Deviation Among Technology Reviews: An Informative Enrichment of Technology Evolution Theory for Marketing

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ERIM REPORT SERIES *RESEARCH IN MANAGEMENT*	
ERIM Report Series reference number	ERS-2010-005-MKT
Publication	January 2010
Number of pages	42
Persistent paper URL	http://hdl.handle.net/1765/17766
Email address corresponding author	stremersch@ese.eur.nl
Address	Erasmus Research Institute of Management (ERIM) RSM Erasmus University / Erasmus School of Economics Erasmus Universiteit Rotterdam P.O.Box 1738 3000 DR Rotterdam, The Netherlands Phone: + 31 10 408 1182 Fax: + 31 10 408 9640 Email: info@erim.eur.nl Internet: www.erim.eur.nl

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REPORT SERIES

RESEARCH IN MANAGEMENT

ABSTRACT AND KEYWORDS	
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Availability	
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Abstract

Understanding technological change is of critical importance to marketers, as it bears new markets, new brands, new customers, and new market leaders. This paper examines the deviation among reviews of a technology's performance and its consequences for inferences on technology evolution patterns. The basic premise of the current paper is that technology evolution literature, while highly relevant, is misguided in that it ignores potential deviation among technology reviews. Using a comprehensive dataset of all published reviews, both before and after FDA approval, of 7 statins for cholesterol reduction (LDL) from 1982 to 2007, the authors find that: (1) there exists vast deviation among reviews of technology performance leading to systematic bias in the portrayal of the path of technology evolution, especially if one relies only on manufacturer's claims, (2) such deviation does not fade over time, (3) technology review (study design) characteristics affect the stated performance and, (4) both higher technology performance and a higher deviation affect sales positively, also when one controls for a firm's marketing expenditures. We discuss the implications of these findings for technology evolution theory, managerial practice and public policy.

Keywords: Technology Evolution; Reviews; Performance; Statins; Sales; Detailing; Marketing; Innovation.

Introduction

Understanding technological change is of critical importance to marketers, as it bears new markets, new brands, new customers, and new market leaders (Chandy and Tellis 1998; Hauser, Tellis and Griffin 2006; Kerin, Varadarajan, and Peterson 1992). Technology evolution scholars map the performance of a technology over time and make theoretical and practical inference based on such maps (for examples, see Christensen 1997; Foster 1986; Sood and Tellis 2005).

The basic premise of the current paper is that technology evolution literature, while highly relevant, is misguided in that it ignores potential deviation among reviews of technology performance. Technology evolution scholars incorporate only a single source of information, usually from the manufacturer, that makes a single statement on the maximum performance of a technology within each time period (Christensen 1997; Dosi 1982; Edwards 2008; Foster 1986; Moore 1997; Sahal 1981; Sood and Tellis 2005; Tushman and Nelson 1990; Utterback 1994). On the basis of that single source, such researchers make inferences on the typical pattern of technology evolution and analyze competition among technologies. They may also make claims on why certain technologies (e.g. digital camera) overtook entrenched incumbent technologies (e.g. analog camera) in sales.

However, on many occasions, multiple reviews of the same technology may exist, with different conclusions on the performance of the technology. For instance, consumer reports would generally disagree with manufacturer claims on battery life of laptops or car mileage. Well-known technology writers, such as Walter Mossberg of the Wall Street Journal or David Pogue of the New York Times, may share different experiences with consumers even on the

same technology. Also the context in which technologies are tested may affect their performance. For instance, gas mileage depends upon driving speed, fuel composition, etc. In the pharmaceutical industry, manufacturers, competitors, and independent organizations produce reviews with different study designs and have different incentives in their reporting of performance.

In this paper, we explore the extent to which deviation among technology reviews exists and whether it fades over time, as one would expect technology reviewers to learn over time. We also explore whether deviation affects the sales of different technologies and whether we can explain the origin of deviation among reviews.

Gathering complete information on all reviews of a technology requires immersing oneself in a specific application area. For this study, we investigate different statin technologies and gather all reviews published in top medical journals by both manufacturers and independent researchers, and both prior to and after FDA approval. We also collect data on the design of such reviews including the number and profile of the patients involved and the dosage of the drug administered in the review. We connect this data on technology performance with data on sales and detailing expenses of manufacturers.

While we cannot claim generalizability of our findings – we believe the extent of deviation and its causes and consequences are highly context-specific – they clearly caution against consistently ignoring deviation among technology reviews, which is current practice in the technology evolution literature. We show that large deviations exist among reviews on their efficacy (LDL reduction), even within a single time period, for all the statin technologies in the study. Contrary to a naive opinion, this deviation does not fade over time; for some technologies, it even increases over time. The main cause for deviation is also not the sponsor of the review

(public policy observers and the media sometimes suspect the pharmaceutical industry of overstating drug efficacy), as sponsorship effects fade when one accounts for different study designs. The deviation among reviews affects sales, beyond the effect of mean performance. Our findings provide a clear motivation for technology evolution scholars to extend their inquiry beyond a single source for performance measurement.

The next section presents the conceptual background on technology evolution. Then we discuss our data gathering procedures and measures, after which we turn to our findings. We end with a discussion of our findings, the study's limitations, and implications of our research.

Conceptual Background: Technology Evolution

Technology evolution scholars plot the performance of a technology over time. The metric they use to operationalize technology performance is the cumulative maximum performance at any given period, or in other words the performance of the historically best-performing product over time (Christensen 1997; Foster 1986; Sood and Tellis 2005). They motivate the use of this metric with three different arguments.

First, the theoretical inferences they intend to draw are on the frontier of technical performance, which supports the use of a cumulative measure (Dosi 1982; Foster 1986). Second, their subsequent interest in competition among technologies, explains their mapping only the best performance of each technology (Christensen 1997; Foster 1986). Third, they use manufacturer-stated performance, as they consider technology performance to be objectively quantifiable and propose the use of this method for developing a technology strategy (Foster 1986).

These arguments can be challenged, especially if one adopts a marketing perspective, which is often done in this literature as it explains competition (Christensen 1997, Foster 1986)

or demand (Utterback 1994). Technology evolution literature ignores that firms that shift the technology frontier may at a later stage withdraw the product that created the shift in the frontier from the market or that later information shows that the performance was overstated or erroneously measured. In such situations, one would expect technology performance to be downgraded, which does not happen with the *cumulative maximum* metric these scholars adhere to. Withdrawals are common, unfortunately, in many markets. Think of recent laptop recalls (e.g. by Dell, HP, and Sony) because of overheating batteries or withdrawals of pharmaceutical drugs (such as Vioxx). Obviously, products that shift the technology frontier are at a higher risk of withdrawal as they are at the frontier of present knowledge. Overstated performance is also quite common, unfortunately. When such overstatement is blatant, regulators may force manufacturers to restate their performance levels. Forced manufacturer restatements on performance are common in the car industry, on performance dimensions such as safety or mileage (Bates et al 2007; Yelkur et al 2001).

We can also challenge the notion that technology performance is objectively quantifiable (Mitra and Golder 2006). Critics, independent reviewers, or independent researchers may all come to different conclusions on the performance of the technology than manufacturers, and manufacturers may disagree among themselves. Thus, substantial variance may exist around the mean perceived performance of the technology, and this deviation would not necessarily be stable over time. That performance is not easily quantifiable and can differ among sources, can be witnessed in the electronics industry (e.g. Mossberg's reviews in the Wall Street Journal may differ quite a bit from manufacturer claims), the pharmaceutical industry (where independent researchers may even disagree among themselves), and the computer industry (where manufacturers may champion different methods of testing product performance).

As marketers, we take a strong interest in the consequences of technology evolution for demand, as it is the major return on innovation dollars. However, demand may be affected by both the level of performance and the deviation among technology reviews. The prevailing opinion is that deviation among technology reviews may generate uncertainty, which may, in turn, suppress sales as customers defer purchase decisions (Dhar 1997). Hence, it is not only important to account for performance improvement but also the deviation associated with multiple measurements of performance in estimating the demand.

The study of technology evolution by its cumulative maximum performance over time has led scholars to conclusions and generalizations on: (1) the shape of technology evolution, (2) the impact of technology evolution on sales, and (3) the impact of technological superiority on market dominance.

The shape of technology evolution (see Figure 1) has been claimed to be S-curve (Dosi 1982; Foster 1986; Sahal 1981; Tushman and Nelson 1990; Utterback 1994), exponential (Edwards 2008; Moore 1997), linear (Christensen 1997) and step function (Sood and Tellis 2005). Proponents of technology evolution in the shape of S-curves suggest that the performance of any technology is low for an initial period after its introduction until technological bottlenecks are resolved. The performance later improves much faster as the technology enters a growth phase. Eventually the technology enters a mature phase when improvements in product performance are small and infrequent (see Figure 1a).

"Insert Figure 1 about here"

Proponents of technological evolution in the shape of an exponential curve suggest that the performance of a technology improves at a constant rate (see Figure 1b). This empirical generalization has been observed across a number of technologies including semiconductors,

biotechnology, nanotechnology, and genomics (Edwards 2008; Moore 2003). Other researchers (e.g. Christensen 1997) theorize technological evolution as a straight line with performance of the technology improving linearly over time (see Figure 1c). Sood and Tellis (2005) theorize the shape of technological evolution as a series of steps with periods of stagnant performance punctuated with jumps in performance (see Figure 1d). Thus, scholars in the technology evolution literature differ in their conceptualization of the shape of technology evolution curve over time. Moreover, since all these reviews use the cumulative maximum performance as the metric, technological evolution is, by design, monotonically increasing.

Likewise, prior findings on the impact of technology evolution on sales are mixed. Some researchers claim that sales increase as technologies improve in performance as better products target larger markets and enable new applications (Golder and Tellis 1997; Rogers 1995). Other researchers claim that sales may drop or remain stagnant even as technologies improve in performance as better products move further from the demands of the mass market (i.e., overshoot) and become more expensive (Adner and Levinthal 2002; Christensen 1997).

Prior researchers also make inferences on the effect of technological superiority on market dominance (Anderson and Tushman 1990; Katz and Shapiro 1985; Suarez 2004). All factors equal, technological superiority should increase the likelihood of market dominance. Opponents of this logic have argued that the best product does not always enjoy market dominance and referred to examples such as the VHS recording technology or the QWERTY keyboard (Christensen 1997; Rosenbloom and Cusumano 1987). Tellis, Yin and Niraj (2009) have convincingly invalidated this opposing logic and shown that high quality products always win over the long term.

Data

We first present the institutional context of the present paper. Then, we discuss the data sources and the data gathering procedure we used.

Institutional Context: Statins

Statins (HMG-CoA reductase inhibitors; ATC: C10aa) influence the rate-limiting enzyme in cholesterol synthesis and, thereby, lower excessive cholesterol levels in the blood, particularly low density lipoprotein (LDL) cholesterol. Reviews show that, to a minor extent, they may also increase high density lipoprotein (HDL) cholesterol and decrease excessive triglyceride levels, while expert interviews with physicians revealed in practice they do not observe such effects from statin intake. To achieve HDL increase and triglyceride decrease, physicians use other platform technologies, such as Omega-3 fatty acids or niacin for HDL and, fibrates or niacin for triglycerides, possibly in combination with a statin (for LDL reduction). For this reason, this paper will focus on LDL reduction as the primary technology dimension[1]. LDL reduction is expressed as the level of LDL in patients at the end of a clinical review over the LDL in those same patients at the start of the clinical review.

Cholesterol can cause the buildup of plaque on the inside walls of arteries. Plaques can grow large enough to significantly reduce the blood's flow through an artery. But most of the damage occurs when plaques become fragile and rupture. Plaques that rupture cause blood clots to form that can block blood flow. If such clots block a blood vessel that feeds the heart, a heart attack may occur. If it blocks a blood vessel that feeds the brain, a stroke may occur. And if

[1] We acknowledge recent reviews (e.g. Liao and Laufs 2005) that show so-called pleiotropic effects of statins beyond LDL reduction (i.e., anti-inflammatory properties).

blood supply to the arms or legs is reduced, it can cause difficulty walking and eventually gangrene or issue death.

Dr Akira Endo and Dr Masao Kuroda of Tokyo commenced research on statins in 1971 (Endo 1992). Merck & Co. successfully isolated the chemical Lovastatin and commercially introduced it as the first statin under the name Mevacor in 1987. Over time, new statin treatments entered the market as well: Pravastatin (by BMS and marketed under the name Pravachol), Simvastatin (also by Merck and marketed under the name Zocor), Fluvastatin (by Novartis and marketed under the name Lescol), Cerivastatin (also by Pfizer and marketed under the name Baycol), Atorvastatin (by Pfizer and marketed under the name Lipitor), and Rosuvastatin (by AstraZeneca and marketed under the name Crestor).[2]

While these technologies have certain commonalities – i.e. focus on the same biological process in the human body, i.e. lowering LDL cholesterol, and to a minor extent, increasing HDL cholesterol and lowering triglycerides – they are different technologies as they are based upon different chemical compositions. For instance, Lovastatin is a natural product. Pravastatin is derived from compactin by biotransformation. Simvastatin is a semisynthetic derivative of Lovastatin. Atorvastatin, Cerivastatin, Fluvastatin, and Rosuvastatin are all fully synthetic products.

Each statin technology also improves incrementally, because of changes in dosage and administration. Firms continue to conduct considerable research and development activities related to lipid lowering mechanisms and the need for greater reductions in LDL cholesterol continues to drive the development of higher doses of currently approved and marketed lipid

[2] Recently, reviews have also cited red yeast rice as a purely natural statin. The substance has been used in the East for many hundreds of years and its usage, based on casual observation, is also increasing in the U.S. and all around the world. Precise data is unavailable, because red yeast rice is sold both as a drug and as dietary supplement, in various formulations.

lowering drugs, combination drugs between existing compounds, different administration methods and the development of new, more effective compounds, or variations of compounds (see Appendix A for details on performance reviews).

Data Gathering Procedures

The data we gathered for this study is drug performance reported in clinical reviews at various stages of its development and commercialization, by both manufacturers and independent researchers, from the category's inception in 1982 till 2007. We use the internationally accepted World Health Organization (WHO)'s Anatomical Therapeutic Chemical (ATC) Classification System to identify the different technologies. The WHO's ATC system is probably the most widely used technology classification system. The drugs are divided into different groups according to the organ or system on which they act on, and their chemical, pharmacological and therapeutic properties.

ATC classifies drugs in groups at five different levels – anatomical main groups, e.g. Cardiovascular System (1^{st} level), therapeutic subgroups, e.g. combinations of lipid modifying agents (2^{nd} level), pharmacological subgroups, e.g. plain lipid modifying agents (3^{rd} level), chemical subgroup, e.g. HMG CoA reductase inhibitors or statins (4^{th} level), and the chemical substance, e.g. Simvastatin (5^{th} level).

We bound our inquiry to the 4^{th} level to include all drugs in the HMG CoA reductase inhibitors category, also known as the C10aa class. Thus, we limit the analyses to drugs with only one active ingredient and exclude reviews that evaluate combinations of drugs/technologies (i.e., drugs with multiple active ingredients, such as a drug that includes both a statin and a fibrate). In our data window, it consists of the following therapeutic technologies (approval dates in parenthesis): Lovastatin (1987), Pravastatin (1991), Simvastatin (1991), Fluvastatin (1993),

Atorvastatin (1996), Cerivastatin (1997), and Rosuvastatin (2003). Pitavastatin is not approved by the FDA yet and thus, as of yet, not available commercially. Thus we inventory all the technologies within a class of chemical subgroup (statins) that all inhibit the enzyme HMG-CoA reductase and thereby reduce low density lipoprotein (LDL) cholesterol.

To inventory all clinical reviews on the above technologies, we use electronic bibliographic databases, such as Medline, EMBASE, the Cochrane Database of Systematic Reviews (CDSR), the Cochrane Central Register of Controlled Trials (CCTR), the Database of Abstracts of Reviews of Effects (DARE), the Science Citation Index, the NHS Economic Evaluation Database (NHS EED), and the Health Technology Assessment Database (NHS HTA). We also searched in all medical journals that belonged to the top 25 percentile (62 journals in total) of the population of all medical journals that belonged to the following four International Survey Industries (ISI) categories: cardiac and cardiovascular systems, critical care medicine, internal medicine, and peripheral vascular disease. Within these 62 journals, a search for all articles that covered at least one statin yielded a total of 663 technology reviews. From these 663 reviews, we identified a total of 171 reviews that gave specific and empirical performance measures (e.g. the reduction in LDL cholesterol levels they empirically recovered). We include both clinical reviews and meta-analysis reviews in the sample, and refer to both as technology reviews henceforth. We excluded two types of reviews: (1) reviews that did not provide the performance of the drug versus a placebo, as we will use this placebo comparison as a base level to measure performance; (2) reviews of multi-interventional therapies (e.g. statins and fibrates) where the independent effect of the drug could not be separated out from the combined effect. We extracted a total of 474 unique drug-dosage combinations from these reviews.

We use two reviewers to extract the data using a standardized form that inventoried: source of funding, duration of the clinical review, dosage during the clinical review, the number of patients involved, and the standing of the journal that the review is published in. A random sample of reviews was coded by both reviewers independently, to check for consensus. We also obtained quarterly data on sales and detailing in the U.S. for each drug, from IMS Health, from 1997 to 2006.

Findings

In this section, we examine the extent to which deviation among technology reviews exists (over time). Then, we investigate the origin of deviation among reviews and whether deviation affects the sales of different technologies.

Deviation among Technology Reviews

We examine deviation among technology reviews through the hetereogeneity in the LDL reduction reported among clinical reviews. As an example, Figure 2a shows the frequency distribution of LDL reduction of Atorvastatin, the top selling drug, among all reviews that evaluated its performance. Interestingly, the variation one finds among reviews is huge, from 8% to 64% LDL reduction with a mean around 40% LDL reduction. Other statins demonstrate a similar deviation among reviews. Table 1 reports the descriptive statistics of LDL reduction reported among reviews for all statins.

"Insert Table 1 about here"

Is this deviation among reviews stable over time? On the one hand, one may expect more recent reviews to show less deviation on the efficacy of a technology. Over time, scientists and physicians acquire better knowledge on the most appropriate use of the technology (e.g. in this

case, dosage and method of administration of drug) (Piantadosi 2005). On the other hand, once successfully tailored to a certain patient body, the technology may be engineered towards different patient types, who may show a very different response to the technology (Ioannidis and Lau 2001). Or, increasingly positive reviews by the manufacturer could provoke increasingly negative reviews by competitors or independent reviewers. Figure 2b shows the LDL reduction of Atorvastatin each review reports in the respective time frame, year-by-year. In the case of Atorvastatin, the deviation does not fade over time. Rather, the deviation among reviews seems to persist over time.

"Insert Figure 2 about here"

We next examine the deviation in performance among reviews measured as the standard deviation among all reviews published each year for each statin in our sample over time (see Figure 3). The figure shows that the deviation is higher for some technologies (e.g. Atorvastatin) than other technologies (e.g. Simvastatin). The deviation decreases over time for some technologies (e.g. Pravastatin) and increases over time for other technologies (e.g. Simvastatin).

"Insert Figure 3 about here"

The Origin of Deviation among Technology Reviews

Where does deviation among technology reviews originate, specifically in the case of medical technologies? As illustrated above, there is a strong belief that manufacturers have an incentive to overstate the performance of their own technology (Sismondo 2008). At the same time, while clinical reviews on medical technologies are designed to provide an unbiased estimate of the performance of a particular treatment, deviation among technology reviews may be driven by systematic differences in study design (Rosenberger and Lachin 2002). Medical literature suggests that the following study design factors may affect results on effectiveness: the

duration of the review, the dosage that is administered, the number of patients in the review, source of funding, and the standing of journal (Meinert 1986; Piantadosi 2005). We also include the duration between the review and FDA approval of the drug as an additional variable to test for differences in measured performance over time.

To examine how the above elements of study design affect the results on technology performance, we model the relationship between the performance of technology *d*, in review *r*, published in year *t* and study design characteristics as follows:

$$(1)\quad PERF_{drt} = \beta_0 + \beta_1 DURATION_{drt} + \beta_2 DOSAGE_{drt} + \beta_3 NUMBER_{drt} + \beta_4 STANDING_{drt} + \beta_5 FUNDING_{drt} + \beta_6 TIMESINCEAPPROVAL_{drt} + \varepsilon_{drt}$$

where

$PERF_{drt}$: Performance (% LDL reduction) of technology *d* reported in review *r* at time *t*;

$DURATION_{drt}$: Duration of review *r* (weeks) for technology *d* at time *t*;

$DOSAGE_{drt}$: Dosage (mg/day) of technology *d* in review *r* (mg/day) at time *t*;

$NUMBER_{drt}$: Number of patients in review *r* on technology *d* at time *t*;

$STANDING_{drt}$: Impact factor of the journal in which review *r* on technology *d* at time *t* review was published;

$FUNDING_{drt}$: Dummy variable for source of funding (which is 1 if the manufacturer funded the review *r* on technology *d* at time *t* and 0 otherwise).

$TIMESINCEAPPROVAL_{drt}$: Duration between review *r* and FDA approval of technology *d*

ε is normally distributed error with $\mathrm{E}(\varepsilon) = 0$ and $\mathrm{Var}(\varepsilon) = \sigma^2$.

Equation 1 is estimated with OLS (Ordinary Least Squares). Table 2 shows the results. The model fit is reasonable, given the few independent variables used to explain a complex phenomenon (Adjusted R-squared=.33). The coefficients suggest that reviews of long duration report lower performance than reviews of short duration (t=-5.1). There are at least two reasons why this may occur. First, reviews of long duration occur in later phase of the drug approval process and contain patients with a larger variation in the (severity of the) condition they suffer from. The technology may be found to be less effective in patient types for which the drug is not ideally suited, lowering the average performance that is reported. Second, reviews of long duration suffer from lower patient adherence than reviews of short duration (Haynes and Haines 1998; Rutherford, Sneed, and Roose 2009). A drug's performance is typically lower in patients that do not strictly adhere to therapy than in patients that strictly adhere to therapy.

"Insert Table 2 about here"

Reviews in which higher dosages are administered to patients show a higher performance than reviews in which low dosages are administered to patients (t=5.4). Our results are in line with earlier findings that report an increase in performance with an increase in the dosage within the broad range of dosages tested among reviews (Aschenbrenner and Venable 2008).

We also find that reviews with few patients do not differ in performance with reviews with larger number of patients (t=.5). Increasing sample size does not translate to a proportionate increase in performance as the sample size of clinical reviews is determined based on careful calculations and estimates of performance stabilize at modest sample sizes. Subsequent increases in sample size serve mainly to increase the power of the test and not the level of performance (Piantadosi 2005).

Our results suggest that performance reported in reviews does not depend upon the standing of the journal in which the review appeared (t=1.1). Even though journals of higher standing are more critical of study design factors (e.g. control variables) (McCarthy 2000; Nathan and Weatherall 1999; Rennie 1996), poor design may lead to both overstating and understating the effect in journals of lower standing (Gluud et al 2005; Kjaergard and Als-Nielsen 2002; Moher et al 1998; Schulz et al 1995). Our sample also excludes journals of low standing, which may be another reason why we find no differences across journal outlets with different standards.

Reviews may be more likely to favor the technology of the funder, if he has a commercial interest in it (Bodenheimer 2000; Lexchin et al 2003). First, manufacturers may choose to fund projects with a higher likelihood of positive results. Second, the manufacturer may choose to stop clinical reviews before completion if initial results on drug performance are disappointing. Contrary to these reasons and to common belief, we find that the source of funding has no effect on the measured performance of the technology once one controls for study design (t=-.2).

Finally, the results suggest that earlier reviews report higher performance than later reviews (t=-9.2), probably because earlier reviews are targeted towards patients with a more severe indication or ideally suited body type, who, hence, show a stronger response to the new drug, as compared to reviews among larger samples. Later reviews possibly target patient profiles which are expected to respond less to the treatment (see Appendix A).

Effects of Deviation Among Technology Reviews on Sales

Next, we examine the effects of performance deviation among reviews on sales. We control for a firm´s marketing efforts through its detailing, which is likely to be endogenous with

sales. Therefore, we estimate a SUR (Seemingly Unrelated Regression) model of sales of technology *d* in quarter *q* and detailing for technology *d* in quarter *q*, as follows:

$$(2)\ \text{SALES}_{dq} = \beta_0 + \beta_1 \overline{PERF}_{dq} + \beta_2 DEVIATION_{dq} + \beta_3 SIMG_q + \beta_4 CERW_q + \beta_{5d} DETAILING_{dq_{-1}} + \beta_6 SALES_{dq_{-1}} + \beta_7 TIME_{dq} + \beta_8 CSALES_{dq_{-1}} + \beta_{9d} TECHNOLOGY_d + \omega_{dq}$$

$$(3)\ \text{DETAILING}_{dq} = \lambda_0 + \lambda_1 \overline{PERF}_{dq} + \lambda_2 DEVIATION_{dq} + \lambda_3 SIMG_q + \lambda_4 CERW_q + \lambda_{5d} DETAILING_{dq_{-1}} + \lambda_6 SALES_{dq_{-1}} + \lambda_7 TIME_{dq} + \lambda_8 CDETAILING_{dq_{-1}} + \lambda_{9d} TECHNOLOGY_d + \nu_{dq}$$

Where,

$SALES_{dq}$	Sales (in thousands of kg) of technology *d* in quarter *q*;
$\overline{PERF}_{dq}$	Mean performance (% LDL reduction) among all reviews for technology *d* in quarter *q*;
$DEVIATION_{dq}$	Deviation on performance, measured as the standard deviation among all reviews for technology *d* in quarter *q*;
$SIMG_q$	Dummy variable for launch of generic Simvastatin (=1 as of launch);
$CERW_q$	Dummy variable for withdrawal of Cerivastatin (=1 as of time of withdrawal);
$DETAILING_{dq_{-1}}$	Lagged detailing expenditure of technology *d* in quarter *q-1*;
$TIME_{dq}$	Time (quarters) since launch of technology *d* in quarter *q*;
$CSALES_{dq_{-1}}$	Total lagged sales (‘000 kg) of other technologies in the same ATC code excluding technology *d* in quarter *q-1*;
$CDETAILING_{dq_{-1}}$	Total lagged detailing expenditure of other technologies in the same ATC code excluding technologies excluding technology *d* in quarter *q-1*;
$TECHNOLOGY_d$	Vector of dummies for each technology *d*;

β and λ are parameters to be estimated, and ω and υ are normally distributed errors, allowed to be correlated between equations, with $E(\omega) = 0$, $E(\nu) = 0$ and $E(\omega, \nu') = \sigma I_T$.

As independent variables, we include both mean performance and deviation around that mean performance, as these are focal to our inquiry, across the different study designs that characterize the technology reviews in our sample. We also control for two events that may have shaken the total sales in the category and the respective technologies, namely the introduction of generic Simvastatin and the withdrawal of Cerivastatin. To control for other technology-level effects that are fixed over time, we include fixed technology effects. We also control for lagged, technology-specific, detailing (in line with prior literature, e.g. Venkataraman and Stremersch 2007), lagged sales (to model contagion and inertia in the sales equation and volume considerations in detailing decisions), time (to control for duration dependence), and competitive sales (in Equation 2) and detailing (in Equation 3) (to control for the impact of competitive effects and behavior on own sales and own detailing decisions).

The model fit and coefficient estimates of the SUR model in Equations 2 and 3 are in Table 3. The model fit is satisfactory (adjusted R-squared for the sales model = .92; adjusted R-squared for the detailing model = .90; system weighted R-squared = .94).

"Insert Table 3 about here"

Consistent with prior findings and naive intuition, we find that improvements in mean performance of the technology enhance the overall sales of a technology (t=2.2). More novel is the finding that an increase in the deviation among reviews also has a positive effect on sales (t=2.2). Consequently, we find that deviation across reviews does not necessarily enhance uncertainty and suppress sales, as commonly believed. Rather, as more reviews are conducted on different patient profiles, physicians and customers may receive more information on the full

contingencies of performance of the technology thereby actually reducing, rather than enhancing, their uncertainty. Such full information on contingencies may positively affect sales.

As to the other variables we control for, we find that the introduction of the generic version of Simvastatin affected the sales of Simvastatin positively (t=4.4), most likely because the generic variant of the technology was sold at a much lower price than the branded variant. The withdrawal of Cerivastatin had a negative, but insignificant effect on sales of Cerivastatin (t=-.5). The reason was that Cerivastatin sales were never high and already very low before it was formally withdrawn. In line with recent findings about heterogeneity of detailing effects (Leeflang, Wieringa, and Wittink 2004; Narayanan and Manchanda 2009; Venkatraman and Stremersch 2007), our results show that only some drugs – Atorvastatin (t=3.8), Pravastatin (t=4.3), and Fluvastatin (t=9.7) benefit from detailing, while other drugs including Lovastatin (t=-1.9), Simvastatin (t=-2.2) and Rosuvastatin (t=.9) show small or even negative effects of detailing. As expected, a higher level of lagged sales results in higher sales (t=4.4) and sales of statins show an increase in sales over time (t=8.8). Competitor sales has no effect on sales (t=.3).

Table 3 also presents the effects of the detailing equation (Equation 3). Increases in mean performance or in deviation of performance do not lead to significant changes in detailing. We find a negative relationship between introduction of generic Simvastatin and detailing expenditures (t=-2.0), because branded firms reduce the detailing of the branded drug after patent expiration and the manufacturer of the generic version rarely details. The coefficient of the withdrawal of Cerivastatin is also negative (t=-2.0), as the manufacturer withdraws all detailing support if the drug is withdrawn from the market. All drugs show a positive effect of both lagged detailing expenditures (t>1.96) and of lagged sales (t=2.1). None of the other covariates significantly influence detailing, except for the fixed effect of Fluvastatin.

As a robustness check, we also ran the same models (Equation 2 and 3) with maximum performance (as is common in technology evolution literature) and the results were not materially different from those reported here.

Discussion

Technology evolution literature uses a single metric, the cumulative maximum performance stated by the manufacturer, to make inference on the typical pattern of technology evolution and analyze competition among technologies. The present paper uncovers that substantial deviation may exist on a technology's performance among technology reviews.

Deviation between technology reviews on a technology's performance may be grounded in different review duration (i.e., longer reviews may show lower performance), different dosage (i.e., reviews that administer a higher dosage of a drug find the drug to be more effective, than reviews that administer a lower dosage), and time since FDA approval (i.e., earlier reviews show higher performance of the technology than later reviews). Beyond such design factors, we did not find any sponsorship (i.e., manufacturer-based versus independent reviews) or publication (i.e. standing of journal) effect. It is easily conceivable that equally large deviation among technology reviews exists in other industries as well. For instance, laptop batteries can perform differently depending upon the applications a laptop is running and its frequency of usage. In fact, this is precisely the reason laptop manufacturers provide a range of battery life and why many laptop users have grown accustomed to widen that range even further, when they think about battery life.

We also found that this substantial deviation, surprisingly, persists over time. One would typically assume that as time progresses and one learns to use a technology to its largest effectiveness (Coscelli and Shum 2004), deviation among reviews about its performance would

fade. In the case of medicine, doctors may learn to adjust dosage, treatment duration and administration or adjust technology choice to patient types. Personalization technologies, search engines, virus protection and voice recognition software may get better as more consumers inform and use them. However, new technology reviews may design the study differently, in consequence showing higher or lower performance than previously believed.

The prime implication of our study is that if substantial deviation on technology performance exists, it may be misleading to infer technological superiority – the frontier of technology evolution – solely based on manufacturers' claims. Figure 4a displays technology evolution, based on the cumulative maximum performance as stated by the manufacturer, while Figure 4b displays technology evolution, based on the cumulative maximum performance as stated by independent reviewers. On the basis of manufacturer-sponsored reviews, the best performing statin technology is initially Lovastatin (Merck), then Simvastatin (Merck), after which Atorvastatin (Pfizer), and Rosuvastatin (Astrazeneca) were the superior technologies (see Figure 4a). However, on the basis of independent reviews, Lovastatin and Rosuvastatin were the superior technologies in the successive periods (see Figure 4b). The divergence on a technology's performance between different sources can be very large. Atorvastatin is probably the best example. While independent reviews rate its performance around 45 to 55% LDL reduction, manufacturer-sponsored reviews rate its performance around 65% reduction as of the end of the '90s (see Figure 4b). We have shown such deviation between manufacturer-sponsored and independent reviews to fade once one accounts for study design. Thus, these differences partially confirm, but also partially disconfirm, the prevalent concerns in the medical literature about industrial funding of clinical reviews (Cho and Bero 1996; Davidson 1986; Kelly et al 2006; Lexchin et al 2003; Stelfox et al 1998).

"Insert Figure 4 about here"

Also theoretical inference on the shape of technological evolution may be misguided, by basing it solely on the cumulative maximum performance reported in manufacturer-sponsored reviews. In line with findings of Sood and Tellis (2005), the plots in Figure 4 support the pattern of technological evolution as a step function (as per Figure 1d), rather than S-shaped (Figure 1a), exponential (Figure 1b), or linear (Figure 1c). We also observe, consistent with Sood and Tellis (2005), but inconsistent with Foster (1986) that technologies enter both below and above the incumbent technologies. While Rosuvastatin enters above the prevailing incumbent (Atorvastatin), according to manufacturer-sponsored reviews, it enters below Atorvastatin, according to independent reviews.

Traditional wisdom on technology evolution suggests that technologies evolve along monotonically increasing curves over time. On the contrary, new information may contradict prior claims of high performance and lead to reduction in observed performance over time. This raises questions regarding the underlying phenomenon of technology evolution when deviation on performance is also accounted for when plotting the path of technological evolution. We also plotted the moving averages of performance reported over all reviews, both manufacturer-sponsored and independent (see Figure 5). The plots suggest that the prior generalization of technology evolution literature that technology evolution is monotonically increasing is valid only when we use the cumulative maximum as the metric. However, when we use mean performance as the metric, many technologies (e.g. Lovastatin and Atorvastatin) demonstrate different outcomes as later reviews deviate from prior reviews. Future research is required on better methods to depict technological evolution.

"Insert Figure 5 about here"

In sum, our findings suggest future avenues for research into deviation among technology reviews as a way to enrich technology evolution theory. However, there are also clear managerial implications from our work.

Some of the findings in our study may greatly concern public policy makers. First, we find that manufacturer-sponsored reviews show on the average higher performance than independent reviews (contrast Figure 4a and 4b), not by overstating performance, but by clever design in duration and dosage (see Table 2). Second, the reported performance declines with time from date of FDA approval suggesting ingenious study design may hide true performance till additional reviews provide more reliable and complete information over time to physicians. Instances in which independent reviews report performance higher than the one reported by the manufacturer are comparatively rare. An example is Saito et al (2003), a review sponsored by Graduate School of Medicine, Chiba University to test the efficacy of Rosuvastatin on Japanese patients with hypercholesterolemia, which reported LDL reductions of 66% at a time when reviews managed by Astra Zeneca had reported a reduction of only 64%. Moreover, sales are favorably associated with more favorable reviews in two ways. As reviews with higher performance are published, the mean performance increases and as such reviews deviate from previously published independent reviews with lower performance, the observed deviation between reviews increases. Both a higher mean performance and higher deviation are associated with higher sales.

Prior research in marketing investigating the effects of detailing has typically abstracted away from scientific evidence. Our sales model reveals that sales respond to not only clinical evidence – as operationalized by mean performance and deviation on performance – but also to detailing, even when controlling for clinical evidence, supporting earlier findings by Azoulay

(2002). Some public policy makers may be of the opinion that only scientific evidence should matter in which drugs are prescribed to patients.

Managers trade off allocating moneys to technology reviews and direct-to-physician marketing efforts. In fact, a clinical review is one way of reaching physicians, while detailing is another. Clinical reviews are often also incorporated in sales conversations. An important implication of our work for managers is to counter disappointing technology reviews from independent reviewers by their own reviews, designed to yield more favorable outcomes. The present study shows that even though diverse reviews may create higher deviation, they lead to a fuller understanding of the technology's performance under different conditions by physicians thereby expanding total sales. This result provides a clear call for more evidence-based management at pharmaceutical firms.

Limitations

This study has several limitations. First we had to limit our analysis to only one category due to the time-consuming nature and difficulty of data collection. Data collection for the current sample took over a year of work of the first author. We also only collected data within one industry, namely the life sciences industry. Prior research has supported the relevance of this industry and clarified its specificity (Stremersch and Van Dyck 2009). Future research that enriches technology evolution theory with deviation among technology reviews in a different industry would be very fruitful. Industries one may consider in such study are the automobile industry (mileage) and the PC industry (battery life), among others.

Second, we limit the analyses to publications in the top 25 percentile of academic journals only. This limitation introduces a sample selection issue, which we conceive as minor, as our premise is that physicians are especially influenced by reviews that appear in the top

quartile of medical journals and to a much lesser extent by reviews that appear in lower tier journals. The publication of reviews is often supported by medical journal advertising. Unfortunately, we do not have data on medical journal advertising for the drugs in the period we study.

More broadly, this study is an open invitation to other scholars that investigate technology evolution to develop a better metric for technology evolution that accounts for the presence of deviation among technology reviews. In our mind, when such deviation exists, mean performance and the standard deviation in technology performance among reviews should be the metric of choice. However, we stopped short on formalizing this and contrasting these measures to other alternate measures, nor did we derive conditions for which metric to use and when. Future research is required on better methods to depict technological evolution.

Table 1:
Deviation on LDL Reduction Among All Statins and All Reviews Included in our Analysis

Drug	Mean Reduction in LDL Among All Reviews	Minimum Reduction in LDL Among All Reviews	Maximum Reduction in LDL Among All Reviews	Std. Deviation of Reduction in LDL Among All Reviews
Lovastatin	33.0%	17.0%	48.0%	7.1
Pravastatin	26.6%	15.7%	50.8%	5.0
Simvastatin	37.1%	15.5%	53.0%	6.1
Atorvastatin	40.5%	6.3%	64.0%	9.9
Fluvastatin	26.5%	15.0%	36.1%	4.8
Cerivastatin	31.4%	11.5%	44.0%	8.5
Rosuvastatin	46.7%	28.0%	70.0%	8.7

Table 2:
The Origin of Deviation Among Technology Reviews:
Impact of Study Design Characteristics on Performance Reported

Variable	Estimate	T-value
Intercept	41.4	17.6
Duration of Review (weeks)	-2.9	-5.1
Dosage (mg/day)	2.0	5.4
Number of Patients	.2	.5
Standing of Journal (Impact Factor)	.1	1.1
Source of Funding (= 1 if funded by manufacturer)	-.3	-.2
Time since FDA Approval (Years)	-.9	-9.2
Adjusted R-Squared	.33	

Table 3:
Impact of Technology Evolution on Sales and Detailing

Variable		Sales		Detailing	
		Estimate	**T-value**	**Estimate**	**T-value**
	Intercept	-19557.6	-9.8	15640.6	1.2
Distribution of Performance	Mean Performance	30.5	2.2	-20.0	-.8
	Deviation on Performance	27.1	2.2	40.6	.9
Control: External Shocks	Introduction of Generic Simvastatin	1739.6	4.4	-1561.7	-2.0
	Withdrawal of Cerivastatin	-225.7	-.5	-1716.0	-2.0
Control: Self Detailing Effects (Lagged)	Lag (Atorvastatin Detailing)	.3	3.8	.8	5.3
	Lag (Lovastatin Detailing)	-.2	-1.9	.9	5.1
	Lag(Pravastatin Detailing)	.3	4.3	.9	7.6
	Lag (Rosuvastatin Detailing)	.1	.9	.5	4.8
	Lag (Simvastatin Detailing)	-.1	-2.2	.9	13.6
	Lag (Fluvastatin Detailing)	.4	9.7	.9	10.7
Control	Lag (Sales)	351.6	4.4	348.9	2.1
	Time	78.0	8.8	-49.2	-.8
Control: Competition	Lag (Competition Detailing)	-	-	.1	.6
	Lag (Competitor Sales)	.2	.3	-	-
Control: Technology effects	Atorvastatin	3971.4	4.0	-10512.6	-1.8
	Lovastatin	15825.3	7.5	-17681.5	-1.2
	Pravastatin	12085.3	7.3	-15520.8	-1.4
	Rosuvastatin	-4198.8	-3.5	1948.8	0.8
	Simvastatin	12271.4	8.1	-12281.6	-1.4
	Fluvastatin	3855.6	4.0	-8254.0	-2.5
Adjusted R-Squared		.92		.91	
System Weighted R-Squared		.93			

Figure 1:
*Different Paths of Technological Evolution**

Figure 1a: S-Shape

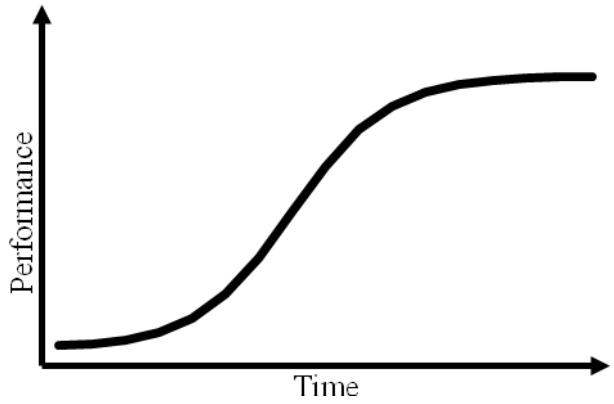


Figure 1b: Exponential Shape

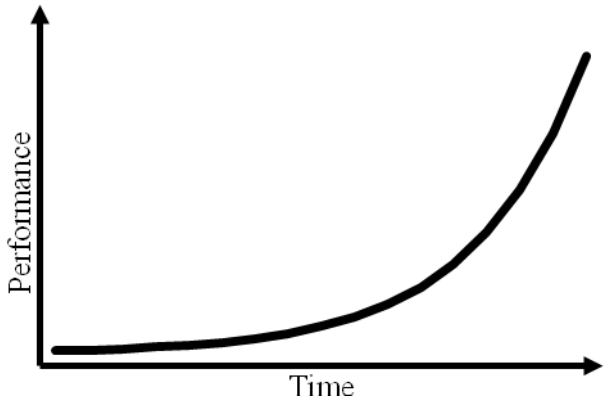


Figure 1c: Linear Shape

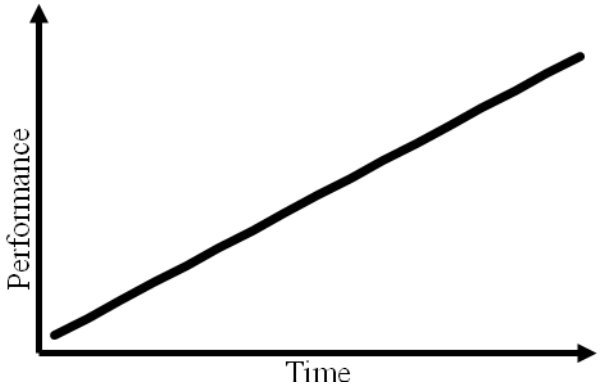
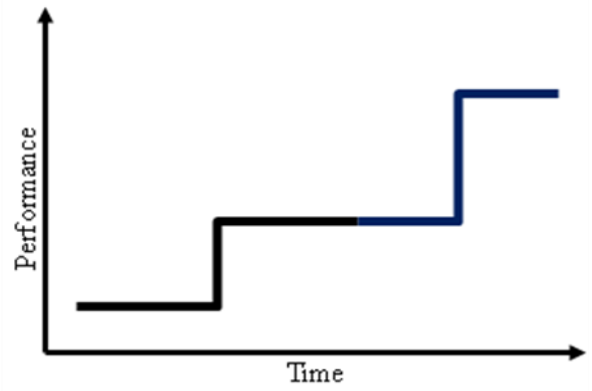


Figure 1d: Step functions



Note: * - All paths are based on the same metric (cumulative maximum performance)

Figure 2a:
Range of LDL Reduction among Reviews of Atorvastatin

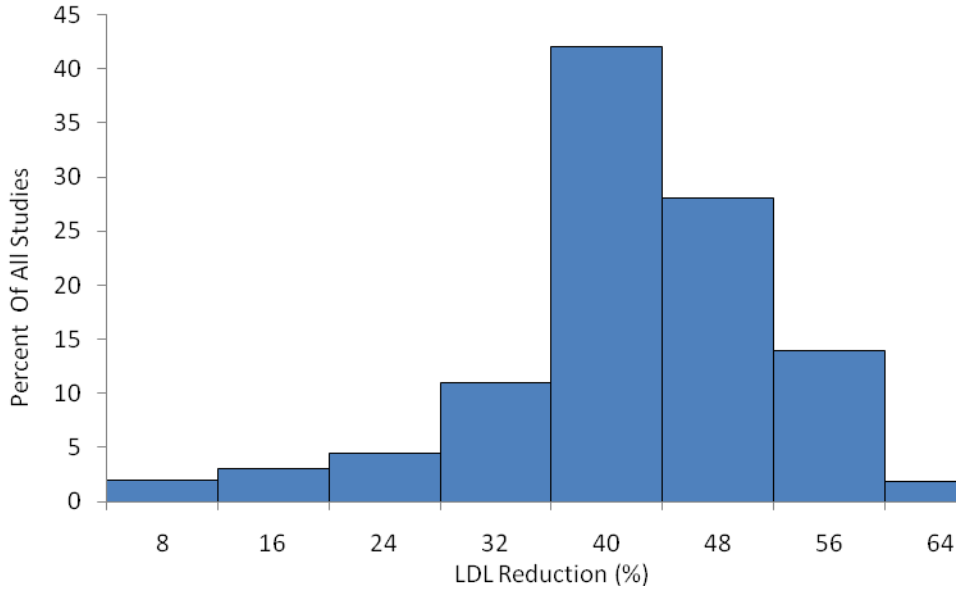


Figure 2b:
Deviation on Atorvastatin for LDL Reduction over Time

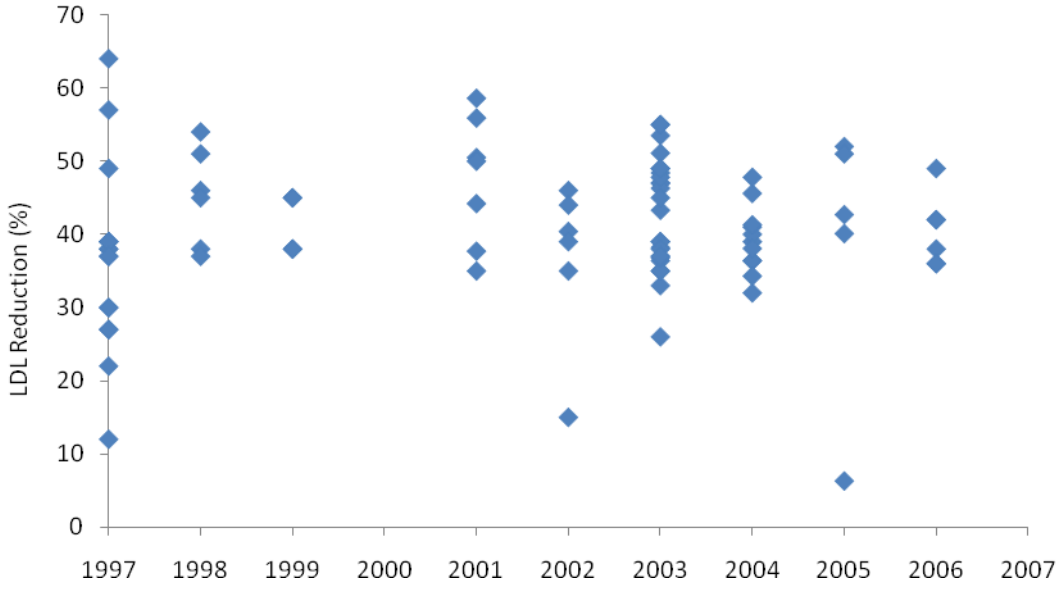


Figure 3:
Evolution of Deviation over Time

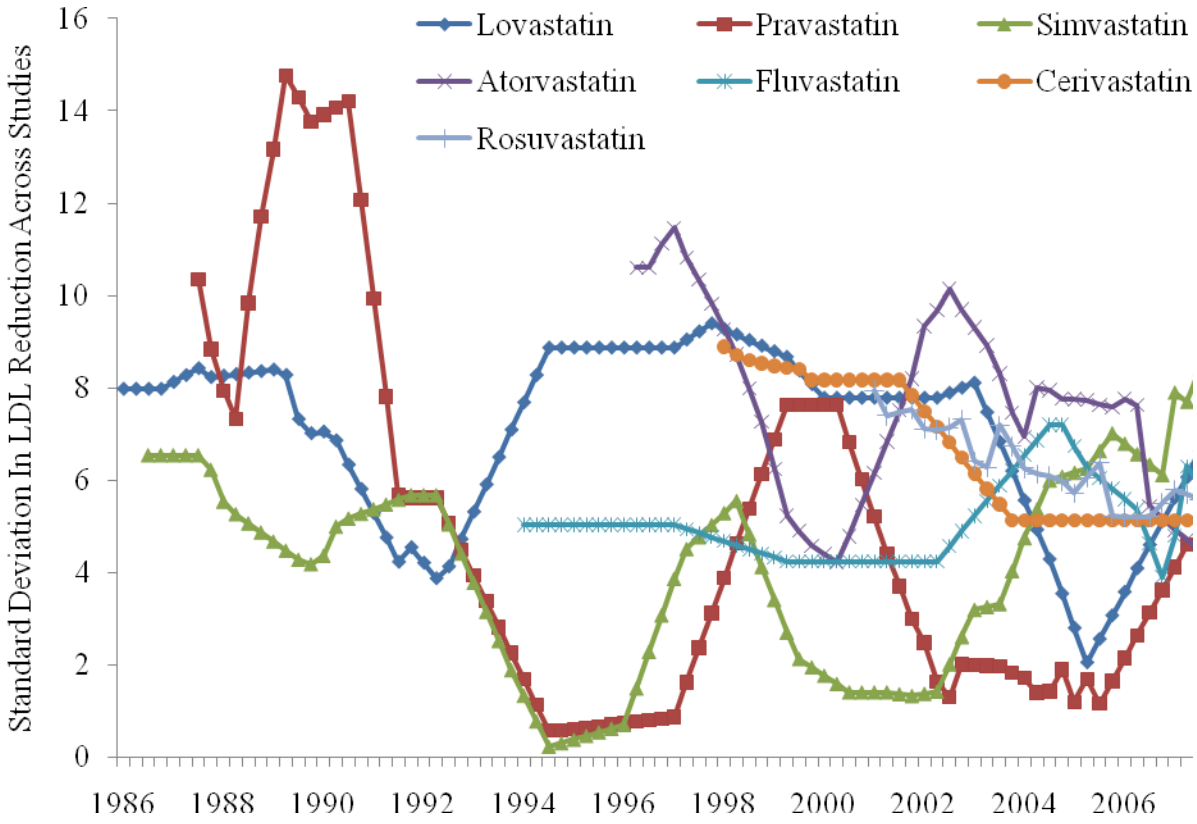


Figure 4a:
Technology Evolution of Cumulative Maximum Performance
(All Drugs; Only Manufacturer-sponsored Reviews)

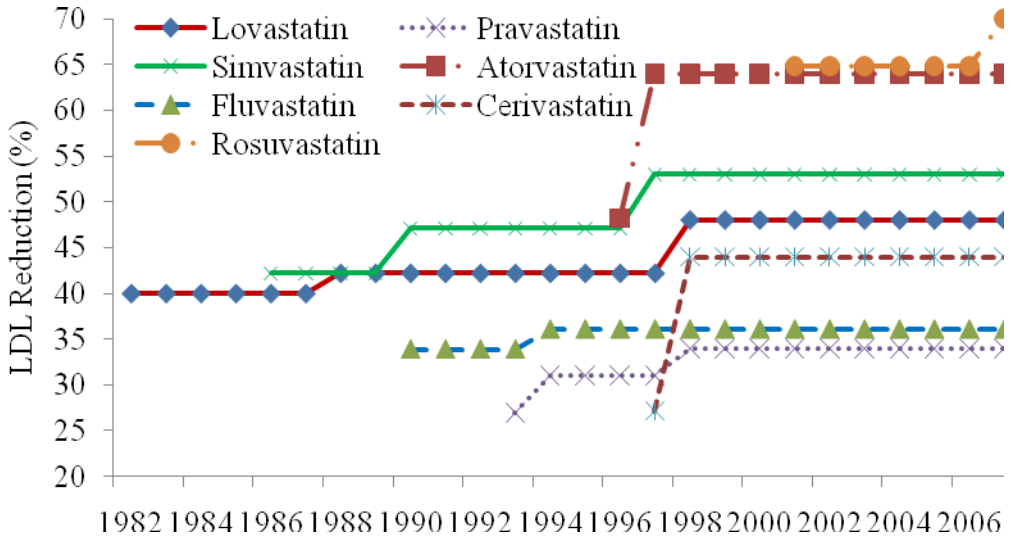


Figure 4b:
Technology Evolution of Cumulative Maximum Performance
(All Drugs; Only Independent Reviews)

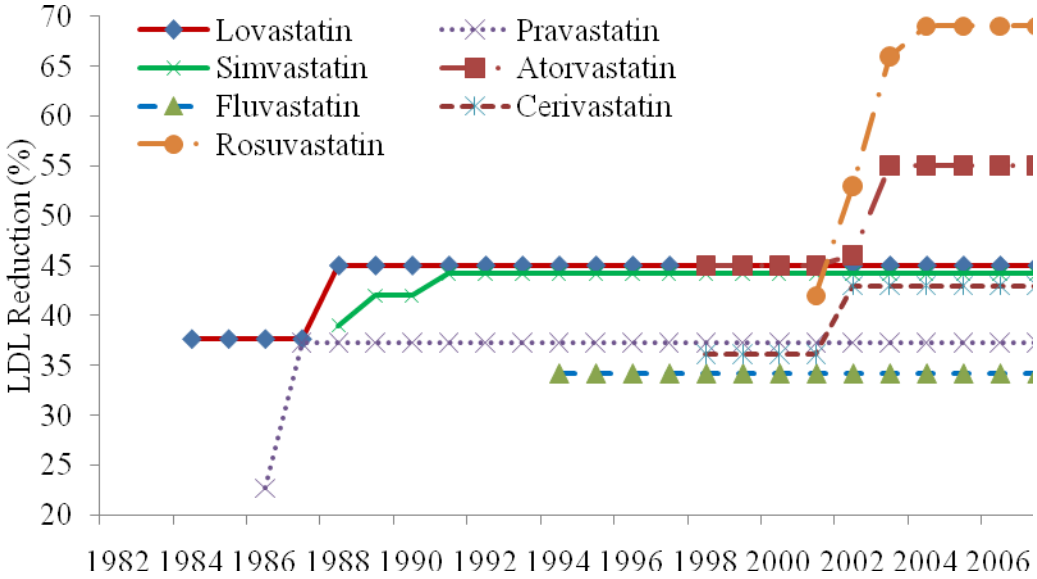
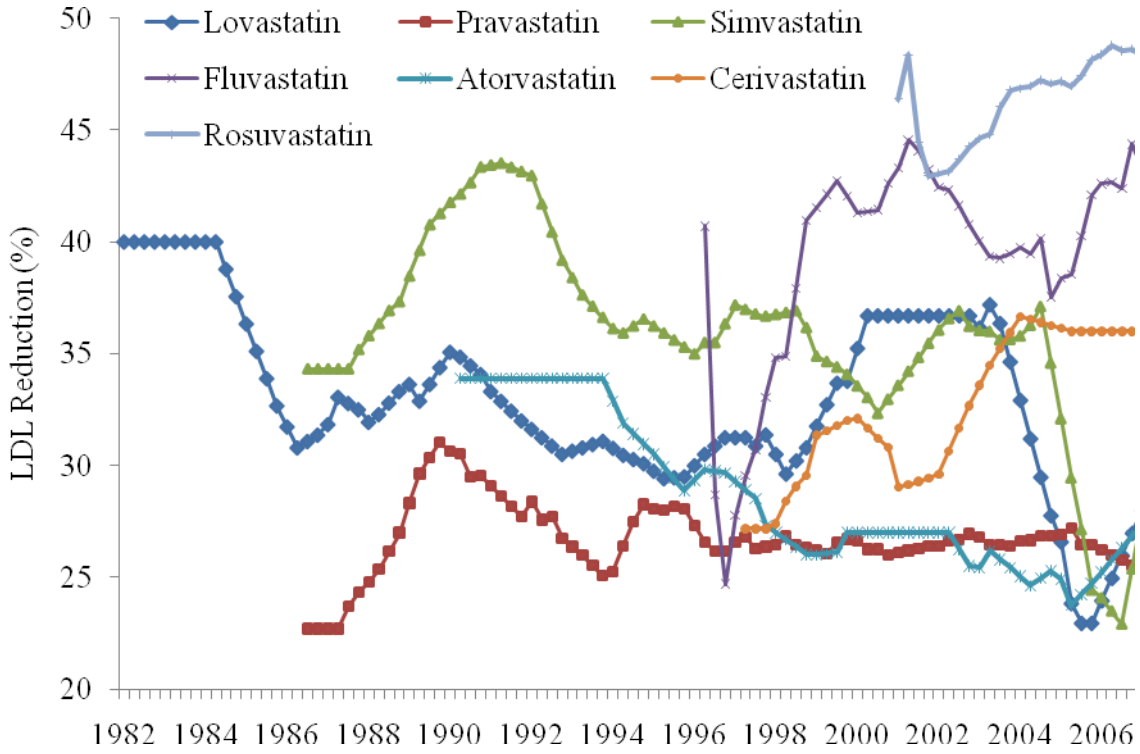


Figure 5:
Technology Evolution of Mean Performance
(All Drugs; Mean Performance reported among All Reviews)



Appendix A:

Performance Reviews of Medical Technologies

In the pharmaceutical industry, accurate measurement of the performance of any new drug approval is an intrinsic and important part of the new product development process. There is an extensive regulation process, overseen by the FDA to ensure that drugs meet the necessary levels of performance and safety before commercialization. After an initial new drug filing, the new drug is tested first in a pre-clinical stage, which entails in vitro (animal tests) and in silico testing (computer simulation). Next, a series of clinical reviews are conducted to test the efficacy and safety of the drug. These reviews are commonly classified into four phases. Each phase is designed to find different information. Phase I reviews are designed to assess the safety, tolerability, process of absorption, distribution, metabolization, and elimination in the body (pharmacokinetics), and action and effects on the body (pharmacodynamics). Phase II reviews are designed to assess how well the drug works, as well as to continue Phase I safety assessments in a larger group of volunteers and patients. Phase III reviews usually compare standard treatments (the treatment most accepted) with treatments that appeared to be good in the small Phase II reviews. Phase III reviews look for longer life, better quality of life, fewer side effects, and fewer cases of the recurrence of the disease. Phase III reviews are randomized controlled multicenter reviews on large patient groups. If all reviews report positive results, drugs may be approved at the end of Phase III reviews. Phase IV reviews, also known as Post Marketing Surveillance reviews, may be required by regulatory authorities or may be undertaken by the sponsoring company for competitive (finding a new market for the drug) or additional testing (for interactions with other drugs).

Performance may be evaluated in terms of potency (amount of drug needed to produce an effect), effectiveness (potential maximum therapeutic response), side effects, duration of effect, cost or other pre-determined measures. Performance is measured by following two groups of patients for a period of time and comparing the two groups on a preselected outcome. In a single clinical review, reported performance is the difference in average improvement in patient sample receiving the drug and a control sample receiving either a placebo or another drug.

Thus, irrespective of the number of patients in a review, each review provides only one measure of average performance. However, multiple measures of performance may be obtained by conducting multiple reviews. In many cases, average performance among multiple clinical reviews may be measured through a meta-analysis. Meta-analyses enhance the generalizability of results, reduce uncertainty, and increase the overall confidence in the technology for treating the particular condition among patients of different backgrounds.

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