Demographic Change and Pharmaceuticals'

Stock Returns

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June 24, 2009

Abstract

We analyze how demographic change 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, 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 long-term forecasted demand changes predict abnormal annual pharmaceutical stock returns for more than 60 firms over the time period from 1986 to 2008. An increase by one percentage point of annual demand growth due to demographic changes predicts an increase in abnormal yearly stock returns in the size of 3–5 percentage points. Short-term forecasted demand changes does predict negative abnormal stock returns for a time horizon below 5 years. A trading strategy taking advantage of the demographic information earns a significant abnormal return between 6 and 8 percentage points per year. Our results are consistent with the model by DellaVigna and Pollet (2007), where investors are inattentive with extrapolation in the distant future and overreact to information in the near future.

Keywords: Demographic Change, Demand Growth, Abnormal Stock Returns, Pharmaceutical Companies, Panel Regression, Investor Attention, Trading Strategies

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 changes on aggregate stock returns (e.g. Bakshi and Chen (1994), Poterba (2001), Brooks (2002), Abel (2003), Davis and Li (2003), Geanakoplos, Magill, and Quinzii (2004), Ang and Maddaloni (2005), Brunetti and Torricelli (2007)), there are only few studies 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 candidates 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, anorexiant 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 are mainly used by old people.

Shifts in demand for different medications 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 we assume that a large cohort is born in 1955. This large cohort will increase the demand for CNS stimulants ten years later, in 1965. Assuming that 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 1965. The timing of abnormally high returns depends on the foresight horizon of the investor. There are three scenarios by Bergantino (1998) for different reactions of the investors and the consequences for abnormal stock returns. The first scenario, the standard model, states that the marginal investor foresees the positive demand shift induced by demographic changes and purchases CNS stimulants firms in 1955. Therefore, when the price of CNS stimulants increases in 1965, the opportunity to receive abnormal returns no longer exists. In the second scenario, 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 1960 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.

These different scenarios of investors' reactions to demand changes due to demographics motivate a test of return predictability among pharmaceutical companies that has – to the knowledge of the authors – not been investigated in the literature before. We test whether demographic information predicts abnormal stock returns across 61 pharmaceutical firms over the period from 1986 to 2008. 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 anorexiant 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.

This article also contributes to the literature of investor attention. Using DellaVigna and Pollet's (2007) model, we distinguish between investors who are rational and have an infinite horizon, investors who are unconditionally inattentive (finite short-sighted horizon without extrapolation), and investors who are inattentive with extrapolation (investors have a short-sight horizon and extrapolate into the future to some extent). Our findings show that investors neglect long-term information and overreact to short-term information. Therefore, our results are different from predictability tests based on performance information measured by past returns (DeBondt and Thaler (1985), Jegadeesh and Titman (1993), Peng, Xiong, and Bollerslev (2007)), accounting ratios (Fama and French (1992)), or earning announcements (Bernard and Thomas (1989), Croci (2007)). These variables include information about future predictability that is not easily factorable into short- and long-term components.

The analyses 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 1986–2008), and Datastream (profits and returns of every company from 1986–2008).

The three main contributions of our paper can be summarized as following:

1. The construction of demand growth rates of more than 60 pharmaceutical companies due to demographic changes for 1986–2008.
2. The investigation of the relationship between changes in forecasted consumer demand for pharmaceutical drugs due to demographic change and pharmaceutical companies' profits and returns. We find abnormal stock returns in the size of 3 to 5 percentage points due to long-term forecastable demand growth.
3. The analysis of a trading strategy taking advantage of the limited attention by investors related to demo-

graphic information which earns an annualized abnormal return between 6 and 8 percentage points.

The outline of the article is as follows. In Section 2, we give an overview of the literature discussing the effect of demographics on corporate decisions and stock returns. Section 3 describes the methodology used in the paper. Section 4 discusses briefly the basic two-stage model used in DellaVigna and Pollet (2007), and illustrates the three hypotheses derived 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 profitability and abnormal stock returns. Section 7 includes the analysis of various trading strategies that take advantage of demographic change. The conclusion follows in Section 8.

2 Demographic Change and Stock Market Returns

The paper is related to the literature on demographic change and its impact 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 based on demographic fluctuations.

Mankiw and Weil (1989) find that the contemporaneous demographic situation explains to some extent 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 arbitrage should reduce predictability, in contrast to housing prices. They find evidence that stock market returns are predicted by forecasted long-term demand growth, rather than by present demand growth. They introduce 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 inattentive (with extrapolation) about the distant future and overvalue short-term information in the near 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.

¹For example 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).

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. Schmookler (1966) documents a statistical association between investment and sales on the one hand, 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. 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. Some recent research has investigated the response of innovation to changes in energy prices. Newell, Jaffee and Stavins (1999) show that a typical air-conditioner became significantly cheaper between 1960 and 1980, but not much more energy-efficient. However, 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.

3 Methodology

The methodology used in this article is as follows. In Section 4, we summarize DellaVigna and Pollet (2007) to establish hypotheses regarding the relation between abnormal stock returns and demographic changes which we then test in Section 6 by 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 predicts 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 and positively related to expected future demand growth one period after the horizon as stated in the second hypothesis.

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

(1) In the first step, we collect actual cohort sizes and demographic forecasts from the U.S. Census Bureau for the years 1900–2040 by age group for every point in time. 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. For 2009 to 2040, we see the projections of the U.S. Census Bureau in the future.

Figure 1: Livebirths in the U.S. from 1900-2040.

This figure displays the livebirths in the U.S. from 1900-2040. Actual livebirths from 1900 to 2008 and livebirth projections from 2009 to 2040 are derived from the U.S. Census Bureau.

(2) In the second step, we estimate age-consumption patterns 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 an indication of 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. MEPS indicates which drug class is predominantly used by which age class. According to DellaVigna and Pollet (2007), we assume that age patterns are stable across time for a given drug class. For example, the age class 60+ has predominantly used Cardiovascular in 1996–1998 and will continue to do so in the following years and has done so in the former years. The demand growth of every drug age class is dependent on the size of the corresponding age group in each year. This supports the use of cohort size as a causal variable for demand.

(3) In the third step, we combine the different age patterns in consumption of drugs derived from MEPS with demographic forecasts data provided by the U.S. Census Bureau and the World Factbook. The output is the forecasted demand growth of each of the five drug age classes (drug class for people aged 0–19, 20–29,

30–49, 50–59, or 60+) 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 1986–2008 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 1986–2008 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 2008. We get yearly demand growth rates for each of the 61 pharmaceutical firms over the last twenty years.

In Section 6, we analyze whether forecasted demand growth due to demographic changes predicts return on equities (ROE) and abnormal stock returns. Short-term demand is defined as the forecasted annualized growth rate of consumption due to demographics over the next j years ($3 \leq j \leq 8$) and long-term demand is defined as the forecasted annualized growth rate of consumption during years j to $2j$ ($3 \leq j \leq 8$). 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 3 – 5 percentage point increase in abnormal returns of the pharmaceutical companies for a time horizon of 8 years. Short-term demand growth predicts negative abnormal return for a time horizon shorter than 5 years. As an alternative approach to control for year effects, we implement Fama-MacBeth regressions (Section 6.3). 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 $t + j$ and $t + 2j$ has an economical effect on abnormal yearly returns for $3 \leq j \leq 7$. The effect is biggest for a time horizon h of 8 years.

Finally, in Section 7, we analyze various trading strategies that take advantage of the limited attention by investors related to demographic changes. We build a zero-investment portfolio that is long in companies that have higher than median forecasted long-term demand growth and short in companies that have lower than median forecasted long-term demand growth at the beginning of every year. The portfolio constructed in this way earns an annualized abnormal return between 6 and 8 percentage points and outperforms several factor models.

4 The Model

In this section, we summarize DellaVigna and Pollet (2007) to establish hypotheses regarding the relation between abnormal stock returns and demographic changes. DellaVigna and Pollet (2007) use a similar methodology as Campell and Shiller (1988), Campell (1991), and Vuolteenaho (2002). DellaVigna and Pollet (2007) consider

a world where investors can be fully attentive (very long foresight horizon) or inattentive (finite short-sighted horizon with/without extrapolation). Short-sighted investors form correct expectations about profitability in the near future but incorrect expectations about profitability in the distant future. From the view of a fully rational investor, DellaVigna and Pollet (2007) derive today's (time t) expected abnormal return for time $t + 1$, $E_t ar_{t+1}$, as the sum of three terms: ²

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

where A is a constant equal to $\rho^h \omega (\phi - \overline{roe})$, $\overline{roe}$ is a constant fixed forecast of the log of the accounting return on equity, $\rho < 1$ is a constant (interpreted as a discount factor), h is the foresight horizon of the investor, ω is a weighting factor between zero and one (can be seen as the weight of inattention: $\omega = 1$ means that investors are unconditionally inattentive, $\omega < 1$ means investors are inattentive with n periods of extrapolation), Δc_{t+1+h} is the future demand growth $h + 1$ periods ahead, ϕ is the constant in the regression of the log of demand shift on the log return of equity, and θ is the elasticity of accounting return on equity with respect to demand growth. In Section 6 we test the three hypotheses derived by DellaVigna and Pollet (2007) and restated below:

Hypothesis 1: If investors are rational (foresight horizon $h \rightarrow \infty$), 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, $E_t \Delta c_{t+1+h}$. Furthermore, $\partial E_t ar_{t+1} / \partial E_t \Delta c_{t+1+h} = \rho^h \theta [1 + (1 - \omega) \rho / ((1 - \rho)n)]$.

Hypothesis 3: If investors are inattentive with extrapolation (h finite and $\omega < 1$), Hypothesis 2 holds and additionally, 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 have an impact on abnormal stock returns. Under the alternative Hypothesis 2, forecastable demand growth $h + 1$ periods ahead affects abnormal stock returns for inattentive investors (they have a finite horizon h). Furthermore, Hypothesis 2 shows the connection between the degree of forecastability and the elasticity of accounting return on equity with respect to demand growth (denoted by 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 $n = 1$). Additionally to positive abnormal

²For more details concerning the model and the derivation of the hypotheses, readers are referred to the paper by DellaVigna and Pollet (2007).

returns due to expected future demand growth $h + 1$ periods ahead (distant future) as stated in Hypothesis 2, Hypothesis 3 makes a prediction about expected abnormal return due to expected future demand growth less than $h + 1$ periods ahead (near future). Hypothesis 3 states that if investors are inattentive about long-term information but extrapolate ($\omega < 1$) to some extent using short-term information, demand growth less than $h + 1$ periods ahead (demand growth in the near future) forecasts abnormal returns negatively whereas demand growth in the distant future still forecasts abnormal returns positively as stated in Hypothesis 2. This is the case because investors overvalue information in the present and near future and neglect information in the distant future.

In our analysis to test these hypotheses we form two demand growth forecasts, one for short-term growth between t and $t + j$, and one for long-term growth between $t + j$ and $t + 2j$, whereas $3 \leq j \leq 8$, respectively $6 \leq 2j = h \leq 16$. In Section 6, we show that our results are consistent with Hypothesis 3 where investors are inattentive with extrapolation about the distant future and overreact to information in the near future.

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: Overview of Data

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 (1900-2040), Number of U.S. persons per age for each year (1900-2008), Population Estimates (1900-2040)	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 and Yearly 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	1986-2008	1984-2008

5.1 Demographic Data

In a first step, we derive U.S. demographic variables from 1900–2040, as for example, U.S. livebirth rates, U.S. actual and forecasted population, 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 actual age profile of the different cohorts between 1900 and 2022, whereas the age profiles between 2009 and 2022 are estimated by the U.S. Census Bureau.

Figure 2: Age Profile of the Five Cohorts.

This figure displays the age profile of the five cohorts (age categories: 0–19, 20–29, 30–49, 50–59, and 60+), in the U.S. from 1900–2022 whereas data from 2009–2022 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 size decreases between 1970 and 1985, due to lower fertility rates during the following years (the Baby Bust), 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, however shifted forward by approximately 20 years. The cohort sizes of the older cohorts vary less, the cohort aged 60+ grows steadily over time. Therefore, there is most variation in demand for goods consumed by young people. For the construction of demand growth rates we use forecasts of cohort sizes for every point in time between 1986 and 2008 provided by the U.S. Census Bureau as well as the World Factbook. They combine data on actual cohort size, mortality, and fertility rates to form forecasts of cohort sizes. We observe that the U.S. Census Bureau makes very precise forecasts according to future population by age for a forecast horizon up to 16 years for every point in time for

our period of interest (1986–2008).

5.2 Age Patterns in Consumption of Drugs

In the second step, we estimate age-consumption patterns 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 an indication in drug class 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. We use MEPS data as an indicator for age patterns in consumption of drug categories, that means we get an indication of which drug class is predominantly used by which age class. Table 7 in Appendix A.1 shows the summary of the disease classification and drug class 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. With the MEPS database we can assign every drug category proportionally to our five cohorts. For example, we can say that drug class Hyperlipidemia are prescribed to the age group 0–19 to a portion of 1%, to the age group 10–29 to a portion of 0%, to the age group 30–49 to a portion of 12%, to the age group 50–59 to a portion of 21%, and to the age group 60+ to a portion of 66%. For further purposes (Section 5.4), we assign this drug class (Hyperlipidemia) to the 60+ cohort (cohort with the highest proportion). Further, we make the assumption that across pharmaceuticals, the age profile of consumption varies substantially.³ Some drugs are mainly consumed by younger people (e.g. Penicillins), others by elderly people (e.g. Hyperlipidemia) (Appendix A.1). Our assignments of each drug class to one age group are based on MEPS data from the years 1996–1998. However, we assume that also in the years before 1996 as well as in the years after 1998, each drug class has been consumed and will continue to be consumed mainly by the same age group. For example, the age class 60+ has predominantly used Hyperlipidemia in 1996–1998 and will continue to do so in the following years (after 1998) and has done so in the former years (before 1996). Further, as discussed in the next section, the demand growth of each drug class will be directly dependent on the size of the corresponding age group (in the example of Hyperlipidemia of the 60+) in each year.

³The assumption is based on DellaVigna and Pollet (2007). They use historical surveys on consumer expenditure from 1935–36, 1960–61, 1972–73, and the 1983–84 Consumer Expenditure Survey to show that age profile of consumption varies substantially. Although they consider other goods as for example toys, bicycles, beer, furniture, life insurance, and nursing homes, we think that we can rely on their assumption for the consumption of drugs.

5.3 Demand Forecasts of Drug Categories

In the third step, we combine the age patterns of consumption of every drug class from the section before with demographic population forecasts from Section 5 in order to forecast demand changes (horizon up to 16 years) for different drugs for the time period between 1986 and 2008. For example in 1990, forecasted population growth of people older than 60 years for 1995 is 4%. Therefore, forecasted demand growth of Hyperlipidemia will also be 4% from 1990 to 1995. We denote by $c_{k,t}$ the forecasted annual consumption of drug class k (k either drug class for 0–19, 20–29, 30–49, 50–59, or 60+ agents) for time t . We compute forecasted demand growth rates from time t to time $t + 1$ by

$$lnc_{k,t+1} - lnc_{k,t} \quad (2)$$

for typical drugs of each age cohort.⁴ We show forecasted absolute demand of a typical drug for old people (60+), e.g. Hyperlipidemia, demand forecasts of a typical drug for young people aged between 0–19, e.g. Penicillins, and demand forecasts of a typical drug for middle-aged people between 30 and 49 years old, e.g. Antipsychotics in Figure 4 in Appendix A.2.

5.4 Demand Growth Rates for Pharmaceutical Companies

In the fourth step, we first consider 61 international pharmaceutical companies that mainly provide the U.S. market with drugs. We include all pharmaceutical companies where all data needed are available. There are firms that disappear or merge during the sample period which are not included in the analysis. GlaxoSmithKline is an example for a product of multiple mergers. However, survivorship bias of this nature is unlikely to affect the predictability results in our context. Although the average return of companies in the sample is too high compared to the true industry return, the covariance between demographic growth and survival is very small. We did not find any correlation between disappearance of these firms and demographic change within this period. Undoubtedly, there are many reasons other than demographic issues why a firm disappears from the market or becomes the object of a merger. Further, within these companies, we collect the sales/expenditures of the top twenty drugs of each company on an annual basis from 1986 to 2008 with the aid of the annual sales data of the Evaluatepharma database. For every pharmaceutical company, we get the corresponding yearly expenditures for each year from 1986 to 2008 and the EphMRA (European Pharmaceutical Market Research Association) ATC Codes of each of the top twenty drugs per company 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 8. With this mapping we can evaluate the core businesses of each company according to their top twenty drugs for each year between 1986 and 2008. We can see the development of the

⁴For the setting with monthly data, we extrapolate linearly the yearly weights for getting monthly weights.

core businesses of each firm over the last twenty years. Secondly, we weight and assign the core businesses of each company according to the expenditures of the respective top drug categories of each firm to our five age cohorts for each year for the time period 1986–2008. For example for Johnson and Johnson, we see that in 1988 0% (1998: 6%, 2008: 23%) of the core drugs (different for every year) belong to the category of the age group 0–19, 39% (1998: 14%, 2008: 7%) belong to the age group 20–29, 60% (1998: 45%, 2008: 35%) belong to the age group 30–49, 0% (1998: 0%, 2008: 0%) belong to the age group 50–59, and 1% (1998: 35%, 2008: 36%) belong to the age group 60+. Combining these annual weights with the annual demand growth rates of each age profile, we obtain annual demand growth rates for 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 2008 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 $t + 1$. We describe by $lnc_{k,t+1} - lnc_{k,t}$ the natural log of the forecasted consumption growth of firm k from year t to year $t + 1$. The following regression is tested:

$$roe_{k,t+1} = const + a * (lnc_{k,t+1} - lnc_{k,t}) + \epsilon_{k,t}. \quad (3)$$

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 (3) both with and without industry and year fixed effects. We allow for heteroscedasticity and correlation across industries by calculating standard errors clustered by year.

Table 2: Summary Statistics

This table shows the summary statistics for the yearly log return on equity and yearly log stock return 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.

Nr.	Company	Yearly Log Return on Equity (ROE)			Yearly Log Stock Return		
		Mean (1)	Std. Dev. (2)	# Years (3)	Mean (4)	Std. Dev. (5)	# Years (6)
1	Abbott Laboratories	0.120	0.029	22	0.134	0.208	23
2	Allergan Inc	0.054	0.057	20	0.130	0.292	19
3	Amgen Inc	0.088	0.057	20	0.232	0.425	23
4	AstraZeneca plc	0.113	0.024	15	0.108	0.235	15
5	Bayer AG	0.060	0.035	22	0.245	0.181	6
6	Bristol-Myers Squibb Co	0.121	0.037	22	0.083	0.277	23
7	Celgene Corporation	0.250	0.648	12	0.206	0.544	21
8	Eisai Co Ltd	0.035	0.015	22	0.113	0.278	23
9	Elan Corp plc	-0.018	0.244	11	0.065	0.837	23
10	Eli Lilly & Co	0.099	0.052	22	0.102	0.265	23
11	Enzon Pharmaceuticals	-0.149	0.234	12	0.018	0.622	23
12	Forest Laboratories	0.067	0.029	22	0.146	0.335	23
13	Genzyme Corp	-0.008	0.046	21	0.162	0.410	22
14	BASF AG	0.051	0.027	22	0.119	0.257	23
15	Glaxosmithkline	0.254	0.112	15	0.117	0.249	23
16	Johnson & Johnson	0.102	0.021	22	0.145	0.168	23
17	KV Pharmaceutical	-0.027	0.264	21	0.046	0.690	23
18	Merck & Co Inc	0.137	0.030	22	0.119	0.330	23
19	MGI Pharma	-0.203	0.211	20	0.090	0.650	23
20	Mylan Laboratories	0.077	0.029	21	0.081	0.368	23
21	Nabi Biopharmaceuticals	-0.027	0.154	16	0.053	0.617	23
22	Novartis AG	0.073	0.014	15	0.153	0.206	23
23	Noven Pharmaceuticals	-0.013	0.093	16	0.074	0.613	20
24	Novo Nordisk	0.064	0.021	23	0.169	0.262	23
25	Ono Pharmaceutical Co Ltd	0.048	0.011	22	0.054	0.312	23
26	Pfizer Inc	0.094	0.038	22	0.118	0.298	23
27	Pondia Pharmaceuticals	-0.592	0.673	11	-0.211	1.137	20
28	Repligen	-0.060	0.128	12	-0.038	0.515	22
29	Roche Holding AG	0.053	0.045	23	0.156	0.209	23
30	Sanofi Aventis	1.234	0.273	10	0.133	0.248	23
31	Savient Pharmaceuticals	-0.027	0.135	16	-0.007	0.796	23
32	Schering-Plough Corp	0.107	0.087	22	0.118	0.313	23
33	Solvay SA	0.058	0.027	22	0.109	0.248	23
34	Taisho Pharmaceuticals Co Ltd	0.039	0.012	22	0.069	0.220	23
35	Takeda Chemical Industries Ltd	0.047	0.014	22	0.114	0.311	23
36	Teva Pharmaceutical Industries Ltd	0.070	0.023	14	0.238	0.339	23
37	Wyeth	0.106	0.113	22	0.098	0.257	23
38	Bentley Pharmaceuticals	-0.105	0.196	12	-0.074	0.754	20
39	Cephalon Inc	-0.123	0.164	14	0.101	0.631	17
40	Columbia Laboratories	0.048	0.002	2	-0.044	0.777	20
41	Daiichi Seiyaku Co Ltd	0.038	0.011	22	0.087	0.280	23
42	Dr Reddy's Laboratories Ltd	0.071	0.042	13	0.246	0.600	18
43	Oscient Pharmaceuticals	-0.174	0.265	18	-0.234	0.956	23
44	OSI Pharmaceuticals	-0.093	0.133	20	0.108	0.832	22
45	Par Pharmaceutical Resources	0.046	0.099	21	0.009	0.647	23
46	Ranbaxy Laboratories Ltd	0.090	0.035	16	0.156	0.502	18
47	Sepracor Inc	0.428	1.154	6	0.056	0.816	17
48	Baxter International Inc	0.067	0.034	23	0.114	0.244	23
49	Dainippon Pharmaceutical Co Ltd	0.019	0.017	22	0.025	0.403	23
50	Human Genome Sciences Inc	-0.143	0.181	13	-0.049	0.789	15
51	Kissei Pharmaceutical Co Ltd	0.020	0.010	18	0.031	0.257	19
52	Kyorin Pharmaceutical Co Ltd	0.010	0.010	4	-0.045	0.276	9
53	Kyowa Hakko Kogyo Co Ltd	0.027	0.010	21	0.048	0.320	23
54	Ligand Pharmaceuticals Inc	0.452	1.709	4	-0.058	0.508	14
55	Meiji Seika Kaisha Ltd	0.016	0.020	22	0.035	0.283	23
56	Santen Pharmaceutical Co Ltd	0.048	0.014	22	0.114	0.283	23
57	Shionogi & Co Ltd	0.022	0.008	22	0.090	0.350	23
58	Teijin Ltd	0.019	0.018	22	0.019	0.362	23
59	Mitsubishi Tanabe Seiyaku Co Ltd	0.024	0.011	22	0.055	0.310	23
60	Vernalis plc	-0.168	0.068	11	-0.345	0.832	16
61	3M	0.098	0.026	23	0.100	0.165	23
Mean of all companies		0.053	0.136	18	0.072	0.438	21

Table 3: Panel Regression of Log Return on Forecasted Demand 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 2008 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 $roe_{k,t+1} = const + a*(lnc_{k,t+1} - lnc_{k,t}) + \epsilon_{k,t}$. 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.

Log Return on Equity (ROE) at t+1						
	<i>const</i>	<i>a</i>	R^2	<i>N</i>	Industry FE	Year FE
(1)	0.528 (0.168)***	2.208 (1.044)**	0.01	N=794		
(2)	0.600 (0.192)***	1.656 (0.780)**	0.02	N=794	x	
(3)	0.512 (0.186)**	1.735 (0.928)*	0.02	N=794	x	x

In Table 3, Line (1), we show the specification of the sample between 1986 and 2008 without industry or year fixed effects. The impact of demographic changes on *roe* is identified by variation in demand growth. The estimated coefficient, $a = 2.208$, is significant at the 5% level. That means that a one percent increase in yearly consumption growth due to demographics increases log return on equity by $a = 2.208$ percentage points. Introducing cross-sectional fixed effects, the estimate for a is still significant at the 5% level, though a little bit smaller than in Line (1), $a = 1.656$ (Line (2)). Introducing time fixed effects as well in Line (3), the coefficient $a = 1.735$ stays roughly the same and is significant at the 10% level. 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 slightly smaller coefficients.

6.2 Abnormal Return Predictability: Panel Regression

Using the same panel framework, we investigate the relationship between forecasted demand growth and the pharmaceutical companies' yearly stock returns. Table 2, Column 4 to 6 show the summary statistics of the yearly stock returns (mean, standard deviation, and the number of years data is available), analogously to ROE in the section before. In the baseline specification we regress yearly⁵ returns on the yearly forecasted growth rate of demand due to demographics from time t to j years later time $t + j$ (short-term demand growth) and $t + j$ to $t + 2j$ (long-term demand growth), where j is between 3 and 8 years (horizon $h = 2j$ between 6 and 16 years). We use beta-adjusted returns to remove market-wide shocks. We choose CRSP value-weighted excess

⁵Appendix A.4 shows the robust results for monthly returns on the monthly forecasted demand growth rate.

return⁶ for the abnormal market returns. 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

$$ar_{k,t,t+1} = (r_{k,t,t+1} - r_{f,t,t+1}) - \beta_{k,t}(r_{m,t,t+1} - r_{f,t,t+1}). \quad (4)$$

The specification of the regression is

$$ar_{k,t,t+1} = \text{const} + d * (\text{lnc}_{k,t+j} - \text{lnc}_{k,t}) + e * (\text{lnc}_{k,t+2j} - \text{lnc}_{k,t+j}) + \epsilon_{k,t}, \text{ for } 3 \leq j \leq 8. \quad (5)$$

Hypothesis 3 of the model by DellaVigna and Pollet (2007) in Section 4 suggests that, if the forecast horizon h is shorter than 5 years ($j \leq 2$), the coefficient d should be positive and e should be zero. If the forecast horizon h 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 $h \rightarrow \infty$), both coefficients should be zero. A significantly positive coefficient indicates that stock prices adjust as the demographic information enters the forecast horizon. Table 4 presents the estimates in equation (5) of the annual abnormal returns for the sample of the 61 pharmaceutical firms during the years 1986–2008 for time horizons $6 \leq h \leq 16$. Table 9 in Appendix A.4 shows the robust results for the regression of monthly abnormal returns on monthly forecasted demand growth rates. In the specification without year and cross-sectional fixed effects for the forecast horizon $h = 6$ (Line (1)), the coefficient on short-term demographics, $d = -2.207$ is negative whereas the coefficient on long-term demographics, $e = 2.875$ is significantly larger than zero. An annualized one percentage point increase in demand growth from year $t + 3$ to year $t + 6$ increases the average abnormal annualized stock return by 2.875 percentage points. The coefficient on short-term demographics, d , is negative because investors overreact to information in the near future. If we introduce fixed industry effects, the coefficient is even higher, $e = 3.215$ (Line (2) in Table 4) and significantly different from zero at the 10 % significance level. If we introduce both, year and industry fixed effects, the coefficient stays nearly the same, $e = 3.148$, and is also significantly different from zero (Line (3)). The coefficient of the short-time demographic changes, d , stays negative and insignificant for Lines (1) to (3). When we increase the horizon h (respectively j), the coefficient d first decreases and then increases but stays negative for all $j \geq 3$, and becomes significant for $4 \leq j \leq 5$. The coefficient e increases with h and has its peak value of $e = 4.581$ at a horizon of $h = 8$ ($j = 4$) years when considering cross-sectional fixed effects (Line (5) in Table 4). e is significantly positive for all $h \leq 12$ and decreases from $j > 4$ (peak at horizon of 8 years). For a horizon $h \geq 12$, e becomes almost zero. This is consistent with the model by DellaVigna and Pollet (2007) where information that is further than 10 years into the future does hardly predict abnormal stock returns. According to DellaVigna and Pollet

⁶Results are robust with respect to the index used (S&P500, Nasdaq100, or Nasdaq Biotechnology).

(2007), that information is still not incorporated in the investor information set at the end of year t . The information that is just on the border of the foresight horizon, instead, is incorporated by investors during year t , and therefore predicts returns. Summarizing, we have shown that the coefficient of long-term demand growth increases with the horizon h and reaches the peak value of 4.581 at the horizon h of 8 years ($j = 4$, Line (5)). The coefficient then decreases for larger h , becoming about half and almost insignificant for $h \geq 12$. Abnormal return predictability is highest for forecasted demand growth occurring 4 to 8 years in the future. The results are consistent with the predictions of the model by DellaVigna and Pollet (2007) for a foresight horizon of 5–10 years. The information that is closer than 5 years into the future does predict negative stock returns because investors overreact to short-term information. Long-term demand growth does predict significant abnormal returns up to a horizon of 10 years because investors neglect information in the distant future. Information that is further away than 10 years does hardly predict stock returns.

We further analyze at which forecast horizon $h = 2j$ abnormal return predictability is the highest. We estimate the univariate regression $ar_{k,t,t+1} = const + b * (lnc_{k,t+h+1} - lnc_{k,t+h}) + \epsilon_{k,t}$ over the time period 1986–2008, and let the horizon h take values between 2 and 12. Figure 3 graphically shows the estimated coefficients b and the corresponding 95% confidence interval. The coefficient b measures to which extent demand growth h years ahead forecasts abnormal stock return in year $t + 1$. For $h \leq 4$, b is small and insignificant. For $h \geq 5$, b becomes significantly positive and reaches the peak value of 4.7 percentage points at the time horizon $h = 8$. For $h > 8$, b decreases for larger h to half value of about 2.1 percent at $h = 12$ and becomes insignificant for even larger h . This is consistent with the findings above where abnormal return predictability is highest for forecasted demand growth occurring 4 to 8 years in the future ($h = 8$).

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 (5) for each year t from 1986–2008. 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 (short-term demand growth) and e (long-term demand growth), 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. We 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. Table 5 presents the results of the Fama-MacBeth regressions. The short-term forecasted demand growth coefficients d are negative and insignificant for all $j = 3, 4, 5, 6, 7$. The long-term forecasted demand growth coefficient e lies between 1.640 (Column (5)) and 3.509 (Column (2)) but is also not statistically significant, however has a p -value between 0.13 and 0.18. The maximum coefficient for long-term demand growth ($e = 3.509$) can be found for demand growth between 4 and 8 years ($j = 4, h = 2j = 8$). This

Table 4: Panel Regression of Annual Abnormal Pharmaceutical Stock Returns on Forecasted Demand Changes for Different Foresight Horizons h

This table shows the results of the panel regression of pharmaceutical abnormal stock returns on forecasted demand changes due to demographic changes for different foresight horizons $6 \leq h \leq 16$ ($3 \leq j \leq 8$). 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 $ar_{k,t,t+1} = const + d * (lnc_{k,t+j} - lnc_{k,t}) + e * (lnc_{k,t+2j} - lnc_{k,t+j}) + \epsilon_{k,t}$ for $3 \leq j \leq 8$. Lines (1) to (3) show the results of the panel regression with a foresight horizon of $2j = 6$ years. Lines (4) to (6) show the results of the panel regression with a foresight horizon of $2j = 8$ years. Lines (7) to (9) show the results of the panel regression with a foresight horizon of $2j = 10$ years. Lines (10) to (12) show the results of the panel regression with a foresight horizon of $2j = 12$ years. Lines (13) to (15) show the results of the panel regression with a foresight horizon of $2j = 14$ years. Lines (16) to (18) show the results of the panel regression with a foresight horizon of $2j = 16$ years. The first lines of each block (Lines (1), (4), (7), (10), (13), (16)) show the results without cross-sectional and year fixed effects. The second lines of each block (Lines (2), (5), (8), (11), (14), (17)) show the results with cross-sectional fixed effects, and the third lines of each block (Line (3), (6), (9), (12), (15), (18)) show the result with both, cross-sectional and year fixed effects. The doubled-clustered standard errors are indicated in brackets. (*) indicates significance at the 10% level, (**) indicates significance at the 5% level, (***) indicates significance at the 1% level.

Yearly Beta-Adjusted Log Pharmaceutical Abnormal Stock Return t+1.							
	j	$const$	d	e	R^2	N	Industry FE Year FE
(1)	$j = 3$	0.058 (0.064)	-2.207 (1.754)	2.875 (1.678)*	0.01	N=892	
(2)	$j = 3$	0.044 (0.068)	-2.315 (1.676)	3.215 (1.939)*	0.01	N=892	x
(3)	$j = 3$	0.035 (0.076)	-2.227 (1.773)	3.148 (1.823)*	0.02	N=892	x x
(4)	$j = 4$	0.079 (0.065)	-3.754 (1.379)***	4.054 (1.506)***	0.01	N=892	
(5)	$j = 4$	0.080 (0.066)	-4.359 (1.504)***	4.581 (1.573)***	0.01	N=892	x
(6)	$j = 4$	0.074 (0.078)	-4.074 (1.579)***	4.277 (1.513)***	0.03	N=892	x x
(7)	$j = 5$	0.087 (0.660)	-2.104 (1.129)*	2.224 (1.250)*	0.01	N=892	
(8)	$j = 5$	0.092 (0.074)	-2.706 (1.262)**	2.728 (1.325)**	0.01	N=892	x
(9)	$j = 5$	0.085 (0.081)	-2.622 (1.317)**	2.670 (1.371)**	0.02	N=892	x x
(10)	$j = 6$	0.095 (0.068)	-1.344 (0.932)	1.335 (1.031)	0.01	N=892	
(11)	$j = 6$	0.108 (0.081)	-1.967 (1.230)	1.820 (1.058)*	0.01	N=892	x
(12)	$j = 6$	0.104 (0.085)	-2.022 (1.210)	1.876 (1.131)	0.02	N=892	x x
(13)	$j = 7$	0.104 (0.070)	-0.840 (0.794)	0.720 (0.864)	0.01	N=892	
(14)	$j = 7$	0.128 (0.078)	-1.472 (0.939)	1.141 (0.938)	0.01	N=892	x
(15)	$j = 7$	0.124 (0.090)	-1.537 (0.966)	1.205 (0.961)	0.02	N=892	x x
(16)	$j = 8$	0.107 (0.080)	-0.474 (0.732)	0.403 (0.800)	0.01	N=837	
(17)	$j = 8$	0.135 (0.091)	-1.068 (0.891)	0.773 (0.872)	0.01	N=837	x
(18)	$j = 8$	0.129 (0.111)	-1.134 (0.909)	0.831 (0.880)	0.02	N=837	x x

Figure 3: Estimated Coefficients

This figure shows the estimated coefficients and the corresponding 95% confidence interval for forecasted yearly demand growth at different time horizons. The estimated coefficients for each horizon are derived from a univariate OLS regression of abnormal returns at time t on forecasted consumption growth between $t+h$ and $t+h+1$ for all 61 pharmaceutical companies between 1986 and 2008.

is consistent with the results of Table 4 and Figure 3 where the maximum coefficient for long-term demand growth was also observed at horizon h of 8 years.

To summarize, the panel regressions above exhibits to two main findings. First, forecastable demand growth due to demographic changes predicts abnormal stock returns. Second, forecastable demand changes in the longer run ($t+j$ to $t+2j$ when $3 \leq j \leq 8$) forecast positive abnormal returns whereas forecastable demand changes in the short run (t to $t+j$, $3 \leq j \leq 8$) do not have significant forecasting power of abnormal returns for $j > 5$ or does even forecast abnormal stock returns negatively for $4 \leq j \leq 5$ (Table 4). 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 3 in Section 4 offers an explanation for our results based on inattention with partial extrapolation. If investors omit information under a particular time horizon $h = 2j$, the abnormal returns at $t+1$ should be positive using long-term demographic information that will happen between $t+h$ and $t+1+h$. Furthermore, if investors overreact to short-term information, the abnormal returns that will happen between t and $t+h$ are even negative at $t+1$. The results in Table 4, Figure 3, and Table 5 show that the horizon h could be between 6 and 12 years, however, the abnormal returns are largest for $h = 8$ years.

Besides, the model in Section 4 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 at most $\hat{\delta}_1 := e = 4.581$ (Table 4, Line (5)), respectively $\hat{\theta} := a = 1.656$

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

This table shows the results of the Fama MacBeth regression of yearly pharmaceutical abnormal stock returns on forecasted demand changes due to demographic changes. We estimate separate cross-sectional regressions of $ar_{k,t,t+1} = const + d * (lnc_{k,t+j} - lnc_{k,t}) + e * (lnc_{k,t+2j} - lnc_{k,t+j}) + \epsilon_{k,t}$ for each year t from 1986-2008 and $j=3,4,5,6,7$ ($h=6,8,10,12,14$). Then we compute the time-series average of the estimated coefficients. 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.

Beta Adjusted Log Pharmaceutical Abnormal Stock Returns							
	j	$const$	d	p-value of d	e	p-value of e	# years
(1)	j=3	0.042 (0.028)	-1.882 (1.983)	0.35	2.682 (1.900)	0.17	N=23
(2)	j=4	0.092 (0.086)	-2.174 (1.843)	0.25	3.509 (2.253)	0.13	N=23
(3)	j=5	0.109 (0.063)	-1.554 (1.366)	0.27	2.355 (1.558)	0.15	N=23
(4)	j=6	0.162 (0.101)	-0.925 (1.233)	0.46	2.091 (1.414)	0.15	N=23
(5)	j=7	0.267 (0.201)	-0.346 (0.835)	0.68	1.640 (1.176)	0.18	N=23

(Table 3, Line (2)). This is not 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 also not consistent with a model of unconditional inattention, but with a model of inattention with partial extrapolation ($\omega < 1$). In our case, if we choose $\hat{\theta} = 1.656$, the extrapolation weight factor $\omega = 0.5$, $h = 8$, the number of periods of extrapolation $n = 4$, and the annual discount factor $\rho = 0.96$, we would expect a $\delta_1 = \rho^h \theta [1 + \frac{(1-\omega)\rho}{(1-\rho)n}] = 4\rho^h \theta = 4.78$ which is slightly larger than our estimated 4.58. Therefore, we see that our results are consistent with the model of inattention with extrapolation by DellaVigna and Pollet (2007) (Hypothesis 3).

7 Analysis of Various Trading Strategies

In the previous section we show that investors have limited attention regarding to long-term demand growth due to demographics. In this section we take advantage of the inattention of investors related to demographic change and analyze if rational market participants could utilize the long-term demand growth information with a trading strategy. We create the zero-investment portfolio for the time period between 1986 and 2008 by buying the companies that have higher-than-median forecasted long-term demand growth and selling the companies that have lower-than-median forecasted long-term demand growth at the beginning of every year. In the following analysis, we define long-term demand growth as the demand growth between time $t = 4$ and

$t = 8$ ($j = 4$, $h = 8$)⁷. We compute monthly portfolio returns for 1986–2008 and regress them on different sets of monthly benchmark factors. We use the 1-factor, 3-factor, and 4-factor models by Fama and French. VWRF is the return on the CRSP value-weighted stock index minus the 1-month treasury rate. SMB and HML are the returns on the Fama-French factor portfolios formed on size and book-to-market. UMD is the return on the factor portfolio on momentum. All factors are taken from the Fama-French website. Heteroskedasticity and autocorrelation consistent standard errors are calculated using the Newey-West estimator with 4 lags (in parentheses). The constant is interpreted as the average monthly abnormal return for the investment strategy. Table 6 presents the performance of the zero-investment portfolio trading strategies. We see in Column 2 (1-Factor Model) that the portfolio earns a significant monthly abnormal return of 0.53 percent. This corresponds to an annualized abnormal return of 6.36 percent which is bigger than the long-term coefficient from Table 4 (4.58 percent). The outperformance remains roughly the same when we include the size and the book-to-market factors (Column 3 (3-Factor Model)), as well as the momentum factor (Column 4 (4-Factor Model)). We get annualized abnormal return of 6.24 percentage points for the 3-Factor Model and even 7.92 percentage points for the 4-Factor Model.

8 Conclusion

We analyze how demographic change 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. Expenditures for every pharmaceutical company from 1986 to 2008 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 drug demand growth rates for each age group over the last twenty years for each of the 61 pharmaceutical firms. The forecasted yearly 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 6–12 years) predicts yearly abnormal stock returns in the size of 3 to 5 percentage points whereas short-term forecastable demand growth does have a significantly negative influence on abnormal stock returns for a horizon below 5 years. We also control for year effects using Fama MacBeth regressions. Although not statistically significant, the coefficients of the Fama MacBeth regressions are consistent with the former findings and we find economical evidence for the influence of demographic growth on annual abnormal stock returns. According to the model of DellaVigna and Pollet (2007), the explanation of our results can be found in the investor’s overreaction to short-term (below 5 years) information and investors’ inattention to long-term information (between 5 and 10 years). A trading strategy taking advantage of this limited attention by investors

⁷Results are robust for long-term demand growth information between different time intervals, not shown in the paper though.

Table 6: Performance of the Zero-Investment Portfolio Trading Strategies

This table shows the performance of the zero-investment portfolio trading strategies. We create the zero-investment portfolio by buying the companies that have higher than median forecasted long-term demand growth and selling the companies that have lower than median forecasted long-term demand growth at the beginning of every year. We compute monthly portfolio returns r and regress them on different sets of monthly benchmark factors. We use the 1-factor, 3-factor, and 4-factor models designed by Fama-French. The formulae for the 1-, 2-, resp. 3-factor models are $r = \text{const} + c(1) \cdot \text{VWRF}$, $r = \text{const} + c(1) \cdot \text{VWRF} + c(2) \cdot \text{SMB} + c(3) \cdot \text{HML}$, resp. $r = \text{const} + c(1) \cdot \text{VWRF} + c(2) \cdot \text{SMB} + c(3) \cdot \text{HML} + c(4) \cdot \text{UMD}$. 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. VWRF is the return on the CRSP valueweighted stock index minus the 1-month treasury rate. SMB and HML are the returns on the Fama-French factor portfolios formed on size and book-to-market. UMD is the return on the factor portfolio on momentum. All factors are taken from the Fama-French website. Heteroskedasticity and autocorrelation consistent standard errors are calculated using the Newey-West estimator with 4 lags (in parentheses). The constant is interpreted as the average monthly abnormal return for the investment strategy.

Dependent Variable: Monthly Returns on the Zero-Investment Portfolios				
	1 - Factor Model	3 - Factor Model	4 - Factor Model	
Constant	0.0053 (0.0028)**	0.0052 (0.0027)**	0.0066 (0.0026)***	
VWRF	0.0474 (0.0728)	0.0544 (0.0806)	0.0216 (0.0817)	
SMB		-0.0288 (0.1917)	-0.0557 (0.1999)	
HML		0.0104 (0.1250)	-0.0940 (0.1566)	
UMD			-0.1242 (0.0823)	
R^2	0.002	0.002	0.010	
N	276	276	276	

related to demographic information earns an annualized abnormal return between 6 and 8 percentage points. Our results are consistent with the model by DellaVigna and Pollet (2007) in which investors are inattentive with partial extrapolation in the distant future and overreact to information in the near future.

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A Appendix

A.1 Disease Classification and Drug Use by Age Group

Table 7: Summary of Disease Classification and Drug Use

This table shows the 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	Anorexiant	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	Antiasmatics, 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

This figure shows the 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) from 1900-2020. We denote by $c_{k,t}$ the forecasted annual consumption of drug class k (k either drug class for 0-19, 20-29, 30-49, 50-59, or 60+ agents) for time t . We compute forecasted demand growth rates from time t to time $t + 1$ by $\ln c_{k,t+1} - \ln c_{k,t}$.

A.3 ATC Codes

Table 8: The EphMRA ATC Codes

This table shows the EphMRA (European Pharmaceutical Market Research Association) ATC Codes and their assignments to the 34 drug categories of the Medical Expenditure Panel Survey (MEPS) used in Acemoglu and Linn (2004).

EphMRA (European Pharmaceutical Market Research Association) ATC Codes	Drug Categories of the Medical Expenditure Panel Survey (MEPS)	EphMRA (European Pharmaceutical Market Research Association) ATC Codes	Drug Categories of the Medical Expenditure Panel Survey (MEPS)
A (Alimentary Tract & Metabolism)		J (General Anti-Infectives Systemic)	
A1 (Stomatologicals, Mouth Preparations, Medicinal Dentifrices Etc)	50	J1 (Systemic Antibacterials)	10
A2 (Antacids, Antiflatulents & Anti-Ulcerants)	50	J2 (Systemic Agents For Fungal Infections)	12
A3 (Functional Gastro-Intestinal Disorder Drugs)	50	J3 (Systemic Sulphonamides)	10
A4 (Antiemetics & Antinauseants)	50	J4 (Antimycobacterials)	10
A5 (Cholagogues & Hepatic Protectors)	50	J5 (Antivirals For Systemic Use)	12
A6 (Laxatives)	50	J6 (Sera & Gamma-Globulin)	80
A7 (Antidiarrhoeals, Oral Electrolyte Replacers & Intestinal Anti-Inflammatories)	50	J7 (Vaccines)	80
A8 (Antiobesity Preparations, Excl. Dietetics)	42	J8 (Other Anti-Infectives)	80
A9 (Digestives, Incl. Digestive Enzymes)	42		
A10 (Drugs Used In Diabetes)	72	K (Hospital Solutions)	
A11 (Vitamins)	61	K1 (Intravenous Solutions)	
A12 (Mineral Supplements)	61	K2 (Plasma Expanders)	
A13 (Tonics)	61	K3 (Whole Blood & Plasma Substitute Solutions)	
A14 (Anabolics, Systemic)	71	K6 (Dialysis Solutions)	
A15 (Appetite Stimulants)	71		
A16 (Other Alimentary Tract & Metabolism Products)	42	L (Antineoplastic & Immunomodulating Agents)	
B (Blood & Blood Forming Organs)		L1 (Antineoplastics)	110
B1 (Antithrombotic Agents)	20	L2 (Cytostatic Hormone Therapy)	110
B2 (Antifibrinolytics, Antidotes To Anti-Coagulants, Inhibitors, Blood Coagulation & Haemostyptics)	20	L3 (Immunostimulating Agents)	80
B3 (Anti-Anaemic Preparations)	20		
B6 (All Other Haematological Agents)	20	L4 (Immunosuppressive Agents)	80
C (Cardiovascular System)		M (Musculo-Skeletal System)	
C1 (Cardiac Therapy)	30	M1 (Anti-Inflammatory & Anti-Rheumatic Products)	140
C2 (Antihypertensives)	30	M2 (Topical Anti-Rheumatics)	140
		M3 (Muscle Relaxants)	101
C3 (Diuretics)	30	M4 (Anti-Gout Preparations)	142
C4 (Cerebral & Peripheral Vasotherapeutics)	30	M5 (Other Drugs For Disorders Of The Musculo-Skeletal System)	142
C5 (Antivaricosis/Anti-Haemorrhoidal Preparations)	30	N (Nervous System)	
C6 (Other Cardiovascular Products)	30	N1 (Anaesthetics)	140
C7 (Beta-Blocking Agents)	30	N2 (Analgesics)	140
C8 (Calcium Antagonists)	30	N3 (Anti-Epileptics)	43
C9 (Agents Acting On The Renin-Angiotensin System)	30	N4 (Anti-Parkinson Drugs)	100
C10 (Lipid-Regulating/Anti-Atheroma Preparations)	60	N5 (Psycholeptics)	41
		N6 (Psychoanaleptics Excl. Anti-Obesity Preparations)	43
C11 (Cardiovascular Multitherapy Combination Products)	30	N7 (Other CNS Drugs)	41
D (Dermatologicals)		P (Parasitology)	
D1 (Antifungals, Dermatological)	90	P1 (Antiprotozoals & Anthelmintics)	150
D2 (Emollients, Protectives)	90	P3 (Ectoparasitocides, Incl. Scabicides, Insecticides & Repellents)	150
D3 (Wound Healing Agents)	90	R (Respiratory System)	
D4 (Anti-Pruritics, Incl. Topical Antihistamines, Anaesthetics, Etc)	90	R1 (Nasal Preparations)	160
D5 (Nonsteroidal Products For Inflammatory Skin Disorders)	90	R2 (Throat Preparations)	160
D6 (Topical Antibiotics, Sulphonamides & Antivirals)	90	R3 (Anti-Asthma & COPD Products)	160
D7 (Topical Corticosteroids)	91	R4 (Chest Rubs & Other Inhalants)	162
D8 (Antiseptics & Disinfectants)	90	R5 (Cough & Cold Preparations)	161
D10 (Anti-Acne Preparations)	90	R6 (Systemic Antihistamines)	161
D11 (Other Dermatological Preparations)	90	R7 (Other Respiratory System Products)	160
G (Genito-Urinary System & Sex Hormones)		S (Sensory Organs)	
G1 (Gynaecological Anti-Infectives)	11	S1 (Ophthalmologicals)	121
G2 (Other Gynaecologicals)	11	S2 (Otologicals)	130
G3 (Sex Hormones & Products With Similar Desired Effects, Systemic Action Only)	73	S3 (Ophthalmological/Otological Combinations)	130
G4 (Urologicals)	71		
H (Systemic Hormonal Preparations (Excl. Sex Hormones))		T (Diagnostic Agents)	
H1 (Pituitary & Hypothalamic Hormones)	70	T1 (Diagnostic Imaging)	none
H2 (Systemic Corticosteroids)	70	T2 (Diagnostic Tests)	none
H3 (Thyroid Therapy)	72		
H4 (Other Hormones)	77	V (Various)	
		V1 (Allergens)	none
		V3 (All Other Therapeutic Products)	none
		V6 (Dietetic Agents)	none

A.4 Annualized Monthly Abnormal Returns

Table 9: Panel Regression of Annualized Monthly Abnormal Pharmaceutical Stock Returns on Forecasted Demand Changes for Different Foresight Horizons h

This table shows the results of the panel regression of pharmaceutical abnormal stock returns on forecasted demand changes due to demographic changes for different foresight horizons $6 \leq h \leq 16$ ($3 \leq j \leq 8$). 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 $ar_{k,t,t+1} = const + d * (lnc_{k,t+j} - lnc_{k,t}) + e * (lnc_{k,t+2j} - lnc_{k,t+j}) + \epsilon_{k,t}$ for $3 \leq j \leq 8$. Lines (1) to (3) show the results of the panel regression with a foresight horizon of $2j = 6$ years. Lines (4) to (6) show the results of the panel regression with a foresight horizon of $2j = 8$ years. Lines (7) to (9) show the results of the panel regression with a foresight horizon of $2j = 10$ years. Lines (10) to (12) show the results of the panel regression with a foresight horizon of $2j = 12$ years. Lines (13) to (15) show the results of the panel regression with a foresight horizon of $2j = 14$ years. Lines (16) to (18) show the results of the panel regression with a foresight horizon of $2j = 16$ years. The first lines of each block (Lines (1), (4), (7), (10), (13), (16)) show the results without cross-sectional and year fixed effects. The second lines of each block (Lines (2), (5), (8), (11), (14), (17)) show the results with cross-sectional fixed effects, and the third lines of each block (Line (3), (6), (9), (12), (15), (18)) show the result with both, cross-sectional and year fixed effects. The doubled-clustered standard errors are indicated in brackets. (*) indicates significance at the 10% level, (**) indicates significance at the 5% level, (***) indicates significance at the 1% level.

Annualized monthly Beta-Adjusted Log Pharmaceutical Abnormal Stock Return t+1.								
	j	$const$	d	e	R^2	N	Industry FE	Year FE
(1)	$j = 3$	-0.421 (0.031)***	-4.944 (1.156)***	1.963 (0.959)**	0.01	N=9997		
(2)	$j = 3$	-0.449 (0.038)***	-5.128 (1.229)***	2.677 (1.092)**	0.01	N=9997	x	
(3)	$j = 3$	-0.432 (0.040)***	-4.924 (1.195)***	2.560 (1.003)**	0.02	N=9997	x	x
(4)	$j = 4$	-0.431 (0.031)***	-2.750 (0.901)***	3.126 (0.796)***	0.01	N=9997		
(5)	$j = 4$	-0.468 (0.040)***	-3.071 (0.995)***	4.078 (0.972)***	0.01	N=9997	x	
(6)	$j = 4$	-0.466 (0.039)***	-3.017 (0.997)***	3.998 (0.973)***	0.02	N=9997	x	x
(7)	$j = 5$	-0.445 (0.031)***	-1.555 (0.723)**	2.043 (0.622)***	0.01	N=9997		
(8)	$j = 5$	-0.495 (0.042)***	-1.913 (0.833)**	3.049 (0.813)***	0.01	N=9997	x	
(9)	$j = 5$	-0.493 (0.041)***	-1.932 (0.844)**	2.807 (0.985)***	0.02	N=9997	x	x
(10)	$j = 6$	-0.451 (0.032)***	-0.730 (0.583)	1.227 (0.493)***	0.01	N=9997		
(11)	$j = 6$	-0.504 (0.044)***	-0.944 (0.693)	2.004 (0.685)***	0.01	N=9997	x	
(12)	$j = 6$	-0.505 (0.044)***	-1.021 (0.710)	1.932 (0.844)***	0.02	N=9997	x	x
(13)	$j = 7$	-0.454 (0.033)***	-0.404 (0.478)	0.870 (0.404)**	0.01	N=9997		
(14)	$j = 7$	-0.516 (0.048)***	-0.539 (0.575)	1.543 (0.590)***	0.01	N=9997	x	
(15)	$j = 7$	-0.446 (0.038)***	-0.659 (0.591)	1.681 (0.616)***	0.02	N=9997	x	x
(16)	$j = 8$	-0.452 (0.036)***	-0.145 (0.446)	0.468 (0.349)	0.01	N=8736		
(17)	$j = 8$	-0.551 (0.056)***	-0.026 (0.545)	1.340 (0.790)	0.01	N=8736	x	
(18)	$j = 8$	-0.552 (0.057)***	-0.031 (0.667)	1.392 (0.668)	0.02	N=8736	x	x