



Baby Boom, Population Aging, and Capital Markets

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Source: *The Journal of Business*, Vol. 67, No. 2 (Apr., 1994), pp. 165-202

Published by: [University of Chicago Press](#)

Stable URL: <http://www.jstor.org/stable/2353102>

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I. Introduction

Demographic changes can affect economic dynamics in various ways. While economists have studied their impact on aggregate consumption, savings, labor supply, and social programs,¹ little work has been done on whether and how demographic fluctuations influence the capital markets. Casual economics suggests that if demographic changes affect such macroeconomic variables, they can also, directly or indirectly, cause price fluctuations in the capital markets. Thus, it is important to understand how, and to what extent, stock price movements are attributable to variations in the population age structure, particularly given the fact that the fraction of persons 65 and older in the U.S. population is ex-

This article tests how demographic changes affect capital markets. The life-cycle investment hypothesis states that at an early stage an investor allocates more wealth in housing and then switches to financial assets at a later stage. Consequently, the stock market should rise but the housing market should decline with the average age, a prediction supported in the post-1945 period. The second hypothesis that an investor's risk aversion increases with age is tested by estimating the resulting Euler equation and supported in the post-1945 period. A rise in average age is found to predict a rise in risk premiums.

* This article is based on chapter 3 of Zhiwu Chen's dissertation written at Yale University. He is especially grateful to his dissertation committee members, Professors Stephen Ross (chairman), Jonathan Ingersoll, and Rick Antle, for their advice and suggestions. The authors have benefited from comments by William Brock, Werner De Bondt, Douglas Diamond (editor), William Goetzmann, Stephen Heston, David Mauer, Alex Triantis, Ken West, and particularly Robert Shiller. The referee's comments and suggestions helped improve the article substantially. We would also like to thank the seminar participants at the Universities of Michigan and Wisconsin. Zhiwu Chen acknowledges research funding from the University of Wisconsin Graduate School. All remaining errors are ours alone.

1. See Clark, Kreps, and Spengler (1978); Hurd (1989); and Lumsdaine and Wise (1990) for surveys and references on the economics of aging.

(Journal of Business, 1994, vol. 67, no. 2)

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0021-9398/94/6702-0001\$01.50

pected to rise from its current level of about one-fifth to as high as two-fifths by the year 2040 (Lumsdaine and Wise 1990).

This topic is important also because older age groups are major market participants. Indeed, Sheshinski and Tanzi (1989) find that in 1985 the group of people aged 65 and older received about 53% of all interest, dividend, and estate incomes in the United States and close to one-third of all capital gains, as reported to the Internal Revenue Service. Prior to 1985, the percentage of total interest and dividend incomes received by this age group had steadily risen (44.1% in 1970, 44.3% in 1974, 46.6% in 1978, 47.0% in 1980, and 50.9% in 1982). The fraction of persons 65 and older in the U.S. population was rising at the same time. It is quite clear that an increasingly larger portion of the nation's wealth is held by this older age group. Therefore, if the investment behavior of the older group is different from that of the younger group, changes in the age distribution will have a significant impact on capital market prices.

This article explores the relations between demographic changes and capital market prices. Specifically, we examine two hypotheses: the life-cycle investment hypothesis, and the life-cycle risk aversion hypothesis. The first hypothesis essentially states that at different stages of an investor's life cycle, the investment needs in terms of types of assets to hold are different. When investors are in their 20s and 30s, housing is a desirable investment. Thus, at this family-building stage, one will probably allocate a higher proportion of wealth to housing and other durables. However, as the investor grows older, the demand for housing will stabilize or decrease and the demand for financial assets will rise. This is the case since, as one grows older, the number of remaining paychecks (human capital) declines and the need to invest for retirement increases. This need is made even stronger by the ever-increasing life expectancy. If this hypothesis is also true in a time-series sense, its implications are immediate: as the population ages, the aggregate demand (as a proportion of aggregate wealth) for housing decreases, which, *ceteris paribus*, depresses housing prices, while that for financial investments increases, which drives up financial prices.

The life-cycle risk aversion hypothesis asserts that an investor's relative risk aversion increases with age. If this is true (both cross-sectionally for all investors and time sequentially for each investor), then equilibrium market risk premiums should be correlated with demographic changes. In particular, market risk premiums should be positively correlated with changes in the age of the "average" or "representative" investor.

There are other ways that demographic changes can influence capital markets. For instance, an aging population may mean higher pressure

on Social Security, Medicare, and other social programs.² To meet such increased obligations, the federal, state, and local governments have to either raise more taxes or issue more debt, and business firms have to put aside more revenues to fulfill pension obligations instead of undertaking more capital investments. The overall effect is that there will be more people who draw down rather than build up their assets, which reduces the aggregate supply of capital and raises the cost of capital for productive investments.

In this article, we focus on the empirical implications of the two hypotheses. For this purpose, a demographic variable is necessary that reflects changes in the entire age distribution (not just changes in one or a few age groups). Since average age appears to satisfy this criterion, we use the average age of the U.S. population of persons 20 and older as a measurement of the age distribution, with the understanding that persons younger than 20 may not play much of a role in economic decision making. We treat average age as the representative investor's age in a representative-agent pricing model. In this context, changes in average age reflect changes in the population age distribution. From now on, we mean "a rising average age" by "an aging population." In other words, the fraction of persons 65 and older can increase, but this does not necessarily mean "the population is aging" because the fraction of young persons may increase at the same time.³

We start with an informal examination of the life-cycle investment hypothesis in Section II. This part of the analysis is based on the time-series paths of the average age, the real Standard and Poor's (S&P) 500 index (indicator of stock market price level), and the real price of housing. It turns out that the post-1945 U.S. economy was particularly supportive of the hypothesis: when the population aged, housing prices went down and stock prices went up, and the reverse is also true. We attribute this finding to the joint workings of the baby boom and the increasing life expectancy. Our reasoning is as follows. While the fraction of persons 65 and older was steadily rising from 1900 to 1990 (due to the increasing life expectancy), there does not appear to be a clear relation between the average age and the stock market price until about 1945 when the baby boom started. From 1945 to 1965, with the baby boom children growing up, parents had to invest

2. To get a sense of the relative importance of Social Security obligations, Feldstein (1978) estimated that in 1955, Social Security "wealth" was 88% of the U.S. GNP. It rose to 133% of GNP in 1965; by 1977, it was as high as 200% of GNP.

3. Note that average age is related to, but different from, life expectancy. The latter reflects the expected remaining lifetime for an age group, while the former is an aggregate measure of the current age distribution. See Sec. II for further discussion. We would like to thank the referee for pointing out the connection, and the distinction, between the two variables.

for their children's education, which boosted financial market prices and depressed housing prices. In the period 1965–80, the baby boomers started to build their own families and invested heavily in housing and less in financial assets. Thus, during this time, stock prices were declining and housing prices were rising. In the 1980s, the baby boomers entered their late 30s and early 40s and began to invest for both their own children's education and their retirement, while, at the same time, the increasing fraction of persons 65 and older also generated a higher demand for financial investments. The result is that stock prices were going up and the real price of housing was going down in the 1980s.

To examine the implications of the life-cycle risk aversion hypothesis, we consider in Section III a representative-agent model in which the representative agent has an age given by the average age of the population. Since the average age fluctuates randomly, so does his age. This abstraction allows us to see the possible relations between demographic changes and asset prices in a simple, straightforward way. As a result, the representative agent's intertemporal marginal rate of substitution (IMRS) in the Euler equation becomes a function of both aggregate consumption and average age. The Euler equation is then tested using the Hansen (1982) generalized method of moments (GMM). We find that for the period 1926–90, the Euler equation is not rejected, with the coefficient on average age significantly consistent with the predictions of the life-cycle risk aversion hypothesis.

Based on the Euler equation, we follow the standard steps to arrive at a pricing equation in which the risk premium for an asset is determined by both consumption and demographic risks. This relation suggests that we can use information concerning aggregate consumption and demographic fluctuations to forecast future risk premiums. We conduct this forecasting exercise by including, in addition to past consumption growth and change in average age, dividend yields as a third predicting variable, since some existing studies have demonstrated the ability of dividend yields to predict future returns (see, e.g., Campbell and Shiller 1988*a*, 1988*b*; and Fama and French 1988*b*, 1989). The results suggest a role for the life-cycle variables for the years from 1900 to 1990: both the change-in-average-age and dividend yield variables are statistically significant predictors of future stock returns and risk premiums. In particular, the coefficient on the change-in-average-age variable is persistently positive in the forecasting equations, meaning that an increase in the average age predicts an increase in the risk premium.

The article is organized as follows. Section II discusses the life-cycle investment hypothesis. Section III introduces a pricing model based on the life-cycle risk aversion hypothesis. In Section IV, we describe the data used in our empirical work. Section V presents the results

from testing the Euler equation via the GMM. In Section VI we test the Euler equation using the Hansen-Jagannathan (1991) bounds and find that it holds only with high parameter values. Section VII reports the results from the forecasting exercise. Concluding remarks are given in Section VIII.

II. The Life-Cycle Investment Hypothesis

A. *The Hypothesis*

The life-cycle theory of savings, pioneered by Modigliani and Brumberg (1954), asserts that the objective of a consumer's consumption-saving decision is to smooth consumption over time so as to maximize his overall lifetime utility. Consequently, his savings rate should follow a life-cycle pattern. Later empirical studies in the macroeconomics literature have found that a typical life-cycle savings pattern is "hump-shaped," with an investor's wealth holdings generally increasing with age (e.g., Modigliani 1986). However, this literature on life-cycle savings does not address how the composition of an investor's savings portfolio may change over the life cycle.

We hypothesize that when allocating savings between financial assets and housing, an investor will put relatively more savings in housing during the first part of the life cycle. At a young and family-building age, the investor spends most of his limited savings on a house. However, as he grows older, he has probably acquired sufficient housing, and at the same time the urgency to cope with the uncertainty of remaining lifetime income becomes more prominent. This generates a stronger need to invest for retirement, which in turn requires the aging investor to put an increasing proportion of savings into financial assets. In particular, due to medical advances, life expectancy has been increasing steadily, which makes it more necessary than ever to invest for retirement. Thus, the demand for financial assets increases with age while that for housing decreases.

At a cross-sectional level, there is some existing empirical evidence supporting the life-cycle investment hypothesis. Most notably, based on the 1970 and 1980 U.S. census data, Mankiw and Weil (1989) report that there is a jump in the demand for housing between the ages of 20 and 30, whereas after the age 40 the demand appears to drop by about 1% per year. In the 1962 consumer finance survey, Bossons (1973) finds that the average percentage of total wealth invested in housing and other durables was 50.2% for the age group 25–34, 51.1% for the age group 35–44, 46.7% for the age group 45–54, 35.8% for the age group 55–64, and 31.0% for persons 65 and older. These findings are consistent with our hypothesis, at least in a cross-sectional sense.

B. Time-Series Evidence

Suppose that the life-cycle investment hypothesis also holds time sequentially. Then an aging population will imply a declining housing price and a rising stock market price. We choose the S&P 500 index as an indicator for stock market prices and follow Mankiw and Weil (1989) by using the residential investment deflator relative to the gross national product (GNP) deflator as the housing price indicator. Our purpose is to compare the real S&P 500 index and the real price of housing with the average age of the population of persons 20 and older.⁴ Since we do not expect demographic changes to affect high-frequency price changes, we concentrate on annual observations. Figure 1 displays the two time series of average age and real S&P 500 index level from 1900 to 1990. Since these two series did not appear to move together before 1945, we redisplay their post-1945 behavior in figure 2 for a better visual effect. Figure 3 shows the time series of real housing price together with that of the average age for the post-1945 period.⁵ Figures 4, 5, and 6 present, respectively, life expectancy,⁶ the fraction of persons 65 and older, and the number of live births in the United States. For more detailed descriptions of the data sources, see Section IV.

For the discussion, we divide the entire period into four subperiods: 1900–1945, 1946–66, 1967–80, and 1981–90. Each subperiod exhibits certain unique demographic features. Consider the pre-1945 period, which experienced a stable birth process, a rising life expectancy, and

4. In Mankiw and Weil (1989), they compare the real price of housing with a “demographic housing demand variable.” More specifically, they first obtain from the 1970 census data the age structure of housing demand, denoted by the coefficients $\{b_0, b_1, \dots, b_{99}\}$, where b_a indicates the amount of housing demanded by a person of age a . Suppose the population size is I . Then, their demographic housing demand variable is defined as

$$D \equiv b_0 \cdot \sum_{i=1}^I \text{DUMMY0}_i + b_1 \cdot \sum_{i=1}^I \text{DUMMY1}_i + \dots + b_{99} \cdot \sum_{i=1}^I \text{DUMMY99}_i,$$

where $\text{DUMMY0}_i = 1$ if investor i is of age 0, $\text{DUMMY1}_i = 1$ if investor i is of age 1, and so on; that is, for each investor, the dummy variables are zero except for one of them. Clearly, this housing demand variable can be viewed as a “generalized weighted average age” of the population. (Divide each term by the population size I and treat each b_a as an “age.”) In our case, we use the simple average age of the population as a proxy for the unobserved aggregate housing demand variable.

5. We could not obtain the real housing prices for the years before 1946.

6. For the years 1900–1954, we could obtain the life expectancy data only for aggregate age groups, such as the age group of ages 65 and over. However, for the period 1955–90, we could obtain data only for groups of each age, such as the group of age 60. Without knowing the exact way the average life expectancy is calculated for each aggregate age group, we chose to report in fig. 4 the life expectancy path from 1955 to 1990 for the group of age 60. Though not reported, the life expectancy path for the years 1900–1954 also increased, as demonstrated in the data (not shown here) for the various aggregate age groups.

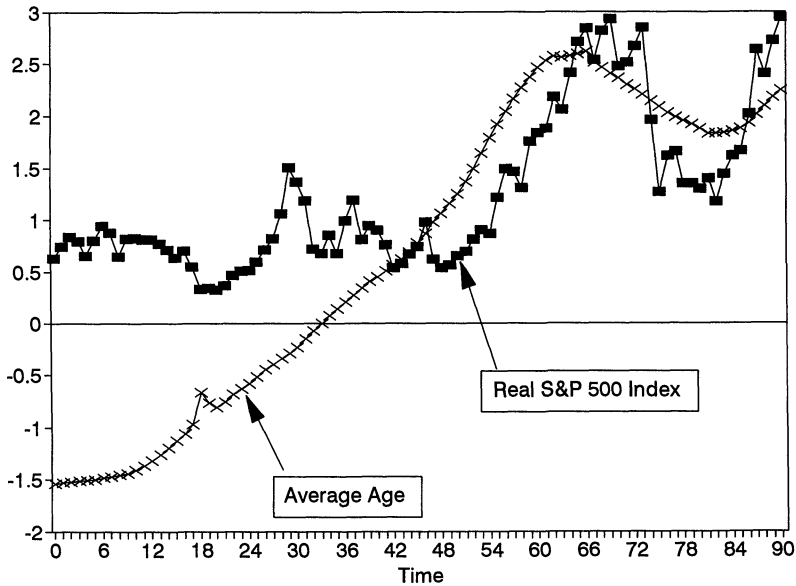


FIG. 1.—Real S&P 500 index and average age. “Average Age” equals the average age of the population 20 years and over minus 41.50 and divided by 1.50. Real S&P 500 index level is the January value of the nominal index divided by the January producer price index. Source: Shiller (1989) and Barsky and DeLong (1990).

consequently a rising average age. For the years between 1900 and 1920, the real S&P 500 level and the average age do not seem to move together, and from 1920 to 1945 there is a slight, but identifiable, co-moving trend. That is, even though life expectancy was increasing, this subperiod was not accompanied by a rising stock market, at least for the years 1900–1920. As we do not have the real housing price for the pre-1945 years, we cannot say much about the possible relation between the average age and the real price of housing for this period.

From 1946 to 1966, both life expectancy and the fraction of persons 65 and older were rising (figs. 4 and 5), while the fraction of persons in the age groups 20–25 and 26–30 was stable.⁷ As a result, the average age was increasing as was the stock market (fig. 2). At the same time, the real price of housing was declining (fig. 3). This is consistent with the predictions of the life-cycle investment hypothesis. For this baby boom period (fig. 6), there is another reason that the stock market should be rising. Parents had to invest for the education of their baby boom children, which increased the demand for financial assets.

7. As we focus on the population of persons 20 and older, the baby boomers are not in our sample yet for this subperiod.

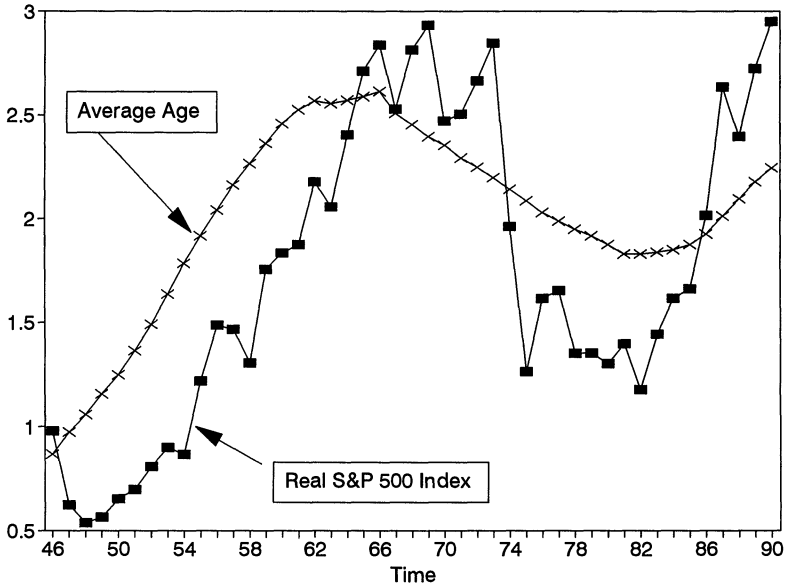


FIG. 2.—Real S&P 500 index and average age. “Average Age” equals the average age of the population 20 years and over minus 41.50 and divided by 1.50. Real S&P 500 index level is the January value of the nominal index divided by the January producer price index. Source: Shiller (1989) and Barsky and DeLong (1990).

For the next subperiod 1966–80, the baby boomers entered our sample population and started building families. Even though both life expectancy and the fraction of persons 65 and older were still increasing during this period, the sudden entry of the baby boomers into the 20–35 age group marked a dramatic change in the demographic structure. In particular, their impact on the housing and the stock markets more than offset the impact caused by the higher fraction of persons 65 and older. While the growing elderly population led to a drop in housing demand, the much larger increase in the population of ages 20–35 generated a rise in housing demand that was much higher than the drop induced by the growing elderly population. This net increase in housing demand raised the price of housing for this subperiod. Figure 3 confirms this prediction of the life-cycle investment hypothesis. In contrast, as figure 2 shows, the stock market was rising in this subperiod, which is again consistent with our hypothesis.

During the last subperiod 1981–90, the baby boomers joined the 35–45 age group, and those who were born in the baby bust years (fig. 6) began to enter the 20–30 age group. This subperiod can be characterized as follows. First, the baby boomers started to invest for both their children’s education and their own retirement, and their

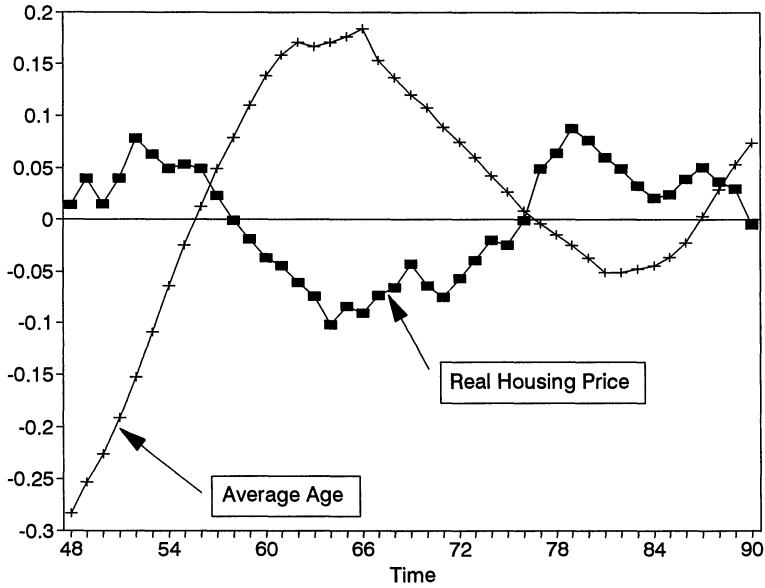


FIG. 3.—Real housing price and average age. “Average Age” equals the average age of the U.S. population 20 years and over minus 44.50 and divided by 5.00. Real housing price is the residential investment deflator divided by the gross national product deflator minus 0.96. Source: CITIBASE (1992).

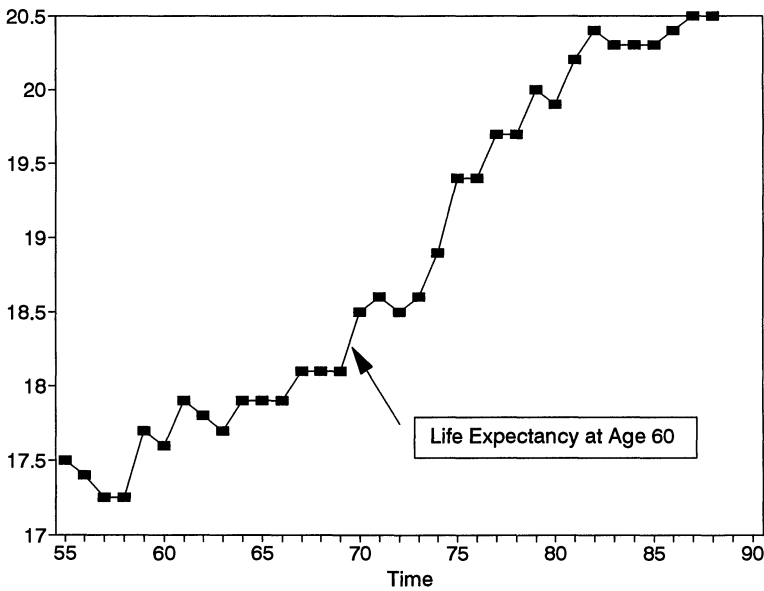


FIG. 4.—Life expectancy at age 60. Source: Bureau of the Census (various years).

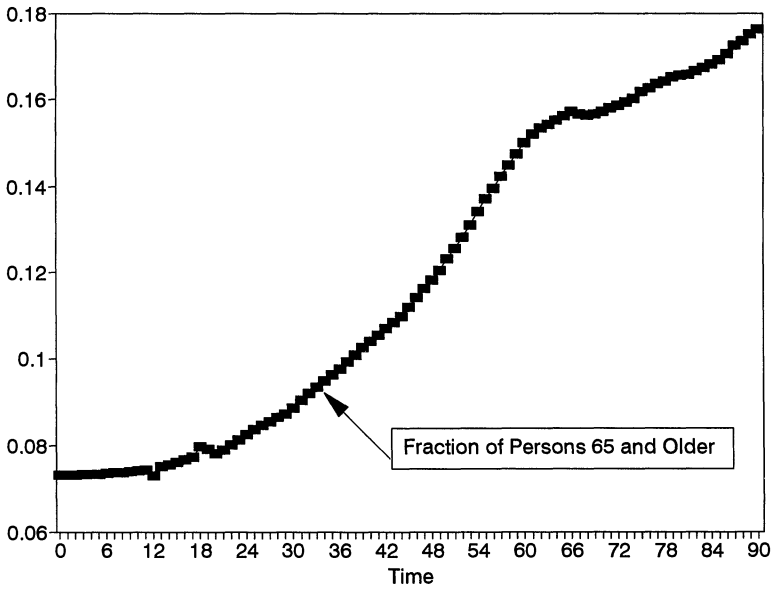


FIG. 5.—Fraction of persons 65 and older. This is the fraction of persons 65 and older in the U.S. population of ages 20 years and over.

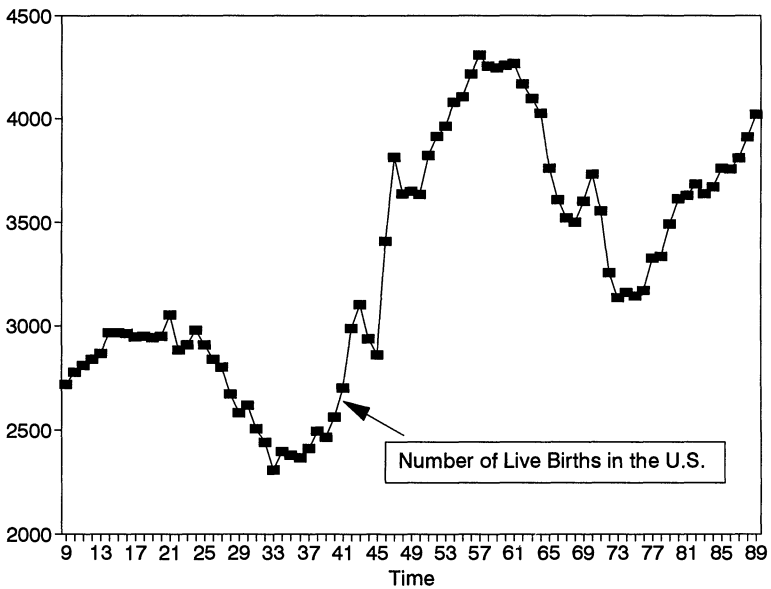


FIG. 6.—Number of live births in the United States. Source: Bureau of the Census (1975).

demand for housing began to stabilize. Second, the large drop in the population of ages 20–30 (due to the baby bust) generated a correspondingly lower demand for new housing, but the impact on the demand for financial investments was not as significant. Finally, the continued increase in the fraction of persons 65 and older (fig. 5) further reduced the demand for housing and led to a higher demand for stocks and other financial investments. Thus, the overall effect of the demographic changes in this subperiod was that the aggregate demand for housing gradually declined and the aggregate demand for financial investments rose. This implies that the stock market price should have increased and the price of housing should have decreased. This is how the two markets actually behaved in the 1980s, as seen in figures 2 and 3.

In summary, we demonstrated that the post-1945 period is remarkably supportive of the life-cycle investment hypothesis. An aging population, as measured by the average age, implies rising stock market prices and declining housing prices. One might argue that the capital market fluctuations in the entire period were unrelated to demographic changes and that they were caused by other economic factors such as productivity and aggregate savings. However, if this were true, we should have observed co-moving housing and stock prices in figures 2 and 3, because changes in aggregate savings or productivity should then have had the same effect on the supply of capital in both the stock and the housing markets. No matter how the age distribution changed, stock market and housing prices should have moved more or less in the same direction. But, this is not what was observed.

It is worth mentioning that the increased life expectancy is the driving force behind the increased fraction of persons 65 and older. Over the years, this factor has played a crucial role in increasing the amount of financial investments demanded by each older age group. However, life expectancy alone cannot be used as an aggregate variable to explain the observed fluctuations in housing and stock market prices in figures 2 and 3, because, while it can indicate how much more financial investment each individual age group may demand, it does not capture the fluctuations in the entire age distribution and hence it cannot be utilized to fully reflect changes in *aggregate asset demand*. As discussed above, the sudden entry of a large cohort into the population may more than offset the effect of an increase in life expectancy. In contrast, the average age variable captures most structural changes in the population age composition, including an increase in life expectancy, and, thus, fluctuations in aggregate asset demand.

III. Population Aging and Asset Price Processes

We now examine the pricing implications of the life-cycle risk aversion hypothesis. Following Lucas (1978) and Cox, Ingersoll, and Ross

(1985), we consider a multiperiod economy and assume the existence of a representative investor. In particular, the representative investor has an age given by the average age of the population. This assumption simplifies the theoretical discussion and draws more attention to the empirical implications examined in later sections.

A. The Life-Cycle Risk Aversion Hypothesis

We hypothesize that an investor's relative risk aversion increases with age. This hypothesis can be justified from different perspectives. For example, we can think of an investor's human capital as an approximately decreasing function of age: when one gets older, the number of remaining paychecks declines. If it is also true that relative risk aversion decreases in human capital, then the former becomes an increasing function of age. Intuitively, with fewer paychecks in the future, one may be less willing to take on a lot of financial risk since there will be fewer opportunities to use labor income to cover potential losses. In addition, as life expectancy continues increasing and one's remaining lifetime becomes more uncertain, a typical investor cannot afford to have his risk aversion decreasing with age. This view is also long held by psychologists. For instance, Botwinick (1978) states: "Both older men and women seemed to be especially cautious in decisions involving financial matters. Not surprisingly, perhaps, for them the lure of substantial financial gains was not worth the possible loss of money-in-hand" (pp. 129–30). Among other arguments, Rubin and Paul (1979) use an evolutionary model to show that the young are more willing to take risk than the old. Brown (1990) demonstrates that in the presence of illiquid assets, the middle-aged will be endogenously less risk averse than the retired.

At a cross-sectional level, there is strong empirical evidence that supports our hypothesis. Based on the 1962 Survey of Consumer Finances in the United States, Bossons (1973) finds that for all individuals in different wealth classes, the average percentage of wealth invested in cash and bonds was 4.6% for the age group 25–34, 7.0% for the age group 35–44, 8.6% for the age group 45–54, 12.9% for the age group 55–64, and 17.6% for persons 65 and older. (See table V-7 of Bossons 1973). In a study on the 1953 Survey of Consumer Finances, Lampman (1962) uncovers a similar pattern: if we take the wealth class of \$200,000–\$300,000 as an example, the average percentage of money in cash and bonds was 11.4% for the age group 30–40, 15.3% for the age group 55–60, and 20.7% for persons of ages 75–80. To quote another piece of evidence, the surveyed asset holdings of Canadian households lead Morin and Suarez (1983) to conclude that the "investor's life-cycle plays a prominent role in portfolio selection behavior, with relative risk aversion increasing uniformly with age" (p. 1201).

B. The Euler Equation

We now begin to build a discrete-time model in which the representative investor makes his consumption-portfolio decisions from time 0 to T , at time intervals of length Δt . Assume for simplicity that there are $N + 1$ traded securities, one risk-free (the 0th asset) and the others risky. The risk-free asset has a constant return r_0 , and the price of the n th risky asset at time t is $P_{n,t}$. Since each individual investor's utility of consumption is a function of his age, the representative investor's utility of consumption depends on the average age of the population and is given by $u(C_t, A_t)$, if his consumption flow and average age are, respectively, C_t and A_t at t , where $u(\cdot, \cdot)$ is assumed to be twice continuously differentiable in both arguments and strictly increasing and concave in consumption. With initial endowment W_0 , the representative investor solves at each decision time t

$$J(W_t, A_t, t) \equiv \max_{C_t, \alpha_t} u(C_t, A_t) + e^{-\kappa \Delta t} E_t[J(W_{t+\Delta t}, A_{t+\Delta t}, t + \Delta t)], \quad (1)$$

subject to

$$W_{t+\Delta t} = W_t \left[1 + r_0 \Delta t + \sum_{n=1}^N \alpha_{n,t} \left(\frac{P_{n,t+\Delta t}}{P_{n,t}} - 1 - r_0 \Delta t \right) \right] - C_t \cdot \Delta t, \quad (2)$$

where $J(\cdot, A_t, t)$ is, given age A_t , the indirect utility of wealth; $\alpha_{n,t}$ is the fraction of wealth invested in the n th risky asset from time t to $t + \Delta t$; $E_t(\cdot)$ is the expectation operator conditional on time t information; and κ is the time preference parameter of the investor.

This is a standard problem whose first-order condition yields the following Euler equation:

$$E_t \left[e^{-\kappa \Delta t} \frac{u_C(C_{t+\Delta t}, A_{t+\Delta t})}{u_C(C_t, A_t)} \cdot \frac{P_{n,t+\Delta t}}{P_{n,t}} \right] = 1 \quad \text{for each } n, \quad (3)$$

where $u_C(\cdot, \cdot)$ stands for the partial derivative with respect to consumption C . Note that when the population age distribution is constant over time, it will be true that $A_t = A_{t+\Delta t}$ for any time t and the intertemporal marginal rate of substitution in consumption (IMRS) will be solely determined by the consumption growth process. This is the case that is assumed and studied by the existing literature on consumption-based asset pricing. However, in an economy with a fluctuating age structure, the IMRS will depend on both the aggregate consumption and the demographic processes.

To test the above Euler equation and the life-cycle risk aversion hypothesis, we need to specify a functional form for $u(\cdot, \cdot)$. In the existing literature on asset pricing, it is common to assume a power utility function, partly because it offers mathematical convenience and

makes interpretations intuitive. We follow this tradition and adjust the relative risk aversion coefficient in the power utility function to reflect our hypothesis. That is, the following utility function is assumed for the representative investor:

$$u(C_t, A_t) = \frac{C_t^{1-(\gamma+\lambda \cdot A_t)}}{1 - (\gamma + \lambda \cdot A_t)}, \quad (4)$$

of which the Arrow-Pratt relative risk aversion is given by $\gamma + \lambda \cdot A_t$. In other words, the representative investor's relative risk aversion is linear in average age. This choice is admittedly ad hoc, but it serves as a convenient first-order approximation of our hypothesis, and it is also consistent with the findings by, among others, Morin and Suarez (1983). According to the life-cycle risk aversion hypothesis, it should hold that $\lambda > 0$, which is a testable restriction. Substituting the utility function in (4) into (3) yields

$$E_t \left[e^{-\kappa \Delta t} \frac{C_{t+\Delta t}^{-(\gamma+\lambda \cdot A_{t+\Delta t})}}{C_t^{-(\gamma+\lambda \cdot A_t)}} \cdot \frac{P_{n,t+\Delta t}}{P_{n,t}} \right] = 1, \quad (5)$$

which forms the basis for some of our empirical tests in the later sections.

Testing the various versions of the Euler equation has been a focal point in the empirical asset pricing literature. For example, Hansen and Singleton (1982) test a version of equation (5) with $\lambda = 0$ and find evidence unresponsive of the standard consumption-based pricing theory.⁸ In this article, we seek to address whether change in risk aversion induced by demographic changes is a significant factor in determining asset returns.

C. The Equilibrium Asset Price Process

This subsection provides a suggestive basis for the forecasting exercise in the later sections. For this purpose, we take the discrete-time model to its continuous-time limit. As is usually the case, using a continuous-time framework improves clarity and technical simplicity.

Note that when the n th asset is substituted by the risk-free asset, equation (3) still holds. Subtracting the corresponding equation for the risk-free asset from (3) gives

$$E_t \left\{ \frac{u_C(C_{t+\Delta t}, A_{t+\Delta t})}{u_C(C_t, A_t)} \cdot \left[\frac{P_{t+\Delta t}}{P_t} - (1 + r_0 \Delta t) \right] \right\} = 0. \quad (6)$$

8. For tests of other formulations of the Euler equation, see, among many others, Epstein and Zin (1991); Ferson and Constantinides (1991); Hansen and Jagannathan (1991); and Ferson and Harvey (1992).

As is standard in the literature, assume that the price process $\{P_{n,t}: t \in [0, \infty)\}$ and the equilibrium consumption process are determined according to, respectively,

$$\frac{P_{n,t+\Delta t} - P_{n,t}}{P_{n,t}} = \mu_{n,t}\Delta t + \sigma_{n,t}X_{n,t}\sqrt{\Delta t} \quad \text{for each asset } n,$$

and

$$\frac{C_{t+\Delta t} - C_t}{C_t} = \mu_{c,t}\Delta t + \sigma_{c,t}X_{c,t}\sqrt{\Delta t},$$

where $X_{n,t}$ and $X_{c,t}$ are unit normal random variables and the other parameters are interpreted in the usual way.

In addition, we need to specify the law of motion for the average age process. To do this, observe that fluctuations in the population age structure are generally due to such random events as births, deaths, and immigration. Let us concentrate on the effect of random deaths. Assume that at time t , any investor i with age A_t^i will survive the next time interval $(t, t + \Delta t)$ with probability $\theta(A_t^i) \cdot \Delta t$, where $\theta(A_t^i)$ is the expected number of survival events per unit of time for investors of age A_t^i . On death, the investor is replaced by another (newly born heir) of age 0, which results in a decrease in age of A_t^i . This is essentially how a family is continued or how an investor lives infinitely. Otherwise, if the investor survives, his age increases by Δt . Survival is independent across investors and across time.⁹ In Chen (1990), it is shown that when the survival process for each investor follows such a Poisson process, the central limit theorem implies that for a large population, its average age process is approximately governed by the following difference equation:

$$A_{t+\Delta t} - A_t = \mu_{a,t} \cdot A_t \Delta t + \sigma_{a,t} \cdot A_t X_{A,t} \sqrt{\Delta t}, \tag{7}$$

where $\mu_{a,t}$ and $\sigma_{a,t}$, which can be functions of A_t , are, respectively, the conditional expected value and standard deviation of change in average age per unit time, and $X_{A,t}$ is a unit normal random variable. In reality, we expect $\sigma_{a,t}$ to be small. However, this does not mean that demographic risk cannot have a significant impact on asset prices.

Having specified the stochastic processes for the economic variables, we can take $\Delta t \rightarrow 0$ in (6) and rely on Ito's lemma. After simplification by using the standard steps, equation (6) becomes

$$\mu_{n,t} - r_0 = \eta_{C,t} \cdot \sigma_{nc,t} + \eta_{A,t} \cdot \sigma_{na,t}, \tag{8}$$

9. It is standard to model the survival process by a Poisson process. See, e.g., Constantinides and Duffie (1992). Implicit in the above assumption is also that the population size is stable over time, and only the age distribution fluctuates. This can be easily relaxed by allowing random births, but the basic conclusion will not be affected.

where

$$\eta_{C,t} \equiv -\frac{C_t u_{CC}}{u_C}, \quad \eta_{A,t} \equiv -\frac{A_t u_{CA}}{u_C},$$

$$\sigma_{nc,t} \equiv \frac{1}{dt} \text{cov}_t \left(\frac{dP_{n,t}}{P_{n,t}}, \frac{dC_t}{C_t} \right), \quad \sigma_{na,t} \equiv \frac{1}{dt} \text{cov}_t \left(\frac{dP_{n,t}}{P_{n,t}}, \frac{dA_t}{A_t} \right),$$

with u_{CC} and u_{CA} being second-order partial derivatives and $\text{cov}_t(\cdot, \cdot)$ being the covariance operator conditional on time t information. Thus, when the age structure fluctuates stochastically, the conditionally expected risk premium will be determined by its covariation with two risk factors: the consumption risk and the demographic risk. Clearly, the Breeden (1979) consumption-based capital asset pricing model (CAPM) obtains when the age distribution does not change stochastically.

To express (8) in a more useful form, assume, as in Breeden (1979), that there exist two portfolios, α^c and α^a , that, respectively, mimic aggregate consumption growth and percentage change in average age perfectly. Substitute the two portfolios separately for asset n in (8) and solve the resulting two simultaneous equations for $\eta_{C,t}$ and $\eta_{A,t}$, which are then substituted back into equation (8). The final version of the equilibrium expected excess return for asset n is given as

$$\mu_{n,t} - r_0 = \beta_{nc,t} \cdot (\mu_{c,t} - r_0) + \beta_{na,t} \cdot (\mu_{a,t} - r_0), \quad (9)$$

where

$$\beta_{nc,t} \equiv \frac{\sigma_{a,t}^2 \sigma_{nc,t} - \sigma_{ca,t} \sigma_{na,t}}{\sigma_{c,t}^2 \sigma_{a,t}^2 - \sigma_{ca,t}^2},$$

and

$$\beta_{na,t} \equiv \frac{\sigma_{c,t}^2 \sigma_{na,t} - \sigma_{ca,t} \sigma_{nc,t}}{\sigma_{c,t}^2 \sigma_{a,t}^2 - \sigma_{ca,t}^2},$$

with $\sigma_{ca,t}$ being the conditional covariance between consumption growth and the percentage change in average age. Equation (9) formalizes the idea that the conditional expected risk premium depends on the consumption beta and the demographic beta of the asset.

To see what may determine the sign of $\beta_{na,t}$, consider the special case in which $\sigma_{ca,t} = 0$. Since $\sigma_{c,t}^2 \sigma_{a,t}^2 - \sigma_{ca,t}^2 > 0$, the sign of $\beta_{na,t}$ is then the same as that of $\sigma_{na,t}$. That is, assets that are positively correlated with demographic changes have positive demographic betas, whereas those that are negatively correlated with the latter have negative demographic betas. Note that in equilibrium, it must hold that $\mu_{a,t} - r_0 > 0$. Thus, the expected risk premium of an asset is increasing in its demographic beta, $\beta_{na,t}$.

IV. Data Description

The continuous time-based pricing relation in (9) is suggestive and provides guidelines for our forecasting exercise to follow. However, as in the case of testing Breeden's (1979) consumption CAPM, we can only conduct empirical tests with discrete, low-frequency data. Our choice of low-frequency data is also due to the fact that the population age structure fluctuates slowly and hence should not have much impact on high-frequency market prices. In addition, as Ferson and Harvey (1992) point out, test results may depend on whether one uses seasonally adjusted or non-seasonally adjusted consumption data when an asset pricing model is tested on monthly and quarterly data. To avoid problems arising from seasonality in consumption and dividends and to explain long swings in asset prices, we use annual economic data for the period 1900–1990. For our tests, the following variables are required:

- C_t = real per capita consumption of nondurables and services in year $(t - 1)$. It is equal to the nominal per capita consumption deflated by the January producer price index of year t . The source of data for this variable is Shiller (1989) for the years 1900–1987 and CITIBASE for the years 1988–90.
- $D\text{CONN}_t$ = percentage change in real consumption of nondurables and services from year $(t - 1)$ to year t .
- RETURN_t = real rate of return on the S&P 500 with dividends included. The real S&P 500 index is the January value of the nominal S&P 500 index, deflated by the January producer price index. The dividends are the most recent year's dividends on the S&P 500 stocks. The data source for the S&P 500 index and dividends is Shiller (1989) for the years 1900–1987 and Barsky and DeLong (1990) for the remaining years.
- DIVYLD_t = dividend yield on the S&P 500. As in Campbell and Shiller (1988*a*) and Fama and French (1989), the dividend yield on the S&P 500 equals the sum of dividends on all S&P 500 stocks over year $(t - 1)$ divided by the January S&P 500 index of year t .
- TBILL_t = real rate of return to investing for 6 months, first in January at the January 4–6-month prime commercial paper rate and then continuing for another 6 months at the July 4–6-month prime commercial paper rate, as reported in Shiller (1989) for the years 1900–1987.

For the years 1988–90, the real interest rate is from Ibbotson Associates (1992).¹⁰

- $RPREM_t$ = the excess return on the S&P 500 index, with dividends included, over the nominal interest rate. Sources: Shiller (1989) for the years 1900–1987 and Ibbotson Associates (1992) for 1987–90.
- DEF_t = default premium, which is the yield spread between Baa-rated corporate bonds and Aaa-rated corporate bonds. This variable is available only for the post-1945 period. Source: *CITIBASE* (1992).
- $TERM_t$ = term premium. It is the difference between the yield on a portfolio of Aaa-rated bonds and the nominal interest rate. This variable is available for the post-1945 period. Source: *CITIBASE* (1992) for the bond yields.
- AGE_t = the year t average age of the adult population. It is constructed as

$$AGE_t \equiv \sum_{i=1}^{12} A_i \cdot \frac{N_{i,t}}{N_t},$$

where N_t is the year t total population of ages 20 and over; $N_{i,t}$ is the year t population of persons in the i th age group; and A_i is the middle age of the i th age group. For instance, the middle age is 22 for the age group 20–24 and 27 for the age group 25–29. A total of 12 age groups are used, and they are age groups 20–24, 25–29, 30–34, 35–39, 40–44, 45–49, 50–54, 55–59, 60–64, 65–69, 70–74, and 75 and over. The population estimates for each year are based on July 1 samples. The population data by age groups come from the book *Historical Statistics of the United States: Colonial Times to 1970* (Bureau of the Census 1975) for the years 1900–1945. The data source is *CITIBASE* (1992) for the period 1946–90.

- $DAGE_t$ = percentage change in average age from year $(t - 1)$ to year t .
- $AGE65_t$ = fraction of persons 65 and older in our sample population of ages 20 and over. The percentage change in $AGE65_t$ from year $(t - 1)$ to t is denoted by $DAGE65_t$.

10. Note that the Ibbotson Associates database does not include prices before 1926. To maintain consistency, we try to use as much data from Shiller's database as possible.

$DHOUS_t$ = percentage change in the real price of housing from year $(t - 1)$ to year t . As in Mankiw and Weil (1989), we use the ratio of the residential investment deflator to the GNP deflator as the real price of housing. *CITIBASE* (1992) is the data source for this variable.

In addition, to construct figure 1 for the life expectancy variable, we used *Current Population Reports* (Bureau of the Census, various years).

Tables 1 and 2 report the summary statistics and correlation matrices for the variables. Most of the stylized facts on annual financial variables are well known (e.g., Mehra and Prescott 1985; Fama 1990; Schwert 1990; and Chen 1991). For example, consumption growth is much less volatile than stock returns. However, two patterns are worth noting. First, in table 1, consumption growth and stock returns are positively autocorrelated in the post-1945 period. In the same period, risk premiums are mildly negatively autocorrelated, whereas, over the longer period from 1900 to 1990, they are positively autocorrelated.

Second, the mean of the average age of the adult population was 44.51 and that of the fraction of persons 65 and older was 15% in the post-1945 period, while the mean of the average age was 42.54 and that of the fraction of persons 65 years and older was 11.8% over the longer 1900–1990 period. This further confirms the basic conclusion from Section II, that the demographic changes in the post-1945 period are quite different from those in the pre-1945 years. In the early years, it is mainly the increasing life expectancy that was driving the movements in the age structure (i.e., AGE_{65} , was steadily rising), whereas in the later years the baby boom and the baby bust generations became a more dominant driving force behind the demographic fluctuations. In tables 1 and 2 both the AGE_t and $AGE_{65,t}$ series are highly autocorrelated. In the post-1945 period, the percentage change in average age, $DAGE_t$, is positively correlated with real stock returns, real interest rate, risk premiums, and dividend yields. A similar pattern exists between financial variables and $DAGE_{65,t}$. Over the longer period from 1900 to 1990, the signs of the correlations remain essentially unchanged. However, their magnitudes are much lower than in the post-1945 subperiod. A negative correlation between $DAGE_t$ and $DHOUS_t$ is recorded in the data, consistent with the discussion in Section II.

V. Testing the Euler Equation

In this section, we apply Hansen's (1982) generalized method of moments to test the Euler equation given in (5). Choosing Δt to be a year

TABLE 1 Summary Statistics

Sample Period and Variable	Mean	SD	$\rho(1)$	$\rho(2)$	$\rho(3)$	$\rho(4)$
1946–90:						
AGE _t	44.510	.670	.90	.80	.69	.59
AGE65 _t	.150	.020	.91	.83	.74	.66
DAGE _t	.001	.002	.91	.85	.77	.73
DAGE65 _t	.009	.007	.91	.84	.77	.71
DCONN _t	.016	.013	.26	.05	.11	.16
RETURN _t	.086	.180	.10	-.16	.16	.25
TBILL _t	.014	.070	.35	.04	.10	.26
RPREM _t	.063	.160	-.02	-.21	.21	.31
TERM _t	.007	.013	.34	-.10	-.12	-.13
DEF _t	.010	.004	.79	.59	.45	.46
DIVYLD _t	.043	.013	.83	.66	.54	.38
DHOUS _t	-.0003	.021	.25	.16	.10	.09
1900–1990:						
AGE _t	42.540	2.164	.97	.95	.95	.90
AGE65 _t	.118	.036	.97	.95	.92	.90
DAGE _t	.001	.002	.60	.52	.54	.54
DAGE65 _t	.009	.008	.48	.42	.46	.46
DCONN _t	.017	.032	-.05	.07	.04	-.21
RETURN _t	.085	.193	.06	-.15	.10	-.01
TBILL _t	.015	.097	.34	.02	.03	-.10
RPREM _t	.064	.195	.01	-.22	.11	-.05
DIVYLD _t	.048	.012	.81	.63	.53	.43

NOTE.—AGE_t is the average age of the population of age 20 and over. DAGE_t is the percentage change in average age from year $(t - 1)$ to year t . AGE65_t is the fraction of persons 65 and older in the adult population, and DAGE65_t is the percentage change in AGE65_t. DCONN_t is the growth rate of per capita nondurable and services consumption. RETURN_t is the real rate of return on the S&P 500 index, including dividends. TBILL_t is the annual real interest rate, obtained by investing for 6 months in January and then in July at the 4–6-month commercial paper rate (Shiller 1989). The risk premium, RPREM_t, is the excess return on the S&P 500 index (including dividends) over the annual interest rate. TERM_t (term premium) is the difference between the yield on a portfolio of AAA-rated bonds and the annual interest rate. DEF_t is the default premium, which is the yield spread between BAA-rated and AAA-rated corporate bonds. The dividend yield, DIVYLD_t, is the sum of the year $(t - 1)$'s dividends on S&P 500 stocks, divided by the January S&P 500 price index of year t . DHOUS_t is the percentage change in the real price of housing, which is the ratio of the residential deflator to the GNP deflator. $\rho(L)$ is the autocorrelation coefficient at lag L .

and treating C_t as annual per capita consumption, we rewrite equation (5) as

$$\begin{aligned}
 0 &= E \left\{ \delta \cdot \frac{C_{t+1}^{-(\gamma + \lambda \cdot \text{AGE}_{t+1})}}{C_t^{-(\gamma + \lambda \cdot \text{AGE}_t)}} \cdot (1 + \text{RETURN}_{t+1}) - 1 \mid Z_t \right\} \\
 &\equiv E \{ \epsilon_{t+1} \mid Z_t \},
 \end{aligned} \tag{10}$$

with $\delta = e^{-\kappa}$, where Z_t stands for time t information and the parameters γ and λ measure the risk-taking attitude of the representative agent. In particular, given the agent's age AGE_t at time t , his relative risk aversion is $\gamma + \lambda \cdot \text{AGE}_t$, which should, according to the life-cycle

TABLE 2 The Contemporaneous Correlation Matrix
A. Sample Period: 1946-90

	RETURN	TBILL	RPREM	TERM	DEF	DIVYLD	DAGE	DAGE65	DHOUS
DCONN	.49	.24	.49	.14	-.34	-.40	-.22	-.26	.15
RETURN		.56	.98	.43	-.30	-.08	.40	.28	.02
TBILL			.40	-.03	.43	-.25	-.01	-.24	-.18
RPREM				.47	-.03	-.01	.35	.39	-.21
TERM					.02	-.16	.20	.17	.08
DEF						.08	-.39	-.37	-.11
DIVYLD							.32	.49	.10
DAGE								.93	-.28
DAGE65									-.18

B. Sample Period: 1900-1990

	RETURN	TBILL	RPREM	DIVYLD	DAGE	DAGE65
DCONN	.49	-.09	.49	-.17	-.12	-.10
RETURN		.27	.87	-.20	.04	.03
TBILL			-.21	.00	-.12	-.14
RPREM				-.41	.18	.17
DIVYLD					.38	.30
DAGE						.75

NOTE.—AGE_{*t*} is the average age of the population of age 20 and over. DAGE_{*t*} is the percentage change in average age from year (*t* - 1) to year *t*. AGE65_{*t*} is the fraction of persons 65 and older in the adult population; and DAGE65_{*t*} is the percentage change in AGE65_{*t*}. DCONN_{*t*} is the growth rate of per capita nondurable and services consumption. RETURN_{*t*} is the real rate of return on the S&P 500 index, including dividends. TBILL_{*t*} is the annual real interest rate, obtained by investing for 6 months in January and then in July at the 4-6-month commercial paper rate (Shiller 1989). The risk premium, RPREM_{*t*}, is the excess return on the S&P 500 index (including dividends) over the annual interest rate. TERM_{*t*} (term premium) is the difference between the yield on a portfolio of AAA-rated bonds and the annual interest rate. DEF_{*t*} is the default premium, which is the yield spread between BAA-rated and AAA-rated corporate bonds. The dividend yield, DIVYLD_{*t*}, is the sum of the year (*t* - 1)'s dividends on S&P 500 stocks, divided by the January S&P 500 price index of year *t*. DHOUS_{*t*} is the percentage change in the real price of housing, which is the ratio of the residential deflator to the GNP deflator.

hypothesis of risk aversion, increase with average age. Thus, our testable hypothesis is

$$\lambda > 0.$$

Under the null hypothesis that equation (10) is true, we have $E\{\epsilon_{t+1}|Z_t\} = 0$; that is, the expected value of the disturbance is zero. The GMM estimations are based on minimizing the quadratic form, $J_T \equiv g_T' W_T g_T$, where g_T is the sample analog of the process $\{\epsilon_t, Z_t\}$ defined in (10) and W_T is a positive-definite symmetric weighting matrix. The minimized value of the quadratic form, called the $J(\text{df})$ statistic, is χ^2 -distributed under the null hypothesis that the model is true with degrees of freedom, df , equal to the number of orthogonality conditions net of the number of parameters to be estimated. The $J(\text{df})$ statistic provides a goodness-of-fit test for the model, and a high value for it implies that the model is misspecified.

The next issue concerns the choice of information instruments to be contained in Z_t . In this regard, theory has little guidance (Hansen and Singleton 1982). Like Epstein and Zin (1991), Ferson and Constantinides (1991), and Ferson and Harvey (1992), we replicate our results using different sets of instruments. We base the selection of instruments on earlier studies that document the ability of the instruments to forecast future consumption growth and stock returns. The sets of instruments, Z_1 and Z_2 , consist of a constant and, respectively, two and three lags each of the real consumption growth and the real stock returns. Fama and French (1989) show that term premiums track business conditions. However, when we included the term premium and the default premium as instruments, the results were similar to what we report in table 3. To save space, we chose to focus on the sets Z_1 and Z_2 . Having additional lags helps reduce the effect of both time aggregation and mismatching of time periods with planning horizons (e.g., Epstein and Zin 1991; Braun, Constantinides, and Ferson 1994). For this reason, Z_1 and Z_2 are different only in the number of lags of the instruments.

To test for robustness and stability of the estimates, we report in table 3 estimation results of the parameters $\{\delta, \gamma, \lambda\}$ for four different time periods: 1946–90, 1926–90, 1900–1990, and 1900–1945. The standard errors in parentheses are calculated using the method outlined in Newey and West (1987) with a lag length of 2. The p -values in brackets below the standard errors test the null hypothesis that the estimated parameter equals zero. While the GMM is a powerful test of the Euler equation restriction, the parameter estimates and hypothesis testing using the GMM are only justified through asymptotic distribution theory. However, Tauchen (1986) found that the GMM test statistic performs well with as few as 50 annual observations. The p -value reported below the $J(\text{df})$ statistic indicates the probability that a χ^2 variate exceeds the minimized sample value of the GMM criterion function.

TABLE 3 The GMM-based Euler Equation Tests
A. Sample Period: 1946–90

Set of Information Instruments	δ	γ	λ	df	$J(df)$ [<i>p</i> -value]	NOBS
Z_1	1.23 (.25) [.00]	-43.24 (18.27) [.00]	1.29 (.63) [.03]	2	1.87 [.39]	45
Z_2	1.27 (.13) [.00]	-42.80 (13.07) [.00]	1.31 (.36) [.00]	4	2.62 [.62]	45
Z_1^*	.995	-32.61 (8.16) [.00]	.81 (.17) [.00]	3	8.07 [.05]	45
Z_2^*	.995	-28.35 (8.24) [.00]	.72 (.18) [.00]	5	7.93 [.16]	45

B. Other Sample Periods

Sample Period and Set of Information Instruments	δ	γ	λ	df	$J(df)$ [<i>p</i> -value]	NOBS
1926–90: Z_2	.98 (.06) [.00]	-8.35 (18.79) [.66]	.25 (.47) [.59]	4	3.95 [.41]	65
Z_2^*	.995	-13.20 (8.16) [.10]	.37 (.18) [.04]	5	4.00 [.54]	65
1900–1990: Z_2	.87 (.12) [.00]	10.81 (36.59) [.76]	-.29 (.97) [.76]	4	3.12 [.53]	91
Z_2^*	.995	-24.61 (11.32) [.02]	.65 (.26) [.01]	5	5.81 [.32]	91
1900–1945: Z_2	.93 (.09) [.00]	-18.99 (90.97) [.83]	.47 (2.26) [.83]	4	2.14 [.71]	46
Z_2^*	.995	-55.25 (43.90) [.21]	1.39 (1.07) [.19]	5	3.72 [.58]	46

NOTE.—Estimation of the Euler equation is based on Hansen's (1982) generalized method of moments (GMM),

$$E\left\{\delta \cdot \frac{C_{t+1}^{-(\gamma+\lambda \cdot AGE_{t+1})}}{C_t^{-(\gamma+\lambda \cdot AGE_t)}} \cdot [1 + \text{RETURN}_{t+1}] - 1 | Z\right\} = 0,$$

where C is the per capita consumption and Z is the set of time t information variables. All the other variables are explained in table 1. Standard errors, calculated using the method outlined in Newey and West (1987) with a lag length of 2, are in parentheses, and p -values are in brackets. The set of information instruments, Z_1 and Z_2 , contain a constant and, respectively, two and three lags each of DCONN_t and RETURN_t . We tried other instrumental variables, but the results are similar to the ones reported here. df is the number of instruments minus the number of parameters to be estimated. The statistic, $J(df)$, is asymptotically $\chi^2(df)$ distributed and tests whether the overidentifying restrictions of the model are true with degrees of freedom equal to df . An asterisk on Z indicates that, for that row, the GMM estimation is performed under the restriction $\delta = 0.995$. NOBS is the number of observations.

Panel A of table 3 reports the results for the sample period from 1946 to 1990. The point estimates of γ and λ are stable across the two sets of instrument variables. While γ is negative and in the range from -42.80 to -43.24 , λ is significantly positive and in the 1.29 – 1.31 range. Here, a negative γ does not imply risk loving because the risk aversion parameter is $\gamma + \lambda \cdot AGE_t$. For instance, with $\gamma = -43$, $\lambda = 1.30$, and $AGE_t = 44$ (the time-series mean of AGE_t), the relative risk aversion coefficient is 14.2 . A positive value for λ is consistent with the life-cycle hypothesis of risk aversion. Standard errors for γ and λ are typically small, and their estimates are many standard errors away from zero. The null hypotheses that $\gamma = 0$ and $\lambda = 0$ are rejected with p -values less than 3%. The discount factor parameter, δ , is estimated to be between 1.23 and 1.27 . The null hypothesis that $\delta = 1$ is rejected in both cases using the candidate instrumental variables, although this result is not reported in table 3. The overidentifying restrictions of the model with time-varying, demographic-driven risk aversion are not rejected using either of the instrument sets, with p -values exceeding 39%.

At the first glance, the result that $\delta > 1$ seems odd, but Constantinides (1990) shows that habit formation resolves the equity premium puzzle with a discount factor greater than one. Based on annual data, Ferson and Constantinides (1991) also obtain a discount factor greater than 1 in estimating both the time-separable expected utility model and the time-nonseparable habit-forming utility model. To assess the stability of our results to a value of δ less than 1, we reestimated the Euler equation in (10) subject to the restriction that $\delta = 0.995$. The corresponding estimation results are reported in the rows denoted by asterisks of table 3 and are similar in spirit to those obtained without this restriction, except that the magnitudes of γ and λ are smaller. Both of the estimated parameters are many standard errors away from zero. The model is again not rejected, with the lowest p -value exceeding 10%.

Panel B of table 3 presents mixed results for the other time periods: 1900–1990, 1926–90, and 1900–1946. Since the average age increased almost linearly while stock returns fluctuated randomly from 1900 to 1945, it may not come as a surprise that the coefficient λ is insignificantly different from zero for certain sample periods. With the instrumental variables Z_2 , the point estimates of λ are insignificant for all the three periods. However, with the instrument set Z_2^* ,¹¹ the parameter λ is positive and statistically significant for the two periods 1926–90 and 1900–1990. The coefficient γ is negative and statistically significant as well for the same two periods. The overidentifying restrictions are

11. An asterisk on the instrument set Z_2 means that the corresponding row represents estimation results obtained under the restriction $\delta = 0.995$.

not rejected, with p -values in excess of 32%. The inclusion of average age as a determinant of the representative investor's IMRS, therefore, improves the fit of the expected utility model.

Next, we plot in figure 7 the time-series path of the implied risk aversion, $\gamma + \lambda \cdot AGE_t$, where the parameters are taken from the sample estimates for the period 1900–1990: $\gamma = -24.61$ and $\lambda = 0.65$. Given the linear specification of the relative risk aversion function, the implied risk aversion shares the same shape with AGE_t . Its mean is 3.04. The lowest risk aversion level for the representative investor is 0.87, and the highest is 4.91, achieved around year 1965.¹²

We can also relate the demographics-determined risk aversion to the Merton (1980) reward-to-risk ratio. For this purpose, we obtained the monthly excess returns on the S&P 500 stocks (including dividends) over the Treasury-bill rate from Ibbotson Associates (1992). The period covers the years from 1926 to 1990. To implement Merton's procedure, we divide the period into 3-year intervals, where, for each interval, the reward-to-risk ratio is assumed to be constant. Then, using the monthly excess returns for each 36-month interval, we estimate the reward-to-risk ratio for the subperiod according to Merton's model 1.¹³ Here, we only report the estimation results in figure 7, where the reward-to-risk ratio is plotted together with the age-implied risk aversion. From 1929 to 1956, the reward-to-risk ratio was increasing, and so was the age-implied risk aversion. Then, both measures went down from 1960 to 1970 and up from 1980 to 1990. Therefore, the Merton reward-to-risk ratio and the age-implied risk aversion are two consistent measures of the representative investor's attitudes toward risk taking. To put it differently, changes in the representative investor's risk aversion over time are at least partly attributable to demographic fluctuations.

12. In addition to the estimation reported here, we tried to estimate the Euler equation with the relative risk aversion parameter given by a quadratic function of age. But, the GMM procedure failed to converge.

13. Following Merton's (1980) model 1, we use a two-step procedure to estimate the reward-to-risk ratio. First, for each 3-year interval, take the sum of all monthly excess returns on the S&P 500 stocks over the Treasury bills and divide it by 36, which gives the mean excess return. Second, for the same 3-year interval, add together the squares of monthly returns on the S&P 500 stocks and divide it by 36, which produces a risk measure. The reward-to-risk ratio is then given by

$$\frac{\sum_{t=1}^{36} (\text{RETURN}_t - \text{TBILL}_t)}{\sum_{t=1}^{36} \text{RETURN}_t^2}.$$

For details on the underlying assumptions, see Merton (1980).

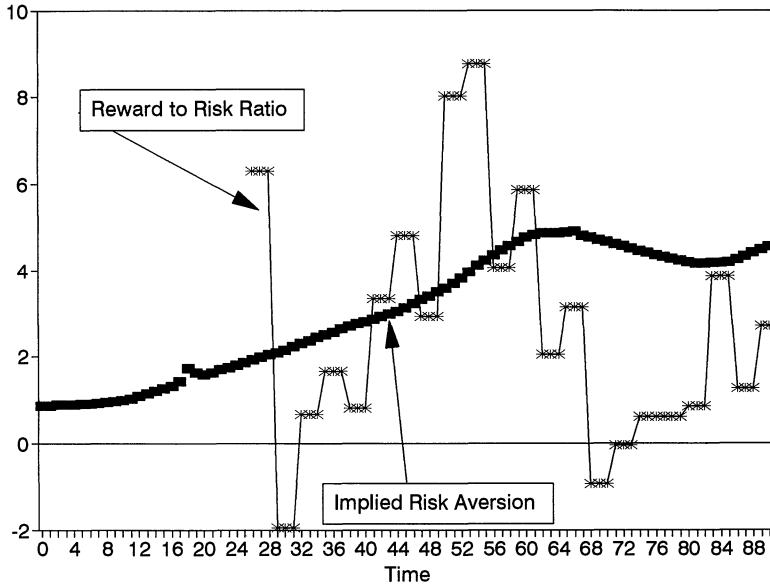


FIG. 7.—Risk aversion versus reward-to-risk ratio. The reward-to-risk ratio has been calculated using model 1 of Merton (1980) with a time interval of 36 months (data source: Ibbotson Associates 1992) and divided by 1.50. The implied risk aversion is given by $RRA_t = \gamma + \lambda \cdot AGE_t$ with a value of $\gamma = -24.61$ and $\lambda = 0.65$.

VI. The Hansen-Jagannathan Bound Tests

In addition to the tests reported in the previous section, we can apply the Hansen-Jagannathan (1991) diagnostic method to check whether the IMRS implied by (5) satisfies the mean-variance bounds for every admissible IMRS or stochastic discount factor. To briefly see the logic behind their method, take a single-period economy from time t to $t + 1$ as an example and suppose there are N traded securities at t , with their time $(t + 1)$ gross returns given by $R_{n,t+1}$. Then, when the law of one price holds at time t , any admissible IMRS m_{t+1} must satisfy

$$E\{m_{t+1} \cdot R_{n,t+1} | Z_t\} = 1 \quad \text{for each } n = 1, \dots, N, \quad (11)$$

where Z_t is the time t information. By the law of iterated expectations, equation (11) implies

$$E\{m_{t+1} \cdot R_{n,t+1}\} = 1 \quad \text{for each } n = 1, \dots, N. \quad (12)$$

Different asset pricing models may propose different forms for m_{t+1} , but all of them have to satisfy the above equation for each asset n . According to the least squares regression theory, this means there must exist a benchmark portfolio return m_{t+1}^* such that

1. $E\{m_{t+1}^* R_{t+1}\} = 1_N$, where R_{t+1} is a column vector stacked with the N gross returns $R_{n,t+1}$ and 1_N is an N vector of ones; and
2. for every admissible IMRS, m_{t+1} , it holds that $m_{t+1} = m_{t+1}^* + \epsilon_{t+1}$, where ϵ_{t+1} is the projection error or residual, uncorrelated with m_{t+1}^* .

Clearly, if $E(m_{t+1}) = E(m_{t+1}^*)$, the above argument implies that $\text{var}(m_{t+1}) \geq \text{var}(m_{t+1}^*)$, where $\text{var}(\cdot)$ stands for the unconditional variance operator. Thus, the variance of the benchmark m_{t+1}^* provides a lower bound for the variance of every admissible IMRS. Hansen and Jagannathan (1991) use this bound as an informal diagnostic test for any asset pricing model: if an asset pricing model is to fit the asset price data, a necessary condition is that its proposed IMRS have a variance at least as large as that of the corresponding benchmark m_{t+1}^* .

To save space, we simply write down the Hansen-Jagannathan bound formula below and refer the reader to their paper (or Ferson and Harvey 1992) for a detailed derivation (time subscripts are dropped here):

$$\text{var}(m) \geq [1_N - E(m)E(R)]' \Sigma(R)^{-1} [1_N - E(m)E(R)], \quad (13)$$

where $E(m)$ is the unconditional mean of the candidate IMRS, and $\Sigma(R)$ is the unconditional variance-covariance matrix of the returns in R . The variance bound is clearly easy to estimate.

With the effect of demographic changes taken into account, we have specified a candidate IMRS given by

$$\text{IMRS} = \delta \frac{C_{t+1}^{-(\gamma+\lambda \cdot \text{AGE}_{t+1})}}{C_t^{-(\gamma+\lambda \cdot \text{AGE}_t)}}. \quad (14)$$

Figure 8 presents the Hansen-Jagannathan bounds, constructed from the annual S&P 500 index and the annual interest rate, and the mean-standard deviation pairs of our candidate IMRS corresponding to different parameter values for γ and λ . For most parameter values that are close to the point estimates in table 3, the candidate IMRS lies outside the Hansen-Jagannathan bounds. Only for relatively large values for $|\gamma|$ and λ can the candidate IMRS lie within the Hansen-Jagannathan bounds. For example, the IMRS is within the bounds for the following parameter value pairs: $(\gamma, \lambda) = (-50.00, 5.50)$, $(\gamma, \lambda) = (105.00, 1.29)$, $(\gamma, \lambda) = (110.00, 1.29)$, where $\delta = 0.995$. Therefore, unless the mean relative risk aversion coefficient ($= \gamma + \lambda \cdot E(\text{AGE}_t)$) is very high, the Hansen-Jagannathan bounds will be violated by the candidate IMRS given in (14). This conclusion is consistent with what is known in the literature on time-separable expected utility (e.g., Hansen and Jagannathan 1991; and Ferson and Harvey 1992).

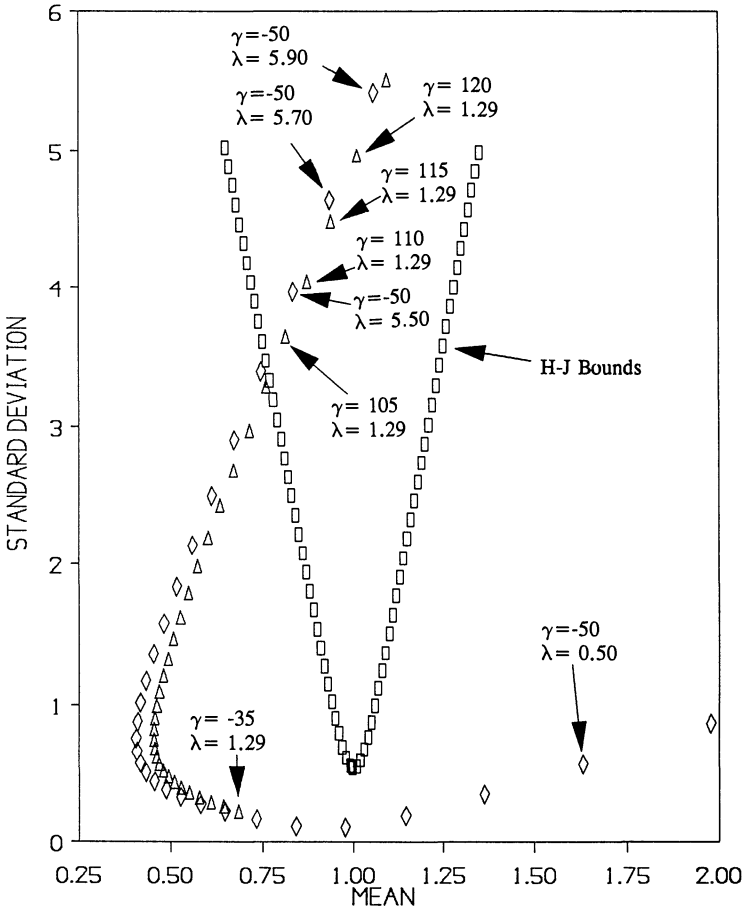


FIG. 8.—Hansen-Jagannathan bounds. The Hansen-Jagannathan bounds, illustrated by the □-curve, are constructed from the annual S&P 500 stock returns (including dividends) and the annual interest rate (see Hansen and Jagannathan 1991). The candidate intertemporal marginal rate of substitution (IMRS) is given by

$$IMRS = \delta \cdot \frac{C_{t+1}^{-(\gamma+\lambda \cdot AGE_{t+1})}}{C_t^{-(\gamma+\lambda \cdot AGE_t)}}$$

The △-curve stands for the mean-standard deviation pairs of the IMRS obtained by fixing $\delta = 0.995$ and $\lambda = 0.995$. The ◇-curve is obtained by fixing $\delta = 0.995$ and $\gamma = 50.00$.

Note that the Euler equation in (10) is rejected in the Hansen-Jagannathan bound test but not in the GMM test reported in the previous subsection. This seemingly puzzling finding is due to the fact that the Hansen-Jagannathan bounds on the second moment of an admissible IMRS are based on the *unconditional* version of the Euler equation in (10). Thus, the Hansen-Jagannathan bound test can be understood as a test of the unconditional Euler equation. In the previous subsection, however, we used instrumental information variables in the GMM estimation and effectively tested a conditional version of the Euler equation. Based on the test results, we conclude that a conditional version of the Euler equation in (10) performs better than its unconditional counterpart.

VII. Predictability of Risk Premiums

According to the discussion in Section III, expected excess returns should, in equilibrium, be determined by both an asset's sensitivity to such systematic factors as aggregate consumption and demographic fluctuations and the risk premiums earned by those factors (see, e.g., Breeden 1979; and Cox, Ingersoll, and Ross 1985 for other models). This conclusion is suggestive. When translated into our sample framework, it means that for the S&P 500 portfolio,

$$E\{\text{RPREM}_{t+1}|Z_t\} = E\{\beta_{ma}(\text{DAGE}_{t+1} - r_0) + \beta_{mc}(\text{DCONN}_{t+1} - r_0)|Z_t\}, \quad (15)$$

where the coefficients β_{ma} and β_{mc} are measurable with respect to time t information. According to this equation, any time t information variables that either determine the factor betas, β_{ma} and β_{mc} , or are predictors of future consumption growth and demographic fluctuations will help forecast future market risk premium. Then, the question is what information variables should be included in Z_t in our forecasting exercise? To answer this question, note that Ferson and Harvey (1991) find most predictability of market risk premium is driven by time-varying economic risk premiums and not by time-varying betas. Therefore, we can limit our attention to those variables that help predict future consumption and/or demographic premiums.

Since both the consumption and the demographic variables, DCONN_{t+1} and DAGE_{t+1} , are serially correlated over time, we should clearly include their time t values, DCONN_t and DAGE_t , in Z_t . In the existing literature, dividend yields, the growth rate of real activity, and various term structure variables have been found to be predictors of future variations in risk premiums (see, among others, Chen, Roll, and Ross 1986; Keim and Stambaugh 1986; Fama and French 1988*b*, 1989; Fama 1990, 1991; Schwert 1990; Chen 1991; Ferson and Harvey 1991;

Harvey 1991). To understand whether the demographic variable offers any additional power in predicting future risk premiums, we include in our exercise the following information variables as well: $DIVYLD_t$, and $TERM_t$. As in previous work, we assume a linear forecasting specification:

$$\begin{aligned} RPREM_{t+1} = & b_0 + b_1 \cdot DAGE_t + b_2 \cdot DCONN_t \\ & + b_3 \cdot DIVYLD_t + b_4 \cdot TERM_t + \epsilon_{t+1}. \end{aligned} \quad (16)$$

This equation incorporates both predicting variables that are known to be significant in the existing literature and our newly introduced variable $DAGE_t$. It is the basis for the ordinary least squares (OLS) regressions to follow.

Before we discuss the test results, it is interesting to observe figure 9, which depicts the time series for $RPREM_t$ and $DAGE_t$. While there does not appear to be a relation between the risk premium and the change in average age for the years before 1940, there is a clear relation for the post-1940 period: both $RPREM_t$ and $DAGE_t$ moved upward in the years 1940–55, downward in the years 1956–75, and then upward again in the period 1976–90. Given this visual impression, we should expect $DAGE_t$ to be significant in predicting future risk premiums, at least for the post-1940 years.

In running the forecasting regressions, we use the method outlined in Newey and West (1987) with a lag length of 2 to calculate the standard errors for the coefficient estimates. Panel A of table 4 presents the results for the period 1946–90. First, the variable $DAGE_t$ is significantly and positively related to future risk premiums. In all the cases, its coefficient estimates are positive and more than 2 standard errors away from zero, with p -values constantly below 5%. Thus, a rise in average age means a higher risk premium in the future, which is consistent with the prediction of the life-cycle hypothesis of risk aversion. Second, the coefficient estimate for $DCONN_t$ is not statistically significant, with t -statistics below 2 and p -values at or above 10%. Consumption growth does not appear to possess much power in predicting future risk premium. Third, as expected from the existing literature, dividend yield, $DIVYLD_t$, has significant predictive power of future risk premium. The coefficient estimates of b_3 are positive and statistically significant, with p -values equal to .00 in each case. At the same time, the coefficient estimates for $TERM_t$ have the right sign but they are all less than 1 standard error away from zero. In addition, with the multivariate forecasting, the adjusted R^2 values are above 33%, meaning that the predictability of annual market risk premium by the included variables is about 33%.

Since consumption growth and term premium do not have significant predictive power, we exclude them from the estimation equation and

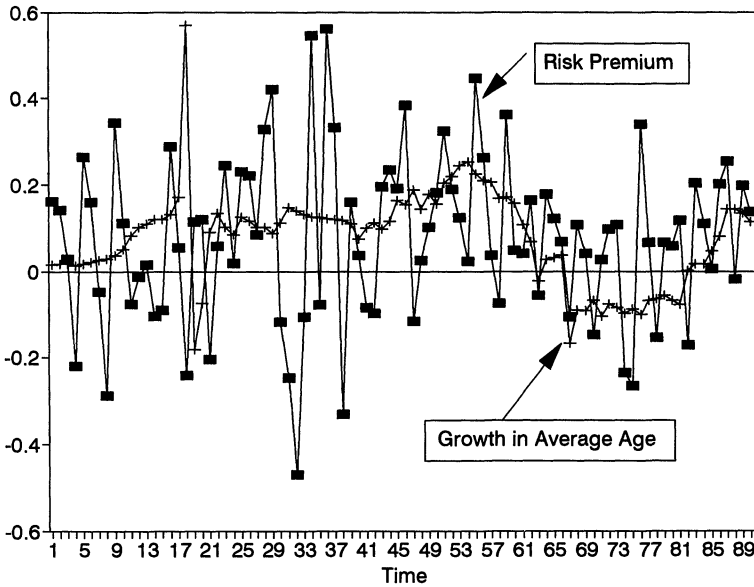


FIG. 9.—Risk premium and growth of average age. Risk premium is the difference between returns on the S&P 500 index (including dividends) and the annual interest rate. Growth of average age is the arithmetic growth rate multiplied by 50. Source: Shiller (1989) and Barsky and DeLong (1990).

TABLE 4 Predictability of Risk Premiums
A. Sample Period: 1946–90

No.	b_0	b_1	b_2	b_3	b_4	R^2	D-W	NOBS
1	-.05 (.06) [.37]	16.48 (7.81) [.03]	-2.84 (1.77) [.11]	3.87 (1.04) [.00]	-1.18 (.96) [.12]	.35	2.22	45
2	-.07 (.06) [.25]	13.81 (6.83) [.04]	-3.01 (1.83) [.10]	4.16 (1.01) [.00]		.33	2.29	45
3	-.17 (.06) [.00]	18.06 (5.78) [.00]		5.40 (1.36) [.00]		.28	2.33	45
4	.04 (.02) [.00]	25.07 (6.45) [.00]				.15	2.41	45
5	.15 (.03) [.00]		-5.49 (1.68) [.00]			.07	2.22	45
6	-.20 (.06) [.00]			6.41 (1.48) [.00]		.20	2.03	45

TABLE 4
(Continued)
B. Other Sample Periods

Sample Periods and No.	b_0	b_1	b_2	b_3	R^2	D-W	NOBS
1926-90:							
1	.26 (1.01) [.79]	18.47 (6.49) [.00]	-.31 (1.00) [.75]	2.19 (1.67) [.18]	.08	1.93	65
2	-.06 (.07) [.37]	18.77 (6.29) [.00]		2.38 (1.87) [.20]	.08	1.94	65
3	.04 (.02) [.06]	23.46 (6.99) [.00]			.06	2.03	65
4	1.00 (1.08) [.35]		-.92 (1.06) [.38]		.01	1.89	65
5	-.07 (.07) [.34]			3.21 (1.97) [.10]	.05	1.83	65
1900-1990:							
6	.43 (.69) [.53]	16.54 (5.28) [.00]	-.47 (.68) [.49]	1.75 (1.26) [.16]	.08	1.96	91
7	-.06 (.05) [.29]	16.92 (5.40) [.00]		1.98 (1.29) [.12]	.08	1.96	91
1900-1945:							
8	.14 (.77) [.86]	18.10 (8.12) [.02]	-.16 (.75) [.83]	.94 (1.51) [.53]	.06	1.79	46
9	-.03 (.08) [.73]	18.29 (2.26) [.02]		1.05 (1.58) [.51]	.03	1.79	46

NOTE.—Estimation of the equation is based on OLS regressions,

$$\text{RPREM}_{t+1} = b_0 + b_1 \cdot \text{DAGE}_t + b_2 \cdot \text{DCONN}_t + b_3 \cdot \text{DIVYLD}_t + b_4 \cdot \text{TERM}_t + \Sigma_{t+1},$$

where the variables are as defined in table 1. Standard errors, calculated using the method outlined in Newey and West (1987) with a lag length of 2, are in parentheses, and p -values are in brackets. D-W is the Durbin-Watson statistic for the error term. The reported R^2 is the adjusted R^2 statistic. NOBS is the number of observations.

find that the statistical significance of both DAGE_t and DIVYLD stays the same. The fourth and fifth rows in panel A of table 4 report the corresponding results. In order to evaluate the individual predictive power of each ex ante variable, we conduct a univariate forecasting test for each of DAGE_t , DCONN_t , and DIVYLD_t . The last three rows in panel A of table 4 show the results. As can be seen, all three vari-

ables in the univariate regressions are statistically significant in forecasting future risk premiums. However, it is worth noting that the coefficient estimate for $DCONN_t$ is negative, while in the multivariate cases the estimates for b_2 are positive. The adjusted R^2 is 20% when $DIVYLD_t$ is the predicting variable and 15% when $DAGE_t$ is used, which indicates the former may be a slightly more significant predictor.

Panel B of table 4 displays the forecasting results for the other time periods. In the sample period 1926–90, which is the period extensively analyzed in Fama and French (1988a, 1988b, 1989) and Hodrick (1992), the collective predictive power of $DAGE_t$, $DCONN_t$, and $DIVYLD_t$ is substantially weaker than in the post-1945 period just discussed, with the adjusted R^2 being only 8%. The demographic variable, $DAGE_t$, turns out to be the only one with a coefficient estimate being 2 standard errors away from zero. $DIVYLD(t)$ is no longer statistically significant, and its p -value is in excess of 10%, which is consistent with the findings by Fama and French (1988b), that dividend yield is not a significant predictor of stock returns for the overall period 1926–87. For this period, the univariate regressions confirm the multivariate result: $DAGE_t$ is significant and $DCONN_t$ and $DIVYLD_t$ are not in predicting future risk premiums. For the other sample periods, 1900–1945 and 1900–1990, the same conclusion can, as seen from panel B of table 4, be drawn: the demographic variable is the sole significant predictor.

In summary, a change in the average age predicts a change in the risk premium during the entire period 1900–1990, and a greater jump in average age implies a larger risk premium. However, except for the post-1945 period, dividend yield and aggregate consumption growth are not significant in predicting risk premiums. In the post-1945 years, $DAGE_t$, $DIVYLD_t$, and $DCONN_t$ can collectively achieve a 33% forecastability of future risk premium.

To see how much predictability of future risk premium can be, respectively attributed to $DAGE_t$ and $DIVYLD_t$, we conduct a variance decomposition of the predicted values, as in Ferson and Harvey (1991) and Ferson and Korajczyk (1992). In the first step, we regress $RPREM_{t+1}$ on $DAGE_t$, $DCONN_t$, $DIVYLD_t$, and $TERM_t$, and calculate the variance of the fitted values, denoted by VR . In the next step, we regress the fitted values obtained in the first step separately on $DAGE_t$ and $DIVYLD_t$, and calculate the variance of the resulting fitted values respectively from each regression. Let VR_1 and VR_2 be the respective variances of the fitted values from the second step. In table 5, we report the ratios VR_1/VR and VR_2/VR . The first ratio, VR_1/VR , reflects the fraction of the predictable variation in $RPREM_{t+1}$ attributable to change in average age, $DAGE_t$, alone. The other ratio indicates the fraction due to dividend yields. As table 5 shows, $DIVYLD$ seems to capture a higher portion of the predictability of future risk premium than $DAGE_t$ for the post-1945 period. However,

TABLE 5 Variance Decomposition of Predicted Market Risk Premium

Sample Period	Percentage of Predicted Variation due to:	
	DAGE	DIVYLD
1946–90	42	61
1926–90	68	57
1900–1990	69	51
1900–1945	85	32

NOTE.—We apply a two-step procedure to decompose the variance of the fitted values for future market risk premium, with $DAGE_t$, $DCONN_t$, and $TERM_t$ as predictors. First, we run the following OLS regression,

$$RPREM_{t+1} = b_0 + b_1 \cdot DAGE_t + b_2 \cdot DCONN_t + b_3 \cdot DIVYLD_t + b_4 \cdot TERM_t,$$

and calculate the fitted values for $RPREM_{t+1}$. Note that $TERM_t$ is present only for the period 1946–90. Second, we regress the fitted values separately on $DAGE_t$ and $DIVYLD_t$ to determine the fraction of predicted variation attributable to each one of the two ex ante variables.

in all other sample periods, 1900–1945, 1900–1990, and 1926–90, the reverse is true: $DAGE_t$ accounts for a higher portion of the predictability. Intuitively, we can think of dividend yields as carrying information about the future productivity of firms (see, e.g., Campbell and Shiller 1988*a*, 1988*b*; and Fama and French 1989), and a change in the average age as carrying information about the future attitudes toward risk taking as well as future aggregate demand for financial assets. In other words, dividend yields reflect information concerning the supply side of the capital markets, whereas the demographic variable carries information about the demand side. Together, they allow one to form expectations about future stock returns and risk compensations.

VIII. Concluding Remarks

A central message of this article is that demographic fluctuations have had significant impact on capital market prices. Given the persistent influence of the baby boomers and the increasing life expectancy on the general economy, they will continue doing so for decades to come. As we have argued, changes in the demographic structure can affect the capital markets in various ways. First, according to the life-cycle investment hypothesis, an investor's asset mix changes with the life cycle. Thus, when the population ages (as indicated by an increase in average age), the aggregate demand for financial investments rises and

that for housing declines. Likewise, when the population becomes younger (as implied by a lower average age), the opposite effect occurs. Second, by the life-cycle hypothesis of risk aversion, an aging population means an increasing average risk aversion, which in turn implies higher equilibrium risk premiums. Therefore, demographic movements can bring about fluctuations in asset demand on capital markets.

Once it holds that changes in the age structure affect capital market prices, it does not seem surprising that demographic changes can predict future stock returns and, in particular, a rise in average age tends to be followed by a rise in market risk premium. The reason is that demographic changes are highly predictable. We have found that of the entire 1900–1990 period, the post-1945 subperiod is the most supportive of our hypotheses.¹⁴ This subperiod is associated with the baby boom generation. To some extent, it provides us with an ideal context in which to examine the effect of demographic changes on capital markets, because it has brought a “much larger than usual” cohort into the population. It is thus interesting to see what happens to the capital markets at different phases of the baby boomers’ life cycle. As demonstrated in this paper, both the baby boom and the increased life expectancy have generated long swings in stock and housing market prices.

In the existing literature on stock return predictability, some studies suggest that low-frequency stock returns seem to be relatively more predictable than high-frequency returns (see, e.g., Keim and Stambaugh 1986; Fama and French 1988*a*, 1988*b*; Poterba and Summers 1988; and Goetzmann and Jorion 1992). Of special relevance to our results is the work by Ferson and Harvey (1991), in which they find that most of the predictable variation in stock returns is due to the variation in market risk premiums and not so much to the time-varying betas. They also report that risk premiums appear to have distinct business-cycle patterns. However, what drives the variation in risk premiums is an unresolved issue. While previous work has associated the variation with instruments that exhibit business-cycle patterns, we have shown that those patterns are at least partly attributable to demographic swings. Our findings are also consistent with a result by Grandmont (1985), in which he shows that, if the older economic agents’ risk aversion is higher than the younger agents’, there will be endogenously generated business cycles.

Of course, “average age,” while measuring the age composition of the population, is only a proxy for demographics-determined asset demand variables. That is, a change in average age per se will not

14. Other studies have also found that the pre-1945 and the post-1945 periods seem to possess different characteristics. Economic models sometimes “perform better” for the post-1945 years than the pre-1945 years. See, e.g., Fama and French (1988*a*, 1988*b*, 1989); and Campbell (1991).

induce any changes in asset prices, unless investors' investment decisions, and their attitudes toward risk, depend on the life cycle. When this dependence follows certain patterns, one can then use average age to approximate the demographics-driven asset demand functions. As mentioned earlier, an increase in life expectancy can only strengthen the life-cycle investment patterns. For instance, it will make older consumers invest more for retirement. In addition, average age is closely related to life expectancy, even though they capture different aspects of demographics. Provided that the population in each age group stays unchanged, an increase in life expectancy will lead to an increase in average age. However, when the population in some age groups changes (e.g., the entry of a baby boom generation), a higher life expectancy may not imply a higher average age. Thus, average age provides a measure of the entire population structure and a proxy for both the housing and the investment demand functions at the macro level.

Further work seems necessary in order to fully understand the empirical evidence documented in this article. Since existing financial models do not take into account the effect of demographic changes, it may be refreshing to incorporate and examine such features.

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