

Can Credence Advertising Effects Be Isolated? Can They Be Negative?: Evidence From Pharmaceuticals¹

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This article explores the relative impact of informative vs. persuasive or credence effects of advertising in the market for prescription drugs. In particular, we examine how direct to consumer advertising for prescription statin medications affects the delay between diagnosis and pharmacological treatment for patients suffering from high cholesterol, as well as the time between treatment initiation and therapy switching. Results of duration models of delay to treatment suggest that over some ranges, advertising increases the likelihood of initiating therapy while over other ranges greater advertising is associated with reductions in the likelihood of treatment. Results for the switching behavior models suggest that on net advertising tends to both discourage switching between drugs and encourage therapy continuation. However, the component of the advertising that represents credence effects are generally positive, which implies that as patients' spell of drug usage lengthen the FDA required warning in advertisements induce consumers into switching away from the pharmaceuticals they are using.

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1. INTRODUCTION

The economic literature on advertising is long, with both theoretical and empirical contributions spanning nearly five decades. While theoretical analysis generally distinguishes between advertising about search, experience and credence characteristics of goods, empirical applications have had difficulty in disentangling these effects. This is largely because welfare effects depend not just on price changes, but also on quality changes, quality being notoriously difficult to measure. In addition, when allowing for a Lancaster/Becker-type framework where goods are conceptualized as bundles of characteristics, it becomes difficult to determine exactly what type of impact any given advertising campaign might have. Thus, for example, when a beer commercial fosters an image of its customers as fun-loving, is it persuading potential customers to believe that the beer has some trait which it actually does not, or does the associated image actually become part of the bundle of characteristics that comprise the brand such that changes in consumer willingness to pay are rational?

This paper will bring several arms of the economic literature together by proposing direct measures of the different components of advertising. We will do so by studying an important class of non-durable experience/credence goods: prescription only statin drugs used to treat elevated blood cholesterol. We argue that these goods provide an ideal context for disentangling informative and credence components of advertising. This is because there is really only one reason to consume these products: to reduce the levels of low-density lipoprotein (LDL) in the blood. Further, the actual value of LDL in consumers' blood is objectively measurable – and observed in our data – which leads us to consider changes to LDL blood levels through time as a strong measure of quality. Our approach will permit us to identify three classes of consumers – completely uninformed (non- or new users), partially informed (short-time users) and more fully informed (patients with long experience or experience with multiple treatment options). As we will see, each group should respond differently to different aspects of advertising.

In Section 2 of this paper we examine the economic literature on advertising generally and the literature on DTC advertising for prescription drugs in particular. We also discuss relevant clinical issues for statin prescriptions, which are used to reduce blood cholesterol levels. Section 3 discusses our conceptual framework which will motivate our empirical model, and provided several specific hypotheses to be tested. Section 4 presents our data and details of the econometric modeling. Section 5 contains the results and discusses the implications of this research.

2. BACKGROUND

2.1. Literature on Advertising

The earliest economic analysis of advertising was skeptical, and viewed the practice as purely persuasive, and thus largely inefficient (J. Bain, 1956). Stigler (G. Stigler, 1961) and Butters (G. Butters, 1977) promoted the idea that advertising may largely serve an informative role, and suggested important welfare-enhancing characteristics of advertising which included reducing search costs, increasing price competition, and improving matching between product characteristics and consumer preferences. Grossman and Shapiro (G. Grossman and C. Shapiro, 1984) show that advertising can lead to increased price competition.

Much of the current economic literature on advertising cites work by Nelson as its antecedent (P. Nelson, 1974, 1970). Nelson asserts that there are two classes of products in the market – those where consumers can evaluate the quality by examination before purchase and those where consumers can evaluate the quality only after purchase and consumption. The former class of goods he labels “search” goods, the latter, “experience” goods. Nelson then analyses the characteristics of advertising for each kind of good and finds that in general, sellers have an incentive to provide accurate information. In addition, Nelson finds that market forces tend to encourage the most advertising for the highest quality goods.

In a related paper, Klein and Leffler (B. Klein and K. Leffler, 1981) further expand the theory of efficient advertising by pointing out that consumers will tend to believe information provided by competitive firms in advertising, since the incentives are for truth-telling. This is because firms that invest large amounts in advertising of brands – even when the products are experience goods – would be unlikely to recoup the costs if the advertising is misleading, which would disappointment associated with consumption that would preclude repeat purchases. The more a firm invests in advertisement, the higher the potential losses from false advertising, and the more likely consumers are to believe the ad. In this case, the advertisement serves as a performance bond. Milgrom and Roberts (P. Milgrom and J. Roberts, 1986) offer a similar theoretical motivation.

The literature has also discussed an additional type of product trait that may be highlighted in advertisement - those traits that cannot be objectively verified even after purchase, but which nonetheless will affect the utility consumers receive from use. These traits have been labeled “credence” or “prestige” traits. (These two terms are not generally used synonymously, but both refer to traits that directly affect utility but which are not directly observable even by long-term users.) Darbi and Karni (M Darbi and Karni E, 1973) were the first to discuss credence goods - though in the context of service purchases. Emons (Willand Emons, 1997, 2001) further explore the role that seller reputation and advertising messages have on the support for markets for credence goods.

In such markets, unobservable quality is always an empirical difficulty for econometric analysis.

2.2. Literature on DTC

The practice of advertising directly to consumers through print and broadcast media has been accelerating since the mid-1990s. The practice was further reinforced in August of 1997 when the Food and Drug Administration (FDA) clarified and relaxed restrictions on what pharmaceutical companies could say in short television and radio advertisements promoting prescription medications. Despite the ubiquity of Direct to Consumer (DTC) advertising today, it remains highly controversial.

There are a variety of economic arguments both support and opposing DTC. The beginnings of the current policy debate on DTC may date to Masson and Rubin (A. Masson and P. Rubin, 1985), who makes several points about the merits of consumer advertising for pharmaceuticals. First, advertising can help consumers to realize that they suffer from an undiagnosed medical condition. For example, thanks to an ad campaign by Pfizer, many people who had been experiencing persistent thirst may have learned that thirst is a symptom of diabetes. Drug advertising also provides information about new treatments to consumers who suffer from diagnosed medical conditions. These effects are probably the two most-cited benefits of DTC by supporters of drug advertising.

On the other side of the argument, one of the recurring themes among critics of DTC is concern that the practice could intrude on the agency relationship between physicians and patients (e.g., (J. Weissman et al., 2003)). Theoretical problems with DTC along these lines are discussed in Brekke and Kuhn (K. Brekke and M. Kuhn, 2006). The work of these authors suggests that DTC can raise prices to patients if DTC is a complement of detailing (one-on-one visits by pharmaceutical sales representatives to individual physicians), or may cause over-consumption if pharmaceuticals have low insurance copayments. Given all this, the medical community is divided about the efficacy of DTC. (A measure of the deep ambivalence toward DTC in the medical community can be found in Holton (M. Holton, 2005).)

2.3. Clinical Issues

With the theoretical effects of DTC uncertain, it is natural to turn to the empirical works on the subject. Several studies from the immediate post-1997 period examined aggregated data on pharmaceutical DTC marketing and sales. In particular, Calfee, Winston and Stempki (J. Calfee et al., 2002) analyzed whether the August 1997 policy change at FDA increased the demand for the statin class of drugs using national aggregate drug sales by class, but was unable to find any significant short run direct effects. These authors suggest that the best way to examine this question may be to look at data on the patient level.

There are, however, only a limited number of studies of DTC that use actual patient data. A study by Zachary et. al. (W. Zachry et al., 2002) used the National Ambulatory Medical Care Survey (NAMCS), along with national levels of advertising for a number of drug classes to examine frequencies of monthly prescribing for 1992 – 1997. While that study found some significant relationships, the measured impacts of DTC are not consistent. Iizuka and Jin (T. Iizuka and G. Zin, 2003) also utilized the NAMCS and found that DTC tended to prompt relatively large increases in physician visits and modest increases in the length of patient visits to physicians, but did not prompt significant changes to actual physician prescribing. Wosinska (M. Wosinska, 2005), using a four-year panel of data from Blue-Shield of California, found that while patient adherence to prescribed statin therapy did rise as a result of DTC, the effect was small in magnitude. Bradford et. al. (W.D. Bradford et al., 2006a) examined the rate of prescribing of Celebrex and Vioxx to osteoarthritis patients and found that increases in DTC lead to a greater flow of patients with osteoarthritis into the practice to seek care, consistent with the patient selection hypothesis of Rubin and Masson. Bradford et. al (W.D. Bradford et al., forthcoming) examined the delay between diagnosis with osteoarthritis and the adoption of daily use of a Cox-2 inhibitor. Using patient comorbidities, the authors were able to identify patients who had indications in favor of Cox-2 inhibitor use, and patients who had contraindications for Cox-2 inhibitor use. The results of this work strongly indicated that DTC was effective at encouraging adoption among patients with favorable indications and discouraging adoption among patients with contraindications, suggesting patients did react to informational content in prescription drug ads. Finally, Bradford et al. (W.D. Bradford et al., 2006b) studied the impact of DTC for statin drugs on patients with elevated cholesterol, and found that higher rates of DTC tended to both increase adherence to therapy and improve health outcomes.

The FDA has approved the use of statins for the treatment of hyperlipidemia and coronary artery disease. Guidelines for the treatment of hyperlipidemia are regularly published. The latest guideline released (National Heart Lung Blood Institute National Institutes of Health, 2001, or "ATP III") emphasizes the importance of non-pharmacologic intervention for the prevention and treatment of hyperlipidemia. ATP III recommends that the use of statins be then based upon lipid measurements and a patient's risk factors (such as age, gender, comorbidities, smoking status, and the like). For patients with 0 – 1 risk factors, statins are not indicated unless LDL levels are greater than 160 milligrams per deciliter (mg/DL) of blood volume. For patients with 2 or more risk factors and a 10 – 20 percent 10 year risk for heart disease, statins should be started in patients with LDL levels greater than 130mg/dL. For patients with known coronary artery disease or its equivalent, statins should be used for patients with LDL levels greater than 100 mg/DL.

These standards guide clinical practice in the use of statin therapy for control of hyperlipidemia. In the analysis that follows we will create clinical indicators that mimic these guidelines using a detailed clinical database.

3. Conceptual Issues

3.1. Framework for Search, Experience and Credence Effects

Building on the framework of Becker and Murphy (GS. Becker and KM. Murphy, 1993), Akerberg (D. Akerberg, 2001) presented an empirical study of the yogurt market. Akerberg exploits panel data to distinguish between advertising effects on experienced and naïve consumers. He points out that while both experienced and inexperienced users should react to credence messages, only inexperienced users should react to information about both search and experience characteristics of the product. (Note that Akerberg labels the unverifiable traits of goods that directly enter the utility function as "prestige" effects - a term that, while accurate, will be limiting in our context.) We will follow a similar strategy in this work – except that, unlike Akerberg, we will have strong measures of product quality and so can control for the potential that both advertising and consumption are driven by unobserved (as in Akerberg's work) quality. Following Akerberg's, our framework is based on the following assumptions:

A. *Assume advertising conveys information about search characteristics:* Search characteristics are those aspects of a good that can be perceived prior to purchase. This component of advertising will clearly be irrelevant to current users (D. Akerberg, 2001), who will already have perceived and considered such factors in the process of earlier consumption. Thus, informative advertising on search characteristics will only have the effect of informing people about the drug's existence and/or what condition it can treat. If DTC has such an impact, then it will be a factor in the decision to begin therapy, but not in the decision of whether to continue treatment.

B. *Assume advertising conveys information about experience characteristics:* As Klein and Leffler demonstrate, even though experience characteristics are those that cannot be validated prior to purchase, consumers have reason to find advertising about those characteristics informative. This is particularly true for non-durables like pharmaceutical products, since no firm could likely be profitable without repeat customers. It is not necessarily the case, however, that consumption of a product can immediately reveal its experience traits. Learning may take time, or signal extraction regarding experience traits may be costly. If perceptions of experience traits are imperfect, then one would expect advertising that emphasizes those traits to have an effect on both naïve users and experienced users. However, the experience information effect should fall as user experience increases. Empirically, as Akerberg argues, this means that an interaction between advertising and the duration of use should have the opposite impact of the main advertising effect.

C. *Assume advertising conveys information about credence characteristics:* The final potential component considered in the literature on advertising is the possibility that

advertising may directly affect utility, as in Becker and Murphy. Becker and Murphy suggest that utility may be affected due to prestige or branded image. In essence, they consider a good to be a bundle of characteristics, as in Lancaster (Kelvin Lancaster, 1971, 1966) where the image that is portrayed by the marketing campaign is one of the characteristics that are used by consumers, through their household production functions, to generate utility.

While such positive though unverifiable claims may be present in the products we examine (e.g., "smart people test their cholesterol and take stain drugs"), there is another source for credence claims in the pharmaceutical industry that is more complex. The FDA exercises broad control over the claims made in consumer-driven advertising for prescription drugs. In particular, the FDA permits manufacturers to make claims about benefits to consumers from use that may require decades to accrue. For example, manufacturers of statin drugs may claim in their ads that reducing cholesterol by taking statins will reduce the incidence of heart disease. This may or may not be true for any individual user - but even if true will likely not be realized by a particular consumer for 10 or more years. Therefore,, the claim is unverifiable at the time of purchase, and for years thereafter.

More interestingly, however, is the FDA requirement that manufacturers highlight a list of serious side effects from using the drug being advertised. Again, these "negative" claims may not apply to any given individual, and even if they are at some (unobservable) risk of the side-effect, this may not occur for many years. As a result - perhaps unique to the pharmaceutical industry - manufactures, in being forced to verbally describe adverse events associated with their product, must deliver negative credence messages in their ads.

This implies that marketing messages about credence traits should enter the utility functions of consumers irrespective of their level of experience with the good. Thus, DTC for prescription drugs should contain both positive and negative credence (prestige) messages. Neither is directly verifiable, which implies that consumers should respond to these messages irrespective of their individual level of experience with the good. However, it is possible that over time the negative credence messages could come to dominate. To see why, note that the one might expect consumers with long use to become inured to positive messages (e.g., "Smart people take statins."); but, the negative messages (e.g. "Cholesterol drugs may cause liver failure.") should continue to be salient, as many side effects increase in likelihood as the period of use increases. Consequently, over time, the negative credence message may become relatively more salient.

D. *The role of product quality:* , Disentangling these search, experience, and prestige trait information effects requires, however, that no major unobservable variables exist which could raise advertising and increase purchasing simultaneously One obvious

omitted variable in past research is quality. Quality is generally very difficult to measure. Thus, when Akerberg finds that higher rates of advertising are associated with greater purchasing for experienced consumers, it is difficult to conclude definitively that this result is due to a prestige effect. This is because firms that produce the highest quality product may have the greatest incentive to advertise, and consumers will simultaneously have the greatest demand for those high quality goods at every possible price level. In order to isolate the prestige effect, therefore, one must control for product quality.

3.2. Isolating Experience and Credence Effects

The nature of the products we study here (statin prescription drugs) and the data that we utilize (chart abstracted clinical data) allow us to have a much clearer measure of quality than is usual in economic analyses. Statin drugs are used, almost exclusively, to reduce levels of LDL cholesterol in the blood. Their use is not obvious to others, such that conspicuous consumption concerns are moot. The effectiveness of the products is relatively well established through clinical trials. Given that the only reason to take the product is to reduce LDL, and that in our data we can observe exactly how much LDL is falling over time for each patient, we can include a direct measure of product quality (changes in LDL from the last time period). By including this measure in our regressions, we will know that any effect of advertising that does not change over time for experienced users, will reflect credence or direct utility enhancing aspects of the advertising, and therefore will not be spurious correlation from unobserved quality.

More formally, assume that DTC for the i th prescription has three components: search trait messages, experience trait messages, and credence trait messages. Further, assume that each person also responds to advertising based upon their characteristics, X , and their underlying responsiveness to ad information components, \underline{a} . Thus we can define a latent variable measuring the impact of DTC on a person's use of a particular drug as,

$$DTC_{ij}^* = \alpha_1 S_i + \alpha_2 E_2 + \alpha_3 C_3 + \alpha X_{ij} + a_{ij}$$

This is a latent variable, in that we do not observe the individual search (S), experience (E) or credence (C) components of the DTC. Further restrictions can be imposed. First, the response to broadcast DTC will depend on each agent's experience (past use) of the product. People who have begun using the i^{th} drug are, by definition, aware of its existence. So, they will show no responsiveness to the search components of the advertising message for the i^{th} drug - i.e., $\alpha_1 = 0$ for users of the i^{th} drug. So:

$$(1) E[DTC_{ij}^* | user = 0] = \alpha_1 S_i + \alpha_2 E_2 + \alpha_3 C_3 + \alpha X_{ij} + a_{ij}$$

and

$$(2) E[DTC_{ij}^* | user = 1] = \alpha_2 E_2 + \alpha_3 C_3 + \alpha X_{ij} + a_{ij}$$

A second restriction to our model incorporates the insight that as people gain more personal experience with a particular drug, their self-generated data on its effectiveness in use (for them) will become more complete. Thus, a person with long experience with a product should rely nearly exclusively on their own estimate of effectiveness (the primary experience trait of a drug) and therefore respond very little to the experience messages in an advertisement. In contrast, a person with little experience with the product will have little personal data on effectiveness and will therefore be more likely to respond to the information on experience traits in the advertisements. This means that the magnitude of a_2 in our expected DTC responsiveness equation should fall as the duration of treatment (t) grows. One simple way to parameterize this is to let

$$a_2 = a_{21}/t$$

such that the experience trait impact for consumers just beginning their use of the product ($t = 1$) is $a_2 = a_{21}$ and the impact for consumers with a very long personal history of use ($t \rightarrow \infty$) is $a_2 = 0$. Thus, a consumer with a sufficiently long history of use will have a response to DTC that will contain only prestige effects:

$$(3) E[DTC_{ij}^* | user = 1, t \rightarrow \infty] = \alpha_3 C_3 + \alpha X_{ij} + a_{ij}$$

Given this, using (1) - (3) we can isolate the search, experience and credence effects from one another. We will derive the specific expectations for our mixed proportional hazard models below.

3.3. Hypotheses

Given the discussion above, we would expect to find the following empirical relationships if advertising contains information on existence/search traits, experience traits, and image effects – once quality is controlled for.

i. The probability of (continued) use should be positively related to the quality of the drug (i.e., the observed reduction in blood LDL);

ii. Inexperienced users (i.e., those who have never yet been prescribed a statin) should exhibit search trait, experience trait and credence effects.

iii. Users with an intermediate duration of use should exhibit no search trait, reduced experience trait, and full credence effects;

iv. Users with the longest duration of use should exhibit only credence effects, and so have the smallest response to advertising. Given the FDA requirement that manufacturers highlight all significant side effects in their ads, and that pharmaceutical side effects often increase in frequency with long use, the net credence effects may be negative.

Taken together, predictions ii. - iv. suggest that we should observe effects of DTC on use at the margin that change with time (in absolute value), but stabilize at some fixed level for customers with long periods of use. Recall, however, that since FDA rules require that DTC must prominently include negative side effects and contraindications, that fixed level, may be positive or negative, depending on the impact of the credence message.

4. EMPIRICAL MODEL

4.1 Econometric Considerations

We normalize the point in time at which an individual is diagnosed with high cholesterol as 0. At some point thereafter, the individual may begin treatment with drug therapy, after which time the treatment may continue uninterrupted, may be switched to an alternative therapy, or may be stopped (switched to “no therapy”). Let the duration from diagnosis to treatment be represented by the random variable T_t and the duration from treatment until a switch occurs be represented by the random variable T_s . Let the variables t_t and t_s represent the realizations of these random variables. Following Albring and van der Berg (J. Ahbring and G. van den Berg, 2004, 2003) (AvdB) we assume that these realizations are explained by the vectors $\{X, V\}$ where X are observed (possibly time varying) covariates and $V = \{V_t, V_s\}$ are unobserved effects.

We will assume that these variables – defined in intrinsically discrete time – can be represented by the hazard rates $\theta_t(t_t | X, V)$ and $\theta_s(t_s | t_t, X, V)$. This identification is motivated by the empirical restriction that treatment initiation must come prior to any switching of therapy (a restriction that will permit a simpler dynamic identification than employed by AvdB – as discussed below), and by the assumption that there are no anticipatory effects. Thus, as in AvdB (2004, page 8), we note that while the delay to treatment may affect the hazard of switching, it is completely pre-determined in the switching half of the model.

Further, we assume that there is no effect of any future treatment spell on the current hazard of switching. Technically, this means that for any current value of t^1 and any future value t^2 for switching $\theta_s(t_s^1 | t_r, X, V) \perp \theta_s(t_s^2 | t_r, X, V)$ as long as $t^1 < t^2$ and that these random variables are drawn from the same individual. That means that the impact of a delay to treatment on the delay to switching is captured by the realized value of t_r and is constant for all subsequent realized values of t_s . This is the no anticipation assumption of AvdB (2003, 2004) and is crucial for econometric identification. This assumption does not mean that agents cannot be forward-looking – in that they may anticipate the likelihood of a switch when contemplating whether to adopt treatment. It does mean, however, that the realization of t_r , once conditioned on X and V , is independent of any such anticipatory forces.

We make the further identifying assumption that $T_r \perp V_s | x, V_r$ which implies that $\theta_r(t_r | X, V_r)$; similarly $T_s \perp V_r | t_r, x, V_s$ which implies that $\theta_s(t_s | t_r, X, V_s)$. This permits us to adopt a Mixed Proportional Hazard specification of the hazard rates, as:

$$(4) \theta_r(t_r | X, V_r) = \lambda_r(t) \phi_r(x) V_r$$

$$(5) \theta_s(t_s | t_r, X, V_s) = \lambda_s(t) \phi_s(x) \delta(t | t_r, x)^{I(t > t_r) V_s}$$

as in AvdB (2004). Here $\lambda_r(t)$ and $\lambda_s(t)$ represent the baseline hazard rates from which the systematic components, $\phi_r(x)$ and $\phi_s(x)$, may deviate. $I(t > t_r)$ is an indicator function which equals 1 if the time is after the onset of treatment and equals 0 otherwise. The multiplicative effect of treatment delay on the delay to switching implies that if $\delta(\cdot) = 1$ then there is no impact from the delay to treatment – which implies that there are no selection effects. If $\delta(\cdot) > 1$ it implies that a longer delay to treatment will increase the instantaneous hazard of a switch – thus shortening the average duration to switching and implying that there is a selection effect. Further, this form of selection effect can accommodate the assumption that not only t_r will affect $\theta_s(\cdot)$, but also that $t - t_r$ can have an effect (i.e., the current time since onset may also be a factor in switching decisions).

To implement equations (1) and (2), we need to specify a particular functional form for the hazard rates. In particular, for this model, however, there is more than one way to end both the spell of delay to treatment and the spell of delay to switching. Individuals may exit the delay to treatment in one of six ways: by adopting one of our three brands (Lipitor, Pravachol, or Zocor), any other statin, some non-statin lipid lowering drug, or by having time run out on our panel before they have adopted anything (i.e., being censored). Similarly, individuals may exit a particular spell of treatment to one of these options (or to nothing). In both cases, we can model right-hand censoring simply enough as just another exit strategy. Modeling the varying exit

strategies calls for a competing risk version of the model in (4) and (5). The hazard of initiating any treatment takes the form of

$$(6) \quad \theta_r(t | x, V_r) = \sum_{j=1}^6 \lambda_j(t) \exp\{x\beta_j + V_r\}$$

Here, the summation from $j=1$ to 6 corresponds to the six possible strategies for exiting the period of waiting to initiate therapy. Similarly, the hazard of switching away from the chosen treatment (conditional on having begun some therapy) is of the form:

$$(7) \quad \theta_s(t | t_r, x, V_r) = \sum_{k=1}^7 \lambda_k(t) \exp\{x\beta_k + \delta_k[t - t_r]I(t > t_r) + V_s\}$$

In the above equation, the summation from $k=1$ to 7 corresponds to the set of strategies that can be followed when switching away from the current treatment (conditional on having begun treatment to start with). These include switching to any of the six options that were available in the treatment initiation hazard (6) plus the option to switch to no treatment.

In both equations, β_j and β_k are parameters to be estimated, $j = \{\text{censored, Zocor, ... , non-statin drug}\}$, and $k = \{\text{censored, Zocor, ... , non-use}\}$. As will be seen below, these models can be estimated using a multinomial logit on appropriately structured data (i.e., constructed with one observation for each person each month). Consequently, the β vectors are not identified without normalizing by one of them. It is typically convenient to set the value of the dependent variable = 0 for the censored cases. We will follow this practice.

The probability that a person is observed to delay treatment for $t=m_1$ months is therefore.

$$(8) \quad L_r = \prod_{j=1}^6 \left[\frac{\lambda_j(m_1) \exp\{x\beta_j + V_r\}}{1 - \sum_{j=1}^6 \lambda_j(m_1) \exp\{x\beta_j + V_r\}} \right]^{d_j} \times \prod_{n=1}^{m_1} 1 - \lambda_j(n) \exp\{x\beta_j + V_r\}$$

where d_j are indicator variables for exit strategies $j = \{\text{censored, Zocor, ... , non-statin}\}$. This is the likelihood function for a multinomial logit, applied to panel data which has been ordered by person-month (see (P Allison, 1982)).

Similarly, the probability that a person is observed to switch to strategy k =censored, Zocor, ..., non-use, after $t=m_2$ periods given that $m_2 > t_r$ is

$$(9) \quad L_s = \prod_{k=1}^7 \left[\frac{\lambda_k(m_2) \exp\{x\beta_k + \delta_k[t - t_r]I(t > t_r) + V_s\}}{1 - \sum_{k=1}^7 (\lambda_k(m_2) \exp\{x\beta_k + \delta_k[t - t_r]I(t > t_r) + V_s\})} \right]^{d_k} \times \prod_{n=1}^{m_2} \left[1 - \sum_{k=1}^7 \lambda_k(m_2) \exp\{x\beta_k + \delta_k[t - t_r]I(t > t_r) + V_s\} \right]$$

which is again the likelihood function for a multinomial logit. Therefore, given the assumed independence of $t_r \mid x, V_r$ and $t_s \mid t_r, x, V_r$ we can write the overall likelihood function as

$$(10) \quad L = L_r * L_s.$$

In the model of AvdB, V_r and V_s are assumed correlated with one another – which may generally be the case. Unfortunately, if there is such correlation then while $t_r \mid x, V_r$ will be orthogonal to $t_s \mid t_r, x, V_r$, it will not be the case that t_r is independent of V_s . Consequently, this correlation will imply that the parameter estimate on t_r will suffer from the usual endogeneity bias associated with an explanatory variable (t_r) which is correlated with the error term (of which V_s is part).

However, the dynamic structure of our model avoids this general problem. In our case, unlike the example of unemployment duration in AvdB (2003), the construct of switching is not defined before treatment is adopted. There is, in fact, no time to switch that can occur before treatment starts, such that (2) can be rewritten as

$$(11) \quad \theta_s(t \mid t_r, x, V_r) = \sum_{k=1}^7 \lambda_k(t) [\exp\{x\beta_k + \delta_k[t - t_r] + V_s\}] \cdot I(t > t_r)$$

where $t = 0 \equiv t_r$. Thus, with respect to the decision to switch away from the drug being used, for all $t \in [0, t_s]$ t_r is completely pre-determined, and thus $t_r \perp V_s$ within the admissible range for switching. In other words, we achieve independence by redefining time to switching from the baseline of diagnosis to the baseline of treatment adoption. As a result, we may proceed with independent estimation of the two multinomial logit models for duration found in (6) and (11).

We are now in a position to calculate the behavioral reactions to experience and search messages in DTC advertising for our statin drugs. First, consider the decision to initiate treatment with the i^{th} statin. Since by definition, people considering starting therapy are non-users, equation (1) above is the general form that applied to this decision. However, (1) must be modified to account for the fact that there is more than one statin that is used, and for which drug DTC is broadcast. Thus, if we let DTC_i represent the broadcast value of DTC for the i^{th} statin and DTC_{-i} represent the value of broadcast ads for all of the statin drugs except for the i^{th} on, then (6) becomes:

$$(12) \quad \theta_r(t | x, V_r) = \sum_{i=1}^6 \lambda_i(t) \exp\{\beta_1 DTC_i + \beta_2 DTC_{-i} + \underline{\beta} x + V_r\}$$

The treatment initiation decision contains behavioral responses to all three messages, search, experience and prestige, and δ_i cannot be further decomposed in this specification.

The matter is different for the switching decision, however. First, we must rewrite (11) to accommodate the fact that more than one statin is advertised and the fact that the behavioral impact of the experience trait messages should change with use:

$$(13) \quad \theta_s(t | t_r, x, V_r) = \sum_{k=1}^7 \lambda_k(t) \left[\exp\left\{ \begin{array}{l} \beta_{11} e^{-t} DTC_i + \beta_{12} DTC_i + \delta_2 DTC_{-i} \\ + x\beta_k + \delta_k [t - t_r] + V_s \end{array} \right\} \right] \cdot I(t > t_r)$$

Second, consider two people: one where $t=1$ (the person is in the first month of treatment used) and one where $t=T$ (where T represents the level of treatment use at which the experience impact of ads becomes trivial). Then,

$$(14) \quad \left(\frac{\partial E[\text{Switching}_i]}{\partial DTC_i} \Big|_{t=T} \right) = e^{-\Delta} \lambda_t \beta_{12} \equiv \tilde{C}_i$$

where $\Delta = \beta_{11} e^{-t} DTC_i + \beta_{12} DTC_i + \delta_2 DTC_{-i} + x\beta_k + \delta_k [t - t_r] + V_s$ and (14) contains only the behavioral response to the credence messages of the DTC for the i^{th} drug. Similarly, for the individual who has just begun treatment their behavioral response to DTC will include responses to both prestige and experience messages, but no responses to messages about search traits, so:

$$(15) \quad \left(\frac{\partial E[\text{Switching}_{it}]}{\partial DTQ_{it}} \Big|_{t=1} \right) - \left(\frac{\partial E[\text{Switching}_{it}]}{\partial DTQ_{it}} \Big|_{t=T} \right) = e^{\Delta \lambda_t} [\beta_{11} e^{-1} + \beta_{12}] - \zeta_t = \tilde{E}_t$$

will contain only \tilde{E}_t , the behavioral response to the experience trait messages. After estimating the final specifications for our mixed proportional hazard models in (12) and (13), we can isolate and recover the pure responses to the prestige and experience messages in advertising for statin drugs.

4.2. Data

We utilize a unique data set consisting of over 600,000 patients (including 3.6 million patient contacts, 3.8 million prescription records, 10.1 million vital signs, 12 million laboratory records, and 1.3 million preventive services records) extracted from the electronic medical records of approximately 90 primary care practices in 33 different states across the U.S. We extract a sub-set of this data on patients who had ever been diagnosed with hypercholesterolemia, who physician had visits in the years 1998-2004, and who had begun treatment with any statin (including, but not limited to, the three statins for which advertising data is available). These patient-level clinical observations were merged with monthly television advertising measures (dollars spent) for both national and local media market advertising for three brands of statin drugs (Lipitor, Pravachol, and Zocor) which represented the bulk of ad spending on statin drugs during this time period. This results in a panel of observations on 328,365 patients for up to 84 months each. The full panel consists of over 12.5 million patient/month observations. Once we eliminate any months before diagnosis with high cholesterol, we are left with 917,834 patient months between diagnosis and first use of a statin (for the adoption models) and 902,552 patient months between adoption of therapy and the end of the study period (or patient departure from the physician practice).

Data were obtained from the Practice Partner Research Network (PPRNet), which is headquartered at the Medical University of South Carolina (MUSC). PPRNet is a practice-based learning and research organization among ambulatory primary care practices across the United States (US) that use a common electronic medical record (Practice Partner™ by Physician Micro Systems, Inc. Seattle WA). Practices pool longitudinal data on diagnoses, laboratory studies, medications, vital signs, and other information quarterly for research and quality improvement activities. Currently, PPRNet has access to all medical record extracts of 91 community-based primary care practices in 32 states. We extracted data on all patients who had a diagnosis for hypercholesterolemia from practices active from 1998 through 2004. Eighty-eight practices are represented in this time frame.

4.3. Dependent Variables

In order to test the predictions outlined above, we will estimate two models of duration. The first model captures the impact of advertising (DTC) on the uninformed consumers - that is, those patients who have not yet begun treatment with a statin. To explore the role of DTC on this group, we estimate a model of duration between the time that the patient is diagnosed with hyperlipidemia and the time they first accept a prescription for a lipid-lowering therapy. This is the time t_i from Section 4.1 above.

We also want to control for the possibility that there are selection effects in the choice to begin therapy. It is possible, for example, that patients who choose to begin therapy with Zocor are systematically different than patients who choose to begin therapy with Pravachol. In the duration literature this is known as heterogeneous frailty; competing risk duration models can address selection effects of this type. In addition, some patients never adopt therapy before the end of our study period (December 2004), and so are censored.

To accommodate the possibility of such self-selection and censoring in our discrete time duration model, we define the instantaneous "dependent" variable as a multichotomous variable where 1=adopt Lipitor, 2=adopt Pravachol, 3=adopt Zocor, 4=adopt some other statin, 5=adopt some non-statin, and 6=never adopt (censored). This variable is measured at each month for each patient. For practical reasons, these are estimated as multinomial (non-ordered) logits.

To test the predictions regarding the impact of DTC on experienced users, we estimate a model of the change in the utilization of lipid-lowering medications. Once a patient has begun treatment with, say, Lipitor, she faces a set of decisions each time period when she may switch away from her current treatment. Thus, our second model estimates the instantaneous hazard of switching away from the current treatment - where the time indicator, t_s , from 4.1. above measures how many months elapse until a switch. As with our time to beginning therapy model, we will want to control for self-selection in switching. In our discrete time framework, this hazard model is algebraically equivalent to a multinomial logit where the dependent variable is defined such that 1=switch from Lipitor, 2=switch from Pravachol, 3=switch from Zocor, 4=switch from other statin, 5=switch from other lipid-lowering medication, and 6=do not switch (censored).

4.4. Explanatory Variables

We obtained national and local advertising information from Competitive Media Reporting, Inc. (CMR), which collects data on media advertising for all products, including pharmaceuticals, at the market (e.g., city) level. The data is specific to the brand name of the product and contains information on which products were advertised and how many dollars were spent on advertising on both national and local television each

month. We used 1000s of dollars in television ad spending by month for each of the three drug brands as our measure of DTC advertising. Patients and physician practices were assigned to the nearest local media market (by mileage to the MSA center). We eliminated practices which were more than 100 miles from the geographic center of the nearest media market. Local and national DTC was then summed for each month by brand, resulting in three measures of current DTC - total spending on Lipitor, total spending on Pravachol, and total spending on Zocor. No other brands of statins were significantly advertised during our time frame (1998 through 2004). Figure 1 presents the monthly television ad spending in total, and for each brand.

However, rather than simply including a measure of DTC spending for the current month), we want to use a measure of DTC that captures all relevant ad exposure. To do this, we calculate the average monthly DTC spending to which the customer is potentially exposed for the entire duration of the spell that the customer is currently in (i.e., the average DTC spending for all months since diagnosis to the present, for customers who have not adopted statin use yet, or the average DTC spending for all months since the current treatment spell began to the present for patients currently using some statin). Finally, rather than entering the raw values of average DTC (which may have a good bit of noisy variation), we calculate deciles of average DTC spending for each product. The relationship between the DTC deciles and average treatment spell length is non-linear. Consequently, we will include DTC decile and DTC decile squared for each product in our duration models.

The independent variables from PPRNET used in each of the models are patient age; indicator for patient gender (female=1); indicator variables for whether the patient has a diagnosis for hypertension, Chronic obstructive pulmonary disease (COPD), coronary disease, or diabetes; the per capita income in the county where the physician practice is located; population in the county where the physician is located; number of Medicare recipients in the county in which the practice is located; number of African-American and Caucasian residents in the county in which the practice is located; physician practice fixed effects; and indicator variables for calendar years 1998-2003 (2004 is the excluded category).

Two explanatory factors require further attention. The first is how we treat the patient's LDL levels. We will measure LDL in two ways. For patients who have been diagnosed with hyperlipidemia but who have not begun treatment yet, we include the current level of LDL (which is the most recently measured value for each month). Once patients begin therapy, however, we include both the current level of LDL (which captures the future value of statin therapy), and also the change in LDL value from the previous month (which captures the effectiveness of the selected treatment). The change in LDL from the previous month is included in the two duration to switching models. Finally, patients' need for reducing LDL is not constant. Clinical guidelines reported by the National Heart, Lung, and Blood Institute classify patients into three groups based on

what their LDL goal should be: patients with goals of 100 mg/DL, patients with goals of 130 mg/DL, and patients with goals of 160 mg/DL. Since the clinical goal will change the importance of LDL reductions, and so the incentives to adopt or switch from therapy, we include indicator variables for whether the patient belongs to the 130 mg/DL and 160 mg/DL groups.

The second explanatory variable that requires attention is how to represent time. The basic problem is that it is unlikely that the marginal effect of time on the instantaneous hazard of leaving the spell is constant.

There are three general responses to this. First, researchers have opted to include higher order polynomials of time in the spell. However, knowing how many polynomials to include is difficult, and duration models have been shown to be sensitive to this decision (Stephen P. Jenkins, 2005). Second, researchers have assumed that the hazard rises or falls throughout (but not both) using distributions such as a Weibull, and estimated models with $\log(\text{time})$ to reflect this. (Stephen P. Jenkins, 2005) However, the hazards we observe do not exhibit this trait. Consequently, we opted to examine the empirical baseline hazard plots, and created set of time period indicator variables to reflect changes in the hazard plot shape. Our examination of the baseline hazards indicate four time periods for the model of delay to treatment adoption (less than 12 months since diagnosis, between 12 and 24 months since diagnosis, between 24 and 65 months since diagnosis, and greater than 65 months since diagnosis) and three time periods for the models of delay to switching from (or to another) treatment option (less than 18 months since beginning treatment, between 18 and 50 months since beginning treatment, and greater than 50 months since beginning treatment).

Table 1 presents the means of our principal variables.

5. Results

5.1 Results of the “Switch To” Model

Table 2 presents the results from the competing risk duration model of the delay to treatment since diagnosis (the realization of T_r). The primary results are found in the parameter estimates that capture the impact of average monthly ad spending on the instantaneous hazard of initiating therapy. With the exception of Pravachol ad spending on the instantaneous hazard of Zocor and other anti-lipid drug initiation, all measures of DTC and DTC squared are significant. Furthermore, with respect to own effects, the linear component is negative, and the quadratic components are positive. This implies that advertising is likely to encourage starting therapeutic treatment only at higher levels of exposure.

Thus, the marginal effect of DTC will vary depending on the level of DTC being considered. Consequently, we graph the estimated marginal effect of DTC decile on the instantaneous hazard of initiating therapy in Figure 2 for our three advertised drugs. (Note that since the instantaneous hazard is modeled as a quadratic, the marginal effects – or first derivatives – with respect to DTC increase at a constant rate with the advertising deciles.) Interestingly, it is only at the highest deciles of DTC spending that advertising has the expected positive effect. For Zocor, DTC spending levels less than the 70th percentile are associated with a lower instantaneous hazard of beginning to use Zocor, while the negative impact of own-DTC for Lipitor extends up to the 90th percentile. Pravachol DTC has a positive effect on the likelihood of adopting Pravachol after the 50th percentile - but these effects are only significant at the 10 percent level.

In addition to the advertising, we found other factors were significant in explaining individual patients' choices in adopting lipid-lowering pharmacotherapy. As expected, the length of time that the spell has lasted is an important predictor of exiting the spell of waiting – with the probability of therapy adoption falling as the spell of non-treatment lengthens. In addition, as expected, higher levels of LDL is often (two of four parameters) predictive of greater probabilities of starting therapy. This is, again, consistent with expectations, since higher levels of LDL imply a greater benefit from statin therapy, and should generally increase demand. While not shown in Table 2, individual physician practice fixed effects, year indicator variables, patient age, and patient clinical comorbidities were generally significant at the one percent level or higher.

5.2 Results of the “Switch Away” Model

Table 3 presents the competing risk duration models for the duration of treatment (in months) before switching away from the chosen (pre-determined in our panel structure) therapy. Recall that our conceptual model suggests two distinct hypotheses. First, higher rates of advertising should be associated with greater adherence to the

selected treatment due to information on the experience characteristics of the products. Second, the impact of the experience characteristics messages should decline with use. Finally, given that the FDA requires manufacturers to verbally emphasize the negative credence traits of their products in DTC, we may find either positive or negative permanent (credence or prestige) impacts of DTC on the instantaneous hazard of switching.

The second implication of our theoretical discussion is that as patients gather their own experience with a drug, they will learn less about experience traits of the product from advertising; thus, as the duration of treatment extends, only prestige messages will continue to have an effect. This should be translated as an attenuation of the main advertising effect as the treatment spell lengthens. Consequently, we expect opposite signs in the parameters on the main (direct) effect of advertising and the parameters on the interaction terms between advertising and treatment vintage (conditional duration).

With respect to the prediction that the DTC effect should be attenuated with experience, our results present strong support for this hypothesis. In each of the three regressions, the coefficient on own advertising divided by length of treatment is negative and significant at better than the 1% level. This implies that experience component of advertising deters consumers from switching away from particular pharmaceuticals, and that this experience component disappears with time. In addition to the separate t-tests on the interactions between DTC and time of use, we test the joint hypothesis that all DTC*time interactions terms have parameter values equal to zero (i.e., that the DTC*time interactions should be excluded from the model) using a likelihood ratio test. The test statistic (with three degrees of freedom) is 1899.4, which greatly exceeds the 1% critical value threshold of 12.84, and thus strongly rejects the null of no experience effects.

5.3. Results on Measuring Quality

Recall that these strong interpretations are possible because we have argued that we have two direct measures of quality in our data: the current level of LDL remaining in the blood, and the change in LDL from previous months. The sign pattern and generally high level of significance of the coefficients on current LDL level and changes in LDL level strongly suggest that these variables are capturing important aspects of quality. The higher the LDL remains in the blood after treatment (which implies lower effectiveness / quality of the chosen treatment) the greater the likelihood that a patient will switch to another treatment option, as indicated by the positive and significant parameters on all but one of the estimated effects (the last being insignificant). Similarly, the more LDL levels have fallen in the past month (which corresponds to a positive sign on the change in monthly LDL) the less likely the patient is to switch therapy.

5.4. Breaking out Credence and Experience Traits:

To examine the relative importance of experience traits and credence traits, we used the parameters in Table 3 to estimate the marginal effect of own-DTC for each duration of treatment from one month through 20 months. The calculated marginal effects on Pravachol do not change with duration of treatment because the interaction between the own-DTC deciles and duration of treatment are insignificant for Pravachol. Thus, we find no evidence of an experience effect in patient responses to Pravachol DTC. The DTC decile * time interactions are significant for both Lipitor and Zocor – which is indicative of an experience effect in patient response to the ads. For these two drugs, the credence effect is defined as the marginal effect of own-DTC for duration of use = 20 months. The experience effect, which diminished with duration of use, is conditional on the number of months of use to date, and is defined as = the current month total own-DTC marginal effect - the 20th month total own-DTC marginal effect.

These marginal effects are illustrated in Figure 3, where the net marginal effects are presented for the 5th decile (median) of DTC exposure. The first thing to note is that the prediction of a time-degrading experience trait effect is strongly confirmed. (Again, while the Pravachol marginal effect exhibits this pattern, the interaction terms are not significantly different from zero.) The second thing to note is that for the 5th decile of DTC, negative credence messages seem to dominate for Zocor and Lipitor, such that the permanent impact of own-DTC is to increase the likelihood that customers switch away; this is not true for Pravachol, where the net permanent effect of own-DTC on the probability of switching away remains negative.

Table 4 presents the calculated magnitudes of the own-DTC credence and experience effects on the instantaneous hazard of switching from Equations (9) and (10). The total impact (experience and credence together) at particular times is presented in the table. The impact at time=0 equals the sum of the full experience and credence effects. The impact at time=∞ equals the credence effects, as at that point the experience effect has gone to 0. As a practical matter, the experience effect is negligible after time=20, which is the time period we choose to use to estimate the credence effect. Thus, the credence effect is that impact at time=20, while the experience impact equals the impact at time=0 minus the credence effect. With respect to the experience effect, taking the marginal effects from Table 4 into account, we see that:

For Zocor –

- moving from the 1st decile of DTC spending (\$20,000 per month) to the 5th decile (\$1.9 million per month) will decrease the instantaneous probability of switching away from Zocor by -1.9% due to the experience effect and increase the probability of switching away by +1.2% due to the credence effect; these effects are calculated by summing the marginal impact of moving from the 1st decile of DTC to

the 2nd decile, plus the marginal impact of moving from the 2nd decile to the 3rd decile, and so forth (in this case of the marginal experience effect for Zocor that is +0.42% - 0.46% - 0.51% - 0.55%.)

- moving from the 5st decile of DTC spending (\$1.9 million per month) to the 10th decile (\$6.5 million per month) will decrease the instantaneous probability of switching away from Zocor by -0.1% due to the experience effect and increase the probability of switching away by +0.3% due to the credence effect.

For Lipitor –

- moving from the 1st decile of DTC spending (\$0 per month) to the 5th decile (\$2.3 million per month) will decrease the instantaneous probability of switching away from Lipitor by -1.4% due to the experience effect and also decrease the probability of switching away by -2.5% due to the credence effect;
- moving from the 5st decile of DTC spending (\$2.3 million per month) to the 10th decile (\$6.5 million per month) will increase the instantaneous probability of switching away from Lipitor by -0.2% due to the experience effect and increase the probability of switching away by -3.4% due to the credence effect.

(Given the irregular patterns of spending for Pravachol, it is difficult to make these average effect conversions.)

6. Conclusions

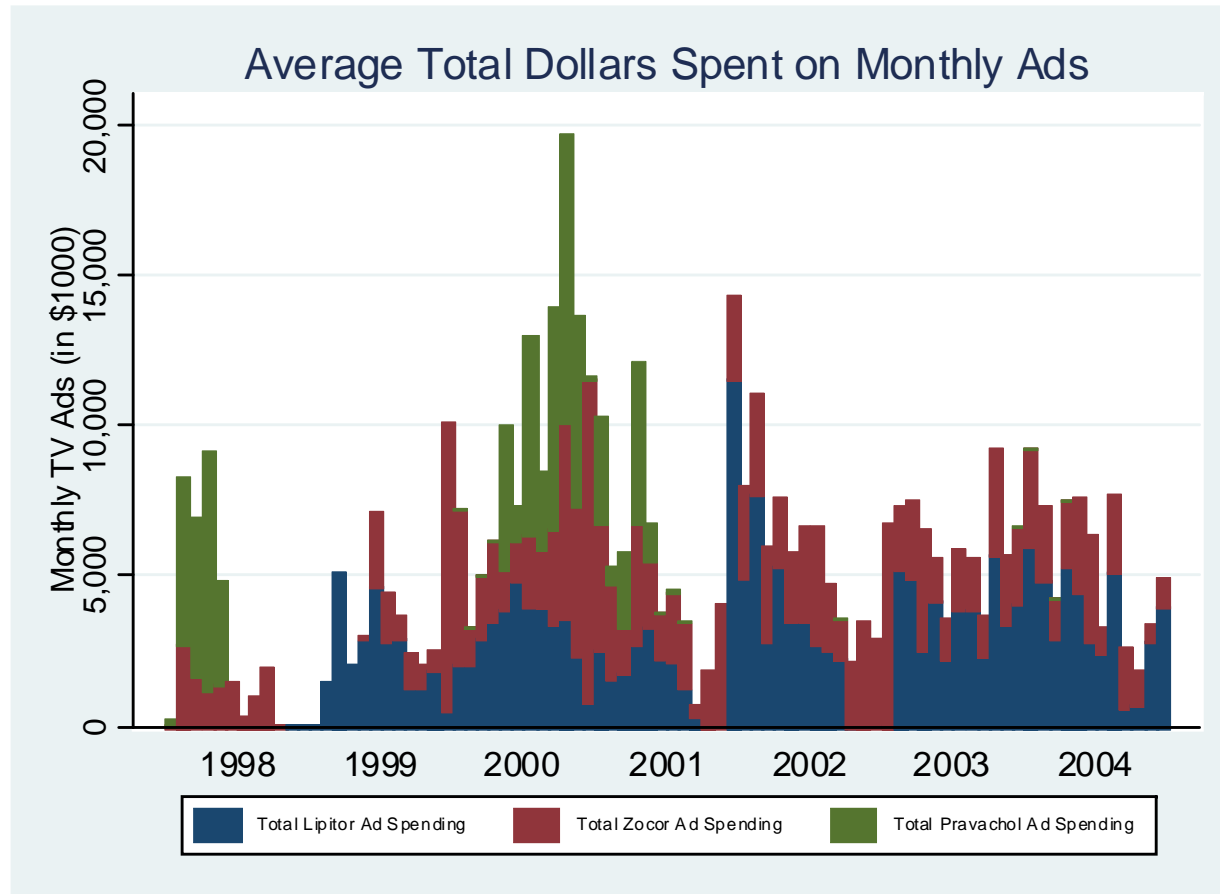
The economic literature has long argued that advertising may exist in order to inform consumers about search characteristics of goods (those aspects of a good that can be confirmed prior to purchase), experience characteristics (those aspects of a good that can only be determined after the product is actually used) and credence characteristics (those aspects of a good that, in being unverifiable, are actually created by the advertising itself, and enter directly into the utility function). While these aspects of advertising have strong theoretical justification, it has been difficult to disentangle them empirically. The primary difficulty lies in the inability to measure quality directly in empirical applications. Since quality should affect demand, and since we may expect high quality products to be advertised more heavily, if one cannot measure quality and include it in regressions of advertising effect, then any estimated parameter on an advertising variable will be biased.

We seek to overcome this dilemma by choosing a setting where "quality" has a more concrete and measurable meaning and utilizing an extensive data base. Since the lipid-lowering drugs, mainly statins, are used only for the reduction of LDL cholesterol, and since we observe the patient's full information set on their own LDL levels, we can control for the productive quality of these drugs. Consequently, any remaining effect of advertising should be unbiased estimates of the effect of advertising on use. In addition, since we have strong *ex ante* reasons to expect differential responses to search, experience, and credence messages in advertising based upon individual consumers' experience level with statins, we can disentangle these three components. Earlier work that has attempted such separation have not been able to eliminate the unobserved quality problem. To our knowledge, we are the first to be able to make this claim.

To untangle the impact of advertising, we estimate a sequential duration model, where the first stage captures the delay between diagnosis and adoption of anti-lipid therapy and the second stage captures the delay between beginning therapy and switching to an alternative treatment. We find that among uninformed consumers (those not yet initiating statin therapy) direct to consumer (DTC) advertising for Lipitor and Zocor have the expected brand-level effects – positive own-price and negative cross-price effects - for the highest level of DTC spending. For customers who are actively using the products, we find strong evidence of a demand-stimulating (decrease in instantaneous hazard of switching) effect that diminished over time, and a permanent impact of own-DTC that is demand reducing (increases the instantaneous hazard of switching). This is strongly consistent with the hypothesis that patients react to experience trait messages in DTC, but eventually substitute their own experience data for the advertisers' messages, and that patients react negatively to the FDA-mandated negative credence traits for pharmaceutical advertising. Further, the evidence indicates that higher product quality increases brand loyalty by reducing the instantaneous hazard of switching. Patients

whose LDL levels decline toward recommended levels are less likely to switch away from the product they are using and toward an alternative anti-lipid drug.

Figure 1



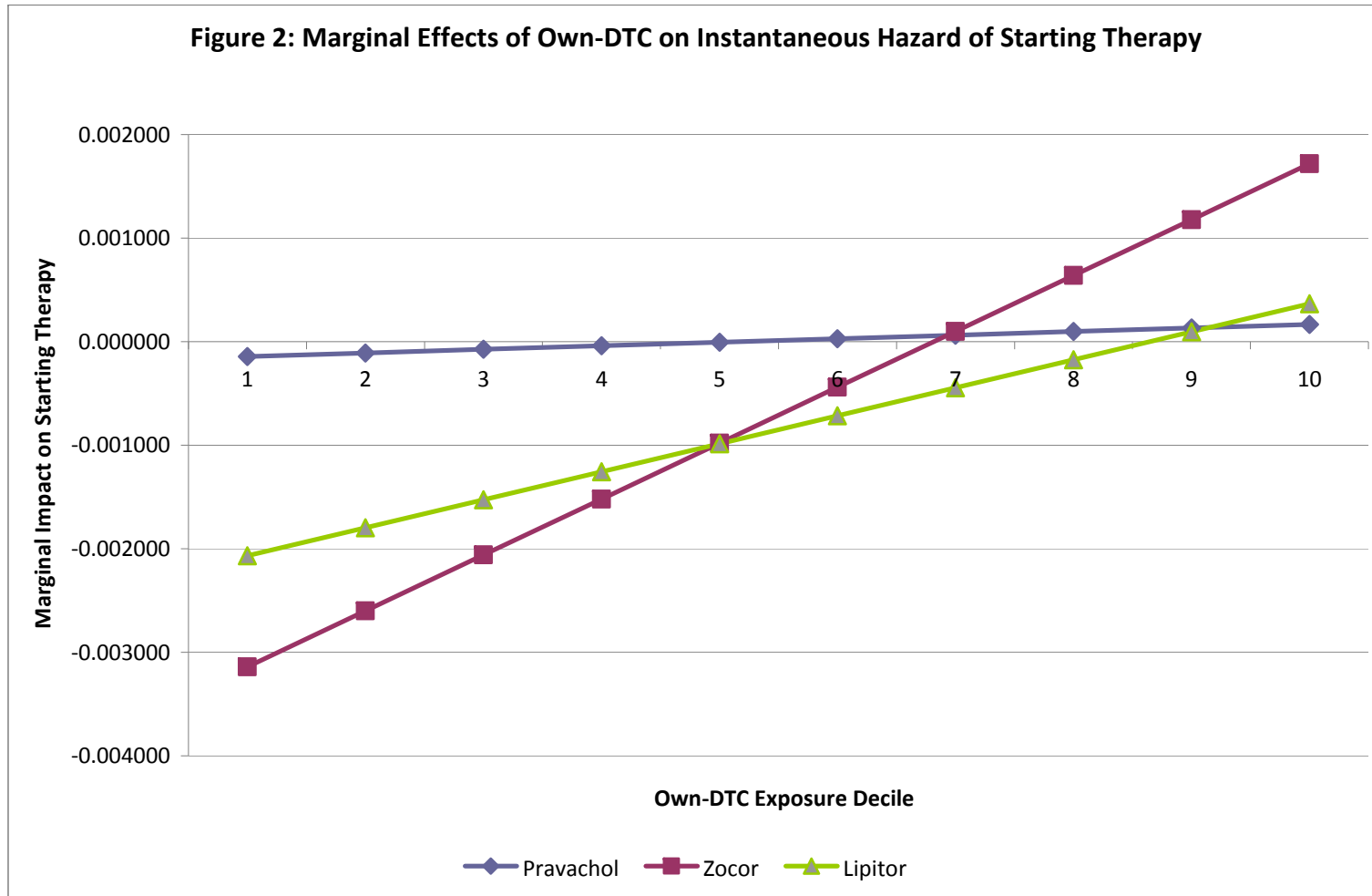


Figure 3: Marginal Effects of DTC on Instantaneous Hazard of Switching
 by treatment spell length, calculated at 5th DTC decile

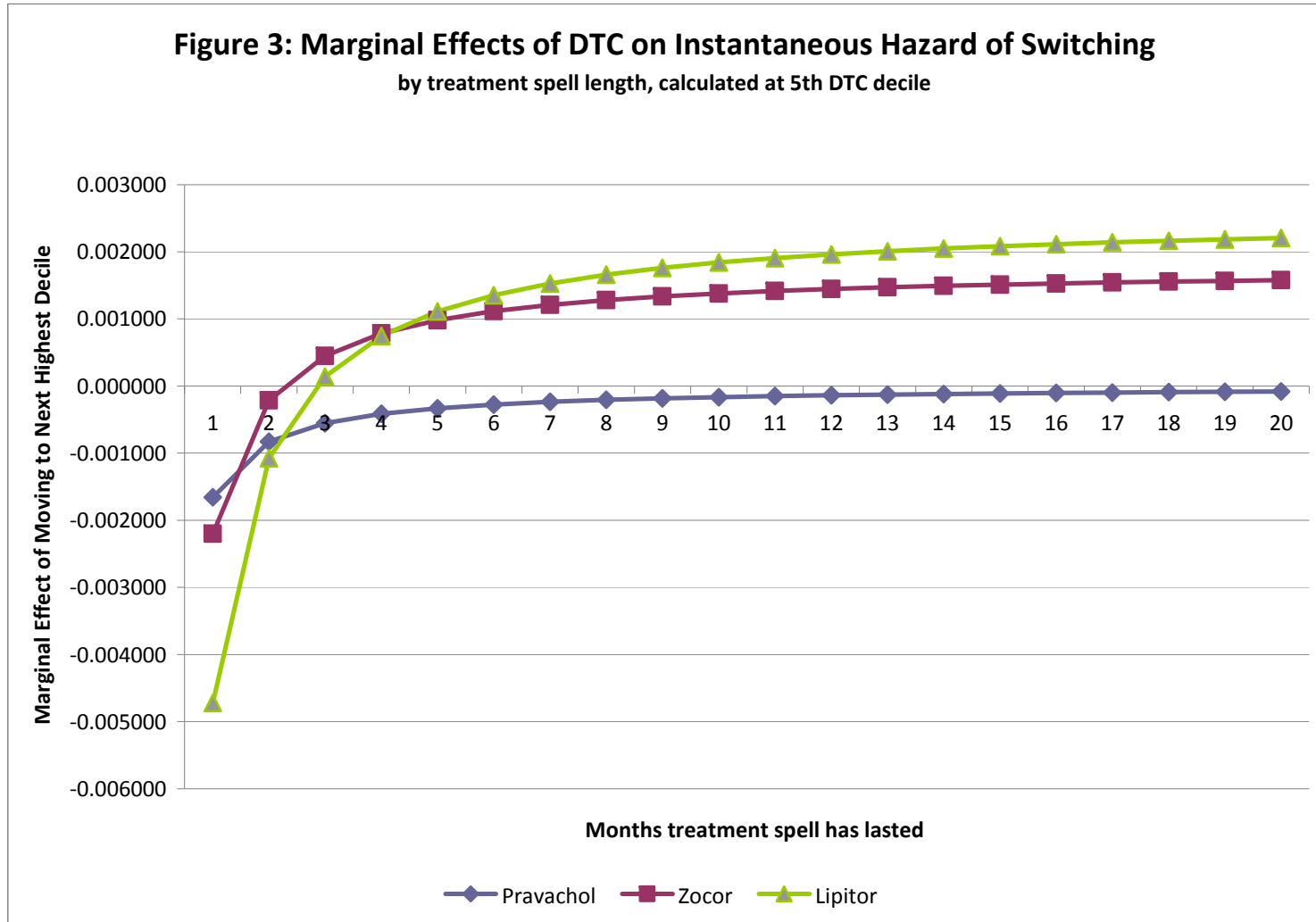


Table 1: Distributions of Selected Model Variables

Variable	Number of Patient/Months	Mean	Minimum	Maximum
Active Lipitor Rx in Month	917,834	0.04	0	1
Active Pravachol Rx in Month	917,834	0.08	0	1
Active Zocor Rx in Month	917,834	0.16	0	1
Active Rx for Other Anti-Lipid in Month	917,834	0.08	0	1
Total Monthly Lipitor Ad Spending	917,834	3063.62	0	11519
Total Monthly Zocor Ad Spending	917,834	2446.53	0	10673.3
Total Monthly Pravachol Ad Spending	917,834	418.75	0	9580.7
Average Delay to Treatment (in Months)	917,834	22.68	1	84
Average Delay to Switching (in Months)	902,522	11.61	0	83
Switch Occurred in Month	902,522	0.09	0	1
Treatment Began in Month	902,522	0.03	0	1
Most Recent LDL Level (in mg/DL)	917,834	125.66	20	520
Change in LDL Level from Previous Month	917,834	0.78	-289.2	311
Patient is Female	917,834	0.53	0	1
Patient Age in Month	917,834	59.00	0	105
Year = 1998	917,834	0.02	0	1
Year = 1999	917,834	0.06	0	1
Year = 2000	917,834	0.08	0	1
Year = 2001	917,834	0.12	0	1
Year = 2002	917,834	0.18	0	1
Year = 2003	917,834	0.24	0	1
Year = 2004	917,834	0.30	0	1

**Table 2: Discrete Time Competing Risk Duration Model
Instantaneous Hazard of Treatment Initiation**

COEFFICIENT	Start with Pravachol	Start with Zocor	Start with Lipitor	Start with Other Rx
Pravachol Spending Decile †	-0.09743* [0.05098]	-0.03213 [0.03475]	-0.08119** [0.03210]	0.03124 [0.03615]
Pravachol Spending Decile Squared	0.00943* [0.00567]	0.00259 [0.00363]	0.00828*** [0.00317]	-0.002 [0.00375]
Zocor Spending Decile†	-0.78629*** [0.06887]	-0.89202*** [0.04387]	-0.84513*** [0.04456]	-0.84784*** [0.05512]
Zocor Spending Decile Squared	0.05660*** [0.00490]	0.06543*** [0.00331]	0.06120*** [0.00336]	0.06155*** [0.00425]
Lipitor Spending Decile †	-0.26871*** [0.04723]	-0.27618*** [0.03476]	-0.26373*** [0.03014]	-0.26071*** [0.04250]
Lipitor Spending Decile Squared	0.01630*** [0.00389]	0.01799*** [0.00279]	0.01525*** [0.00256]	0.01520*** [0.00354]
LDL Cholesterol Blood Level	0.0031** [0015]	0.0026** [0.0012]	0.0041 [0.0010]	0.0015*** [0.0006]
Most Recent Change in LDL Cholesterol Blood Level	-0.0001 [0017]	0.0015 [0.0011]	-0.0042*** [0.0010]	-0.00003 [0.0006]

917, 834 observations. Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Coefficients for practice identifiers, personal and local characteristics, six month calendar time, and duration time identifiers are not shown.

†DTC spending deciles are defined for DTC averaged over each month since high cholesterol diagnosis

**Table 3: Discrete Time Competing Risk Duration Model
Instantaneous Hazard of Switching From Current Prescription**

<i>COEFFICIENT</i>	<i>Switch from Pravachol</i>	<i>Switch from Zocor</i>	<i>Switch from Lipitor</i>	<i>Switch from Other Rx</i>	<i>Switch from No Rx</i>
Pravachol Spending Decile †	0.0431 [0.0425]	0.0386 [0.0297]	-0.0046 [0.0343]	-0.1876*** [0.0404]	0.1722 [0.1154]
Pravachol Spending Decile Squared	-0.0035 [0.0048]	-0.0074** [0.0030]	0.001 [0.0037]	0.0176*** [0.0045]	-0.0171 [0.0110]
Pravachol Spending Decile / Current Treatment Spell Length	-0.1262*** [0.0273]	-	-	-	-
Zocor Spending Decile†	0.2428*** [0.0342]	0.2998*** [0.0362]	0.2482*** [0.0334]	0.2522*** [0.0330]	0.0484 [0.0480]
Zocor Spending Decile Squared	-0.0191*** [0.0029]	-0.0164*** [0.0027]	-0.0185*** [0.0027]	-0.0210*** [0.0027]	-0.0012 [0.0041]
Zocor Spending Decile / Current Treatment Spell Length	-	-0.3031*** [0.0255]	-	-	-
Lipitor Spending Decile †	-0.0695 [0.0424]	-0.1892*** [0.0250]	-0.1563*** [0.0327]	-0.1978*** [0.0265]	0.1650*** [0.0605]
Lipitor Spending Decile Squared	0.0100*** [0.0037]	0.0208*** [0.0023]	0.0252*** [0.0023]	0.0228*** [0.0023]	-0.0091** [0.0046]
Lipitor Spending Decile / Current Treatment Spell Length	-	-	-0.2709*** [0.0250]	-	-
Number of Switches in Past	0.0676*** [0.0198]	0.0922*** [0.0174]	0.0063 [0.0106]	0.0619*** [0.0149]	-0.0955*** [0.0218]
LDL Cholesterol Blood Level	0.0093***	0.0038***	0.0033***	0.0085***	-0.0008

	[0.0007]	[0.0006]	[0.0006]	[0.0006]	[0.0007]
Most Recent Change in LDL Blood Level	-0.0015***	0	-0.0016***	-0.0013***	0.0020**
	[0.0005]	[0.0004]	[0.0002]	[0.0005]	[0.0009]
Duration of Completed Spell of Waiting to Start Therapy (tr)	-0.0048	-0.0042***	-0.0026***	0.0036*	0.0334***
	[0.0031]	[0.0016]	[0.0008]	[0.0020]	[0.0026]

902, 522 observations. Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Coefficients for practice identifiers, personal and local characteristics, six month calendar time, and duration time identifiers are not shown.

[†]DTC spending deciles are defined for DTC averaged over each month since high cholesterol diagnosis

Table 4: Marginal Effects of Average DTC Monthly Exposure on the Instantaneous Hazard of Switching
calculated at average DTC over spell of treatment

	<i>Switch from Pravachol</i>	<i>Switch from Zocor</i>	<i>Switch from Lipitor</i>	
At Treatment Spell = 1	-0.001655	-0.00047	-0.01014	Marginal Effects at Lowest DTC Category
At Treatment Spell = 10	-0.000166	0.00310	-0.00358	
At Treatment Spell = 20	-0.000083	0.00330	-0.00322	
Credence Effect	-0.000083	0.00330	-0.00322	
Experience Effect	-0.001573	-0.003777	-0.00693	
At Treatment Spell = 1	-0.001655	-0.00242	-0.00404	
At Treatment Spell = 10	-0.000166	0.00116	0.00252	
At Treatment Spell = 20	-0.000083	0.00136	0.00288	
Credence Effect	-0.000083	0.00136	0.00288	
Experience Effect	-0.001573	-0.003777	-0.00693	
At Treatment Spell = 1	-0.001655	-0.00436	0.00205	Marginal Effects at Highest DTC Category
At Treatment Spell = 10	-0.000166	-0.00078	0.00862	
At Treatment Spell = 20	-0.000083	-0.00058	0.00898	
Credence Effect	-0.000083	-0.00058	0.00898	
Experience Effect	-0.001573	-0.003777	-0.00693	

All marginal effects are statistically significant at the 1% level, except for the Pravachol DTC decile / duration of use interaction.

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