# THE EFFECT OF PRICE ON PHARMACEUTICAL R&D

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**Abstract:**

This work extends prior research that finds drug development is driven by demand factors such as mortality rates of the diseases new drugs are aimed at. Here we find that the number of drugs in the development pipeline is strongly positively related to the price of existing drugs treating those diseases. [JEL: O-34, I-11]

## Introduction

The link between drug development and drug prices is an important consideration in the policy debate about the importation of drugs into the United States from other countries such as Canada or even India. India does not respect intellectual property rights to drugs; internet sales of on-patent drugs manufactured there are priced at a fraction of the retail U.S. price. Canada prices for similar drugs are also substantially less than the U.S. price.

In prior research, we have shown that the incidence and severity of disease drives drug development, but that this is almost exclusively a U.S. effect.[1] Drug development is measured by the number of drugs in the development pipeline as well as investment expenditures. We look at the distribution of drug development by disease and link this to the economic harm caused by disease as measured by mortality. U.S. mortality by disease is positively related to drug development, but mortality across the rest of the world is either unrelated or even negatively related.

Our current research corroborates these earlier findings and extends the analysis by looking at drug prices. We link U.S. retail prices by therapeutic category to drug development. We collect retail prices for around 600 drugs from online sources. We use an improved data source to measure the drug development pipeline, again by therapeutic application. We measure the economic harm of various diseases by mortality and morbidity rates.

We find a positive relation between the average U.S. price for on-patent drugs in a therapeutic category and the number of new drugs in development. Our estimates imply that a 50 percent decrease in drug prices, holding disease incidence and severity constant, decreases drug development by 14 to 24 percent. This result implies that allowing drug importation into the United States will substantially reduce drug development.

## Prior Research

A number of studies have found a robust relationship between potential market size and pharmaceutical research and development. Acemoglu and Linn (2004) analyze the effect of potential market size on pharmaceutical innovations using U.S. demographical data. They find a large effect of potential market size (in the United States) on the entry of new drugs. Civan and Maloney (2006) look at the distribution of drug development by disease and link this to the potential market size measured by worldwide mortality. Lichtenberg (2005) reaches the same conclusion by a similar methodology.

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[1] Civan & Maloney (2006).

Lichtenberg (2006) examines the cross-sectional relationship between pharmaceutical innovation and market size among different types of cancer. Pharmaceutical innovation is measured by number of distinct chemotherapy regimens for treating a cancer site, and the number of articles published in scientific journals pertaining to drug therapy for that cancer site. Innovation is found to be increasing with disease incidence. Using his theoretical model and coefficients from the empirical findings he estimates that a 10 percent decline in drug prices would result a 5 to 6 percent decline in pharmaceutical innovation.

Grabowski and Vernon (1981, 2000) used firm level data to examine the determinants of pharmaceutical R&D. Their hypothesis was R&D expenditure is a function of expected returns. They analyzed the relationship between individual firms R&D expenditures to sales ratio and the relative success of the recent new drugs in the market. In order to measure expected returns they used the total sales of newly introduced NCE in the last three years. They found that expected returns and cash flows are important explanatory variables for research intensities. Mahlichi and Schluga (2006) employed the same methodology for Japanese pharmaceutical firms. Similar to Grabowski and Vernon they found expected returns to be an important determinant of R&D spending in the Japanese drug industry, albeit considerably smaller than in the U.S even though some reservations of the econometric technique are put forward.

Giacotto, Santerre and Vernon (2007) use time series aggregate data for major pharmaceutical companies in the US. They criticize the use of firm data because most pharmaceutical firms operate on wide range of fields in addition to drugs, such as herbicides and pesticides, medical instruments and supplies, hair care products, dental products, and nutritional products. Thus industry level data are deemed to be more appropriate. Their conclusions are consistent with other findings: pharmaceutical R&D spending rises with real drug prices. They estimate that if real drug prices had not grown at all between 1980 and 2001 there would have been approximately 350 fewer drugs brought to market.

Abbot and Vernon (2005) employed Monte Carlo simulation techniques to model the effects of future price controls on R&D expenditures. They estimate that a 40–50 percent reduction in drug prices would lower R&D by 30–60 percent. Golec and Vernon (2006) document that as a result of stricter price controls and lower prices in EU countries, EU consumers enjoyed lower pharmaceutical price inflation than U.S. consumers. However EU pharmaceutical R&D which exceeded the United States in 1986, trailed U.S. R&D by 2004.

On other accounts strict price regulation has been shown to affect the marketing decisions of multinational pharmaceutical companies. Danzon and Ketcham (2003) show that removing pricing power by regulation matters. They show that due to policy changes, pharmaceutical companies decided not to introduce some of the newest drugs in New Zealand market. Danzon Wang and Wang (2003) show that price regulation delays new drug launches.

## Methodoly & Data

Our maintained hypothesis is that the research and development in the pharmaceutical industry should be directly linked to drug prices. We propose to test this hypothesis by looking at a cross section of drug development stratified by disease. We observe the number of drugs that are being developed to treat each disease and the characteristics of the market for those drugs.

We can write the model as:

$$N_i = f\left[\sum_{t=b,T+b}\left[P_{it}Q_{it} - c_i\right]\delta_t - K_i\right] \qquad 1$$

where $i$ indexes diseases. $N_i$ is the number of drugs in development to treat the $i^{th}$ disease. $P_{it}$ is the expected price of a new drug and $Q_{it}$ is the expected quantity sales of a new drug when it enters the market to treat the $i^{th}$ disease. $K_i$ and $c_i$ are development and manufacturing costs, respectively. Price times quantity minus manufacturing cost is net revenue. This is discounted at $\delta_t$ from the time the drug is introduced at $b$ through the life of the drug $T$. Our argument is that the number of drugs in development is a function of the expected present discounted value of a new drug, that is, $f'(.)>0$.

The number of drugs in the development pipeline is our measure of pharmaceutical research and development. Data on the drug pipeline is taken from the Adis R&D Insight database by Wolters Kluwer Health. The Adis R&D database includes medicines currently in clinical trials or at FDA for review. Drugs reported in Adis R&D Insight start with the early laboratory reports and continue through to world market launch. Adis R&D Insight is compiled from information collected from many sources; direct contact with companies involved with research and development, information collected from drug and therapeutic literature published in medical and biomedical journals, attendance at international meetings and conferences, company annual reports, news services, and press releases. Adis R&D Insight database is one of the leading data source for professionals and researchers in pharmaceutical R&D, universities, and healthcare institutions, and is highly regarded. The Pharmaceutical Research and Manufacturers of America (PhRMA) provides Adis R&D database on its website free of charge to inform patients about potential treatments in the future.

In order to measure the expected present value of a new drug, we need price and quantity. Price data is available for existing drugs used to treat each disease. We discuss these data below. For quantity, we use the health consequences of each disease measured by mortality and morbidity. The argument is that the more people a disease affects and the more strongly they are affected, the more doses of a drug treating the disease will be demanded.

The expected value of a new drug also depends on the cost of development and manufacture. Unfortunately, these data are not available. We are forced to assume that variation in innovation and production cost is not systematically related to revenue potential. Ultimately our empirical implementation of equation (1) is limited to proxies for $P_{ib}$ and $Q_{ib}$ which are the expected price and quantity of the drug when it enters the market.

Data on the health consequences of each disease come from the Global Burden of Disease Project by the World Health Organization (WHO) for 2002. WHO draws on a wide range of data sources to develop consistent estimates of incidence, severity, and duration of diseases and mortality for over 130 causes for the WHO member states. A summary measure of disease burden that combines mortality and non-fatal health outcomes has been developed. This is an indicator of years of life lost and years of life lived with disabilities: Disability Adjusted Life Years (DALY). One unit of DALY is intended to measure one lost year of "healthy" life.[2] Since all illnesses do not affect the quality of life in the same way, the researchers in the WHO study weight each health problem by combining expert opinions with survey answers.

[2] "DALY is a health gap measure that extends the concept of potential years of life lost due to premature death (PYLL) to include equivalent years of 'healthy' life lost by virtue of being in states of poor health or disability. The DALY combines in one measure the time lived with disability and the time lost due to premature mortality. One DALY can be thought of as one lost year of 'healthy' life and the burden of disease as a measurement of the gap between current health status and an ideal situation where everyone lives into old age free of disease and disability." <Dth_DALY_WHOMemberStates_2002.xls>, NOTES page, line 42, www.who.org.

As a part of Global Burden of Disease Project, WHO released the mortality information of member states. Cause of death is defined as "the disease or injury which initiated the train of morbid events leading directly to death" in accordance with the rules of the International Classification of Diseases.

We use both mortality and morbidity (DALY) data from WHO for the United States as measures of the quantity of drugs demanded. The higher are mortality and morbidity in each disease class, the greater the expected quantity demanded for a new drug to treat the disease.

Data on drug prices were obtained from <www.Medco.com> over the period of May through August 2005. Medco is an administrator for drug benefit programs included in health insurance plans. Medco serves universities and corporations. We acquired the price information using the employee access at our university. Medco quotes the retail price that it pays for the drugs.[3]

Originally, drugs were collected from the top 200 drugs ranked by sales and by prescriptions in 2004 and in 2005 based on information reported by <www.RxList.com>. Only drugs that treat life threatening ailments were included. The list was augmented by referencing the drugs in the *Nursing Drug Handbook* 2001 (NDH). The NDH classifies drugs by approved therapeutic uses of which there are 92 categories. For any category that was included in our preliminary sample, we added all of the drugs listed in the NDH that could be found in Medco.

We ended up with 2070 observations on 609 different drugs. Multiple observations result from the fact that drugs are sold in different strengths and forms. For drugs with different strengths and forms, each was converted to a standard dose of the active ingredient so that the price per dose was comparable across strengths and forms.[4] We average the price across these.

Price varies in our sample by form and strength. Consider a drug like Lipitor. It comes in 10, 20, 40, and 80mg strengths. The price per pill is identical for the 20mg through 80mg strengths. To compute an active ingredient dosage, we divide by 2 through 8. This means that the price varies considerably across the strengths in which the drug is sold. On the other hand, some drugs are sold at a constant price per unit of the active ingredient. Hence, there is no variation in price across strengths. We are interested in seeing how this affects the average price in general.

Drugs are categorized by the existence of competitors in the active ingredients. Some drugs face no competition. By and large, these are drugs that are still patent protected. Some face competition from other brand-named products with the same active ingredient, and then some face competition from generic competitors. Generic competition is identified in the data by Medco.

For all of the drugs in our sample, we collected the indications that the medicine is intended to treat. These indications are then grouped in two ways. First we separate the drugs by ailment and treatment type. Obvious examples are things like drugs that treat specific cancers. Some drugs treat many different cancers and we link these drugs to all of them. The drugs are grouped by the area of the body or type of ailment generally following the taxonomy of the International Classification of Diseases. However, we also separate drugs based on palliative versus recuperative functions. That is, we separate drugs that treat symptoms such as pain from

[3] This is what Medco says on its website, but it cannot be precisely true because it offers drugs at a discount when purchased from it by mail. The discount price varies across drugs but not in a systematic way.

[4] A standard dose is usually defined as a thirty day supply of the smallest milligram strength offered by the manufacturer. Some drugs such as antibiotics are prescribed for episodic treatments that may be in days or weeks. In these cases the standard dose is the basic therapeutic application of the drug, which is usually the way the price is quoted.

cancer or excessive fluid from pneumonia from drugs that attack tumors and kill bacteria. Our approach is to create a taxonomy that groups drugs into treatment rivals. In this sense, a cancer pain drug is not a rival to a tumor suppression drug. We call this taxonomy the drug's "rival class."

Secondly, we classify drugs by the severity of the disease that they are intended to treat. Here we use the WHO morbidity taxonomy directly. So in this scheme we include all drugs that treat cancer whether the drug has curative or palliative properties. We call this taxonomy the drug's "disease class."

The price-rival taxonomy allows us to construct a price equation in which each drug's price is a function of the number of strengths and forms in which it is sold, the variance of the price across strengths and forms, the age of the drug, and the average price of rival drugs. Price variance in this dimension seems to occur when drug dosage varies by the severity of the disease. For instance, some people taking cholesterol drugs may take high dosages and some low. The drug is commonly priced the same per pill regardless of the amount of the active ingredient. Given the way that we calculate price, this causes the drug to have high variance in price across strengths.[5] Similarly, casual observation suggests that drug companies add strengths and forms over time, and we do expect that the older the drug, the lower the price. Obviously, we expect there to be a positive relation between own price and rival price.

Summary statistics are shown in Table 1. Price varies substantially and predictably by competition. The average prescription cost of a drug without competition is $489 per normal treatment usually meaning a monthly supply. The average overall is $199, which means that the average for drugs facing competition is around $45. The most expensive drug in our sample costs $24,000 per treatment. It is a lung cancer drug that is indicated for use after all others fail. Table 1 reports drugs that cost less than $1 for a month's supply. The actual dollar value in the sample is around $4 but when we divide by the amount of the active ingredient the price falls to trivial amounts for the largest strengths. The average age of drugs without direct ingredient competition is nearly 15 years. The range goes from 2.5 to 65. The median is 11 years. Most of these drugs are on patent although some do not face direct competition for other reasons.[6]

Table 2 shows a regression of price for all drugs on several characteristics: price variance, number of forms and strengths, and market condition categories. The omitted category is generics facing a single brand-named drug. We do not include age in these regressions because age and the market condition categories are highly correlated. Two specifications are shown. Column (1) is the price regression without fixed effects. In column (2) the rival group fixed effects are included.

Most of the market conditions are self explanatory. The most obvious is the category for drugs without direct competition, Brand Named with No Competition. We see that these drugs are 200 percent more costly than basic generic products. The category, Brand Named with Multiple Labels, occurs in a small portion of the sample. This is when a manufacturer markets an ingredient under two different brand names. There is no difference in the price effect between these two categories and we will merge them for the rest of the analysis.

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[5] Note that this effect does not go unnoticed. From time to time the popular press reports stories about people attempting to reduce their drug cost by buying high strength pills and halving or quartering them.

[6] Drugs may not face competition for a variety of reasons. Patents can last a long time especially if a drug receives a new patent for a new indication. For this reason, age is not a indicator of whether or not a drug is on patent. Drug manufacture may involve trade secrets that stop generic entry into the market as is the case for the oldest drug in the sample Premarin. Finally, sometimes the market is not large enough to support a second entrant.

We see that competition reduces price. In the most standard case of generic competition, a drug that was on patent faces generic competition. This is the case labeled, Single Brand Name Facing Generics. Here we see that the brand-named drug fetches a price 80 percent higher than the generics. This result holds with and without the rival-group fixed effects.

The price relations across the other competitive categories are more ambiguous to the inclusion of fixed-effects. This may be due to limited sample sizes in these classifications. Nonetheless these basic price regressions are revealing especially in regard to drugs that have monopoly status: these are the drugs in which we are most interested.

Table 3 shows the regression for 206 drugs that do not have direct (i.e., ingredient) competition. We are interested in these drugs because the price that these drugs fetch is the best measure of the revenue potential of the drugs in the development pipeline. Table 1 reports 213 drugs without direct competition. Seven are without rival competition so they fall out of Table 3 regressions. The price regressions in Table 3 include age and rival price. Rival price is the average of the other drugs without direct competition that are treatment substitutes.

The thing that we are most interested in Table 3 is the age effect. It is estimated with some precision. We will use this estimate to forecast the entry level price of a new drug. The other coefficients in Table 3 are consistent with the estimates that we saw in Table 2. The variance of price across forms and strengths increases average price. This effect is some combination of price discrimination and convenience. The number of forms decreases price. The effect of rival price is positive but less than one. That is, as the prices of other drugs in a therapeutic class increase, the price of a competitor drug will increase also, but by less than one.[7]

The number of rivals is not statistically significant but the sign makes sense. As the number of competitors increases, price falls. The age of the competition also makes sense. As competitors get older their competitive force weakens and price increases.

## Price Elasticity of R&D

We now move to the main focus of our inquiry, that is, to assess the impact of drug prices on drug development. To do this, we regress the number of drugs in the development pipeline on the price of existing drugs. We reclassify existing drugs by disease class. We use the WHO classifications, for which our existing drugs can be placed into 48 different groups. Of these, we are able to match drugs in the development pipeline to 36 groups. We regress the number of drugs-in-pipeline on the average price of the existing drugs in use in each disease class, the number of existing drugs, and the health severity of the disease class.

Table 4 shows the disease classes, the number of drugs-in-pipeline, the price and number of existing drugs, and the health severity of the diseases in the United States. Price is the average of the existing drugs in each category net of the age effect estimated in Table 3. That is, the age effect is negative so we multiple the age of each drug by this estimated coefficient (0.76) and add this to the price of the existing drug. This gives us an estimate of the price, $P_{ib}$, that a new drug will sell for when it first goes on the market.

Table 5 shows the regressions. We use negative binomial estimators because we are dealing with count data.[8] We use two different estimates of price and two different health

[7] If the rival price effect were greater than one, the market would be unstable. A theoretical discussion of product substitutability between rivalrous monopoly markets that shows this effect is available from the authors upon request.

[8] The fact that the dispersion parameter is statistically significant indicates that the negative binomial rather than the poison is the better estimator.

indicators. In columns (1) and (2) we use observed price net of the age effect as discussed above. In columns (3) and (4) we use the predicted price from Table 3 net of the age effect.[9] In columns (1) and (3) we measure the severity of disease by the mortality level in the United States for each disease category. In columns (2) and (4) we use the WHO morbidity measure, the DALY, as our measure of the health impact of the disease. The dependent variable is the same in all cases. By and large, predicted price and the DALY give the more accurate estimates but all estimates are substantively the same.[10] We calculate pseudo $R^2$ by regressing the actual number of drugs-in-pipeline on the predicted values from the negative binomial regressions. These pseudo-$R^2$ values are around 0.4 for all specifications.

The estimates support the hypothesis that price is an important determinant of drug development. The price of existing drugs is statistically significant at the 1 and 2 percent level in all regressions. The coefficients on price are elasticities. They range from 0.28 to 0.49. They say that a 50 percent decline in price will cause drug development to decline from between 14 and 24 percent.

The number of existing drugs in each disease category positively affects the number of drugs in development. We imagine that the number of existing drugs is an indicator of the size of the market. Similarly mortality and morbidity are positively related to the number of drugs in development. Again, the health severity of disease is an indicator of how many people will be attracted to a new drug. Both of these market size indicators are substantial. Based on the number of existing drugs, the elasticity of drug development to market size is close to 0.5; based on the health impact, the elasticity of drug development to market size is between 0.3 and 0.4.

### *Corroboration of Early Findings*

Finally, we include the health severity across the rest of the world in each of the disease classes. To do this we include mortality and morbidity totaled across developed countries other than the United States and separately totaled across underdeveloped countries. In our prior work, we found that drug development was basically and United States phenomenon. That is, as the health severity of disease in the United States increased, drug development increased, but that there was no such relation for the rest of the world.

Table 6 shows evidence that this same phenomenon is revealed when we account for drug prices. Table 6 adds mortality and morbidity in the developed and underdeveloped countries to models estimated in Table 5. Here we only look at observed price net of the age effect; predicted price gives similar results to those shown in Table 6. The number of existing drugs is arguably a world-wide characteristic of the market. Price is the value for the United States. It would be better if we had price for each other country. However, these data are problematic for many reasons and generally not available.

What we do see in Table 6 is that health severity in the rest of the world is not positively related to drug development. These results are generally consistent with our earlier findings. Earlier we found a perverse effect (a negative relation between health severity and drug development) for underdeveloped countries. Here we find the significant perverse effect for developed countries. The effect is statistically significant at the 5 percent level. This perverse

[9] We use all 213 drugs with no ingredient competition even though the age effect was estimated for only 206. For the seven drugs with no therapeutic rivals, we use observed price in place of forecast price.

[10] We also use the price of existing drugs without netting out the age effect. The results are only trivially different.

effect is probably driven by a few countries but, importantly, it is probably the countries that allow transshipment of drugs across country borders.

Detailed investigation of the perverse drug development effect is outside the scope of this research. Suffice to say that we once again find that drug development seems to be a market driven exclusively by the United States. This makes the price elasticity estimates that we have found even more poignant. If the price paid by U.S. consumers to drug companies falls, it is very likely that drug development will also decline.

## Conclusions

The results of our research clearly indicate that society is getting something for the money that people in the United States spend on prescription drugs. The retail price of existing drugs causes new drugs to be developed. The higher are the prices of existing drugs in a therapeutic category, the larger is the number of drugs in the development pipeline in that therapeutic category. We find this result by looking cross-sectionally at the drug development pipeline sorted by the types of diseases that new drugs are aimed at.

The estimated price elasticity of drug development is between 28 and 49 percent. This says that if drug prices decline by 50 percent, a number well within the range of possibility if drug reimportation becomes common, the number of drugs in the development pipeline could decline by 14 to 24 percent.

Of course, our estimates are based on a cross-sectional analysis of the marginal choice of drug companies to develop drugs in one category versus another. These estimates may not apply to an across-the-board decline in prices. However, as we have shown before the fact that the U.S. drives drug development means that these estimates of price elasticity must be considered carefully in the debate over drug reimportation. It is possible that lowering price will kill the goose that lays the golden eggs.

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**Table 1. Summary Statistics for Drug Prices**

| *Variable* | *Obs.* | *Mean* | *Std. Dev.* | *Minimum* | *Maximum* |
|---|---|---|---|---|---|
| | | *All Drugs* | | | |
| Price | 609 | 199.30 | 1076.03 | 0.42 | 24152.80 |
| Variance of Price | 455 | 8489.01 | 71219.14 | 0 | $1243\ 10^3$ |
| Number of Types | 609 | 3.37 | 2.76 | 1.00 | 20.00 |
| Age | 609 | 18.35 | 13.01 | 2.20 | 66.86 |
| | | *Brand Name Drugs without Competition* | | | |
| Price | 213 | 489.36 | 1778.41 | 2.88 | 24152.80 |
| Variance of Price | 132 | 12776.15 | 66175.11 | 0.12 | $575\ 10^3$ |
| Number of Types | 213 | 2.75 | 2.32 | 1.00 | 15.00 |
| Age | 213 | 14.92 | 11.17 | 2.59 | 64.83 |

Notes: Number of Types refers to the number of different forms and strengths. Price is the average across the different forms and strengths. Price has no variance if all strengths are priced identically based on the amount of the active ingredient. Age is the number of years since the FDA approval of the first form and strength.

**Table 2. Price Regressions for All Drugs**

| *Independent Variables* | (1) | (2) |
|---|---|---|
| Number of Types | -0.386 [a] | -0.190 [a] |
| | (0.074) | (0.044) |
| Variance of Price | 0.486 [a] | 0.577 [a] |
| $\div 10^5$ | (0.085) | (0.073) |
| Brand Named with No Competition | 2.287 [a] | 1.996 [a] |
| | (0.137) | (0.081) |
| Brand Named; Multiple Labels | 2.174 [a] | 2.055 [a] |
| | (0.432) | (0.326) |
| Multiple Brand Names; No Generics | 0.806 [a] | -0.947 [a] |
| | (0.373) | (0.193) |
| Multiple Brand Names with Generics | 0.051 | -0.719 [a] |
| | (0.293) | (0.120) |
| Generic Facing Multiple Brand Names | -0.390 | -0.982 [a] |
| | (0.432) | (0.176) |
| Brand Name Facing Older Generic | 1.072 | 1.412 |
| | (1.267) | (0.846) |
| Older Generic Facing Brand Name | 1.010 | .976 |
| | (0.574) | (0.629) |
| Single Brand Name Facing Generics | 0.832 [a] | .806 [a] |
| | (0.138) | (0.075) |
| Intercept | 2.787 [a] | 2.503 [a] |
| | (0.126) | (0.620) |
| | 0.434 | 0.594 |
| Observations | 609 | 1544 |

Notes: Regressions in column (2) include fixed effects for 125 Rival Groups; the fixed effects are significant at the 1 percent level. Heteroskedasticity adjusted standard errors in parentheses below coefficients. Price, age, and number of types in logs. Superscripts indicate statistical significance: (a) 1 percent. Drugs with multiple indications show up in multiple rival groups. The omitted category is a basic generic drug that faces a single brand-named competitor that was marketed before the generic. Some drugs are marketed by two or more brand-named products but without generic competition. For some drugs, the generic competition was approved before the brand-named product.

**Table 3. Price Regression For Drugs without Direct Competition**

| *Independent Variables* | (*a*) | (*b*) |
|---|---|---|
| Age | -0.793 [a] | -0.760 [a] |
| | (0.135) | (0.136) |
| Variance of Price | 0.568 [a] | 0.550 [a] |
| ($\div 10^5$) | (0.157) | (0.157) |
| Number of Types | -0.413 [a] | -0.357 [a] |
| | (0.127) | (0.132) |
| Rival Price | 0.722 [a] | 0.725 [a] |
| | (0.087) | (0.087) |
| Number of Rivals | | -0.128 |
| | | (0.085) |
| Avg. Age of Rivals | 0.807 [a] | 0.822 [a] |
| | (0.203) | (0.203) |
| Intercept | 1.503 | 1.668 |
| | (0.758) | (0.764) |
| *R*-squared | 0.452 | 0.458 |
| Observations | 206 | 206 |

Notes: See Table 2. Heteroskedasticity adjusted standard errors in parentheses below coefficients. All variables in logs. Superscripts indicate statistical significance: (a) 1 percent. Seven drugs are lost from this sample compared to Table 1 because they do not have rival group price competition.

**Table 4. Drugs in Development Pipeline and Existing, and Health Severity by Disease Classification**

| | | | *Existing Drugs* | | | |
|---|---|---|---|---|---|---|
| *Code* | *Disease* | *Drugs in Pipeline* | *Price* | *Number* | *U.S. DALY* | *U.S. Mortality* |
| W009 | HIV/AIDS | 119 | 6.933 | 29 | 380220 | 13140 |
| W010 | Diarhoeal Diseases | 18.4 | 6.989 | 4 | 84227 | 1488 |
| W017 | Meningitis | 11.8 | 6.923 | 3 | 36147 | 1070 |
| W018 | Hepatitis B | 18 | 5.776 | 1 | 18103 | 1192 |
| W019 | Hepatitis C | 46 | 5.812 | 3 | 75849 | 4954 |
| W039 | Lower Respiratory Infections | 68.6 | 6.546 | 14 | 279705 | 59834 |
| W040 | Upper Respiratory Infections | 10 | 6.285 | 7 | 12423 | 190 |
| W041 | Otitis media | 2 | 5.841 | 2 | 32919 | 37 |
| W064 | Colon and Rectum Cancers | 115 | 7.843 | 2 | 572328 | 64632 |
| W066 | Pancreas Cancer | 44 | 6.792 | 1 | 217997 | 29538 |
| W067 | Trachea and Lung Cancers | 183.5 | 7.598 | 6 | 1228923 | 157676 |
| W068 | Melanoma and other Skin Cancers | 100.3 | 7.258 | 2 | 121230 | 11035 |
| W069 | Breast Cancer | 148 | 6.808 | 11 | 601622 | 45344 |
| W072 | Ovary Cancer | 79.5 | 8.575 | 4 | 138225 | 14048 |
| W073 | Prostate Cancer | 157.8 | 6.474 | 2 | 240293 | 35250 |
| W074 | Bladder Cancer | 23.2 | 9.553 | 2 | 117061 | 13512 |
| W075 | Lymphomas and other melanomas | 210.4 | 6.657 | 3 | 321142 | 39661 |
| W076 | Leukaemia | 211.7 | 7.708 | 6 | 221100 | 24085 |
| W078 | Other Neoplasms | 35 | 7.014 | 1 | 98716 | 15092 |
| W079 | Diabetes mellitus | 159 | 5.011 | 8 | 1280198 | 76813 |
| W080 | Endocrine Disorders | 268 | 6.239 | 7 | 788287 | 30820 |
| W085 | Epilepsy | 13 | 5.388 | 3 | 142061 | 1490 |
| W087 | Alzheimer and other demantias | 67 | 6.420 | 1 | 1142129 | 93160 |
| W089 | Multiple sclerosis | 47 | 8.456 | 1 | 104908 | 3185 |
| W095 | Migraine | 26 | 5.829 | 1 | 446320 | 0 |
| W106 | Hypertensive Heart Disease | 36 | 5.081 | 22 | 299984 | 43748 |
| W107 | Ichaemic Heart Disease | 90 | 5.281 | 11 | 2957620 | 514450 |
| W108 | Cerebrevascular Disease | 32 | 5.765 | 2 | 1467037 | 163768 |
| W112 | Chronic Obstructive Pulmonary Disease | 34 | 4.886 | 3 | 1621485 | 128605 |
| W113 | Asthma | 81 | 5.609 | 8 | 689928 | 4986 |
| W116 | Peptic Ulcer | 8 | 6.241 | 3 | 43590 | 4620 |
| W121 | Nephrytis | 20 | 6.234 | 3 | 243587 | 42738 |
| W122 | Benign Prostatic Hyperplesia | 13 | 5.769 | 1 | 72541 | 498 |
| W124 | Skin diseases | 185.2 | 6.653 | 12 | 64247 | 4172 |
| W126 | Rheumatoid arthritis | 77 | 7.282 | 2 | 285455 | 2941 |
| W127 | Osteoarthritis | 29 | 5.866 | 3 | 742613 | 1044 |

Notes: Code is the WHO disease category. Drug price is in logs and is the average of the prices of the existing drugs in each category net of the age effect based on the estimate in Table 3. Drugs-in-pipeline is in fractions because some drugs are parsed over multiple categories (see text for discussion). U.S. DALY and mortality are for 2002.

**Table 5. Regressions of Drugs-in-Pipeline on Demand Indicators**

| *Independent Variables* | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Price of Existing Drugs | 0.282 [b] | 0.403 [a] | 0.360 [b] | 0.493 [a] |
| | (0.120) | (0.122) | (0.151) | (0.150) |
| Number of Existing Drugs | 0.469 [a] | 0.515 [a] | 0.467 | 0.508 [a] |
| | (0.121) | (0.117) | (0.119) | (0.115) |
| Health Severity | 0.299 [a] | 0.403 [a] | 0.295 [a] | 0.396 [a] |
| | (0.064) | (0.091) | (0.064) | (0.091) |
| Intercept | -1.364 | -4.412 | -1.808 | -4.859 |
| | (0.983) | (1.481) | (1.138) | (1.603) |
| Dispersion | 0.391 | 0.389 | 0.390 | 0.399 |
| | (0.094) [a] | (0.095) [a] | (0.094) [a] | (0.095) [a] |
| Pseudo *R*-squared | 0.373 | 0.397 | 0.443 | 0.447 |

Notes: Coefficients estimated by negative binomial regressions. All right-hand-side variables in logs. Heteroskedasticity adjusted standard errors in parentheses. Superscripts represent levels of statistical significance: (a) 1 percent; (b) 2 percent. Pseudo *R*-squared calculated by OLS regression of actual on predicted values. Health Impact measured by the WHO morbidity value for the U.S. by disease in columns (2) and (4) (36 observations) and by U.S. mortality from each disease in columns (1) and (3) (35 observations). In columns (1) and (2) price of existing drugs is the average of the observed price across forms and strengths net of the estimated age effect from Table 3; in columns (3) and (4) it is the predicted price from Table 3 net of the age effect.

**Table 6. Regressions of Drugs in Pipeline on International Mortality and Morbidity as well as U.S. Factors**

| *Independent Variables* | (1) | (2) |
|---|---|---|
| Price of Existing Drugs | 0.191 [b] | 0.354 [a] |
| | (0.096) | (0.109) |
| Number of Existing Drugs | 0.572 [a] | 0.603 [a] |
| | (0.102) | (0.101) |
| Health Severity in the United States | 0.728 [a] | 0.905 [a] |
| | (0.131) | (0.196) |
| Health Severity in Developed Countries | -0.406 [b] | -0.516 [b] |
| | (0.185) | (0.259) |
| Health Severity in Underdeveloped Countries | -0.183 | -0.172 |
| | (0.369) | (0.118) |
| Intercept | 1.538 | -0.776 |
| | (0.988) | (1.556) |
| Dispersion | 0.225 | 0.251 |
| | (0.060) [a] | (0.065) [a] |
| Pseudo *R*-squared | 0.730 | 0.712 |

Notes: Estimates based on negative binomial model. All right-hand-side variables in logs. Superscripts indicate statistical significance: (a) 1 percent; (b) 5 percent; (c) 10 percent. Pseudo *R*-squared calculated by OLS regression of actual on predicted values. Price is the log of the average of price across forms and strengths net of the age effect. Health Impact measured by mortality from each disease in column (1) (35 observations), and by the WHO morbidity value by disease in column (2) (36 observations).