Do Demographic Changes Affect Pharmaceutical Companies' Returns?

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Abstract

In this paper we analyze how demographic change has affected profits and returns across pharmaceutical industries over the last twenty years. Fluctuations in different age group sizes influence the estimated demand changes for age-sensitive drugs, such as antibacterials for young people, antidepressants for middle-aged, and antithrombotics for old people. These demand changes are predictable as soon as a specific age group is born. We use consumption and demographic data to forecast future consumption demand growth for drugs caused by demographic changes in the age structure. We find that forecasted demand changes over a horizon of 5 to 10 years predict abnormal annual pharmaceutical stock returns for more than 60 firms over the time period from 1986 to 2006. An increase by one percentage point of annualized demand growth due to demographic changes predicts an increase in abnormal annualized stock returns in the size of 2–3 percentage points. However, forecasted demand changes over a horizon of 0–5 years do not predict abnormal stock returns. Our results are consistent with the model by DellaVigna and Pollet (2007), where investors are unconditionally inattentive about the distant future.

Keywords: Demographic Change, Demand Growth, Abnormal Stock Returns, Pharmaceutical Companies, Panel Regression, Fama MacBeth

JEL Codes: C23, J10, J11

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1 Introduction

What is the impact of demographic change on stock returns and profits of pharmaceutical companies? While there is plenty of literature about the impact of demographic fluctuations on aggregate stock returns (e.g. Abel (2003), Ang and Maddaloni (2005), Bakshi and Chen (1994), Poterba (2001), Geanakopolos, Magill, and Quinzii (2004), Brunetti and Torricelli (2007)), there is little evidence on the effect of demographic change on cross-sectional returns. A paper investigating this effect is DellaVigna and Pollet (2007). Although they do not consider pharmaceutical companies as a cross-section, they examine age-sensitive sectors such as toys, bicycles, beer, life insurance, and nursing homes. As pharmaceutical firms are very sensitive to demographic changes given that every drug has its specific age-pattern, pharmaceutical companies are ideal to investigate the influence of demographic changes on stock returns and profits.

This paper analyzes the possible relationship between demographic shifts in age group (cohort) sizes (children (0–19), young people (aged 20–29), younger middle-aged people (aged 30–49), older middle-aged people (aged 50–59), old people (aged 60+)) and the demand of different pharmaceutical drugs as well as its influence on abnormal stock returns. Since different goods have different age profiles of consumption, forecastable changes in the age distribution lead to forecastable shifts in demand for different goods. For example, anorexiants and CNS stimulants are mainly used by young people whereas antidepressants and antifungals are mainly used by middle-aged people and adrenal corticosteroids and blood glucose by old people.

Shifts in demand have an influence on profitability and returns of pharmaceutical industries. Consequently, the timing of the stock market reaction to these demand changes is important regarding the investor's response to predictable changes in future profitability. For example, assuming that a large cohort is born in 1955, this large cohort will increase the demand for CNS stimulants as of 1966. If the CNS stimulants industry is not perfectly competitive, the pharmaceutical companies that have their core businesses in the CNS stimulants industry will experience an increase in abnormal profits in 1966. The timing of abnormally high returns depends on the foresight horizon of the investor. There are three scenarios for different reactions of the investors and the consequences for abnormal stock returns (Bergantino (1998)). The first scenario, the standard analysis, states that the marginal investor foresees the positive demand shift induced by demographic changes and purchases CNS stimulants in 1955. Therefore, when the price of CNS stimulants increases in 1965, the opportunity to receive abnormal returns no longer exists. Alternatively, investors could be inattentive to information about future changes in the demand shift that is further away than five years (their reasonable foresight horizon). In this case, stock returns of firms selling CNS stimulants will not respond in 1955, but will be abnormally high in 1965 when investors start paying attention to the future shift. A third scenario is that investors overreact to demographic information and shifts in demand of different drugs. In this case, abnormal stock returns would be high in 1955, and low in the following years, as realized profits fail to meet inflated expectations. In the last two scenarios, but not in the standard model, demographic information available in 1955 predicts industry abnormal returns between 1955 and 1965. Inattention leads to positive abnormal returns, while overreaction leads to negative abnormal returns given that forecastable demand increases due to demographic changes. In the standard model, forecastable fluctuations in cohort size do not generate predictability because stock prices react immediately to demographic information.

This example motivates a test of cross-sectional return predictability among pharmaceutical companies that has – to the knowledge of the authors – not been investigated in the literature before. In this paper we test whether demographic information predicts abnormal stock returns across 61 pharmaceutical firms over the period from 1986 to 2006. We find evidence that population age structure does affect stock market prices and real returns of different pharmaceutical companies over the last twenty years. We divide firms in an effort to separate drugs with different age profiles in consumption. Several drugs have an obvious association with a demographic age group. For example, in the life cycle of consumption, CNS stimulants and anorexiants are followed by antidepressants and antifungals. Later in life, individuals consume more androgens and anabolic steroids. The life cycle ends with the consumption of corticosteroids and blood glucose by old people.

The analyzes in this study are based on data from the U.S. Census Bureau (demographic data and forecasts from 1900 to 2040), Medical Expenditure Panel Survey (drug age patterns), Evaluatepharma Database (sales of 20 main drugs of each of the 61 pharmaceutical companies from 1986–2006), and Datastream (profits and returns of every company from 1986–2006).

The outline of the article is as follows. In Section 2, we give an overview of literature discussing the effect of demographics on corporate decisions and stock returns. Section 3 describes the methodology used in the paper. Section 4 discusses the basic two-stage model used in DellaVigna and Pollet (2007), and derives the three hypotheses from the model. Section 5 includes the construction of demographic-based forecasts of demand growth by drug of different pharmaceutical companies. Section 6 analyzes whether forecasted demand growth due to demographic changes predicts return on equities and abnormal stock returns. The conclusion follows in Section 7.

2 Literature Review

2.1 Demographic Changes and Its Impact on Stock Market Returns

The paper is related to the literature on demographic changes and its impacts on aggregate stock market returns due to demand shifts of financial assets.[1] In this paper, the focus is on the cross-sectional predictability of pharmaceutical companies' returns induced by changes in consumer demand.

Mankiw and Weil (1989) find that contemporaneous cohort size partially explains the time-series behavior of housing prices. DellaVigna and Pollet (2007) generalize their approach by analyzing 48 industries and examining stock market returns. They assume that, unlike for housing prices, arbitrage should reduce predictability. They

[1] Bakshi and Chen (1994), Yoo (1994), Poterba (2001), Brooks (2002), Abel (2003), Davis and Li (2003), Ang and Maddaloni (2005), Geanakoplos, Magill, and Quinzii (2004), Brunetti and Torricelli (2007).

find evidence that stock market returns are predicted by forecasted demand growth in distant future, rather than by contemporaneous demand growth. They present a trading strategy exploiting demographic information that earns an annualized risk-adjusted return of 5 to 7 percent. They present a model of inattention to information about the distant future that is consistent with these findings. We will use the model of DellaVigna and Pollet (2007) and show that our results are consistent with the model in which investors are unconditionally inattentive about the distant future.

Acemoglu and Linn (2004) investigate the introduction of new drugs in pharmaceutical companies in response to predictable demand increases due to demographics. Their main data source for drug use is the Medical Expenditure Panel Survey (MEPS), which is a sample of U.S. households over the years 1996–1998. They find economically significant and relatively robust effects of market size on entry of new drugs. Their results indicate that a one percent increase in potential market size for a drug category leads approximately to a 4 percent growth in the entry of new nongeneric drugs and new molecular entities. This provides evidence that R&D and technological change are directed toward more profitable areas. However, Acemoglu and Linn (2004) do not examine the effects on the stock market returns of these firms.

Our paper complements this literature since we focus on the pharmaceutical industry and the predictability of returns induced by changes in consumer demand of different drugs. There are no other papers known to the authors that examine the relationship between changes in forecasted consumer demand for drugs due to demographic change and pharmaceutical companies' returns.

There are a number of other studies related to Acemoglu and Linn' s (2004) work. First, Schmookler (1966) documents a statistical association between investment and sales, on the one hand, and patents and innovation, on the other, and argues that the causality ran largely from the former to the latter. The classical study by Griliches (1957) on the spread of hybrid seed corn in the U.S. agriculture also provides evidence consistent with the view that technological change and technology adoption are closely linked to profitability and market size. In more recent research, Morton (1999) and Reiffen and Ward (2002) study the decision of firms to introduce a new generic drug and find a positive relationship between entry into a new market and expected revenues in the target market. However, none of these studies exploit a potentially exogenous source of variation in market size. Second, some recent research has investigated the response of innovation to changes in energy prices. Most notably, Newell, Jaffee and Stavins (1999) show that between 1960 and 1980, the typical air-conditioner sold at Sears became significantly cheaper, but not much more energy-efficient. On the other hand, between 1980 and 1990, there was little change in costs, but air-conditioners became much more energy-efficient, which was a response to higher energy prices. These findings are consistent with the hypothesis that the type of innovation responds to profit incentives, though they do not establish causality.

2.2 Perception Allocation in Economics and Finance

This article also contributes to the literature of perception allocation in economics and finance. We distinguish between investors who are rational and have an infinite horizon, investors who are unconditionally inattentive, and investors who are inattentive with extrapolation.

Barber and Odean (2002) propose an alternative model of decision-making in which agents are confronted with many alternatives, leading to attracting attention to qualities. Preferences matter only after attention has limited the choice set. They state that when there are many alternatives and search costs are high, attention may affect choice more profoundly than preferences. Barber and Odean's theoretical model predicts that when investors are most influenced by attention, the stocks they buy will subsequently underperform those they sell. The authors find strong empirical support for this prediction. It seems that attention-based buying influences subsequent stock returns. Gabaix, Laibson, Moloche, and Weinberg (2004) study the information acquisition process. They experimentally analyze a cognition model based on partially myopic cost-benefit calculations: the DC (Directed Cognition) model. They find that the DC model successfully explains the patterns of information acquisition. When the DC model and the fully rational model make different predictions, the DC model does a better job of matching the laboratory evidence. Hirshleifer, Lim, and Teoh (2004) model limited attention as an incomplete use of publicly available information. Informed players decide whether or not to disclose information to an audience who sometimes neglects either disclosed signals or the implications of nondisclosure. They find that, in equilibrium, observers are unrealistically optimistic and that disclosure is incomplete, that a negligence of disclosed signals increases disclosure, and that a disregard of a failure to disclose reduces disclosure. They also find that these insights extend to a setting in which observers choose ex ante how to allocate their limited attention. In a setting with multiple arenas of disclosure, they find that disclosure in one arena affects perceptions in fundamentally unrelated arenas and that disclosure in one arena can displace a disclosure in another. Huberman and Regev (2001) show that enthusiastic public attention induces a permanent rise in share prices of biotechnology stocks, even though no real new information had been presented. Peng and Xiong (2006) show that limited attention leads to categorical behavior. For example, investors tend to process more sector-level information than firm-specific information. This endogenous structure of information, when combined with investor overconfidence, generates important features observed in return comovement that are otherwise difficult to explain with standard rational expectations models. In addition, their model demonstrates new implications for the cross-sectional patterns of return predictability. First, firms with higher firm-specific return variation tend to have higher bias-driven return predictability. Second, a piece of ignored public information will have less predictive power for those firms with higher firm-specific return variation.

Our findings suggest that investors may simplify complex decisions by neglecting long-term information. This evidence is different from predictability tests based on performance information measured by previous returns (DeBondt and Thaler (1985), Jegadeesh and Titman (1993)), accounting ratios (Fama and French (1992)), or earning announcements (Bernard and Thomas (1989)). These variables include information about future predictability that is not easily factorable into short- and long-term components.

3 Methodology

The methodology used in this article is as follows. In Section 4, we discuss the basic two-stage model by Mankiw and Whinston (1986), used also in DellaVigna and Pollet (2007). We derive three hypotheses from the model and test them using U.S. data on pharmaceutical companies' returns. The first hypothesis states that if investors are rational (i.e. that their foresight horizon goes to infinity), the expected abnormal return is independent of expected future demand growth. The second hypothesis states that if investors are inattentive (i.e. foresight horizon is finite), the expected abnormal return is positively related to expected future demand growth one period after the horizon. The third hypothesis declares that if investors are inattentive with extrapolation using short-term expectations, the expected abnormal return is negatively related to expected future demand growth less than one period ahead.

In Section 5, we include the construction of demographic-based forecasts of demand growth by drug of different pharmaceutical firms in four steps:

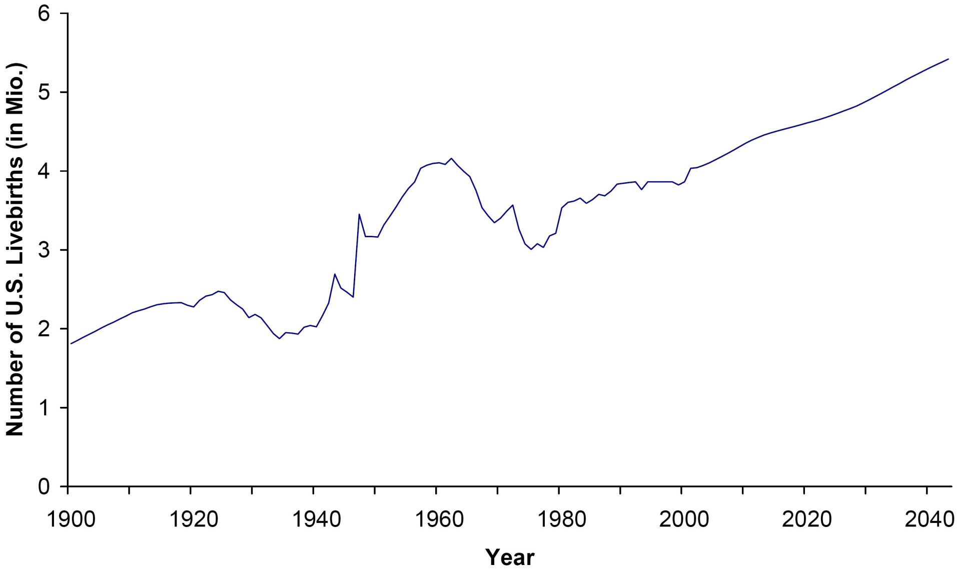
(1) In the first step, we collect cohort sizes from the U.S. Census Bureau for the years 1900–2006. The main source of variation in age-specific cohort sizes is the size of birth cohorts. As can be seen in Figure 1, after a large cohort in the early 20th century, a small cohort in the 1930s was followed by the large Baby Boom cohorts in the late 1950s. The small Baby Bust cohorts of the 1960s and early 1970s led to larger birth cohorts in the 1980s. There is a continuous increase in livebirths in the 1990s and 2000. From 2007 to 2040, we see the projections of the U.S. Census Bureau in the future.

(2) In the second step, we estimate age-consumption profiles for the 34 drugs in the sample. We construct five age groups, 0–19, 20–29, 30–49, 50–59, and 60+. These divisions are motivated by drug age patterns of these age groups. Our main data source for drug use by age group is the Medical Expenditure Panel Survey (MEPS), which is a sample of U.S. households over the years 1996-1998. The survey includes age and income data for each household member and covers about 25'000 individuals in each year. In all, there are about 500'000 medications prescribed. Following Acemoglu and Linn (2004), we construct drug use per person and expenditure share for each category and each of our five age groups. We observe that across goods, the age profile of consumption varies substantially. We assume that for a given good, the age profile is quite stable across time. These findings support the use of cohort size as a causal variable for demand.

(3) In the third step, we combine the age profiles of consumption from the MEPS data with demographic forecasts data provided by the U.S. Census Bureau. The output is the drug-by-drug forecasted demand growth caused by demographic changes.

(4) In the fourth step, we consider 61 international pharmaceutical firms which mainly provide the U.S. market with drugs. Within these firms, we elicit the expenditures of the top twenty drugs from 1986-2006

Figure 1: Livebirths in the U.S. from 1900-2040. Projections for years 2007 to 2040 are derived from the U.S. Census Bureau.



with the aid of the Evaluatepharma database. The Evaluatepharma database includes detailed data of 95% of the pharmaceutical companies of the world. Data are taken from annual company reports and are updated every month. For every pharmaceutical company, we obtain the corresponding yearly expenditures from 1986-2006 and the EphMRA (European Pharmaceutical Market Research Association) ATC Codes (The Anatomical Therapeutic Chemical Classification System) of each of the top twenty drugs out of the database. We weight the core businesses of each company according to the expenditures and ATC Codes of the top twenty drugs to our five age cohorts (0-19, 20-29, 30-49, 50-59, 60+) for the time period from 1986 to 2006. Summarizing, we get monthly drug demand growth rates for each age cohort over the last twenty years for each of the 61 pharmaceutical firms.

In Section 6, we analyze whether forecasted demand growth due to demographic changes predicts return on equities (ROE) and abnormal stock returns. We define short-term demand as the forecasted annualized growth rate of consumption due to demographics over the next 5 years and we define long-term demand as the forecasted annualized growth rate of consumption during 5 to 10 years. In the panel regressions, we find that long-term demand growth forecasts annual stock returns. An increase by one percentage point in the annualized long-term demand growth rate due to demographics predicts a significant 2 to 3 percentage point increase in abnormal returns of the pharmaceutical companies. The effect of short-term demand growth on returns is not statistically significant.

Finally, we also implement Fama-MacBeth regressions as an alternative approach to control for year effects.

Using this methodology and choosing short-term demand growth and long-term demand growth as the independent variables, we find that forecasted long-term growth between year $t+5$ and $t+10$ has an economical effect on abnormal yearly returns. The coefficient of short-term growth between t and $t+5$ is negative and has no effect on abnormal yearly returns. If we only choose long-term demand growth due demographic changes as the independent variable, we observe a statistically and economically significant effect.

4 The Model

4.1 Stock Returns

In this part we show how returns of firms in an industry should respond to demographic changes given that demand shifts affect profitability. Following DellaVigna and Pollet (2007), we consider a model where investors can be fully attentive (very long foresight horizon) or inattentive (short-sighted horizon). DellaVigna and Pollet (2007) use a similar methodology as Campell and Shiller (1988), and Campell (1991), and Vuolteenaho (2002).

Consider a generic, not necessarily rational, expectation operator $\hat{E}_t[\cdot]$, with the properties $\hat{E}_t[ca_{t+j}+b_{t+k}] = c\hat{E}_t a_{t+j} + \hat{E}_t b_{t+k}$ and $a_t = \hat{E}_t a_t$. As shown in DellaVigna and Pollet (2007), the unexpected return can be expressed as a change in expectations about profitability (measured by the accounting return on equity, ROE) and stock returns:

$$r_{t+1} - \hat{E}_t r_{t+1} = \Delta\hat{E}_{t+1} \sum_{j=0}^{\infty} \rho^j roe_{t+1+j} - \Delta\hat{E}_{t+1} \sum_{j=1}^{\infty} \rho^j r_{t+1+j} \tag{1}$$

In this expression, $r_{t+1} = \log(1+R_{t+1})$ is the log return between t and $t+1$, $roe_{t+1} = \log(1+ROE_{t+1})$ is the log of the accounting return on equity between t and $t+1$, $\rho < 1$ is a constant (interpreted as a discount factor) associated with the log-linear approximation, and $\Delta\hat{E}_t[\cdot] = \hat{E}_{t+1}[\cdot] - \hat{E}_t[\cdot]$ is the change in expectations between periods. The transversality condition for the derivation of equation (1) is $lim_{j\to\infty}\rho^j(r_{t+1+j} - roe_{t+1+j}) = 0$. roe and r cannot diverge too much in the distant future even if the transversality condition is not satisfied, as long as changes in expectations about the bubble are unrelated to demographic shifts, the predictions of the theory remain unchanged.

Short-sighted investors have correct short-term expectations but incorrect long-term expectations about profitability. Let $E_t^\star[\cdot]$ be the expectation operator for short-sighted investors at time t. Similarly, let $E_t[\cdot]$ be the fully rational (very long-sighted) expectation operator for period t. Short-sighted investors have rational expectations regarding dividend growth for the first h (h is the foresight horizon of the investor) periods after t, $E_t^\star roe_{t+1+j} = E_t roe_{t+1+j} \quad \forall j < h$. For periods beyond $t+h$, they form incorrect expectations of profitability based on a constant term, $\overline{roe}$, and an extrapolation from the expected (rational) average log return on equity for periods $t+1+h-n$ to $t+h$:

$$E_t^{\star} roe_{t+1+j} = w * \overline{roe} + (1-w) \sum_{i=1}^{n} \frac{E_t roe_{t+1+h-i}}{n} \quad \forall j \geq h, \tag{2}$$

where ω is a weighting factor between zero and one, and n are the periods of extrapolation. Finally, we assume that short-sighted investors believe that expected log returns are characterized by a log version of the conditional CAPM:

$$E_t^{\star} r_{t+1+j} = E_t r_{f,t+1+j} + E_t \beta_{t+j} (r_{m,t+1+j} - r_{f,t+1+j}) \quad \forall j \geq 0 \tag{3}$$

where $r_{f,t+1+j}$ is the log riskless interest rate and $r_{m,t+1+j} - r_{f,t+1+j}$ is the excess log market return.

We consider three leading cases of the model:

i) In the limiting case when $h \to \infty$, investors possess rational expectations about future profitability.

ii) If h is finite and $w = 1$, then investors exhibit unconditional inattention. Investors expect that the return on equity after period $t + h$ will equal a constant, $\overline{roe}$.

iii) If h is finite and $w < 1$, then investors exhibit inattention with extrapolation (n periods of extrapolation). Investors form expectations for the return on equity after period $t + h$ with a combination of a fixed forecast, $\overline{roe}$, and an extrapolation based on the average expected return on equity for the n periods before $t + 1 + h$.

This model of inattention assumes that investors carefully form expectations about profitability in the immediate future, but adopt rules of thumb to evaluate profitability in the more distant future. In a world with costly information processing, these rules of thumb could be approximately optimal. The short-term forecasts embed most of the available information about profitability in the distant future. However, investors disregard useful information by neclecting long-term demographic variables. They do not realize that these demographic variables provide relatively precise forecasts of profitability even at long horizons.

Let $E_t^{\star}[\cdot]$ characterize the short-sighted expectations of a representative agent. According to DellaVigna and Pollet (2007), we can substitute the short-sighted expectations, $E_t^{\star}[\cdot]$, for the generic operator $\hat{E}_t[\cdot]$ in (1) and use (3) to get an expression for the unexpected return for short-sighted investors:

$$
\begin{aligned}
r_{t+1} - E_t^{\star} r_{t+1} &= \Delta E_{t+1}^{\star} \sum_{j=0}^{\infty} \rho^j roe_{t+1+j} - \Delta E_{t+1}^{\star} \sum_{j=1}^{\infty} \rho^j r_{t+1+j} \qquad (4)\\
&= \Delta E_{t+1} \sum_{j=0}^{h-1} \rho^j roe_{t+1+j} + \rho^h \left[E_{t+1} roe_{t+1+h} - w\overline{roe} - (1-w) \sum_{i=1}^{n} \frac{E_t roe_{t+1+h-i}}{n} \right] \\
&+ (1-w) \sum_{j=h+1}^{\infty} \rho^j \left[\sum_{i=1}^{n} \frac{E_{t+1} roe_{t+2+h-i}}{n} - \sum_{i=1}^{n} \frac{E_t roe_{t+1+h-i}}{n} \right] \\
&- \Delta E_{t+1} \sum_{j=1}^{\infty} \rho^j (r_{f,t+1+j} + \beta_{t+j}(r_{m,t+1+j} - r_{f,t+1+j})).
\end{aligned}
$$

The unexpected return, $r_{t+1} - E_{t+1}^{\star} r_{t+1}$, depends on the value of the return on equity only up to period $t+1+h$. Later periods are not incorporated, since investors are short-sighted.

We define abnormal or risk-adjusted return ar_{t+1} to be consistent with the log version of the conditional CAPM:

$$
ar_{t+1} = r_{t+1} - r_{f,t+1} - \beta_t (r_{m,t+1} - r_{f,t+1}).
$$

Taking conditional rational expectations at time t (using $E_t[\cdot]$) and applying the law of iterated expectations, we derive the expected abnormal return $E_t ar_{t+1}$ from the perspective of the fully rational investor:

$$
\begin{aligned}
E_t ar_{t+1} &= \rho^h w (E_t roe_{t+1+h} - \overline{roe}) + \rho^h (1-w) \sum_{i=1}^{n} E_t [roe_{t+1+h} - roe_{t+1+h-i}]/n \\
&+ \frac{\rho^{h+1}}{1-\rho} \frac{(1-w)}{n} E_t [roe_{t+1+h} - roe_{t+1+h-n}]. \qquad (5)
\end{aligned}
$$

The expected return between time t and time $t+1$ depends on the sum of three terms. For rational investors ($h \to \infty$), all terms converge to zero (given $\rho < 1$) and we obtain the standard result of unforecastable returns. For investors with unconditional inattention (h finite and $w = 1$), only the first term is relevant: $E_t ar_{t+1} = \rho^h (E_t roe_{t+1+h} - \overline{roe})$. Returns between year t and year $t+1$ are predictable using the difference between the expected return on equity $h+1$ years ahead and the constant $\overline{roe}$. For inattentive investors with extrapolation (h finite, $w = 0$, and n periods of extrapolation), only the last two terms are relevant. Abnormal returns depend positively on the expected return on equity $h+1$ years ahead and negatively on the expected return on equity during the previous n years (because these agents rely too heavily on the short-term expectations about roe). In general, for inattentive investors (h finite), stock returns between time t and $t+1$ are forecasted positively by the expected return on equity $h+1$ years ahead, and negatively by the expected return on equity for the n years prior to $t+1+h$.

4.2 Derivation of the Three Hypotheses

DellaVigna and Pollet (2007) give the intuition of the above. Between year t and $t+1$, investors update their expectations by incorporating the expected profitability in period $t+1+h$, which was previously ignored. This information replaces the earlier forecast that was created using $\overline{roe}$ and the expected return on equity between years $t+1+h-n$ and $t+h$. Expected returns are an increasing function of the update about future profitability. This update depends positively on expected profitability in period $t+1+h$ and negatively on $\overline{roe}$ and on expected profitability between $t+1+h-n$ and $t+1+h$.

DellaVigna and Pollet (2007) show that the accounting return on equity responds to contemporaneous demand changes if the changes are not known before the decision about the entry. Under additional conditions, they show that the relationship between the log return on equity and the log of the demand shift α is linear:

$$roe_{t+1+j} = \phi + \theta \Delta c_{t+1+j} + v_{t+1+j}, \tag{6}$$

where $v_{t+1+j} = \theta\omega_{t+1+j} + z_{t+1+j}$. For simplicity, we assume that $E_{t+j}v_{t+1+j} = 0$ for any $j \geq 0$. Substituting expression (6) into equation (5), we obtain

$$\begin{aligned} E_t ar_{t+1} &= A + \rho^h w\theta E_t \Delta c_{t+1+h} + \rho^h (1-w)\theta \sum_{i=1}^{n} E_t[\Delta c_{t+1+h} - \Delta c_{t+1+h-i}]/n \\ &+ \frac{\rho^{h+1}}{1-\rho}\frac{(1-w)}{n}\theta E_t[\Delta c_{t+1+h} - \Delta c_{t+1+h-n}], \end{aligned} \tag{7}$$

where A is a constant equal to $\rho^h\omega(\phi - \overline{roe})$. Using equation (7), we derive Hypotheses 1-3:

Hypothesis 1: *If investors are rational ($h \to \infty$), the expected abnormal return, $E_t ar_{t+1}$, is independent of expected future demand growth, $E_t\Delta c_{t+1+j}$ for any $j \geq 0$.*
Hypothesis 2: *If investors are inattentive (h finite, $\omega = 1$), the expected abnormal return $E_t ar_{t+1}$, is positively related to expected future demand growth $h+1$ periods ahead, $E_t\Delta c_{t+1+h}$. Moreover, $\partial E_t ar_{t+1}/\partial E_t \Delta c_{t+1+h} = \rho^h\theta[1 + (1-\omega)\rho/((1-\rho)n)]$.*
Hypothesis 3: *If investors are inattentive with extrapolation (h finite and $\omega < 1$), the expected abnormal return $E_t ar_{t+1}$ is negatively related to expected future demand growth less than $h+1$ periods ahead, $E_t\Delta c_{t+1+h-i}$ for all $1 \leq i \leq n$.*

Hypothesis 1 states that under the null hypothesis of rational investors, forecastable demographic changes do not affect abnormal stock returns. Under the alternative hypothesis (Hypothesis 2), forecastable demand growth $h+1$ periods ahead predicts abnormal stock returns for inattentive investors (they have a infinite horizon h). Hypothesis 2 shows the connection between degree of forecastability to the sensitivity of accounting return on equity to demand growth θ. The value of $\partial E_t ar_{t+1}/\partial E_t \Delta c_{t+1+h}$ can be between $\rho^h\theta$ (for $\omega = 1$) and $\theta[1 + \rho/(1-\rho)]$ (for $\omega = 0$ and $n = 1$). Finally, if investors are inattentive with extrapolation ($\omega < 1$), then demand growth less than $h + 1$ periods ahead forecasts abnormal returns negatively (Hypothesis 3).

In this analysis we form two demand growth forecasts, one for short-term growth between t and $t + 5$, and one for long-term growth between $t + 5$ and $t + 10$. In section 6, we show that our results are consistent with Hypothesis 2 where investors are unconditionally inattentive about the distant future ($\omega = 1$ because $\rho^h\theta > \theta$).

5 Demographic Data and Forecasted Demand Growth

In this section, we present the data used in the paper. Table 1 provides an overview of the data used. Demographic data is shown in column 1, data of the age patterns of the different drugs in column 2, sales and expenditure data in column 3, and the fourth and last column shows profit and return data.

Table 1: This table provides an overview of the data used in the paper. The demographic data is shown in column 1, the data of the age patterns of the different drugs in column 2, sales and expenditure data in column 3, and the fourth and last column shows profit and return data.

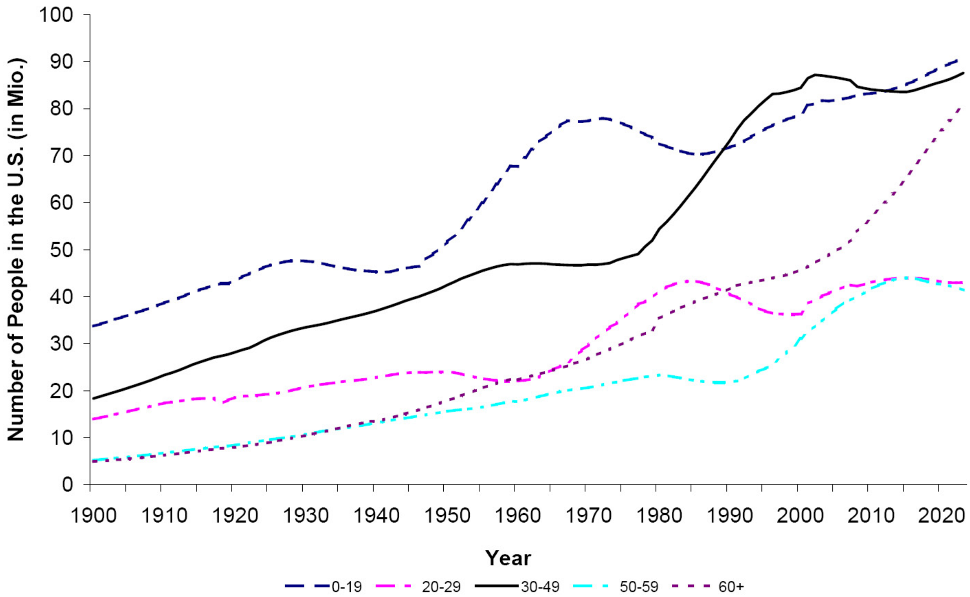
	Demographic Data	Drug Age Patterns	Sales/Expenditures	Profits and Returns
Description	Livebirths, Number of U.S. persons per age for each year, Estimates for 2007-2040	Age and Income Data for 25'000 individuals in each year, 500'000 medications prescribed, Drug use per person and expenditure share	ATC Codes and Annual Sales for the top twenty drugs of each of the leading 61 international pharmaceutical companies --> Monthly Extrapolation	Monthly Profits and Returns of all 61 pharmaceutical companies
Source	U.S.Census Bureau and Factbook	Medical Expenditure Panel Survey used in Acemoglu and Linn (2004)	Evaluatepharma Database	Datastream
Time Period	1900-2040	1996-1998	1986-2006	1984-2006

5.1 Demographic Data

In a first step, we derive U.S. demographic variables from 1900–2040, as for example, U.S. population and projected population for the future from data of the U.S. Census Bureau as well as the World Factbook. We split the entire population into five cohorts, the cohort aged 0–19, 20–29, 30–49, 50–59, and 60+. Figure 2 shows the age profile of the different cohorts between 1900 and 2023, whereas the age profiles between 2007 and 2023 are estimated by the U.S. Census Bureau.

The time-series behavior of the cohort size aged 0-20 can be divided into four periods: (i) the cohort size decreases between 1935 and 1945, reflecting the low fertility of the 1930s, (ii) the cohort size decreases between 1945 and 1975, reflecting the Baby Boom of the 1940s and particularly during the years 1947 – 1960, (iii) the cohort decreases between 1970 and 1985, due to lower fertility rates during the following years (the Baby Bust),

Figure 2: Age profile of the five cohorts in the U.S. from 1900-2022 whereas data from 2007-2022 are estimated by the U.S. Census Bureau.

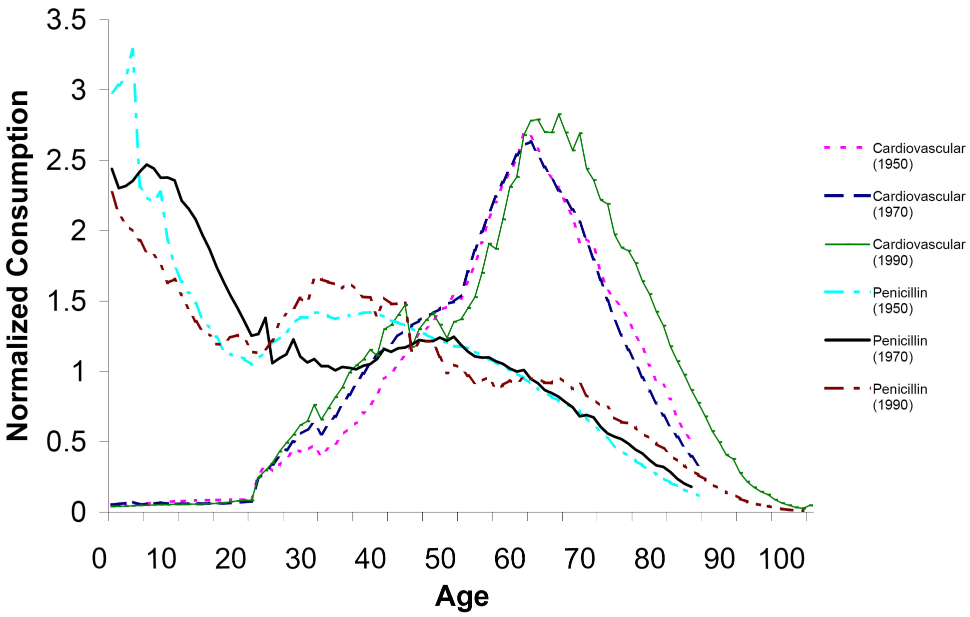


and (iv) the cohort increases again after 1985, in response to the parental age of the Baby Boom cohort. The cohort size aged 30–49 follows a similar time-series pattern as the cohort 0–20, shifted forward by approximately 20 years. The cohort sizes of the older cohorts vary less. In particular, the cohort aged 60+ grows steadily over time. Demographic shifts induce the most variation in demand for goods consumed by the young cohorts.

5.2 Age Patterns in Consumption of Drugs

In the second step, we estimate age-consumption profiles for the 34 drugs in the sample. We construct five age groups, 0-19, 20-29, 30-49, 50-59, and 60+. These divisions are motivated by drug age patterns of these age groups. Our main data source for drug use by age group is the Medical Expenditure Panel Survey (MEPS), which is a sample of U.S. households over the years 1996-1998. The survey has age and income data for each household member, and covers about 25'000 individuals in each year. In total, there are about 500'000 medications prescribed. Following Acemoglu and Linn (2004), we construct drug use per person and expenditure share for each category and for each of our five age groups. Table 6 in Appendix A.1 shows the summary of the disease classification and drug use by age group from 1996-1998 by Acemoglu and Linn (2004). The first number indicates the use per person, that is, the mean number of drugs in the class used per person of the age group. The second number indicates the share of use (expenditure share), that is, the fraction of drugs used in the category by the age group. We can assign every drug category to one of our five cohorts. Based on this, we can make two assumptions. First, across pharmaceuticals, the age profile of consumption varies substantially. Some drugs are mainly consumed by younger people (e.g. Penicillins), others by elderly people (e.g. Cardiovascular). Second, for a given drug, the age profile is quite stable across time. These assumptions support the use of cohort size as a causal variable of demand. Figure 3 shows the age profile of normalized consumption for Cardiovascular and Penicillins for three different time points: 1950, 1970, and 1990. We can see that Cardiovascular is mainly needed by older persons (peak at 65-year olds) whereas Penicillins is mainly needed by young persons aged between 0 and 10 years. We can also see that the normalized consumption has shifted in parallel from 1950 to 1990 for Cardiovascular.

Figure 3: The figure shows the age profile of consumption for Cardiovascular (typical drug for old persons) and Penicillins (typical drug for young people) for the years 1950, 1970, and 1990. Expenditures are normalized so that the average consumption for all ages is equal to 1.



5.3 Demand Forecasts

In the third step, we combine the age profile of consumption from the subsection before with the demographic situation derived by the U.S Census Bureau in order to forecast demand changes for different drugs for the time period between 1900 and 2020. Let $c_{k,t}$ be the forecasted annual consumption of drug k for individuals at different ages for time t.

For example, we consider a demand forecast of a typical drug for old people (60+), e.g. Hyperlipidemia, a demand forecast of a typical drug for young people aged between 0-19, e.g. Penicillins, and a demand forecast of a typical drug for middle-aged people between 30 and 49 years old, e.g. Antipsychotics. Figure 4 in Appendix A.2 shows the forcasted absolute demand of these three types of drugs. We compute demand growth rates from time t to time $t+1$ by

$$lnc_{k,t+1} - lnc_{k,t} \tag{8}$$

for typical drugs of each age cohort.

5.4 Pharmaceutical Companies and their Core Businesses

In the fourth step, we first consider 61 international pharmaceutical companies that mainly provide the U.S. market with drugs. Within these companies, we collect the sales/expenditures of the top twenty drugs from 1986 to 2006 with the aid of the annual sales data of the Evaluatepharma database. For every pharmaceutical company, we get the corresponding yearly expenditures from 1986 to 2006 and the EphMRA (European Pharmaceutical Market Research Association) ATC Codes of each of the top twenty drugs out of the database. Each ATC Code can be assigned to one of the 34 drug categories of the Medical Expenditure Panel Survey (MEPS) used in Acemoglu and Linn (2004). The EphMRA ATC Codes and its assignment to the 34 drug categories of MEPS are listed in Appendix A.3, Table 7. Secondly, we weight the core businesses of each company according to the expenditures of the top twenty drugs to our five age cohorts for the time period 1986-2006. Finally, we extrapolate linearly the yearly weights for getting monthly weights. Combining these monthly weights with the demand growth rates of each age profile, we obtain monthly demand growth rates over the last twenty years for each of the 61 pharmaceutical companies.

6 Empirical Tests of the Model Hypotheses

In this section, we first investigate whether forecasted demand changes predict pharmaceutical ROE. Finally, we examine absolute return predictability using the panel regression approach and also a Fama-MacBeth framework.

6.1 ROE Predictability: Panel Regression

As a measure of profitability, we use a measure of accounting return on equity (ROE). For each company, we compute the ROE at time $t+1$ as the ratio of earnings from the end of fiscal year t through the end of fiscal year $t+1$ to the book value of equity at the end of fiscal year t. Annual pharmaceutical return on equity $ROE_{k,t+1}$ for firm k for t between 1986 and 2006 are taken from Datastream. We construct the log return on equity, $roe_{k,t+1} = log(1 + ROE_{k,t+1})$. Columns 1 through 3 of Table 2 present the summary statistics for the log annual return on equity (mean and standard deviation), and the number of years for which data is available for each of the 61 firms in the sample.

In Table 3 we test the predictability of the one-year pharmaceutical company log return on equity using the forecasted contemporaneous growth rate in consumption due to demographics from year t to $t+2$. We describe

Table 2: Summary statistics for the log annual return on equity for each firm k. Column 1 displays the mean of $roe_{k,t+1}$, column 2 reports the within-industry standard deviation, and the number of years for which data is available for each of the 61 companies in the sample is reported in column 3. Column 4 shows annual log stock returns of each firm k, column 5 describes the standard deviation within firms, and column 6 reports the number of years for which data is available in Datastream.

		Log Yearly Return on Equity (ROE)			Annual Log Stock Return (AR)		
		Mean	Std. Dev.	# Years	Mean	Std. Dev.	# Years
Nr.	Company	(1)	(2)	(3)	(4)	(5)	(6)
1	Abott Laboratories	-0.038	0.246	21	0.150	0.062	24
2	Allergan Inc	-0.151	0.421	10	0.140	0.082	19
3	Amgen Inc	0.071	0.374	14	0.249	0.111	24
4	AstraZeneca plc	0.036	0.332	12	0.144	0.068	15
5	Bayer AG	0.077	0.328	21	0.292	0.086	5
6	Bristol-Myers Squibb Co	-0.021	0.342	21	0.107	0.065	24
7	Celgene Corporation	0.324	1.481	14	0.201	0.193	21
8	Eisai Co Ltd	0.040	0.224	21	0.124	0.091	24
9	Elan Corp plc	0.011	1.204	8	0.116	0.207	24
10	Eli Lilly & Co	-0.025	0.601	19	0.139	0.078	24
11	Enzon Pharmaceuticals	0.243	1.239	8	0.071	0.191	24
12	Forest Laboratories	0.053	0.236	18	0.159	0.102	24
13	Genzyme Corp	0.113	1.263	10	0.144	0.125	22
14	BASF AG	0.027	0.581	21	0.163	0.066	24
15	Glaxosmithkline	0.073	0.770	12	0.157	0.073	24
16	Johnson & Johnson	0.140	0.440	16	0.153	0.060	24
17	KV Pharmaceutical	-0.399	0.867	16	0.133	0.147	24
18	Merck & Co Inc	0.009	0.171	21	0.153	0.073	24
19	MGI Pharma	0.053	0.815	17	0.057	0.174	24
20	Mylan Laboratories	-0.053	0.608	21	0.155	0.116	24
21	Nabi Biopharmaceuticals	-0.177	2.252	6	0.031	0.209	24
22	Novartis AG	0.023	0.329	12	0.187	0.063	24
23	Noven Pharmaceuticals	-0.137	0.686	13	0.110	0.197	20
24	Novo Nordisk	0.026	0.123	21	0.134	0.080	24
25	Ono Pharmaceutical Co Ltd	-0.019	0.127	21	0.053	0.111	24
26	Pfizer Inc	0.013	0.495	21	0.139	0.071	24
27	Poniard Pharmaceuticals	0.033	0.865	11	-0.178	0.295	20
28	Repligen	0.113	1.036	10	-0.045	0.218	22
29	Roche Holding AG	0.069	0.317	17	0.170	0.061	24
30	Sanofi Aventis	0.251	0.237	7	0.165	0.074	24
31	Savient Pharmaceuticals	0.090	1.171	11	0.023	0.194	24
32	Schering-Plough Corp	0.256	0.692	19	0.157	0.076	24
33	Solvay SA	0.046	0.262	18	0.172	0.074	24
34	Taisho Pharmaceuticals Co Ltd	-0.079	0.268	21	0.085	0.076	24
35	Takeda Chemical Industries Ltd	0.034	0.152	21	0.142	0.077	24
36	Teva Pharmaceutical Industries Ltd	0.320	0.614	12	0.250	0.113	24
37	Wyeth	0.016	0.484	19	0.117	0.068	24
38	Bentley Pharmaceuticals	0.204	0.951	10	-0.076	0.196	20
39	Cephalon Inc	0.071	1.026	11	0.093	0.183	14
40	Columbia Laboratories	0.023	0.910	1	-0.004	0.233	0
41	Daiichi Seiyaku Co Ltd	-0.010	0.204	21	0.119	0.088	24
42	Dr Reddy's Laboratories Ltd	0.049	1.021	11	0.296	0.138	18
43	Oscient Pharmaceuticals	0.132	0.971	17	-0.122	0.244	24
44	OSI Pharmaceuticals	0.219	0.833	18	0.056	0.209	22
45	Par Pharmaceutical Resources	-0.577	1.784	14	0.072	0.163	24
46	Ranbaxy Laboratories Ltd	0.064	0.624	8	0.193	0.111	18
47	Sepracor Inc	0.661	0.839	6	0.088	0.195	17
48	Baxter International Inc	0.039	1.312	19	0.097	0.078	24
49	Dainippon Pharmaceutical Co Ltd	-0.046	0.689	17	0.065	0.097	24
50	Human Genome Sciences Inc	0.085	0.805	11	0.052	0.197	14
51	Kissei Pharmaceutical Co Ltd	-0.080	0.547	16	0.018	0.091	24
52	Kyorin Pharmaceutical Co Ltd	0.646	5.714	2	0.005	0.097	9
53	Kyowa Hakko Kogyo Co Ltd	0.006	0.406	21	0.061	0.099	24
54	Ligand Pharmaceuticals Inc	0.203	1.313	6	-0.004	0.175	14
55	Meiji Seika Kaisha Ltd	-0.158	0.893	19	0.044	0.089	24
56	Santen Pharmaceutical Co Ltd	0.005	0.254	20	0.104	0.093	24
57	Shionogi & Co Ltd	-0.007	0.571	21	0.081	0.096	24
58	Teijin Ltd	-0.127	0.879	19	0.058	0.094	24
59	Mitsubishi Tanabe Seiyaku Co Ltd	0.001	0.487	21	0.060	0.094	24
60	Vernalis plc	0.122	0.641	12	-0.184	0.155	16
61	3M	0.038	0.351	21	0.123	0.059	24
	Mean of all companies	0.050	0.765	15	0.099	0.123	22

Table 3: Panel Regression of Log Return on Equity on Forecasted Demand Changes Due to Demographic Changes

This table shows the results of the panel regression of log return on equity on forecasted demand changes due to demographic changes. Annual pharmaceutical return on equity $ROE_{k,t+1}$ for firm k for t between 1986 and 2006 are taken from Datastream. We construct the log return on equity, $roe_{k,t+1} = log(1 + ROE_{k,t+1})$. We test the regression $roe_{k,t+1} = const + a * (lnc_{k,t+2} - lnc_{k,t}) + \epsilon_{k,t}$.

	Log Return on Equity (ROE) at t+1					
	$const$	a	R^2	N	Industry FE	Year FE
(1)	-0.054 (0.0495)	6.479 (4.352)*	0.02	N=781		
(2)	-0.065 (0.055)	7.520 (5.085)*	0.04	N=781	x	
(3)	-0.065 (0.058)	7.520 (5.267)*	0.04	N=781	x	x

Line (1) shows the results of the panel regression without cross-sectional and year fixed effects. Line (2) shows the results with cross-sectional fixed effects, and Line (3) with both cross-sectional and year fixed effects. The standard errors are indicated in brackets. (*) indicates significance at the 10% level, (**) indicates significance at the 5% level, (***) indicates significance at the 1% level.

by $lnc_{k,t+2} - lnc_{k,t}$ the natural log of the forecasted consumption growth of firm k from year t to year $t + 2$. The following regression is tested:

$$roe_{k,t+1} = const + a * (lnc_{k,t+2} - lnc_{k,t}) + \epsilon_{k,t}. \tag{9}$$

The coefficient a indicates the responsiveness of the log return on equity in year $t + 1$ to contemporaneous forecasted changes in demand due to demographic changes. We run the panel regression (9) both with and without industry and year fixed effects. We allow for heteroskedasticity and correlation across industries by calculating standard errors clustered by year.

In Table 3, Line (1), we show the specification of the sample between 1986 and 2006 without industry or year fixed effects. The impact of demographic changes on roe is identified by variation in demand growth. The estimated coefficient, $a = 6.479$, is significant on the 10% level and economically large. A one percent increase in yearly consumption growth due to demographics increases log return on equity by $a = 6.479$ percentage points. Introducing cross-sectional fixed effects, the estimate for a is significant and larger than in Line (1), $a = 7.520$ (Line (2)). Introducing time fixed effects as well, the coefficient $a = 7.520$ stays the same and is significant at the 10% level as in Line (2). Summarizing, forecasted demand growth due demographics has a statistically and economically significant effect on pharmaceutical companies' profitability. Comparing our outcomes to the results by DellaVigna and Pollet (2007), we obtain similar results but larger and slightly less significant coefficients. In contrast to DellaVigna and Pollet (2007), we did not drop firms with negative book values.

6.2 Abnormal Return predictability: panel regression

Using the same panel framework, we investigate the relationship between forecasted demand growth and the pharmaceutical companies' monthly stock returns. Table 2, Column 4 to 6 show the results (mean, standard deviation, and the number of years data is available), analogously to ROE in the section before. In the baseline specification we regress monthly returns on the monthly forecasted growth rate of demand due to demographics from time t to five years later time $t+5$ (short-term) and $t+5$ to $t+10$ (long-term). We use beta-adjusted returns to remove market-wide shocks. We choose Nasdaq100[2] for the market returns because the technology boom in 2000 also infected the pharmaceutical market and abnormal returns will be smoothed this way. We define $r_{k,t,t+1}$ as the natural log of the stock return for firm k between the end of year t and the end of year $t+1$. The log of the market return and of the risk-free rate over the same horizon are $r_{m,t,t+1}$ and $r_{f,t,t+1}$. Further, let $\beta_{k,t}$ be the coefficient of a regression of monthly pharmaceutical companies' excess returns on market excess returns over the 48 months previous to year t. We define abnormal log return by

$$ar_{k,t,t+1} = (r_{k,t,t+1} - r_{f,t,t+1}) - \beta_{k,t}(r_{m,t,t+1} - r_{f,t,t+1}). \tag{10}$$

The specification of the regression is

$$ar_{k,t,t+1} = const + d * (lnc_{k,t+5} - lnc_{k,t}) + e * (lnc_{k,t+10} - lnc_{k,t+5}) + \epsilon_{k,t}. \tag{11}$$

The model by DellaVigna and Pollet (2007) in Section 4 suggests that, if the forecast horizon h is shorter than 5 years, the coefficient d should be positive and e should be zero. If the forecast horizon is between 5 and 10 years, the coefficient d should be zero or negative and the coefficient e should be positive. Finally, if the investors have a horizon greater than 10 years (including rational investors with $h \to \infty$), both coefficients should be zero. A significantly positive coefficient indicates that stock prices adjust as the demographic information enters the forecast horizon. Table 4 present the estimates (11) of the monthly abnormal returns for the sample of the 61 pharmaceutical firms during the years 1986-2006. In the specification without year and cross-sectional fixed effects (Line (1)), the coefficient on short-term demographics, $d = -0.678$ is not significantly different from zero whereas the coefficient on long-term demographics, $e = 1.601$ is significantly larger than zero. An annualized one percentage point increase in demand growth from year 5 to year 10 increases the average abnormal yearly stock return by 1.60 percentage points. If we introduce fixed industry effects, the coefficient is even higher, $e = 3.050$ (Line (2) in Table 4) and significantly different from zero at the 1 % significance level. If we introduce both, year and industry fixed effects, the coefficient is $e = 2.956$ and also significantly different from zero (Line (4)). The coefficient of the short-time demographic changes, d, stays negative and insignificant for all Lines (1) to (4).

[2]Results are robust with respect to the index used (S&P 500, Nasdaq100, or Nasdaq Biotechnology).

Table 4: Panel Regression of Pharmaceutical Abnormal Stock Returns on Forecasted Demand Changes Due to Demographic Changes

This table shows the results of the panel regression of pharmaceutical abnormal stock returns on forecasted demand changes due to demographic changes. We define abnormal log return by $ar_{k,t,t+1} = (r_{k,t,t+1} - r_{f,t,t+1}) - \beta_{k,t}(r_{m,t,t+1} - r_{f,t,t+1})$. We test the regression $ar_{k,t,t+1} = const + d * (lnc_{k,t+5} - lnc_{k,t}) + e * (lnc_{k,t+10} - lnc_{k,t+5}) + \epsilon_{k,t}$.

	Annual Beta-Adjusted Log Pharmaceutical Abnormal Stock Return t+1						
	$const$	d	e	R^2	N	Industry FE	Year FE
(1)	-0.299 (0.012)***	-0.678 (0.283)	1.601 (0.259)**	0.01	N=9366		
(2)	-0.390 (0.019)***	-1.127 (0.247)	3.050 (0.249)***	0.01	N=9426	x	
(3)	-0.229(0.009)***	-1.132 (0.278)	0.951 (0.289)*	0.24	N=9426		x
(4)	-0.382 (0.014)***	-1.079 (0.304)	2.956 (0.014)**	0.01	N=9366	x	x

Line (1) shows the results of the panel regression without cross-sectional and year fixed effects. Line (2) shows the results with cross-sectional fixed effects, Line (3) with year fixed effects and Line (4) with both, cross-sectional and year fixed effects. The standard errors are indicated in brackets. (*) indicates significance at the 10% level, (**) indicates significance at the 5% level, (***) indicates significance at the 1% level.

6.3 Abnormal Return predictability: Fama-MacBeth Regression

To control for time-series patterns, we implement a Fama-MacBeth regression as an alternative estimation approach according to DellaVigna and Pollet (2007). We estimate separate cross-sectional regressions of equation (11) for each year t from 1986–2006. We choose January 1 as the reference date of every year's abnormal return.[3] We then compute the time-series average of the estimated coefficients. Year effects that may be correlated with absolute returns and with demographics do not contribute to the identification of the coefficient d and e, because the regression is estimated separately for each year. The standard errors are based on time-series variation of the OLS coefficients using a Newey-West estimator with three lags. Table 5 presents the results of the Fama-MacBeth regressions.

We first estimate the regression for yearly beta-adjusted returns as the dependent variable and short- and long-term demand growth due demographic changes as the independent variables. The short-term forecasted demand growth coefficient $d = -0.108$ is negative and insignificant. The long-term forecasted demand growth coefficient $e = 2.180$ is positive but not statistically significant. The p-value of e is around 0.17. Subsequently, we estimate the regression for the independent variable of long-term demand growth only. As a result, the coefficient $e = 1.914$ is positive and significantly different from zero.

The panel regression above exhibits to two main findings. First, forecastable demand growth due to demo-

[3]The results are robust to different reference dates.

Table 5: Fama MacBeth Regression of Pharmaceutical Abnormal Stock Returns on Forecasted Demand Changes Due to Demographic Changes

This table shows the results of the Fama MacBeth regression of pharmaceutical abnormal stock returns on forecasted demand changes due to demographic changes. We estimate separate cross-sectional regressions of $ar_{k,t,t+1} = const + d * (lnc_{k,t+5} - lnc_{k,t}) + e * (lnc_{k,t+10} - lnc_{k,t+5}) + \epsilon_{k,t}$ for each year t from 1986-2006. We choose January first for the key date of every year's abnormal return. Then we compute the time-series average of the estimated coefficients.

	Beta Adjusted Log Pharmaceutical Abnormal Stock Returns					
	const	*d*	p-value of d	*e*	p-value of e	Number of years
(1)	-2.491 (1.766)	-0.108 (1.720)	0.95	2.180 (1.549)	0.17	N=22
(2)	-2.904 (1.934)			1.914 (1.314)*	0.10	N=22

The standard errors are indicated in brackets. (*) indicates significance at the 10% level, (**) indicates significance at the 5% level, (***) indicates significance at the 1% level.

graphic changes predicts abnormal stock returns. Second, forecastable demand changes in the longer run ($t+5$ to $t+10$) forecast abnormal returns whereas forecastable demand changes in the short run (t to $t+5$) do not have significant forecasting power of abnormal returns. These findings are in contrast to the model of fully rational investors. Hypothesis 1 in Section 4 states that if investors are fully rational, abnormal stock returns would not be forecastable using expected demand changes. Alternatively, Hypothesis 2 in Section 4 offers an explanation for our results based on inattention. If investors omit information under a particular time horizon h, the returns at $t+1$ should be predictable using long-term demographic information that will happen between $t+h$ and $t+1+h$. The results in Table 4 and 5 show that the horizon h could be between 5 and 10 years.

The model in Section 4 also makes a prediction regarding the coefficient on long-term forecasted demand growth in the abnormal return panel regressions from Table 4. The estimates for the coefficients of the regressions with cross-sectional fixed effects are $\hat{\delta_1} := e = 3.05$ (Table 4), respectively $\hat{\theta} := a = 7.52$ (Table 3). This is consistent with the model of unconditional inattention ($\omega = 1$) which predicts that δ_1 should be smaller than θ because of $\delta_1 = \rho^h \theta < \theta$. The results of DellaVigna and Pollet (2007) are not consistent with a model of unconditional inattention, but with a model of inattention with partial extrapolation ($\omega < 1$). In our case (model of unconditional inattention), if $\hat{\theta} = 7.52$, $\omega = 1$, $h = 7.5$, and $\rho = 0.96$, we would expect a $\delta_1 = \rho^h \theta = 5.5$ which is larger than our estimated 3.05. Therefore, according to the model, even larger abnormal returns of pharmaceutical companies according to demographic changes are possible.

7 Conclusion

We analyze how demographic change has affected profits and returns across 61 pharmaceutical companies over the last twenty years. Different drugs have different age patterns of consumption. Forecastable shifts in cohort size by age allows us to predict forecasts of demand growth due to demographic changes. Monthly expenditures for every pharmaceutical firm from 1986 to 2006 are extracted from the annual sales figures as reported in the pharmaceutical sales database (Evaluatepharma). We weight the core businesses of each company according to the expenditures of the top twenty drugs to our five age groups (0–19, 20–29, 30–49, 50–59, 60+). Summarizing, we obtain monthly drug demand growth rates for each age group over the last twenty years for each of the 61 pharmaceutical firms. The forecasted monthly demand growths by company predict the return on equity of each of the 61 pharmaceutical firms. We further present evidence from panel regressions that long-term forecastable demand growth (horizon of 5-10 years) predicts annual abnormal stock returns in the size of 2 to 3 percentage points, whereas short-term forecastable demand growth does not have a significant influence on abnormal stock returns. We also control for year effects using Fama MacBeth regressions. Although coefficients are large in size, we did not find statistically significant evidence for the influence of demographic growth on annual abnormal stock returns. According to the model of DellaVigna and Pollet (2007), the explanation can be found in the short-sighted and omitted information by the investors beyond a 5 to 10-year horizon. Our results are consistent with the model in which investors are unconditionally inattentive about the distant future.

References

Abel, A. B. (2003): "The Effects of a Baby Boom on Stock Prices and Capital Accumulation in the Presence of Social Security," *Econometrica*, 71, 551-578.

Acemoglu, D. and J. Linn (2004): "Market Size in Innovation: Theory and Evidence from the Pharmaceutical Industry," *The Quarterly Journal of Economics*, 19(3), 1049–1090.

Ang, A. and A. Maddaloni (2005): "Do Demographic Changes Affect Risk Premiums? Evidence from International Data," *Journal of Business*, 78, 341–380.

Bakshi, G. S. and Z. Chen (1994): "Baby Boom, Population Ageing and Capital Markets," *Journal of Business*, 67, 165–202.

Barber, M. B. and T. Odean (2002): "All that Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors," *Working Paper.*

Bergantino, S. M. (1998): "Life Cycle Investment Behavior, Demographics, and Asset Prices," *PhD Dissertation, MIT.*

Bernard, V. L. and J. K. Thomas (1989): "Post- Earnings-Announcement Drift: Delayed Price Response or Risk Premium?," *Journal of Accounting Research*, 27, 1–36.

Brooks, R. (2002): "Asset-Market Effects of the Baby Boom and Social-Security Reform," *The American Economic Review*, 92(2), 402–406.

Brunetti, M. and C. Torricelli (2007): "The role of demographic variables in explaining financial returns in Italy," *Working Paper.*

Campell, J. Y. (1991): "A Variance Decomposition for Stock Returns," *Economic Journal*, 101, 157–179.

Campell, J. Y. and R. J. Shiller (1988): "The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors," *Review of Financial Studies*, 1, 195–228.

Davis, E. P. and C. Li (2003): "Demographics and Financial Asset Prices in the Major Industrial Economies," mimeo, Brunel University, West London.

DeBondt, W. F. M and R. Thaler (1985): "Does The Stock Market Overreact?," *Journal of Finance*, 40, 793–805.

DellaVigna, S. and J. M. Pollet (2007): "Demographics and Industry Returns," *American Economic Review*, 97(5), 1667–1702.

Fama, E. F. and K. R. French (1992): "The Cross-section of Expected Stock Returns," *Jounal of Finance*, 47, 427–465.

Gabaix, X., Laibson, D., Moloche, G., and S. Weinberg (2004): "Information Acquisition: Experimental Analysis of a Boundedly Rational Model," *Working Paper.*

GEANAKOPLOS, J., MAGILL, M., AND M. QUINZII (2004): "Demography and the Long-Run Predictability of Stock Market," *Brookings Papers on Economic Activity*, Vol. 2004 (1), 241–307.

GRILICHES, Z. (1957): "Hybrid Corn: An Exploration in the Economics of technological change," *Econometrica*, 25 (4), 501–522.

HIRSHLEIFER, D., LIM, S. S., AND S. H. TEOH (2004): "Disclosure to an Audience with Limited Attention," *Working Paper.*

HUBERMANN, G. AND T. REGEV (2001): "Contagious Speculation and a Cure for Cancer: A Nonevent that Made Stock Prices Soar." *Journal of Finance*, 56, 387–396.

JEGADEESH, N. AND S. TITMAN (1993): "Returns to Buying Winners and Selling Losers: Implications For Stock Market Efficiency." *Journal of Finance*, 48, 65–91.

MANKIW, N. G. AND D. N. WEIL (1989): "The Baby Boom, the Baby Bust, and the Housing Market," *Regional Science and Urban Economics*, 19, 235–258.

MANKIW, N. G., GREGORY N., AND M. D. WHINSTON (1986): "Free Entry and Social Inefficiency," *RAND Journal of Economics*, 17, 48–58.

NEWELL, R. G., JAFFE, A. B., AND R. N. STAVINS (1999): "The Induced Innovation Hypothesis and Energy-Saving Technological Change," *The Quarterly Journal of Economics*, 114(3), 941–975.

PENG, L. AND W. XIONG (2006): "Limited Attention and Asset Prices," *Journal of Financial Economics*, 80(3), 563–602.

POTERBA, J. M. (2001): "Demographic Structure and Asset Returns," *Review of Economics and Statistics*, 83, 565-584.

REIFFEN, D. AND M. R. WARD (2002): "Recent Empirical Evidence on Discrimination by Regulated Firms," *Review of Network Economics*, 1(1), 39-53.

SCHMOOKLER, J. (1966): "Invention and Economic Growth," *Harvard University Press.*

SCOTT MORTON, F. (1999): "Entry Decisions in the Generic Drug Industry." *The Rand Journal*, 30, 421–440.

VUOLTEENAHO, T. (2002): "What Drives Firm-Level Stock Returns." *Journal of Finance*, 57, 233–264.

YOO, P. S. (1994): "Age Dependent Portfolio Selection," Federal Reserve Bank of St. Louis, *Working Paper*, 94–003A.

A Appendix

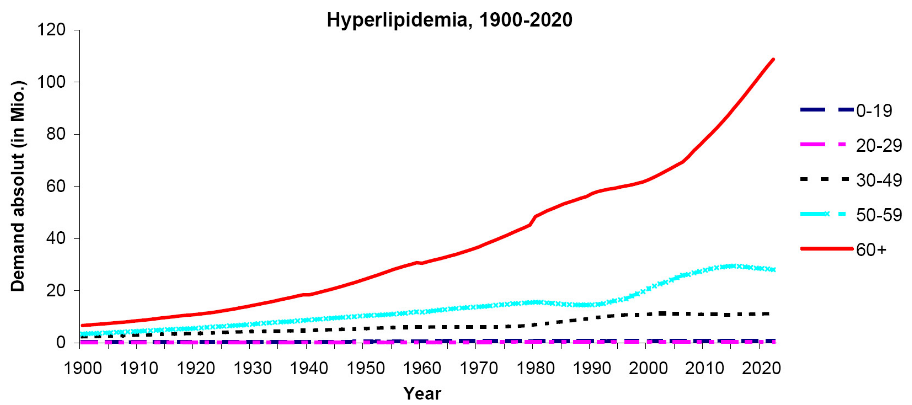
A.1 Disease Classification and Drug Use by Age Group

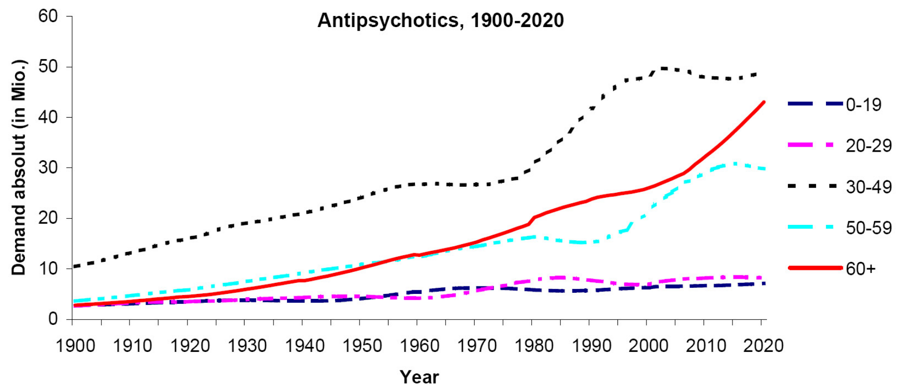
Table 6: Summary of Disease Classification and Drug Use by age group, 1996-1998. The first number indicates the use per person, that is the mean number of drugs in the class used per person in the age group. The second number indicates the share of use (expenditure share), that is the fraction of drugs used in the category by the age group. Age group with largest expenditure is the broad age group with the greatest expenditure on the corresponding category.

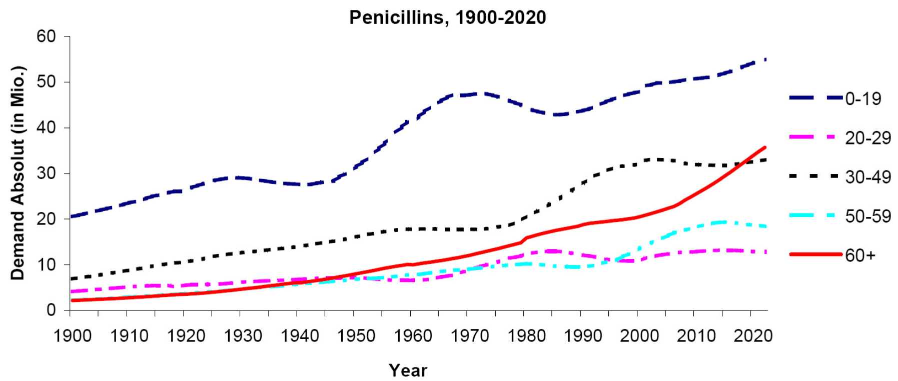
Class	Description	0-19	20-29	30-49	50-59	60+	Age group with largest expenditure
10	Penicillins, Cephalosporins, Lincosamides, Sulfonamides, Misc. Antibacterials	0.61 0.40	0.30 0.09	0.38 0.26	0.44 0.10	0.45 0.16	0-19
11	Tetracyclines, Urinary Tract Antiseptics, Quinolones	0.02 0.11	0.06 0.13	0.06 0.31	0.09 0.14	0.12 0.30	30-49
12	Antifungals, Antivirals	0.03 0.16	0.03 0.08	0.08 0.43	0.09 0.15	0.07 0.18	30-49
20	Hematologics	0.00 0.01	0.00 0.01	0.03 0.11	0.11 0.12	0.43 0.75	60+
30	Cardiovascular - Renal	0.05 0.01	0.10 0.01	0.69 0.15	2.68 0.19	6.05 0.65	60+
40	Sedatives/Hypnotics, Antianxiety	0.01 0.02	0.04 0.04	0.16 0.23	0.27 0.38	0.41 0.33	50-59
41	Antipsychotics/Antimania, Antidepressants	0.08 0.06	0.19 0.07	0.57 0.46	0.70 0.18	0.57 0.23	30-49
42	Anorexiants	0.04 0.46	0.01 0.07	0.03 0.35	0.02 0.09	0.01 0.04	0-19
43	Misc. Central Nervous System	0.11 0.75	0.01 0.04	0.01 0.09	0.01 0.03	0.02 0.08	0-19
50	Gastrointestinals	0.03 0.03	0.08 0.04	0.24 0.27	0.52 0.19	0.83 0.47	60+
60	Hyperlipidemia/Electrolyte Replenishment/Regulation, Calcium Metabolism	0.01 0.01	0.01 0.00	0.13 0.12	0.67 0.21	1.37 0.66	60+
61	Vitamins/Minerals	0.06 0.20	0.09 0.16	0.07 0.27	0.09 0.12	0.13 0.25	60+
70	Adrenal Corticosteroids	0.05 0.13	0.04 0.06	0.09 0.29	0.14 0.14	0.24 0.38	60+
71	Androgens/Anabolic Steroids, Estrogens/Progestins	0.02 0.02	0.38 0.13	0.34 0.26	1.30 0.33	0.67 0.26	50-59
72	Blood Glucose, Thyroid	0.02 0.01	0.10 0.03	0.35 0.22	1.02 0.21	1.70 0.54	60+
73	Contraceptives	0.01 0.06	0.21 0.47	0.10 0.42	0.01 0.02	0.01 0.03	20-29
80	Immunologics	0.00 0.08	0.01 0.09	0.02 0.33	0.02 0.14	0.03 0.36	60+
90	Dermatologics, Topical Anti-Infectives	0.09 0.25	0.09 0.26	0.09 0.27	0.12 0.12	0.17 0.11	20-29
91	Topical Steroids	0.01 0.18	0.01 0.07	0.01 0.27	0.02 0.11	0.04 0.37	60+
100	Extrapyramidal Movement	0.00 0.03	0.01 0.03	0.03 0.34	0.03 0.11	0.08 0.49	60+
101	Skeletal Muscle Hyperactivity, Anticonvulsant	0.05 0.08	0.11 0.08	0.26 0.44	0.29 0.16	0.27 0.23	30-49
110	Oncolytics	0.00 0.02	0.01 0.03	0.05 0.25	0.16 0.27	0.17 0.44	60+
120	Misc. Ophthalmics, Glaucoma	0.00 0.00	0.00 0.01	0.01 0.05	0.06 0.08	0.41 0.86	60+
121	Ocular Anti-Infective	0.06 0.23	0.05 0.09	0.05 0.22	0.08 0.11	0.16 0.36	60+
130	Topical Otics	0.02 0.30	0.01 0.07	0.01 0.22	0.03 0.14	0.04 0.27	0-19
131	Vertigo/Motion Sickness	0.02 0.12	0.01 0.05	0.03 0.24	0.05 0.13	0.13 0.47	60+
140	General Analgesics, Narcotic Analgesics, Antiarthritics, NSAID	0.09 0.05	0.29 0.08	0.59 0.35	0.89 0.17	1.13 0.35	30-49
141	Non-Narcotic Analgesics	0.00 0.06	0.01 0.03	0.02 0.32	0.04 0.17	0.07 0.43	60+
142	Antigout	0.00 0.00	0.00 0.00	0.01 0.13	0.06 0.19	0.14 0.68	60+
143	Central Pain Syndromes	0.01 0.15	0.01 0.10	0.02 0.45	0.02 0.15	0.01 0.15	30-49
150	Antiparasitics	0.00 0.07	0.01 0.07	0.03 0.37	0.03 0.12	0.05 0.37	30-49
160	Antiashmatics, Nasal Decongestants	0.20 0.20	0.14 0.07	0.22 0.23	0.47 0.16	0.66 0.35	60+
161	Antitussives, Antihistamines, Corticosteroids	0.15 0.17	0.20 0.10	0.29 0.33	0.45 0.17	0.41 0.24	30-49
162	Cold Remedies	0.07 0.29	0.05 0.09	0.07 0.31	0.08 0.12	0.08 0.18	30-49

A.2 Forecasted Absolute Demand of a typical Drug for Young, Middle-aged, and Old People

Figure 4: Forecasted Absolute Demand of a typical drug for old people (e.g. Hyperlipidemia), a typical drug for middle-aged people (e.g. Antipsychotics), and a typical drug for young people (e.g. Penicillins).







A.3 ATC Codes

Table 7: The EphMRA ATC Codes and their assignments to the 34 drug categories of MEPS.

EphMRA (European Pharmaceutical Market Research Association) ATC Codes	Drug Categories of the Medical Expenditure Panel Survey (MEPS)
A (Alimentary Tract & Metabolism)	
A1 (Stomatologicals, Mouth Preparations, Medicinal Dentifrices Etc)	50
A2 (Antacids, Antiflatulents & Anti-Ulcerants)	50
A3 (Functional Gastro-Intestinal Disorder Drugs)	50
A4 (Antiemetics & Antinauseants)	50
A5 (Cholagogues & Hepatic Protectors)	50
A6 (Laxatives)	50
A7 (Antidiarrhoeals, Oral Electrolyte Replacers & Intestinal Anti-Inflammatories)	50
A8 (Antiobesity Preparations, Excl. Dietetics)	42
A9 (Digestives, Incl. Digestive Enzymes)	42
A10 (Drugs Used In Diabetes)	72
A11 (Vitamins)	61
A12 (Mineral Supplements)	61
A13 (Tonics)	61
A14 (Anabolics, Systemic)	71
A15 (Appetite Stimulants)	71
A16 (Other Alimentary Tract & Metabolism Products)	42
B (Blood & Blood Forming Organs)	
B1 (Antithrombotic Agents)	20
B2 (Antifibrinolytics, Antidotes To Anti-Coagulants, Inhibitors, Blood Coagulation & Haemostyptics)	20
B3 (Anti-Anaemic Preparations)	20
B6 (All Other Haematological Agents)	20
C (Cardiovascular System)	
C1 (Cardiac Therapy)	30
C2 (Antihypertensives)	30
C3 (Diuretics)	30
C4 (Cerebral & Peripheral Vasotherapeutics)	30
C5 (Antivaricosis/Anti-Haemorrhoidal Preparations)	30
C6 (Other Cardiovascular Products)	30
C7 (Beta-Blocking Agents)	30
C8 (Calcium Antagonists)	30
C9 (Agents Acting On The Renin-Angiotensin System)	30
C10 (Lipid-Regulating/Anti-Atheroma Preparations)	60
C11 (Cardiovascular Multitherapy Combination Products)	30
D (Dermatologicals)	
D1 (Antifungals, Dermatological)	90
D2 (Emollients, Protectives)	90
D3 (Wound Healing Agents)	90
D4 (Anti-Pruritics, Incl. Topical Antihistamines, Anaesthetics, Etc)	90
D5 (Nonsteroidal Products For Inflammatory Skin Disorders)	90
D6 (Topical Antibiotics, Sulphonamides & Antivirals)	90
D7 (Topical Corticosteroids)	91
D8 (Antiseptics & Disinfectants)	90
D10 (Anti-Acne Preparations)	90
D11 (Other Dermatological Preparations)	90
G (Genito-Urinary System & Sex Hormones)	
G1 (Gynaecological Anti-Infectives)	11
G2 (Other Gynaecologicals)	11
G3 (Sex Hormones & Products With Similar Desired Effects, Systemic Action Only)	73
G4 (Urologicals)	71
H (Systemic Hormonal Preparations (Excl. Sex Hormones))	
H1 (Pituitary & Hypothalamic Hormones)	70
H2 (Systemic Corticosteroids)	70
H3 (Thyroid Therapy)	72
H4 (Other Hormones)	77

EphMRA (European Pharmaceutical Market Research Association) ATC Codes	Drug Categories of the Medical Expenditure Panel Survey (MEPS)
J (General Anti-Infectives Systemic)	
J1 (Systemic Antibacterials)	10
J2 (Systemic Agents For Fungal Infections)	12
J3 (Systemic Sulphonamides)	10
J4 (Antimycobacterials)	10
J5 (Antivirals For Systemic Use)	12
J6 (Sera & Gamma-Globulin)	80
J7 (Vaccines)	80
J8 (Other Anti-Infectives)	80
K (Hospital Solutions)	
K1 (Intravenous Solutions)	
K2 (Plasma Expanders)	
K3 (Whole Blood & Plasma Substitute Solutions)	
K6 (Dialysis Solutions)	
L (Antineoplastic & Immunomodulating Agents)	
L1 (Antineoplastics)	110
L2 (Cytostatic Hormone Therapy)	110
L3 (Immunostimulating Agents)	80
L4 (Immunosuppressive Agents)	80
M (Musculo-Skeletal System)	
M1 (Anti-Inflammatory & Anti-Rheumatic Products)	140
M2 (Topical Anti-Rheumatics)	140
M3 (Muscle Relaxants)	101
M4 (Anti-Gout Preparations)	142
M5 (Other Drugs For Disorders Of The Musculo-Skeletal System)	142
N (Nervous System)	
N1 (Anaesthetics)	140
N2 (Analgesics)	140
N3 (Anti-Epileptics)	43
N4 (Anti-Parkinson Drugs)	100
N5 (Psycholeptics)	41
N6 (Psychoanaleptics Excl. Anti-Obesity Preparations)	43
N7 (Other CNS Drugs)	41
P (Parasitology)	
P1 (Antiprotozoals & Anthelmintics)	150
P3 (Ectoparasiticides, Incl. Scabicides, Insecticides & Repellents)	150
R (Respiratory System)	
R1 (Nasal Preparations)	160
R2 (Throat Preparations)	160
R3 (Anti-Asthma & COPD Products)	160
R4 (Chest Rubs & Other Inhalants)	162
R5 (Cough & Cold Preparations)	161
R6 (Systemic Antihistamines)	161
R7 (Other Respiratory System Products)	160
S (Sensory Organs)	
S1 (Ophthalmologicals)	121
S2 (Otologicals)	130
S3 (Ophthalmological/Otological Combinations)	130
T (Diagnostic Agents)	
T1 (Diagnostic Imaging)	none
T2 (Diagnostic Tests)	none
V (Various)	
V1 (Allergens)	none
V3 (All Other Therapeutic Products)	none
V6 (Dietetic Agents)	none