Technical Report: Want to know how diffusion speed varies across countries and products? Try using a Bass model

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For global product managers, one big question is how fast a new product is likely to sell in different countries. This question is daunting. But slowly research and data are building up that can answer that question. In a "meta-analysis" of "diffusion speed" research, Christophe Van den Bulte takes the mystery out of diffusion speed - and gives product managers a useful quantitative tool for measuring it in certain product categories in certain regions of the world.

How does the speed at which new products get adopted and diffuse through the market vary across countries and products? One way to try to answer that question is by collecting data on the diffusion of a large number of products in a large number of countries, and analyzing them to identify systematic patterns.

However, building such a database would be an enormous task. Fortunately, there is an alternative. For over four decades, sociologists and marketing academics have been studying the diffusion of new products. So, the alternative is to pool the results of all published studies and look for patterns. This piggy-back strategy where one does not collect new raw data but instead analyzes other people's analyses has long been accepted in medicine and psychology. It is called "meta-analysis." This is the research strategy I will follow. But how does one quantify diffusion speed?

Using the Bass model

For over 30 years, marketing scientists have been using a simple mathematical model to study the diffusion of innovations. It is often referred to as the Bass model, after Professor Frank M. Bass who first applied it to marketing problems. Here is how the model works.

There is a market consisting of $m$ consumers who will ultimately adopt. (I use the word consumers, but the model can be applied to business markets as well.) Let's call $N(t-1)$ the number of people who have already adopted before time $t$. The model

In 1980, the U.S. department of Energy used the Bass model to forecast the adoption of solar batteries. It performed a survey of home builders to assess their perceptions of the marketplace to obtain reasonable values for $p$ and $q$. Feeding them into the model, the researchers came to the conclusion that the technology was not far enough along to generate positive word-of-mouth. As a consequence, they decided to postpone wide scale introduction until the technology had improved enough so that users would be quite satisfied with it, resulting in a higher $q$ and hence faster sales growth after launch.

In the early 1990s, DirecTV planned the launch of its subscription satellite television service. It wanted to obtain prelaunch forecasts over a five-year horizon. The forecast were based on the Bass model, and the values for its parameters were obtained from a survey of stated intentions combined with the history of analogous products. The forecasts obtained in 1992 proved to be quite good in comparison with actual subscriptions over the five-year period from 1994 to 1999.

Several firms have reported using the Bass model to their satisfaction. Often, they end up extending the simple model to further aid their decision making. In the mid-1980s, RCA used an extension of the Bass model to forecast the sales of
assumes that the probability that someone adopts given that he or she has not adopted yet consists of two factors. First, there is a fixed factor $p$ that reflects people's intrinsic tendency to adopt the new product. Second, there is a factor that reflects "word of mouth" or "social contagion," such that people are more likely to adopt the larger the proportion of the market that has already adopted. Since that proportion is simply $N(t-1)$ divided by $m$, the rate at which new people adopt is $p + qN(t-1)/m$, where $q$ captures the influence of word of mouth. So, since the number of people who have not adopted yet before time $t$ is $m - N(t-1)$, and the rate at which these people turn into new adopters is $p + qN(t-1)/m$, one can express the number of adoptions occurring at time $t$ as:

$$N(t) - N(t-1) = \left[ p + qN(t-1)/m \right] \times \left[ m - N(t-1) \right]$$

The model has three unknown parameters: the market size $m$, the coefficient of innovation $p$, and the coefficient of imitation $q$. The parameters can be estimated from real data using standard statistical software or even using the Solver tool embedded within Microsoft Excel.

**Attractive properties**

The model has several attractive properties. When $q$ is larger than $p$, the cumulative number of adopters $N(t)$ follows the type of S-curve often observed for really new product categories. When $q$ is smaller than $p$, the cumulative number of adopters follows an inverse J-curve often observed for less risky innovations such as new grocery items, movies, and music CDs. Exhibit 1 shows these patterns, where I rescaled the curves to be cumulative penetration curves by dividing $N(t)$ by $m$. Exhibit 2 on this page shows the corresponding patterns for the proportion of new adoptions occurring at time $t$, i.e. $\left[ N(t) - N(t-1) \right]/m$. Note that an S-curve as shown in Exhibit 1 for the cumulative proportion corresponds to the familiar bell-shaped curve for the non-cumulative proportion of adopters (Exhibit 2) described in Geoffrey Moore's popular books like *Crossing the Chasm*.

**Diffusion speed is captured by $p$ and $q$**

The parameters $p$ and $q$ provide us information about the speed of diffusion. A high value for $p$ indicates that the diffusion has a quick start but also tapers off quickly. A high value of $q$ indicates that the diffusion is slow at first but accelerates after a while. Of course, the number of new adopters must start to decline at some point in time, since the number of people who have not adopted yet $\left[ m - N(t-1) \right]$ becomes smaller and smaller. Interestingly, once one knows $p$ and $q$, one can calculate the time at which the peak number of adoptions occurs as:
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\[ t^* = \ln \left( \frac{q}{p} \right) / (p + q) \]

In short, the Bass model is a handy model that one can use to quantify the speed of diffusion. Better still: assuming that we start at the time of launch (where \( t = 0 \) and \( N(0) = 0 \)), and that we have values for \( m \), \( p \) and \( q \) that we feel comfortable about, the model can also be used to forecast future adoptions using the following formula:

\[ N(t) = m \times \frac{[1 - \exp\{- (p+q) t\}]}{[1 + (q/p) \exp\{- (p+q) t\}]} \]

**How \( p \) and \( q \) vary**

Having found a way to quantify diffusion speed in terms of \( p \) and \( q \) and having chosen to perform a meta-analysis, I can translate the broad question I started with into something feasible: Taking all published applications of the Bass diffusion model, what can one say about the speed of diffusion of innovations as captured in the parameters \( p \) and \( q \)? Specifically, how do \( p \) and \( q \) vary across products and countries?

**Constructing the database**

I constructed a database containing 1586 sets of \( p \) and \( q \) parameters, from 113 papers published between January 1969 and May 2000. Note that some of these 1586 observations include multiple \( p \) and \( q \) values for the same diffusion process. For instance, many studies have investigated the diffusion of color television in the U.S. I drastically reduced this database. First, I deleted all entries relating to films and drugs, because these products diffused much faster than average. Next, I kept only those 40 countries for which I have data about the extent of collectivism and risk avoidance of their national culture. Furthermore, I only kept data relating to the period between 1950 and 1992, since this is the only window for which high-quality international data on purchasing power per capita are available. Finally, I collapsed multiple observations of the same product in the same country into a single average value. These several steps reduced the data set to 188 unique sets of \( p \) and \( q \).

Averages are better than nothing, but market analysts and managers want more fine-grained information. Say you have a new product that perhaps is not even launched yet. Based on the diffusion history of previous product categories, what kind of diffusion curve can you expect for your new product? That is, what values for \( p \) and \( q \) should you use in the last equation given above to forecast your adoption curve? The answers from my statistical analyses are given in Exhibits 3 and 4. As a baseline, I took consumer durables launched in the US in 1976. The exhibits give values for \( p \) and \( q \) for such cases, and also indicate how you should change those values if your case does not fit that baseline. The exhibits also report 90 percent confidence intervals. Those are intervals or "windows" of values such that one would expect the (unknown) true value to fall within that interval with a 90 percent probability. As such, the
When applying the values in Exhibits 3 and 4 to your own case, it would be a good idea to do so for several values within the confidence intervals. This will allow you to see how sensitive the predicted curve is to the level of uncertainty in my analysis. Also, as a general rule in forecasting, you should not use only forecasts from the Bass model, or from any other model or technique. It would be better to obtain several estimates of the level of adoptions using different methods, and then to average them.

The results shown in Exhibit 3 and Exhibit 4 describe differences across product categories and countries. I also performed several additional analyses to explain why such differences occur. Space constraints do not allow me to present detailed results, so I limit myself to the main conclusions.

First, in countries with a collectivistic rather than individualistic culture (e.g., Japan vs. US), $q$ is higher. This makes a lot of sense, since people in collectivistic cultures care more about others' opinions. The effect, however, is not very strong.

Second, in countries with higher purchasing power per capita, $p$ is higher. That makes perfect sense as well, since having a higher purchasing budget makes it easier to adopt new products immediately. Finally, products and technologies that exhibit network effects (like the VCR and the fax machine) or require heavy investments in complementary infrastructure by suppliers (like television or cellular telephone) have a higher $q$. This is consistent with prior research indicating that for such categories, people tend to wait until enough other people have adopted and, when there are competing standards, until it has become clear what technology will survive. Interestingly, $p$ also tends to be lower for products with network effects, making the S-shape even more pronounced.

**Conclusions**

There are systematic differences in diffusion of global products which emerge using a Bass model analysis. Here are my conclusions:

- The Bass model is a handy tool to look at diffusion patterns. Moreover, the quantitative "best guesses" from metaanalysis can be useful for predicting future adoptions, even when the product has not been launched yet.
- There are systematic regional differences in diffusion patterns.
- The average coefficient of innovation $p$ (speed of take-off) in Europe and Asia is roughly half of that in the U.S.
- The average coefficient of imitation $q$ (speed of late growth) in Asia is roughly a quarter less than that in the U.S. and Europe.
- Also, economic differences explain national variations in speed better than cultural differences do.
- There are systematic product differences in diffusion patterns. For instance, take-off is slower for nondurable products with competing standards that require heavy investments in infrastructure, while late growth is faster for industrial products and products with competing standards which require heavy investments in infrastructure.

**Endnotes:**

