Drug Innovations and Welfare Measures Computed from Market Demand: The Case of Anti-Cholesterol Drugs*

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Abstract

The pharmaceutical industry is characterized as having substantial investment in R&D and a large number of new product introductions, which poses special problems for price measurement caused by the quality of drug products changing over time. This paper applies recent demand estimation techniques to individual level data to construct a constant-quality price index for anti-cholesterol drugs. Although the average price for anti-cholesterol drugs does not change over the sample period, I find that the constant-quality price index drops by 27 percent, a pace more in line with our expectations in such a dynamic segment of the industry.

1 Introduction

The growth in medical technology is a driving force behind the rising costs of medical care, accounting for as much as 50 percent of cost growth in recent decades.[1] Although new technologies

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[1]Based on studies by Newhouse (1992), Cutler (1995), and Smith et al. (2000), the Congressional Budget Office (2008) estimates that new technologies account for approximately 50 percent of cost growth in medical care in recent

may lead to higher expenditures on medical care, they also affect the quality of treatment, typically improving patient welfare and lowering the quality-adjusted cost of treatment.[2] The rapid shift in product quality over time poses special challenges for price measurement. In the medical care sector, price index estimates that hold quality fixed are critical for measuring real output and may also inform public policies related to innovation.[3]

This paper focuses on the measurement of prices for anti-cholesterol drug treatments, which is one of the more important areas of innovation in the pharmaceutical sector over the past three decades. Extensive medical evidence has shown that high cholesterol is a contributing factor in 56 percent of the cases of clinical heart disease, which is the leading cause of death in the United States. The introduction of the statin class of cholesterol-lowering drugs starting in 1987 has proven to be a key development for preventing heart disease.[4] Innovations in this area have led to rapid growth in this market, with the use of anti-cholesterol medications increasing more than 400 percent over the period of study from 1996 to 2007.

This paper uses a demand model for anti-cholesterol drugs to construct a price index that accounts for quality changes resulting from new product introductions. The approach applied in this paper has been used to assess the value of new goods in a variety of industries.[5] However, relatively few papers have applied these techniques to examine the impact of innovations in the medical care sector. One of the seminal papers examining innovation in the medical care industry is Trajtenberg (1989) that looks at the CT scanner market. More recent work has focused on the pharmaceutical industry with Cleanthous (2004) studying innovations in the market for depression drugs and Lucarelli and Nicholson (2009) looking at new colorectal cancer drugs.

decades. A more recent study by Smith et al. (2009) estimates that medical technology explains 27-48 percent of health spending growth since 1960.

[2]For example, see Cutler et al. (1998), Cutler and McClellan (2001), and Berndt et al. (2002).

[3]If the price index falls as innovative products enter the market, then this would suggest that innovations have led to improved treatments, relative to the cost, and we should continue supporting policies that promote innovation. Conversely, if the price index increases when new products enter the market, then one might conclude that innovations, in some sense, were not worth the cost.

[4]Many individuals with high cholesterol can expect to gain many months or years of additional life by using statin treatments. The U.K. study by Ward et al. (2007) and the Heart Protection Study Collaboration Group (2010) provide nice reviews of the literature looking at statin drug effectiveness.

[5]The areas of study include automobiles (Berry, Levinsohn, and Pakes (1993) and Petrin (2002)), computers (Greenstein (1996)), and breakfast cereals (Nevo (2003)). For a more complete review of the literature see Bresnahan and Gordon (1997).

In this paper, the demand for anti-cholesterol drugs is modeled using a discrete-choice framework similar to Berry (1994) and Berry, Levinsohn, and Pakes (1995; henceforth BLP). In contrast to the previous work that uses aggregate data to examine innovations in the medical care sector, the model presented here uses detailed, nationally representative individual-level data that includes information on health conditions, demographics, health insurance, drug insurance, and individual-specific drug choices. The model permits flexible substitution patterns that are affected by the observed health conditions and demographics of individuals in the market. This model is particularly well-suited for estimating the welfare from new medications since the effectiveness of drugs and their side effects may vary depending on the severity of the condition, the specifics of the disease, and other demographic factors. If individual health conditions are not observed it may be difficult to separately identify a demand increase resulting from an improvement in the quality of a drug from one caused by the growing prevalence or awareness of a condition. Using individual level information on drug insurance coverage I am also able to control for potential moral hazard effects that may distort the market valuation of anti-cholesterol drugs. Many papers, including Gaynor and Vogt (2003), Petrin (2002), and Goolsbee and Petrin (2004), have found the use of consumer level data to vastly improve differentiated product demand estimates.

The results indicate that the quality-adjusted price of anti-cholesterol drugs has fallen considerably since 1996, reflecting the importance of innovation in this market. Relative to the CPI, the quality-adjusted price *fell* by 9 percent from 1996 to 2005, while the average price *grew* by 37 percent and a Laspeyres index (similar to that used by the Bureau of Labor Statistics (BLS)) *grew* by 9 percent. Both the average price and the quality-adjusted price fell sharply after 2005 following the entry of generics. The decline in quality-adjusted price observed over the study period is large, but likely understates the decline that has occurred over a longer horizon. In fact, much of the innovation in the market may be attributable to the introduction of statin drugs that were available prior to the study period, which accounted for 72 percent of consumer welfare in the initial year of this study.

The next section describes the market for anti-cholesterol drugs. Section 3 presents the model. Section 4 describes the data, followed by a discussion of the results in section 5. Section 6 concludes.

2 The Market for Anti-Cholesterol Drugs in the United States

The World Health Organization (2002) reports that high cholesterol causes 4.4 million deaths in the world each year. High cholesterol continues to be a prevalent and serious health condition, but significant improvements have been made in the treatment of high cholesterol over the last forty years. According to estimates from the Centers for Disease Control and Prevention, 28 percent of individuals over 20 had high cholesterol in the late 1970s. That figure is around 16.3 percent today and much of the decline is likely attributable to the introduction of new cholesterol-lowering drugs and an increase in the number of individuals being treated.[6] There is particularly rapid growth in both the awareness of high cholesterol and the use of anti-cholesterol medication from 1996 to 2007. The percentage of people 20 or older that report having high cholesterol has increased from 3.5 percent in 1996 to 17.2 percent in 2007.[7] In addition to a growth in the number of individuals reporting high cholesterol, there has also been a substantial increase in the fraction of individuals with high cholesterol using anti-cholesterol medication, as shown in Figure 1.

[Figure 1. The Fraction of Individuals with High Cholesterol Over 20 that Use an Anti-Cholesterol Drug]

Several factors have contributed to the growing use of anti-cholesterol medications. First, mounting clinical evidence strongly links high cholesterol and heart disease, and verifies the effectiveness of cholesterol-lowering treatments to reduce heart disease. The development of more effective drugs and the introduction of several low-priced generics may have also increased patient usage of anti-cholesterol drugs. Increases in the level of advertising for these drugs, and the consequent increase in public awareness of high cholesterol as a serious health condition, may also be a factor.

This study looks at the full spectrum of anti-cholesterol drug treatments, including some that have been around for more than four decades. There are five classes of drugs used to treat high cholesterol including: nictonic acid derivatives, fibric acid derivatives, bile acid sequestrants, ezitimbe, and statins. While medications in each of these drug classes can lower cholesterol, the

[6] These statistics are reported in Health United States (2009). High cholesterol is defined as serum cholesterol levels of 240 or higher. The estimates are based on actual cholesterol readings, which include the effects of medication on cholesterol levels.

[7] These figures are from the MEPS data, discussed in greater detail in the data section. These estimates include individuals that would have high cholesterol if they were not taking cholesterol lowering treatment.

introduction of the statin class of anti-cholesterol drugs in the 1980s has been revolutionary for the treatment of high cholesterol. Statin drugs have several advantages: they are easy to administer, have few side effects, and are the most effective at lowering LDL or "bad" cholesterol, the primary target of drug therapy according to the National Cholesterol Education Program (2001). These factors led statins to become the top selling class of drugs in the U.S. during the period between 1999 to 2008.[8] Compared to other cholesterol treatments, statin drugs are relatively new; the first drug in this class, Mevacor, was introduced in 1987. Several drugs have entered the statin class since then, including Pravachol, Zocor, Lescol, Baycol, Advicor, Vytorin, Lipitor, and Crestor. Table 1 below shows market shares of the various statin drugs from 1996 to 2007, along with the market share of non-statin medications. A key event during the period of study was the entry of Lipitor in 1997, which became the top selling drug in the U.S. by 1999 and remained the top selling drug over the next decade.[9] At the time of Lipitor's entry into the market it was the most effective drug for lowering LDL cholesterol. Another important shift in cholesterol treatments has been the introduction of generic statins, including the generic version of Mevacor, which lost patent protection in 2002, and the generic versions of Pravachol and Zocor, which lost patent protection in 2006.[10]

[Table 1. Market Shares of Users of Cholesterol Drugs - MEPS Data]

In general, the non-statin medications are less effective at reducing LDL cholesterol and have more severe side effects than the drugs in the statin class; consequently the market share of these other drugs has declined from its 21 percent high in 1996 and has not exceeded 11 percent since 1998. Table A1 in the appendix displays attributes of anti-cholesterol drugs related to the effectiveness of each drug at lowering cholesterol. For example, it shows that Lipitor and Crestor are the most effective at lowering LDL cholesterol.[11] Table A1 also shows that higher doses of the drugs tend to be more effective, but higher doses also tend to come with more severe side effects. There are many differences among anti-cholesterol drug treatments, but there is also an idiosyncratic component to the quality of these drugs, so that some individuals may respond better to certain drug treatments

[8] Matthew Herper, "Statins Dethroned," *Forbes,* March 30, 2009.

[9] From IMS Health pharmaceutical sales estimates.

[10] Generic manufacturers can legally offer new products in a market using the active molecule of a drug when its patent expires.

[11] There are many attributes not shown in Table A1. Drugs may also differ in their side effects (e.g. muscle pain or liver damage) and proven effectiveness based on clinical outcomes. For instance, Zocor was one of the first drugs shown to be effective in clinical trials at reducing cardiovascular deaths. See the Scandinavian Simvastatin Survival Study (1994).

relative to others taking the same medication.

Another important feature of anti-cholesterol drugs is their pricing. Figure 2 demonstrates differences in pricing across medications and over time. The bold line in Figure 2 shows the overall average price of a daily dose of treatment, where a daily dose is a single pill. Figure 2 also shows pricing trends for specific daily dose treatments, such as the 10 mg dose of Lipitor and the 10 mg dose of Zocor.[12] The overall average price from 1996 to 2005 grew substantially because of a growing demand for newly introduced drugs that tend to be more expensive. In addition, prices have trended upward on many of the more popular drugs (i.e. Lipitor, Zocor, and Pravachol). For much of the sample period, the most popular branded drugs had an unexpired product patent and did not face generic competition. As a result, generic firms could not enter the market, and average prices remained relatively high at around $2 to $3 per pill for most statins. The introduction of generic versions of Zocor and Pravachol in 2006, with prices 75 percent less than the branded versions, led to a dramatic decline in the average price in 2006 and 2007.

[Figure 2. Drug Prices For Selected Cholesterol Drugs and Market Average Price]

Figure 1 and Figure 2 present conflicting descriptive evidence regarding welfare changes. If Figure 1 is viewed as a quantity index then one might infer, through revealed preference, that individuals are better off in 2005 than in 1996 because more individuals with high cholesterol are taking anti-cholesterol medications. On the other hand, looking at the increase in average price in Figure 2, one might conclude that welfare has declined. The quality-adjusted price index derived from market demand, constructed in this paper, may be viewed as an approach for weighing the relative importance of price and quality changes.

3 Econometric Model of Demand

In contrast to most purchasing decisions, in prescription drug markets individuals rely on their doctors to tell them which drug, if any, is best suited to treat their condition. At the same time, the insurer induces price sensitivity through the structure of the insurance plan, which is important since the full price of the selected drug ultimately has an effect on premiums. For these reasons, one might view the choice of the prescription drug as a joint decision of the individual, the insurer, and

[12] The overall average price is greater than those for the selected drugs because many of the more expensive higher dose treatments are not shown in Figure 2.

the physician. In the case where the doctor and insurer act in the best interest of the individual, the individual is able to optimally choose a medication. This is the maintained assumption throughout the presentation of the model. However, to the extent that market distortions are present, then the model below will only be an approximation to individual utility, and may be more appropriately viewed as a market demand function.

In every period each individual chooses a product that maximizes her utility. The set of options is $\{0, ..., J_t\}$ where J_t is the number of products available in period t. Here the option 0 is the choice not to take a drug. Individual i chooses option $j \in \{0, ..., J_t\}$ in period t if $u_{ijt} > u_{ikt} \quad \forall k \neq j$, and each individual only chooses one option. I assume that individual i's indirect utility for product j where, $j \neq 0$, at time t is given by $u_{ijt} = \alpha_{it} p_{jt} + \beta_{it} x_{jt} + \xi_{jt} + \epsilon_{ijt}$ where p_{jt} is the price of drug j in period t, x_{jt} is the vector of characteristics of drug j in period t, ξ_{jt} is the value of the unobserved (by the econometrician) product characteristic, and ϵ_{ijt} is the idiosyncratic component of individual i's indirect utility for drug j. The indirect utility of the outside good is normalized to be zero. The response of individual i to the price and product characteristics consists of a component that is common to all individuals and a component that depends upon her observed characteristics, z_{it}, so that $\alpha_{it} = \alpha_0 + \alpha_1 z_{it}$ and $\beta_{it} = \beta_0 + \beta_1 z_{it}$. For example, the health conditions of the patient enter the model through z_{it}. Thus, the indirect utility of each product may be decomposed into a mean component, $\delta_{jt} = \alpha_0 p_{jt} + \beta_0 x_{jt} + \xi_{jt}$, that is common to all individuals in the sample, and a component that is individual specific, $\alpha_1 z_{it} p_{jt} + \beta_1 z_{it} x_{jt} + \epsilon_{ijt}$.

Estimating Equations: To estimate the above model using micro-level data, I follow the approach outlined in Berry, Levinsohn, and Pakes (2004). The estimation procedure has two stages. In the first-stage, the mean component of utility is estimated along with the individual specific parameters. For this first-stage, I assume that ϵ_{ijt} takes on an extreme value distribution, so the probability of choosing option j takes the logit form:

$$Prob_{it}(j|z, x, \delta, \alpha, \beta) = \frac{exp(\delta_{jt} + \alpha_1 z_{it} p_{jt} + \beta_1 z_{it} x_{jt})}{\Sigma_{k=0}^{J_t} exp(\delta_{kt} + \alpha_1 z_{it} p_{kt} + \beta_1 z_{it} x_{kt})}. \tag{1}$$

Equation (1) is estimated by maximum likelihood, which identifies the α_1 and β_1 vectors of parameters along with mean utility, δ_{jt}.[13] The mean utility is then used as a dependent variable in the second-stage estimation, where mean utility is regressed on price and drug characteristics:

[13]Note that when one has individual level data, then δ_{jt} may be estimated directly using maximum likelihood, so it is not necessary to solve for δ_{jt} as is typical when only aggregate level data is available.

$$\delta_{jt} = \alpha_0 p_{jt} + \beta_0 x_{jt} + \xi_{jt}. \tag{2}$$

When estimating the second-stage, the issue of price endogeneity is addressed using both drug-strength fixed effects and instrumental variables.[14]

Instruments: It is often challenging to find valid instruments that affect a firm's pricing strategy, but are uncorrelated with unobserved product characteristic, ξ_{jt}. Common instruments are factors that affect marginal cost, but the marginal cost of production is typically low for pharmaceuticals and is likely to have a limited impact on price setting strategies. For this reason, an alternative instrumental variable (IV) strategy is applied that exploits the detailed micro-level data and the first-stage demand estimates.

The instruments are constructed using the first-stage logit estimates to predict market demand, but with drug prices and the unobserved product characteristic set to zero (i.e. the potentially endogenous terms are removed). The instruments formed from the first-stage demand estimates include linear predictions of demand, but also nonlinear functions of demand that may capture different aspects of the potential pricing strategies of firms. For instance, price may be chosen based on a markup term that depends on both the demand for the product and the derivative of demand with respect to price, $markup = p_{jt} - mc_{jt} = \frac{D_{jt}}{\frac{\partial D_{jt}}{\partial p_{jt}}}$. Both the demand function and the derivative may be calculated by summing individual demand predictions and individual responses to price. Specifically, the market demand for product j at time t is calculated as:

$$D_{jt} = \sum_{i=1}^{I} Prob_{it}(j|z, x, \delta, \alpha, \beta) = \sum_{i=1}^{I} \frac{exp(\delta_{jt} + \alpha_1 z_{it} p_{jt} + \beta_1 z_{it} x_{jt})}{\Sigma_{k=0}^{J_t} exp(\delta_{kt} + \alpha_1 z_{it} p_{kt} + \beta_1 z_{it} x_{kt})}, \tag{3}$$

and the responsiveness to price is measured as:

$$\frac{\partial D_{jt}}{\partial p_{jt}} = \sum_{i=1}^{I} \frac{\partial Prob_{it}(j|z, x, \delta, \alpha, \beta)}{\partial p_{jt}}. \tag{4}$$

Instruments are constructed by using equations (3) and (4) to calculate predicted demand and the predicted markup where $\alpha_{it} = 0$ and $\xi_{jt} = 0$:

[14] Although it appears that the model could potentially be estimated using a simple conditional logit model, it is likely that the price variable will be endogenous. In fact, several studies have found evidence of price endogeneity, despite using micro level data, including Villas-Boas and Winer (1999), Gaynor and Vogt (2003), Goolsbee and Petrin (2004), and Chintagunta et al. (2005).

$$D^I_{jt}(j|z,x,\xi=0,\alpha=0,\beta), \tag{5}$$

$$\frac{D^I_{jt}(j|z,x,\xi=0,\alpha=0,\beta)}{\frac{\partial D^I_{jt}(j|z,x,\xi=0,\alpha=0,\beta)}{\partial p_{jt}}}. \tag{6}$$

Since generics often compete with other generics and may also have costs that are different from the branded firm's, a second set of instruments is constructed by interacting a generic dummy with the two instruments, $generic_{jt} \cdot D^I_{jt}$ and $generic_{jt} \cdot \frac{D^I_{jt}}{\frac{\partial D^I_{jt}}{\partial p_{jt}}}$. One might expect the branded products with greater predicted demand to have higher prices; while generic products with greater predicted demand may have more entry and lower prices.[15]

The basic idea behind this IV strategy is that an individual's choice is affected by her specific demographic characteristics when selecting a product, as reflected in the first-stage choice model. However, individual information is conditioned out of the model in the first-stage, so it should not enter the mean unobserved component of demand, ξ_{jt}. Therefore, individual demographics will not be correlated with mean unobserved demand; but the aggregate preferences of individuals in the market should be correlated with the price because profit maximizing firms will consider the overall market demand (including population characteristics) when setting price.

A similar set of instruments was applied by Gaynor and Vogt (2003).[16] This approach is also related to the common strategy of using product characteristics to instrument for price as in BLP (1995) because they both depend on consumer preferences and are impacted by the consumer's value of the product attributes. Rather than using product characteristics to predict price, this

[15] While the above strategy is the approach used in the main estimates of the paper, the appendix of the paper shows that the estimates are robust to the chosen instrumenting strategy. This includes estimates that exclude the markup terms from the set of instrumental variables and another robustness check that is not based on first-stage demand estimates. One reason for checking alternative instrumenting strategies is that one may be concerned with using first-stage demand estimates if manufacturers are able to price discriminate based on population demographics. This type of price discrimination could potentially violate the assumption that the instruments are uncorrelated with ξ_{jt}.

One complication with constructing the estimate for $\frac{\partial D^I_{jt}}{\partial p_{jt}}$ is that it depends on α, which is not observed. To address this problem I estimate an alternative demand model where I use D^I_{jt} and $D^I_{jt} \cdot generic_{jt}$ to instrument for price. I then use the estimate of α from this IV regression to obtain an estimate of $\frac{\partial D^I_{jt}}{\partial p_{jt}}$.

[16] Another example is Romeo (2010) that uses consumer demographics as instruments in a discrete-choice model with random coefficients using aggregate data.

approach uses the predicted consumer preferences for the different drug treatments.

3.1 Quality-Adjusted Price Measures

The quality-adjusted price index in this paper is based on the changes in the compensating variation derived from the estimated demand model. The compensating variation provides a measure of how much income would need to change across the two periods to leave individuals indifferent between the old choice set and the new choice set. Given the logit functional form, the compensating variation from period $t-1$ to period t for individual i is calculated as $\Delta W_{it} = \frac{\mathrm{E}(u_{it}) - \mathrm{E}(u_{it-1})}{\alpha_{it}}$, where $\mathrm{E}(u_{it})$ is the unconditional indirect utility and α_{it} is the marginal utility of income. The value of the unconditional indirect utility is computed by integrating over the extreme value distribution. Using the derivation of McFadden (1981), the unconditional compensating variation is calculated as:

$$\Delta W_{it} = \frac{\ln(\sum_{j=0}^{J_t} \exp(\alpha_{it} p_{jt} + \beta_{it} x_{jt} + \xi_{jt})) - \ln(\sum_{j=0}^{J_{t-1}} \exp(\alpha_{it} p_{jt-1} + \beta_{it} x_{jt-1} + \xi_{jt-1}))}{\alpha_{it}}. \quad (7)$$

As described in greater detail by Trajtenberg (1990), the compensating variation can be converted into a price index by solving for the factor by which all prices are multiplied in period t in order to get the same welfare effect as ΔW_{it} for each individual. More precisely, given the change in welfare, ΔW_{it}, from (7), the change in the quality-adjusted price is calculated by solving for φ_{it} such that:

$$\Delta W_{it} = \frac{\ln(\sum_{j=0}^{J_t} \exp(\alpha_{it} p_{jt} \cdot (1 + \varphi_{it}) + \beta_{it} x_{jt} + \xi_{jt})) - \ln(\sum_{j=0}^{J_t} \exp(\alpha_{it} p_{jt} + \beta_{it} x_{jt} + \xi_{jt}))}{\alpha_{it}}.$$

If welfare increases across the two periods, then φ_{it} will be a negative value; and if welfare decreases across the two periods, then φ_{it} will be a positive value. The index will be specific to each individual in the data and depend on her observed characteristics.[17] To solve for the value of φ_{it} an iterative

[17] The price index used here depends on the current period prices and product characteristics, which produces more conservative estimates that tend to understate the reductions in quality-adjusted price from innovation, relative to an alternative measure that uses the base period prices and product characteristics. Theoretically, using the base

search procedure is applied for each individual. An aggregate price index is constructed by averaging over individual price changes.[18]

Work by Nevo (2003) suggests that researchers should exercise caution when using market demand to construct quality-adjusted prices. He shows that the demand for breakfast cereals may be impacted by whether unobserved demand, ξ_{jt}, and trend variables are treated as changes in the "taste" for a product or changes in actual product attributes. In particular, one might be concerned that there is simply a growing trend in the treatment of high cholesterol that represents a growing "taste" for anti-cholesterol medications, although the products (and studies on the effectiveness of the products) have not changed. If changes in the trend or ξ_{jt} represent changes in the "taste" of the product, then they should not be allowed to vary when conducting welfare analysis. On the other hand, if these values capture unobserved quality changes, then they should be allowed to vary. Although it is practically impossible to determine the correct assumption, I attempt to address the importance of this issue by examining alternative estimates, including estimates that allow the trend variable and the mean unobserved utility to vary and other estimates that hold these values fixed over time.

The presence of drug insurance creates another concern. Drug insurance may cause a divergence between the private value of a product and its social value because of a moral hazard effect. To explore the impact of drug insurance on quality-adjusted prices, I remove the effects of drug insurance from individual demand. I will explore how alternative assumptions affect quality-adjusted prices by computing and reporting various indexes (e.g. calculating a quality-adjusted price index that fixes the trend variable and removes the effect of drug insurance).

Hedonic Price Index. The quality-adjusted price index is contrasted with three alternative price indexes. Two of these indexes do not adjust for quality: the average price and the Laspeyres index. The third index accounts for quality changes using a hedonic methodology. Unlike the quality-adjusted price index that uses market demand to control for quality changes, the hedonic approach relies on measurable characteristics of anti-cholesterol drugs to capture differences in quality. Anti-cholesterol drugs are well-suited to the application of hedonic methods because individuals primarily

period prices and product characteristics can produce a price index with negative values when there are substantial innovations.

[18] In constructing the aggregate price index, I weight each individual by their population weights and the amount of welfare they receive from anti-cholesterol drugs. Whether individual weights are applied has little influence on the results. For instance, focusing on the median price change or an unweighted average produces similar results.

take these drugs to lower LDL cholesterol, which is a measurable attribute of all anti-cholesterol drugs (see Table A1 of the appendix). The hedonic model is estimated by regressing the log of price on the characteristics of the drug, C_j, and time dummies, t. The hedonic regression is $\log(p_{jt}) = \beta_c C_j + \eta_t + e_{jt}$.

Three drug effectiveness measures are included in the hedonic regression: the medication's average effectiveness in lowering LDL cholesterol (bad cholesterol), effectiveness in increasing HDL cholesterol (good cholesterol), and the ability to lower triglyceride levels (also bad). The regression also includes a dummy variable for whether the drug is a statin. I find that only the LDL effectiveness is important in pricing anti-cholesterol drugs, which is consistent with the clinical guidelines that suggest the primary goal of drug therapy is to lower LDL cholesterol. The hedonic regression estimates are reported in Table A7 of the appendix. Using the standard approach described in Aizcorbe and Nestoriak (2010), the hedonic price change from period t to period $t+1$ is $\frac{\exp(n_{t+1})}{\exp(\mathrm{n}_t)}$.

4 Data

The main data source used in the demand estimation is the Medical Expenditure Panel Survey (MEPS) from 1996 to 2007. The survey contains extensive information on medical care in the United States. The MEPS is used to provide national estimates on health care use, medical expenditures, and insurance coverage for the U.S. civilian, non-institutionalized population. It follows the individuals for two years, during which it records information on individuals over 6 periods, where each period is approximately 4-6 months.[19] The data recorded in each period includes details on the individual's insurance, demographic characteristics, health conditions, and medical expenditures. The data set is an overlapping panel with approximately 15,000 individuals entering the data each year.

For the analysis that follows, I limit the sample to those with either a cholesterol disorder or heart disease. Based on this selection rule, the total number of individuals included in the analysis is 21,991 and the number of individual periods is 106,510.[20]

[19] While there are actually 5 rounds to the survey, the third round reaches across two years and is split into two distinct periods.

[20] For individuals excluded from the sample, only 0.48 percent are observed using anti-cholesterol medication. It is likely that individuals using medication in the excluded sample have other risk factors or a combination of risk factors such as diabetes, hypertension, or a family history of heart disease.

4.1 Variables

The dependent variable used in this paper is the treatment choice in a period. The treatment choices include the anti-cholesterol drugs that are available in the market in various strengths during the period and the no-drug treatment option. The dependent variable is a binary variable that is equal to one if individual i uses treatment option j in period t, and zero otherwise.

I turn next to a description of the explanatory variables, starting with the individual characteristics, z_{it}. Individual i's health conditions in period t are described by four dummy variables: $High\ Cholesterol_{it}$, $Heart\ Disease_{it}$, $Diabetes_{it}$, and $Hypertension_{it}$. Since cholesterol levels tend to increase with age, and men are at a higher risk of heart disease at a younger age, I also include the variable Age_{it} and an indicator for $Male_{it}$ and nonlinear functions of these variables. In addition to these objective risk factors, I also observe a subjective risk measure where individuals indicate their perceived health. The variable $PerceivedGoodHealth_{it}$ is an indicator that is one if health is perceived as excellent and zero otherwise.

The various health-related variables mentioned in the previous paragraph are used to construct a measure of composite risk, $RiskScore_{it}$. This variable is constructed by estimating a probit model of whether individuals in the sample take an anti-cholesterol drug conditional on the above risk factors, and then setting $RiskScore_{it}$ to be the predicted probability. Estimates are reported in Table A2 of the appendix.[21]

Binary variables are used to capture differences in insurance coverage. The variables $DrugIns_{it}$ and $MedIns_{it}$ are dummy variables indicating whether an individual has drug and medical care insurance, respectively.[22] The model also includes information on individual i's household income and is measured in 2007 dollars as $Log(Inc_{it}+1)$. It also includes the number of years of education, $EducYear_{it}$.

The characteristics of the drugs, x_{jt}, that are invariant over time are captured using drug-strength dummies. Many of the drugs are offered in multiple strengths, so that different strength

[21] Although an ideal risk measure would be computed by weighting the risk factors based on likely health outcomes, this information was not available.

[22] Individuals on private plans, Medicaid, Medicare, or other public insurance plans are classified as medically insured. I also assume that individuals with prescription drug insurance coverage also have medical coverage because it is rare for individuals with drug insurance not to have medical insurance. Additional dummy variables are included to indicate whether an individual has either $Medicare_{it}$ or $Medicaid_{it}$ insurance.

categories are considered distinct products.[23] The perceived value of anti-cholesterol drugs may systematically vary over time. Given the large expansion in the use of anti-cholesterol drugs, a trend variable, $Trend_t$, is included in the model to capture general shifts in the value of drug treatments relative to the no-drug treatment option.[24] In addition to a market trend, the model also includes the age of each molecule, $log(AgeMolecule_{jt})$, to account for the time it may take for the market to realize the value of a new molecule.[25]

The price of drug j in period t is denoted $Price_{jt}$. The price of the drug is the full price of the drug paid to the retail pharmacy (i.e. the amount paid by the insurer plus the amount paid out-of-pocket by the individual). The total payment is used because the goal of the model is to measure the total market value of the product, and individuals ultimately bear the full cost of the payment through higher out-of-pocket costs, higher individual premiums, or lower wages (for employer paid premiums).[26] Although one might attempt to analyze the consumer's response to co-payments, I do not observe the co-payments for all available drugs. Moreover, even if I observed the co-payments for the different treatment options, this would not necessarily capture the market's response to the full price of the prescription drug. In particular, it may ignore the price sensitivity of individuals as reflected in their selection of insurance options. One might argue that an individual's drug choice may occur when selecting insurance. For example, a person who is both highly risk averse and highly price sensitive might prefer a plan that covers the full price of the lowest cost drug option, but provides no coverage for alternative drug choices.

All individual characteristics, z_{it}, enter the model through interactions with product characteristics, x_{jt}. For instance, to account for differences in the value of anti-cholesterol drug treatments relative to the no-drug treatment option, the model includes interactions between individual health

[23] The less frequently used strength categories are aggregated with the more frequently used strengths that are closest in value. For example, the 5 mg strength category for Zocor is purchased infrequently, so it is aggregated with the 10 mg category. Appendix A1 provides a list of the different categories used in the estimation. I found that the results presented here are not sensitive to alternative aggregations.

[24] The trend variable is the difference between the date of the observation and January 1, 1996 (i.e. the intial date of the sample) measured in years.

[25] The age of the molecule is the median date in the current round minus the date in which the molecule was approved for sale by the FDA divided by 365. I assume the effect of the molecule's age on demand stops after 10 years, so the maximum value of this variable is log(10). The results are robust to alternative assumptions, such as not setting a limit on the age variable.

[26] A similar argument is made by Cutler et al. (1998) looking at the value of new heart attack treatments.

conditions and a dummy variable indicating a drug treatment option.[27] The model also allows for several variables to affect price sensitivity by interacting individual characteristics with $Price_{jt}$, including the $RiskScore_{it}$, $DrugIns_{it}$, and $Log(Inc_{it}+1)$. One might expect that those individuals with more severe conditions, higher incomes, and those with drug insurance may be less sensitive to price. I allow flexibility in how drug insurance affects the responsiveness to market price because insurance may induce price sensitivity through tiering or formulary restrictions. Therefore, in addition to an interaction between $DrugIns_{it}$ and $Price_{jt}$, I also allow drug insurance to have an effect on the probability of choosing any anti-cholesterol medication regardless of the price.

To allow for flexibility in how individuals respond to the different prescription drug offerings, the model contains interaction terms between individual risk factors (having high cholesterol, heart disease and age) and dummy variables for the active molecules for each of the anti-cholesterol drugs. The model also includes an interaction between the severity of the patient's condition, as measured by $RiskScore_{it}$, and the trend variable. The interaction with the trend variable allows for changing guidelines for cholesterol treatment over time.[28] Additional notes on the data set and variable construction are provided in the appendix.

4.2 Summary Statistics

Table 2 provides descriptive statistics on the population in the selected sample. The first column provides the mean of each variable, while the following columns show the quartiles. Overall Table 2 shows considerable variation in many of the demographic variables and also reveals that those in the sample (i.e. those with high cholesterol or heart disease) are quite distinct from the national population. The median age is 63 which is much higher than the national median age of about 35. This is not surprising since cholesterol increases with age as does the incidence of heart disease. A high fraction of individuals are enrolled in Medicare, so just 4 percent of the selected sample has no medical insurance, relative to the national average of about 16 percent. Table 2 also shows the prevalence of both hypertension and diabetes that are relatively more common in the sample

[27] By default, all individual information enters the model through an interaction with a dummy variable indicating a drug treatment option because the utility of the no-drug treatment option is set to zero.

[28] Studies over this time period suggest that individuals may benefit from more aggressive treatment, so that lower risk individuals may be more likely to purchase anti-cholesterol drugs in later years of the sample (see the National Cholesterol Education Program (2001)).

compared to the overall population.

[Table 2. Demographics]

5 Results

Recall that the first-stage of the demand estimation is a discrete choice model, which measures the impact of individual characteristics on drug choices and estimates the value of the mean utility of each drug choice. Table 3 shows some of the estimates from the first-stage discrete choice model. The estimates show that all of the risk factors have a significant and positive effect on the probability of purchasing an anti-cholesterol drug (i.e. the composite risk score, age, male, high cholesterol, heart disease, diabetes, perceived health, and hypertension). The estimates also reveal that several factors affect price sensitivity. Those with more severe conditions, those with drug insurance, and those with higher incomes tend to be less sensitive to price. In addition to reducing price sensitivity the estimates also show that drug insurance has a positive and significant effect on the probability of taking any medication. The coefficient on the trend variable is positive, indicating greater demand for anti-cholesterol drugs over time. However, the interaction between the risk score variable and the trend variable is negative, suggesting that those with less severe conditions are more likely to take anti-cholesterol drugs later in the sample.[29] Table A3 of the appendix presents parameter estimates from the remaining interactions.

[Table 3. First-Stage Results from Conditional Logit Estimation]

Using estimates of mean utility derived from the first-stage, the second-stage demand estimation regresses mean utility on price and other product characteristics. The exogenous variables in the second-stage are the drug-strength dummy variables, with the 10 mg version of Lipitor as the excluded alternative. Table 4 reports the second-stage results. The first column shows the results from the IV estimation that accounts for the potential endogeneity of price. The results show that the coefficient on price is negative and highly significant with a coefficient, -1.61. Note that the price coefficient is much larger than the coefficient on the interaction of price and drug insurance of

[29] The $\log(Age\ of\ Molecule)$ is another important determinant of the demand for anti-cholesterol medications. The estimates show a very heterogeneous effect on the age of the molecule depending on the characteristics of individuals. The estimates show that older individuals are less likely to adopt new medications in favor of medications that have been in the market longer, perhaps due to greater familiarity with older products. In contrast, individuals with higher risk conditions, as reflected by their risk score, are more likely to adopt new medications earlier.

0.05 (reported in Table 3), which implies that those with prescription drug insurance are actually quite responsive to market price.

[Table 4. Second-Stage Demand Estimates]

Several checks are performed on the IV estimation. Table A4 in the appendix shows that the instruments have good explanatory power. Applying a Cragg-Donald test, I find that the null hypothesis that the instruments are weak is strongly rejected. The model also produces reasonable price elasticity with a mean of -3.11 (s.d. 1.59) that is consistent with profit maximizing behavior of drug manufacturers. As a comparison to the IV approach, the second column of Table 4 shows estimates from an OLS regression. The OLS model shows that the price coefficient is negative, but very small and insignificant, implying a potential bias from firms that charge higher prices when unobserved demand shocks are larger.

A potentially important variable that is omitted in the above analysis is advertising to physicians and consumers. Estimates that include a proxy for advertising are included in Table A5 of the appendix, which produces similar results. More generally, note that even if advertising were in the model, it is unclear how it should enter the welfare analysis. Similar to the issue that arises with the unobserved product characteristic, ξ_{jt}, the effects of advertising could represent an effect on individual taste, which should not be considered a change in product characteristics; or it may be informative and change the objective value of the product, which should be counted as a shift in product characteristics. This issue will be explored in greater detail in the next subsection.

Additional robustness checks are reported in Table A5 of the appendix. These checks fall into two categories: (1) applying alternative sets of instruments to evaluate the robustness of the selected IV strategy, and (2) exploring the restrictiveness of the logit-error assumption. In general, these robustness checks produce qualitatively similar results to the IV estimates reported in Table 4.[30]

Welfare Analysis. The overall welfare from the availability of anti-cholesterol medications is calculated using the market demand estimates. The consumer welfare is large and the growth has been enormous, increasing from $1.5 billion in 1996 to more than $9.3 billion in 2007, an increase of more than 600 percent. Much of this growth in welfare is caused by an increase in the number of users, from 5.4 million in 1996 to 29.3 million in 2007. However, the growth is also partly due to an increase in the welfare per user of the drug, which has increased from $277 per user in 1996 to

[30] The results from these robustness checks tend to produce quality-adjusted price indexes that fall more rapidly than the quality-adjusted price index implied by the main specification.

$321 per user in 2007.[31]

To highlight the importance of individual characteristics when conducting welfare analysis, Table 5 shows expected welfare for individuals with different types of health conditions and demographics for 2006. The first row shows the welfare distribution for the entire population. The mean expected welfare per year is $219, but there is a wide range in consumer welfare per individual with the individuals at the 10th percentile valuing the drugs at $125 and those at the 90th percentile valuing the drugs at $300. In general, Table 5 shows that those with more serious risk factors (i.e. heart disease, diabetes, hypertension, and age over 55) tend to value these drugs more. Financial factors also have a large impact on the value of these drugs. Both those with drug insurance and those with health insurance value anti-cholesterol drugs more than those without insurance. The average difference in valuation for someone with health insurance compared to someone without health insurance is around $81, about the same effect as a serious risk factor, such as hypertension or heart disease. To summarize, Table 5 shows that individual health and demographic variables may have a large effect on consumer welfare, which demonstrates the importance of including this detailed individual information in the analysis.

[Table 5. Individual Annual Welfare by Condition and Demographic Factors]

This section has used the demand estimates to look at welfare levels in the market, the next section examines how welfare changes over time may be translated into quality-adjusted prices.

5.1 Quality-Adjusted Prices

The demand estimates above are used to construct a quality-adjusted price index. Figure 3 shows the quality-adjusted price compared to two benchmark price indexes: the average price and the hedonic price. While the average price increases by almost 37 percent from 1996 to 2005, the price index based on the demand estimates fell by 9 percent. The hedonic index is much closer to the quality-adjusted price index and increases by only 4 percent over this period, confirming the important role of quality in the determination of price in this market. There are clear differences across these indexes pre-2005, but post-2005 all three indexes show a large decrease in price after

[31] Welfare figures assume 75 percent compliance, which is discussed in greater detail in the appendix. Although it is tempting to interpret these figures, it may be difficult to isolate particular factors affecting welfare without further analysis (i.e. the introduction of new products, price changes, generic entry, or changing health of the population using anti-cholesterol drugs).

the introduction of the generic versions of Zocor and Pravachol.

[Figure 3. Price Index Comparison]

Several assumptions were made in constructing the quality-adjusted price index shown in Figure 3. To explore the importance of these assumptions, Table 6 presents alternative quality-adjusted price indexes along with the average price, the hedonic price, and an additional benchmark price, the Laspeyres index. The Laspeyres index uses prior period expenditures to weigh price changes, similar to how price indexes are currently constructed at the BLS. The following are the different assumptions made for the four different quality-adjusted price indexes reported in Table 6: (1) ignores moral hazard issues caused by private drug insurance and allows the trend variable and unobserved product characteristic, ξ_{jt}, to vary over time; (2) controls for moral hazard issues by removing the effects of drug insurance, but allows the trend variable and unobserved product characteristic to vary over time (the result reported in Figure 4 above); (3) removes drug insurance effects and fixes the trend variable to its initial value, but allows the unobserved product characteristic to vary over time; (4) removes drug insurance effects, fixes the trend variable to its initial value, and the unobserved product characteristic is held constant over time. The results show some variation among the price indexes, but the differences appear relatively minor when compared to the effect of not correctly measuring the value of new goods. The quality-adjusted prices are all 13 to 18 percentage points lower than the Laspeyres price index by 2005.

[Table 6. Price Index Comparison and Alternative Assumptions (adjusted to 2007 $ using CPI)]

Each of the four indexes differ substantially from the average price, but the large price reduction observed in 1997 using index (4) is quite different from indexes (1), (2), and (3) that each show a small price increase followed by a gradual price decline. The reason for this difference is that index (4) fixes the value of ξ_{jt} over time, which implies that a drug like Lipitor, that acquires greater share in later years, may have a larger initial effect on the quality-adjusted price index. Although this initial difference is interesting, index (4) moves closer to indexes (1) through (3) over time and remains much lower than the average price over the entire period.

The quality-adjusted price indexes all show a substantial decline in the real price of anti-cholesterol drugs, regardless of whether demand changes due to trends or whether unobserved mean utility (ξ_{jt}) is allowed to vary. This finding contrast with results in Nevo (2003) who finds that quality-adjusted price indexes vary greatly for breakfast cereals depending on these assumptions. A critical difference between Nevo's analysis and the market studied here is that unlike breakfast

cereals, where innovations are relatively small, the innovations in prescription drug markets may be substantial. In particular, the innovations are large enough that alternative assumptions do not affect the basic result of declining prices for anti-cholesterol drugs. Therefore, while policy-makers should remain cautious in applying market demand estimates to construct quality-adjusted prices for a broad range of products, it may be useful to take this approach for constructing price indexes in innovative markets, such as prescription drugs, where accounting for quality changes is likely to be critical for obtaining meaningful price measures.

The quality-adjusted prices reported in Table 6 rely heavily on the estimates of the price coefficient, α, which weighs the importance of price and the quality of the various products. To check the sensitivity of the results presented here, Table A6 in the appendix shows the reported price indexes for different values of α, ranging from the 5th percentile ($\alpha = -2.40$) to the 95 percentile ($\alpha = -.82$). The results show that over this range of values the quality-adjusted price remains about 15 to 28 percentage points below the Laspeyres index in 2005.

Although several new product introductions occur during the period of study that affect quality-adjusted prices, the primary innovation in this market – the introduction of statin drugs – occurred prior to 1996. To show the importance of statin drugs at the beginning of the sample, welfare estimates from the availability of statin drugs are calculated for 1996, the initial year of the sample. Comparing consumer welfare estimates when statins are available to counterfactual welfare estimates when statins are not available, I find that statin drugs accounted for 72 percent of consumer welfare in 1996.[32] Therefore, capturing quality-adjusted price declines from 1996 to 2007 may greatly understate the true quality-adjusted price decline that may be observed over a longer horizon.

6 Conclusion

The impact of innovation on welfare is measured using a price index that holds the quality of anti-cholesterol drug treatments fixed over time. The quality-adjusted price index is based on welfare measures constructed from market demand estimates. This price index fell by 9 percent from 1996 to 2005, which contrasts sharply with the average price that increased by 37 percent and also differs from the Laspeyres index that grew by 9 percent. Thus, accounting for changes in quality appears

[32] A more detailed analysis of the welfare gains from the introduction of statin drugs is reported in Table A9 of the appendix.

to be very important for properly measuring prices in the market for anti-cholesterol drugs. This result highlights the potential importance of accounting for quality changes when measuring prices and output in the health sector where technology is a primary driver of expenditure growth.

The demand model used to calculate a quality-adjusted price index in this paper reflects the market's willingness-to-pay for prescription drugs. While this appears to provide a reasonable and useful approximation to the value of anti-cholesterol drugs over time, it is possible that frictions in the physician-insurer-patient relationship may cause the market's willingness-to-pay for a drug to not reflect the patient's preferences. For example, over-valuation of new technologies by physicians would lead to an over-estimation in the welfare growth from the introduction of new drugs. Evidence of the important role of physicians in the decision making process has been documented in the literature with the work by Hellerstein (1998) who shows that the likelihood of prescribing generics is largely determined by the physician and not the patient's characteristics. More recently, Iizuka (2007) looking at the Japanese market for anti-hypertensive drugs shows that physicians in Japan, who also dispense prescription drugs, may select a prescription for a patient based on both the patient's preferences, but also their own profit motivation. More work needs to be done to study the value of new technologies for *patients* when there are potential agency problems with physicians or insurers.

One alternative approach for valuing new medical technology is to compare health expenditures with health outcomes (see Cutler et al. (1998), Cutler and McClellan (2001), and Berndt et al. (2002)), which does not rely on the physician-patient relationship. In particular, it may be interesting to examine whether there are differences in the value of new technologies based on health outcomes compared to the predicted value of technologies based on market preferences.[33] Another approach for measuring the patient's value of new technologies is to model the decisions and incentives of the various agents (i.e. patients, insurers, and physicians), which would require significantly more information than is available from known data sources.

[33] Although the two approaches are similar in their objective to measure the value of new technologies, they actually answer distinct questions that provide different insight into the value of new goods. The market-based approach is a reflection of the market's valuation of a product, while the outcomes based approach attempts to objectively measure the welfare from medical treatments based on cost-effectiveness studies that compare health outcomes and the cost of inputs.

References

[1] Aizcorbe, Ana, and Nicole Nestoriak, (2010), "Price Indexes for Drugs: A Review of the Issues", Manuscript.

[2] Berry, Steven, James Levinsohn, and Ariel Pakes, (1993), "Estimating Discrete Choice Models of Product Differentiation", *RAND Journal of Economics*, 25 pgs 242-262.

[3] Berry, Steven, (1994), "Estimating Discrete-Choice Models of Product Differentiation", *RAND Journal of Economics*, 25(2) pgs 242-262.

[4] Berry, Steven, James Levinsohn, and Ariel Pakes, (1995), "Automobile Prices in Market Equilibrium", *Econometrica*, 63(4) pgs 841-890.

[5] Berry, Steven, James Levinsohn, and Ariel Pakes, (2004), "Differentiated Products Demand Systems from a Combination of Micro and Macro Data: The New Car Market", *Journal of Political Economy* 112(1) pgs 68-105.

[6] Berndt, Ernst, Anupa Bir, Susan H. Busch, Richard Frank, Sharon-Lise T. Normand, (2002), "The Medical Treatment of Depression, 1991-1996: Productive Inefficiency, Expected Outcome Variations, and Price Indexes", *Journal of Health Economics*, 21(3) pgs 373-396.

[7] Bresnahan, Timothy and Robert Gordon, (1997), "The Economics of New Goods", NBER Book Series Studies in Income and Wealth.

[8] Chintagunta, Pradeep, Jean-Pierre Dube, and Kim Yong Goh, (2005), "Beyond the Endogeneity Bias : The Effect of Unmeasured Brand Characteristics on Household-level Brand Choice Models", *Management Science*, 51(5), pgs 832-849.

[9] Cleanthous, Paris, (2004), "Patient Welfare Implications of Innovation in the U.S. Antidepressant Market", Working Paper.

[10] Cutler, David, (1995), "Technology, Health Costs, and the NIH", *National Institutes of Health Roundtable on the Economics of Biomedical Research.*

[11] Cutler, David, Mark McClellan, Joseph Newhouse, and Dalia Remler, (1998), "Are Medical Prices Declining? Evidence From Heart Attack Treatments", *Quarterly Journal of Economics*, 63(4) pgs 691-1024.

[12] Culter, David and Mark McClellan, (2001), "Is Technological Change in Medicine Worth It?", *Health Affairs*, 20(5) pgs 11-29.

[13] Congressional Budget Office, (2008), "Technological Change and the Growth of Health Care Spending", The Congress of the United States, Congressional Budget Office. January.

[14] Gaynor, Martin and William Vogt, (2003), "Competition Among Hospitals", *RAND Journal of Economics*, 34(4) pgs 764-785.

[15] Goolsbee, Austan, and Amil Petrin, (2004), "The Consumer Gains from Direct Broadcast Satellites and the Competition with Cable TV", *Econometrica*, 72(2) pgs 351-381.

[16] Greenstein, Shane, (1996), "From Superminis to Supercomputers: Estimating Surplus in the Computing Market", The Economics of New Goods, University of Chicago Press, Chapter 8 pgs 329-372.

[17] Heart Protection Study Collaborative Group, (2010), "Statin Cost-Effectiveness in the United States for People at Different Vascular Risk Levels", Circulation: Cardiovascular Quality and Outcomes, 2 pgs 65-72.

[18] Lucarelli, Claudio and Sean Nicholson, (2009), "A Quality-Adjusted Price Index for Colorectal Cancer Drugs", NBER Working Paper Series, Working Paper 15174.

[19] Mcfadden, D., (1981) "Econometric Models of Probabilistic Choice," in C. Manski and D. McFadden, Structural Analysis of Discrete Data, Cambridge, MA: The MIT Press.

[20] National Cholesterol Education Program, (2001), "Detection, Evaluation, and Treatment of High Blood Cholesterol in Adults (Adult Treatment Panel III)", National Institutes of Health, National Heart, Lung, and Blood Institute.

[21] Newhouse, Joseph, (1992), "Medical Care Costs: How Much Welfare Loss?", *Journal of Economic Perspectives*, 6(3) pgs 3-21.

[22] Nevo, Aviv, (2003), "New Products, Quality Changes, and Welfare Measures Computed from Estimated Demand Systems" *The Review of Economics and Statistics*, 85(2) pgs 266-275.

[23] Pakes, Ariel, Steven Berry, and James Levinsohn, (1993), "Applications and Limitations of Some Recent Advances in Empirical I.O.: Price Indexes and Analysis of Environmental Change." *American Economic Review*, 83(2) pgs 240-46.

[24] Petrin, Amil, (2002), "Quantifying the Benefits of New Products: The Case of the Minivan", *Journal of Political Economy*, 110(4) pgs 705-729.

[25] Romeo, Charles, (2010), "Filling Out the Instrument Set in Mixed Logit Demand Systems for Aggregate Data", U.S. Department of Justice, Working Paper.

[26] Scandinavian Simvastatin Survival Group, (1994), "Randomized Trial of Cholesterol Lowering in 4,444 Patients with Coronary Heart Disase: the Scandanavian SimvaStatin Survival Study (4S)", *Lancet*, 344 pgs 1383-9.

[27] Smith, Sheila, Stephen Heffler and Mark Freeland, (2000), "The Impact of Technological Change on Health Care Cost Increases", Working Paper.

[28] Smith, Sheila, Joseph Newhouse, and Mark Freeland, (2009), "Income, Insurance, and Technology: Why Does Health Spending Outpace Economic Growth", *Health Affairs*, 28(5) pgs 1276-84.

[29] Trajtenberg, Manuel, (1989), "The Welfare Analysis of Product Innovations, with an Application to Computed Tomography Scanners", *Journal of Political Economy*, 97(2) pgs 444-479.

[30] Trajtenberg, Manuel, (1990), "Product Innovation, Price Indices, and the (Mis)Measurement of Economic Performance", National Bureau of Economic Research, Working Paper No. 3261.

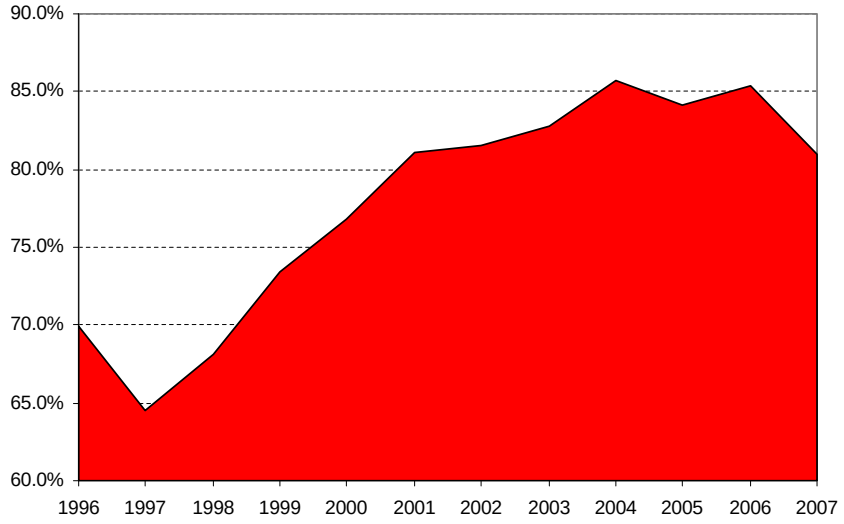
[31] Villas-Boas, J. and Russell Winer, (1999), "Endogneity in Brand Choice Models", *Management Science*, 45 pgs 1324-1338.

[32] Ward, S., M. Lloyd Jones, A Pandor, M Holmes, R Ara, A Ryan, W Yeo, and N Payne, (2007), "A Systematic Review and Economic Evaluation of Statins for the Prevention of Coronary Events", Health Technology Assessment, 11(14).

[33] World Health Organization, (2002), "World Health Report 2002: Reducing Risks, Promoting Healthy Life", Geneva.

7 Tables

Figure 1. The Fraction of Individuals with High Cholesterol Over 20 that Use an Anti-Cholesterol Drug



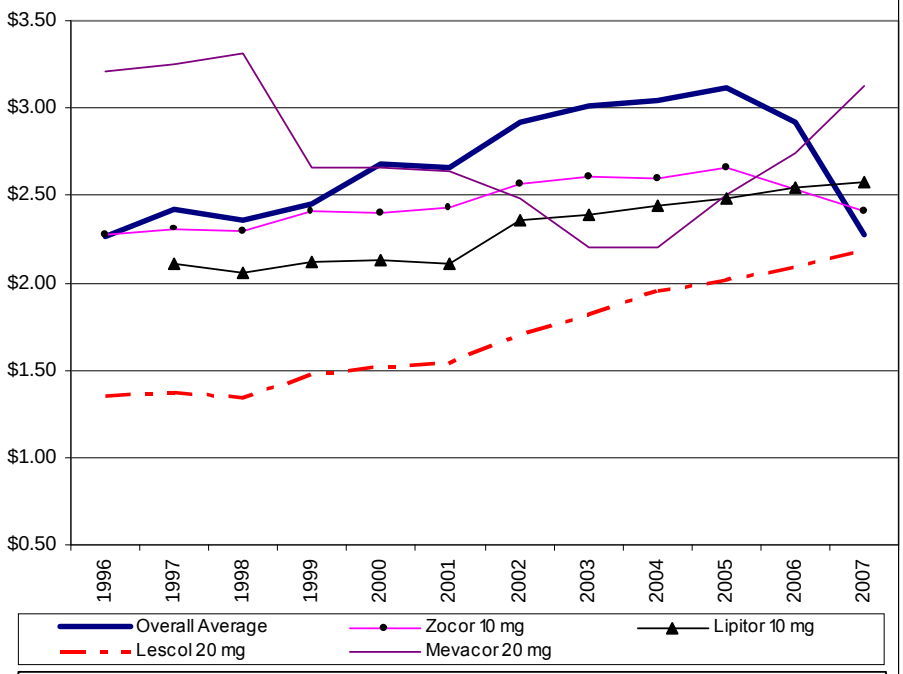
Source: Author's calculations using MEPS data for those individuals reporting high cholesterol.

Table 1. Market Share of Users of Anti-cholesterol Drugs

Drug Name	Chemical	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Lipitor	Atorvastatin Calcium		11.8%	28.2%	34.6%	39.1%	44.3%	44.2%	45.2%	43.5%	42.0%	38.4%	32.2%
Zocor	Simvastatin	27.2%	28.1%	24.8%	25.6%	24.9%	26.2%	26.7%	25.1%	23.4%	21.7%	13.0%	4.4%
Generic Zocor	Simvastatin											8.1%	21.5%
Pravachol	Pravastatin Sodium	21.8%	18.3%	17.1%	15.6%	12.8%	11.5%	11.5%	9.9%	8.2%	6.3%	3.4%	1.6%
Generic Pravachol	Pravastatin Sodium											1.2%	3.3%
Mevacor	Lovastatin	18.2%	12.6%	7.1%	5.1%	4.8%	2.7%	0.5%	1.3%	0.9%	0.3%	0.5%	0.6%
Generic Mevacor	Lovastatin							4.2%	4.3%	5.3%	8.1%	9.1%	9.3%
Crestor	Rosuvastatin Calcium								0.4%	4.4%	4.6%	6.4%	6.9%
Baycol	Cerivastatin Sodium			1.3%	3.0%	4.7%	4.6%						
Vytorin	Ezetimibe/Simvastatin									0.4%	4.3%	7.6%	8.5%
Lescol	Fluvastatin Sodium	11.6%	12.1%	9.3%	5.7%	4.1%	3.5%	4.2%	3.6%	2.5%	2.2%	2.1%	1.2%
Advicor	Lovastatin/Niacin							0.1%	0.4%	0.6%	0.6%	0.3%	0.3%
Non-statins	-	21.3%	17.1%	12.3%	10.5%	9.7%	7.2%	8.5%	9.8%	10.7%	9.9%	9.9%	10.2%

Source: Author's calculations using MEPS data. The unit of observation is the share of users of anti-cholesterol drugs. Baycol voluntarily withdrew in August of 2001 because it was linked to over 31 deaths caused by muscle cell damage.

Figure 2. Drug Prices For Selected Anti-cholesterol Drugs and Market Average Price



Source: Author's estimates using MEPS and MarketScan data sources. Prices are normalized to 2007 dollars using the CPI. The overall average is constructed by weighting the price of a single pill by the number of users of that pill in each period.

Table 2. Summary Statistics: Demographics

Variable	Mean	25th Percentile	50th Percentile	75th percentile
Health Related Demographics				
Age	62.08	52	63	74
Health Index	0.47	0.20	0.58	0.67
Male	0.48			
Has High Cholestorol	0.68			
Has Heart Disease	0.48			
Has Diabetes	0.25			
Has Hypertension	0.53			
Perceived Health is Good	0.10			
Other Demographics				
Family Income (in 2007 $s)	$54,591	$18,663	$40,123	$74,755
Number of Years of Education	11.87	10	12	14
Drug Insurance	0.74			
Health Insurance	0.96			
Medicare	0.52			
Medicaid	0.16			
Number of Observations	106,510			

Source: Author's calculations using MEPS data.

Table 3. First-Stage Results from Conditional Logit Estimation

Variable	Coef.	z-stat
Price*Risk Score	0.192	(3.3)
Price*Drug Insurance	0.045	(2.61)
Price*Income	0.015	(2.21)
Drug Insurance	0.201	(3.65)
Health Insurance	0.491	(7.42)
Log(Household Income/1000+1)	-0.006	(-0.27)
High Cholesterol	4.354	(10.05)
Heart Disease	0.813	(10.98)
Age	0.121	(3.47)
Age^2	0.001	(1.68)
Age^3	0.000	(-5.05)
Age>=40	0.413	(4.16)
Age*Male	-0.011	(-5.41)
Perceived Good Health	-0.305	(-7.58)
Risk Score	2.013	(1.7)
Education	0.020	(4.95)
Medicare Health Insurance	0.052	(1.31)
Medicaid Health Insurance	-0.069	(-1.78)
Male	1.107	(7.13)
Hypertension	0.457	(9.77)
Diabetes	0.465	(9.24)
Log(Age Molecule)	-0.699	(-7.66)
Age*log(Age Molecule)	0.012	(7.88)
Risk Score*log(Age Molecule)	-0.173	(-1.61)
Trend	0.132	(5.99)
Risk Score*Trend	-0.157	(-7.35)
Number of Observations	106,510	
Pseudo R^2	0.444	

Notes: Reported Z-statistics are based on robust standard errors clustered by individual. Additional estimates of molecule drug interactions reported in the appendix. Each variable reported here is relative to the no-drug treatment option that has a utility normalized to zero.

Table 4. Second-Stage Demand Estimation

	IV Estimation		OLS	
Variable	Coef.	z-stat	Coef.	z-stat
Price	-1.613	(-4.01)	-0.107	(-0.67)
Lipitor 20mg	0.878	(1.42)	-0.817	(-1.94)
Lipitor 40mg	0.461	(0.66)	-1.611	(-3.65)
Baycol .3mg	-3.745	(-5.38)	-2.711	(-4.57)
Baycol .4mg	-3.753	(-4.7)	-2.777	(-3.99)
Cholestrimine	-5.435	(-8.37)	-3.549	(-8.36)
Vytorin 20mg	-2.015	(-3.3)	-2.797	(-5.28)
Vytorin 40mg	-1.972	(-3.24)	-2.743	(-5.18)
Zetia	-2.371	(-4.34)	-2.864	(-5.9)
Fenofibrate	-0.675	(-1.53)	-1.064	(-2.71)
Lescol 20mg	-4.475	(-9.39)	-3.563	(-9.23)
Lescol 40mg	-3.931	(-8.36)	-3.070	(-7.98)
Generic Lopid	-3.050	(-3.51)	-0.186	(-0.38)
Lopid	-3.112	(-6.48)	-2.175	(-5.62)
Advicor	-2.346	(-4.71)	-2.322	(-5.11)
Generic Mevacor 20mg	-4.447	(-5.63)	-2.149	(-4.17)
Generic Mevacor 40mg	-4.130	(-6.31)	-2.542	(-5.24)
Mevacor 20mg	-2.377	(-5.31)	-3.050	(-8.02)
Mevacor 40mg	-1.505	(-2.09)	-3.715	(-8.41)
Generic Niaspan	-6.437	(-6.75)	-3.210	(-6.32)
Niaspan	-5.029	(-7.77)	-3.182	(-7.41)
Generic Pravachol 20mg	-5.933	(-6.45)	-3.961	(-5.51)
Generic Pravachol 40mg	-4.937	(-5.62)	-3.249	(-4.57)
Pravachol 20mg	-1.585	(-3.86)	-1.649	(-4.41)
Pravachol 40mg	-0.699	(-1.35)	-1.898	(-4.81)
Crestor 10mg	-1.388	(-2.47)	-2.086	(-4.27)
Crestor 20mg	-2.524	(-4.5)	-3.213	(-6.58)
Generic Zocor 10mg	-5.346	(-6.11)	-3.687	(-5.19)
Generic Zocor 20mg	-2.888	(-3.76)	-2.353	(-3.41)
Generic Zocor 40mg	-2.166	(-2.82)	-1.644	(-2.38)
Zocor 10mg	-1.596	(-3.85)	-1.831	(-4.89)
Zocor 20mg	1.659	(1.85)	-1.319	(-2.69)
Zocor 40mg	1.121	(1.33)	-1.627	(-3.43)
Constant	-12.901	(-13.27)	-16.368	(-35.77)
Number of Observations	266		266	
R^2	0.4566		0.606	

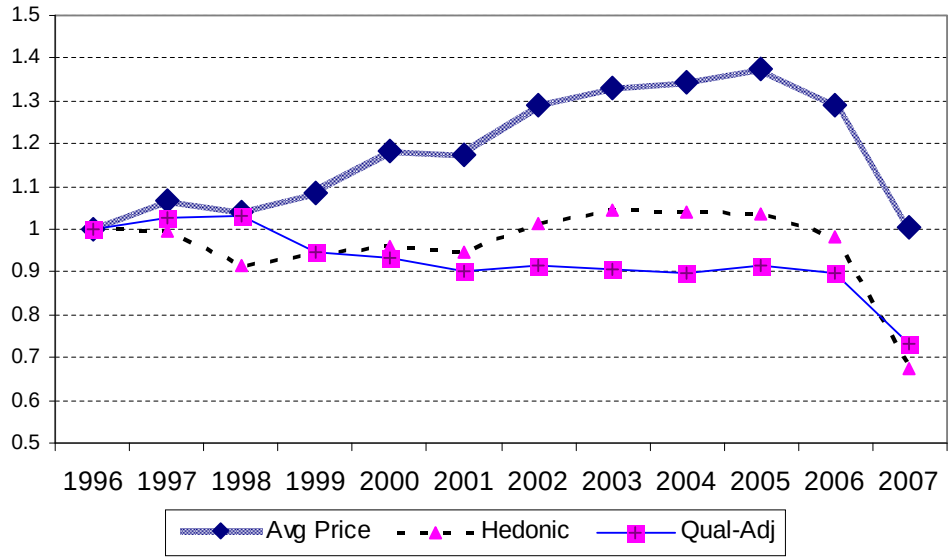
Notes: This Table shows estimates of mean utility on price, which are based on the 266 product-year observations. The instruments used in the IV specification are discussed in greater detail in the text. The 10 mg strength of Lipitor is the excluded dummy variable.

Table 5. Individual Annual Welfare by Condition and Demographic Factors

	Mean	Median	10th Percentile	90th Percentile
Overall	$219.29	$225.35	$125.35	$300.15
Heart Disease				
No	$204.78	$214.10	$113.06	$274.70
Yes	$274.01	$276.11	$200.63	$343.83
Has Diabetes				
No	$206.05	$213.35	$112.06	$279.47
Yes	$252.74	$256.44	$165.11	$331.86
Has Hypertension				
No	$181.78	$193.37	$85.82	$253.53
Yes	$244.55	$248.56	$173.91	$316.13
Age Greater Than 55				
No	$157.68	$167.05	$67.72	$228.79
Yes	$247.94	$247.14	$187.92	$313.94
Has Health Insurance				
No	$145.34	$127.91	$53.51	$265.24
Yes	$225.63	$228.64	$147.58	$301.64
Has Drug Insurance				
No	$180.77	$189.72	$89.16	$256.44
Yes	$230.82	$236.74	$146.93	$308.27

Notes: Author's calculation of expected welfare for different categories of the population in the MEPS data reporting high cholesterol in 2006. These estimates are based on an assumption of 75 percent compliance per period.

Figure 3. Price Index Comparison



Notes: The quality-adjusted price index is calculated as described in the text. Prices are normalized to 2007 dollars using the CPI. The hedonic regression estimate used to calculate the hedonic price index is reported in the appendix.

Table 6. Price Index Comparison Under Alternative Assumptions

				Quality-Adjusted Price Indexes			
Year	Avg Price	Laspeyres	Hedonic	(1)	(2)	(3)	(4)
1996	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1997	1.07	0.99	0.99	1.03	1.03	1.04	0.87
1998	1.04	0.98	0.92	1.03	1.03	1.05	0.85
1999	1.08	1.01	0.94	0.94	0.95	0.97	0.87
2000	1.18	1.01	0.96	0.93	0.93	0.96	0.87
2001	1.17	1.00	0.95	0.90	0.90	0.93	0.87
2002	1.29	1.04	1.01	0.91	0.92	0.95	0.91
2003	1.33	1.07	1.04	0.90	0.90	0.94	0.89
2004	1.34	1.07	1.04	0.89	0.90	0.93	0.89
2005	1.37	1.09	1.04	0.91	0.91	0.96	0.91
2006	1.29	1.08	0.98	0.89	0.90	0.95	0.91
2007	1.00	0.88	0.67	0.74	0.73	0.77	0.74
				With Insurance	Removing Insurance	Removing Insurance	Removing Insurance
				With Trend	With Trend	No Trend	No Trend
				With Error	With Error	With Error	No Error

Notes: The quality-adjusted price index is calculated as described in the text. These figures are adjusted to 2007 dollars using the CPI. The hedonic regression estimate used to calculate the hedonic price index is reported in the appendix. The Laspeyres index follows the BLS methodology where generics and Branded versions of the same molecule are treated as an identical product and the price index is computed using a geometric mean.