Attention, Demographics, and the Stock Market*

Stefano DellaVigna
UC Berkeley
sdellavi@econ.berkeley.edu

Joshua Pollet
Harvard University
jpollet@econ.fas.harvard.edu

This version: October 24, 2003.

Abstract

Do investors pay attention to long-term fundamentals? We consider the case of demographic information. Large cohorts, such as the baby boom, generate forecastable positive demand changes over time to the toys, bicycle, beer, life insurance, and nursing home sectors, to name a few. These demand changes are predictable once a specific cohort is born. In this paper, we use lagged consumption and demographic data to forecast future consumption demand growth induced by changes in age structure. We find that these demand forecasts predict profitability by industry. Moreover, forecasted demand growth 5 to 10 years into the future predicts one-year returns by industry. An additional one percentage point of annualized demand growth due to demographics induces a 4 to 6 percentage point increase of annual abnormal industry stock returns. The forecastability is stronger for concentrated industries and for the more recent time period. Forecasted consumption growth 0 to 5 years into the future instead does not predict stock returns. The results are consistent with short-sightedness with respect to long-run information.

*PRELIMINARY VERSION, PLEASE DO NOT QUOTE WITHOUT PERMISSION. We thank John Campbell, Liran Einav, Caroline Hoxby, Michael Jansson, Lawrence Katz, David Laibson, Ronald Lee, Ulrike Malmendier, Jack Porter, Andrei Shleifer, Jeremy Stein, Geoff Tate, seminar participants in Trento and in the Economics Departments of Berkeley, Harvard, and Stanford for their comments. Jessica Chan, Fang He, and Terry Yee helped collect the dataset of industries. Christine Ayee and Saurabh Bhargava provided excellent research assistance. We thank Ray Fair and John Wilmoth for making demographic data available to us. For financial support, DellaVigna thanks the CEDA and the Academic Senate in Berkeley.

1 Introduction

According to the theory of efficient financial markets, stock prices should incorporate all available information. Do they? Evidence on post-earnings announcement drift and short-horizon momentum effects suggest that investors incorporate new information slowly.

In this paper, we suggest a novel test of underreaction to information. We consider the market reaction to changes in the demographic structure. Different goods have distinctive age profiles of consumption, and therefore changes in the age distribution generate shifts in demand across goods. These shifts in demand induce changes in profits across industries.

One unusual feature characterizes these profit changes—they are forecastable years in advance. Current cohort sizes, in combination with mortality and fertility tables, generate accurate forecasts of future cohort sizes even at long horizons. Therefore, we can use demographic changes to examine if investors are attentive to long-term determinants of profitability. This test is quite different from other tests of forecastability that consider events with news about profitability, such as announcements of quarterly earnings, or previous performance information measured by recent returns or accounting ratios.

If investors incorporate fully the long-run effects of demographic variables, the forecastable changes in profits due to demographics will be incorporated in the stock prices of companies within the related industries. If investors, instead, are inattentive to demographics, this information will be incorporated only slowly. As a consequence, demographic variables will predict industry asset returns.

This paper helps address two questions. First, how do markets evaluate information about long-term outcomes? Beyond demographics, other factors that affect long-term profitability include new plant openings and research and development (Hall and Hall, 1992). The evidence in this paper complements the existing results on the response to short-term events, such as earnings surprises. Second, do individuals consider demographic variables when making decisions about job choices,public policy, and portfolio allocations? While the evidence in this paper addresses only stock market investment, it has broader implications for other economic decisions affected by demographics. This question is of particular relevance given the large demographic changes faced by American and European societies.

We illustrate the basic idea of this paper with an example. Assume that a large cohort is born in 2004. This large cohort will increase the demand for school buses as of 2010. As long as the school bus industry is not perfectly competitive, the companies in the industry will enjoy an increase in abnormal profits in 2010. When should stock prices increase in anticipation of higher future profitability? According to the standard analysis with attentive investors, the marginal investor foresees the positive demand shift induced by demographic changes and invests in school bus stocks in 2004. The price of school bus shares should increase in 2004 until the opportunity to receive abnormal returns has dissipated. If, instead, investors are inattentive to demographic changes, stock prices will not increase sufficiently in 2004 and move upward subsequently. Therefore, the industry abnormal return between 2005 and 2010 will be predictable using the information available in 2004.

This suggests a simple test of the hypothesis of inattention to demographic changes. In the standard model, forecastable fluctuations in cohort size do not generate predictability for stock returns, since stock prices react immediately to the demographic information. Under the alternative hypothesis of inattention, current demographic information forecasts future stock returns.

In this paper we implement this test of attention to demographic information for a set of 48 US industries over the period 1935-2002. The industry classification attempts to cover all final consumption goods. We disaggregate industries in an effort to separate goods with different age profiles in consumption. Several goods have an obvious association with a demographic cohort. In the life cycle of consumption, books for children are followed by toys and books for K-12. Bicycles are followed by motorcycles, cars, and housing. Later in the life cycle, individuals consume life insurance, health care services, and pharmaceuticals. Sadly, the life cycle ends with nursing homes and funeral homes. Other expenditure categories, like beer, food, and property insurance, have a less obvious association with a specific age group. For each good, we use consumer expenditure surveys to estimate the age profile of consumption.

The empirical strategy follows five steps, described in detail in Section 3. In the first step, we use cohort size, mortality table, and fertility rates to forecast future cohort sizes. The forecasted cohort growth rates for the ages 10-70 are very close to the actual ones, with an R^2 of about 80 percent. The forecasts are substantially less precise at the two extremes of the age distribution, i.e., for future births and for the older generations. Unforecastable fluctuations in fertility and mortality have the most impact on these two groups.

In the second step, we estimate age consumption profiles for the 48 goods in the sample. We use historical surveys on consumer expenditure from 1935-36, 1960-61, and 1972-73 to complement the more standard Consumer Expenditure Survey for the years 1983-85. For each good, we disaggregate the household consumption into individual-level expenditure. We attempt to determine how much of consumption is attributable to the age of the household head, the age of the spouse, or the presence of children. We find that: (i) consumption of most goods depends significantly on the demographic composition of the household; (ii) across goods, the age profile of consumption varies substantially; (iii) for a given good, the age profile is quite stable across the different surveys. These findings support the use of cohort size as a predictor of consumer demand.

In the third step we combine the demographic forecasts with the age profiles of consumption for each good. The output is the good-by-good forecasted demand growth due caused by demographic changes. The forecasted one-year growth rates of consumption have an average within-good standard deviations of .57 percent. We identify the 20 industries with the highest within-good standard deviation of growth as the subsample most affected by demographic changes.

In the last two steps, we match the consumption forecasts with accounting information from *Compustat* and stock returns data from *CRSP*. In order to perform this match, we disaggregate the industry classification beyond the 4-digit SIC code level. For example, we separate the SIC codes for book producers 2730-2739 into 4 industries depending on the age-group targeted. In the fourth step we examine whether the forecasted consumption growth predicts profitability for companies in an industry. The identification comes from variation in forecasted consumption growth across the 48 industries and over 51 years, this is obvious. For the subset of demographics-exposed industries, the accounting return on equity increases by 1.2 to 1.6 percentage points for each contemporaneous 1 percent consumption growth induced by demographics. The estimates are quite precise, with a standard error of approximately .3 percentage points. For the whole sample of industries, these effects are somewhat smaller. The response of profitability to demand changes is more pronounced in industries with a more concentrated industrial structure, a proxy for the presence of barriers to entry. As expected, demand changes have a larger impact on profitability in industries where firms can extract the rents from demand changes.

In the final step we test for underreaction to demographic information using stock market returns. We regress annual industry stock returns on measures of medium-term and long-term forecasted demand growth while adjusting for aggregate returns. The medium-term measure is the forecasted annualized growth rate of consumption due to demographics over the next 5 years. The long-term measure is the forecasted annualized growth rate of consumption over the years 5 to 10. While the medium-term demand growth measure does not generate any forecastability, the long-term demand growth can forecast annual stock returns. A one percentage point increase in the annualized demand growth rate due to demographics predicts a 5 to 7 percentage point increase in abnormal industry return.

The predictability of returns is more substantial in sectors with high concentration, as measured by the share of industry revenue produced by the largest 4 firms. In these sectors a one-percent yearly growth rate due to demographics induces a significant 11 to 15 percent additional yearly return for the industry. In the sample of low-concentration industries, instead, stock returns are not significantly affected by the demand changes. This second result conforms to the predictions of the theory. In competitive markets demand changes do not translate into additional profits, and therefore, have no impact on returns. The presence of some barrier to entry is a necessary condition for the test of attention.

Finally, we test whether the forecastability of industry-level stock returns produces a portfolio strategy that outperforms the market. We construct a zero-cost portfolio that is long in industries with high forecasted demand growth for years 5 to 10 and short in industries with low forecasted demand growth. For the subset of demographic industries, this portfolio outperforms the market significantly by 5 to 7 percentage points per year, even after controlling for a four-factor model. The outperformance is almost twice as large for the more recent period (1975 to 2001). For the entire sample of industries, the portfolio outperforms the market by about 2 percentage points per year. A similar portfolio constructed using only high-concentration industries achieves returns of 5 to 6 percentage points.

In Section 4 we interpret these results in light of a model of short-sighted investors (Section 2). We assume that investors only consider information about future profitability within a horizon of h years. For the periods further into the future, investors evaluate earnings using a combination of a parametric estimate for the long-term growth and extrapolation from the near-term forecasts. This model embeds the standard framework for h approaching infinity. We provide suggestive evidence regarding the horizon h using the forecasts of earnings from the I/B/E/S, one of the most comprehensive data sets for analyst forecasts. While forecasts of earnings 1, 2, or even 3 years into the future are readily available for most companies, earnings forecasts beyond the 4 year horizon are available for less than 10 percent of the companies. If analysts do not create long-term forecasts of earnings, most investors are unlikely to have access to information about long-term profitability. This evidence suggests that the horizon h may be between 3 and 5 years. In forming valuations of companies, investors may therefore take into account medium-term demographic changes, but neglect longer-term demographic patterns.

For a horizon h of approximately 5 years, the empirical findings are consistent with our model of investor inattention. Forecastable demographic shifts occurring up to 5 years into the future are taken into account by investors, and therefore, are already incorporated into the price. As a consequence, the medium-term demand forecasts do not predict industry-level stock returns. Demographic shifts occurring beyond 5 years into the future are initially neglected by investors. As time unfolds and these changes get nearer, investors react to the upcoming demographic shift by altering their investment in the relevant industries. As a consequence, long-term demand shifts due to demographics predict yearly industry stock return.

In Section 4 we also examine some alternative interpretations of the findings. An alternative attention-based interpretation is that individuals underreact to slowly-moving trends like demographic variables. We also discuss alternative interpretations of our results based on rational predictability, agency problems, limits to arbitrage, and improvements in data analysis.

While we do find evidence that forecastable demographic changes predict industry returns, our evidence also indicates that stock prices reflect demographic information well before the actual demographic changes take place. Therefore, investors display at least a partial reaction to future forecastable demographic trends.

The most relevant literature in finance considers the forecastability of returns for individual stocks, industries, or specific portfolios using publicly known information including previous returns (de Bondt and Thaler, 1985; Jegadeesh and Titman, 1993; Moskowitz and Grinblatt 1999; Hong, Touros, and Valkanov, 2002), accounting ratios (Basu 1983; Fama and French 1992), and earnings announcements (Watts 1978, Bernard and Thomas 1989). In particular, stock returns display positive autocorrelation at short horizons (momentum effect) and positive earning surprises are followed in the subsequent dates by positive abnormal returns (post-earnings announcement drift) in the subsequent weeks. The behavioral explanation for these two phenomena requires investors to 'underreact' to news in the short-term. Our findings suggests that investors underreact to long-term forecastable information as well.

This paper also relates to the literature on the effects of demographic variables on economic outcomes, including social security (Auerbach and Lee, 2001; Gruber and Wise, 1999, and Hurd, 1990), college graduation (Card and Lemieux, 2000 and Bound and Turner, 2003), macro variables (Fair and Dominguez, 1991), and family choices (Easterlin, 1987). One implication is that voters are likely to underestimate the effect of demographic changes on social security, therefore lowering the political support for social security reforms. Along similar lines, Zarkin (1985) considers the choice of college students to be certified for elementary school and high-school teaching. He finds that students respond strongly to current wages but display essentially no response to future wages predicted by forecastable changes in cohort size.

A more closely related literature has examined the effects of demographic changes on the demand for stocks and bonds and therefore aggregate stock market returns. The evidence for this effect is mixed (Poterba, 2001; Goyal, forthcoming; Ang and Maddaloni, 2003; Geneakoplos, Magill, and Quinzii, 2002). The test we undertake differs markedly from this literature because it focuses on changes in demand across consumption goods rather than on aggregate shifts in demand for financial assets. Mankiw and Weil (1989, 1991) find that contemporaneous changes in the age structure in the population help explain the time-series behavior of housing prices. We generalize their idea by looking at 48 industries and focusing on stock market returns where, unlike for housing prices, arbitrage should eliminate the predictability. We find that, unlike in their paper, contemporaneous demographic trends do not have predictive power.

Finally, this paper also contributes to the growing empirical literature regarding the role of attention allocation within economics. (Barber and Odean, 2002; Gabaix et al., 2002; Huberman and Regev, 2001). The empirical evidence in this paper suggests that individuals may simplify complex decisions by neglecting long-term information.

The rest of the paper is structured as follows. Section 2 presents a stylized model of the effect of a demand shock on accounting variables and on stock returns with inattentive investors. Section 3 presents the empirical analysis in its five steps, from the forecasts of cohort size to the forecasts of stock returns. Section 4 interprets the results in light of the model of Section 2 and discusses alternative interpretations. Section 5 concludes.

2 A model

Industrial structure. We model the industrial structure as a two-stage game (Mankiw and Whinston, 1986). In the first period a set of potential entrants decides whether to pay a fixed cost K and enter a market. In the second period, the N firms entering the market decide the production q_N in a Cournot game. Each entrant has convex costs of production c satisfying $c(0) = 0$, $c'(q) > 0$, and $c''(q) \geq 0$ for all q. We consider symmetric equilibria with all firms entering choosing the same quantity q_N. The aggregate demand function in the market is $Nq_N = (1+\alpha) D(p)$ .where α is a percentage demand shifter that captures demographic changes. We can invert the function D to get the inverse demand function $p = P[Nq_N/(1+\alpha)]$. We assume $P'(q) < 0$ and $P''(q) < 0$ for all q. The first assumption is simply a requirement that demand curves be downward-sloping. The second assumption is a technical requirement that guarantees strict concavity of the profit function and, therefore, the uniqueness of the solution. The firm profits equal $\pi_N = P[Nq_N/(1+\alpha)]\, q_N - c(q_N) - K$.

Consider first the effect of an increase in demand from α_0 to $\alpha_1 > \alpha_0$ after the decision to enter has been made, that is, for fixed number of firms N. Given non-decreasing marginal costs, firms increase production at most proportionally with the demand shift, that is, $q^*(\alpha_0) < q^*(\alpha_1) \leq (1+\alpha_1)\, q^*(\alpha_0)/(1+\alpha_0)$. Consider the first order conditions for the firms:

$$P'_q[Nq_N/(1+\alpha)]\frac{q}{1+\alpha} + P[Nq_N/(1+\alpha)] - c'(q_N) = 0. \tag{1}$$

If these conditions are satisfied for $q^*(\alpha_0)$ at $\alpha = \alpha_0$, it is easy to check that the left-hand side of (1) is (weakly) negative for $q = (1+\alpha_1)\, q^*(\alpha_0)/(1+\alpha_0)$ at $\alpha = \alpha_1$. Since the objective function is strictly concave, $q^*(\alpha_1) \leq (1+\alpha_1)\, q^*(\alpha_0)/(1+\alpha_0)$ follows. Similarly, the left-hand side of (1) is positive for $q = q^*(\alpha_0)$ at α_1, because, for constant q, an increase in α increases the left-hand side of (1). Using again the concavity of the profit function, we can conclude $q^*(\alpha_0) < q^*(\alpha_1)$. This proves the desired inequality for q^* as a function of α. In turn, this implies $0 < \partial q^*(\alpha)/\partial\alpha \leq q^*(\alpha)/(1+\alpha)$.

Second, consider the impact of a demand shift on firm profitability. The derivative of firm profit π_N with respect to a demand change α is

$$\frac{\partial \pi_N}{\partial \alpha} = -P'_q \frac{Nq_N}{1+\alpha}\left(\frac{q_N}{1+\alpha} - \frac{\partial q_N}{\partial \alpha}\right) q_N + (P - c'(q_N))\frac{\partial q_N}{\partial \alpha} \geq 0 \tag{2}$$

where the last inequality makes use of $0 \leq \partial q^*(\alpha)/\partial\alpha \leq q^*(\alpha)/(1+\alpha)$, of the assumption $P'_q < 0$, and of the fact that price P is higher than marginal cost $c'(q_N)$ by (1). Therefore, profitability is increasing in the demand shift α in the short-run.

While in the short-run the number of firms is constant, in the long-run firms enter until profits are zero. In particular, ignoring for simplicity the integer constraint on the number of firms N, the long-run number of entrants N^* is solution of

$$P[(q_N + (N-1)\, q_{-N})/(1+\alpha)]\, q_N - c(q_N) - K = 0. \tag{3}$$

By definition the demand shifter α does not affect long-run profits which are always zero.

A special case of the analysis above is the one with constant marginal costs: $c(q_N) = cq_N$. In this situation, expression (1) implies that in the short-run $\partial q^*(\alpha)/\partial\alpha = q^*(\alpha)/(1+\alpha)$. As a consequence, the expression in (2) simplifies to

$$\frac{\partial \pi_N}{\partial \alpha} = (P - c)\frac{q_N}{1+\alpha} = \frac{\pi_N + K}{1+\alpha}.$$

The short-run derivative of profits with respect to demand shifts is increasing in the entry costs K.

To summarize, in the short-run profits are increasing in the demand shifter, while in the long-run profits are independent of demand shifts. An industry is more likely to display large profit changes due to anticipated demand changes if either the demand shift occurs before firms can enter (high barriers to entry), or the potential entrants ignore demographic changes. In Section 3 we use concentration measures as a proxy for barriers to entry.

Stock returns. Assume that demand shifts affect profitability to some extent, and consequently, influence dividend growth. How should stock returns for an industry respond if investors are short-sighted? Using the log-linear approximation for stock returns from Campbell and Shiller (1988) and Campbell (1991), the unexpected log return can be expressed as a change in expectations about dividend growth and expected returns. Assume that the representative agent has a generic expectation operator (not necessarily rational), denoted $\widehat{E}[.]$, with the properties $x_t = \widehat{E}_t[x_t]$ and $\widehat{E}_t[a+b] = \widehat{E}_t[a] + \widehat{E}_t[b]$. The result is

$$r_{t+1} - \widehat{E}_t r_{t+1} = \Delta\widehat{E}_{t+1}\sum_{j=0}^{\infty}\rho^j \Delta d_{t+1+j} - \Delta\widehat{E}_{t+1}\sum_{j=1}^{\infty}\rho^j r_{t+1+j} \tag{4}$$

In expression (4) r_{t+1} is the log return between t and $t+1$, Δd_{t+1} is the change in the log dividend between t and $t+1$, ρ is a constant (interpretable as a discount factor) associated with the derivation of the linear model, and $\Delta\widehat{E}_{t+1}[.] = \widehat{E}_{t+1}[.] - \widehat{E}_t[.]$ is the change in expectations between periods. Equation (4) relates the unexpected log return to the change in expectations about dividend growth and expected returns.

Short-sighted investors have correct short-term expectations but incorrect long-term expectations for dividend growth. Let $E_t^*[.]$ be the expectation operator for short-sighted investors at time t. Similarly, let $E_t[.]$ be the fully rational expectation operator for period t. Formally, we assume that inattentive investors have rational expectations regarding dividend growth for the first h periods after t, $E_t^*\Delta d_{t+1+j} = E_t\Delta d_{t+1+j}\ \forall\ j < h$. For the later periods, inattentive investors incorrectly assume that expected dividend growth equals a convex combination of a constant, g^*, and the average expected (rational) dividend growth rate for periods $t+h-n$ to $t+h$:

$$E_t^* \Delta d_{t+1+j} = wg^* + (1-w) \sum_{i=1}^{n} \frac{E_t \Delta d_{t+1+h-i}}{n} \;\forall j \geq h. \tag{5}$$

Finally, we assume that short-sighted investors believe that expected returns are constant: $E_t^* r_{t+1+j} = \bar{r} \;\forall t, \forall\; j \geq 0$.

We can consider three special limit cases of the model. The standard case of *rationality* obtains for h diverging to ∞; investors have fully rational expectations about future earnings. The case of *unconditional inattention* occurs for $w = 1$. In this situation, investors expect that future earnings will grow at a constant rate g^*. Finally, the case of *interpolation* occurs for $w = 0$. Investors assume that earnings for periods past $t + h$ will keep growing at the average growth rate for the near future. In the subcase with $w = 1$ and $n = 1$ the investor projects the dividend growth of period $t + h$ into the future.

In the case of a representative investor with short-sighted expectations given by $E^*[.]$, we can substitute the irrational expectations $E^*[.]$ for the generic operator $\widehat{E}[.]$ in (4) to get

$$r_{t+1} - E^* r_{t+1} = \Delta E_{t+1}^* \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - \Delta E_{t+1}^* \sum_{j=1}^{\infty} \rho^j r_{t+1+j}.$$

Using the definition of $E_t^*[.]$ we obtain

$$\begin{aligned} r_{t+1} - \bar{r} &= \Delta E_{t+1}^* \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} = \\ &= \Delta E_{t+1} \sum_{j=0}^{h-1} \rho^j \Delta d_{t+1+j} + \rho^h \left(E_{t+1} \Delta d_{t+1+h} - wg^* - (1-w) \sum_{i=1}^{n} \frac{E_t \Delta d_{t+1+h-i}}{n} \right) \\ &\quad +(1-w) \sum_{j=h+1}^{\infty} \rho^j \left(\sum_{i=1}^{n} \frac{E_{t+1} \Delta d_{t+2+h-i}}{n} - \sum_{i=1}^{n} \frac{E_t \Delta d_{t+1+h-i}}{n} \right) \end{aligned}$$

The last equation presents the 'unexpected' return for short-sighted investors when $E^*[.]$ governs the behavior of the representative agent. Notice that returns $r_{t+1} - \bar{r}$ depend on the value of dividend growth only up to period $t + 1 + h$. Taking conditional rational expectations at time t (that is, using $E_t[.]$) and applying the law of iterated expectations, we obtain an expression on return predictability from the perspective of the fully rational investor.

$$\begin{aligned} E_t r_{t+1} - \bar{r} &= \rho^h w \left(E_t \Delta d_{t+1+h} - g^* \right) + \rho^h \frac{(1-w)}{n} \sum_{i=1}^{n} E_t[\Delta d_{t+1+h} - \Delta d_{t+1+h-i}] \\ &\quad + \frac{\rho^{h+1}}{1-\rho} \frac{(1-w)}{n} E_t[\Delta d_{t+1+h} - \Delta d_{t+1+h-n}] \end{aligned} \tag{6}$$

Expected returns between time t and time $t + 1$ depend on the sum of three terms. For rational investors ($h \to \infty$), all terms converge to zero and we obtain the standard results that returns are not forecastable. For short-sighted investors (h finite), instead, stock returns between time t and $t+1$ are forecasted positively by dividend growth $h+1$ years ahead and negatively by dividend growth between $h+1-n$ and h years ahead. The intuition is as follows. Returns between year t and $t+1$ are determined by the adjustment during the year of the incorrect expectation about future dividend. The investor updates the expectations by incorporating the dividend growth in period $t+h+1$. If period $t+h+1$ is characterized by high dividend growth, stock returns will increase since the investors will bid up the price of the security during the year. Conversely, dividend growth between $h+1-n$ and h years ahead contributes negatively to returns because it is replaced in the forecasting by new information.

Following Vuolteenaho (2002), we can write expression (6) as a function of $roe_t = \log(1 + ROE_t)$, where ROE_t is the accounting return on equity at time t. Following the same steps in the derivation, we obtain

$$\begin{aligned} E_t r_{t+1} - \bar{r} &= \rho^h w \left(E_t roe_{t+1+h} - g^*\right) + \rho^h \frac{(1-w)}{n} \sum_{i=1}^{n} E_t[roe_{t+1+h} - roe_{t+1+h-i}] \\ &+ \frac{\rho^{h+1}}{1-\rho} \frac{(1-w)}{n} E_t[roe_{t+1+h} - roe_{t+1+h-n}] \end{aligned} \tag{7}$$

In particular, assume that log return on equity depends on two components, the expected increase in profitability due to demographics and expected increase in profitability due to other factors:

$$roe_t = \beta \Delta c_t + v_t, \tag{8}$$

where Δc_t the growth rate of demand due to demographics at time t and β is the response of the return on equity to (forecastable) demand changes. This leads us to rewrite (7) as follows:

$$\begin{aligned} E_t r_{t+1} - \bar{r} &= A + \rho^h w \beta E_t \Delta c_{t+1+h} + \rho^h \frac{(1-w)}{n} \beta \sum_{i=1}^{n} E_t[\Delta c_{t+1+h} - \Delta c_{t+1+h-i}] \\ &+ \frac{\rho^{h+1}}{1-\rho} \frac{(1-w)}{n} \beta E_t[\Delta c_{t+1+h} - \Delta c_{t+1+h-n}] \end{aligned} \tag{9}$$

where A incorporates both the terms in g^* as well as the terms in Ev.

For investors with unconditional inattention ($w = 1$), only the first term applies: $E_t r_{t+1} - \bar{r} = A + \rho^h \beta E_t \Delta c_{t+1+h}$. Returns at time t are predictable using the forecasted demographic changes that influence dividend growth $h+1$ years ahead with a coefficient of $\rho^h \beta$. For investors with interpolation ($w = 0$), only the last two terms apply. For the special case $n = 1$, these two terms simplify to $\rho^h / (1-\rho) * \beta E_t[\Delta c_{t+1+h} - \Delta c_{t+1+h-1}]$. Returns depend positively on demand growth $t+h+1$ periods ahead and negatively on demand growth $t+h$ periods ahead. The coefficient on demand growth $t+h+1$ periods ahead equals $\rho^h \beta / (1-\rho)$ and is substantially larger than in the case of unconditional attention. For the more general case of $w = 0$ and $n > 1$, returns depend positively on dividend growth $t+h+1$ periods ahead and negatively on dividend growth in the previous n periods.

A note of caution regards the assumption of homogeneity of agents. This highly stylized model includes only inattentive investors. In a more general model with a fraction of fully rational agents, the arbitrage by these latter agents will weaken the stock return predictability. However, in the presence of limited arbitrage (DeLong et al., 1990; Shleifer, 2000) caused by risk aversion or agency problems, some predictability will still remain.

A simplifying assumption in this stylized model is that all investors have an horizon of exactly h periods. While this is clearly not realistic, the model provides intuition for the case in which the horizon varies across individuals and industries. If the horizon varies between h and $h + H$, industry returns would be forecastable using a combination of dividend growth rates between years h and $h + H$. The empirical specification in Section 3.6 acknowledges that horizons may vary and that the precision of the data does not allow to separately estimate the impact of future consumption growth for all time periods h. We therefore form two consumption growth forecasts, one for medium-run growth between year 0 and 5, and one for long-run growth between years 5 and 10.

3 Empirical Analysis

The empirical specification consists of five steps. The two preliminary steps are the formulation of demographic forecasts and the identification of age patterns in the consumption data. In the third step we aggregate the demographic forecasts with the consumption data to obtain demographic-based forecasts of consumption by good. In the fourth step we use these forecasts to check the predictability of industry-level revenue and return on equity using demographic variables. In the last step we turn to predictability of industry-level stock returns using demographic information.

3.1 Demographic forecasts

We combine data sources on cohort size, mortality, and fertility rates to form forecasts of subsequent cohort sizes. All the demographic information is disaggregated by gender and by one-year-age groups. The cohort size data is from the *Current Population Reports, Series P-25* (US Department of Commerce, Bureau of the Census). The data are estimates of the total population of the United States, including armed forces overseas. We use mortality rates from period life tables for the years 1920-2000 from *Life Tables for the United States Social Security Area 1900-2080*. Finally, we take age-specific birth rates from Heuser (1976) and the *Vital Statistics of the United States: Natality.*.[1]

We use demographic information available in year t_0 to forecast the age distribution by

[1]Additional detail on the demographic data, as well as on the consumption, the accounting, and the stock data are in the Appendix.

gender and one-year age groups for years $t > t_0$. We assume that fertility rates for the years $t > t_0$ equal the fertility rates for year t_0. We also assume that future mortality rates equal mortality rates in year t_0 except for a backward-looking percentage adjustment. We obtain the adjustment regressing mortality of the current decade on mortality in the previous decade for the 50 years previous to the forecast year. The adjustment coefficient is allowed to differ by 10-year groups of age. The estimated percentage improvement in mortality rates for the ages 0-10 is about 25 percent per decade. For the ages 50-59 it is about 9 percent per decade.

Using cohort size in year t_0 and these forecasts of future mortality and fertility rates, we form preliminary forecasts of cohort size for the years $t > t_0$. Finally, to account for migration, we compare actual cohort size to the preliminary forecasted cohort size for the 10 years prior to year t_0. We interpret the average percentage difference between the actual and the preliminary forecasted population size as the average historical net migration. We do the comparisons separately for each 10-year age group. For the 0-10 age group, the imputed net migration is about .5 percent per year, while for the 50-59 age group, it is about .1 percent per year. We apply this imputed adjustment for migration to the initial population forecasts made at time t_0.

We denote by $\hat{\mathbf{A}}_{g,t|t_0} = \left[\hat{A}_{g,0,t|t_0},\ \hat{A}_{g,1,t|t_0},\ \hat{A}_{g,2,t|t_0}, ...\right]$ the future forecasted age distribution so obtained. $\hat{A}_{g,j,t|t_0}$ is the number of people of gender g alive at t with age j forecasted using demographic information available at t_0. Figure 1a plots the actual series of population aged 30-34 over the years 1930-2002, as well as three forecasts as of 1935, 1955, and 1975. The forecasts track actual cohort size quite well, except for very long-term forecasts when they depend on predicting future births. Figure 1b for the age group 70-74 shows that the forecasts for older people are less precise. In Table 1 we regress the 1-year actual growth of the population on the 1-year ahead forecasted growth. Each observation is a (gender)*(year of forecast)*(1-year age) cell. We run the regressions separately by 10-year groups of age. The forecasts for the ages between 1 and 69 are quite accurate, with R-squares around .8. The forecasts for the older ages and for the unborn are significantly less precise due to substantial uncertainty about fertility rates and mortality rates for the old.[2]

3.2 Age patterns in consumption

Unlike demographic information, exhaustive information on consumption of different goods is available only after 1980. For the previous years, we use three different surveys: the *Study of Consumer Purchases in the United States, 1935-1936,* the *Survey of Consumer Expenditures, 1960-1961,* and the *Survey of Consumer Expenditures, 1972-1973.*[3]. We combine these early

[2]The forecasting error for the oldest should not have a large impact, given the small size of this population group. The size of the unborn population matters for a limited number of goods.

[3]Costa (1999) discusses the main features of these surveys.

surveys with the 1983-1984 cohorts of the ongoing *Consumer Expenditure Survey*[4]. Taken altogether, these four cross-sections provide information on the age distribution of consumption throughout the past century. Table 2 reports summary statistics on the most important household demographics. Family size decreases over time, while the proportion of urban households is increasing. The sample sizes and sampling rules differ across surveys. While the post-War surveys cover a representative sample of the US population, the 1935-36 survey includes only married couples and is therefore biased toward younger families. The bottom part of the Table presents information on average yearly income and total consumption in 1982-84 dollars.

We cover all main expenditures in final goods included in the survey data. The selected level of aggregation attempts to distinguish goods with potentially different age-consumption profiles. For example, within the category of alcoholic beverages, we separate beer and wine from hard liquor expenditure. Similarly, within insurance we distinguish between health, property, and life insurance expenditures. We attempt to generate these categories in a consistent way across the survey years. Unfortunately, expenditures are coded differently across the four survey so that for some surveys we do not have enough information to define an expenditure category. This problem is especially serious for the 1960-61 survey which features consumption data only by broad categories. Table 3 presents the summary statistics on good-by-good annual household expenditure for each survey year. The expenditures are in 1982-84 dollars.[5] Despite substantial differences across the four surveys in the sample, the survey procedure, and the definition of the goods, the mean household expenditure by good category is relatively stable over time.

More importantly, we can compare the age profile of consumption across survey years and across expenditure categories. To illustrate the age profile of selected goods, we use kernel regressions of household consumption on the age of the head[6]. Figure 2a, for example, plots normalized[7] expenditure on bicycles and drugs for the 1935-36, 1960-61, 1972-73, and 1983-84 surveys. Across the two surveys, the consumption of bicycles (Figure 2a) peaks between the ages of 35 and 40. At these ages, the household heads are most likely to have 5 to 10-year-old children. The demand for drugs (Figure 2a), instead, is increasing in age, particularly for the later consumption surveys. Older individuals demand more pharmaceuticals. The differences in age profiles occur not just between goods targeted to the young generations (e.g., bicycles) and goods targeted to the old (e.g., drugs), but also within a broad category, such as alcoholic beverages. The peak consumption of beer and wine (Figure 2b) occurs about 20 years earlier than the peak consumption of hard liquor (Figure 2b). This pattern is similar across the two

[4]The cohorts in the Consumer Expenditure Survey are followed for four quarters after the initial interview. The data for the fourth cohort of 1984, therefore, includes 1985 consumption data.

[5]Details about the composition of the various goods are available form the authors upon request.

[6]We use an Epanechnikov kernel with a bandwidth of 5 years of age for all the goods and years.

[7]For each survey-good pair we divide the age-specific consumption figure by the average expenditure across ages for that particular good.

surveys for which disaggregated data on alcoholic consumption is available. To give another example, purchases of large appliances peak at 25-30 years of age, while purchases of small appliances are fairly constant across the years 25-50. Large appliances are largely associated with the purchase of the first house, while small appliances are purchased on a more regular basis.

Overall, this preliminary evidence suggests three features. First, the amount of consumption for each good depends significantly on the age of the head of household. Patterns of consumption for most goods are not flat with respect to age. Second, these age patterns vary substantially across goods. Some goods are consumed mainly by younger heads (child care and toys), some in middle ages (life insurance and cigars), others at older ages (cruises and nursing homes). Third, the age profile of consumption for a given good is quite stable across time. For example, the expenditure on glasses and eye care peaks at the ages 45-50, whether we consider the 1935-36, the 1960-61, the 1972-73, or the 1983-84 cohorts. Altogether, this suggests that changes in age structure of the population have the power to affect consumption patterns in a substantial and consistent way.

With this evidence in the background, we now present the methodology we use to estimate age consumption patterns. In order to match the consumption data with the demographic data, we transform the household-level consumption data into individual-level information. We use the variation in demographic composition of the families to extract individual-level information—consumption of the head, of the spouse, and of the children—from household-level consumption data. We use an OLS regression in each of the four cross-sections. Denote by $c_{i,k,t}$ the consumption by household i of good k in year t and by $H_{i,t}$ a set of dummies for the age groups of the head of household i in year t. In particular, $H_{i,t} = [H_{18,i,t}, H_{27,i,t}, H_{35,i,t}, H_{45,i,t}, H_{55,i,t}, H_{65,i,t}]$ where $H_{j,i,t}$ is a dummy equal to 1 if the head of household i at time t is older than j and younger than the next age group. For example, $H_{35,i,t}$ indicates that the head of household i is aged 35 to 44 in year t. The dummy $H_{65,i,t}$ indicates a head older than 65 years of age. Similarly, let $S_{i,t}$ be a set of dummies for the age groups of the spouse. Finally, we add discrete variables $O_{i,t} = [O_{0,i,t}, O_{6,i,t}, O_{12,i,t}, O_{18,i,t}, O_{65,i,t}]$ that indicate the total number of other individuals (children or old relatives) living with the family in year t. For example, $O_{0,i,t} = 2$ indicates that two children aged 0 to 5 live with the family in year t.

The regression specification is

$$c_{i,k,t} = B_{k,t}H_{i,t} + \Gamma_{k,t}S_{i,t} + \Delta_{k,t}O_{i,t} + \varepsilon_{i,k,t}.$$

This OLS regression is run separately for each good k and for each of the four cross-sections t. The purpose is to obtain an estimate of annual consumption of good k for individuals of different ages. For example, the coefficient $B_{35,\text{cars},1960}$ indicates the average total amount that a (single) head aged 35 to 44 spends on cars in 1960. For robustness, we consider also alternative specifications with smaller bins for the age of the head and spouse (ages 18, 25, 30, 35, ..., 65), as well as larger bins (ages 18, 35, 50, 65). Finally, we consider a specification with no spouse dummies $S_{i,k,t}$.[8]

3.3 Forecasts of consumption

In the third step of the research design, we combine these age profiles of consumption with the demographic forecasts in order to forecast future demand for different goods. Consider for example a forecast of toys consumption in 1975 as of 1965. Age-by-age, we multiply the forecasted cohort sizes for 1975 by the age-specific consumption of toys estimated on the most recent consumption data, the 1960-61 survey. We then aggregate across all the age groups to obtain the forecasted overall demand for toys for 1975.

Formally, we denote by $\hat{\mathbf{A}}^b_{g,t|t_0}$ the aggregation of $\hat{\mathbf{A}}_{g,t|t_0}$ into the same age bins that we used for the consumption data. For example, $\hat{A}^b_{f,35,t|t_0}$ is the forecasted number of females aged 35 though 44 alive in year t forecasted as of year t_0. We combine the forecasted age distribution $\hat{\mathbf{A}}^b_{g,t|t_0}$ with the age-specific consumption coefficients B_{k,t_0}, Γ_{k,t_0}, and Δ_{k,t_0} for good k. In order to do so, for each age group j we estimate the shares $h_{g,j,t}$, $s_{g,j,t}$, and $o_{g,j,t}$ of people in the population. For example, $h_{f,35,t}$ is the number of female heads 35-44 over total number of females aged 35-44 in the consumption data at time t. We can then obtain a demographic-based forecast of the demand for good k at time t which we label $\hat{C}_{k,t|t_0}$:

$$\hat{C}_{k,t|t_0} = \sum_{g\in\{f,m\}} \sum_{j\in\{0,6,12,18,\ldots,65\}} \hat{A}_{g,j,t|t_0} \left(h_{g,j,t_0} B_{j,k,t_0} + s_{g,j,t_0} \Gamma_{j,k,t_0} + o_{g,j,t_0} \Delta_{j,k,t_0}\right)$$

The coefficients B, Γ, and Δ in this expression are estimated using the most recent consumption survey antecedent to year t_0 with information on good k. This forecast implicitly assumes that the tastes of consumers for different products depend on age and not on cohort of birth. We assume that 35-year olds in 1965 will consume in 1975 the same bundles of good that 35-year olds consume in 1965. The high correlation between forecasts based on consumption data from different surveys supports this assumption. In addition, we are holding prices of goods constant when computing the future demand.

Table 4 presents the average 1-year forecasted consumption growth for each good averaged over the years 1936-2001. These average yearly growth rates vary from 0 to 2 percent growth due to different age profiles, with a standard deviation in average growth of 0.30 percent. The average within-good standard deviation in one-year growth is 0.57 percent, indicating an appreciable effect of changing demographics on consumption.

[8] We do not include spouse dummies in the 1935-36 survey (only married couples were interviewed) and in the 1960-61 survey (age of the spouse not reported). In addition, in the 1935-36 survey we always use the larger bins for age since the sample is only a third to a half as large as in the other surveys.

We use the within-good standard deviation to identify the expenditure categories that are mostly affected by cohort size changes. The subsample 'Demographic Goods' includes the 20 expenditure categories with the highest standard deviations (Column 4). This sample includes the expenditure on children as well as on funeral homes, cruises, beer (and wine), among others.

Figure 3 shows the consumption growth due to demographics for three subcategories of the general book category—books for K-12 schools, books for higher education, and other books (mostly fiction). Formally, we plot $\ln \hat{C}_{k,t|1975} - \ln \hat{C}_{k,1975|1975}$ for $t = 1976, 1977, ..., 1995$, that is, the cumulated percentage changes in consumption forecasted as of 1975 twenty years into the future. For each of the three goods, we produce forecasts using the age-consumption profiles estimated from each of the four consumption datasets. The demand for K-12 books is predicted to experience a large decline as the baby-bust generation keeps entering schools. The demand for college books is predicted to first increase and then decline, as the cohorts entering college are first large (baby boom generation) and then small (baby bust generation). Finally, the demand for other books, which is mostly driven by adults in the 30s through 50s, is predicted to keep growing due to baby-boomers gradually reaching these ages. These patterns are quite consistent, independent of whether the age-consumption pattern is estimated from the 1935-36, the 1960-61, 1972-73, or 1983-84 data. (Throughout the rest of the project, we only use only the most recent consumption data set—in this case, the 1972-73 survey—for forecasts) Overall, Figure 3 shows that within the book categories there is substantial variability in the pattern of consumption growth across the subcategories, and that these patterns are fairly similar across different consumption surveys.

We provide additional evidence that the time-series variation in consumption growth is mostly due to demographic changes and not to differences in the consumption age profile across the four surveys. For each good we generate one-year consumption forecasts for the years 1936-2001 holding constant the consumption coefficients estimated from one consumption survey. The correlations between the growth forecasts across all goods are in the .7-.8 range (Table 5). The correlations for one specific good—for instance, cars—are on average higher. These high correlations confirm that the consumption patterns are very similar across surveys, and that therefore differences across surveys are unlikely to generate the variation in the forecasts. The bottom part of Table 5 addresses a different concern, that is, the importance of error in forecasting demographics. We compute a measure of forecasted growth that uses the actual demographics growth, rather than the forecasted one. The correlation between the two measures is .69, indicating that errors in demographic forecasts are unlikely to have a large role.

3.4 ROE predictability

In the fourth step of the research design, we test whether forecastable demand changes affect profit rates by industry, a necessary condition for the attention test. As a measure of profitability we use the rate of return on equity (ROE). For each firm, the return on equity at time t is defined as the ratio between book value of equity (*Compustat* data item 60) plus earnings (*Compustat* data item 172) in year t and the book value of equity in year $t-1$. In order to obtain an industry-level measure of profitability, we compute the average rate of returns over the companies in the industry weighted by the book value in year $t-1$.

Since some industries require a higher level of disaggregation than provided by the standard 4-digit SIC codes, we create the industry classification ourselves whenever necessary. Using a company-by-company search within the relevant SIC codes we partitioned the companies into the relevant groups. For example, the SIC code 5092 on 'toys' included both companies producing toys for children as well as companies manufacturing golf equipment, two goods clearly associated with consumption by different age groups. Column 2 in Table 1 displays the SIC codes associated with a particular industry. The SIC codes in parentheses are those that are shared by different industries, and therefore require a company-by-company search. For larger industries such as automobiles, oil, coal, etc. our SIC grouping system is very similar to the groups used by Fama and French when they form 48 industry portfolios.

We construct the one-year aggregate industry return on equity $ROE_{k,t}$ using only companies that already belonged to the industry categorization in year t_0. We therefore exclude companies entering the SIC code classification between t_0 and t_0+1. We deal with inter-industry mergers and industry reclassifications by excluding companies that exit the industry between t_0 and t_0+1. The final measure is the log return on equity, that is, $\log(1+ROE_{k,t})$. Table 6 presents summary statistics on the log yearly return on equity (mean and standard deviation), the average number of firms included in the industry over time, and the number of years for which the ROE data is available. The average log return ranges from 8 percent (golf) to 24 percent (motorcycle). The within-industry standard deviation of the return is often as high as 8 percent. In order to avoid the possibility of return outliers driving our results, we winsorize the log return measure at the 5 percent level. The longest series run for 51 years, but most series are shorter.

In Table 8 we test the predictability of the one-year industry log return on equity (Table 6) using the forecasted one-year growth rate in consumption due to demographics (Table 4). Denote by $\hat{c}_{k,t|t_0}$ the natural log of the forecasted consumption of good k in year t forecasted as of year t_0.The specification adopted is motivated by equation (8):

$$\log(1+ROE_{k,t_0+1}) = \alpha + \eta_k I_K + \Gamma T_t + \beta\left[\hat{c}_{k,t_0+1|t_0-2} - \hat{c}_{k,t_0|t_0-2}\right] + \varepsilon_{k,t_0} \qquad (10)$$

The regression allows for industry dummies I_k and a quartic polynomial in year $T_t = [(t-1935)\,,\ (t-1935)^2\,,\ (t-1935)^3\,,\ (t-1935)^4]$. The forecast of consumption growth between years t_0

and t_0+1 uses only demographic and consumption information available up to year t_0-2. This lag ensures that all information should be of public knowledge by the time of the forecast. The identification in this regression comes from variation both in the industry k and the year t_0 when the forecasts are created.

In this panel setting it is unlikely that the error terms across industries are independent since there may be common shock that affect multiple industries. We therefore allow for arbitrary correlation across industries at any given time by calculating 'robust' standard errors clustered by year, under the assumption that the residuals are independent across time periods. Formally, define Ω as the error covariance matrix and X as the matrix of explanatory variables, then the covariance matrix for the coefficient estimator is $(X'X)^{-1}X'\Omega X(X'X)^{-1}$. If we assume that the errors for each cross-section are independent, then $X'\Omega X = \sum_{t=1}^{T} X_t'\Omega_t X_t$ where X_t is the matrix of explanatory variables and Ω_t is the error covariance matrix for each cross-section. Since Ω_t is unknown we estimate $X_t'\Omega_t X_t$ with $X_t'\widehat{\varepsilon}_t\widehat{\varepsilon}_t' X_t$, and similarly, $X'\Omega X$ using $\sum_{t=1}^{T} = X_t'\widehat{\varepsilon}_t\widehat{\varepsilon}_t' X_t$ where the vector of estimated residuals for each cross-section is denoted $\widehat{\varepsilon}_t$.

In the baseline specification of Table 8 we use the subsample of Demographic Industries. Column 1 presents the results for the model without industry dummies or year controls. Column 2 introduces industry dummies. In this case, the identification depends only on time-series changes in the growth rates and not on between-industries differences. In Column 3 we control for time trends with a quartic polynomial in $(year-1935)$. Across the three specifications the coefficient $\hat{\beta}$ equals 1.3 with a standard error of approximately .3. For a one percent increase in yearly consumption growth due to demographics, the return on equity increases from an average of 10.5 percent to an average of 11.8 percent (Column 1), a 12 percent increase. In Columns 3-4 we reestimate the model for the period from 1975 on. The accounting data for the earlier period is noisier since the accuracy of the industry classification increases with proximity to the present[9]. In addition, the industry-level measure of return on equity is likely to be more precise since the number of companies covered in the accounting data increased substantially over time. In this later time period the magnitude of $\hat{\beta}$ is comparable to the previous magnitudes, although the estimates are less precise given the smaller number of observations. Finally, in Columns 7 through 12 we reestimate the same models for the whole sample of 48 industries. The point estimates for $\hat{\beta}$ are slightly lower than the corresponding ones for the subset of Demographic Goods, but still large and significantly different from 0. The standard errors in the whole sample are as large as in the demographic sample, despite a threefold increase in sample size, suggesting a higher signal-to-noise ratio for the non-demographic industries. Overall, forecasted demand changes due to demographics have a statistically and economically

[9]The company-level information used to generate, for example, the book subcategories is accurate for the present (2003), but less likely so the earlier in time.

significant effect on industry-level profits. It appears that entry into the market does not fully undo the effect of forecastable demand changes on profitability.

3.5 Industry concentration

An important effect that we have neglected so far is that fact that the qualitative impact of a demand change on profitability depends on the market structure. At one extreme, in a perfectly competitive industry with no barriers to entry, the consumers capture all the surplus arising from a positive demand shift. In this scenario, demographic changes affect industry revenues but not abnormal profits. At the other extreme, a monopolist in an industry with high barriers to entry generates both additional revenues and additional profits from a positive demand change. We address this issue in the regression of profit rates on forecasted consumption growth.

As a measure of barriers to entry we use 4-concentration ratios, that is, the ratio of the industry revenue produced by the 4 largest companies in an industry. This measure is available from the *Bureau of Manufacturers* for the manufacturing sector for the 4-digit SIC codes 2000-3999. The measure is computed for the years 1947, 1954, 1958, 1963, 1966, 1967, 1970, 1972, 1977, 1982, 1987, and 1992. We create an industry concentration index as the average 4-concentration ratio for the SIC codes included in the definition in the range 2000-3999. The average is weighted by the aggregate revenue for an SIC code and is evaluated in the first year for which the concentration data is available. Unfortunately, this measure is not defined for industries like insurance and utilities that have no SIC code in the range 2000-3999. Table 7 reports the 4-concentration ratios for the industries in the sample. There is substantial variation across industries in the concentration measure. To avoid industries switching concentration ratio groups over time, we use the earliest measure of the concentration ratio to classify each industry. For almost all industries the concentration ratio measure is taken from 1947.

Table 9 reports a breakdown of the profitability regression (10) in two subsamples of industries: the industries with concentration ratio C-4 higher than .40 and the industries with concentration ratio lower than (or equal to) .40. In the sample of concentrated industries (Columns 1 through 3) the effect of an increase in demand due to demographics is statistically significant and somewhat larger than in the overall sample. In the sample of unconcentrated industries (Columns 3 and 4), instead, the coefficient $\hat{\beta}$ is small and not significantly different from zero. This evidence supports the prediction that the demand changes due to demographics should alter profits more substantially in the presence of barriers to entry.

3.6 Returns predictability

In the fifth and final step we test the effect of demographic changes on stock returns. We use the stock return performance data from *CRSP* and aggregate it by Standard Industrial Classification (SIC) Codes augmented by specific company-by-company searches[10] to form value-weighted industry returns. Table 7 displays the summary statistics on one-year value-weighted stock returns (mean and standard deviations), average number of firms, and years covered. The sample is larger than the revenue sample, since returns are available for a longer panel and for more companies than accounting data. The mean yearly stock return varies from -9 percent (eye glasses) to 19 percent (motorcycles). The standard deviation of the yearly stock returns is quite large—32 percent on average—and is negatively correlated with the number of firms in the industry.

We choose specifications motivated by expression (9) in the Theory Section and investigate when stock prices incorporate the forecastable consumption changes generated by demographic variables. In the baseline specification we regress yearly returns on the forecasted growth rate of demand due to demographics 0 to 5 years ahead (the medium-run) and 5 to 10 years ahead (the long-run). We adjust the yearly industry returns with a beta correction. Formally, denote by r_{k,t,t_0} the natural log of the stock return for good k between year t_0 and year t. The natural log of the market return over the same horizon is given by r_{m,t,t_0}. Further, denote by $\hat{\beta}_{k,t_0}$ the coefficient of a regression of monthly industry-level returns on market returns over the 48 months previous to year t_0. The return adjustment removes the market-wide macroeconomic shocks allowing greater focus on the industry specific component of returns. As a consequence, we can interpret the dependent variable as an abnormal log return. The specification of the regression is

$$r_{k,t_0+1,t_0}-\hat{\beta}_{k,t_0}r_{m,t_0+1,t_0} = \gamma+\delta_0\left[\hat{c}_{k,t_0+5|t_0-2}-\hat{c}_{k,t_0|t_0-2}\right]/5+\delta_1\left[\hat{c}_{k,t_0+10|t_0-2}-\hat{c}_{k,t_0+5|t_0-2}\right]/5+\varepsilon_{k,t} \tag{11}$$

The renormalization by 5 implies that the coefficient δ_1 indicates the increase in abnormal yearly returns for each one percent additional annual growth in demographics over the years 5 to 10. Once again, the forecasts of consumption as of time 0 only use information released up to time t_0-2.

The model in Section 2 suggests that, if the forecast horizon h is shorter than 5 years, the coefficient δ_0 should be positive and δ_1 should be zero. If the forecast horizon is between 5 and 10 years, the coefficient δ_0 should be zero, but δ_1 should be positive. Finally, if the agents have a long horizon ($h \geq 10$ years), as in the standard model, both coefficients should be zero. A significantly positive coefficient denotes that, as the demographic information slowly leaks into the market, the prices of the industrial sectors adjust, generating industry-level forecastability of returns.

[10] The results are robust to the exclusion of the industry-by-industry reclassification.

Table 10 presents the estimates of (11). In the benchmark specification for the sample of 'Demographic Industries' (Column 1), the coefficient on medium-term demographics $\hat{\delta}_0$ equals -1.7 and is not significantly different from zero. The coefficient on long-term demographics $\hat{\delta}_1$ equals 5.1 and is significantly larger than zero. A one percent annualized increase in demand from year 5 to year 10 generates an additional abnormal yearly stock returns of 5.1 percent. The coefficients have approximately the same magnitude when industry dummy (Column 2) and year polynomials (Column 3) are introduced, although $\hat{\delta}_1$ is not significant in the first case. Over the more recent sample (Columns 4 through 6), we obtain the same pattern: the coefficient on medium-term demographics is insignificant, while the coefficient on long-term demographics is large and significant. In the overall sample (Columns 7 through 12), the coefficients have comparable and somewhat smaller magnitudes than in the Demographic Sample.

In Table 11, we perform the inattention test separately for the concentrated and the unconcentrated industries. As we discussed above, testing inattention using stock market reaction to demand changes is meaningful only for industries with substantial market power. We use a concentration measure as a proxy for market power and replicate the specification (11) separately for the industries with 4-concentration ratio above and below 40. Not surprisingly, for the sample of unconcentrated industries (Columns 3 and 4) there is no significant effect of demand changes on stock returns. In the sample of concentrated industries (Columns 1 and 2), instead, the effect is significant in two specifications out of three and twice as large as in the baseline specification. In industries where the measure of market power is high we find stronger evidence of industry returns forecastability using available demographic information.

Robustness. In Table 12 we replicate the results of Table 10 using different measures for medium-term and long-term consumption growth. Instead of using multi-year annualized growth rates, we use forecasted single-year growth rate of consumption between 2 and 3 years ahead and between 5 and 6 years ahead[11]. The regression specification is

$$r_{k,t_0+1,t_0} - \hat{\beta}_{k,t_0} r_{m,t_0+1,t_0} = \gamma + \delta_2 \left[\hat{c}_{k,t_0+3|t_0-2} - \hat{c}_{k,t_0+2|t_0-2} \right] + \delta_3 \left[\hat{c}_{k,t_0+6|t_0-2} - \hat{c}_{k,t_0+5|t_0-2} \right] + \varepsilon_{k,t}. \tag{12}$$

The coefficient $\hat{\delta}_2$ on consumption growth 2 to 3 years ahead is negative and insignificant, while the coefficient $\hat{\delta}_3$ on consumption growth 5 to 6 years ahead is positive and significant: one percent higher consumption growth 5 to 6 years ahead increases stock returns by over 4 percentage points. Again, the medium-term consumption growth is insignificant, while the long-term consumption growth forecasts stock returns.

[11]The results do not change if we use instead years 1 to 2 and 4 to 5, or 3 to 4 and 6 to 7.

3.7 Demographic Portfolio Returns

The regressions in the previous section provide evidence of predictability of industry-level stock returns using consumption growth due to demographics between 5 and 10 years into the future. In this Section, we analyze whether one can exploit the underreaction to long-term demographic information by creating a portfolio strategy that generates abnormal returns.

First, we construct a portfolio of stocks from 1938 to 2002 using the companies belonging in the sample of Demographic Industries. Each year the industries are sorted by the forecasted consumption growth in years 5-10. The zero-cost portfolio is long in the stocks of industries in the top third of the consumption growth measure and is short in companies belonging to industries in the bottom third. We compute a series of monthly stock returns equally-weighted by industry from this portfolio.

We then control for market performance by regressing the series on the CRSP value-weighted stock index net of the 1-month Treasury rate. The standard errors are corrected for heteroskedasticity and autocorrelation using the Newey-West estimator with 6 lags. The results of this regression appears in Table 13, Column 1. The constant in the regression is the annualized abnormal return of the portfolio relative to the market return. The zero-cost portfolio achieves a significant abnormal return of 5.4 percentage points annually. The outperformance becomes somewhat larger if, in addition to controlling for the market return, we control also for the size and the book-to-market factor (Column 2) and for the momentum factor (Column 3). These magnitudes are consistent with the estimates of the return regressions in Table 11. The abnormal return of 5.4 percentage points is approximately the product of the estimated $\hat{\delta}_1$ in equation (11) by the difference between the value of $\hat{c}_{k,t_0+10|t_0-2} - \hat{c}_{k,t_0+5|t_0-2}$ in the top and in the bottom third. This difference is 1.5 percent which, when multiplied by a $\hat{\delta}_1$ of 5.1, gives an estimate in the same order of magnitude as the 5 percent yearly outperformance.

In Columns 4 through 6 we report the abnormal performance of a portfolio formed in a similar way over the second half of the sample. During this time period, the portfolios are chosen out of a substantially larger set of industries, and each industry contains more firms. In addition, the industry classification is likely to be more accurate. This portfolio has abnormal annual returns of over 10 percentage points per year. Finally, in Columns 7 through 9 we restrict the industry categorization to depend only on SIC code classification, and not on manual reclassification of companies within an SIC code. For example, the categories of books for children, for K-12, and for college disappear, since they depend on a company-by-company classification. Other categories, while still defined, are categorized less precisely: for example, the toy industry now contains golf equipment retailers. The portfolios formed with this restricted subsample outperform the market by a (marginally significant) annual return of around 4 percentage points. The outperformance appears to be reduced by the rougher classification system, but does not disappear.

In Table 14 we present the results for a similar zero-cost portfolio constructed using the whole sample of 48 industries. The portfolio is long in the stocks of industries in the top third of the consumption growth measure and is short in companies belonging to industries in the bottom third. The sample is restricted to the years past 1947, the first year of availability of concentration data. The portfolio so constructed attains annual abnormal returns of 2 percentage points (Columns 1 through 3). The lower returns on this larger sample are consistent with the substantially smaller difference between the average forecasted consumption growth in the top third and bottom third, .6 percentage points.

In Columns 4 through 9 of Table 14 we construct two additional zero-cost portfolios. The first includes only companies in industries with concentration ratio higher than .40, while the second includes only companies in industries with concentration ratio smaller than or equal to .40. The portfolio return in the sample of high-concentration industries is over 5 percentage points and significant, while the portfolio return in the sample of low-concentration industries is below 2 percentage points and insignificant. This difference is consistent with the earlier results that the abnormal returns are substantially higher in the high-concentration sample.

Overall, the portfolio returns from trading on long-term demographic information appear to be quite large. The underreaction to demographic information is not corrected despite substantial positive returns of trading on demographic variables.

4 Attention and Other Interpretations

Three stylized facts emerge from the section discussing industry returns. First, forecastable future demand changes due to demographic variables predict annual stock returns. Second, this predictability result is stronger in industries with higher concentration (a proxy for the ability of companies to extract rent) and with more variable demand shifts caused by demographics. Third, medium-term (0 to 5 years) demographic changes do not appear to forecast returns, while long-term (5 to 10 years) demographic changes do. These results extend to portfolio measures of abnormal returns.

The second set of results lends itself readily to interpretations based on the industrial organization of the industry and the nature of the demand shift. In industries with low barriers to entry, demand changes should not have a significant impact on firm profits. Demand shifts in these industries lead to entry or exit, profits are unchanged and stock returns should not respond. Similarly, in industries with relatively uniform age profiles of consumption, changes in cohort sizes have a limited impact on revenue. As a consequence, in this situation earnings and stock prices do not respond either. These results fit well also with the empirical relationship between demand shifts and return on equity. Profitability responds strongly to contemporaneous demographic shocks only in industries where measured concentration is high and where the consumption profile depends markedly on age.

The third set of results points to the nature of the mispricing that gives rise to forecastability. We can interpret the results within the framework of Section 2. The lack of predictability from medium-run demographic changes suggests that medium-run demographic changes are already embedded into asset prices. In the language of the model, the investor horizon h is probably at least as long as 5 years. In particular, consistently with the model this term has a negative coefficient (although not significant), as we would have expected from equation (9).

Conversely, the forecastability from long-run demographic changes suggests that the information regarding long-run demographic changes is not (yet) fully incorporated by market participants. According to the model, the investment horizon h lies between 5 and 10 years. The results in Table 12 suggest that the horizon may well be approximately 5 years.

The model in Section 2 makes also predictions regarding the magnitudes of the coefficients. In particular, the model with unconditional inattention ($w = 1$) suggests that the coefficient $\hat{\delta}$ of returns on consumption growth $h+1$ years ahead should be smaller than the responsiveness $\hat{\beta}$ of log ROE to demand changes: $\hat{\delta} = \rho^h \hat{\beta}$. Instead, the estimated coefficient $\hat{\delta}$ (≈ 5) is approximately four times larger than $\hat{\beta}$ (≈ 1.3). A model with inattention with some extrapolation ($w < 1$) can fit the magnitudes. The coefficient $\hat{\delta}$ should be a convex combination of $\rho^h \hat{\beta}$ (first term in equation (9)) and $\rho^{h+1}\hat{\beta}/n\,(1-\rho)$ (third term in equation (9)), plus another positive term (second term in equation (9)). A yearly discount factor ρ of .95 and an extrapolation interval $n = 2$ imply that $\rho^{h+1}\hat{\beta}/n\,(1-\rho)$ is approximately ten times larger than $\rho^h \hat{\beta}$. Therefore, the finding of a large effect of demand changes on stocks (large $\hat{\delta}$) is consistent with a version of the model with some extrapolation.

Overall, the interpretation of the empirical results suggested by the model is that investors are short-sighted and do not pay attention to earnings changes that occur more than 5 years into the future.

Stylized evidence on analyst forecasts is consistent with this conclusion. In Table 15 we use the I/B/E/S data to document the pattern of earnings forecasts by analysts at different horizons. In Column 1 we consider forecasts made in 1990 and report the number of companies with at least one earning forecast h years into the future. Almost all companies in the sample appear to have earnings forecasts for the next two years. The number of forecasts further in the future, however, decays very quickly with distance. Less than half of the companies have forecasts 3 years ahead and less than 10 percent of the companies have forecasts 5 years out. Forecasts beyond 5 years are not even reported in the data set. Not surprisingly, the share of firms with forecasts 3, 4, and 5 years ahead is higher among the firms with at least 5 analysts (Columns 2 and 3). However, even in this group the percentage of firms with 5-year-ahead forecasts is only 15 percent. Columns 4 through 6 show the same statistics for forecasts made in year 2000. The share of firms making forecasts 4 and 5 years out is somewhat smaller than in 1990.

Overall, analysts do not appear to produce forecasts of yearly earnings beyond 3 to 5 years in the future. An alternative possibility is that they do produce them but do not report them in this data. In either case, this information is unlikely to be easily available to investors. This evidence suggests that, while investors are likely to have access to earning forecasts for the next couple of years, they are unlikely to have information beyond five years into the future. Given this, it would not be surprising if investors, as a rule of thumb, considered only outcome up to 3 to 5 years into the future.

The possibility that investors may be short-sighted with respect to future information should not be surprising. Most of the time, neglect of events in the distant future is a reasonable strategy. Most long-term trends, including consumer taste changes, are already present in the short-term trend, making such long-term trends redundant information. Other long-term events, such as the approval of some legislation, are surrounded by so much uncertainty to justify their neglect. In the case of demographic information, however, investors neglect a change in demand that is estimated precisely and that may differ significantly from the short-term trend.

Neglect of slowly-moving variables. A second attention-based interpretation of the results is based on the neglect of slowly-moving variables. In the frenzy of earnings and merger announcements, liquidity-driven orders, and media headlines about world news, investors are likely to disregard trending variables that display little daily variation, like demographics. If investors focus on daily changes, they may in fact never notice a change in these variables. Studies on just-noticeable differences (Weber, 1834) suggest a minimum size of a stimulus necessary for detection, let alone to attract attention. Recent studies of visual perception have analyzed conditions under which subjects detect a change between two scenes. Simons, Franconeri, and Reimer (2000) expose one group of subjects to a 12-second movie of a natural scene where one item in the scene gradually changes color. In the control group, subjects watch for 11 seconds the first image of the same movie, and then see the final image. The subjects in the gradual-change condition detect 31% of the color changes, while subjects in the abrupt-change condition detect 92% of the changes.

Overall, the experimental evidence suggests that discrete changes are likely to be detected and capture attention. Small, continuous changes, instead, are less likely to be noticed and attended to. In general, the strategy of considering only variables that exhibit daily large changes is quite effective. Focusing on the daily news and ignoring the trends is a rational choice for most days. However, neglecting trends forever is not the optimal strategy. Attentive investors should periodically evaluate the trends.

The findings in this paper are consistent with individuals neglecting information generated by slowly-moving variables. Demographic trends are an important example of such a variable. If investors neglect demographic trends, long-term demographic news can forecast the stock market. The baseline model of neglect of slowly-moving variables however suggests, counter-factually, that short-term consumption growth due to demographics should also forecast the stock market. A slightly more general version of the model, however, can fit the evidence. Assume that demographic trends over the next 2 years are strongly correlated with contemporaneous trends, and therefore are largely reflected in current accounting variables such as revenue and return on equity. Given that inattentive investors price correctly discrete events such as earnings announcements, medium-run demographic trends would be incorporated in stock prices. In this case, short-term trends would not lead to forecastability, while long-term trends would.

Limits to arbitrage. Other interpretations of the results are possible. Certainly, limits to arbitrage (De Long et al., 1990; Shleifer, 2000) are relevant for an explanation of our results. We could embed the model in Section 2 within a model with heterogeneity of beliefs among investors and limited arbitrage (due to risk aversion or agency considerations). The noise traders in this situation ignore demographic trends, while rational investors take them into account The standard noise trader models would predict that market arbitrageurs do not fully eliminate the mispricing of this information.

Rational Forecastability. Demographic information could proxy for a state variable that systematically alters the future investment opportunity set, in which case returns would be rationally predictable (Merton, 1973).

Limited computing power. Other interpretations of the results do not rely on inattention. The results may be due to superior forecasting technology that was not available in the past. Although the empirical strategy in this paper is simple, it still requires least-squares regressions on consumption surveys and matrix computations to obtain forecasts of future demand. Both operations would have been very tedious in 1960, and close to impossible in 1930. A partial test of this hypothesis is the fact that the evidence of forecastability of returns for the years after 1975 (Table 10) appears to be stronger than for the overall sample. Yet, in the years since 1975 computing has become increasingly available. This finding is inconsistent with the explanation of the results based on lack of computing power.

Agency problem. The results could also be due to agency problem within the money management business. Traders may be well aware of demographic trends. However, if their performance is evaluated at a yearly horizon, they may pay little attention to variables that increase performance in the long-run but not necessarily in the short-run. Although this is plausible, our results suggest forecastability of stock returns already at a yearly horizon.

5 Conclusions

We have presented evidence relating demographic variables to consumption patterns, company sales, profits, and stock returns. For consumption patterns, we find that different goods have substantially different age patterns of consumption and that these patterns are persistent over the years. While some age patterns are obvious—childhood- and old age-related goods—, other patterns are not. For example, consumption of liquor peaks 20 years after consumption of beer and wine, and purchases of small appliances lag purchases of large appliances.

We combine our estimates of consumption by age with forecasts of cohort size by age. The result is a set of forecasts of growth of consumption due to demographic changes for 48 different expenditure categories and over 66 years. We match the expenditure categories to industry-level measures of accounting and stock market returns. The forecasted growth rates in consumption predict rates of return on equity across industries and over time. The forecastability of profit rates is higher for more concentrated industries and for industries with more pronounced age patterns of consumption.

Finally, we regress industry returns on growth rates of consumption due to demographics. We find that long-term growth rates of consumption can forecast annual stock returns, but medium-term growth rates do not. The forecastability is stronger for the industries in which profits rates respond to demographic changes, that is, more concentrated industries and in industries with stronger age patterns.

We interpret the results in light of an inattention story. The evidence supports the hypothesis that investors are short-sighted and neglect information about long-term events. In particular, investors appear to neglect information beyond a five year horizon. This finding is consistent with the near absence of analyst forecasts for periods beyond 5 years in the future.

The paper points to a novel form of mispricing in financial markets. The finding of investor short-sightedness has implications for other economic decisions beyond portfolio choices. Voters and consumers may neglect relevant information about long-run outcomes in their decisions. Workers may disregard forecastable future demand changes in their choice of jobs (Zarkin, 1985). Managers may neglect long-term trends in demand in their strategy decisions. Further tests of the response to future anticipated events will cast more light on the phenomenon uncovered in this paper.

References

[1] Ang, Andrew and Angela Maddaloni. ”Do Demographic Changes Affect Risk Premiums? Evidence from International Data,” ECB Working Paper no. 208, January 2003.

[2] Auerbach, Alan and Ronald Lee, ed. *Demographic Change and Fiscal Policy.* Cambridge University Press, Cambridge, January 2001.

[3] Bakshi, Gurdip S, and Zhiwu Chen. ”Baby Boom, Population Aging, and Capital Markets,” *Journal of Business,* Vol. 67(2), 165–201, 1994.

[4] Barber, Brad M. and Terrance Odean. ”All that Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors,” UC Berkeley Working Paper, April 2002.

[5] Barberis, Nick and Andrei, Shleifer. ”Style Investing”, forthcoming, *Journal of Financial Economics.*

[6] Basu, Sanjoy. ”The Relationship Between Earnings Yield, Market Value, and Return for NYSE Common Stocks: Further Evidence,” *Journal of Financial Economics,* Vol. 12, 129-156, 1983.

[7] Bell, Felicitie C., Alice H. Wade, and Stephen C. Goss. ”Life Tables for the United States Social Security Area 1900-2080,” Actuarial Study No. 107, SSA Pub. No. 11-11536.

[8] Bernard, Victor L. and Jacob K. Thomas. ”Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium?” *Journal of Accounting Research*, Vol. 27, 1-36, 1989.

[9] Bound, John and Sarah Turner. ”Cohort Crowding: How Resources Affect Collegiate Attainment?”, mimeo, University of Michigan, Ann Arbor, March 2003.

[10] Campbell, John Y. “A Variance Decomposition for Stock Returns”, *Economic Journal,* Vol. 101, 157–179, 1991.

[11] Campbell, John Y. and Robert J. Shiller. “The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors”, *Review of Financial Studies,* Vol. 1, 195–228, 1988a.

[12] Campbell, John Y. and Robert J. Shiller. “Stock Prices, Earnings, and Expected Dividends”, *Journal of Finance,* Vol. 43, 661–676, 1988b.

[13] Card, David, and Lemieux, Thomas. ”Dropout and Enrollment Trends in the Post-War Period: What Went Wrong in the 1970s?” in J. Gruber, ed. *An Economic Analysis of Risky Behavior Among Youth.* University of Chicago Press, Chicago, 2000, 439–482.

[14] Costa, Dora. "American Living Standards: Evidence from Recreational Expenditures," NBER Working Paper 7148, May 1999.

[15] De Long, J. Bradford, Andrei Shleifer. Lawrence H. Summers, Robert J.Waldmann. "Noise Trader Risk in Financial Markets." *Journal of Political Economy,* August 1990, Vol. 98(4), pp. 703–738.

[16] DeBondt, Werner F.M. and Thaler, Richard. "Does The Stock Market Overreact?" *Journal of Finance,* Vol. 40, 793–805, 1985.

[17] Easterlin, Richard A. *Birth and Fortune: The Impact of Numbers on Personal Welfare.* University of Chicago Press, Chicago, 1987.

[18] Fair, Ray C. and Kathryn M. Dominguez. "Effects of the Changing U.S. Age Distribution on Macroeconomic Equations," *American Economic Review,* Vol. 81(5), 1276–1294, December 1991.

[19] Fama, Eugene F., and Kenneth R. French, "Permanent and temporary components of stock prices", *Journal of Political Economy,* Vol. 96, 246–273, 1988a.

[20] Fama, Eugene F., and Kenneth R. French, "Dividend yields and expected stock returns," *Journal of Financial Economics,* Vol. 22, 3–27, 1988b.

[21] Fama, Eugene F., and Kenneth R. French, "The cross-section of expected stock returns," *Journal of Finance,* Vol. 47, 427–465, 1992.

[22] Gabaix, Xavier and David Laibson "Bounded rationality and directed cognition", Mimeo, MIT, 2002.

[23] Gabaix, Xavier, David Laibson, Guillermo Moloche and Stephen Weinberg "The allocation of attention: Theory and evidence", Mimeo, MIT, 2002.

[24] Geneakoplos, John, Michael J.P. Magill and Martine Quinzii. "Demography and the Long-Run Predictability of the Stock Market", Yale Cowles Foundation Discussion Paper no. 1380, August 2002.

[25] Goyal, Amit. "Demographics, Stock Market Flows, and Stock Returns," *Journal of Financial and Quantitative Analysis,* Forthcoming.

[26] Gruber, Jonathan and David Wise. "Social Security Programs and Retirement around the World," *Research on Labor Economics,* Vol. 18, 1999, 1-40.

[27] Hall, Brownyn, and Hall, Robert E."The Value and Performance of U.S. Corporations," *Brookings Papers on Economic Activity,* (1), 1-50, 1993.

[28] Heuser, Robert L. "Fertility tables for birth cohorts by color." U.S. Department of Health, Education, and Welfare. DHEW Publication No. 76-1152, 1976.

[29] Hong, Harrison, Torous, Walter, and Ross Valkanov. "Do Industries Lead the Stock Market?" Mimeo, UCLA, July 2003

[30] Huberman, Gur, and Regev, Tomer. "Contagious Speculation and a Cure for Cancer: A Nonevent that Made Stock Prices Soar", *Journal of Finance*, Vol. 56(1), 387–396, February 2001.

[31] Hurd, Michael D. "Research on the Elderly: Economic Status, Retirement, and Consumption and Saving," *Journal of Economic Literature,* Vol. 28(2), 565-637, June 1990.

[32] Jegadeesh, Narasimhan, and Sheridan Titman. "Returns to Buying Winners and Selling Losers: Implications For Stock Market Efficiency," *Journal of Finance,* Vol. 48, 65-91, 1993.

[33] Lakonishok, Josef, Andrei Shleifer, and Robert. W. Vishny. "Contrarian Investment, Extrapolation, and Risk." *Journal of Finance,* Vol. 49(5), 1541-1578, 1994.

[34] Moskowitz, Tobias J. and Mark Grinblatt. "Do Industries Explain Momentum?" *Journal of Finance,* Vol. 54(4), 1249-1290, August 1999.

[35] Mankiw, Gregory N. and David N. Weil. "The Baby Boom, the Baby Bust, and the Housing Market," *Regional Science and Urban Economics,* Vol. 19, 235-258, 1989.

[36] Mankiw, Gregory N. and David N. Weil. "The Baby Boom, the Baby Bust, and the Housing Market: A Reply to Our Critics," *Regional Science and Urban Economics,* Vol. 21, December 1991.

[37] Mankiw, Gregory N. and Michael D. Whinston. "Fee Entry and social Inefficiency," *RAND Journal of Economics,* Vol. 17(1), 48–58, Spring 1986.

[38] Poterba, James M. "Demographic Structure and Asset Returns," *The Review of Economics & Statistics,* Vol. 83(4), 2001, 565-584.

[39] Rashes, Michael. "Massively Confused Investors Making Conspicuously Ignorant Choices (MCI-MCIC)", *Journal of Finance,* Vol. 56(5), 1911–1927, October 2001.

[40] Shleifer, Andrei. *Inefficient markets: An introduction to behavioral finance. Clarendon Lectures in Economics.* Oxford and New York: Oxford University Press, 2000.

[41] Simons, Daniel J. and Steven L. Franconeri, Rebecca L. Reimer. "Change Blindness in the Absence of a Visual Disruption". *Perception,* Vol. 29, 1143-1154, 2000.

[42] Simons, Daniel J. and Levin. "Failure to Detect Change to People in a Real-World Interaction", *Psychonomic Bulletin and Review,* 5(4), 644–649, 1998.

[43] U.S. Department of Commerce, Bureau of the Census. "Estimates of the Population of the US by Age, Sex, and Race" in *Current Population Reports,* Series P-25 (Numbers 311, 519, 917, 965, and 985) Washington DC: US Government Printing Office, various years.

[44] U.S. Department of Labor. Bureau of Labor Statistics. *Consumer Expenditure Survey, 1960-1961.* ICPSR 9035. Ann Arbor, MI: Inter-university Consortium for Political and Social Research, 1983

[45] U.S. Department of Labor. Bureau of Labor Statistics *Survey of Consumer Expenditures, 1972-1973.* ICPSR 9034. Inter-university Consortium for Political and Social Research, 1987.

[46] U.S. Department of Labor, Bureau of Labor Statistics and United States Department of Agriculture, Bureau of Home Economics, et al. *Study of Consumer Purchases in the United States, 1935-1936.* ICPSR 8908. Ann Arbor,MI: Inter-university Consortium for Political and Social Research, 1999.

[47] US Department of Health and Human Services, Public Health service, Centers for Disease Control and Prevention, National Center for Health Statistics, *Vital Statistics of The United States 1992: Natality* Vol. 1, 1996.

[48] Vuolteenaho, Tuomo. "What Drives Firm-Level Stock Returns", *Journal of Finance,* Vol. 57(1), 233–264, 2002.

[49] Watts, Ross L. "Systematic 'Abnormal' Returns After Quarterly Earnings Announcements," *Journal of Financial Economics*, Vol. 6, 127-150, 1978.

[50] Weber, E. H. *De Pulsu, Resorptione, Auditu, et Tactu. Annotationes Anatomicae et Physiologicae.* Koehler, Leipzig, 1834.

[51] Zarkin, Gary. "Occupational Choice: An Application to the Market for Public School Teachers", *Quarterly Journal of Economics,* Vol. 100(2), 409–446, 1985.

Figure 1a. Forecasts of Total Population Ages 30-34

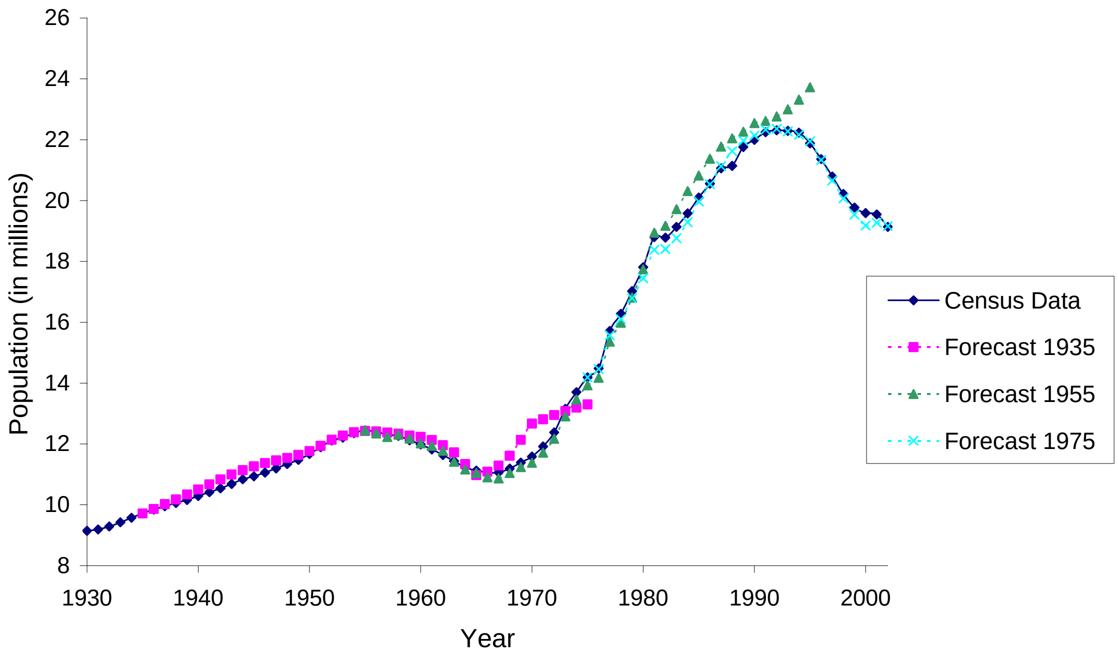
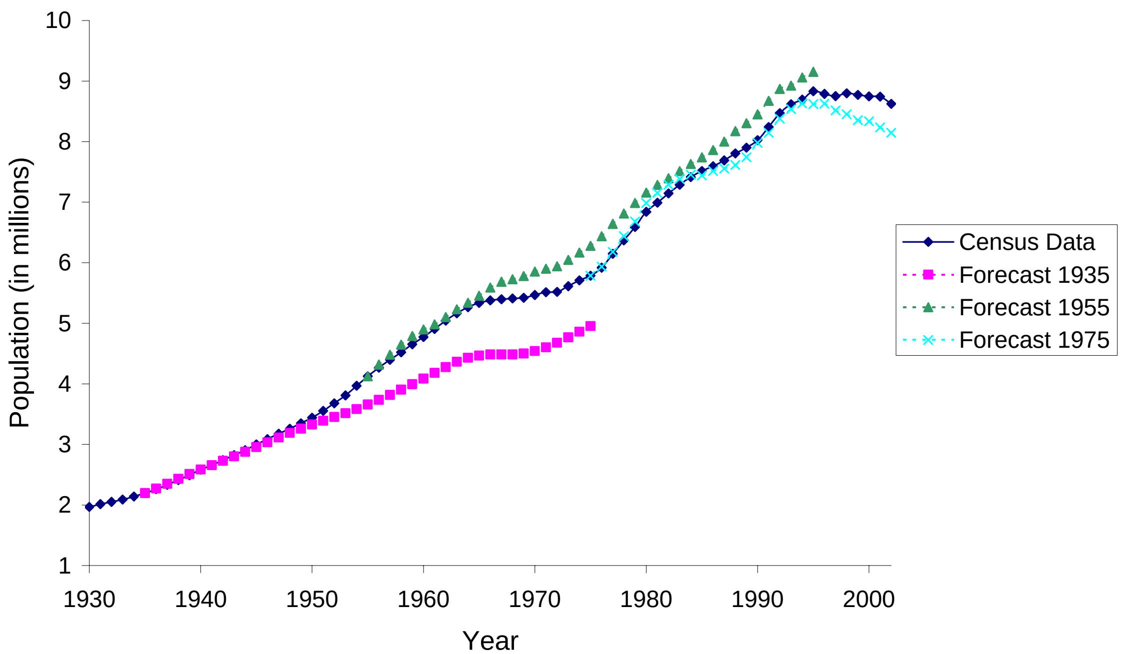


Figure 1b. Forecasts of Total Population Ages 70-74



Note. Figures 1a and 1b display time series of actual and forecasted cohort size for the age groups 30-34 and 70-74. Each Figure shows the actual time series as well as three different 40-year forecasts as of 1935, 1955, and 1975. Details on the forecasting methodology are in the text.

Figure 2a. Age Profile of Bicycle and Drugs Consumption

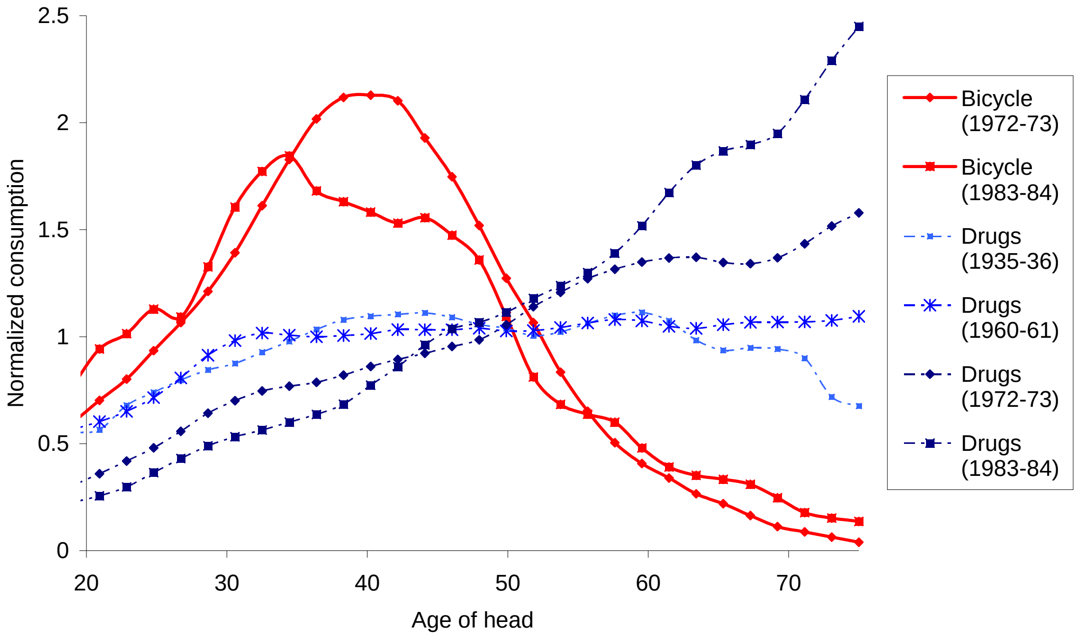
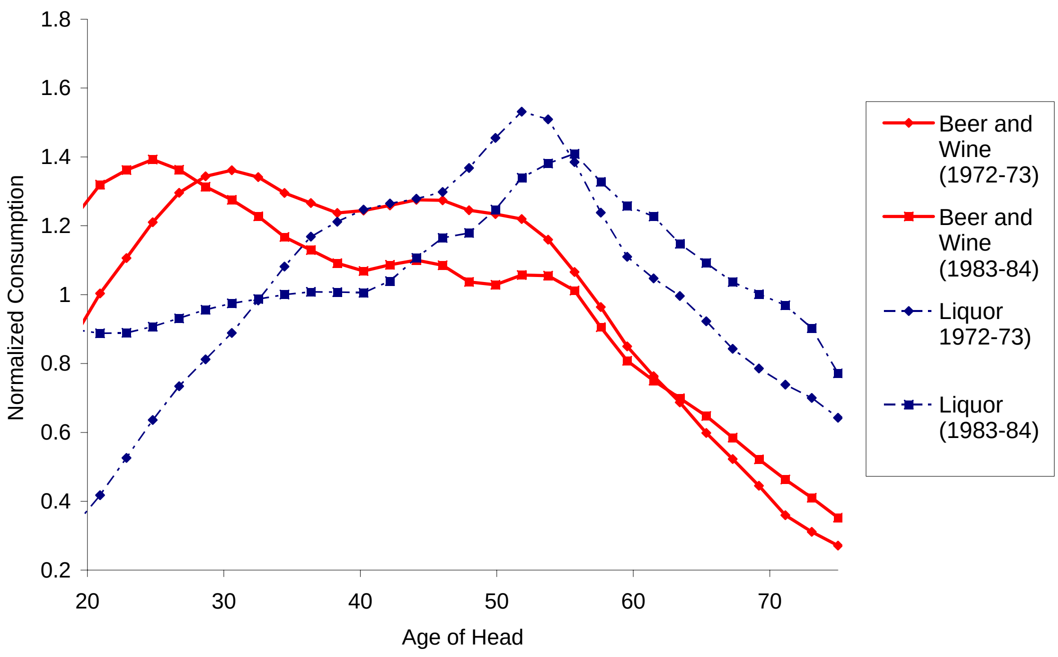
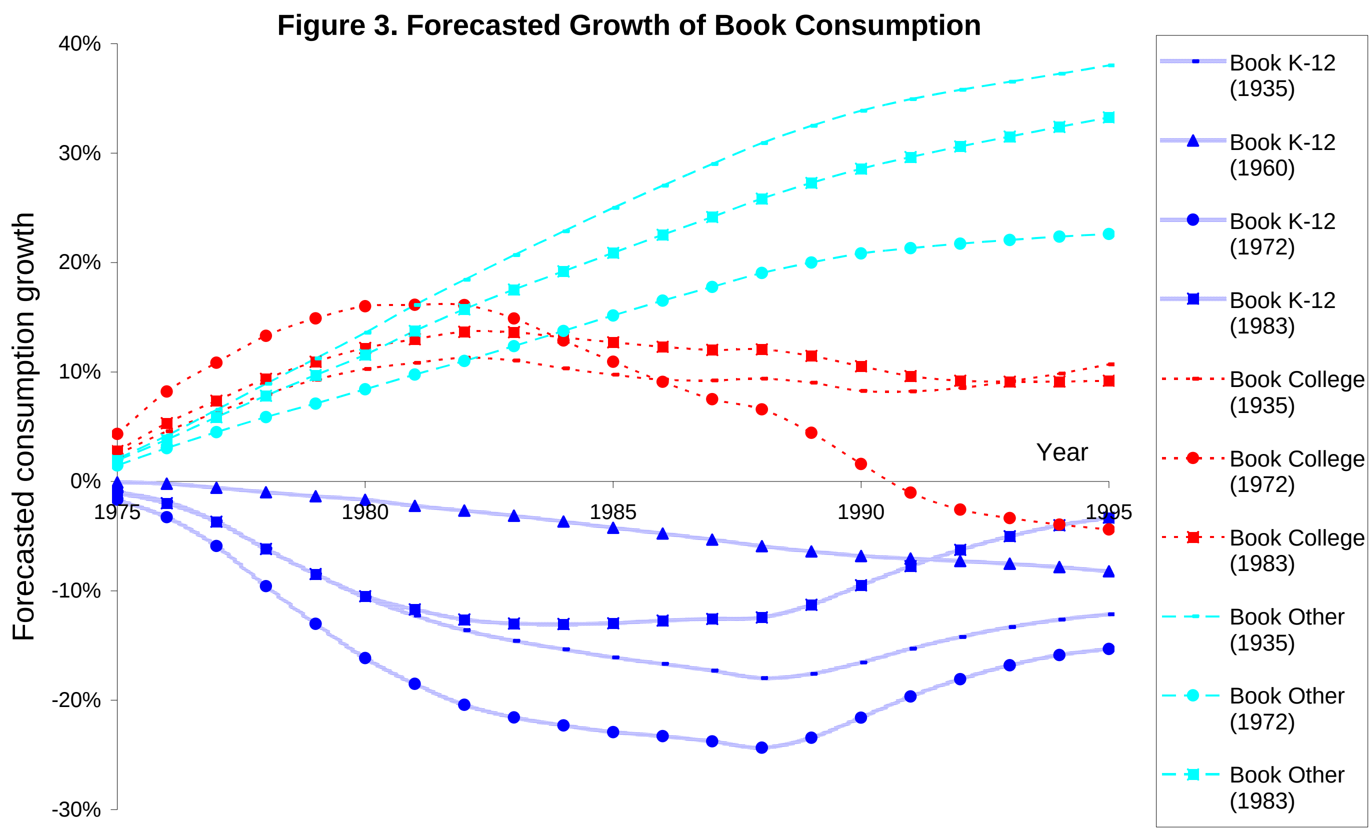


Figure 2b. Age Profile of Beer and Liquor Consumption



Note. Figures 2a and 2b display a kernel regression of normalized household consumption on a good as a function of the age of the household head. The regressions use an Epanechnikov kernel and a bandwidth of 5 years. The expenditure figure is normalized so that the average consumption on a good across all ages equals 1. Each different line for a good uses an age-consumption profile from a different consumption survey. For bicycles and alcohol consumption, no data is available for the 1935-36 and the 1960-61 surveys.



Note. Figure 3 displays the predicted consumption growth due to forecasted demographic changes for three subcategories of books: books for K-12 schools, books for higher educations, and other books (mainly fiction). The forecasts are computed combining the demographic information of year 1975 and age-consumption profiles for the 1935-36, 1960-61, 1972-73, and 1983-84 consumption surveys. Each different line for a good uses an age-consumption profile from a different data set. The forecast for higher education books and other books for 1960 is missing since the 1960-61 survey does not record book expenditure to the same level of detail.

Table 1: Predictability of Population Growth Rates By Age Group

	Dependent variable: Annual Population growth rates for each age										
	Newborns	Ages 1-9	Ages 10-19	Ages 20-29	Ages 30-39	Ages 40-49	Ages 50-59	Ages 60-69	Ages 70-79	Ages 80-89	Ages 90-99
Constant	0.0135	0.0009	0.0020	0.0012	0.0029	0.0030	0.0029	0.0043	0.0068	0.0296	0.0400
	(0.0039)***	-0.0006	(0.0004)***	(0.0006)*	(0.0006)***	(0.0006)***	(0.0005)***	(0.0004)***	(0.0005)***	(0.0007)***	(0.0008)***
Forecasted annual population growth	0.8540	0.8450	0.9260	0.8379	0.8058	0.8189	0.7997	0.7328	0.6775	0.1133	0.2429
	(0.0905)***	(0.0109)***	(0.0074)***	(0.0112)***	(0.0115)***	(0.0108)***	(0.0111)***	(0.0138)***	(0.0143)***	(0.0099)***	(0.0146)***
R^2	0.4064	0.8342	0.9216	0.8100	0.7894	0.8141	0.7966	0.6808	0.6297	0.0895	0.1743
N	*N* = 132	*N* = 1188	*N* = 1320	*N* = 1320	*N* = 1320	*N* = 1320	*N* = 1320	*N* = 1320	*N* = 1320	*N* = 1320	*N* = 1320

Notes: Reported coefficents from the regression of annual population growth rates by age and gender onto the corresponding 1 year ahead forecasted annual growth rates. The regression specification is $y_{it} = \alpha + \beta x_{it} + \varepsilon_{it}$ where t is a year ranging form 1935 to 2000 and i is a age-gender observation within the relevant age range indicated at the top of each column. The OLS standard errors are in parentheses. The actual and estimated growth rates are defined as the difference in the log population for a particular age-gender pair.

***** Actual growth rates for ages 0 to 99 are calculated using the P-25 Series from the *Current Population Reports* provided by U.S. Census. Estimated growth rates are calculated using the previous year's P-25 data and mortality rates from the period life table at the beginning of the decade from *Life Tables for the United States Social Security Area 1900-2080.* The estimated growth rate for the population of newborns is calculated by applying birth rates from the previous year to the forecasted age profile of the female population. Details on the data and the forecasting procedure are in the text.

Table 2. Summary Statistics on Household Demographics

Consumer Survey	1935-36	1960-61	1972-73	1983-84
Demographic Variables	(1)	(2)	(3)	(4)
Age of Head	44.26	48.28	47.87	44.17
	(12.7)	(15.68)	(17.38)	(18.3)
Male Head	1.00	0.83	0.78	0.66
	(.)	(.37)	(.42)	(.47)
White Head	0.90	0.88	0.90	0.85
	(.29)	(.32)	(.3)	(.35)
Married Head	1.00	.77*	0.68	0.52
	(.)	(.42)	(.47)	(.5)
Age of Spouse	40.36	(.)*	42.96*	43.16*
	(12.12)	(.)	(15.1)	(15.54)
Number of Children Living at Home	1.29	1.12	1.05	0.74
	(1.28)	(1.46)	(1.52)	(1.15)
Number of Old People Living at Home	0.06	0.04	0.03	0.03
	(.26)	(.21)	(.18)	(.18)
Family Size	3.76	3.28	2.99	2.57
	(1.59)	(1.87)	(1.86)	(1.6)
Urban Household	0.50	0.75	0.84	0.91
	(.5)	(.43)	(.37)	(.28)
Economic Variables				
Total Income (in $)	11094.56	21144.98*	27347.78*	31262.18*
	(15087.03)	(16164.53)	(28872.33)	(37026.55)
Total Consumption (in $)	10030.84	16792.38	18108.06	17935.47
	(8132.27)	(10247.24)	(11743.3)	(13339.84)
Number of Observations	*N* = 6113	*N* = 13728	*N* = 19975	*N* = 13133

Notes: Columns 1-4 present household-level summary statistics on demographic and economics variables in the consumption surveys. Column 1 refers to the *Study of Consumer Purchases in the United States, 1935-36.* Column 2 refers to the *Survey of Consumer Expenditures, 1960-1961.* Column 3 refers to the *Survey of Consumer Expenditures, 1972-1973.* Column 4 refers to the *Consumer Expenditure Survey., 1983-84.*

***** The information on the age of the spouse is missing in the 1960-61 survey. The variable Age of spouse is defined for 13,534 (in 1972-73) and 6,798 (in 1983-84) observations. The variable Married Head is defined for 13,722 observations in the 1960-61 survey. The variable Total income is defined for 13,694 observations in 1960-61, 18,861 observations in 1973-73, and 9,230 observations in 1984-84.

Table 3. Summary Statistics on Expenditure by Good

Consumer Survey	1935-36		1960-61		1972-73		1983-84	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expenditure Category	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Child Care	1.43	(32.36)	(.)	(.)	91.31	(384.58)	117.20	(602.53)
Children's Books	(.)	(.)	(.)	(.)	0.47	(15.59)	2.70	(39.01)
Children's Clothing	7.42	(35.16)	18.56	(65.07)	21.37	(87.63)	38.42	(122.59)
Toys	24.90	(56.37)	(.)	(.)	13.77	(65.22)	75.36	(211.85)
Books -- college text books	12.94	(99.)	(.)	(.)	20.87	(141.47)	32.50	(129.94)
Books -- general	8.82	(56.52)	(.)	(.)	18.00	(92.56)	37.41	(102.77)
Books -- K-12 school books	25.09	(53.24)	(.)	(.)	5.75	(41.59)	5.15	(30.4)
Movies	84.33	(135.7)	(.)	(.)	101.76	(256.79)	77.44	(168.88)
Newspapers	101.31	(78.9)	147.71	(161.14)	53.16	(70.7)	87.27	(95.45)
Cruises	(.)	(.)	(.)	(.)	2.40	(73.91)	12.79	(334.96)
Dental Equipment	92.26	(220.23)	151.89	(331.08)	148.63	(400.42)	122.33	(396.62)
Drugs	75.18	(138.43)	223.29	(300.52)	109.58	(214.28)	105.30	(219.93)
Glasses (not Sunglasses)	30.37	(79.92)	53.79	(104.78)	57.24	(123.39)	54.43	(151.36)
Health Care (Services)**	338.53	(688.64)	688.70	(890.59)	800.52	(1160.57)	549.19	(1035.64)
Health Insurance**	338.53	(688.64)	688.70	(890.59)	800.52	(1160.57)	549.19	(1035.64)
Medical Equipment**	338.53	(688.64)	688.70	(890.59)	800.52	(1160.57)	549.19	(1035.64)
Funeral Homes and Cemet.	21.03	(248.98)	(.)	(.)	3.24	(95.05)	51.98	(531.13)
Nursing Home Care	18.70	(208.13)	(.)	(.)	14.31	(273.54)	13.84	(298.35)
Construction Equipment*	64147.75	(62280.86)	36572.52	(28994.04)	46082.30	(40330.29)	56074.95	(52995.65)
Floors	37.51	(167.73)	86.83	(358.19)	94.26	(389.43)	59.37	(400.31)
Furniture	87.56	(297.42)	246.19	(578.63)	295.62	(772.49)	277.51	(1078.15)
Home Appliances Big	164.52	(408.67)	231.24	(495.04)	408.62	(666.92)	322.09	(675.65)
Home Appliances Small	15.17	(48.06)	25.01	(65.31)	54.77	(150.7)	61.53	(179.32)
Housewares	18.18	(55.41)	46.01	(121.71)	21.36	(94.45)	31.66	(125.94)
Linens	44.17	(80.35)	108.89	(177.62)	108.02	(238.89)	75.46	(226.54)
Residential Construction*	64147.75	(62280.86)	36572.52	(28994.04)	46082.30	(40330.29)	56074.95	(52995.65)
Residential Development*	64147.75	(62280.86)	36572.52	(28994.04)	46082.30	(40330.29)	56074.95	(52995.65)
Residential Mortgage	217.45	(636.88)	379.23	(735.42)	636.00	(1449.82)	1140.54	(2635.34)
Beer (and Wine)	61.02	(255.37)	525.30	(1116.88)	337.49	(802.86)	508.11	(849.15)
Cigarettes	137.78	(203.99)	299.85	(328.04)	264.14	(365.08)	201.98	(304.69)
Cigars and Other Tobacco	63.36	(133.88)	(.)	(.)	24.90	(110.19)	14.43	(67.44)
Food	3130.90	(2041.04)	4104.13	(2369.29)	3968.45	(2847.73)	3084.30	(2004.85)
Liquor	(.)	(.)	(.)	(.)	19.55	(54.01)	(49.36)	(114.78)
Clothing (Adults)	931.04	(1054.04)	1092.44	(1163.94)	868.30	(989.58)	605.21	(865.95)
Cosmetics	69.53	(96.77)	(.)	(.)	148.58	(243.73)	111.70	(165.3)
Golf	12.80	(99.65)	(.)	(.)	(.)	(.)	(.)	(.)
Jewelry	4.33	(13.33)	(.)	(.)	30.05	(195.)	83.30	(493.15)
Sporting Equipment	21.84	(68.1)	98.29	(254.94)	103.80	(210.47)	80.49	(229.07)
Life Insurance	672.52	(1462.62)	460.57	(838.06)	531.77	(951.55)	240.33	(866.86)
Property Insurance	98.15	(169.49)	329.21	(339.97)	389.85	(431.1)	442.40	(555.45)
Airplanes	(.)	(.)	(.)	(.)	97.26	(353.83)	179.70	(633.14)
Automobiles	764.45	(2105.43)	1002.87	(2437.16)	1571.92	(3323.69)	1729.10	(5085.54)
Bicycles	6.49	(37.03)	(.)	(.)	24.06	(83.33)	11.19	(98.27)
Motorcycles	(.)	(.)	(.)	(.)	36.38	(296.6)	27.06	(331.38)
Coal	205.40	(254.93)	(.)	(.)	11.14	(70.34)	2.84	(42.57)
Oil	480.00	(614.89)	1504.18	(964.36)	893.12	(811.44)	1076.62	(930.53)
Telephone	106.19	(141.12)	253.18	(224.38)	390.99	(339.01)	409.22	(359.85)
Utilities	383.44	(350.99)	1161.90	(792.22)	768.81	(568.66)	1045.84	(832.67)
Number of households	N = 6113		N = 13728		N = 19975		N = 13133	

Notes: Columns 1, 3, 5, and 7 present the average yearly household expenditure in the featured category. Columns 2, 4, 6, and 8 present the standard deviation across households. Columns 1 and 2 refer to the *Study of Consumer Purchases in the United States, 1935-36.* Columns 3 and 4 refer to the *Survey of Consumer Expenditures, 1960-1961.* Columns 5 and 6 refer to the *Survey of Consumer Expenditures, 1972-1973.* Columns 7 and 8 refer to the *Consumer Expenditure Survey., 1983-84.*

***** The consumption in the categories "Construction Equipment", "Residential Construction" and "Residential Development" is the estimated value in the dwelling of residence. Details are in the Appendix.

****** The consumption in the categories "Health Cares (Services)", "Health Insurance" and "Medical Equipment" is the total expenditure in health insurance, physicians, and hospitals. Details are in the Appendix.

Table 4: Summary Statistics For Predicted Demand Growth Rates

Expenditure Category	Grouping	Avg. Predicted 1-Year Growth Rate of Consumption	Std. Dev. Predicted 1-Year Growth Rate of Consumption	Demographic goods	Number of Observations
	(1)	(2)	(3)	(4)	(5)
Child Care	Children	0.0139	(0.0164)	Yes	65
Children's Books	Children	0.0164	(0.0165)	Yes	28
Children's Clothing	Children	0.0138	(0.0109)	Yes	65
Toys	Children	0.0138	(0.0069)	Yes	65
Books -- college text books	Media	0.0105	(0.0123)	Yes	65
Books -- general	Media	0.0122	(0.0049)	No	65
Books -- K-12 school books	Media	0.0116	(0.0152)	Yes	65
Movies	Media	0.0115	(0.0071)	Yes	65
Newspapers	Media	0.0127	(0.0037)	No	65
Cruises	Health	0.0167	(0.0057)	Yes	28
Dental Equipment	Health	0.0117	(0.0040)	No	65
Drugs	Health	0.0137	(0.0022)	No	65
Glasses (not Sunglasses)	Health	0.0124	(0.0025)	No	65
Health Care (Services)	Health	0.0132	(0.0028)	No	65
Health Insurance	Health	0.0132	(0.0028)	No	65
Medical Equipment	Health	0.0132	(0.0028)	No	65
Funeral Homes and Cemet.	Senior	0.0187	(0.0069)	Yes	53
Nursing Home Care	Senior	0.0144	(0.0046)	No	65
Construction Equipment	House	0.0004	(0.0091)	Yes	65
Floors	House	0.0129	(0.0046)	No	65
Furniture	House	0.0114	(0.0067)	Yes	65
Home Appliances Big	House	0.0112	(0.0044)	No	65
Home Appliances Small	House	0.0117	(0.0040)	No	65
Housewares	House	0.0128	(0.0045)	No	65
Linens	House	0.0131	(0.0037)	No	65
Residential Construction	House	0.0004	(0.0091)	Yes	65
Residential Development	House	0.0130	(0.0032)	No	65
Residential Mortgage	House	0.0135	(0.0052)	No	65
Beer (and Wine)	Perishable	0.0116	(0.0066)	Yes	65
Cigarettes	Perishable	0.0104	(0.0053)	No	65
Cigars and Other Tobacco	Perishable	0.0134	(0.0020)	No	65
Food	Perishable	0.0122	(0.0021)	No	65
Liquor	Perishable	0.0155	(0.0041)	No	28
Clothing (Adults)	Clothing	0.0122	(0.0055)	No	65
Cosmetics	Clothing	0.0118	(0.0059)	Yes	65
Golf	Clothing	0.0127	(0.0072)	Yes	65
Jewelry	Clothing	0.0121	(0.0057)	Yes	65
Sporting Equipment	Clothing	0.0111	(0.0053)	No	65
Life Insurance	Insurance	0.0129	(0.0034)	No	65
Property Insurance	Insurance	0.0138	(0.0029)	No	65
Airplanes	Transport	0.0166	(0.0038)	No	28
Automobiles	Transport	0.0115	(0.0055)	Yes	65
Bicycles	Transport	0.0110	(0.0104)	Yes	65
Motorcycles	Transport	0.0107	(0.0058)	Yes	28
Coal	Utilities	0.0124	(0.0025)	No	65
Oil	Utilities	0.0119	(0.0034)	No	65
Telephone	Utilities	0.0125	(0.0035)	No	65
Electricity	Utilities	0.0124	(0.0025)	No	65
Total Consumption		0.0125	(0.0041)	No	65

Notes: Complete list of expenditure categories, grouping in 10 broader groups (Column 1), average predicted one-year demand growth rate due to demographic changes (Column 2), standard deviation of predicted demand growth rate due to demographic change (Column 3), definition of subsample "*Demographic Goods*" (Column 4), number of years with demand growth estimates for each type of expenditure (Column 5). The subsample "Demographic Goods" is formed by the 20 expenditure categories with the highest within-good standard deviation of consumption growth due to demographics.

Table 5. Correlation between Forecasts of 1-Year Consumption Growth

Goods:	Consumption surveys:	1935-36 Survey	1960-61 Survey	1972-73 Survey	1983-85 Survey
All expenditure categories	**1935-36 Survey**	1 (*N* = 3015)			
	1960-61 Survey	0.777 (*N* = 2211)	1 (*N* = 2211)		
	1972-73 Survey	0.7934 (*N* = 2881)	0.8430 (*N* = 2211)	1 (*N* = 3216)	
	1983-85 Survey	0.8240 (*N* = 2881)	0.8453 (*N* = 2211)	0.8419 (*N* = 3216)	1 (*N* = 3216)
		1935-36 Survey	**1960-61 Survey**	**1972-73 Survey**	**1983-85 Survey**
Expenditure on Cars	**1935-36 Survey**	1 (*N* = 67)			
	1960-61 Survey	0.8939 (*N* = 67)	1 (*N* = 67)		
	1972-73 Survey	0.8743 (*N* = 67)	0.9846 (*N* = 67)	1 (*N* = 67)	
	1983-85 Survey	0.8962 (*N* = 67)	0.9827 (*N* = 67)	0.9951 (*N* = 67)	1 (*N* = 67)

	Source of demogr. data:	Actual Demographic Data	Forecasted Demographic Data
All expenditure categories	**Actual Demogr. Data**	1 (*N* = 3053)	
	Forecasted Demographic Data	0.6858 (*N* = 3042)	1 (*N* = 3144)

Note: This table presents simple correlation coefficients among different versions of the forecasted 1-year growth rate of consumption due to demographic changes. The sample includes the 48 expenditure categories over the years 1936-2002. The first set of correlations varies the source of the consumption coefficients. The consumption foreccasts in the first column are obtained using the age profile of consumption estimated on data from the *Study of Consumer Purchases in the United States, 1935-36* . The consumption forecasts in the second column use data from the *Survey of Consumer Expenditures, 1960-1961.* The third column uses data from the *Survey of Consumer Expenditures, 1972-1973.* and the last column uses the *Consumer Expenditure Survey., 1983-84* . The first set of correlation is for the whole sample of 49 expenditure categories, while the second set uses only the expenditure on cars. The last set of correlations holds constant the age profile of consumption and varies the source of demographic data. The first column uses the actual demographic cohort size data from the P-25 Bureau of Census Series. The second column uses forecasted demographic data to c

Table 6. Summary Statistics: Compustat Accounting Data

	Log Yearly Return on Equity			
	(1)	(2)	(3)	(4)
Industry Category	**Mean**	**Std. Dev.**	**No. Years**	**No. Firms**
Child Care	0.1379	(0.1181)	28	2.31
Children's Books	0.0923	(0.0720)	21	1.95
Children's Clothing	0.1746	(0.0845)	39	1.92
Toys	0.1423	(0.0746)	36	8.53
Books -- college text books	0.1904	(0.0502)	19	1.70
Books -- general	0.1394	(0.0610)	40	6.43
Books -- K-12 school books	0.1377	(0.0451)	33	2.11
Movies	0.1230	(0.0965)	51	16.19
Newspapers	0.1822	(0.0930)	50	13.69
Cruises	0.2025	(0.0692)	15	3.40
Dental Equipment	0.1115	(0.0895)	36	2.63
Drugs	0.1911	(0.0229)	51	82.35
Glasses (not Sunglasses)	0.1099	(0.1197)	20	2.58
Health Care (Services)	0.1569	(0.0855)	33	37.79
Health Insurance	0.1176	(0.0455)	30	10.10
Medical Equipment	0.1454	(0.0338)	51	53.19
Funeral Homes and Cemet.	0.1004	(0.0578)	34	2.15
Nursing Home Care	0.0987	(0.0827)	32	11.97
Construction Equipment	0.1378	(0.0675)	40	19.08
Floors	0.0926	(0.0384)	45	4.57
Furniture	0.1060	(0.0343)	51	14.44
Home Appliances Big	0.1677	(0.0615)	51	17.31
Home Appliances Small	0.1678	(0.0381)	51	4.31
Housewares	0.1112	(0.0619)	36	2.84
Linens	0.1271	(0.0651)	36	3.89
Residential Construction	0.1139	(0.0698)	37	10.41
Residential Development	0.1102	(0.0503)	39	36.30
Residential Mortgage	0.1603	(0.1009)	36	9.76
Beer (and Wine)	0.1396	(0.0474)	51	6.19
Cigarettes	0.1811	(0.0606)	51	3.79
Cigars and Other Tobacco	0.2002	(0.1130)	51	4.10
Food	0.1505	(0.0451)	51	155.63
Liquor	0.1134	(0.0563)	51	4.65
Clothing (Adults)	0.1515	(0.0392)	51	41.90
Cosmetics	0.2267	(0.0920)	46	8.22
Golf	0.0878	(0.0752)	29	3.93
Jewelry	0.1141	(0.0464)	35	8.41
Sporting Equipment	0.1493	(0.0816)	47	5.48
Life Insurance	0.1186	(0.0471)	37	11.84
Property Insurance	0.1251	(0.0563)	26	17.15
Airplanes	0.1391	(0.0648)	51	32.31
Automobiles	0.1460	(0.0738)	51	50.75
Bicycles	0.1149	(0.0952)	34	1.32
Motorcycles	0.2416	(0.0872)	16	1.00
Coal	0.1079	(0.0915)	44	6.41
Oil	0.1285	(0.0393)	51	138.92
Telephone	0.1027	(0.0432)	51	17.52
Electricity	0.1319	(0.0197)	43	132.37
Total Consumption	0.1222	(0.0194)	51	2956.82

Notes: The yearly return on equity is the weighted average of the company-level ROE. The latter is the ratio of book value of equity (Compustat data60) plus earnings (Compustat data172) in year t on the book value of equity in year t-1. Companies entering the industry between time t-1 and time t are excluded. Companies exiting the industry between time t-1 and time t are also excluded. Column 2 reports the within-industry standard deviation of the measure in Column 1. Also featured are the number of years for which the data is available (Column 3) and the average number of firms in the industry (Column 4).

Table 7. Summary Statistics: CRSP Data and Concentration Ratios

	Value Weighted Yearly Stock Return				Concentration Ratio	
	(1)	(2)	(3)	(4)	(5)	(6)
Industry Category	**Mean**	**Std. Dev.**	**No. Years**	**No. Firms**	**Largest 4 Firms**	**Year Measured**
Motorcycles	0.1960	(0.3800)	20	1.48	0.420	1947
Bicycles	0.0277	(0.4302)	35	1.50	0.420	1947
Books -- college text books	0.1468	(0.2985)	40	2.00	0.180	1947
Children's Books	0.0698	(0.2933)	23	2.17	0.180	1947
Funeral Homes and Cemet.	0.0392	(0.4978)	40	2.61	0.260	1947
Books -- K-12 school books	0.1041	(0.2755)	39	2.77	0.180	1947
Children's Clothing	0.0747	(0.3462)	40	2.93	0.120	1963
Dental Equipment	0.0488	(0.3613)	66	3.13	0.400	1947
Housewares	0.0856	(0.3148)	40	3.24	0.554	1947
Child Care	0.0951	(0.4335)	28	3.48	(.)	(.)
Glasses (not Sunglasses)	-0.0991	(0.5572)	27	3.64	(.)	(.)
Cruises	0.1546	(0.3136)	16	3.82	(.)	(.)
Linens	0.0973	(0.5577)	37	4.58	0.303	1947
Cigarettes	0.1214	(0.2172)	66	5.31	0.900	1947
Home Appliances Small	0.1245	(0.2498)	53	5.46	0.410	1963
Golf	0.0616	(0.3743)	29	5.63	(.)	(.)
Liquor	0.1259	(0.2342)	66	5.81	0.750	1947
Floors	0.0711	(0.3717)	66	6.12	0.400	1992
Cigars and Other Tobacco	0.1232	(0.2175)	66	6.24	0.749	1947
Sporting Equipment	0.0684	(0.4013)	66	6.61	0.240	1947
Beer (and Wine)	0.1052	(0.2385)	66	8.39	0.256	1947
Books -- general	0.1096	(0.2478)	40	8.49	0.180	1947
Cosmetics	0.0996	(0.3053)	66	8.90	0.240	1947
Coal	0.0924	(0.2558)	66	10.15	(.)	(.)
Jewelry	0.1090	(0.3501)	40	11.22	0.130	1947
Toys	0.0649	(0.4471)	40	11.98	0.390	1947
Residential Construction	0.0707	(0.4588)	40	12.80	(.)	(.)
Health Insurance	0.0888	(0.2234)	40	13.59	(.)	(.)
Residential Mortgage	0.0869	(0.3759)	40	14.49	(.)	(.)
Newspapers	0.1205	(0.3030)	66	14.76	0.257	1947
Furniture	0.0851	(0.2852)	66	14.79	0.260	1947
Property Insurance	0.1000	(0.2143)	64	15.35	(.)	(.)
Nursing Home Care	0.0245	(0.4317)	33	16.97	(.)	(.)
Home Appliances Big	0.0988	(0.3216)	66	20.27	0.400	1947
Movies	0.1017	(0.3121)	66	21.97	(.)	(.)
Construction Equipment	0.1098	(0.2421)	40	24.22	0.420	1963
Telephone	0.0749	(0.2331)	66	24.58	(.)	(.)
Life Insurance	0.1122	(0.2778)	39	35.08	(.)	(.)
Airplanes	0.1051	(0.2777)	66	38.96	0.590	1958
Clothing (Adults)	0.0936	(0.2684)	66	48.43	0.093	1947
Residential Development	0.0713	(0.3153)	40	51.78	(.)	(.)
Health Care (Services)	0.1088	(0.3460)	34	55.74	(.)	(.)
Medical Equipment	0.1437	(0.2351)	66	57.93	0.484	1963
Automobiles	0.0968	(0.2558)	66	65.18	0.353	1947
Drugs	0.1225	(0.1967)	66	90.64	0.280	1947
Electricity	0.0876	(0.1828)	66	140.73	(.)	(.)
Oil	0.1078	(0.1820)	66	166.15	(.)	(.)
Food	0.1085	(0.1716)	66	181.87	0.325	1947
Total Consumption	0.0921	(0.1938)	66		(.)	(.)

Notes: The measure of value-weighted yearly stock return in year t is the average yearly stock return for all companies belonging to the industry between December 31 in year t-1 and December 31 in year t (Column 1). The average is value-weighted by the market capitalization at the end of year t-1. Column 2 reports the within-industry standard deviation. Also featured are the number of years for which the data is available (Column 3) and the average number of firms in the industry (Column 4). The measure of concentration ratio is the ratio of revenue produced by the largest 4 companies over the total industry revenue. The year of measurement is the first year of availabiliy of data. The source is the Bureau of Manifacturers. The measure is the average across all the 4-digit SIC codes that define the industry, weighted by the revenue in the sector. The measure is missing for industries with no SIC codes within the manufacturing range (2000-3999).

Table 8: Predictability of Return on Equity Using Demographic Changes

	Dependent variable: Annual Log Return on Equity (ROE)											
	Demographic Industries						All Industries					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Constant	0.1269	0.1856	0.4065	0.1314	0.1785	-28.2704	0.1305	0.2325	0.3391	0.1317	0.1805	-26.1552
	(0.0051)***	(0.0180)***	(0.2036)*	(0.0071)***	(0.0192)***	(8.4523)***	(0.0045)***	(0.0212)***	(0.1483)**	(0.0063)***	(0.0191)***	(6.0791)***
Forecasted annual demand growth due to demographics	1.2754	1.3498	1.3856	1.0584	1.9123	0.9137	0.8174	1.1853	1.1821	0.8158	1.7507	0.8331
	(0.2843)***	(0.3389)***	(0.3442)***	(0.3992)**	(0.5064)***	(0.4575)*	(0.2779)***	(0.3616)***	(0.3237)***	(0.3713)**	(0.5255)***	(0.4256)*
Industry Fixed Effects		X			X			X			X	
Quartic Polynomial in Year (Normalized)			X			X			X			X
Year >= 1975				X	X	X				X	X	X
Clustering by Year	X	X	X	X	X	X	X	X	X	X	X	X
R^2	0.0193	0.2286	0.0217	0.0111	0.2193	0.027	0.0047	0.1994	0.0097	0.004	0.2583	0.0159
N	*N = 708*	*N = 708*	*N = 708*	*N* = 491	*N* = 491	*N* = 491	*N* = 1851	*N* = 1851	*N* = 1851	*N* = 1236	*N* = 1236	*N* = 1236

Notes: Columns 1 through 12 report the coefficients of OLS regressions of log yearly return on equity (Table 6) on the forecasted annual demand growth due to demographics (Table 4). The subset, "Demographic Industries", denotes the 20 industries in Table 4 with the highest within-industry standard deviation of 1-year consumption growth due to demographics. The Quartic Polynomial in Year is actually a polynomial in time=year-1935. Robust standard errors clustered by year in parentheses.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 9: Predictability of Return on Equity and Industry Concentration

	Dependent variable: Annual Log Return on Equity (ROE)					
	Sample: All industries					
	High-concentration (C-4>.40)			Low-concentration (C-4<=.40)		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.143	0.0923	-0.3101	0.1474	0.1276	0.27
	(0.0095)***	(0.0229)***	(0.30)	(0.0066)***	(0.0139)***	(0.16)
Forecasted annual demand growth due to demographics	1.2208	2.3565	1.7185	0.1742	-0.3847	0.7672
	(0.5147)**	(1.0117)**	(0.4795)***	(0.4129)	(0.4415)	(0.4856)
Industry Fixed Effects		X			X	
Quartic Polynomial in Year (Normalized)			X			X
Clustering by Year	X	X	X	X	X	X
R^2	0.0113	0.2107	0.0809	0.0002	0.2013	0.0321
N	*N* = 359	*N* = 359	*N* = 359	*N = 830*	*N = 830*	*N = 830*

Notes: Columns 1 through 6 report the coefficients of OLS regressions of log yearly return on equity (Table 6) on the forecasted annual demand growth due to demographics (Table 4). Columns 1 through 3 report the results for the subsample of industries with concentration-ratio 4 higher than .40. Columns 4 through 6 report the results for the subsample of industries with concentration-ratio 4 lower than or equal to .40. Details on the concentration ratio measure are in Table 7 and in the text. The Quartic Polynomial in Year is actually a polynomial in time=year-1935. Robust standard errors clustered by year in parentheses.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 10: Predictability of Stock Returns Using Demographic Changes

	Dependent variable: Beta-Adjusted Log Industry Stock Returns											
	Demographic Industries						All Industries					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Constant	-0.0466	-0.0389	0.2205	-0.0613	-0.0979	39.431	-0.0394	0.1271	0.1229	-0.061	0.0913	36.6428
	(0.0263)*	(0.0793)	(0.1180)*	(0.0380)	(0.0870)	(63.8180)	(0.0293)	(0.0836)	(0.0720)*	(0.0483)	(0.0934)	(55.5774)
Forecasted annualized demand growth between *t* and *t+5*	-1.7056	-1.6604	-3.2689	-0.1972	1.0944	-2.5889	-1.9954	-1.5751	-1.4739	-1.3925	-0.3705	-3.3948
	(2.3731)	(2.7416)	(2.1772)	(3.2636)	(3.9234)	(2.5738)	(2.4191)	(2.7516)	(1.9994)	(4.2131)	(5.1171)	(2.5819)
Forecasted annualized demand growth between *t+5* and *t+10*	5.1315	5.5251	5.2975	5.2768	7.5632	5.5173	4.7958	4.6478	3.4049	5.7534	7.8961	5.1964
	(2.3623)**	(3.7227)	(2.1187)**	(2.4651)**	(4.3768)*	(2.1375)**	(2.2978)**	(3.3267)	(1.9103)*	(2.6648)**	(3.9617)*	(2.1557)**
Industry Fixed Effects		X			X			X			X	
Quartic Polynomial in Year (Normalized)			X			X			X			X
Year >= 1975				X	X	X				X	X	X
Clustering by Year	X	X	X	X	X	X	X	X	X	X	X	X
R^2	0.0108	0.0322	0.021	0.0165	0.0533	0.0493	0.006	0.0286	0.0145	0.01	0.0587	0.0368
N	*N = 790*	*N = 790*	*N = 790*	*N=498*	*N=498*	*N=498*	*N = 2161*	*N = 2161*	*N = 2161*	*N = 1227*	*N = 1227*	*N = 1227*

Notes: Columns 1 through 12 report the coefficients of OLS regressions of log yearly beta-adjusted industry stock returns (Table 6) on the forecasted annual demand growth due to demographics (Table 4). The industry betas for year *t* are obtained regressing monthly industry returns on market returns for the 48 months previous to year *t*. The coefficients on the forecasted annual demand growth are normalized by the number of years of the forecast (5 for both coefficients). The coefficient indicates the typical increase for the annual industry abnormal log stock return due to an annualized one percentage point increase in consumption due to demographics over the years 0 to 5 (or 5 to 10). The subset, "Demographic Industries", denotes the 20 industries in Table 4 with the highest within-industry standard deviation of 1-year consumption growth due to demographics. The Quartic Polynomial in Year is actually a polynomial in time=year-1935. Robust standard errors clustered by year in parentheses.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 11: Predictability of Stock Market Returns and Industry Concentration

	Dependent variable: Beta-Adjusted Log Industry Stock Returns					
	High-concentration Industries (C-4>.40)			Low-concentration Industries (C-4<=.40)		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-0.0471	-0.2056	-0.0588	-0.0291	-0.0893	-0.2207
	(0.0318)	(0.0663)***	(0.5487)	(0.0367)	(0.0885)	(0.5414)
Forecasted annualized demand growth between *t* and *t+5*	-7.0237	-3.0716	-6.1174	-2.404	-2.3483	-3.0355
	(5.1885)	(5.1186)	(7.0779)	(2.6346)	(2.8974)	(2.1250)
Forecasted annualized demand growth between *t+5* and *t+10*	12.6689	15.8353	11.5284	3.3997	3.0838	0.7148
	(5.2645)**	(6.6269)**	(6.6301)*	(2.7686)	(3.7145)	(2.2122)
Industry Fixed Effects		X			X	
Quartic Polynomial in Year (Normalized)			X			x
Clustering by Year	x	X	x	x	X	x
R^2	0.0325	0.0964	0.0343	0.0025	0.0261	0.0146
N	*N* = 360	*N* = 360	*N* = 360	*N = 908*	*N = 908*	*N = 908*

Notes: Columns 1 through 6 report the coefficients of OLS regressions of log yearly beta-adjusted industry stock returns (Table 6) on the forecasted annual demand growth due to demographics (Table 4). The industry betas for year *t* are obtained regressing monthly industry returns on market returns for the 48 months previous to year *t*. The coefficients on the forecasted annual demand growth are normalized by the number of years of the forecast, 5. The coefficient indicates the increase in log industry abnormal stock return due to an anualized one percentage point increase in consumption due to demographics over the years 5 to 10. Columns 1 through 3 report the results for the subsample of industries with concentration-ratio 4 higher than .40. Columns 4 through 6 report the results for the subsample of industries with concentration-ratio 4 lower than or equal to .40. Details on the concentration ratio measure are in Table 7 and in the text. The Quartic Polynomial in Year is actually a polynomial in time=year-1935. Robust standard errors clustered by year in parentheses.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 12: Predictability of Stock Returns Using Demographic Changes (Robustness Check)

	Dependent variable: Beta-Adjusted Log Industry Stock Returns											
	Demographic Industries						All Industries					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Constant	-0.0405	-0.0294	0.2005	-0.0528	-0.0848	37.812	-0.0317	0.129	0.1225	-0.0524	0.0896	35.0446
	(0.0253)	(0.0733)	(0.1139)*	(0.0378)	(0.0809)	(62.7680)	(0.0281)	(0.0818)	(0.0704)*	(0.0483)	(0.0917)	(55.0174)
Forecasted annual demand growth between *t+2* and *t+3*	-1.7175	-1.3838	-2.874	-1.5882	-1.1929	-4.4124	-2.0275	-1.7077	-1.7869	-2.8848	-2.7847	-5.0819
	(2.2186)	(2.3631)	(2.1041)	(3.3720)	(3.9585)	(2.9925)	(2.3578)	(2.4936)	(2.0205)	(4.3800)	(4.8234)	(2.9962)
Forecasted annual demand growth between *t+6* and *t+7*	4.3068	4.425	4.1781	5.5024	8.3743	6.1337	3.9828	4.0008	3.1001	6.0949	8.9858	5.8163
	(1.7291)**	(2.5401)*	(1.5762)**	(2.0563)**	(4.1819)*	(1.9514)***	(1.7241)**	(2.3600)*	(1.5861)*	(2.3738)**	(3.6589)**	(2.0118)***
Industry Fixed Effects		X			X			X			X	
Quartic Polynomial in Year (Normalized)			X			X			X			X
Year >= 1975				X	X	X				X	X	X
Clustering by Year	X	X	X	X	X	X	X	X	X	X	X	X
R^2	0.0102	0.0319	0.0205	0.0167	0.0538	0.0512	0.0049	0.0281	0.0147	0.0099	0.059	0.0379
N	*N = 790*	*N = 790*	*N = 790*	*N=498*	*N=498*	*N=498*	*N = 2161*	*N = 2161*	*N = 2161*	*N = 1227*	*N = 1227*	*N = 1227*

Notes: Columns 1 through 12 report the coefficients of OLS regressions of log yearly beta-adjusted industry stock returns (Table 6) on the forecasted annual demand growth due to demographics (Table 4). The industry betas for year *t* are obtained regressing monthly industry returns on market returns for the 48 months previous to year *t*. The coefficients on the forecasted annual demand growth are normalized by the number of years of the forecast (5 for both coefficients). The coefficient indicates the typical increase for the annual industry abnormal log stock return due to an annualized one percentage point increase in consumption due to demographics for the two one-year periods. The subset, "Demographic Industries", denotes the 20 industries in Table 4 with the highest within-industry standard deviation of 1-year consumption growth due to demographics. The Quartic Polynomial in Year is actually a polynomial in time=year-1935. Robust standard errors clustered by year in parentheses.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 13: Performance of the Zero Cost Portfolio For Demographic Industries

	Dependent variable: Monthly Return on Zero Cost Portfolio								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	0.0541	0.0582	0.0714	0.1006	0.1017	0.1219	0.0355	0.0379	0.0484
	(0.0185)***	(0.0183)***	(0.0200)***	(0.0224)***	(0.0248)***	(0.0269)***	(0.0205)*	(0.0216)*	(0.1829)***
VW Index Excess Return	-0.1216	-0.1037	-0.1164	-0.0997	-0.0747	-0.0878	-0.1469	-0.1346	-0.1557
(VWRF)	(0.0498)**	(0.0507)**	(0.0522)**	(0.0692)	(0.0775)	(0.0796)	(0.0495)***	(0.0458)***	(0.0494)**
Size Factor Return		-0.1023	-0.1143		-0.1180	-0.1046		-0.0681	0.0882
(SMB)		(0.0845)	(0.0763)		(0.1020)	(0.0908)		(0.0967)	(0.0802)
Value Factor Return		-0.0553	-0.0833		-0.0167	-0.0169		-0.0315	-0.0783
(HML)		(0.0829)	(0.0695)		(0.0940)	(0.0821)		(0.1117)	(0.0854)
Momentum Factor Return			-0.1019			-0.1472			-0.1700
(UMD)			(0.0688)			(0.0696)**			(0.0799)**
Year >= 1975				X	X	X			
SIC Classification Only							X	X	X
R^2	0.0152	0.0205	0.0278	0.009	0.0165	0.0337	0.0190	0.0209	0.0383
N	*N = 780*	*N = 780*	*N = 780*	*N = 336*	*N = 336*	*N = 336*	*N = 780*	*N = 780*	*N = 780*

Notes: Columns 1 through 9 report the coefficients of OLS regressions of the zero cost portfolio monthly returns on different sets of monthly benchmark factors. The zero cost portfolio is long industries with high predicted long-term demand growth and short industries with low predicted long-term demand growth. 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-mimicking portfolios for size and book-to-market, respectively. UMD is the return on the factor-mimicking portfolio for momentum. For Columns 7 through 9 the classification of companies into industries only uses Standard Industry Classification (SIC) codes instead of SIC codes in conjunction with the authors' company-by-company classfication using historical information. The constant has been annualized to make its interpretation more straightforward. Heteroskedasticity and autocorrelation consistent standard errors are calculated using the Newey-West estimator with 6 lags (in parentheses).

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 14: Performance of the Zero Investment Portfolio For All Industries

	Dependent variable: Monthly Return on the Zero Investment Portfolio								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	0.0242	0.0197	0.0218	0.0576	0.0623	0.0508	0.0169	0.0142	0.0085
	(0.0120)**	(0.0131)	(0.0127)*	(0.0246)**	(0.0252)**	(0.0251)**	(0.0177)	(0.0183)	(0.0195)
VW Index Excess Return	-0.0725	-0.0520	-0.0533	-0.0220	-0.0180	-0.0114	-0.0803	-0.0597	-0.0563
(VWRF)	(0.0290)**	(0.0320)*	(0.0314)*	(0.0460)	(0.0472)	(0.0467)	(0.0561)	(0.0553)	(0.0533)
Size Factor Return		-0.0279	-0.0287		-0.1061	-0.1020		-0.0630	-0.0609
(SMB)		(0.0467)	(0.0464)		(0.0910)	(0.0866)		(0.0804)	(0.0780)
Value Factor Return		0.0707	0.0671		-0.0623	-0.0437		0.0449	0.0546
(HML)		(0.0480)	0.0474		(0.0892)	(0.0873)		(0.0653)	(0.0681)
Momentum Factor Return			-0.0167			0.0866			0.0447
(UMD)			0.0335			(0.0568)			(0.0787)
Concentration Ratio > 0.4				X	X	X			
Concentration Ratio <= 0.4							X	X	X
Year >= 1947	X	X	X	X	X	X	X	X	X
R^2	0.0142	0.0211	0.0216	0.0004	0.0049	0.0092	0.0078	0.0113	0.0131
N	*N=632*	*N=632*	*N=632*	*N=632*	*N=632*	*N=632*	*N=632*	*N=632*	*N=632*

Notes: Columns 1 through 9 report the coefficients of OLS regressions of the zero investment portfolio monthly returns on different sets of monthly benchmark factors. The zero investment portfolio is long industries with high predicted long-term demand growth and short industries with low predicted long-term demand growth. Long-term demand growth is measured from years 5 to 10 and the constituent portfolios of the strategy are rebalanced every year. 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-mimicking portfolios for size and book-to-market, respectively. UMD is the return on the factor-mimicking portfolio for momentum. The concentration ratio measure is the first available data from the Census of Manufacturers for the ratio of revenue for the largest 4 firms to total industry revenue taken. Since this measure rarely exists before 1947 the sample does not include data before 1950. The constant has been annualized to make its interpretation more straightforward. Heteroskedasticity and autocorrelation consistent standard errors are calculated using the Newey-West estimator with 6 lags (in parentheses).

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 15: Analyst Forecasts of Earnings at Different Time Horizons

	Number of companies with at least one forecast for the fiscal period					
	(1)	(2)	(3)	(4)	(5)	(6)
Fiscal Year 1	4454	1375	3079	8399	2926	5473
Fiscal Year 2	4300	1375	2925	7386	2869	4517
Fiscal Year 3	2007	987	1020	4149	2358	1791
Fiscal Year 4	576	313	263	692	421	271
Fiscal Year 5	360	196	164	269	155	114
Fiscal Year 6	0*	0*	0*	13	7	6
Fiscal Year 7	0*	0*	0*	4	2	2
Fiscal Year 8	0*	0*	0*	1	1	0
Analysts >= 5 for FY1		X			X	
Analysts < 5 for FY1			X			X
Year of Forecast	1990	1990	1990	2000	2000	2000

Notes: The sample for columns 2 and 5 is restricted to companies with at least 5 analysts making forecasts for fiscal year 1 and the sample for columns 3 and 6 is restricted to companies with fewer than 5 analysts making forecasts for fiscal year 1.

* In 1990 there are no reported forecasts beyond year 5, however, analysts may have created forecasts beyond the five year horizon that I/B/E/S decided not to record.

Appendix Table 1: Industries and their Standard Industrial Classification (SIC) Codes

Expenditure Category	Grouping	Standard Industrial Classification Codes
Child Care	Children	8350-8359
Children's Books	Children	(2730-2739)
Children's Clothing	Children	2360-2369, 5640-5649, (5130, 5137)
Toys	Children	(3940), 3941-3948, (3949), (5090), 5092, (5940), 5945, (6711), (7990)
Books -- college text books	Media	(2730-2739)
Books -- general	Media	5942, (2720-2739, 5192)
Books -- K-12 school books	Media	(2720-2739)
Movies	Media	7810-7819, 7820-7849
Newspapers	Media	2710-2729, (2730-2739, 5192)
Cruises	Health	4480-4489, (4410, 4411, 7990, 7999)
Dental Equipment	Health	3843, 8020-8029, (3840, 5047, 8090)
Drugs	Health	2830-2839, 5120-5129 (8090)
Glasses (not Sunglasses)	Health	3850-3859, 5048, (5040)
Health Care (Services)	Health	8000-8019, 8030-8049, (8050-8059), 8060-8071, (8072), 8080-8089, (8090-8092)
Health Insurance	Health	6320-6329
Medical Equipment	Health	3840-3842, 3844-3849, 5047, (5040, 5120-5129, 8090)
Funeral Homes and Cemet.	Senior	3995, 7260-7269, (3990, 6550, 6553)
Nursing Home Care	Senior	8050-8059, (6510, 6513, 6798, 8080-8089, 8360-8361)
Construction Equipment	House	3531, 5031-5039, 5210-5259, (3530, 5080, 5082)
Floors	House	2270-2279, 5713, (5020, 5710, 5719)
Furniture	House	2510-2519, 5021, 5712 (5020, 5710, 5719)
Home Appliances Big	House	3631-3633, 3639, 5720-5729 (3630, 3651, 5060, 5075, 5078)
Home Appliances Small	House	3634, (3630, 3645, 5020, 5023, 5060)
Housewares	House	3262, 3263, 3914, (3260, 3269, 3910, 5944, 5719)
Linens	House	2391-2392, 5714, (2390, 5020, 5710, 5719)
Residential Construction	House	1520-1529, (1540-1549)
Residential Development	House	6513, 6530-6539, 6552, (1520-1529, 6510, 6550)
Residential Mortgage	House	6160-6169
Beer (and Wine)	Perishable	2082, 2083, 2084, 5181, (2080, 2084, 2085, 5180, 5182, 5813)
Cigarettes	Perishable	2100-2119
Cigars and Other Tobacco	Perishable	2120-2199
Food	Perishable	0100-0299, 2000-2079, 2086, 2087, 2090-2099, 5140-5149, 5400-5499, 5812 (581
Liquor	Perishable	2085 (2080, 2084, 5180, 5182, 5810, 5813, 5920-5921)
Clothing (Adults)	Clothing	2310-2349 5136, 5137, 5610-5619, (5130), 5136
Cosmetics	Clothing	2844, 7231, (2840, 5120, 5122, 5130)
Golf	Clothing	(2320, 2329, 3940, 3949, 5090, 5130, 5940, 7990, 7999)
Jewelry	Clothing	3911, 3915, 5944, (3910, 5090, 5094, 5940)
Sporting Equipment	Clothing	3949, 5941, (2320, 2329, 2390, 3940-3948, 5090-5091, 5130, 5940, 5945, 7999)
Life Insurance	Insurance	6310-6319
Property Insurance	Insurance	6330-6339
Airplanes	Transport	3720-3729, 4511-4512, (4510, 4513)
Automobiles	Transport	3010-3019, 3710-3719, 5010-5019, 5510-5529
Bicycles	Transport	(3710, 3750-3759, 3714, 5090)
Motorcycles	Transport	(3750-3759, 3571)
Coal	Utilities	1200-1299
Oil	Utilities	1300-1399, 2910, 2911
Telephone	Utilities	4810-4811, 4813-4819
Utilities	Utilities	4910-4959

Notes: Complete list of expenditure categories (Column 1), grouping in 10 broader groups (Column 2) and SIC industry classification (Column 3). Each expenditure category is associated to two sets of codes. The first set of codes (not in parentheses) corresponds to the 4-digit SIC codes that are uniquely identified with one category. The second set of codes (in parentheses) identifies the SIC codes that are associated with multiple categories. Details on the company-by-company partition within these codes is available in Appendix.