Idiosyncratic Consumption Risk and the Cross-Section of Asset Returns

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Abstract

This paper investigates the importance of idiosyncratic consumption risk for the cross-sectional variation in average returns on stocks and bonds. If idiosyncratic consumption risk is not priced, the only pricing factor in a multiperiod economy is the rate of aggregate consumption growth. We offer evidence that the cross-sectional variance of consumption growth is also a priced factor. This demonstrates that consumers are not fully insured against idiosyncratic consumption risk, and that asset returns reflect their attempts to reduce their exposure to this risk. We find that over the sample period the resulting two-factor pricing model has lower Hansen-Jagannathan distances than the CAPM and the Fama-French three-factor model. Moreover, in the presence of the market factor and the size and book-to-market factors, the two consumption based factors retain explanatory power. Together with the results of Lettau and Ludvigson (2000), these findings indicate that consumption-based asset pricing is relevant for explaining the cross-section of asset returns.

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Keywords: cross-sectional asset pricing; consumption-based model; idiosyncratic consumption risk; incomplete markets; measurement error.

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1 Introduction

If agents manage to perfectly insure themselves against idiosyncratic consumption risk, the only relevant pricing factor in a standard multiperiod model without frictions is the growth rate of aggregate consumption. However, the workhorse representative-agent models that reflect this allocation are not able to explain even fairly elementary data on aggregate returns, such as the risk premium on equity. Their performance in a cross-sectional context is weak and has certainly not been sufficiently satisfactory to threaten alternative cross-sectional models such as the Capital Asset Pricing Model (CAPM).[1]

However, if agents cannot perfectly insure themselves against idiosyncratic consumption risk[2], factors other than aggregate consumption growth become relevant to price assets. Under this assumption, all higher moments of the cross-sectional distribution of consumption growth are relevant pricing factors. Researchers have long realized that changes in these moments may be of critical importance to explain changes in asset prices (see Mehra and Prescott (1985)). Building on this insight, a number of studies have investigated the importance of market incompleteness for the equity premium puzzle and the risk-free rate puzzle (see Telmer (1993), Constantinides and Duffie (1996), Heaton and Lucas (1996), Jacobs (1999), Vissing-Jorgensen (1999), Cogley (1999), Brav, Constantinides and Geczy (1999) and Balduzzi and Yao (2000)). These studies provide mixed evidence on market incompleteness and the literature has not yet fully matured, but it is a safe conclusion that models with uninsurable idiosyncratic consumption risk and potentially limited market participation stand a better chance to explain the data than standard representative-agent models.

This paper further investigates the importance of uninsurable idiosyncratic risk by examining its importance for the cross-section of asset returns. In principle, one can investigate the set of intertemporal restrictions associated with the cross-section of returns using a number of alternative procedures. For instance, one can specify a utility function and use a distributional assumption to obtain a pricing kernel that is a well-defined nonlinear parametric transformation of consumption-based pricing factors. Constantinides and Duffie (1996) use such a setup with constant relative risk aversion and a lognormality assumption on idiosyncratic income shocks. They obtain two consumption-based pricing factors, representing the rate of consumption growth and the cross-sectional variance of consumption

[1] A recent paper by Lettau and Ludvigson (2000) demonstrates that consumption-based models can challenge the CAPM along certain dimensions. This research is discussed below.

[2] At this point, it is important to elaborate on the terminology used in this paper in order to avoid confusion. In the literature on the CAPM, standard terminology splits up the risk of an individual asset into market risk and idiosyncratic risk. In this paper the focus is on idiosyncratic risk for an individual consumer. It is standard in the incomplete markets literature to refer to this risk as “idiosyncratic income risk” or “idiosyncratic risk”. In this paper we do not investigate a full general equilibrium model but focus exclusively on equilibrium intertemporal consumption allocations. Therefore we refer to this idiosyncratic risk as “idiosyncratic consumption risk”. This terminology is slightly unsatisfactory but preferable to the use of “idiosyncratic risk”, which could be confused with the terminology used in the context of the CAPM.

growth. Alternatively, Cogley's (1999) analysis illustrates the importance of additional pricing factors representing higher moments of the cross-sectional distribution of consumption. We follow a slightly different approach, designed to keep the econometric analysis relatively simple and to allow us to conduct a search over different specifications. To do this, we investigate a variety of pricing kernels that are linear in average consumption growth and the cross-sectional variance of consumption growth.

We investigate the empirical performance of these pricing kernels using household consumption data from the Consumer Expenditure Survey (CEX). We examine the performance of the pricing kernels using four different datasets. The first two datasets use data on nondurables and services consumption. The difference between the two samples is that the first dataset is based on all households that fulfill certain selection criteria, whereas the second dataset only contains households that hold assets. The difference between the third and the fourth dataset is also based on whether the household holds assets, but both these datasets use data on total consumption. Moreover, for each of the resulting four datasets, we construct the consumption-based pricing factors in different ways. First, we compute average consumption growth and variance of consumption growth factors by using data on individual household consumption. However, we know that the presence of measurement error is a serious problem when using household consumption data. To deal with this problem, we reconstruct the consumption-based factors using data on the consumption of a synthetic cohort of individuals, rather than a single individual.

The choice of dataset turns out to be critically important. For idiosyncratic consumption risk to be of interest to explain the equity premium puzzle, it has to be the case that the cross-sectional variance of consumption growth is larger in recessions. Intuitively this leads to an increase in the risk faced by an individual agent, and this leads to a larger risk premium to induce investors to hold risky assets. However, we find that whereas the first consumption-based factor (average consumption growth) always displays the expected positive correlation with returns, we only obtain robust estimates of negative correlation between returns and the variance factor when considering data on total consumption, and only when limiting the sample to asset holders.

This finding is not surprising. Other studies that investigate the importance of idiosyncratic consumption risk for the equity premium puzzle conclude that consumption data on assetholders conforms more to theory than data on non-assetholders. Moreover, durable consumption is the most cyclical component of individual consumption. Therefore, the data simply tell us that the less wealthy cut back a lot more than the wealthy on their consumption in recessions and make up for it in expansions. However, because it is relatively harder to cut back on nondurable consumption, they implement this through their expenditures on durable consumption. Finally, it must be noted that these findings are obtained using pricing factors constructed from cohort data. When using individual data, estimates are often insignificant and not very robust. This finding is consistent with the findings of Brav, Constantinides and Geczy (1999) in the context of the equity premium puzzle.

To evaluate the significance of these findings, we investigate their robustness and compare the performance of the pricing factors against a number of alternatives. To demonstrate their robustness, we report additional test results. These estimation exercises indicate that our findings are very robust. In terms of pricing performance, the consumption-based factors have lower Hansen-Jagannathan (1991,1997) distances associated with them than the CAPM over the sample period under consideration. Moreover, we also compare the performance of the pricing factors with that of the size and market-to-book pricing factors proposed by Fama and French (1992,1993). Once again, over the sample period the consumption-based pricing factors have lower Hansen-Jagannathan distances than this alternative model. Finally, we investigate pricing kernels that combine the Fama-French factors and/or the CAPM factor with the consumption-based factors. It is shown that even after accounting for these alternative pricing factors, the consumption-based factors are estimated significantly in the pricing equation.

2 Idiosyncratic Consumption Risk and the Cross-Section of Asset Returns

Following the seminal contributions by Lucas (1978) and Breeden (1979), a number of papers have conducted empirical investigations of representative-agent consumption-based asset pricing models. Even though these models have a wide range of empirical implications, a large part of the literature has a rather limited focus. In fact, much of the empirical research on consumption-based models has focused exclusively on the returns on a riskless asset and the market index, leading to the so-called equity premium and riskfree rate puzzles.[3] A small number of papers study the performance of the consumption-based model in a cross-sectional context. Mankiw and Shapiro (1986) and Breeden, Gibbons and Litzenberger (1989) conclude that the performance of the consumption-based model is unsatisfactory and that the consumption-based model performs no better than the CAPM. However, more recently Lettau and Ludvigson (2000) show that those negative conclusions about the performance of the consumption-based model are due to the fact that those empirical studies investigate an unconditional linear factor model. When investigating a conditional factor model, the model's performance is about as good as that of the three-factor Fama-French model, when using a specific conditioning variable that is suggested by theory. Campbell and Cochrane (2000) provide an explanation for why consumption-based asset pricing models perform better conditionally than unconditionally.

[3]Hansen and Singleton (1982,1984), Mehra and Prescott (1985) and Grossman, Melino and Shiller (1985) focus exclusively on a riskless and a risky asset. Other papers such as Hansen and Singleton (1983) and Epstein and Zin (1991) focus on the equity premium puzzle but investigate some other risky assets. However, none of these papers specifically focuses on the cross-section of returns.

This paper reaffirms that consumption-based asset pricing models are valuable for the study of the cross-section of asset returns. It shows that this is the case even when studying unconditional models, as opposed to the conditional models studied by Lettau and Ludvigson (2000). The key to this finding is that one has to move away from the rigid construction of a representative agent economy, which implies the irrelevance of idiosyncratic consumption risk. To appreciate the importance of this modeling approach, it is instructive to review the importance of complete markets and the representative agent assumption for the equity premium and riskfree rate puzzles.[4] The complete markets assumption is critical for the representative agent model. Individual agents that are faced with a complete markets structure can insure themselves against idiosyncratic consumption risk. As a consequence, the prices of assets in the economy are equivalent to the prices in a closely related representative agent economy.

Whereas the complete markets assumption is a convenient modeling technique, casual observation as well as empirical testing has convinced most researchers that it is not very realistic (see Cochrane (1991), Mace (1991), Hayashi, Altonji and Kotlikoff (1994)). It is therefore not surprising that a growing number of studies investigate to what extent market incompleteness is of interest to explain the empirical rejections of the consumption-based models. A number of these studies investigate this issue by using simulation-based models. Whereas early studies by Telmer (1993) and Heaton and Lucas (1996) do not manage to generate large enough risk premia for most realistic parameterizations of the economy, later studies by Telmer, Storesletten and Yaron (1997) and Constantinides, Donaldson and Mehra (1998) have managed to generate larger risk premia under the assumption that idiosyncratic shocks are fairly persistent. A number of other studies (Jacobs (1999), Vissing-Jorgensen (1999), Cogley (1999), Brav, Constantinides and Geczy (1999) and Balduzzi and Yao (2000)) have analyzed market incompleteness from another perspective, by investigating Euler equations that hold even if markets are incomplete. Sarkissian (1998) analyzes incomplete risk sharing between countries. The test results in these papers are mixed, but a robust conclusion is that risk aversion implied by restrictions from incomplete markets is lower than risk aversion implied by representative agent models. Taken together, the findings in the literature on market incompleteness seem to indicate that accounting for idiosyncratic consumption risk has at least some potential to explain the structure of asset returns.

[4]The literature contains other attempts to explain the equity premium puzzle and riskfree rate puzzle. A number of papers have focused on the importance of time aggregation (see Grossman, Melino and Shiller (1987) and Heaton (1993)). Also, an extensive literature has studied the modeling of alternative preferences for the representative agent (see Abel (1990), Campbell and Cochrane (1999), Cochrane and Hansen (1992), Constantinides (1990), Detemple and Zapatero (1990), Epstein and Zin (1991), Ferson and Constantinides (1991), Heaton (1995), and Sundaresan (1989)) . These approaches alleviate some of the problems with representative agent models and it is possible that they would also improve the cross-sectional performance of consumption-based models. See Kocherlakota (1996) and Campbell, Lo and MacKinlay (1997) for overviews of this literature.

Given that models with incomplete markets have had some success explaining the equity premium and risk-free rate puzzles, it seems therefore natural to investigate if they can be used to explain a wider cross-section of asset returns. In cross-sectional asset pricing, the Capital Asset Pricing Model (CAPM) is the dominant paradigm. It is therefore a natural benchmark to evaluate the performance of a consumption-based model with market incompleteness. Cochrane (1996) shows that the traditional form of factor pricing models such as the CAPM can be implemented by using the intertemporal optimality condition

$$E[M_t R_{j,t} | \Omega_{t-1}] = 1 \tag{1}$$

where M_t is the pricing kernel, $R_{j,t}$ is the return on asset j at time t and Ω_{t-1} is the information set available to the econometrician at time $t-1$. For the CAPM, the pricing kernel M_t is specified as follows

$$M_t = \beta_0 + \beta_1 R_{M,t} \tag{2}$$

where $R_{M,t}$ is the return on the market portfolio at time t. We now outline a framework that allows us to compare the performance of a pricing kernel that accounts for idiosyncratic consumption risk with the performance of the CAPM as evaluated in (1) and (2). The intertemporal optimality condition associated with individual i's investment in asset j implies that

$$E[M_{i,t}(cg_{i,t}) R_{j,t} | \Omega_{t-1}] = 1 \tag{3}$$

where the pricing kernel $M_{i,t}$ which is indexed by individual i depends on consumption growth $cg_{i,t} = c_{i,t}/c_{i,t-1}$ in the context of a consumption-based asset pricing model. Averaging this orthogonality condition for asset j over all N consumers we get

$$E[(1/N) \sum_{i=1}^{N} M_{i,t}(cg_{i,t}) R_{j,t} | \Omega_{t-1}] = 1 \tag{4}$$

The pricing kernel in (4) will also be referred to as $M_t = (1/N)\sum_{i=1}^{N} M_{i,t}(cg_{i,t})$. Evaluating the performance of this kernel in the cross-section can then be accomplished by specifying the underlying structure of the economy. For instance, if individual consumers have time-separable constant relative risk aversion (TS-CRRA), this average intertemporal Euler equation for consumer i and asset j is

$$E[(1/N)\ e^{-\theta} \sum_{i=1}^{N} (cg_{i,t})^{-\alpha} R_{j,t} | \Omega_{t-1}] = 1 \tag{5}$$

where α is the rate of relative risk aversion and θ is the rate of time preference. The cross-section of asset returns can therefore be analyzed by using the generalized method of moments to evaluate (5) directly. However, the disadvantage of this approach is that the resulting econometric problem is highly nonlinear. This may complicate the optimization and the comparison with the benchmark CAPM because of the existence of local optima.

Constantinides and Duffie (1996, henceforth CD) follow a different approach. Using a TS-CRRA specification, they specify an economy that leads to an Euler equation that specifies explicitly how the pricing kernel depends on the moments of the cross-sectional distribution of consumption growth. Specifically, their economy yields the following intertemporal Euler equation

$$E[e^{-\theta}(c_t/c_{t-1})^{-\alpha}\exp(\frac{\alpha(\alpha+1)}{2}y_t^2)R_{j,t}|\Omega_{t-1}] = 1 \tag{6}$$

where c_t is aggregate consumption at time t and y_t^2 can be interpreted as the variance of the cross-sectional distribution of $\log[(c_{i,t}/c_t)/(c_{i,t-1}/c_{t-1})]$. Balduzzi and Yao (2000) use a slightly different setup which leads to a different Euler equation. In their economy the second factor is not the cross-sectional variance of log consumption growth, but the difference of the variance in cross-sectional consumption. They also use this kernel to study the cross-section of asset returns. Finally, in his analysis of the equity premium puzzle, Cogley (1999) shows how in general the pricing kernel will depend on all moments of the cross-sectional distribution. When omitting moments higher than the second moment and specializing the analysis to a TS-CRRA utility function, he shows that one obtains an Euler equation similar to (6).

For the purpose of analyzing the cross-section of asset returns, analysis of this type of Euler equations has disadvantages similar to the ones experienced when directly analyzing (5). The econometric analysis is harder and one may have to deal with local optima. As a result, it is more difficult to compare the results to the CAPM. For this reason, we approach the problem in a slightly different way. It is clear that in all cases the pricing kernel depends on the cross-sectional moments of consumption growth. Moreover, because it is difficult to estimate higher moments precisely, it is preferable to limit attention to the first two moments. The precise nature of the relationship between the pricing kernel and these moments depends on the specification of the utility function. We therefore assume that the pricing kernel depends in a simple linear way on the first two cross-sectional moments of consumption growth[5]

$$M_t = \beta_0 + \beta_1 mcg_t + \beta_2 vcg_t \tag{7}$$

where $mcg_t = (1/N)\sum_{i=1}^{N}(cg_{i,t})$ and $vcg_t = (1/N)\sum_{i=1}^{N}(cg_{i,t} - mcg_t)^2$. Implicitly of course this linear kernel corresponds to some utility function. If this utility function is a poor approximation of reality, this will affect the performance of the pricing kernel negatively.[6]

[5] Heaton and Lucas (2000) also investigate linear pricing kernels with measures of idiosyncratic income risk as pricing factors. They find that the existence of entrepreneurial income risk has a significant influence on asset returns.

[6] In the CD pricing kernel (6), one can interpret the variance of the logarithm of consumption growth

We also compare the performance of the consumption-based factors to a benchmark other than the CAPM. A logical choice is to make a comparison with the size and book-to-market factors proposed by Fama and French (1992,1993). We use the kernel for the Fama-French three factor model

$$M_t = \beta_0 + \beta_1 R_{M,t} + \beta_2 SMB_t + \beta_3 HML_t \tag{8}$$

where SMB_t is the size factor and HML_t is the book-to-market factor. To evaluate the relative performance of the consumption-based factors compared to the Fama-French factors, we investigate a number of kernels where we interact the consumption-based factors with the size and/or book-to-market and/or market factors. These kernels are described in more detail in the tables.

3 Data Description

This section discusses three different issues related to data construction. The empirical procedure is implemented as follows. First, consumption data are used to construct pricing factors that estimate the first and the second moment of the cross-sectional distribution of consumption growth. The approach used to construct the consumption data is described in Section 3.2 In a second stage, these pricing factors are taken as given in an econometric investigation of the intertemporal relation (1) for a wide cross-section of asset returns. This cross-section of asset returns is described in Section 3.1. It must be noted at this point that the uncertainty involved in constructing the pricing factors is neglected in this econometric analysis. A final critical issue related to data construction is the construction of synthetic cohorts described in Section 3.3. The motivation for using synthetic cohorts is the well-documented existence of substantial measurement error in household consumption data. Finally, Section 3.4 discusses at length the statistical properties of the four different samples used in the analysis and the factors used in the pricing equation.

3.1 Asset Return Data

We use a set of test portfolios that includes the twenty-five size and book-to-market portfolios of Fama and French (1993), a long term government bond, a long term corporate bond, and the 3-month Treasury bill rate. The data are quarterly, and they are constructed from the corresponding monthly data, ranging from April 1984 to December 1995. The Fama-French

instead of the variance of the level of consumption growth as the second factor. Also, given that the pricing kernel is a nonlinear function of consumption growth, we can also see it as a nonlinear function of the logarithm of consumption growth. Therefore, when taking an expansion one could justify expanding around the logarithm of consumption growth instead of the level of consumption growth. As a robustness exercise, we therefore repeat the empirical analysis using the mean and the variance of the logarithm of consumption growth as explanatory factors. The resulting test results are very similar portfolios are now widely used. They are value-weighted portfolios of stocks listed on the NYSE, AMEX, and NASDAQ. These portfolios are sorted on firm size and book-to-market equity and exhibit strong cross-sectional dispersion in average returns. (For more details on the portfolios, see Fama and French (1993)). For the bond returns, we use the total return on Treasury bonds (the CRSP variable GBTRET), the total return on long term corporate bonds (the CRSP variable CBTRET), and the three-month T-bill rate.[7] For the market portfolio of the CAPM, we use the CRSP value-weighted portfolio of stocks listed on NYSE, AMEX, and NASDAQ that Fama and French use to proxy for the market portfolio. Also included in our empirical tests are the size (SMB) and book-to-market (HML) factors of Fama and French. All the variables are in real terms.

3.2 Consumption Data

To construct the pricing factors, we use data on household consumption from the Consumer Expenditure Survey (CEX). The CEX data have been used by a number of researchers to analyze the importance of idiosyncratic consumption risk for the equity premium puzzle (e.g. see Brav, Constantinides and Geczy (1999), Vissing-Jorgensen (1999), Cogley (1999) and Balduzzi and Yao (2000). Balduzzi and Yao (2000) also present an analysis of cross-sectional pricing using their (different) pricing kernel. The advantage of the CEX is that it provides a measure of total consumption, unlike other datasets such as the Panel Study of Income Dynamics. The CEX is not a genuine panel dataset, but a series of cross-sections with a limited time dimension. However, in the context of the exercise proposed in this paper, this is not necessarily a very serious problem, because at each time we simply use every available cross-section to construct cross-sectional moments.

We proceed to construct the pricing factors using two measures of household consumption. The first measure corresponds to nondurable consumption plus services. The second measure corresponds to total consumption, including durable consumption. The frequency of the data is an important issue. Participants in the CEX are interviewed on a quarterly basis. After each quarter they are asked detailed questions about their consumption patterns in the past three months. It is possible to construct monthly consumption data from these interviews. However, the resulting time series is fairly constant over a three-month period and then jumps to another level. Therefore, we follow most of the available literature that uses the CEX and construct quarterly data (see Brav, Constantinides and Geczy (1999), Vissing-Jorgensen (1999) and Cogley (1999)). Balduzzi and Yao (2000) construct monthly data from the CEX. The CEX data are available from 1984 to 1995. Because we use data on consumption growth, the first available quarter is therefore the second quarter of 1984. Also, because of a data matching problem, we cannot use data on the first quarter of 1986.

[7] The differences between the average returns on the two bonds and the bill reflect the term premium as well as the default premium.

Moreover, several indicators revealed low data quality for the last quarter available (the fourth quarter of 1995). We therefore exclude this quarter. This leaves us with 45 quarterly observations.

Another issue that deserves thorough discussion is family composition. As with most datasets that provide consumption information, reported consumption is consumption for the household unit. This complicates the analysis, because as a result one of the factors driving cross-sectional and time-series differences in consumption is changes and differences in family size. There are several ways to correct for this when estimating intertemporal optimality conditions in the presence of idiosyncratic consumption risk. First, one can include a function of family size in the definition of consumption in period t. This is useful when directly analyzing the Euler equation (5) (see Jacobs (1999)). An second alternative is to simply divide household consumption by the number of members of the household. Whereas this is of course done when using aggregate per capita consumption data, the issue is less straightforward when using household data because the data reveal that household consumption is a complicated nonlinear function of household size. A third alternative is to correct for family size using a given scale which is used in the literature or estimated from the data.

The first technique is not applicable in the context of this paper, because we do not analyze the intertemporal optimality conditions directly. We first construct the factors and then use those factors in a regression framework. We attempted to correct for household size using the second and third alternatives. Because this did not make a difference, we present results using household consumption as the unit of observation.

A final robustness issue is the presence of seasonalities. It is well known that seasonalities are present in consumption data and that they are important for asset pricing (see Miron (1986) and Ferson and Harvey (1992)). When inspecting the raw CEX household consumption data, seasonalities seem to be even more pronounced than for quarterly NIPA data. The most obvious manifestation of this finding is the well known dent in consumption in the first quarter. Reported results do not adjust for seasonality, in accordance with other papers that use the CEX (see Attanasio and Weber (1995), Brav, Constantinides and Geczy (1999), Vissing-Jorgensen (1999), Cogley (1999) and Balduzzi and Yao (2000)). We performed a robustness exercise by controlling for seasonality using the census X11 method as implemented in EVIEWS. Even though the resulting seasonal adjustment factors are nonnegligible (as is the case for NIPA data), this did not affect test results.

In the expanding literature that investigates the equity premium puzzle using disaggregate data, one important conclusion is that asset market participation is of great importance. It seems that the consumption patterns of households that hold assets are more in accordance with economic theory. One of the strengths of the CEX is that it contains a wealth of information on asset holdings. We therefore conduct our analysis for a sample that contains all households, but also for a sample that only contains assetholders. Given the wealth of asset information in the CEX, several selection criteria can be used and existing studies have constructed widely different samples of assetholders. For example, the CEX reports data on holdings of checking and savings accounts, bonds and stocks, and participation in private and public pension plans. Moreover, the CEX reports data on the income received from a certain asset (a flow variable) as well as the holdings of the same asset (a stock variable). Also, in the CEX all these questions are asked in reference to two points in time, the first and the last (fifth) quarter that the households are in the sample. To determine which households are assetholders, we use the answer referring to the first quarter.

Ideally we would like to construct a sample of individuals who hold any type of asset and also a sample of individuals who hold stocks. Unfortunately, this is not possible because the CEX does not ask a direct question on whether an individual holds stocks either directly or indirectly through a pension plan. We therefore proceed to construct a sample of households who are very likely to hold stocks. It consists of households that report the existence of at least one of the following: (i) holdings of stocks or bonds, (ii) dividend income, and/or (iii) contributions to an IRA. It is clear that this is an imperfect measure of stock ownership. However, in our opinion it is the best one can do with the CEX.

A final issue regarding the construction of this sample of assetholders is that we only construct a sample of households who report positive holdings of assets. Interestingly, several papers have constructed additional samples containing only households who report holdings above certain positive thresholds (e.g. $1,000, $5,000 etc.). We do not attempt to do this because of two reasons. First, unlike other papers we construct a sample of assetholders using different questions. Therefore, imposing thresholds is less straightforward. Second, our construction of synthetic cohorts described in the next section is only meaningful if the sample size is large enough. By eliminating more and more households due to increasingly stringent asset holding criteria, this exercise becomes problematic.

3.3 Dealing with Measurement Error: Constructing Synthetic Cohorts

We start out by constructing pricing factors using the cross-section of individual consumption growth at every time t. This gives us time series of factors consisting of 45 observations. Subsequently, we use these pricing factors in a cross-sectional pricing relationship. The problem with this approach is the existence of measurement error in household consumption data, which is well documented (e.g. see Altonji (1986), Altonji and Siow (1987)) and Zeldes (1989)). Several studies that use household consumption data to analyze asset pricing relationships try to mitigate the influence of measurement error. For example, Vissing-Jorgensen (1999) uses log-linearized Euler equations because it is well-known that measurement error can be more effectively dealt with in a linear framework. Mankiw and Zeldes (1991) and Balduzzi and Yao (2000) construct time series of average household consumption using household data. This minimizes the impact of measurement error under plausible assumptions.

One can argue that in our approach the effects of measurement error are less serious because we do not analyze the nonlinear Euler equations. However, the potential problem with measurement error still arises in the construction of the cross-sectional factors. To deal with this problem, we adopt the synthetic cohorts approach which is popular in the economics literature. This approach was previously used by (among others) Browning, Deaton and Irish (1985) and for the CEX data by Attanasio and Weber (1995). It basically involves the construction of a representative consumer for a typical group which can be defined by observable characteristics such as age. It is clear that for most plausible parameterizations of measurement error this construction will mitigate its effects, without eliminating them. It must also be noted that the motivation for this technique is of course very similar to the motivation for testing the CAPM using portfolios instead of individual assets, as originally implemented by Black, Jensen and Scholes (1972) and Fama and MacBeth (1973).

Unfortunately, the choice of grouping method for the construction of synthetic cohorts is not obvious. On the one hand, one does not want the groups to be too small, because in that case the effects of measurement error are not likely to disappear. On the other hand, by making the groups too large, it is clear that one constructs away the potential impact of idiosyncratic consumption risk. It is not obvious that there is a realistic optimal solution to this problem. The optimal choice depends on the size and the type of the measurement error, and by definition we do not know a lot about this. We choose to construct synthetic cohorts based on two very simple grouping variables, namely the age and the education of the household head. To understand the problems implied by this choice, note that for all specifications we work with two samples, one with all households and another with assetholders only. It is clear that the choice to hold assets or not critically depends on age and education. Therefore, the composition and size of a given cohort will be different in both samples, and this could influence test results. To minimize these (potential) problems, we impose a constraint on the cohort construction: we only include individuals older than 24 and younger than 64 in the sample to increase the probability of having a sufficient number of observations in each cohort. An additional advantage of this constraint is that it eliminates the households with the largest deviation from average family size. This is of some importance as discussed in Section 3.2., because we use family consumption as opposed to per capita consumption.

We then proceed to construct factors in the following two ways. The first set of factors is based on age only: a cohort consists of all households with a household head of a certain age. We are therefore constructing the pricing factors in each quarter using 39 observations (cohorts). A second construction uses age as well as education as a sorting variable. In the CEX, there are seven educational categories. We use this educational information to create a sample of consumers who have at least completed a college education, and another sample of consumers who have not. This construction gives us a maximum of 78 (39×2) cohorts in each time period to construct the pricing factors. However, in practice this number is sometimes lower because we do not have observations on certain cohorts.

The final issue regarding cohort construction is what we choose to aggregate on within the cohort. Whereas the object of interest is consumption growth, one can also compute consumption growth after aggregating on the level of consumption. For certain types of measurement error, this may actually be preferable. We therefore decide to report results using both methods. We now turn to a complete description of the construction of these factors, using the different methods. We refer to the construction of factors using individual data using a subscript 1, that is

$$mcg_{1,t} = (1/N) \sum_{i=1}^{N} (cg_{i,t}) \qquad vcg_{1,t} = (1/N) \sum_{i=1}^{N} (cg_{i,t} - mcg_{1,t})^2$$

where $cg_{i,t} = (c_{i,t}/c_{i,t-1})$ and $c_{i,t}$ is the consumption of individual i at time t.

Now consider averaging over consumption growth to obtain the consumption growth of a representative cohort j, $cohcg_{2,j,t} = (1/N_{j,t}) \sum_{i=1}^{N_{k,t}} (cg_{i,t})$ where $N_{j,t}$ is the number of observations on this cohort at time t. With H the number of cohorts, the factors based on this construction can then be computed as

$$mcg_{2,t} = (1/H) \sum_{j=1}^{H} (cohcg_{2,j,t}) \qquad vcg_{2,t} = (1/H) \sum_{j=1}^{H} (cohcg_{2,j,t} - mcg_{2,t})^2$$

Alternatively, consider the consumption of a representative cohort k at time t, which is given by $cohc_{k,t} = (1/N_{k,t}) \sum_{i=1}^{N_{k,t}} (c_{i,t})$. We then define $cohcg_{3,k,t} = (cohc_{k,t}/cohc_{k,t-1})$ and the factors

$$mcg_{3,t} = (1/H) \sum_{k=1}^{H} (cohcg_{3,k,t}) \qquad vcg_{3,t} = (1/H) \sum_{k=1}^{H} (cohcg_{3,k,t} - mcg_{3,t})^2$$

Summarizing, factors with a 1 subscript denote factors obtained using individual data. Factors with a 2 subscript denote cohort-based factors, where averaging is done on consumption growth. Factors with a 3 subscript denote cohort-based factors, where averaging is done on the consumption level.

3.4 Descriptive Statistics for Consumption Growth and Pricing Factors

Descriptive statistics for the consumption data and the consumption-based factors are given in Tables I through III. Table I provides descriptive statistics for the individual consumption data. Table II provides summary statistics on cohort consumption growth. Table III summarizes the statistical properties of the pricing factors.

Table I presents descriptive statistics on individual consumption growth. Panel A lists the first four moments, the sample size and the minimum and maximum consumption growth for each of the four samples under investigation. One of the most important conclusions from this table is that the distribution of consumption growth does not conform to the normal distribution, with the statistics indicating positive skewness and excess kurtosis. this can also be seen from comparing the different panels in Figure 1. Interestingly, the kurtosis is much higher for the distributions based on nondurable and services consumption (the first two rows) than for the distributions based on total consumption (the last two rows). It must be noted in this respect that nondurable and services consumption is fairly narrowly defined in this study. This is in line with some of the other studies that use panel data, but very different from the NIPA data. To see this, consider panel B which presents data on the level of household consumption. Whereas a comparison with the NIPA data is not straightforward, because we are working with household data, we note that Panel B indicates that in our data total consumption is more than twice as high as nondurables and services consumption. Over the same period, this difference is much smaller in the NIPA data. The problem lies in the construction of services from the available data on household consumption, which is not straightforward. The consequence is that when working with nondurables and services, we have a relatively high component of consumption that is not likely to vary much over the business cycle. Unlike other studies, we therefore include an analysis of total consumption as well as nondurable and services consumption.

When comparing mean consumption growth in Panel A with NIPA numbers, it is also clear that they are very different. Whereas the growth rates for total consumption are much higher than those for nondurables and services consumption, both growth rates are far in excess of NIPA numbers. The key to this finding is of course that NIPA growth rates are obtained by aggregating on consumption levels, and not on consumption growth as in Panel A. To verify the accuracy of the CEX data, we aggregated on consumption levels in each quarter and used these numbers to compute aggregate growth rates. While there are some interesting differences between the NIPA and the numbers constructed from the CEX, the average growth rate over the whole sample is very similar.

A central issue in this paper is the difference between the consumption growth of assetholders and non-assetholders. However, in Panel A, the distribution of the consumption growth for assetholders does not seem to differ very much from the distribution of consumption growth based on all consumers. When comparing row 1 with row 2 and row 3 with row 4, the moments are almost identical for each pairwise comparison. When doing these comparisons, note that the percentage of assetholders is approximately 28%, which is comparable to the number in Mankiw and Zeldes (1991) but lower than the number in Cogley (1999).

Panels C and D repeat the analysis in Panels A and B, but descriptive statistics are computed on a quarter by quarter basis. To conserve space, we only report on four selected quarters and we only present data on total consumption.[8] The motivation for presenting these statistics is that they are of more significant interest than the ones in panels A and B. We construct factors on a quarter-by-quarter basis, and therefore some of the deviations from normality evident in panels A and B are caused by aggregate fluctuations that do not show up in the quarter-by-quarter statistics. Most importantly, a comparison of Panels C and D with the results in panels A and B indicates that the kurtosis is dramatically lowered. Nevertheless, the deviations from normality are still significant.

Finally, what does Table I tell us about measurement error? It is clear that the presence of measurement error in these data has to be taken into account. The real question is whether the presence of measurement error invalidates the use of this type of data. Inspection of Panel A indicates that a few households consume 20 times as much or ten times less in a given quarter compared to the previous quarter. In fact, row three indicates that in one instance, a household only consumes 2.5% of its previous quarter's consumption. Surely, these are aberrations caused by measurement error or perhaps a misinterpretation of the questionnaire. However, in our view these outliers are not necessarily a critical problem. First, inspection of Panel C gives an indication of minima and maxima in a given quarter. Apparently, tenfold increases or decreases in consumption in a given quarter are exceptional. Furthermore, inspection of Figure 1 indicates exactly how uncommon these outliers are. There are very few cases for which consumption increases more than five-fold. Inspection of Figure 1 also confirms that the distribution of total consumption is different from that of nondurable and services consumption. The right tail of the distribution is more pronounced for total consumption.

Table II presents the same descriptive statistics as Table I, but for cohort consumption. Because cohort consumption growth is constructed in several different ways, the table contains a large number of panels. Panels A, B and C contain information on consumption growth and the level of consumption for cohorts constructed on the basis of age. Panels D, E and F contain information for cohorts constructed on the basis of age and education. Panels A and D list descriptive statistics for cohorts constructed by averaging over individual consumption growth. Panels B and E list descriptive statistics for cohorts constructed by averaging over individual consumption. Panels C and F list information on the level of consumption.

The most important observation from Table II is the difference with the statistics presented in Table I. As expected, the distribution of cohort consumption growth is much more adequately described by a normal distribution compared to the distribution of individual consumption growth. While it is tempting to attribute these differences (especially the lower variance) to the elimination of measurement error, it is also possible that by constructing the cohorts, we have eliminated some genuine variability in consumption which is the result of unanticipated shocks that were not fully insured. A comparison between

[8] Tables containing descriptive statistics for all quarters can be obtained from the authors on request.

panels A and B on the one hand and panels D and E on the other hand is also instructive. First, note that the mean consumption growth rates in panels A and D are much larger than the corresponding ones in panels B and E. The growth rates in panels B and E, which use cohorts obtained by averaging over individual consumption levels, are much more similar to the growth rates we obtain using aggregate consumption data such as the NIPA. Again, whereas it is perhaps tempting to conclude that the cohort construction used in panels B and E is therefore superior, one can also interpret this as an indication of the deficiencies of aggregate data. In the absence of knowledge of the structure of measurement error in the household data, it is impossible to tell which construction is preferable.[9] Finally, the last three columns of each panel in Table II contain information on cohort construction. It can be seen that the construction of the cohorts is not straightforward. For most samples, there will be at least one cohort that contains very few observations. In fact, when using the age-and-education cohorts, the minimum size of a cohort is 1 for all samples. On the positive side, the average cohort size is fairly large in all cases. Also, as expected, the average cohort size is much larger for the sample consisting of all consumers as compared to the sample consisting of assetholders only.

To address the problem that some cohorts contain very few observations, we investigate the robustness of our results using an alternative construction. Remember that $N_{k,t}$ denotes the number of households in cohort k at time t and N_t the total number of households at time t. Define $w_{k,t} = N_{k,t}/N_t$. We then define the alternative factors as

$$mcg_{2A,t} = \sum_{j=1}^{H} w_{j,t}(cohcg_{2,j,t}) \qquad vcg_{2A,t} = \sum_{j=1}^{H} w_{j,t}(cohcg_{2,j,t} - mcg_{2A,t})^2$$

where as before $cohcg_{2,j,t} = (1/N_{k,t})\sum_{i=1}^{N_{k,t}}(cg_{i,t})$ and H is the number of cohorts. Also

$$mcg_{3A,t} = \sum_{k=1}^{H} w_{k,t}(cohcg_{3,k,t}) \qquad vcg_{3A,t} = \sum_{k=1}^{H} w_{k,t}(cohcg_{3,k,t} - mcg_{3A,t})^2$$

where $cohcg_{3,k,t} = (cohc_{k,t}/cohc_{k,t-1})$ and $cohc_{k,t} = (1/N_{k,t})\sum_{i=1}^{N_{k,t}}(c_{i,t})$. In words, these alternative factors use the same cohort information but weigh the results according to the number of households in each cohort. When we repeat the analysis with these alternative

[9] We also computed descriptive statistics for cohort consumption growth on a quarter-by-quarter basis. As was the case with individual consumption growth in Table I, the key observation is that skewness and excess kurtosis are much lower when computed on a quarter-by-quarter basis. A statistic which deserves some comment is the minimum and maximum consumption growth in a given individual quarter. If the numbers on individual consumption growth in Table I are contaminated by measurement error, it is clear that the cohort construction deals with this problem very effectively. In most quarters consumption growth rates are bounded between 0.7 and 1.5. Very large and very small outliers have all but disappeared. Tables containing descriptive statistics on a quarter-by-quarter basis can be obtained from the authors on request.

factors, our conclusions are not affected. We therefore conclude that the small size of a few cohorts is not contaminating the paper's conclusions.

Table III presents the descriptive statistics for the pricing factors for each of the four samples. Inspection of this table reveals some interesting stylized facts, some of which are of course foreshadowed by the material in Tables I and II. A first interesting set of findings concerns the differences between nondurables and services consumption and total consumption. The cross-sectional variance of total consumption is much higher than that of nondurables and services consumption. This is true regardless of whether one looks at vcg_1(using data on individual consumption) or vcg_2 and vcg_3 (different methods of cohort construction). Also, regardless of the measure one uses, the growth rate of total consumption is always much higher than the growth rate of nondurables and services consumption. Another observation concerns the differences between the factors constructed using all households in the sample and the factors constructed using data on assetholders only. Consider the difference between Panel A and Panel B for nondurable and services consumption. Perhaps surprisingly, when using the factors based on individual data, consumption growth for asset holders is not very different from consumption growth for all households combined. However, when considering vcg_2 and vcg_3 the variance is higher for asset holders. When comparing Panels C and D we obtain the same conclusion. At the very least, these findings confirm the importance of the cohort construction and therefore potentially of measurement error. This is of course reinforced by inspecting the differences between descriptive statistics in a given panel. In all cases vcg_2 and vcg_3 are much smaller than vcg_1. Because the differences between mcg_1 on the one hand and mcg_2 and mcg_3 on the other hand are not as large, it will probably be the case that the adoption of the cohort construction influences the estimation of the sign and magnitude of the second factor much more than that of the first factor.

4 Empirical Findings

4.1 The Testing Method

To evaluate the significance of the cross-sectional distribution of consumption growth, we apply the generalized method of moments (GMM, Hansen (1982)). This testing method has recently been implemented in various empirical studies of cross-sectional asset pricing. For example, see Cochrane (1996), Jagannathan and Wang (1996), and Heaton and Lucas (2000). We test the unconditional version of the orthogonality conditions

$$E[M_t(\beta)R_{j,t}] = 1 \tag{9}$$

where $R_{j,t}$ is the return on the i-th test asset, and $M_t(\beta)$ is the pricing kernel. We provide test results for the kernels discussed in Section 2 and some combinations of the pricing factors discussed there. Specifically, we consider pricing kernels of the form

$$\sum_k b_k f_{k,t} = b' f_t \tag{10}$$

where f is the vector of factors and b is a vector of constant parameters. It is now well-known that the above linear pricing kernel represents a multifactor model, which can be equivalently expressed in a linear multifactor beta pricing form (see e.g. Cochrane (1996) for details).

We implement a standard iterated GMM testing procedure. The iterated procedure is recommended by Ferson and Foerster (1994) after an extensive Monte Carlo study. We proceed as follows. In the initial round, we choose parameter values that minimize the Hansen and Jagannathan (1991, 1997) distance measure of pricing errors. This measure is computed as follows. Let

$$\mu_T = \frac{1}{T} \sum_{t=1}^{T} [M_t(\beta) R_t - 1] \tag{11}$$

where R_t is the vector of returns on the test assets. The weighting matrix for the HJ distance is

$$W_{HJ} = \frac{1}{T} \sum_{t=1}^{T} R_t R_t'. \tag{12}$$

The HJ distance is then given by

$$d = \{\mu_T' W_{HJ}^{-1} \mu_T\}^{\frac{1}{2}}. \tag{13}$$

This HJ measure is the maximum pricing error among all portfolio payoffs that have a unit second moment. It is also the least-square distance between the given candidate pricing kernel and the nearest point to it in the set of all pricing kernels that price assets correctly. Moreover, the measure is robust to portfolio formation. See Hansen and Jagannathan (1997) for details.

After the initial round, we go through an iterating procedure. In the second round, the weighting matrix is set to be the sample covariance matrix of $M_t(\beta)R_t - 1$ evaluated at the previous (first stage) estimate of β. Then the weighting matrix is used to compute the second stage estimates. This procedure is repeated until the estimates converge. Using the iterated estimates, we then compute Hansen's J test statistic of over-identifying restrictions. This test statistic has a limiting chi-squared distribution. To check for the robustness of our results, we also examine the first and second stage GMM results.

4.2 Test Results

Table IV presents the test results. The table contains four panels: Panel A contains test results obtained using data on all households, and consumption is defined as nondurables and services consumption. In panel B we repeat the same tests, again with nondurables and services consumption, but now only assetholders are included in the sample. Panels C and D repeat the analysis of panels A and B with consumption defined as total consumption, including durables. In each panel the top half presents results obtained using cohorts formed by grouping households in age cohorts, and the bottom part presents results obtained using cohorts formed by grouping households in age-education cohorts. Also, as mentioned in Section 2, each of the kernels is used with pricing factors constructed using individual data and also with pricing factors constructed using different types of cohort data. Factors with a 1 subscript denote factors obtained using individual data. Factors with a 2 subscript denote cohort-based factors, where averaging is done on consumption. Factors with a 3 subscript denote cohort-based factors, where averaging is done on the consumption ratio.

In each panel in table IV, we present results for estimation of (9) using the different kernels for individual data and two sets of cohort data, leading to a total of 13 sets of results for every panel. Each row represents a set of estimation results and the J-statistic associated with the estimation exercise is listed in the last column.

Panel A presents results for nondurables and services consumption, and all households are included in the sample. First consider the results associated with the pricing factors based on the individual consumption data in rows 1 and 7. In both cases the consumption growth factor has the expected negative sign and is significantly estimated.[10] However, in rows 1 and 7 the vcg_1 factor is estimated with a negative sign. For the cross sectional variance to be helpful in explaining the equity premium puzzle, we need this sign to be positive (e.g. see Constantinides and Duffie (1996)). Interestingly, in both cases the test statistics are lower than for the CAPM kernel in row 13.[11]

The use of factors based on cohorts instead of on individual data in rows 2, 3, 8 and 9 does not change these conclusions. In all cases the sign of the cross sectional variance factor is negative. Nevertheless, the test statistics are lower than the statistic for the CAPM in row 13. Interestingly, in terms of statistical significance, the variance factors indexed with a 3 are estimated more significantly compared to the variance factors indexed with a 2.

[10]Positive correlation (conditional on the other factors) between the asset returns and the mcg factors shows up with a negative sign, and negative correlation (conditional on the other factors) between the asset returns and the vcg factors shows up with a positive sign.

[11]It must be noted in this context that estimating a negative sign is only disappointing in the context of the equity premium puzzle. These signs are statements about the evolution of the cross sectional distribution of consumption growth in recessions and expansions. To explain one particular empirical phenomenon, the equity premium puzzle, we need the sign to be positive. In reference to a host of other issues, estimating a significant coefficient of any sign is of interest because it indicates that consumption growth is not the only factor of interest for asset pricing.

Finally, consider the test results in rows 4, 5, 6, 10, 11 and 12. These results are obtained by combining two consumption-based factors with the market factor. In most cases point estimates and statistical significance are quite similar to the corresponding cases in rows 1, 2, 3, 7, 8 and 9, which are obtained using two consumption-based factors by themselves.

Panel B also presents results for nondurables and services consumption, but only households that own assets are included in the sample. The results can be summarized very briefly. When using the individual data to construct the pricing factors in rows 1 and 7, we again obtain a negative sign for average consumption growth and a negative sign for the variance of consumption growth. Compared to Panel A, statistical significance is usually higher. When using synthetic cohorts in rows 2, 3, 8 and 9, in some cases the factor vcg yields a positive sign. Finally, for the specifications where the kernel depends on three factors in rows 4, 5, 6, 10, 11 and 12, the results are not very different from those in Panel A. Summarizing, limiting the sample to assetholders does change the empirical results but test results are not necessarily consistent when constructing the cohorts in different ways.

Panel C presents results obtained using all households, but the consumption measure used is total consumption instead of nondurables and services consumption. Inspection of Tables I through III indicates that the cross-sectional distribution of the different consumption measures is quite different. However, when using individual consumption data in rows 1 and 7, results are again not encouraging. The factor mcg_1 is estimated with the anticipated negative sign and is statistically significant. Whereas the vcg_1 factor is estimated with a positive sign in some cases, the more relevant observation is that all estimates are statistically insignificant. When using synthetic cohorts in rows 2, 3, 8 and 9, results are different. In most cases we estimate the vcg_2 and vcg_3 factors with a statistically significant positive sign. When the market factor is included as an additional factor, the consumption-based factors are still estimated significantly in most but not all cases. One observation that stands out is that the results obtained using the vcg_3 factor conform more to the theory than the results obtained using the vcg_2 factor. This observation is similar to the findings in Panel B.

Given the results in Panels B and C, the results in Panel D are perhaps not totally surprising. This panel reports estimates obtained using data on total consumption, but only for households who hold assets. When using individual data in rows 1 and 7, estimates are not statistically significant. However, when constructing synthetic cohorts, the variance factors in rows 2, 3, 8 and 9 all yield statistically significant positive point estimates. Also, when adding the market factor to the two consumption-based factors in rows 5, 6, 11 and 12 empirical results for the consumption-based factors are not dramatically different.

We perform a large number of robustness exercises that are not presented in the tables because of space constraints. As mentioned above, we repeat the analysis after deseasonalising the data using the census X11 method implemented in EVIEWS. Second, we correct the household consumption data for family size in two different ways: by computing per capita data and by correcting for household size using a scale that is estimated from the data. Third, to address the problem that some cohorts contain few observations, we construct cohort pricing factors that are weighed by the size of the cohort. None of these adjustments impact significantly on the results.

Table V further investigates the robustness of the results obtained in Table IV, Panel D, using data on total consumption for asset holders only. We only report these results using one of the datasets to limit the number of tables. Table V clearly indicates the robustness of the results. Panel A presents the first stage GMM estimates obtained by minimizing the HJ distance measure (13). We obtain positive estimates for the variance factors in all pricing kernels where we use factors based on cohort construction. It must be noted that the point estimates are not as significant as the ones in Table IV, but this is to be expected because the first stage GMM estimation is less efficient. The advantage of minimizing the HJ distance is that we can make comparisons of the HJ-distances obtained using the different kernels. The performance of the consumption-based pricing factors is clearly impressive. The HJ-distance for the CAPM is 2.41 and serves as a benchmark. The HJ distances obtained when using factors constructed from individual consumption data in rows 1 and 7 are 2.33 in both cases. This is a lower HJ distance than for the CAPM, even though the variance factor is estimated insignificantly. Most interestingly, the HJ distances are much lower when using factors based on cohorts. This is especially the case for the cohorts based on age in rows 2 and 3. When using a pricing kernel with two consumption-based factors and the market factor in rows 5, 6, 11 and 12, the HJ statistic drops even further. Panel B of Table V provides two-step GMM estimates. Again, the results confirm those of Table IV. The variance factors are estimated significantly positive whenever we use cohorts to construct the pricing factors.

Table VI addresses an issue that was omitted from Tables IV and V because of space constraints. In Tables IV and V we always present consumption-based models with two factors. Given that this is an unconditional model and that we know that one-factor consumption-based models do not perform well in an unconditional setting, we therefore implicitly concluded that the extra second factor added explanatory power. Table VI verifies this conclusion by presenting test results for pricing kernels including only the first consumption-based factor. The results in rows 1, 2, 3, 7, 8 and 9 indicate that the performance of this consumption-based model is very similar to that of the CAPM, judging by the HJ distance measures. We can therefore safely conclude that it is the inclusion of the cross-sectional variance factor that drives the HJ distances down.

Finally, Table VII reports on a more ambitious exercise designed to subject the consumption based pricing factors to a potentially more stringent test. Instead of using the CAPM as a benchmark, we compare the performance of the consumption-based factors to the three-factor model proposed by Fama and French (1992,1993), that includes size and book-to-market factors as well as the market portfolio. We report estimated coefficients obtained using the iterated GMM procedure but also the HJ distances for each model obtained in the first stage. The results are very encouraging. First, when combining the consumption-based factors in a kernel with (a subset of) the three factors, the consumption-based factors show up significantly with the expected sign. Second, when adding the consumption based factors to (subsets of) the Fama-French factors the resulting HJ statistic is significantly lower. It is perhaps also interesting that the resulting HJ statistics are quite a bit lower than the ones obtained in Table V for the pricing kernel with two consumption-based factors only. While one has to keep in mind that there is no adjustment for the number of factors when computing the HJ statistic, this finding may not necessarily be surprising given the fact that the size and book-to-market factors are so successful in capturing empirical patterns in stock returns (Fama and French (1996)). In other words, this result is probably as indicative of the explanatory power of the Fama-French factors as of the performance of the consumption-based factors. This conclusion is reinforced by the results in rows 4, 5, 6, 10, 11 and 12 in Table VI. When adding the Fama-French factors to a single consumption-based factor, the HJ distances are dramatically lower.

5 Concluding Remarks

A number of recent papers have demonstrated that the presence of uninsurable idiosyncratic consumption risk is relevant to explain well-established puzzles in the asset-pricing literature, such as the equity premium puzzle and the riskfree rate puzzle. This paper shows that the presence of such risk is also useful to construct pricing factors that can explain the cross-section of asset returns. We investigate the performance of a pricing kernel linear in the first and the second moment of the cross-sectional distribution of consumption growth. We find that it is extremely important to address the presence of measurement error in consumption by constructing synthetic cohorts. Using the consumption factors based on synthetic cohorts, we find that the consumption-based pricing factors are almost always significantly estimated. However, whereas the first moment of the cross-sectional distribution is always estimated with the theoretically expected sign, the sign estimated for the second moment depends on the dataset. For idiosyncratic consumption risk to be of interest for the equity premium puzzle, the variance of the cross-sectional distribution of consumption growth has to be negatively correlated with returns. We find that this is more likely the case when using data on total consumption (as opposed to nondurables and services consumption) and when using data on households that hold assets (as opposed to data on assetholders and non-assetholders). When using data on total consumption and assetholders only, the factor based on the cross-sectional variance of consumption growth is estimated significantly and with the sign suggested by theory in all cases, regardless of the method used to construct cohorts.

We evaluate the importance of this finding by comparing the pricing performance of the consumption-based factors against some well-established benchmarks, using the HJ distance as a yardstick. First, the HJ distances associated with the consumption-based kernels are lower than those associated with the CAPM over the sample period. Second, the HJ distances for these kernels are also lower than those associated with the Fama-French three factor model. Finally, when estimating kernels that combine the CAPM or Fama-French factors with the consumption-based factors, the consumption-based factors are still estimated significantly with the same signs. They therefore seem to contribute to cross-sectional pricing by capturing empirical patterns that are different from those present in alternative models of cross-sectional asset pricing.

The traditional view is that consumption-based models are not very helpful for cross-sectional asset pricing. However, in a recent paper Lettau and Ludvigson (2000) demonstrate that conditional versions of consumption based models perform much better than unconditional versions. This paper provides further evidence that the empirical performance of consumption-based models is probably more satisfactory than we thought. Given that these factors are suggested by theory within the context of a well-specified multiperiod model, they deserve to be given close attention. To build an even stronger case, two exercises related to the ones in this paper come to mind. First, the analysis in this paper is limited to unconditional models. Given the analysis in Lettau and Ludvigson (2000), an extension to conditional models seems worthwhile. Second, the descriptive statistics in Tables I through III strongly suggest that the distribution of cross-sectional consumption growth is non-normal. Therefore, an extension of the analysis in this paper to pricing models that incorporate higher moments may prove worthwhile.[12]

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Table I

Summary Statistics for Household Consumption Growth

This table presents descriptive statistics for household consumption growth and the level of household consumption in the four samples under investigation. It presents the first four moments, the minimum and the maximum. Panels A and B present descriptive statistics for the total sample consisting of 45 quarterly observations. Panels C and D present descriptive statistics on a quarter-by-quarter basis. To conserve space, in panels C and D we only present results for consumption growth, only for four quarters and only for data on total consumption. NDS stands for Nondurable and Services Consumption, TOT for total consumption, AH denotes asset holders and ALL indicates that the sample includes all households.

Panel A: Individual Consumption Growth, All Quarters

	# obs	mean	std	skew	exc. kurt	min	max
NDS, ALL	83249	1.049	0.396	9.030	356.955	0.086	25.259
NDS, AH	23467	1.051	0.407	8.896	312.446	0.101	20.237
TOT, ALL	83222	1.135	0.708	4.936	52.054	0.025	20.034
TOT, AH	23456	1.144	0.706	4.457	47.971	0.072	19.673

Panel B: Individual Consumption Level, All Quarters

	# obs	mean	std	skew	exc. kurt	min	max
NDS, ALL	83249	2298	1385	3.097	29.781	31	43205
NDS, AH	23467	2789	1643	3.529	36.850	161	43205
TOT, ALL	83222	5290	4180	3.479	26.508	113	96734
TOT, AH	23456	6877	4981	3.349	24.179	526	96734

Table I (Continued)

Panel C: Individual Consumption Growth, Individual Quarters
Total Consumption, All Households

	# obs	mean	std	skew	exc. kurt	min	max
1985, q2	1759	1.165	0.734	3.538	17.744	0.117	7.012
1988, q3	1793	1.191	0.807	4.146	26.688	0.150	10.083
1991, q1	1893	1.048	0.680	7.040	92.831	0.034	13.708
1993, q4	1919	1.117	0.672	4.352	30.488	0.140	7.682

Panel D: Individual Consumption Growth, Individual Quarters
Total Consumption, Asset Holders

	# obs	mean	std	skew	exc. kurt	min	max
1985, q2	528	1.203	0.791	2.931	12.027	0.117	7.012
1988, q3	481	1.236	0.826	4.022	24.774	0.234	8.750
1991, q1	499	1.033	0.721	6.355	61.850	0.189	9.890
1993, q4	544	1.088	0.582	3.036	14.493	0.184	5.169

Table II

Summary Statistics for Cohort Consumption Growth

This table presents descriptive statistics for cohort consumption growth in the four samples under investigation, for both methods of cohort construction. It presents the first four moments, the minimum and the maximum. It also presents the average cohort size, as well as the minimum and maximum cohort size. Descriptive statistics are presented for the total sample consisting of 45 quarterly observations. Descriptive statistics are also presented for the level of consumption. NDS stands for Nondurable and Services Consumption, TOT for total consumption, AH denotes asset holders and ALL indicates that the sample includes all households. Cohort construction type 2 means that consumption growth for cohort j is given by $cohcg_{2,j,t} = (1/N_{k,t})\sum_{i=1}^{N_{k,t}}(cg_{i,t})$ where $cg_{i,t} = (c_{i,t}/c_{i,t-1})$, $c_{i,t}$ is the consumption of individual i at time t and $N_{k,t}$ is the number of observations on this cohort at time t. Cohort construction type 3 means that consumption growth for cohort j is given by $cohcg_{3,k,t} = (cohc_{k,t}/cohc_{k,t-1})$ where $cohc_{k,t} = (1/N_{k,t})\sum_{i=1}^{N_{k,t}}(c_{i,t})$.

Panel A: Cohort Consumption Growth, All Quarters
Age Cohorts, Cohort Construction Type 2

	mean	std	skew	exc. kurt	min	max	# obs	av.cs	min.cs	max.cs
NDS, ALL	1.049	0.077	0.632	2.655	0.838	1.593	1755	47.43	17	84
NDS, AH	1.050	0.132	2.282	23.479	0.667	2.800	1753	13.38	2	32
TOT, ALL	1.138	0.128	0.817	1.801	0.784	1.802	1755	47.42	17	84
TOT, AH	1.150	0.232	1.661	7.485	0.653	3.217	1753	13.38	2	32

Panel B: Cohort Consumption Growth, All Quarters
Age Cohorts, Cohort Construction Type 3

	mean	var	skew	exc. kurt	min	max	# obs	av.cs	min.cs	max.cs
NDS, ALL	0.999	0.0063	0.019	0.164	0.769	1.355	1755	47.435	17	84
NDS, AH	1.001	0.0166	0.405	1.408	0.602	1.737	1753	13.386	2	32
TOT, ALL	1.015	0.0175	0.532	1.080	0.651	1.638	1755	47.420	17	84
TOT, AH	1.037	0.0502	1.085	3.960	0.397	2.743	1753	13.380	2	32

Table II (Continued)

Panel C: Cohort Consumption Level, All Quarters
Age Cohorts

	mean	std	skew	ex.kur.	min	max	# obs	av.cs	min.cs	max.cs
NDS, ALL	2288	378	0.197	-0.091	1254	3694	1755	47.43	17	84
NDS, AH	2722	601	0.441	1.098	810	6337	1753	13.38	2	32
TOT, ALL	5253	964	0.356	0.133	2739	9314	1755	47.42	17	84
TOT, AH	6722	1668	0.629	0.952	1785	15830	1753	13.38	2	32

Panel D: Cohort Consumption Growth, All Quarters
Age-and-Education Cohorts, Cohort Construction Type 2

	mean	std	skew	exc. kurt	min	max	# obs	av.cs	min.cs	max.cs
NDS, ALL	1.053	0.120	2.150	19.832	0.636	22.700	3510	23.71	1	64
NDS, AH	1.049	0.180	1.654	11.459	0.454	3.175	3484	6.73	1	23
TOT, ALL	1.139	0.195	1.842	10.760	0.497	3.372	3510	23.71	1	64
TOT, AH	1.152	0.361	3.279	23.591	0.303	5.302	3484	6.73	1	23

Panel E: Cohort Consumption Growth, All Quarters
Age-and-Education Cohorts, Cohort Construction Type 3

	mean	std	skew	exc. kurt	min	max	# obs	av.cs	min.cs	max.cs
NDS, ALL	1.003	0.119	0.763	4.405	0.509	2.100	3510	23.71	1	64
NDS, AH	1.008	0.180	0.954	4.635	0.465	2.484	3484	6.73	1	23
TOT, ALL	1.025	0.198	1.426	8.488	0.322	3.272	3510	23.71	1	64
TOT, AH	1.061	0.361	3.310	26.104	0.268	5.302	3484	6.73	1	23

Panel F: Cohort Consumption Level, All Quarters
Age-and-Education Cohorts

	mean	std	skew	exc. kurt	min	max	# obs	av.cs	min.cs	max.cs
NDS, ALL	2457	699	1.688	7.110	1001	9803	3510	23.71	1	64
NDS, AH	2757	852	1.434	6.169	586	10532	3484	6.73	1	23
TOT, ALL	5797	1987	1.968	10.586	2384	30413	3510	23.71	1	64
TOT, AH	6845	2547	2.305	19.161	1440	45815	3484	6.73	1	23

Table III

Summary Statistics for Consumption-Based Pricing Factors

This table presents descriptive statistics for the three sets of consumption-based pricing factors. It presents the mean, maximum, minimum and standard deviation of each factor in the sample, which consists of 45 quarterly observations. The first set of factors is based on consumption data for individual households

$$mcg_{1,t} = (1/N)\sum_{i=1}^{N}(cg_{i,t}) \qquad vcg_{1,t} = (1/N)\sum_{i=1}^{N}(cg_{i,t} - mcg_{1,t})^2$$

where $cg_{i,t} = (c_{i,t}/c_{i,t-1})$, $c_{i,t}$ is the consumption of individual i at time t and N is the number of households in the cross-section. The second and third set of pricing factors are based on cohort data. The second set of factors is obtained by averaging over the consumption growth of the individuals in that cohort. For cohort j $cohcg_{2,j,t} = (1/N_{k,t})\sum_{i=1}^{N_{k,t}}(cg_{i,t})$, where $N_{k,t}$ is the number of observations on this cohort at time t. Given H cohorts the factors are

$$mcg_{2,t} = (1/H)\sum_{j=1}^{H}(cohcg_{2,j,t}) \qquad vcg_{2,t} = (1/H)\sum_{j=1}^{H}(cohcg_{2,j,t} - mcg_{2,t})^2$$

For the second set of factors, consider the consumption of a representative cohort k at time t $cohc_{k,t} = (1/N_{k,t})\sum_{i=1}^{N_{k,t}}(c_{i,t})$. Define $cohcg_{3,k,t} = (cohc_{k,t}/cohc_{k,t-1})$. The factors then are

$$mcg_{3,t} = (1/H)\sum_{k=1}^{H}(cohcg_{3,k,t}) \qquad vcg_{3,t} = (1/H)\sum_{k=1}^{H}(cohcg_{3,k,t} - mcg_{3,t})^2$$

Table III (Continued)

Panel A: Nondurable and Services Consumption, All Households

Age Cohorts

	mcg_1	vcg_1	mcg_2	vcg_2	mcg_3	vcg_3
mean	1.0491	0.1598	1.0492	0.0040	0.9989	0.0043
min	0.9433	0.0879	0.9438	0.0011	0.8884	0.0019
max	1.1204	0.4239	1.1249	0.0143	1.0580	0.0184
st.dev.	0.0475	0.0774	0.0476	0.0028	0.0500	0.0025

Age-and-Education Cohorts

	mcg_1	vcg_1	mcg_2	vcg_2	mcg_3	vcg_3
mean	1.0491	0.1598	1.0523	0.0124	1.0025	0.0122
min	0.9433	0.0879	0.9371	0.0052	0.8933	0.0049
max	1.1204	0.04239	1.1213	0.0474	1.0718	0.0274
st.dev.	0.0475	0.0774	0.0498	0.0079	0.0514	0.0045

Panel B: Nondurable and Services Consumption, Asset Holders

Age Cohorts

	mcg_1	vcg_1	mcg_2	vcg_2	mcg_3	vcg_3
mean	1.0510	0.1642	1.0502	0.0158	1.0010	0.0147
min	0.9237	0.0821	0.9229	0.0061	0.8724	0.0058
max	1.1285	0.7067	1.1354	0.0878	1.0858	0.0676
st.dev.	0.0588	0.1184	0.0590	0.0163	0.0579	0.0092

Age-and-Education Cohorts

	mcg_1	vcg_1	mcg_2	vcg_2	mcg_3	vcg_3
mean	1.0510	0.1642	1.0497	0.0330	1.0078	0.0321
min	0.9237	0.0821	0.9169	0.0157	0.8742	0.0133
max	1.1285	0.7067	1.1360	0.1931	1.0972	0.1607
st.dev.	0.0588	0.1184	0.0600	0.0268	0.0598	0.0214

Table III (Continued)

Panel C: Total Consumption, All Households

Age Cohorts

	mcg_1	vcg_1	mcg_2	vcg_2	mcg_3	vcg_3
mean	1.1355	0.5047	1.1385	0.0132	1.0143	0.0148
min	1.0063	0.2475	1.0034	0.0054	0.8923	0.0059
max	1.2173	0.8349	1.2166	0.0312	1.0911	0.0265
st.dev.	0.0608	0.1217	0.0624	0.0055	0.0582	0.0051

Age-and-Education Cohorts

	mcg_1	vcg_1	mcg_2	vcg_2	mcg_3	vcg_3
mean	1.1355	0.5047	1.1385	0.0352	1.0240	0.0368
min	1.0063	0.2475	0.9974	0.0141	0.8938	0.0160
max	1.2173	0.8349	1.2223	0.0958	1.0990	0.0910
st.dev.	0.0608	0.1217	0.0638	0.0154	0.0595	0.0148

Panel D: Total Consumption, Asset Holders

Age Cohorts

	mcg_1	vcg_1	mcg_2	vcg_2	mcg_3	vcg_3
mean	1.1436	0.4925	1.1489	0.0521	1.0361	0.0499
min	0.9658	0.2385	0.9796	0.0217	0.8563	0.0193
max	1.2747	1.1243	1.2787	0.2047	1.1561	0.2162
st.dev.	0.0801	0.1569	0.0804	0.0341	0.0723	0.0311

Age-and-Education Cohorts

	mcg_1	vcg_1	mcg_2	vcg_2	mcg_3	vcg_3
mean	1.1436	0.4925	1.1504	0.1268	1.0599	0.1280
min	0.9658	0.2385	0.9858	0.0478	0.8812	0.0450
max	1.2747	1.1243	1.2773	0.3337	1.1842	0.2968
st.dev.	0.0801	0.1569	0.0817	0.0660	0.0755	0.0661

Table IV

Testing for Significance of Consumption-Based Factors

The following forms of the pricing kernel M_t are tested

$$M_t(\beta) = \beta_0 + \beta_1 R_{M,t}$$

$$M_t(\beta) = \beta_0 + \beta_1 mcg_t + \beta_2 vcg_t$$

$$M_t(\beta) = \beta_0 + \beta_1 mcg_t + \beta_2 vcg_t + \beta_3 R_{M,t}$$

where $R_{M,t}$ is the return on the market portfolio, mcg_t and vcg_t are cross-sectional mean and variance of consumption growth. Our test assets consist of the twenty-five Fama-French size and book-to-market portfolios, the long term government bond, the corporate bond, and the T-bill. (See Section 3 for a description of the asset return data.) A standard GMM procedure is implemented for testing the moment conditions $E[M_t(\beta)R_{it}] = 1$, where R_{it} is the return on the i-th test asset. In the initial round, the HJ-distance measure is minimized. Then the iterated GMM estimates are obtained, i.e., at each round, the weighting matrix is updated using the estimates from the previous round, and the procedure is repeated until estimates converge. Reported in the table are the iterated estimates and the J test statistics that are based on the iterated estimates. In parentheses under the estimates are standard errors and in the parentheses under the J statistics are the p-values. Reported in panels A through D are tests using four different consumption data sets: (i) nondurable and services consumption for all households, (ii) nondurable and services consumption for asset holders, (iii) total consumption for all households, and (iv) total consumption for asset holders. The consumption factors are the three pairs based on consumption growth (mcg_j and vcg_j, $j = 1, 2, 3$), defined in Table III (or see Section 3).

Table IV (Continued)

Panel A: Nondurable and Services Consumption, All Households

row	constant	mcg_1	vcg_1	mcg_2	vcg_2	mcg_3	vcg_3	R_M	J-Test
				Age Cohorts					
1	-2.38	5.94	-18.81						34.00
	(5.13)	(4.97)	(4.88)						(0.108)
2	9.50			-7.48	-150.81				38.90
	(5.25)			(4.96)	(56.93)				(0.038)
3	7.98					-6.75	-64.74		40.01
	(4.83)					(4.99)	(133.13)		(0.029)
4	26.32	-16.54	-7.74					-6.13	36.40
	(8.65)	(7.30)	(2.76)					(3.36)	(0.050)
5	59.54			-41.55	-433.30			-12.29	38.98
	(8.40)			(7.40)	(89.19)			(3.30)	(0.027)
6	15.44					-4.98	-830.64	-6.46	41.78
	(5.38)					(5.09)	(157.95)	(1.98)	(0.014)
				Age-and-Education Cohorts					
7	-2.38	5.94	-18.81						34.00
	(5.13)	(4.97)	(4.88)						(0.108)
8	12.70			-10.34	-44.74				38.07
	(5.96)			(5.61)	(23.86)				(0.046)
9	5.89					-3.92	-71.82		39.50
	(4.90)					(5.05)	(41.32)		(0.033)
10	26.32	-16.54	-7.74					-6.13	36.40
	(8.65)	(7.30)	(2.76)					(3.36)	(0.050)
11	39.74			-21.80	-49.71			-14.11	36.64
	(6.60)			(5.09)	(30.80)			(3.86)	(0.048)
12	8.41					4.42	-177.52	-9.16	36.96
	(5.63)					(4.12)	(65.97)	(2.76)	(0.044)
13	6.06							-4.94	39.54
	(1.91)							(1.82)	(0.043)

Table IV (Continued)

Panel B: Nondurable and Services Consumption, Asset Holders

row	constant	mcg_1	vcg_1	mcg_2	vcg_2	mcg_3	vcg_3	R_M	J-Test
					Age Cohorts				
1	48.97	-38.86	-41.58						30.55
	(10.43)	(9.73)	(9.41)						(0.204)
2	7.09			-4.81	-72.53				38.07
	(5.23)			(5.08)	(31.92)				(0.046)
3	21.02					-23.34	194.30		42.73
	(3.29)					(3.31)	(25.18)		(0.015)
4	44.53	-32.12	-37.53					-3.37	31.81
	(9.90)	(9.03)	(9.33)					(4.16)	(0.132)
5	8.44			-5.35	-66.09			-0.85	38.36
	(6.11)			(5.04)	(31.53)			(2.84)	(0.032)
6	26.88					-14.20	-4.46	-10.95	40.02
	(5.37)					(4.72)	(38.59)	(2.79)	(0.021)
					Age-and-Education Cohorts				
7	48.97	-38.86	-41.58						30.55
	(10.43)	(9.73)	(9.41)						(0.204)
8	-2.15			4.72	-52.89				37.73
	(4.11)			(4.24)	(18.10)				(0.049)
9	43.52					-49.11	267.82		31.33
	(7.27)					(7.32)	(53.17)		(0.178)
10	44.53	-32.12	-37.53					-3.37	31.81
	(9.90)	(9.03)	(9.33)					(4.16)	(0.132)
11	12.91			-3.54	-17.90			-7.32	39.36
	(6.45)			(4.36)	(18.64)			(3.01)	(0.025)
12	43.24					-49.54	264.98	0.75	31.50
	(7.36)					(7.45)	(53.84)	(2.41)	(0.140)
13	6.06							-4.94	39.54
	(1.91)							(1.82)	(0.043)

Table IV (Continued)

Panel C: Total Consumption, All Households

row	constant	mcg_1	vcg_1	mcg_2	vcg_2	mcg_3	vcg_3	R_M	J-Test
				Age Cohorts					
1	12.31	-10.22	0.30						41.87
	(4.79)	(4.61)	(1.45)						(0.019)
2	17.02			-16.14	164.36				41.41
	(3.28)			(2.89)	(29.59)				(0.021)
3	16.21					-20.67	380.76		38.79
	(2.13)					(2.45)	(47.06)		(0.039)
4	34.81	-11.00	-1.07					-19.84	37.95
	(6.98)	(4.18)	(2.41)					(3.42)	(0.035)
5	20.81			-12.12	159.32			-8.01	40.26
	(4.13)			(2.19)	(35.09)			(2.27)	(0.020)
6	30.04					-12.76	55.09	-16.15	37.95
	(5.74)					(3.48)	(45.86)	(3.28)	(0.035)
				Age-and-Education Cohorts					
7	12.31	-10.22	0.30						41.87
	(4.79)	(4.61)	(1.45)						(0.019)
8	9.93			-7.75	-5.85				41.11
	(3.67)			(3.19)	(9.70)				(0.022)
9	5.16					-6.20	62.11		39.84
	(2.68)					(2.77)	(19.43)		(0.030)
10	34.81	-11.00	-1.07					-19.84	37.95
	(6.98)	(4.18)	(2.41)					(3.42)	(0.035)
11	71.59			-24.42	-68.08			-38.63	33.14
	(10.33)			(5.62)	(24.32)			(5.40)	(0.101)
12	34.54					-18.27	141.04	-18.56	33.29
	(7.89)					(5.24)	(33.67)	(4.15)	(0.098)
13	6.06							-4.94	39.54
	(1.91)							(1.82)	(0.043)

Table IV (Continued)

Panel D: Total Consumption, Asset Holders

row	constant	mcg_1	vcg_1	mcg_2	vcg_2	mcg_3	vcg_3	R_M	J-Test
					Age Cohorts				
1	32.19	-26.13	-0.41						36.67
	(8.00)	(7.07)	(1.37)						(0.062)
2	36.65			-33.90	70.53				33.76
	(6.80)			(5.83)	(15.59)				(0.113)
3	9.17					-9.33	30.41		40.61
	(2.90)					(2.75)	(8.82)		(0.025)
4	65.63	-23.94	2.47					-36.77	35.85
	(8.01)	(4.02)	(2.61)					(4.85)	(0.057)
5	51.99			-31.01	41.48			-16.59	35.52
	(6.41)			(4.96)	(12.46)			(4.84)	(0.061)
6	33.16					-30.26	90.83	-5.23	38.08
	(6.45)					(5.07)	(18.97)	(3.20)	(0.034)
					Age-and-Education Cohorts				
7	32.19	-26.13	-0.41						36.67
	(8.00)	(7.07)	(1.37)						(0.062)
8	31.68			-28.85	24.20				35.17
	(6.27)			(5.47)	(4.62)				(0.085)
9	31.18					-31.45	27.54		35.58
	(5.35)					(5.03)	(4.31)		(0.078)
10	65.63	-23.94	2.47					-36.77	35.85
	(8.01)	(4.02)	(2.61)					(4.85)	(0.057)
11	58.91			-42.10	21.67			-10.95	26.93
	(9.18)			(7.73)	(5.52)			(4.32)	(0.308)
12	38.76					-30.57	33.71	-8.45	36.23
	(7.21)					(5.32)	(7.03)	(3.11)	(0.052)
13	6.06							-4.94	39.54
	(1.91)							(1.82)	(0.043)

Table V

Two Stage GMM and HJ-Distance

The following forms of the pricing kernel M_t are estimated

$$M_t(\beta) = \beta_0 + \beta_1 R_{M,t}$$

$$M_t(\beta) = \beta_0 + \beta_1 mcg_t + \beta_2 vcg_t$$

$$M_t(\beta) = \beta_0 + \beta_1 mcg_t + \beta_2 vcg_t + \beta_3 R_{M,t}$$

where $R_{M,t}$ is the return on the market portfolio, mcg_t and vcg_t are the cross-sectional mean and variance of consumption growth. Our test assets consist of the twenty-five Fama-French size and book-to-market portfolios, the long term government bond, the corporate bond, and the T-bill. (See Section 3 for a description of the asset return data.) A standard GMM procedure is implemented for testing the moment conditions $E[M_t(\beta)R_{it}] = 1$, where R_{it} is the return on the i-th test asset. Reported in panel A are the first stage GMM estimates which are the parameter values that minimize the HJ-distance measure. That is, the weighting matrix $W_{HJ} = \frac{1}{T}\sum_{t=1}^{T} R_t R_t'$, where R_t is the vector of returns on the test portfolios. Then the first stage GMM estimates are obtained using this weighting matrix. See Section 4 for more details. In panel B are the second stage GMM estimates and the J test statistics. This table is based on the data for the total consumption for asset holders. The consumption factors are the three pairs based on consumption growth (mcg_j and vcg_j, $j = 1, 2, 3$) derived from the data set of total consumption for asset holders, all defined in Table III.

Table V (Continued)

Panel A: First Stage GMM Estimates and HJ-Distances

row	constant	mcg_1	vcg_1	mcg_2	vcg_2	mcg_3	vcg_3	R_M	HJ-d
				Age Cohorts					
1	16.03	-14.56	3.34						2.33
	(5.63)	(5.26)	(2.43)						
2	17.96			-16.82	49.05				2.16
	(5.59)			(5.02)	(20.36)				
3	17.00					-18.72	73.86		2.19
	(7.04)					(7.83)	(35.56)		
4	26.07	-16.08	2.65					-7.74	2.26
	(7.30)	(4.99)	(3.15)					(4.45)	
5	28.04			-18.91	48.36			-7.44	2.10
	(8.54)			(4.76)	(20.71)			(5.80)	
6	28.67					-21.98	76.33	-8.19	2.11
	(9.37)					(7.41)	(35.27)	(5.59)	
				Age-and-Education Cohorts					
7	16.03	-14.56	3.34						2.33
	(5.63)	(5.26)	(2.43)						
8	14.76			-13.37	13.09				2.29
	(5.34)			(4.81)	(5.66)				
9	12.70					-12.97	16.35		2.26
	(4.76)					(4.70)	(6.49)		
10	26.07	-16.08	2.65					-7.74	2.26
	(7.30)	(4.99)	(3.15)					(4.45)	
11	27.01			-16.28	13.97			-8.77	2.21
	(7.67)			(5.11)	(5.90)			(4.15)	
12	23.82					-15.77	16.64	-7.98	2.19
	(6.69)					(4.69)	(6.42)	(3.89)	
13	6.77							-5.62	2.41
	(3.39)							(3.24)	

Table V (Continued)

Panel B: Second Stage GMM Estimates and J Tests

row	constant	mcg_1	vcg_1	mcg_2	vcg_2	mcg_3	vcg_3	R_M	J-Test
					Age Cohorts				
1	14.86	-13.04	2.09						42.24
	(3.95)	(3.61)	(1.24)						(0.017)
2	19.89			-18.58	51.23				41.30
	(4.19)			(3.65)	(8.59)				(0.021)
3	15.54					-16.79	61.03		40.41
	(3.86)					(3.83)	(13.35)		(0.026)
4	26.12	-14.89	1.66					-8.64	41.39
	(4.02)	(3.53)	(1.29)					(2.44)	(0.015)
5	31.12			-20.98	49.04			-8.12	40.64
	(4.55)			(3.39)	(11.31)			(2.94)	(0.018)
6	27.44					-21.07	68.33	-7.60	41.01
	(5.80)					(4.58)	(15.70)	(2.40)	(0.017)
					Age-and-Education Cohorts				
7	14.86	-13.04	2.09						42.24
	(3.95)	(3.61)	(1.24)						(0.017)
8	16.80			-15.16	13.61				42.30
	(3.32)			(2.91)	(2.34)				(0.017)
9	13.72					-13.95	16.74		42.45
	(2.69)					(2.55)	(3.19)		(0.016)
10	26.12	-14.89	1.66					-8.64	41.39
	(4.02)	(3.53)	(1.29)					(2.44)	(0.015)
11	31.41			-19.36	13.37			-9.42	42.04
	(4.75)			(3.08)	(3.29)			(2.95)	(0.013)
12	24.74					-16.50	17.43	-8.17	42.27
	(3.86)					(2.55)	(3.71)	(2.42)	(0.012)
13	6.68							-5.53	39.56
	(1.84)							(1.75)	(0.043)

Table VI

Testing for Significance of Consumption Growth

The following forms of the pricing kernel M_t are tested

$$M_t(\beta) = \beta_0 + \beta_1 mcg_t$$

$$M_t(\beta) = \beta_0 + \beta_1 mcg_t + \beta_2 R_{M,t} + \beta_3 \mathrm{SMB}_t + \beta_4 \mathrm{HML}_t$$

where SMB and HML are the size and book-to-market factors of Fama and French, mcg_t is the cross-sectional mean of consumption growth. Our test assets consist of the twenty-five Fama-French size and book-to-market portfolios, the long term government bond, the corporate bond, and the T-bill. (See Section 3 for a description of the asset return data.) A standard GMM procedure is implemented for testing the moment conditions $E[M_t(\beta)R_{it}] = 1$, where R_{it} is the return on the i-th test asset. In the initial round, the HJ-distance measure is minimized. Then the iterated GMM estimates are obtained, i.e., at each round, the weighting matrix is updated using the estimates from the previous round, and the procedure is repeated until estimates converge. Reported in the table are the iterated estimates and the J test statistics that are based on the iterated estimates. In the parentheses under the estimates are standard errors and in the parentheses under the J statistics are the p-values. The HJ distances are also included. The consumption factors (mcg_j, $j = 2, 3$) are constructed with the age cohorts and age-education cohorts, respectively, derived from the data set of total consumption for asset holders. All the consumption factors are defined in Table III.

Table VI (Continued)

row	const.	mcg_1	mcg_2	mcg_3	R_M	SMB	HML	J-Test	HJ-d
				Age Cohorts					
1	34.31	-28.14						36.68	2.36
	(7.41)	(6.31)						(0.08)	
2	15.83		-12.56					40.21	2.39
	(5.55)		(4.73)					(0.04)	
3	6.80			-5.62				40.37	2.42
	(3.45)			(3.28)				(0.04)	
4	76.22	-30.41			-38.32	-14.10	-23.70	31.17	2.18
	(10.60)	(5.02)			(8.65)	(6.47)	(8.18)	(0.119)	
5	67.12		-19.46		-41.34	-5.02	-33.41	28.60	2.22
	(10.91)		(4.53)		(7.23)	(4.77)	(6.02)	(0.194)	
6	58.82			-15.48	-39.34	0.28	-31.60	28.59	2.29
	(9.45)			(4.44)	(6.22)	(4.03)	(4.69)	(0.194)	
				Age-and-Education Cohorts					
7	34.31	-28.14						36.68	2.36
	(7.41)	(6.31)						(0.08)	
8	10.00		-7.75					39.85	2.38
	(3.50)		(2.98)					(0.04)	
9	7.48			-6.13				39.75	2.41
	(3.09)			(2.87)				(0.04)	
10	76.22	-30.41			-38.32	-14.10	-23.70	31.17	2.18
	(10.60)	(5.02)			(8.65)	(6.47)	(8.18)	(0.119)	
11	68.40		-34.34		-26.67	-24.09	-22.12	28.99	2.21
	(10.55)		(6.31)		(8.02)	(7.77)	(6.50)	(0.181)	
12	103.08			-32.79	-63.44	-4.28	-47.90	26.05	2.27
	(11.54)			(5.48)	(8.92)	(6.35)	(6.18)	(0.299)	

Table VII

Testing for Significance of the Cross-Sectional Distribution of Consumption Growth in the Presence of the Size and Book-to-Market Factors

The following forms of the pricing kernel M_t are tested

$$M_t(\beta) = \beta_0 + \beta_1 \mathrm{SMB}_t + \beta_2 \mathrm{HML}_t$$

$$M_t(\beta) = \beta_0 + \beta_1 R_{M,t} + \beta_2 \mathrm{SMB}_t + \beta_3 \mathrm{HML}_t$$

$$M_t(\beta) = \beta_0 + \beta_1 mcg_t + \beta_2 vcg_t + \beta_3 \mathrm{SMB}_t + \beta_4 \mathrm{HML}_t$$

$$M_t(\beta) = \beta_0 + \beta_1 mcg_t + \beta_2 vcg_t + \beta_3 R_{M,t} + \beta_4 \mathrm{SMB}_t + \beta_5 \mathrm{HML}_t$$

where SMB and HML are the size and book-to-market factors of Fama and French, mcg_t and vcg_t are cross-sectional mean and variance of consumption growth. Our test assets consist of the twenty-five Fama-French size and book-to-market portfolios, the long term government bond, the corporate bond, and the T-bill. (See Section 3 for a description of the asset return data.) A standard GMM procedure is implemented for testing the moment conditions $E[M_t(\beta)R_{it}] = 1$, where R_{it} is the return on the i-th test asset. In the initial round, the HJ-distance measure is minimized. Then the iterated GMM estimates are obtained, i.e., at each round, the weighting matrix is updated using the estimates from the previous round, and the procedure is repeated until estimates converge. Reported in the table are the iterated estimates and the J test statistics that are based on the iterated estimates. In the parentheses under the estimates are standard errors and in the parentheses under the J statistics are the p-values. The HJ distances are also included. The factors are constructed with the age cohorts and age-education cohorts, respectively, derived from the data set of total consumption for asset holders. The consumption factors are the two pairs based on consumption growth (mcg_j and vcg_j, $j = 2, 3$). These factors are defined in Table III.

Table VII (Continued)

const.	mcg_2	vcg_2	mcg_3	vcg_3	R_M	SMB	HML	J-Test	HJ-d
1.03						2.50	-3.73	38.27	2.43
(0.05)						(3.16)	(2.50)	(0.043)	
20.28					-17.92	49.98	-20.99	31.45	2.35
(2.54)					(2.41)	(5.53)	(4.72)	(0.141)	
				Age Cohorts					
50.40	-45.96	67.85				-34.30	-10.52	20.15	2.15
(6.50)	(5.47)	(20.54)				(6.42)	(5.96)	(0.633)	
23.15			-26.59	122.60		33.59	54.36	30.14	2.18
(4.84)			(5.28)	(25.93)		(8.28)	(6.87)	(0.145)	
68.96	-29.97	28.77			-33.15	8.12	-34.32	27.65	2.02
(10.70)	(6.84)	(16.06)			(6.27)	(8.42)	(6.92)	(0.188)	
80.73			-36.45	78.42	-43.47	12.36	-33.90	29.13	2.04
(10.55)			(7.37)	(30.89)	(6.67)	(6.10)	(5.59)	(0.141)	
				Age-and-Education Cohorts					
42.21	-38.13	23.26				-27.08	-4.10	27.69	2.26
(7.33)	(6.21)	(5.36)				(6.60)	(4.72)	(0.228)	
29.99			-29.83	19.87		-15.72	3.27	33.91	2.24
(5.70)			(5.29)	(4.61)		(5.11)	(3.28)	(0.067)	
75.72	-37.70	14.02			-31.26	-5.69	-32.65	24.43	2.05
(10.61)	(6.74)	(5.18)			(6.93)	(7.13)	(8.11)	(0.325)	
72.31			-41.88	24.32	-28.53	-15.38	-20.54	28.56	2.07
(10.80)			(7.11)	(6.97)	(7.28)	(6.60)	(7.10)	(0.158)	

Figure1: Cross Sectional Distribution of Individual Consumption Growth