1999, Tellis et al. 2003, Yaveroglu and Donthu 2002). Building on prior research and introducing some additional arguments from sociology, we hypothesize how the  $q/p$  ratio should vary across these four dimensions if social contagion affects diffusion. The hypothesis relating individualism to  $q/p$  is based on social-normative pressure, and that relating uncertainty avoidance to  $q/p$  is based on social learning under uncertainty. The hypotheses on power distance and masculinity are based on status considerations.

**2.1.1. Individualism.** Individualism is the opposite of collectivism, which is the extent to which "people from birth onwards are integrated into strong, cohesive in-groups" (Hofstede 2001, p. 225). Because individualist cultures deemphasize conformity to social norms and group behavior (e.g., Bond and Smith 1996), they expectedly have lower  $q$  values if contagion is a social-normative process. Also, because 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 expectedly have higher  $p$  values. Hence we posit:

**HYPOTHESIS 1.** *The  $q/p$  ratio is negatively associated with individualism.*

Consistent with this prediction, Yaveroglu and Donthu (2002) report that individualism was correlated positively with  $p$  and negatively with  $q$ . Two studies provide further indirect support for Hypothesis 1. Jain and Maesincee (1998) report a negative association between individualism and  $q$ , but it was significant (at 95% confidence) for only three of the six products they studied. In a survey of over 3,000 consumers in 11 European countries, Steenkamp et al. (1999) find a positive association between the country's individualism and its citizens' consumer innovativeness, an individual-level construct 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). To the extent that diffusion is driven by social learning under uncertainty, a possibility often advanced by marketing scientists (e.g., Horsky 1990, Kalish 1985), one would expect high  $q$  values in high uncertainty avoidance countries. Also, one would expect a lower intrinsic tendency to adopt innovations ( $p$ ) 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 under uncertainty, the following hypothesis should hold:

**HYPOTHESIS 2.** *The  $q/p$  ratio is positively associated with uncertainty avoidance.*

Yaveroglu and Donthu (2002) report that uncertainty avoidance is correlated positively with  $q$  and negatively with  $p$ . Studies by Jain and Maesincee (1998), Steenkamp et al. (1999), and Tellis et al. (2003) provide additional indirect support. The first finds a negative relation between  $p$  and uncertainty avoidance, but only for three of the six products

investigated. The second finds a negative association between the country's uncertainty avoidance and its citizens' consumer innovativeness. The third finds that new products took off faster in countries with low uncertainty avoidance.

**2.1.3. Power Distance.** This 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 sensitive people are to status differences and how much people are motivated by the need to conform with those in their status group or in status groups to which they aspire (Roth 1995).<sup>1</sup> This has direct implications for social contagion, because people buy and use products not only for functional purposes, but also to construct a social identity (Baudrillard 1981, Douglas and Isherwood 1979) and to confirm the existence and support the reproduction of social status differences (Bourdieu 1984). The extent to which status differences are 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 to avoid appearing 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, people will seek to emulate the consumption behavior of their superiors (Tarde 1903) and aspiration groups (Simmel 1971) and will also quickly pick up innovations adopted by others of similar status 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 hypothesis should hold:

**HYPOTHESIS 3.** *The  $q/p$  ratio is positively associated with power distance.*

Apart from an early intimation by Tarde (1903, p. 198) that the "common people have always been inclined to copy kings and courts and upper classes according to the measure in which they have submitted to their rule" and Yaveroglu and Donthu's (2002)

<sup>1</sup> Note that power distance and income inequality are very different concepts. First, power distance is the extent to which people expect and accept differences in social status and other inequalities, not the extent to which such differences are large or small (Hofstede 2001). Second, social status is defined not only by income and wealth but also by occupation, education, aesthetic preferences, place of residence, lineage, and race (e.g., Blau 1977, Lamont 1992). Still, although conceptually distinct, power distance and income inequality covary (Hofstede 2001, pp. 128–130), because income inequality is likely to be greater in cultures that accept social differentiation and because 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.

recent study reporting a negative correlation between power distance and  $p$ , we are not aware of prior work suggesting a similar hypothesis. Jain and Maesincee (1998) do not investigate power distance, Steenkamp et al. (1999) state that it cannot be related to consumer innovativeness, and Tellis et al. (2003) report having found neither theoretical arguments nor empirical evidence linking it to the take-off time of new products.

**2.1.4. Masculinity.** This 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" (Hofstede 2001, p. 297). Importantly for consumer behavior, 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 in particular are 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 attach 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. That the typical diffusion curve is sigmoid even in wealthy countries such as the United States 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, we expect the following hypothesis to hold:

**HYPOTHESIS 4.** *The  $q/p$  ratio is positively associated with masculinity.*

We are not aware of prior research advancing a similar hypothesis. Jain and Maesincee (1998) do not investigate masculinity, nor do Yaveroglu and Donthu (2002). Whereas Gatignon et al. (1989) and Talukdar et al. (2002) investigate relationships between Bass model parameters and the female labor participation rate (they find none), our hypothesis pertains not to whether women work but to the prevalence of values of wealth, material success, and achievement. Steenkamp et al. (1999) find a positive association with consumer innovativeness, but do not investigate the  $q/p$  ratio. Tellis et al. (2003), finally, do not find a positive relation between masculinity and faster take-off.

## 2.2. Social Contagion and Competing Standards

When faced with competing standards, even innovative consumers might 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 higher  $q/p$  ratio because of both a lower intrinsic tendency to adopt and a higher level of endogenous feedback. The presence of competing standards and the related issue of the provision of complements have an important supply-side element that is absent from the purely demand-side social contagion processes discussed above (Stoneman 2002). To acknowledge and assess this alternative explanation for variation in the  $q/p$  ratio, we posit:

**HYPOTHESIS 5.** *The  $q/p$  ratio is higher for products with competing standards.*

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

The effect of competing standards on adoption might vary across cultures. Competing standards exacerbate the uncertainty faced by early adopters, and this effect is expectedly more pronounced in uncertainty-avoiding cultures. Multiple standards expectedly are 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 peers, hence reducing the fear of being left with a technological orphan and reducing the benefits of waiting until the overall market has decided which standard wins. Multiple standards are also less likely to deter initial adoption in power-distant and masculine cultures, because the more the product is adopted for symbolic reasons the less consumers care about the risk of ending up with a technological orphan that provides little functional value. Using the minority technology might even signal that one is indeed different from the majority of consumers (an attribution long exploited in advertisements for Apple computers). Hence, we posit:

**HYPOTHESIS 6.** *The effect of competing standards on  $q/p$  is larger in (a) individualistic and (b) uncertainty avoidant cultures and is smaller in (c) power-distant and (d) masculine cultures.*

Jain and Maesincee (1998) report 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 find a negative relation between uncertainty avoidance and  $p$ , but only for the latter set of products. Although Jain and Maesincee do not interpret these findings in terms of competing standards, they are consistent with Hypotheses 6(a) and 6(b).

### 3. Income Heterogeneity

We consider two types of heterogeneity-based diffusion models: threshold models and Bemmaor’s (1994) G/SG model. Threshold models posit 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 distribution, then the cumulative number of adopters, i.e., the diffusion curve, will be S-shaped (Duesenberry 1949). For instance, if utility increases linearly and the thresholds are normally distributed, the diffusion curve is the cumulative normal curve (Dernburg 1958). If the distribution of reservation prices is log normal and prices decrease exponentially, then the normal curve results again (Bonus 1973). Many other combinations of exogenous change and threshold distribution are possible. The main result is that S-shaped diffusion curves, including skewed ones such as the lognormal curve (Davies 1979) and the Bass curve (Chatterjee and Eliashberg 1990), can result without any contagion.<sup>2</sup>

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

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

where  $b$  is a scale parameter that is constant across all actors and  $\eta > 0$  represents the intrinsic tendency to adopt late (the higher  $\eta$ , the higher the expected adoption time). Next, the model assumes that the intrinsic tendency  $\eta$  varies according to a Gamma distribution. This distribution has two parameters: a shape parameter  $\alpha$  and a scale parameter  $\beta$ , 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 obtains the following expression for the c.d.f. of adoption times:

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

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

The threshold and G/SG models do not specify what the dimension is along which relevant heterogeneity exists. However, economic theory and prior

<sup>2</sup> Changes in the utility might be a function of previous adoptions. Hence, while contagion and threshold heterogeneity are alternative explanations, they are not mutually exclusive (e.g., Chatterjee and Eliashberg 1990).

research offer a candidate for the case of consumer durables, namely income (e.g., Bonus 1973, Chatterjee and Eliashberg 1990, Dernburg 1958, Russell 1980). Consequently, we focus on income heterogeneity.

The two heterogeneity models have very distinct implications for the effect of income distribution on the  $q/p$  ratio. Whereas threshold models imply that the shape of the diffusion curve will be determined mostly by the shape of the threshold distribution, the G/SG model implies that  $q/p$  is determined by the scale parameter of the income distribution. We detail each model in turn.

### 3.1. Threshold Models

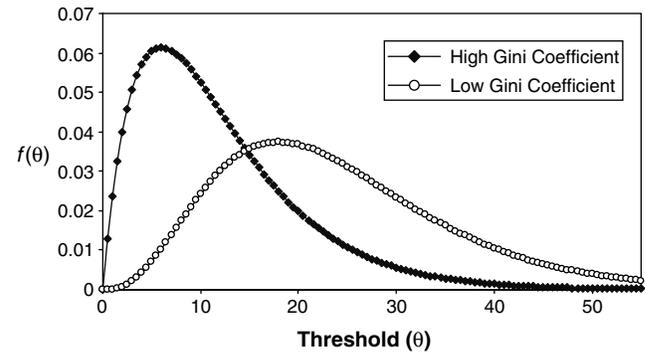
Income threshold models imply that the diffusion curve is determined mostly by the shape of the income distribution. Assuming that prices decline over time and that income determines reservation prices, one can make the general claim that diffusion curves “will be flatter in countries...in which income 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 according to threshold models and the threshold distribution reflects the income distribution, the following should hold:

**HYPOTHESIS 7.** *The  $q/p$  ratio is positively associated with the Gini coefficient of income inequality.*

This prediction is unique to the income heterogeneity interpretation and cannot be derived from the contagion interpretation. Actually, reasoning that contagion requires interaction, that interaction is less prevalent in heterogeneous populations due to homophily (“birds of a feather flock together”), and that income is a social dimension affecting interaction frequency implies a negative rather than positive association between income inequality and  $q$ . The positive association between  $q$  and the Gini coefficient reported by Talukdar et al. (2002) is not consistent with the social contagion interpretation of diffusion, but provides indirect support for the effect on  $q/p$  predicted in Hypothesis 7.

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. Income distributions typically have longer tails to the right than to the left 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  $\theta_i$ . Both are Gamma and have the same scale parameter  $\beta = 6$ . The distributions vary in their shape parameter: One has

**Figure 1** Gamma Threshold Distributions with High and Low Gini Coefficient

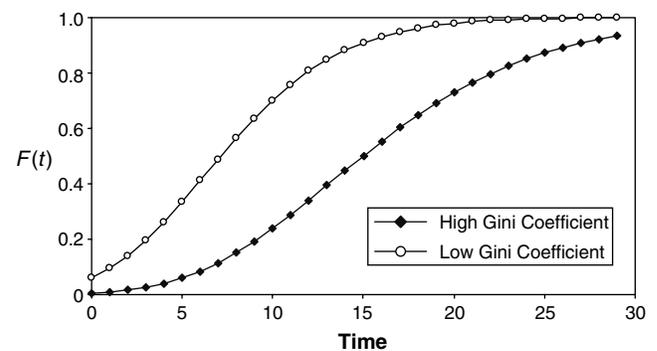


$\alpha = 2$  and the other has  $\alpha = 4$ . The corresponding Gini coefficients are 0.375 and 0.273, reasonable values for national income distributions. A consumer  $i$  adopts as soon as the price falls below her reservation price,  $\theta_i > p(t)$ . As a result, the proportion of consumers that have adopted by time  $t$ ,  $F(t)$ , equals  $1 - F_\theta(p(t))$ , where  $F_\theta$  is the c.d.f. of the threshold distribution. Because the price of innovations tends to decrease exponentially (e.g., Agarwal and Bayus 2002), we assume  $p(t) = 45 e^{-0.1t}$ . 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 has a higher  $q/p$  ratio. Fitting the Bass model to each curve and forcing the ceiling to 1 to avoid right-censoring bias yields estimated  $q/p$  ratios of 20 and 6.

### 3.2. G/SG Model

The G/SG model implies that the  $q/p$  ratio varies with the scale parameter  $\beta$  of the heterogeneity distribution of  $\eta$ . Because high values of  $\eta$  lead to late adoption, it cannot be interpreted as income but can be interpreted as the reciprocal of income. Because the G/SG model assumes  $\eta$  to be Gamma( $\alpha, \beta$ ) 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  $[\beta^2(\alpha - 1)^2(\alpha - 2)]^{-1}$ . Hence, if diffusion

**Figure 2** Corresponding Diffusion Curves, Assuming  $p(t) = 45 e^{-0.1t}$



operates as described by the G/SG model and  $\eta$  is reciprocal to income, then the following hypothesis should hold:

**HYPOTHESIS 8.** *The  $q/p$  ratio is positively associated with the scale of the reciprocal of income, assuming income is inverse Gamma distributed.*

As Equation (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 to test Hypothesis 8: Estimates of  $q/p$  obtained from a traditional Bass model tend to approximate  $\beta$  even when the true data-generating process is G/SG with  $\alpha > 1$  (see appendix).

### 3.3. Income Heterogeneity and Competing Standards

To the extent that competing standards result in excess inertia and endogenous feedback, they might dampen the extent to which the diffusion curve reflects the shape or scale of the income distribution. Hence we posit:

**HYPOTHESIS 9.** *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.*

## 4. Methods

### 4.1. Research Design

We use a meta-analysis of published  $q/p$  ratios of consumer durables. Whereas meta-analysis is often used to synthesize prior research, it can also be used to test hypotheses of theoretical interest (Geyskens et al. 1999, Miller and Pollock 1994). We consider only consumer products, because the income heterogeneity hypotheses are less applicable to businesses and other organizations, and only durables because their non-negligible price makes them a more relevant domain to test our hypotheses: Income thresholds are more likely to matter, products are more likely to convey status, and adoption is more likely to present financial and social risk.

### 4.2. Literature Search and Inclusion Criteria

We performed a forward citation search in the *Social Science Citation Index (SSCI)*, retrieving all publications between January 1969 and May 2000 that cite the Bass (1969) paper. We also performed subject searches in the *ABI Inform* and *EconLit* databases for the same period, and manually checked early volumes of *Marketing Letters* and the *International Journal of Research in Marketing* excluded from the SSCI, three edited book volumes (Mahajan and Wind 1986, Mahajan et al. 2000, Wind et al. 1981), and our file drawers for additional publications before May 2000.

To be included, a study had to report estimates for the Bass model, possibly extended with control variables, applied to new consumer durables. Both  $\hat{p}$  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 consumer durables in 77 countries and reported in 54 publications. For 44 of those countries and 694 observations, Hofstede culture scores are available. The requirements that the publication identify the start and end year of the data series used for estimation and that data be available on the average income and Gini coefficient for that country in that period reduced the sample size to 302. Finally, we deleted observations for which  $\hat{p}$  or  $\hat{q}$  was smaller than zero or larger than 1. Our final data set contains 293 observations on 52 consumer durables in 28 countries 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 (−0.68) and kurtosis (5.38), compared with the normal (0 and 3).

**4.3.2. National Culture.** We use Hofstede's national culture scores UAI, IDV, PDI, and MAS based on data collected in the early 1970s. Replication studies have shown differences among countries to be stable over time (Hofstede 2001, Søndergaard 1994).

**4.3.3. Competing Standards.** We use a dummy variable for products with competing standards: COMPSTAND equals 1 for PCs, VCRs, and cellular telephones, 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). So, to assess robustness, we also created a separate CELLTEL dummy variable. The mean effects of cellular telephones were not different from those of other products with competing standards.

**4.3.4. Income Heterogeneity.** The most commonly used measure of income inequality is the Gini concentration index, or Gini coefficient,  $C$ . Another popular index 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. The first index measures relative inequality such that scaling all incomes in a country proportionally does not affect the value of the index, whereas the latter measures 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, multiplying the relative

index by twice the mean value  $\mu$  leads to the absolute index (Johnson et al. 1994):

$$\text{GMD} = 2C\mu. \quad (5)$$

This identity allows us to operationalize the scale parameter  $\beta$  as a function of available macroeconomic data on the mean and Gini coefficient of national income distributions. Recall that Hypotheses 8 and 9(b) assume that income is Inverse Gamma distributed with mean  $\mu = [\beta(\alpha - 1)]^{-1}$  and standard deviation  $\sigma = [\beta(\alpha - 1) \cdot (\alpha - 2)^{1/2}]^{-1}$ , where  $\alpha$  and  $\beta$  are the parameters of the G/SG diffusion model. This implies  $\sigma/\mu = (\alpha - 2)^{-1/2}$ . Because many moderately skewed distributions have  $\sigma \approx \text{GMD}$  (Hosking and Wallis 1997), Equation (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  $\mu$  is the average income and  $C$  is the Gini coefficient of the income distribution.

To make valid comparisons across countries and over time, 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). Because the Penn World Table covers the period 1950–2000, our data set contains only estimates from data series within that period.

We use the Gini coefficients calculated by Deininger and Squire (1996) and published by the World Bank. To maintain consistency with our measure of average income, we use Gini values computed using personal rather than household income. 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.

Because 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  $q$ . Because 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 eight zero values of  $\hat{p}$  and four zero values of  $\hat{q}$  to 0.01. We therefore add control dummy variables, PNULL and QNULL, which 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 product of a particular manufacturer rather than the whole product category. One would expect the former to have a less-pronounced S-shape. The second is INFRA, which equals 1 for one-to-many broadcasting products requiring large investments in infrastructure (black-and-white TV, cable TV, color TV, and radio). 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.

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 and the bias stemming from different levels of left-truncation across different analyses of the same product in the same country.

We also control for variation in the  $\hat{q}/\hat{p}$  ratio induced by differences in how the estimates were obtained. First, we allow for differences across estimation techniques (Sultan et al. 1990). Using nonlinear least squares as the baseline, we coded three dummy variables: ESTOLS for OLS, ESTMLE for maximum likelihood, and ESTOTH for others such as Dekimpe et al.'s (1998) staged procedure.

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

Third, we use two variables to control for the number of observations used in the estimation. WINDOW10 captures the number of years covered by the data series, expressed in decades. LNFREQ is the natural logarithm of the data frequency (1 for annual, 4 for quarterly, 12 for monthly). Research documenting systematic changes in  $\hat{p}$  and  $\hat{q}$  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 might 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 use of data on sales rather than actual adoptions or penetration rates, which leads to contamination by replacement and additional purchases, a problem likely to be exacerbated in data series covering many years (Lilien et al. 2000, Parker and Neelamegham 1997, Putsis 1998, Putsis and Srinivasan 2000). Hence, we use 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.

**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	

Fifth, we use three dummies indicating whether  $p$ ,  $q$ , or  $m$  (the ceiling parameter) were allowed to vary as a function of covariates (P\_CONTROL, Q\_CONTROL, M\_CONTROL).

Finally, the dummy variable PROPCEILING indicates whether  $m$  was allowed to vary over time as a proportion of the total population (e.g., Bayus 1992, Horsky 1990). Because failing to control for growth in the ceiling (and hence the population at risk) underestimates the empirical hazard rate early on and overestimates how much it increases over time, we expect both M\_CONTROL and PROPCEILING to be negatively associated with  $\hat{q}/\hat{p}$ .

**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 United States accounts 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 by Sultan et al. (1990). Table 1 reports descriptive statistics for the variables of substantive interest.

**4.5. Statistical Model**

Because we have repeated observations across products and countries, we use a multilevel model allowing for random effects in 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

$$\ln(\hat{q}/\hat{p})_{ijk} = \gamma_{0ij} + \sum_s \gamma_{sij} x_{sijk} + \varepsilon_{ijk} \quad (s: 1, \dots, S), \quad \text{where}$$

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

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

$$U_{sj} \sim N(0, \nu_s^2). \quad (6)$$

Because the panel is very unbalanced with many product-country combinations having no or very few observations, we impose a variance components structure,  $\text{Cov}(U_{si}, U_{s'i'}) = 0$  and  $\text{Cov}(U_{sj}, U_{s'j'}) = 0$ . We estimate the model using residual maximum likelihood. We use the Bayesian information criterion (BIC) to identify the simplest yet statistically defensible error structure.<sup>3</sup> We use  $t$ -tests to assess whether the  $\gamma_s$  parameter estimates are significantly different from zero. Note that the model allows for a random effect when the mean effect  $\gamma_s$  is forced to zero. When performing robustness checks pertaining to treating cellular telephones as a separate category, we find that allowing for a random country effect for cellular telephones better captures the error correlation structure than doing so for all products with competing standards, so we report models allowing for such random effects.

**5. Results**

Table 2 reports the fixed or mean effects ( $\gamma_s$ ) 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 includes all covariates. The pseudo- $R^2$  values, which are the squared Pearson correlations between the predicted and actual values, indicate that all three models capture the variation in the  $q/p$  ratio about equally well.

Because 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 captures whether these effects are different from those for products with competing standards. Because we mean-centered the culture and income variables

<sup>3</sup> We also used a 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.

**Table 2** Effects of Culture, Heterogeneity, and Competing Standards on  $\ln(q/p)$

Independent variables	Model 1: National culture <sup>a</sup>		Model 2: Income heterogeneity <sup>b</sup>		Model 3: Full model <sup>c</sup>	
	$\gamma$	$t$	$\gamma$	$t$	$\gamma$	$t$
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 × IDV	0.115***	4.17			0.124**	1.97
COMPSTAND × UAI	0.041**	2.08			0.157***	3.13
COMPSTAND × PDI	-0.002	-0.07			-0.097*	-1.83
COMPSTAND × MAS	-0.244**	-2.53			-0.292***	-3.25
COMPSTAND × LNGINI			-5.414***	-2.78	-16.094***	-4.37
COMPSTAND × 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
LNFRQ	-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 × 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 <sup>d</sup>		990.5		970.6		969.3
Pseudo- $R^2$ (%)		93.4		93.3		93.7

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

<sup>a</sup> Coefficients with random effects across countries are ESTOLS ( $\text{Var}(U) = 1.32$ ), 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).

<sup>b</sup> Coefficients with random effects across countries are ESTOTH ( $\text{Var}(U) = 2.49$ ) 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).

<sup>c</sup> Coefficients with random effects across countries are ESTOTH ( $\text{Var}(U) = 2.56$ ) 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).

<sup>d</sup> Because the residual likelihood function corrects for the number of fixed effects ( $\gamma$  coefficients), one cannot compare the likelihoods of models with different explanatory variables, even if nested.

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 (although 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, is quite large but not excessive, considering

the difference in range between the explanatory and the dependent variable. 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 five 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, we extended Model 3 with the number of ethnic groups, religions, and languages in each country (Parker 1997) as measures of social heterogeneity that, due to homophily, might negatively affect the amount of interaction in the population and depress the  $q/p$  ratio. None of these variables had a significant effect ( $p > 0.10$ ). More importantly, none of the cultural or income effects changed appreciably, with the exception of the confidence level for the IDV effect, that increased to 95%. Fourth, as a check against collinearity artifacts involving LNSCALE and the culture variables, we reestimated Model 3 without LNSCALE. This reduced the coefficient of IDV from  $-0.109$  to  $-0.053$  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 be dismissed as a collinearity artifact (Myers 1990). Rather, the significant effect of LNSCALE in Model 2 is likely to be an omitted variable bias artifact stemming from ignoring the effects of IDV and PDI with which LNSCALE is correlated rather strongly. Finally, we expanded our data set with 107 observations from data series starting in 1949. Because we average income over the entire length of the data series, imputing the 1950 income values for the 1949 values can create only a very low level of measurement error in the covariates. Adding these 107 observations, all from the United States, brings the total sample size to 400 and increases the number of products from 52 to 62, although most new observations pertain to clothes dryers ( $N = 46$ ) and room air conditioners ( $N = 42$ ). Reestimating 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

There are five key substantive results. 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. More collectivistic cultures tend to have a higher  $q/p$  ratio. This is consistent with social-normative cohesion accounts of contagion. Also, cultures with high power-distance

and masculine values have a higher  $q/p$  ratio. This is consistent with a competition for status account of social contagion. Surprisingly, cultures with high uncertainty avoidance tend to have lower rather than higher  $q/p$  ratios. This is inconsistent with the interpretation that  $q$  captures social learning under uncertainty. However, we do find evidence that uncertainty-avoiding cultures have higher  $q/p$  ratios for products with competing standards. Because such products exhibit arguably high levels of uncertainty, this interaction effect is consistent with social learning under uncertainty.<sup>4</sup>

Third, the  $q/p$  ratio varies positively with the Gini coefficient of income inequality. This is consistent with theories explaining 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  $\eta$  is interpreted as the reciprocal of income. The evidence, however, might be an omitted variable bias artifact, because the effect disappears after controlling for national culture.

Finally, the presence of competing standards not only has a large main effect on the  $q/p$  ratio, but also interacts with both culture and income heterogeneity. Strikingly, the interaction effect between each variable and COMPSTAND is about as large as each variable's linear effect, but with the reverse sign. This indicates that cultural and income heterogeneity effects are not just moderated, but are entirely swamped by technology considerations.

## 5.3. Results of Methodological Interest

Using longer time series (WINDOW10) and using data with higher frequency (LNFREQ) is associated with lower  $\hat{q}/\hat{p}$  values. The effect of WINDOW10 is quite sizable: Increasing the number of observations from 10 to 20 is associated with an expected decline in the  $\hat{q}/\hat{p}$  ratio of about 75% ( $1 - e^{-1.35}$ ) in Model 3.

Using sales rather than adoption or penetration data systematically affects parameter estimates, and this effect varies with the length of the data series, as indicated by the significant effects of NONADOP and its interaction term with WINDOW10.

We find no statistically significant differences among the three main estimation techniques (NLS, OLS, and MLE) that are consistent among the three

<sup>4</sup> The negative effect of UAI on  $q/p$  might be an artifact operating via the set of potential adopters. In highly uncertainty-avoidant countries, many consumers might prefer to avoid innovations altogether. As a result, the set of potential adopters consists primarily of very innovative consumers, resulting in a low  $q/p$ . This explanation is consistent with the finding that uncertainty-avoidant cultures use fewer insurance products, presumably because consumers prefer to avoid thinking about uncertainty altogether (de Mooij 1998).

models in Table 2. Using other techniques is associated with a higher  $\hat{q}/\hat{p}$  ratio, which might simply reflect that researchers resort to such alternatives when standard techniques fail to produce reasonable estimates.

As to extending the Bass model with marketing and other control variables, allowing for changes in  $p$  does not affect the  $\hat{q}/\hat{p}$  ratio. The effects of controlling for changes in  $q$  are quite marginal. However, those of controlling for changes in the market ceiling  $m$  are robust across models and significant at 90% confidence or better. Expressing the ceiling as a proportion of a time-varying total population affects  $\hat{q}/\hat{p}$  even more.

## 6. Discussion

### 6.1. Implications for Diffusion Theory

Our results provide empirical support for the role of income heterogeneity in diffusion of consumer innovations. That heterogeneity without contagion could generate Bass-type diffusion curves has long been known. Our results imply that this can no longer be bracketed as merely an interesting but empirically vacuous analytical result. More generally, our meta-analysis of 293 diffusion processes corroborates findings from in-depth case studies that S-shaped diffusion curves and increasing hazards of adoption need not necessarily indicate the presence of contagion (e.g., Van den Bulte and Lilien 2001).

Although our results indicate that income heterogeneity indeed matters, our results regarding culture and competing standards indicate that social contagion is at work as well. More importantly, we are also able to shed some light on the nature of the contagion process, with the key finding being that the extent of contagion is better explained by social-normative cohesion and status considerations than by social learning under uncertainty. The ideas of emulation being driven by social norms and status concerns have a very long tradition in sociology (Burt 1987, Simmel 1971), but have been ignored in diffusion modeling by marketers. This is of particular relevance to research in international new product growth and consumer innovativeness. Prior studies have mostly used a subset of cultural traits. The dimension of power distance, in particular, has been ignored. Our study provides arguments to also include status considerations and the power-distance dimension associated with it in international diffusion theory and research.

The presence of competing standards is associated with more strongly S-shaped diffusion patterns. This corroborates earlier analytical (Choi 1997) and empirical (Van den Bulte 2000) results. Interestingly, we also find interaction effects between the presence of competing standards and cultural dimensions associated with different contagion mechanisms. Because products with competing standards have strong

technological network effects, our findings can also be interpreted as evidence that technological network effects and culturally moderated social contagion effects need not operate independently from each other (compare Choi 1997). The results support our original hypotheses that culture moderates fears of getting stuck with a losing product technology, but the effect sizes can also be interpreted as indicating that cultural effects are simply swamped by technology considerations.

### 6.2. Implications for Empirical Diffusion Modeling

The findings regarding the methodological control variables confirm several concerns about inflated  $\hat{q}/\hat{p}$  ratios and spurious evidence of contagion. The results about the length of the data window and the data frequency are consistent with the simulation results on bias and systematic change of Van den Bulte and Lilien (1997). Whereas Bemmaor and Lee (2002) have shown that using short data series can deflate rather than inflate the  $\hat{q}/\hat{p}$  ratio when the data exhibit more right skew than the Bass model can account for, our results show that this reverse pattern is the exception rather than the rule for consumer durables. The implication is obvious: Short data series should be avoided.

The results regarding the use of sales data when estimating models of adoption (i.e., first-time purchase) are equally clear: Sales data lead to different parameter estimates than adoption or penetration data, and the size and direction of the deviation is a function of the length of the data series. The implication 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. Trying to avoid data contamination by using shorter data series is not a proper solution because it exacerbates the bias problem just mentioned.

As expected, failing to account for growth in the overall population or the number of ultimate adopters also tends to inflate the  $\hat{q}/\hat{p}$  ratio. Even when no data are available beyond the size of the total population, using this information might help one avoid spurious evidence of contagion.

Our finding that income heterogeneity and national culture are associated with the  $q/p$  ratio has an important implication for multinational diffusion studies of cross-country spill-overs (e.g., Elberse and Eliashberg 2003, Kumar and Krishnan 2002, Putsis et al. 1997). Because income inequality and culture tend to be spatially autocorrelated (i.e., more similar across nearby countries than across distant countries) and because not controlling for relevant attributes that are spatially autocorrelated can lead to spurious spill-over effects (Arbia 1989), studies of intercountry contagion should control not only for economic variables, but also for

national culture. Failure to do so might lead to spurious evidence of contagion and misleading policy recommendations.

### 6.3. Limitations and Recommended Research

We did not assess the role of heterogeneity in general but the narrower—and refutable—claim of income heterogeneity as a driver of diffusion under both the threshold model and G/SG structures. Similarly, we did 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. Future research might seek to empirically assess the roles of heterogeneity and contagion using different substantive theories than those we used.

We used cross-cultural variation in diffusion model parameters to infer different contagion mechanisms. Sharper identification of different mechanisms could be obtained from investigating individuals' adoptions using duration models that incorporate direct measures of their risk aversion, status concerns, and susceptibility to normative influence.

Our meta-analysis could also be complemented by primary studies explicitly designed to assess 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 database of diffusion time series and price level time series for multiple products, 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 standard diffusion models assuming contagion. As to the G/SG model, our operationalization of the scale parameter  $\beta$  assumes that the Gini mean difference is a good approximation of the coefficient of variation. This might not be true for countries with very skewed income distributions. Also, the  $q/p$  estimates we analyzed were obtained from the Bass model where  $\alpha$  is forced to equal 1. Both assumptions introduced some error in our operationalization of  $\beta$ , very probably rendering our test of the G/SG model conservative. Future research that estimates  $\alpha$  freely might find more supportive evidence for the G/SG model. Moreover, it will allow one to relate not only the scale parameter  $\beta$ , but also the shape parameter  $\alpha$  to income inequality.

### 6.4. Conclusion

Our study provides three findings that raise questions about the importance and nature of social contagion. First, diffusion curves of consumer durables partly reflect the shape of the income distribution, so contagion need not be as important as commonly held.

Second, several methodological choices affect the estimated  $q/p$  ratio, further increasing the risk of spurious evidence of contagion. Third, the cross-cultural patterns point to contagion based on social-normative and status considerations rather than to social learning under uncertainty. Discriminating among these different mechanisms might allow one to more directly capture contagion in future research, which should help to address the skepticism raised by the first two findings.

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### Appendix

When  $\alpha > 1$ , Bemmaor's G/SG model is not identical to the Bass model, and  $\beta$  need not exactly equal  $q/p$ . This is likely to happen when the distribution of the adoption propensity  $\eta$  reflects the income distribution, because in most countries household and personal income is well described using a Gamma or inverse Gamma distribution with  $\alpha > 1$ . In our dataset, the Gini coefficients range from 0.314 and 0.615. Assuming for computational convenience a Gamma income distribution, the corresponding  $\alpha$  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  $\beta$  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. Because allowing for values of  $\alpha$  greater than 1 shifts the G/SG diffusion curve toward the right on the time axis without affecting the curve's shape very much (Bemmaor and Lee 2002), and because most studies using the Bass model do not use the actual launch time but the start of the available data series to set the year at which  $t = 0$  (Parker 1994), assuming  $\alpha = 1$  even when  $\alpha > 1$  does not affect the estimated  $q/p$  ratio much. We illustrate this with a small numerical exercise.

We simulated six data series of the G/SG model, all with  $p = 0.03$  and  $q = 0.38$  (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  $\alpha$  shifts the G/SG diffusion curve toward 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 nonlinear 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 a 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

**Table A.1** Estimating a Bass Model to Left-Censored G/SG Data with  $\alpha > 1$  Does Not Affect the Estimated  $q/p$  Ratio Much

$\alpha$	$\hat{p}$	$\hat{q}$	$\hat{q}/\hat{p}$	Percentage error
Cumulative data, continuous-time model				
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%
Noncumulative data, discrete-time model				
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%

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 upward, the  $\hat{q}/\hat{p}$  ratio did not diverge very much—certainly compared with random estimation error and previously documented biases—from the true value of  $\beta$  in the data-generating process (Table A.1). We also fit a discrete-time Bass model that does not use any information (or assumption) about the launch time to the noncumulative 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  $\beta$  in the discrete-time operationalization might occur because that operationalization does not require making any assumption about the (unknown) true launch time.

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