The London School of Economics and Political Science

Consumption, Housing and Financial Wealth, Asset Returns, and Monetary Policy

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Declaration

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Abstract

This work analyzes the linkages between consumption, housing and financial wealth, asset returns, and monetary policy.

In Chapter I, I show, from the consumer's budget constraint, that the residuals of the trend relationship among consumption, financial wealth, housing wealth and labor income, *cday*, should better predict stock returns than a variable like *cay* from Lettau and Ludvigson (2001), and that this is due to: (*i*) the ability to track changes in the wealth composition; and (*ii*) the faster rate of convergence of the coefficients to the "long-run equilibrium" parameters.

In Chapter II, I analyze the empirical relationship between wealth shocks and portfolio composition, and find evidence consistent with counter-cyclical risk aversion. I also show that: (*i*) there is no evidence of inertia; and (*ii*) time-variation in expectations about future returns partially explains changes in the risky asset share.

In Chapter III, I show that monetary policy contractions have a large and negative impact on housing prices, although the reaction is extremely slow. On the contrary, the effect on stock markets is small and very quick.

In Chapter IV, I analyze the importance of the risks for the long-run, and show that they explain a large fraction of the cross-sectional variation of average returns. I also find that the preference for a smooth path of consumption, a low intertemporal elasticity of substitution, and a high risk aversion, imply that agents demand large equity risk premia when they fear a reduction in economic prospects.

In Chapter V, I investigate the role of three major sources of risk: future changes in the housing consumption share, *cr*, future labour income growth, *lr*, and future consumption growth, *lrc*. I show that the predictability of many empirical proxies can be achieved without relying on a specific functional form for consumer's preferences.

Keywords: financial wealth, housing wealth, consumption, expected returns, risk aversion, housing prices, monetary policy, structural VARs, Epstein-Zin preferences, intertemporal budget constraint, consumption capital asset pricing, expectations, shocks, housing share.

JEL classification: E21, E44, D12, G11, E37, E52, E24, G12.

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To my parents,
To my grandparents,
To my sister,
To Raffaella

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General Introduction

This dissertation analyzes the relationship between consumption, housing and financial wealth, labor income, asset returns and monetary policy.

The linkages between wealth and other macroeconomic variables and their importance for long-term predictability of asset returns have been documented in the empirical literature of asset pricing. However, despite the emphasis on developing models of consumer choice and building empirical proxies for expectations about future returns, the importance of wealth composition has received little attention and has generally been considered in the context of the (wealth) effects that different assets have on consumption.

In Chapter I, I argue that the composition of portfolios might also be important in the context of forecasting asset returns. I use the representative consumer's intertemporal budget constraint to derive an equilibrium relationship between the transitory deviations from the common trend in consumption, housing and financial wealth, and labor income, *cday*, and expected future asset returns. Then, I show that *cday* helps to better predict asset returns than *cay* from Lettau and Ludvigson (2001) and that this is due to: (*i*) its ability to track changes in the wealth composition; and (*ii*) the faster rate of convergence of the coefficients to the "long-run equilibrium" parameters.

The empirical proxy *cday* summarizes agent's expectations of future returns on assets and consumption growth: when average asset returns (that is, housing asset returns and/or financial asset returns) are expected to be higher in the future, forward-looking investors will allow consumption to rise above its common trend with housing and financial wealth, and labor income.

As in Lettau and Ludvigson (2001), investors try to insulate future consumption from fluctuations in expected returns. However, financial wealth effects on consumption are significantly different from housing wealth effects. Moreover, housing and financial wealth have different empirical properties: under a Bayesian framework, it is shown that housing wealth shocks have very persistent effects, whilst financial wealth shocks are mainly transitory.

The empirical findings suggest that *cday* is statistically significant in the estimation of the financial wealth growth equation, but the same proxy does not help predicting housing wealth growth. Additionally, *cday* predicts better future returns than *cay*. Why? Portfolios with different compositions of assets are subject to different taxation, transaction costs or degrees of liquidity. Wealth composition is, therefore, an important source of risk that *cday* is able to capture. Moreover, the superior forecasting power of *cday* seems to be due to the fact that its coefficients converge to the "long-run equilibrium" parameters at a faster rate.

In Chapter II, I test empirically the assumption of constant relative risk aversion (CRRA) that is commonly used in macroeconomics and asset pricing. I also look at the implications that the models of optimal consumer choice have not only for time-variation in risk premium but also for time-variation in portfolio shares. Specifically, I use macroeconomic data to look at the relationship between unexpected wealth variation and changes in the risky asset allocation.

I show that the risky asset share exhibits a cyclical behavior and it is significantly (and positively) affected by wealth shocks. There is, therefore, evidence suggesting that risk aversion is countercyclical and supporting the existence of preferences that depart from the assumption of constant relative risk aversion, such as wealth-dependent preferences, habit-formation utility functions or loss or disappointment aversion risk preferences. This relationship does not reflect possible price or asset return effects and it is not the consequence of time-variation in expectations about future returns or in the volatility of asset returns. In fact, the estimations suggest that wealth shocks remain significant and are responsible for the bulk of the variation observed in the portfolio composition.

Finally, considering a variety of wealth definitions, and using a Bayesian framework, it is shown that, although significant, wealth effects on asset allocation are mainly temporary: the explanatory power of wealth shocks quickly falls over horizons of three quarters. Additionally and contrary to the findings of Brunnermeier and Nagel (2006), there is weak evidence of inertia or slow adjustment in asset allocation.

In Chapter III, I analyze the effect of monetary policy on housing prices, by focusing the attention on different identification schemes. I analyze evidence both from the U.S. and the U.K., at both monthly and quarterly frequencies, and experiment with a large number of procedures to identify the monetary shocks. I ask how housing markets in general, and housing prices in particular, are affected by monetary policy shocks, and - to the extent that there is a link -, how large are these effects and for how long do they persist.

The empirical findings suggest that monetary policy contractions (positive interest rate shocks) have a large and significantly negative impact on real housing prices. Nevertheless, the reaction is extremely slow: monetary policy shocks cause almost negligible movements in housing prices during the first few quarters following the shock, but their effect becomes large later and reaches its maximum impact after about 10 quarters. As a result, governments and central banks should pay a special attention to the behavior of housing markets.

Using different sub-samples, it is also shown that, although important, the magnitude of the effects of monetary policy on housing prices has fallen over time, particularly, since the eighties, a feature that may be associated with the restructuring of the housing finance system and the broadening of financial instruments. This is in accordance with the "Great Moderation", that is, the substantial decline in macroeconomic volatility observed over the past twenty years.

Additionally, I look at the effects of monetary policy shocks on stock markets. The goal is to analyze whether the monetary policy has an impact on the stock market, and, if so, whether the magnitude of the reaction is different from the one observed for the housing market. I show that monetary policy shocks do not seem to have a significant effect on the stock market: the reaction is small and very quick.

In Chapter IV, I retake the natural economic explanation for differences in expected returns across assets that is based on differences in risk. I combine Epstein-Zin preferences, the intertemporal budget constraint and the homogeneity property of the Bellman equation to derive a relationship that highlights the role of risks for the long-run in explaining the cross-sectional variation of average returns.

I find that: (*i*) risks for the long-run are important determinants of both real returns and asset returns over a Treasury bill rate; and (*ii*) when risks for the long-run are used as conditioning information for the Consumption Capital Asset Pricing Model (C-CAPM), the resulting linear factor model explains a large fraction of the variation in observed average returns across the 25 Fama and French portfolios, prices correctly the small growth portfolio, and outperforms the standard C-CAPM with power utility.

The main novelty is that the intertemporal elasticity of substitution and the risk aversion are estimated simultaneously by using the consumption-aggregate wealth ratio, cay, or the market return, R^m, to recover the return on aggregate wealth. In this sense, the model provides a more informative summary of the representative agent's characteristics than the majority of the optimal choice models developed in the literature of asset pricing.

I show that the intertemporal elasticity of substitution is relatively small and that the coefficient of risk aversion is relatively high and that the model captures: (*i*) the preference of investors for a smooth path for consumption as implied by the intertemporal budget constraint; and (*ii*) the separation between a low intertemporal elasticity of substitution and a high risk aversion, implying that agents demand large equity risk premia because they fear that a rise in economic uncertainty or reduction in economic prospects will lower asset prices.

In Chapter V, I question about the major sources of risk that explain future returns, and whether one is able to generate predictability without relying on a specific description of preferences. I use the consumer's budget constraint to derive a relationship between stock market returns, the residuals of the trend relationship among consumption, aggregate wealth, and labour income, cay, and three major sources of risk: future changes in the housing consumption share, cr, future labour income growth, lr, and future consumption growth, lrc.

Using a VAR, I model the joint dynamics of changes in the non-housing consumption share, consumption growth, wealth growth, income growth, asset returns, consumption-wealth ratio and dividend-price ratio. Then, I obtain measures of expected and unexpected long-run changes in the major determinants of asset returns.

I find that: (*i*) *cay*, *cday*, expected *lr*, *cr*, *lrc* and ex-ante expected long-run real returns, *lrret*, strongly forecast future asset returns; (*ii*) unexpected *lrc* and unexpected *lrret* contain some predictive power for asset returns; (*iii*) unexpected *lr* and unexpected *cr* do not predict future asset returns.

The results also show that expectations of high future labor income, expectations of high future consumption growth, and expectations of high non-housing consumption share are associated with lower stock market returns, and low labor income growth expectations, low consumption growth expectations and low non-housing consumption share expectations are associated with higher than average real returns. As a result , the success of empirical proxies such as *lr*, *cr*, and *lrc* seems to be due to their ability to track risk premia. On the other hand, shocks to long-run expectations seem to play a negligible role as its forecasting power for current returns is, in general, very low.

Chapter I

Consumption, (Dis)Aggregate Wealth, and Asset Returns

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Abstract

In this work, I show, from the consumer's budget constraint, that the residuals of the trend relationship among consumption, financial wealth, housing wealth and labor income (summarized by the variable *cday*) should better predict U.K. quarterly stock market returns than a variable like *cay* from Lettau and Ludvigson (2001), which considers aggregate wealth instead.

I show that the superior forecasting power of *cday* is due to: (*i*) its ability to track the changes in the composition of asset wealth; and (*ii*) the coefficients converge faster to the "long-run equilibrium" parameters.

Unlike Lettau and Ludvigson (2001, 2004), the results suggest that, while financial wealth shocks are mainly transitory, fluctuations in housing wealth are very persistent. Governments and central banks should, therefore, pay special attention to the behavior of housing markets when defining macroeconomic policies.

Keywords: financial wealth, housing wealth, consumption, expected returns.

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1 Introduction

A growing body of empirical literature has documented the long-term predictability of asset returns and the linkages between wealth and other macroeconomic variables.[1] An important reason for the interest in this relation is that expected excess returns on assets appear to vary with the business cycle. Different explanations have been offered for this empirical result, namely: inefficiencies of financial markets (Fama (1970, 1991, 1998), Fama and French (1996), Farmer and Lo (1999)); the rational response of agents to time-varying investment opportunities driven by variation in risk aversion (Sundaresan (1989), Constantinides (1990), Campbell and Cochrane (1999)) or in the joint distribution of consumption and asset returns (Duffee (2005), Santos and Veronesi (2006)).

More recently, the literature on asset pricing has moved towards the development of many economically motivated variables and focused on their predictability for asset returns. In this spirit, Lettau and Ludvigson (2001) show that the transitory deviation from the common trend in consumption, aggregate wealth and labor income, cay, is a strong predictor of asset returns. Fernandez-Corugedo *et al.*(2003) use the same approach but incorporate the relative price of durable goods, whilst Julliard (2004) focus on the importance of the labor income risk. Yogo (2006) and Piazzesi *et al.*(2007) emphasize the role of nonseparability of preferences in explaining the countercyclical variation in equity premium. Lustig and Van Nieuwerburgh (2005) show that the housing collateral ratio shifts the conditional distribution of asset prices and consumption growth.

Despite the emphasis on building models of consumer choice and generating empirical proxies for expectations about future returns, the importance of wealth composition has been given little attention and has generally been considered in the context of the (wealth) effects that different assets have on consumption. In fact, whilst a simple formulation of the life-cycle model suggests that consumers spread the increases in anticipated wealth over time and that the wealth effects on consumption should be the same in magnitude whichever is the component of wealth considered, the responsiveness of consumers to financial and housing wealth shocks can be different for several reasons:[2] (*i*) differences in liquidity (Pissarides, 1978; Muellbauer and Lattimore, 1999); (*ii*) utility derived from the property right of an

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[1] See, for example, Fama and French (1988), Campbell and Shiller (1988), Poterba and Summers (1995), Richards (1995), Lettau and Ludvigson (2001, 2004).

[2] For a more detailed discussion, see Case *et al.*(2005). Note, however, that the empirical evidence in this area is still inconclusive. Elliott (1980), Levin (1998) and Mehra (2001) found that the wealth effect is independent of the category of wealth. Thaler (1990), Sheiner (1995), and Hoynes and McFadden (1997) investigated the correlation between individual saving rates and changes in house prices and found a weak relation. In contrast, Skinner (1989), Case (1992), Kent and Lowe (1998), Case *et al.*(2005), and Dvornak and Kohler (2003) found evidence of a considerable housing wealth effect on consumption.

asset, such as housing services or bequest motives (Poterba, 2000); (*iii*) different distributions of assets across income groups (Banks *et al.*, 2002; Bajari *et al.*, 2005); (*iv*) expected permanency of changes of different categories of assets; (*v*) mismeasurement of wealth;[3] and (*vi*) 'psychological factors' (Shefrin and Thaler, 1988).

The current paper argues that the wealth composition might also be important because it has implications for the predictability of asset returns. I use the representative consumer's intertemporal budget constraint to derive an equilibrium relation between the transitory deviation from the common trend in consumption, housing wealth, financial wealth and labor income, *cday*, and expected future asset returns. Then, I show that *cday* helps to predict better asset returns than *cay* from Lettau and Ludvigson (2001) and that this is due to: (*i*) its ability to track changes in the wealth composition; and (*ii*) the coefficients converge faster to the "long-run equilibrium" parameters.

These results follow from the fact that *cday* summarizes agent's expectations of future returns on assets and consumption growth: when average asset returns (this is, housing asset returns and/or financial asset returns) are expected to be higher in the future, forward-looking investors will allow consumption to rise above its common trend with housing wealth, financial wealth, and labor income. As in Lettau and Ludvigson (2001), in this way investors may insulate future consumption from fluctuations in expected returns. However, I also show that financial wealth effects are significantly different from housing wealth effects: the point estimates for the parameters associated with financial wealth and housing wealth in the long-run trend relationship among consumption, financial wealth, housing wealth, and labor income are, respectively, 0.17 and 0.04, reflecting the importance of wealth disaggregation. The implied shares of financial wealth, housing wealth and labor income in aggregate wealth are, respectively, 0.23, 0.06 and 0.71. These are very plausible figures, since they correspond, approximately, to shares of capital and labor of, respectively, 0.29 and 0.71, consistent with the values that one would expect in a production function with Cobb-Douglas technology.

Consistent with Lettau and Ludvigson (2004), I also show that deviations from the shared trend in consumption, financial wealth, housing wealth, and labor income are mainly described as transitory movements in financial wealth and that financial wealth shocks produce only temporary effects on consumption (and, therefore, are not important for economic policy considerations). However, the other component of aggregate wealth - that is, housing wealth - has different empirical properties. First, under a Bayesian framework, it is shown that housing wealth shocks are important because they have very persistent effects on consumption. Second, changes in housing wealth contain an important

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[3] This may be especially so for houses which are less homogenous and less frequently traded than shares. Also many consumers may not be aware of the exact value of their indirect share holdings. For example, Sousa (2003) shows that directly held stock market wealth effects are significantly different from indirectly held stock market wealth effects.

persistent component but are not responsible for the short-term adjustment, that is, when consumption deviates from its habitual ratio with financial wealth, housing wealth and labor income, it is financial wealth (and not housing wealth) that is forecast to adjust until the equilibrating relationship is restored.

I then assess the importance of wealth composition for predicting stock market fluctuations. The empirical proxy *cay* developed by Lettau and Ludvigson (2001) considers wealth at the aggregate level, that is, contrary to *cday*, changes in the composition of wealth are neglected by *cay*. These changes are, however, important because they convey important information about future asset returns. First, the empirical findings show that *cday* is statistically significant in the estimation of the financial wealth growth equation, but the same proxy does not help predicting housing wealth growth. Equivalently, only deviations in financial wealth from the shared trend with consumption, housing wealth, and labor income reveal a significant transitory variation. Second, I show that *cday* predicts better future returns than *cay*: in both the estimation of excess returns and real returns, *cday* explains 4% of the variation in next quarter, while *cay* explains only 1%. The predictive impact of *cday* on future returns is also larger than that of *cay*: the point estimate of the coefficient on *cday* is about 1.595 for real returns and only 0.893 in the case of *cay*. Therefore, a one-standard-deviation increase in *cday* leads to, approximately, a 132.92 basis points rise in the expected real return on MSCI-UK Total Return Index, that is, a 5.42% increase at an annual rate. By its turn, a one-standard-deviation increase in *cay* leads to approximately a 59.5 basis points rise in the expected real return on MSCI-UK Total Return Index, that is, a 2.40% increase at an annual rate.

The evidence presented highlights that *cday* directly tracks the risk associated with the composition of wealth and constitutes a better proxy for agents' expectations about future returns. Portfolios with different compositions of assets are subject to different taxation, transaction costs or degrees of liquidity: for example, agents who hold portfolios where the exposure to housing wealth is larger bear an additional risk associated with the (il)liquidity of these assets and the high transaction costs involved in trading them up or down. Wealth composition is, therefore, an important source of risk that *cday* - but not *cay* - is able to explain.

In addition, the superior forecasting power of *cday* seems to be due to the fact that its coefficients converge faster to the "long-run equilibrium" parameters than *cay*. A very simple exercise where the coefficients of *cday* and *cay* are recursively estimated by adding one observation at each time suggests this is so and, therefore, provides an additional explanation for why *cday* is able to outperform *cay*.

The empirical findings also show that *cday* provides information about future asset returns that is not captured by lagged values of returns. Moreover, the forecasting power of *cday* does not reflect predictability of consumption growth: *cday* tracks changes in the composition of wealth and summarizes agents' expectations of future returns instead of signalling changes in future consumption growth. The superiority of *cday* over *cay* is also patent over business cycle frequencies: *cday* accounts for a substantial fraction of the variation in future returns at 3 and 4 quarters (around 0.20); for the same horizons, *cay* explains between 0.12 and 0.14 of the variation. The results are robust regarding potential spurious regression problems and "look-ahead" bias.

The rest of the paper is organized as follows. In Section 2, I present the theoretical framework. In Sections 3 and 4, I present the data, estimate the model and discuss the results. Finally, in Section 5, I conclude and refer the main limitations of the model and the lines of direction for future research.

2 The Consumption-(Dis)Aggregate Wealth Ratio

Consider a representative agent economy in which wealth is tradable. Defining W_t as time t aggregate wealth (human capital plus asset wealth), C_t as time t consumption and $R_{w,t+1}$ as the return on aggregate wealth between period t and $t+1$, the consumer's budget constraint can be written as:[4]

$$W_{t+1} = (1 + R_{w,t+1})(W_t - C_t) \tag{1}$$

Campbell and Mankiw (1989) show that equation (1) can be approximated by a first-order Taylor expansion, giving an expression for the log difference in aggregate wealth

$$\Delta w_{t+1} \approx k + r_{w,t+1} + (1 - 1/\rho_w)(c_t - w_t) \tag{2}$$

where ρ_w is the steady-state ratio of new investment to total wealth, $(W - C)/W$, and k is a constant that plays no role in the analysis.[5] Solving this difference equation forward and imposing that $\lim_{i \to \infty} \rho_w^i \left(c_{t+i} - w_{t+i}\right) = 0$, the log consumption-wealth ratio can be written as

$$c_t - w_t = \sum_{i=1}^{\infty} \rho_w^i (r_{w,t+i} - \Delta c_{t+i}). \tag{3}$$

Taking conditional expectations of both sides of (3), one can obtain

$$c_t - w_t = E_t \sum_{i=1}^{\infty} \rho_w^i (r_{w,t+i} - \Delta c_{t+i}), \tag{4}$$

where E_t is the expectation operator conditional on information available at time t.

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[4] Labor income does not appear explicitly in this equation because of the assumption that the market value of tradable human capital is included in aggregate wealth.

[5] I define $r := \log(1 + R)$, and use lowercase letters to denote log variables throughout. Unimportant linearization constants in the equations are omitted from now on.

To overcome the fact that human capital is not observable, Lettau and Ludvigson (2001) assume that the nonstationary component to human capital, denoted H_t, can be well described by aggregate labor income, Y_t, implying that $h_t = k + y_t + z_t$, where k is a constant and z_t is a mean zero stationary random variable.

(Dis)Aggregate wealth can be decomposed as

$$W_t = F_t + U_t + H_t, \tag{5}$$

where F_t is financial wealth and U_t is housing wealth. Moreover, this expression can be approximated as

$$w_t \approx \alpha_f f_t + \alpha_u u_t + (1 - \alpha_f - \alpha_u)h_t, \tag{6}$$

where α_f and α_u equal, respectively, the share of financial asset holdings in total wealth, F/W, and the share of housing asset holdings in total wealth, U/W.

The return to (dis)aggregate wealth can be decomposed into the returns of its components

$$1 + R_{w,t} \approx \alpha_f(1 + R_{f,t}) + \alpha_u(1 + R_{u,t}) + (1 - \alpha_f - \alpha_u)(1 + R_{h,t}). \tag{7}$$

Campbell (1996) shows that (7) can be transformed into an approximation equation for log returns taking the form

$$r_{w,t} \approx \alpha_f r_{f,t} + \alpha_u r_{u,t} + (1 - \alpha_f - \alpha_u)r_{h,t}. \tag{8}$$

Substituting (6) and (8) into the ex-ante budget constraint (4) gives

$$c_t - \alpha_f f_t - \alpha_u u_t - (1 - \alpha_f - \alpha_u)h_t = E_t \sum_{i=1}^{\infty} \rho_w^i \left\{ [\alpha_f r_{f,t+i} + \alpha_u r_{u,t+i} + (1 - \alpha_f - \alpha_u)r_{h,t+i}] - \Delta c_{t+i} \right\}. \tag{9}$$

To remove the unobservable variable h_t from this equation, $h_t = k + y_t + z_t$, is replaced into (9), and it can be rewritten as

$$c_t - \alpha_f f_t - \alpha_u u_t - (1 - \alpha_f - \alpha_u)y_t = E_t \sum_{i=1}^{\infty} \rho_w^i \left\{ [\alpha_f r_{f,t+i} + \alpha_u r_{u,t+i} + (1 - \alpha_f - \alpha_u)r_{h,t+i}] - \Delta c_{t+i} \right\} + \eta_t, \tag{10}$$

where $\eta_t = (1 - \alpha_f - \alpha_u)z_t$.

I denote the trend deviation term $c_t - \alpha_f f_t - \alpha_u u_t - (1 - \alpha_f - \alpha_u)y_t$ as $cday_t$, and Equation (10) shows that $cday_t$ will be a good proxy for market expectations of future financial, $r_{f,t+i}$, and housing asset returns, $r_{u,t+i}$, as long as expected future returns on human capital, $r_{h,t+i}$, and consumption growth Δc_{t+i}, are not too variable. Since this equation takes into account the composition of asset wealth, $cday_t$ should provide a better proxy for market expectations of future returns $(r_{f,t+i}, r_{u,t+i})$ than cay_t from Lettau and Ludvigson (2001).[6]

After this presentation, I briefly describe the data, estimate the trend relationship among consumption, financial wealth, housing wealth and labor income, and present the main results, which is done in the next Section.

3 Estimating the Trend Relationship Among Consumption, (Dis)Aggregate Wealth and Income

The methodology adopted for the estimation of the model consists of two stages. First, I estimate the long-run relation among consumption, financial wealth, housing wealth and income. Then, I proceed with the analysis of short-run dynamics using a Vector-Error Correction Model (VECM).

3.1 Data

In the estimations, I use quarterly, seasonally adjusted data for the United Kingdom and all variables are measured at 2001 prices, and expressed in the logarithmic form of per capita terms. The definition of consumption excludes durable and semi-durable goods consumption. Data on income includes only labor income. Original data on wealth correspond to the end-period values. Therefore, I lag once the data, so that the observation of wealth in t corresponds to the value at the beginning of the period $t+1$. The main data source is the Office for National Statistics (ONS), although for housing wealth, I also use data from Halifax plc, the Nationwide Building Society and the Office of the Deputy Prime Minister. In Appendix A, I present a detailed discussion of data.

3.2 The Long-Run Relation

I first use the Phillips-Perron (PP) tests[7] to determine the existence of unit roots in the series and conclude that all the series are first-order integrated, $I(1)$. Next, I analyze the existence of cointegration among the series using the methodology of Engle and Granger (1987), and find evidence that supports this hypothesis. The results of the PP tests and the cointegration tests are presented in Appendix

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[6] Lettau and Ludvigson (2001) do not consider the issue of wealth disaggregation. Their specification is given by $cay_t = E_t \sum_{i=1}^{\infty} \rho_w^i \left\{ \left[\alpha r_{a,t+i} + (1-\alpha) r_{h,t+i} \right] - \Delta c_{t+i} \right\} + (1-\alpha) z_t$, where cay_t denotes the trend deviation term $c_t - \alpha a_t - (1-\alpha) y_t$, c_t is consumption, a_t is total asset holdings, y_t is labor income, and α is the share of total asset holdings in total wealth.

[7] The ADF (Augmented Dickey-Fuller tests) generate the same results, although they have lower power.

B.[8] Finally, I estimate the trend relationship among consumption, wealth and labor income following Davidson and Hendry (1981), Blinder and Deaton (1985), Ludvigson and Steindel (1999), and Davis and Palumbo (2001) among others. However, since the impact of different assets' categories on consumption can be different (Zeldes, 1989; and Poterba and Samwick, 1995), I disaggregate wealth into its main components: financial wealth and housing wealth. Following Saikkonen (1991) and Stock and Watson (1993), I use a dynamic least squares (DOLS) technique, specifying the following equation

$$c_t = \mu + \beta_f f_t + \beta_u u_t + \beta_y y_t + \sum_{i=-k}^{k} b_{f,i}\Delta f_{t-i} + \sum_{i=-k}^{k} b_{u,i}\Delta u_{t-i} + \sum_{i=-k}^{k} b_{y,i}\Delta y_{t-i} + \varepsilon_t, \tag{11}$$

where the parameters β_f, β_u,β_y represent, respectively, the long-run elasticities of consumption with respect to financial wealth, housing wealth, and labor income, Δ denotes the first difference operator, μ is a constant, and ε_t is the error term.[9]

Implementing the regression in (11) using data for the United Kingdom in the period 1977:4 - 2001:1,[10] generates the following estimates (ignoring coefficient estimates on the first differences) for the shared trend among consumption, financial wealth, housing wealth and income:

$$c_t = \underset{(3.31)}{1.37} + \underset{(6.43)}{0.17} f_t + \underset{(2.88)}{0.04} u_t + \underset{(5.72)}{0.52} y_t. \tag{12}$$

where the Newey-West (1987) t-corrected statistics appear below the coefficient estimates.[11]

The estimations show that the long-run elasticity of consumption with respect to financial wealth (0.17) is more than four times greater than the long-run elasticity with respect to housing wealth (0.04), reflecting the importance of this component of wealth and, simultaneously, the significance of the disaggregation of wealth. As expected, the coefficients of equation (12) do not sum to unity, since I

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[8] These methodologies have limitations and Harris (1995) and Maddala and Kim (1998) present a detailed description of the panoply of alternative tests for cointegration.

[9] The parameters β_f, β_u,β_y should in principle equal $R_f F/(Y+R_f F+R_u U)$, $R_u U/(Y+R_f F+R_u U)$ and $Y/(Y+R_f F+R_u U)$, respectively, but, in practice, may sum to a number less than one, because only a fraction of total consumption expenditure is observable (Lettau and Ludvigson, 2001). Therefore, I decided to write β_f, β_u and β_y instead of α_f, α_u and α_y to distinguish long-run elasticities of *the definition* of consumption from long-run elasticities of *total* consumption.

[10] As an additional issue of the estimation, I analyze the stability of the cointegrating vector using the methodology of Seo (1998) and splitting the sample in subsamples. The results suggest that the cointegrating vector is relatively stable over time and if there is a structural break, this is close to the beginning point of the sample, at the time of the oil shocks. This is in contrast with Lettau and Ludvigson (2004), who argue that for the U.S. the sample instability comes from the large appreciations of the stock markets during the nineties.

[11] I experimented with various lead/lag lengths in estimating the DOLS specification. For the results reported in (12), I use the value of $k = 1$. However, neither the cointegrating parameter estimates nor the forecasting results I present below are sensitive to the particular value of k. In the case of the consumption-wealth ratio, cay_t, it is computed as $cay_t = c_t - 0.12a_t - 0.83y_t$, where c_t is consumption, a_t is total asset holdings, and y_t is labor income. For the U.S., Lettau and Ludvigson (2001) compute cay_t as $c_t - 0.31a_t - 0.59y_t$.

exclude from the definition of consumption the durable and semi-durable goods' consumption. However, the average share of this measure of consumption in total consumption in the sample is 76%, which is approximately equal to the sum of the coefficients of equation (12), namely, 73%. Finally, the implied shares, calculated by scaling the coefficients on financial wealth, housing wealth and income by the inverse sum of the coefficients are, respectively, 0.23, 0.06 and 0.71, which are very plausible figures, since they correspond, approximately, to shares of capital and labor of 0.29 and 0.71, respectively.

3.3 The Short-Term Dynamics

I proceed with the analysis of how consumption reacts to shocks on wealth and how this deviation from the long-run relation is corrected. I want to determine whether deviations from the shared trend in consumption, financial wealth, housing wealth and income are better described as transitory movements in financial wealth and/or housing wealth or as transitory movements in consumption and labor income.

The estimated model is specified as follows:

$$\Delta \mathbf{X}_t = \theta + \gamma\beta' \mathbf{X}_{t-1} + \Gamma(L)\Delta \mathbf{X}_{t-1} + e_t, \tag{13}$$

where $\mathbf{X}_t = (c_t, f_t, u_t, y_t)$ is the vector of consumption, financial wealth, housing wealth, and labor income, $\gamma_t = (\gamma_c, \gamma_f, \gamma_u, \gamma_y)'$ is a (4×1) vector, $\beta_t = (1, -\beta_f, -\beta_u, -\beta_y)'$ is the vector of estimated cointegration coefficients shown in equation (12), Δ denotes the first difference operator, $\Gamma(L)$ is a finite-order distributed lag operator, θ is a vector of constants, and e_t is the vector of error terms,. Thus, γ_t is the short-run adjustment vector telling us how the variables react to the last period's cointegrating error while returning to long-term equilibrium after a deviation occurs; β_t measures the long-run elasticities of one variable respective to another; the term $\beta_t' \mathbf{X}_{t-1}$ measures the cointegrating residual, $cday_{t-1}$. Table 1 presents the results of the estimation using a one-lag cointegrated VAR.[12]

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[12] The lag length was chosen in accordance with findings from Akaike and Schwarz tests.

Table 1: Estimates from a cointegrated VAR.

The table reports the estimated coefficients from cointegrated vector-autoregressions (VAR).

Symbols *, **, *** represent, respectively, significance level of 1%, 5% and 10%.

Newey-West (1987) corrected t-statistics appear in parenthesis. The sample period is 1977:4 to 2001:1.

	Equation			
Dependent variable	Δc_t	Δf_t	Δu_t	Δy_t
Δc_{t-1}	-0.211***	0.359	0.408**	-0.379**
(t-stat)	(-1.870)	(0.487)	(2.082)	(-2.430)
Δf_{t-1}	-0.003	-0.052	-0.010	0.020
(t-stat)	(-0.195)	(-0.467)	(-0.332)	(0.828)
Δu_{t-1}	0.041	0.020	0.777*	0.177*
(t-stat)	(1.186)	(0.087)	(12.790)	(3.665)
Δy_{t-1}	0.135***	0.672	0.237***	-0.014
(t-stat)	(1.876)	(1.422)	(1.890)	(-0.143)
θ	0.123	-1.991*	0.007	-0.413*
(t-stat)	(1.282)	(-3.170)	(0.041)	(-3.115)
$\widehat{cday}_{t-1}$	-0.086	1.467*	-0.005	0.307*
(t-stat)	(-1.222)	(3.192)	(-0.045)	(3.162)
$\bar{R}^2$	0.065	0.103	0.709	0.139

The table reveals some interesting properties of the data on consumption, financial wealth, housing wealth, and labor income.[13] First, estimation of the consumption growth equation shows that $\widehat{cday}_{t-1}$ does not predict consumption growth. The sign of the coefficient is negative and its value (approximately, -0.09) is small, suggesting that the correction is very slow. On the other hand, consumption growth is somewhat predictable by the lag of consumption growth as noted by Flavin (1981), Campbell and Mankiw (1989), which can be interpreted as a sign of some delay in the adjustment of consumption. The lagged values of labor income growth are also statistically significant, which may follow from habit persistence, near-rational rules of thumb, or liquidity constraints.[14] Second, estimation of the financial

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[13] As an additional issue of the estimation, I also analyze the stability of the short-term adjustment vector and the presence of an asymmetric behavior in the response of consumption to different wealth shocks. The results suggest that the short-term adjustment vector remains relatively stable over time and that there is no evidence of an asymmetric behaviour.

[14] This evidence differs from the results of Lettau and Ludvigson (2001), who find that only lagged consumption growth is significant.

wealth growth equation shows that $\widehat{cday}_{t-1}$ is statistically significant. Moreover, the estimated coefficient (1.467) suggests that $\widehat{cday}_{t-1}$strongly predicts financial wealth growth and implies that deviations in financial wealth from its shared trend with consumption, housing wealth, and labor income reveal a significant transitory variation in financial wealth. Third, estimation of housing wealth growth equation shows that $\widehat{cday}_{t-1}$ does not help to predict housing wealth growth: the estimated coefficient is very small (-0.005) and it is not statistically significant. However, it is shown that the lagged values of consumption growth, of housing wealth growth and of labor income growth are statistically significant. Moreover, the $\bar{R}^2$ statistic shows that this equation explains more than 70% of the housing wealth growth.

In sum, these results suggest that deviations from the shared trend in consumption, financial wealth, housing wealth, and labor income are mainly described as transitory movements in financial wealth. On the other hand, changes in house wealth contain an important persistent component and are not responsible for the short-term adjustment. Therefore, when consumption deviates from its habitual ratio with financial wealth, housing wealth and labor income, it is financial wealth that is forecast to adjust until the equilibrating relationship is restored; forward-looking households foresee changes in the return of their future financial wealth. This is in contrast with Lettau and Ludvigson (2001, 2004) who argue that total asset wealth changes are mainly transitory. In fact, the results suggest that only the financial component of asset wealth change is transitory.

4 Does the (Dis)Aggregation of Wealth Help to Predict Better Asset Returns?

Equation (10) shows that transitory deviations from the long-run relationship among consumption, (dis)aggregate wealth and income mainly reflect agents' expectations of future changes in asset returns. Moreover, since I disaggregate asset wealth into its main components (financial and housing wealth) and take, therefore, into account the different composition and specificities of the asset holdings, I argue that $\widehat{cday}_t$ should provide a better forecast than a variable like $\widehat{cay}_t$ in Lettau and Ludvigson (2001).

4.1 Forecasting Quarterly Asset Returns

I look at total asset returns - namely, the MSCI - UK Total Return Index - for which quarterly data are available and should provide a good proxy for the non-human component of asset wealth. I denote r_t the log real return of the index in consideration and $r_{f,t}$ the log real yield rate of 3-month

Treasury Bill (the "risk-free" rate). The log excess return is $r_t - r_{f,t}$.

Figures 1 and 2 plot, respectively, the standardized trend deviations, $\widehat{cday}_t$ and $\widehat{cay}_t$, and the excess return on the MSCI - UK Total Return Index over the period 1977:4 and 2001:1. They show a large diversity of episodes for which $\widehat{cday}_t$ is able to forecast better future asset returns than $\widehat{cday}_t$, namely: the housing market boom of 1977-1979; the stock market crash of 1987; the housing market boom of 1986-1989; and most of the stock market fluctuations of the nineties.

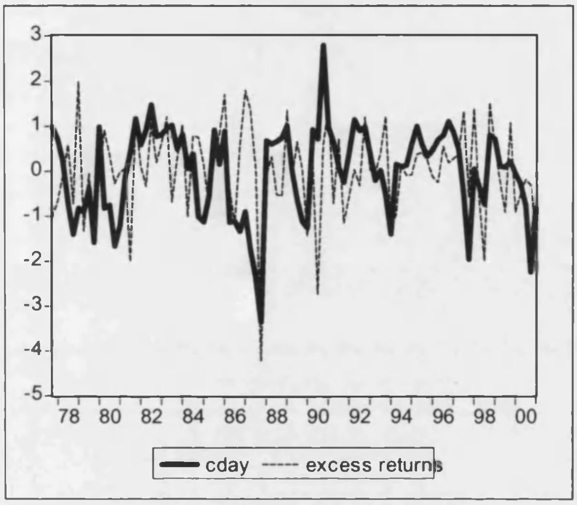

Figure 1: Times series of cday and excess returns.

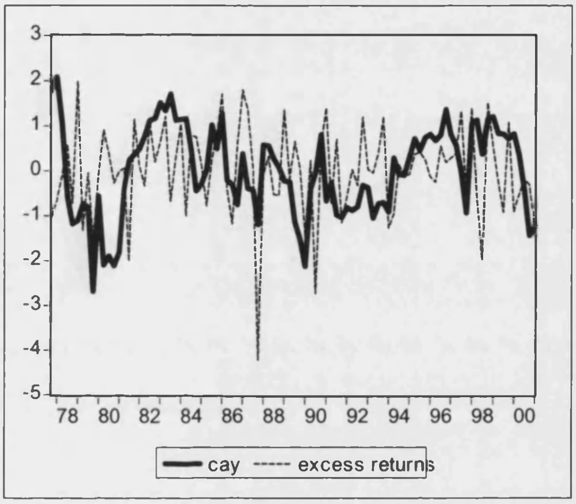

Figure 2: Times series of cay and excess returns.

Both series are normalized to standard deviations of unity. The sample period is 1977:4 to 2001:1.

Table 2 summarizes the forecasting power of $\widehat{cday}_t$ - the deviations of consumption from its trend relationship with financial wealth, housing wealth and income - and compares it with cay_t- the deviations of consumption from its trend relationship with aggregate wealth and income. It reports estimates from OLS regressions of log one-period ahead real returns (Panel A) and excess returns (Panel B) on the variables named at the head of a column.

Table 2: Forecasting quarterly excess returns using $\widehat{cday}$ and $\widehat{cay}$.

The table reports estimates from OLS regressions of returns on lagged variables named at the head of a column. Symbols *, **, *** represent, respectively, significance level of 1%, 5% and 10%.

Newey-West (1987) corrected t-statistics appear in parenthesis. The sample period is 1977:4 to 2001:1.

Constant (t-stat)	lag (t-stat)	$\widehat{cday}_t$ (t-stat)	$\widehat{cay}_t$ (t-stat)	$\bar{R}^2$
Panel A: Real Returns				
0.025*	-0.071			0.00
(3.193)	(-1.001)			
-2.153**		1.595**		0.04
(-2.487)		(2.520)		
0.225**			0.893***	0.01
(2.170)			(1.934)	
-2.634**	-0.162***	1.950*		0.06
(-2.468)	(-1.770)	(2.498)		
0.252**	-0.104		1.005***	0.01
(2.190)	(-1.444)		(1.964)	
Panel B: Excess Returns				
0.017**	-0.112			0.00
(2.148)	(-1.460)			
-2.039**		1.505**		0.04
(-2.305)		(2.328)		
0.198**			0.810***	0.01
(2.003)			(1.832)	
-2.638**	-0.202**	1.947**		0.07
(-2.456)	(-2.306)	(2.479)		
0.233**	-0.142***		0.960***	0.02
(2.120)	(-1.863)		(1.947)	

It can be seen that the regressions of returns on one lag of the dependent variable (Panel A, for real returns; and Panel B, for excess returns) are quite weak. This model has no forecasting power for both real returns and excess returns.

By its turn, the trend deviations explain an important fraction of the variation in next quarter's return. It is shown that $\widehat{cday}$ helps to better predict future returns than $\widehat{cay}$: in both the estimation of excess returns and real returns, $\widehat{cday}$ explains 4% of the variation in next quarter, while $\widehat{cay}$ explains only 1%. The predictive impact of $\widehat{cday}$ on future returns is larger than that of $\widehat{cay}$: the point estimate of the coefficient on $\widehat{cday}$ is about 1.595 for real returns (0.893 in the case of $\widehat{cay}$) and about 1.505 for excess returns (0.810 in the case of $\widehat{cay}$). Thus, a one-standard-deviation increase in $\widehat{cday}$ leads to, approximately, a 132.92 basis points rise in the expected real return on MSCI-UK Total Return Index and a 125.42 basis points increase in the expected excess returns, this is, respectively, a 5.42% and a 5.11% increase at an annual rate. On the other hand, $\widehat{cay}$ has a standard deviation of about 0.015, implying that a one-standard-deviation increase in $\widehat{cay}$ leads to, approximately, a 59.5 basis points rise in the expected real return on MSCI-UK Total Return Index and a 54 basis points increase in the expected excess returns, this is, respectively, a 2.40% and a 2.18% increase at an annual rate.

Finally, regressions of real returns and excess returns on their own lags and on one lag of trend deviation, produce roughly the same results as the previous regressions.

These results are in line with the framework presented in Section 2. When returns on assets are expected to decrease, investors will temporarily allow consumption to fall below its long-term relationship with financial wealth, housing wealth and labor income in order to smooth it and insulate it from lower returns Therefore, deviations in the long-term trend among c, f, u and y should be positively related to future asset returns.

4.2 Long-horizon Forecasts

I also examine the relative predictive power of $\widehat{cday}$ for returns at longer horizons and compare it with $\widehat{cay}$. In principle, $\widehat{cday}$ could be a proxy for expected future consumption growth, asset returns, or both.[15] Tables 3, 4, and 5 present the results of the regressions of consumption growth, and real returns and excess returns, over horizons spanning 1 to 4 quarters, on trend deviation $\widehat{cday}$ and compare them with $\widehat{cay}$. In the estimation of the regressions of consumption growth, the dependent variable is the H-period consumption growth rate $\Delta c_{t+1} + ... + \Delta c_{t+H}$; in the estimation of the regressions of excess returns, the dependent variable is the H-period log excess return on the MSCI - UK Total Return Index, $r_{t+1} - r_{f,t+1} + .. + r_{t+H} - r_{f,t+H}$; finally, in the estimation of the regressions of real returns, the dependent variable is the H-period log real return on the MSCI - UK Total Return Index, $r_{t+1} + ... + r_{t+H}$. The tables report the estimates from OLS regressions on $\widehat{cday}$ (Panel A) and $\widehat{cay}$ (Panel B).

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[15] For a discussion on the empirical proxies for the consumption-wealth ratio and their forecasting power see Hahn and Lee (2006) and Rudd and Whelan (2006).

Consistent with the estimation of the cointegrated VAR summarized in Table 1 and with Lettau and Ludvigson (2001), the results shown in Table 3 suggest that $\widehat{cday}$ has no predictive power for future consumption growth. The individual coefficients are not statistically significant, are small in magnitude and the $\bar{R}^2$ are all close to zero.

Table 3: Long-run horizon regressions for consumption growth.

The table reports results from long-horizon regressions of consumption growth on $\widehat{cday}_t$ and $\widehat{cay}_t$.

The dependent variable is H-period consumption growth $\Delta c_{t+1} + ... + \Delta c_{t+H}$.

Symbols *, ** and *** represent significance at a 1%, 5% and 10% level, respectively.

Newey-West (1987) corrected t-statistics appear in parenthesis. The sample period is 1977:4 to 2001:1.

	Forecast Horizon H			
Regressor	1	2	3	4
	Panel A: Consumption Growth, using $\widehat{cday}_t$			
$\widehat{cday}_t$	-0.03	-0.17***	-0.12	-0.17
(t-stat)	(-0.36)	(-1.68)	(-0.67)	(-0.83)
$\bar{R}^2$	[0.00]	[0.03]	[0.00]	[0.01]
	Panel B: Consumption Growth, using $\widehat{cay}_t$			
$\widehat{cay}_t$	0.09	0.08	0.21***	0.25***
(t-stat)	(1.26)	(0.90)	(1.72)	(1.83)
$\bar{R}^2$	[0.02]	[0.00]	[0.05]	[0.05]

Table 4 reports results from forecasting of the log real returns on the MSCI - UK Total Return Index. Panel A shows that $\widehat{cday}$ has a significant forecasting power for future real returns, particularly at 3 and 4 quarters horizons, with the $\bar{R}^2$ statistic reaching 0.20. In comparison, Panel B shows that $\widehat{cay}$ performs worse: the coefficient estimates are less statistically significant, smaller in magnitude and, for the same horizons, the $\bar{R}^2$ statistic ranges between 0.12 and 0.14.

Table 5 reports results from forecasting of the log excess returns on the MSCI - UK Total Return Index, which roughly replicate those found in the previous Table.

Table 4: Long-run horizon regressions for real returns.

The table reports results from long-horizon regressions of real returns on $\widehat{cday}_t$ and $\widehat{cay}_t$.

The dependent variable is H-period real return $\Delta r_{t+1} + \ldots + \Delta r_{t+H}$.

Symbols *, ** and *** represent significance at a 1%, 5% and 10% level, respectively.

Newey-West (1987) corrected t-statistics appear in parenthesis. The sample period is 1977:4 to 2001:1.

	Forecast Horizon H			
Regressor	1	2	3	4
	Panel A: Real Returns, using $\widehat{cday}_t$			
$\widehat{cday}_t$	1.59**	3.13*	4.91*	5.40*
(t-statistic)	(2.52)	(3.31)	(4.11)	(4.17)
$\bar{R}^2$	[0.04]	[0.10]	[0.20]	[0.20]
	Panel B: Real Returns, using $\widehat{cay}_t$			
$\widehat{cay}_t$	0.89***	2.07**	3.21*	3.81*
(t-statistic]	(1.93)	(2.50)	(3.22)	(3.81)
$\bar{R}^2$	[0.01]	[0.06]	[0.12]	[0.14]

Table 5: Long-run horizon regressions for excess returns.

The table reports results from long-horizon regressions of excess returns on $\widehat{cday}_t$ and $\widehat{cay}_t$.

The dependent variable is H-period excess return $\Delta r_{t+1} + \ldots + \Delta r_{t+H}$.

Symbols *, ** and *** represent significance at a 1%, 5% and 10% level, respectively.

Newey-West (1987) corrected t-statistics appear in parenthesis. The sample period is 1977:4 to 2001:1.

	Forecast Horizon H			
Regressor	1	2	3	4
	Panel A: Excess Returns, using $\widehat{cday}_t$			
$\widehat{cday}_t$	1.51**	2.89*	4.61*	5.08*
(t-stat)	(2.33)	(3.02)	(3.88)	(3.85)
$\bar{R}^2$	[0.04)	[0.10]	[0.19]	[0.19]
	Panel B: Excess Returns, using $\widehat{cay}_t$			
$\widehat{cay}_t$	0.81***	1.84**	2.94*	3.56*
(t-stat)	(1.83)	(2.25)	(2.93)	(3.54)
$\bar{R}^2$	[0.01]	[0.05]	[0.10]	[0.13]

In sum, the results suggest that the disaggregation of wealth into its main components is an important issue in the context of forecasting future asset returns. Not only $\widehat{cday}$ performs better than $\widehat{cay}$, but its relative predictive power is also greater for larger periods. As in Lettau and Ludvigson (2001), the results also show evidence that $\widehat{cday}$ has no predictive power for future consumption growth and that lagged returns do not forecast next quarter's variation both of real returns and excess returns.

4.3 Out-of-Sample Forecasts

This section compares the forecasting power of $\widehat{cday}_t$ and $\widehat{cay}_t$ in an out-of-sample context.[16] This exercise faces several econometric issues.

First, Ferson *et al.*(2003) argue, with a simulation exercise, that if both expected returns and the predictive variable are highly persistent the in-sample regression results may be spurious, and both $\bar{R}^2$ and statistical significance of the regressor are biased upward.[17] The autocorrelation of realized returns is low in the data,[18] nevertheless the degree of persistence of expected returns is not observable.[19] On the other hand, since $\widehat{cday}$ and $\widehat{cay}$ are autocorrelated, this could give rise to spurious regression results.[20] As a consequence, in addition to in-sample predictions presented in the previous Section, I also perform out-of-sample forecasts.[21]

Second, a "look-ahead" bias might arise from the fact that the coefficients used to generate $\widehat{cday}_t$ and $\widehat{cay}_t$ are estimated using the full data sample, this is, using a fixed cointegrating vector.[22] To address this issue, I also look at out-of-sample forecasts where $\widehat{cday}_t$ and $\widehat{cay}_t$ are reestimated every period, using only the data available at the time of the forecast, and the predictive regressions are estimated recursively using data from the beginning of the sample to the quarter immediately preceding the forecast period. The difficulty with this technique, as argued in Lettau and Ludvigson (2002), is that it can strongly understate the predictive ability of the regressor, which would make it difficult for $\widehat{cday}$ (and $\widehat{cay}$) to display forecasting power if the theory is true.

With these caveats in mind, I compare the forecasting ability of $\widehat{cday}_t$ and $\widehat{cay}_t$ using the Root Mean

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[16] Foster *et al.* (1997) and Rapach and Wohar (2006) provide a theoretical analysis of data mining in predictive regression models.

[17] See also Torous *et al.* (2005).

[18] The autocorrelation of the realized MSCI-UK returns is -0.11.

[19] The return may be considered to be sum of an unobservable expected return plus a unpredictable noise, and the predictable component could be highly autocorrelated.

[20] This is a common problem for both $\widehat{cday}_t$ and $\widehat{cay}_t$, but is likely to be less severe for the former than the latter since their first autocorrelations are, respectively, 0.55 and 0.71.

[21] Inoue and Kilian (2004) show that in-sample and out-of-sample tests of predictability are, under the null of no predictability, asymptotically equally reliable.

[22] For a discussion on the potential "look-ahead" bias, see Brennan and Xia (2005).

Squared Error, the Theil's U, the McCracken (2000) MSE-F statistic, and the Clark and McCracken (2001) ENC-NEW statistic.[23]

Tables 6 and 7 compare the out-of-sample forecasting power of $\widehat{cday}_t$ (Panel A) and $\widehat{cay}_t$ (Panel B) for real and excess returns over horizons of 1, 2 and 4 quarters, using a fixed cointegrating vector; Tables 8 and 9 repeat the same exercise, but the cointegrating vector is instead reestimated every period using only the data available at the time of the forecast. Moreover, since Brennan and Xia (2005) show that changing the starting point of the out-of-sample forecast might dramatically change the measured performance, I use three different starting points for the out-of-sample forecast: 1987:4, 1992:4 and 1997:4, corresponding, respectively, to the first ten, fifteen and twenty years of available data.

The results shown in Tables 6 and 7 show that $\widehat{cday}_t$ performs better than $\widehat{cay}_t$ in forecasting real and excess returns. It can be seen $\widehat{cday}_t$ has a significant out-of-sample forecasting ability, corroborated by the different statistics used. Moreover, the predictive power also increases substantially as the horizon over which future returns should be predicted increases, in accordance to the in-sample forecasting power reported in the previous sub-Section.

Tables 8 and 9 provide results which are not so striking, showing that the performance of $\widehat{cday}_t$ is similar to $\widehat{cay}_t$ in forecasting real and excess returns. This is, however, not very surprising since consistent estimation of the parameters requires a large number of observations, and an out-of-sample exercise tends to generate an important sampling error in the estimates at early recursions, as argued by Lettau and Ludvigson (2002).

In addition to these out-of-sample forecasts, I also perform a very simple exercise: the coefficients of $\widehat{cday}$ and $\widehat{cay}$ are first estimated using the smallest number of observations; then, one observation is added at each time and the coefficients are recursively estimated. This exercise provides an idea about the rate of convergence of the coefficients to the "long-run equilibrium" coefficients. Figures 3, 4 and 5 plot the pattern of the coefficients of $\widehat{cday}$, while Figures 6 and 7 plot the pattern of the coefficients of $\widehat{cay}$. Despite the instability associated to early estimations, it is clear that the coefficients of $\widehat{cday}$ converge to the "long-run equilibrium" coefficients faster than $\widehat{cay}$. This is, therefore, an important element that helps to explain the superior forecasting power of $\widehat{cday}$ relative to $\widehat{cay}$.

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[23] The Theil's U is the ratio of the root-mean-squared errors for the unrestricted and restricted regression model forecasts. If the mean-squared error (MSE) for the unrestricted model forecasts is less than the MSE for the restricted model forecasts, then U <1. In the estimations, the restricted or benchmark model is the model of constant returns. By its turn, the MSE-F statistic is a variant of the Diebold and Mariano (1995) and West (1996) statistic and is used to test whether the unrestricted regression model forecasts are significantly superior to the restricted model forecasts. Finally, the ENC-NEW statistic is a variant of the Harvey *et al.* (1998) statistic designed to test for forecast encompassing.

Table 6: Out-of-sample forecasts of real returns, fixed cointegrating vector.

The table reports results from out-of-sample forecasts of real returns based on $\widehat{cday}_t$ and $\widehat{cay}_t$.

The dependent variable is H-period real return $\Delta r_{t+1} + ... + \Delta r_{t+H}$. The first forecast period is stated at the left of the table.

The coefficients used to generate $\widehat{cday}_t$ and $\widehat{cay}_t$ are estimated using the full data sample, this is, using a fixed cointegrating vector.

The predictive regressions are estimated recursively using data from the beginning of the sample to the quarter immediately preceding the forecast period.

Symbols *, ** and *** represent significance at a 1%, 5% and 10% level, respectively.

	Forecast Horizon H											
	1				2				4			
	Panel A: Real Returns, using $\widehat{cday}_t$											
First Forecast Period	RMSE	Theil's U	MSE-F	ENC-NEW	RMSE	Theil's U	MSE-F	ENC-NEW	RMSE	Theil's U	MSE-F	ENC-NEW
1987:4	0.0705	0.656	0.689***	2.431**	0.0915	0.551	2.213***	5.329*	0.1139	0.428	4.950**	9.597*
1992:4	0.0653	0.661	1.332***	1.602**	0.0895	0.571	0.166	1.652***	0.1048	0.417	6.873**	6.524**
1997:4	0.0859	0.811	-0.842	-0.144	0.1157	0.776	-1.811	-0.528	0.1351	0.686	-2.683	-0.600
	Panel B: Real Returns, using $\widehat{cay}_t$											
First forecast period	RMSE	Theil's U	MSE-F	ENC-NEW	RMSE	Theil's U	MSE-F	ENC-NEW	RMSE	Theil's U	MSE-F	ENC-NEW
1987:4	0.0714	0.713	0.591	1.055	0.0926	0.600	1.339	2.747***	0.1192	0.480	4.383***	7.044*
1992:4	0.0676	0.686	-1.175	-0.077	0.0934	0.589	-2.876	-0.180	0.1191	0.463	-1.807	2.221
1997:4	0.0869	0.772	-1.276	-0.513	0.1195	0.723	-2.751	-1.063	0.1540	0.670	-4.936	-1.681

Table 7: Out-of-sample forecasts of excess returns, fixed cointegrating vector.

The table reports results from out-of-sample forecasts of excess returns based on $\widehat{cday}_t$ and $\widehat{cay}_t$.

The dependent variable is H-period excess return $\Delta r_{t+1}+\ldots+\Delta r_{t+H}$. The first forecast period is stated at the left of the table.

The coefficients used to generate $\widehat{cday}_t$ and $\widehat{cay}_t$ are estimated using the full data sample, this is, using a fixed cointegrating vector.

The predictive regressions are estimated recursively using data from the beginning of the sample to the quarter immediately preceding the forecast period.

Symbols *, ** and *** represent significance at a 1%, 5% and 10% level, respectively.

	Forecast Horizon H											
	1				2				4			
	Panel A: Excess Returns, using $\widehat{cday}_t$											
First Forecast Period	RMSE	Theil's U	MSE-F	ENC-NEW	RMSE	Theil's U	MSE-F	ENC-NEW	RMSE	Theil's U	MSE-F	ENC-NEW
1987:4	0.0717	0.725	0.487	2.051**	0.0915	0.630	1.841***	4.364**	0.1166	0.523	3.881**	7.490**
1992:4	0.0650	0.726	1.407***	1.515**	0.0879	0.646	0.410	1.557***	0.1048	0.503	7.102**	6.209*
1997:4	0.0858	0.852	-0.641	-0.079	0.1133	0.821	-1.642	-0.491	0.1329	0.747	-2.508	-0.560
	Panel B: Excess Returns, using $\widehat{cay}_t$											
First Forecast Period	RMSE	Theil's U	MSE-F	ENC-NEW	RMSE	Theil's U	MSE-F	ENC-NEW	RMSE	Theil's U	MSE-F	ENC-NEW
1987:4	0.0723	0.791	0.659***	0.909	0.0919	0.690	1.589***	2.334***	0.1199	0.5865	5.448**	6.539**
1992:4	0.0672	0.763	-0.929	-0.048	0.0916	0.675	-2.436	-0.192	0.1188	0.5614	-1.209	2.144***
1997:4	0.0869	0.832	-1.089	-0.443	0.1169	0.787	-2.512	-0.998	0.1512	0.748	-4.821	-1.668

Table 8: Out-of-sample forecasts of real returns, cointegrating vector reestimated.

The table reports results from out-of-sample forecasts of real returns based on $\widehat{cday}_t$ and $\widehat{cay}_t$.

The dependent variable is H-period real return $\Delta r_{t+1} + ... + \Delta r_{t+H}$. The first forecast period is stated at the left of the table.

The coefficients used to generate $\widehat{cday}_t$ and $\widehat{cay}_t$ are reestimated every period, using only the data available at the time of the forecast.

The predictive regressions are estimated recursively using data from the beginning of the sample to the quarter immediately preceding the forecast period.

Symbols *, ** and *** represent significance at a 1%, 5% and 10% level, respectively.

	Forecast Horizon H											
	1				2				4			
Panel A: Real Returns, using $\widehat{cday}_t$												
First Forecast Period	RMSE	Theil's U	MSE-F	ENC-NEW	RMSE	Theil's U	MSE-F	ENC-NEW	RMSE	Theil's U	MSE-F	ENC-NEW
1987:4	0.0722	0.739	-14.875	-3.752	0.0964	0.658	-25.297	-2.052	01282	0.549	-38.542	-1.542
1992:4	0.0670	0.763	-2.402	-0.895	0.0927	0.711	-4.766	-1.259	0.1192	0.597	-8.614	-0.496
1997:4	0.0822	0.835	0.419	0.252	0.1086	0.820	1.093	0.671	0.1153	0.698	3.636***	2.217***
Panel B: Real Returns, using $\widehat{cay}_t$												
First Forecast Period	RMSE	Theil's U	MSE-F	ENC-NEW	RMSE	Theil's U	MSE-F	ENC-NEW	RMSE	Theil's U	MSE-F	ENC-NEW
1987:4	0.0722	0.742	-16.152	-4.702	0.0963	0.663	-25.270	-6.051	0.1278	0.554	-34.591	-1.248
1992:4	0.0676	0.745	-4.775	-1.557	0.0932	0.688	-11.179	-2.776	0.1219	0.579	-17.776	0.166
1997:4	0.0832	0.847	-1.431	-0.030	0.1047	0.714	-2.191	1.506	0.0793	0.397	-4.187	7.458***

Table 9: Out-of-sample forecasts of excess returns, cointegrating vector reestimated.

The table reports results from out-of-sample forecasts of excess returns based on $\widehat{cday}_t$ and $\widehat{cay}_t$.

The dependent variable is H-period excess return $\Delta r_{t+1} + ... + \Delta r_{t+H}$. The first forecast period is stated at the left of the table.

The coefficients used to generate $\widehat{cday}_t$ and $\widehat{cay}_t$ are reestimated every period, using only the data available at the time of the forecast.

The predictive regressions are estimated recursively using data from the beginning of the sample to the quarter immediately preceding the forecast period.

Symbols *, ** and *** represent significance at a 1%, 5% and 10% level, respectively.

	Forecast Horizon H											
	1				2				4			
	Panel A: Excess Returns, using $\widehat{cday}_t$											
First Forecast Period	RMSE	Theil's U	MSE-F	ENC-NEW	RMSE	Theil's U	MSE-F	ENC-NEW	RMSE	Theil's U	MSE-F	ENC-NEW
1987:4	0.0732	0.830	-12.891	-3.650	0.0959	0.775	-19.647	-3.418	0.1300	0.698	-28.997	-4.975
1992:4	0.0667	0.867	-2.925	-0.949	0.0913	0.847	-6.374	-1.440	0.1199	0.777	-11.947	-0.580
1997:4	0.0823	0.920	0.553	0.353	0.1054	0.916	1.422***	0.934	0.1090	0.802	5.137**	3.400***
	Panel B: Excess Returns, using $\widehat{cay}_t$											
First Forecast Period	RMSE	Theil's U	MSE-F	ENC-NEW	RMSE	Theil's U	MSE-F	ENC-NEW	RMSE	Theil's U	MSE-F	ENC-NEW
1987:4	0.0732	0.832	-16.016	-4.786	0.0958	0.780	-23.960	-5.605	0.1298	0.705	-30.387	-0.948
1992:4	0.0669	0.837	-5.573	-1.558	0.0917	0.808	-13.740	-2.894	0.1222	0.736	-21.382	0.433
1997:4	0.0834	0.833	-1.431	-0.030	0.1023	0.671	-2.191	1.506	0.0781	0.356	-4.187	7.458***

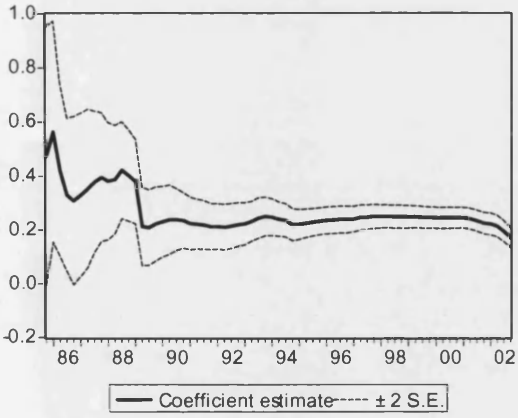

Figure 3: Coefficient associated to financial wealth.

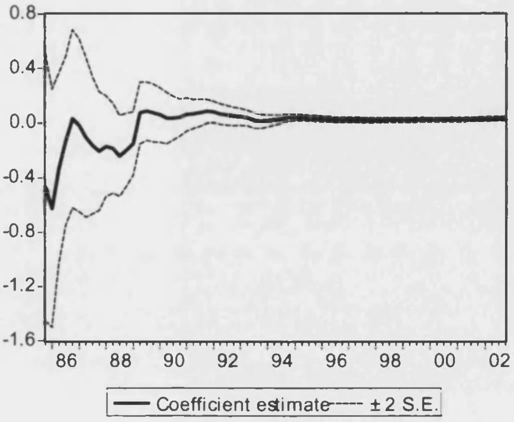

Figure 4: Coefficient associated to housing wealth.

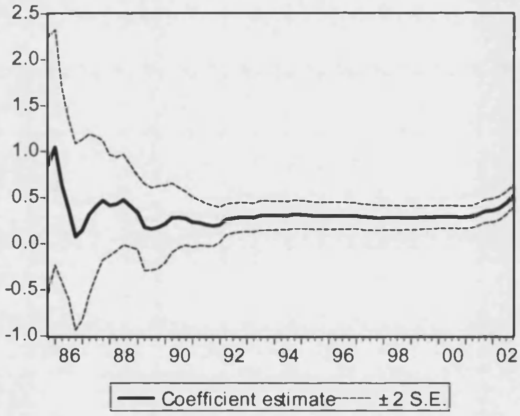

Figure 5: Coefficient associated to labor income.

The figures plot the recursive estimates of the coefficients (± 2 standard errors). The coefficients of $\widehat{cday}$ are first estimated using the smallest number of observations; then, one observation is added at each time and the coefficients are reestimated.

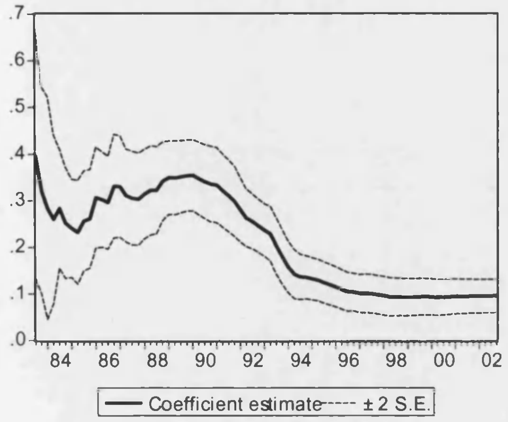

Figure 6: Coefficient associated to asset wealth.

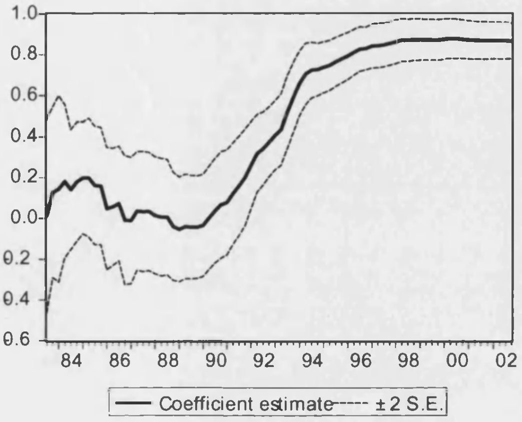

Figure 7: Coefficient associated to labor income.

The figures plot the recursive estimates of the coefficient (± 2 standard errors). The coefficients of $\widehat{cay}$ are first estimated using the smallest number of observations; then, one observation is added at each time and the coefficients are reestimated.

In sum, the results suggest that $\widehat{cday}$ performs better than $\widehat{cay}$ in an out-of-sample context and that the predictive ability is stronger over longer horizons, corroborating the results found in the in-sample exercise shown in the previous sub-Section. Moreover, it is shown that the coefficients of $\widehat{cday}$ converge to the "long-run equilibrium" faster than $\widehat{cay}$. Therefore, the disaggregation of wealth into its main components is an important issue in the context of forecasting future asset returns.

4.4 A Skeptical Look at the Data Using a VAR Approach

As a robustness check of the previous results, this sub-Section does not impose the theoretical restrictions implied by the budget constraint in equation (10).[24] The results are consistent and show that the joint estimation of the forecasting equations for real returns,[25] consumption growth, financial wealth growth, housing wealth growth, and labor income growth imply that: (*i*) lagged returns do not have forecasting power, but *cday* is an important proxy for the expectations about future asset returns;

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[24] In a recent paper, Koop *et al.* (2005) question the key findings of Lettau and Ludvigson (2001, 2004), namely, that most changes in wealth are transitory and have no effect on consumption. The authors use a Bayesian model averaging and argue that there is model uncertainty with regards to the number of cointegrating vectors, the form of deterministic components, lag length and whether the cointegrating residuals affect consumption and income directly.

[25] The same results are obtained when I use excess returns instead.

(*ii*) financial wealth changes are mainly transitory; and (*iii*) housing wealth changes are very persistent.

I estimate the following Vector Autoregressive Model (VAR)

$$\mathbf{X}_t = \theta + A(L)\mathbf{X}_{t-1} + \xi_t, \tag{14}$$

where $\mathbf{X}_t = (r_t, \Delta c_t, \Delta f_t, \Delta u_t, \Delta y_t)$ is the vector of real returns, consumption growth, financial wealth growth, housing wealth growth, and labor income growth, $A(L)$ is a finite-order distributed lag operator, θ is a vector of constants, χ is a vector of coefficients associated with with $\widehat{cday}_{t-1}$, and ξ_t is a vector of error terms.[26] For comparison, I also estimate the following VAR that adds $\widehat{cday}_{t-1}$as an exogenous variable

$$\mathbf{X}_t = \theta + A(L)\mathbf{X}_{t-1} + \chi\widehat{cday}_{t-1} + \xi_t. \tag{15}$$

Tables 10 and 11 present the results of the estimation of (14) and (15). Table 10 shows that the forecasting regression of real returns has no explanatory power in line with the results in Table 2. It can also be seen that asset returns are an important explanatory of financial wealth growth. Moreover, the housing wealth growth regression confirms the persistence of the variation in this component of asset wealth: the lagged housing wealth growth is highly significant and this equation explains 71% of the variation in housing wealth.

Table 11 provides very similar results. The most important feature of this estimation is that it shows that *cday* conveys important important for forecasting asset returns: the $\bar{R}^2$ reaches 0.05 and the coefficient associated to *cday* is significant and important in magnitude (1.898) in line with the results of Table 2.

Using the VAR estimated in Table 10,[27] I also assess the change in expected future returns and consumption growth caused by a shock to any of the forecasting variables considered. Under a diffuse prior, the posterior distribution of the estimated VAR can be factorized as the product of an inverse Wishart and, conditional on the covariance matrix, a multivariate normal distribution

$$\beta|_{\Sigma} \sim N(\hat{\beta}, \Sigma \otimes (X'X)^{-1})$$

$$\Sigma^{-1} \sim Wishart((n\hat{\Sigma})^{-1}, n-m)$$

where β is the vector of VAR coefficients, Σ is the covariance matrix of the residuals, the variables with a hat denote the corresponding estimates, X is the matrix of regressors, n is the sample size and m is the number of estimated parameters (Zellner, 1971; Schervish, 1995; Bauwens *et al.*, 1999).[28] I compute

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[26] The selected optimal lag length is 1, in accordance with findings from Akaike and Schwarz tests. However, the results are not sensible to different lag lengths.

[27] The same results are obtained using the VAR estimated in Table 11 and specified in equation (15).

[28] This result is exact under normality and the Jeffrey's prior $f(\beta, \Sigma) \propto |\Sigma|^{-(p+1)/2}$ (where p is the number of left hand side variables), but can also be obtained as an asymptotic approximation around the posterior MLE.

50,000 draws from the posterior distribution of the VAR coefficients and report 95 percent confidence intervals from the Monte Carlo iterations. The procedure is described in Appendix C.

Figures 8 and 9 report, respectively, the impulse-response functions of quarterly real returns and consumption growth to a one standard deviation impulse in each of the regressors. Figure 8 shows that while financial wealth shocks have a negative effect on real returns, housing wealth shocks have a positive effect on real returns. Figure 9 shows that housing wealth shocks have a very persistent effect on consumption, while financial wealth shocks are mainly transitory.

Table 10: Estimates from vector-autoregressions (VAR) specified in equation (14).

The table reports the estimated coefficients from vector-autoregressions (VAR) specified in equation (14). Symbols *, **, *** represent, respectively, significance level of 1%, 5% and 10%. Newey-West (1987) corrected t-statistics appear in parenthesis. The sample period is 1977:4 to 2001:1.

	Equation				
Dependent variable	r_t	Δc_t	Δf_t	Δu_t	Δy_t
r_{t-1}	-0.108	0.015	0.525*	0.019	0.029**
(t-stat)	(-1.034)	(1.587)	(16.325)	(1.206)	(2.175)
Δc_{t-1}	-1.218	-0.261**	0.625***	0.391**	-0.261***
(t-stat)	(-1.005)	(-2.424)	(1.675)	(2.092)	(-1.695)
Δf_{t-1}	-0.218	0.008	-0.056	-0.005	-0.000
(t-stat)	(-1.215)	(0.473)	(-1.017)	(-0.174)	(-0.015)
Δu_{t-1}	0.240	0.055***	-0.081	0.781*	0.142*
(t-stat)	(0.634)	(1.639)	(-0.696)	(13.408)	(2.963)
Δy_{t-1}	-0.528	0.152**	0.487**	0.240***	-0.062
(t-stat)	(-0.663)	(2.138)	(1.984)	(1.957)	(-0.616)
θ	0.037*	0.005*	-0.001	-0.001	0.005*
(t-stat)	(3.053)	(5.048)	(-0.268)	(-0.617)	(3.582)
$\bar{R}^2$	0.000	0.075	0.751	0.713	0.090

Table 11: Estimates from vector-autoregressions (VAR) specified in equation (15).

The table reports the estimated coefficients from vector-autoregressions (VAR) specified in equation (15).

Symbols *, **, *** represent, respectively, significance level of 1%, 5% and 10%.

Newey-West (1987) corrected t-statistics appear in parenthesis. The sample period is 1977:4 to 2001:1.

	Equation				
Dependent variable	r_t	Δc_t	Δf_t	Δu_t	Δy_t
r_{t-1}	-0.187***	0.020**	0.514*	0.022	0.018
(t-stat)	(-1.740)	(2.099)	(15.199)	(1.277)	(1.324)
Δc_{t-1}	-2.022***	-0.205***	0.513	0.414**	-0.373**
(t-stat)	(-1.644)	(-1.851)	(1.322)	(2.122)	(-2.405)
Δf_{t-1}	-0.072	-0.003	-0.036	-0.009	0.020
(t-stat)	(-0.388)	(-0.161)	(-0.613)	(-0.310)	(0.855)
Δu_{t-1}	0.473	0.039	-0.049	0.775*	0.175*
(t-stat)	(1.238)	(1.129)	(-0.404)	(12.779)	(3.629)
Δy_{t-1}	-0.219	0.130***	0.530**	0.231***	-0.019
(t-stat)	(-0.278)	(1.831)	(2.130)	(1.848)	(-0.194)
θ	-2.554**	0.187***	-0.362	0.076	-0.356*
(t-stat)	(-2.323)	(1.891)	(-1.042)	(0.433)	(-2.567)
$\widehat{cday}_{t-1}$	1.898**	-0.133***	0.264	-0.056	0.265*
(t-stat)	(2.356)	(-1.837)	(1.039)	(-0.440)	(2.607)
$\bar{R}^2$	0.049	0.099	0.752	0.711	0.146

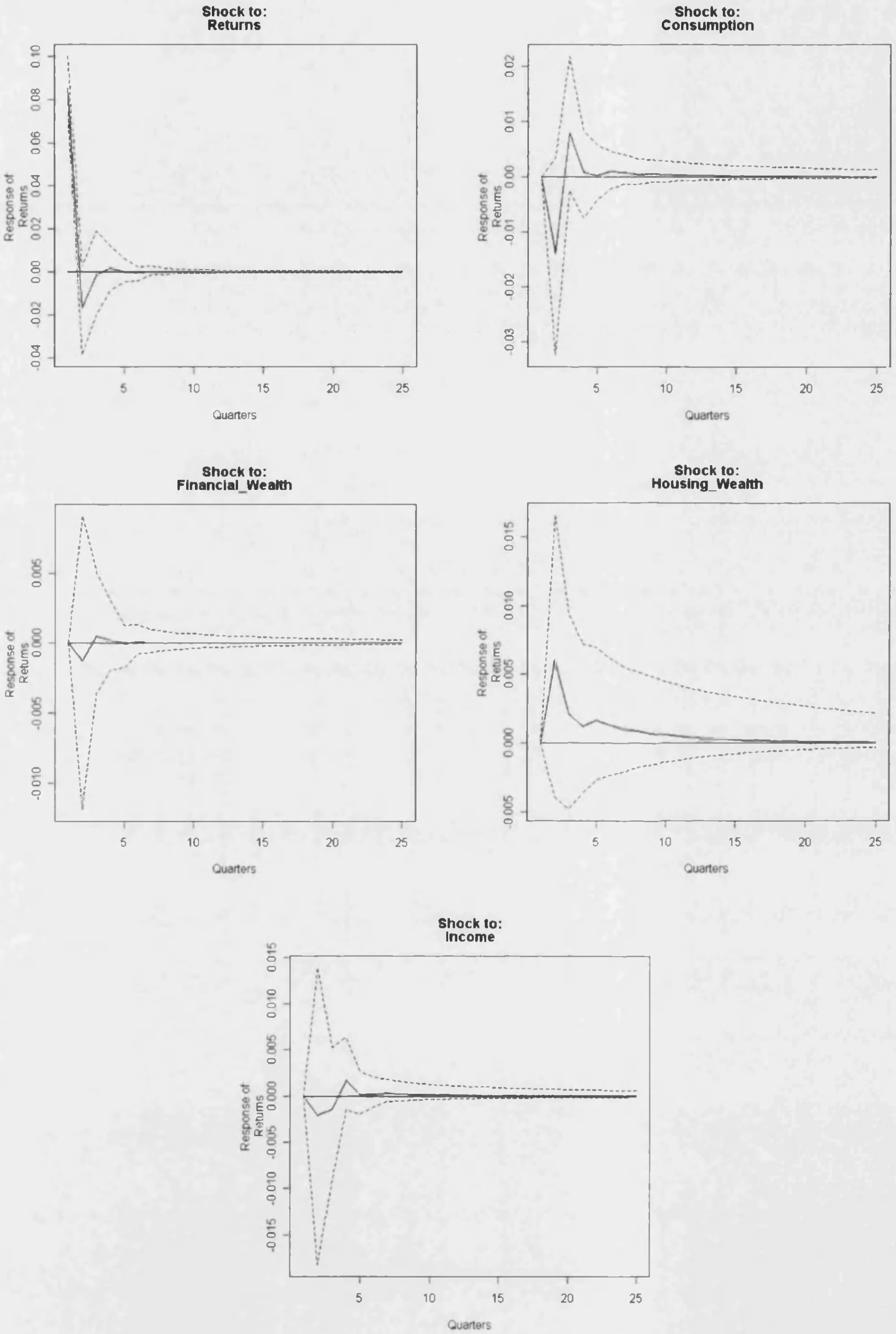

Figure 8: Impulse-response functions of real returns.

The figure depicts the impulse-response functions of real returns based on the Vector Auto-Regression (VAR) model estimated in equation (14).

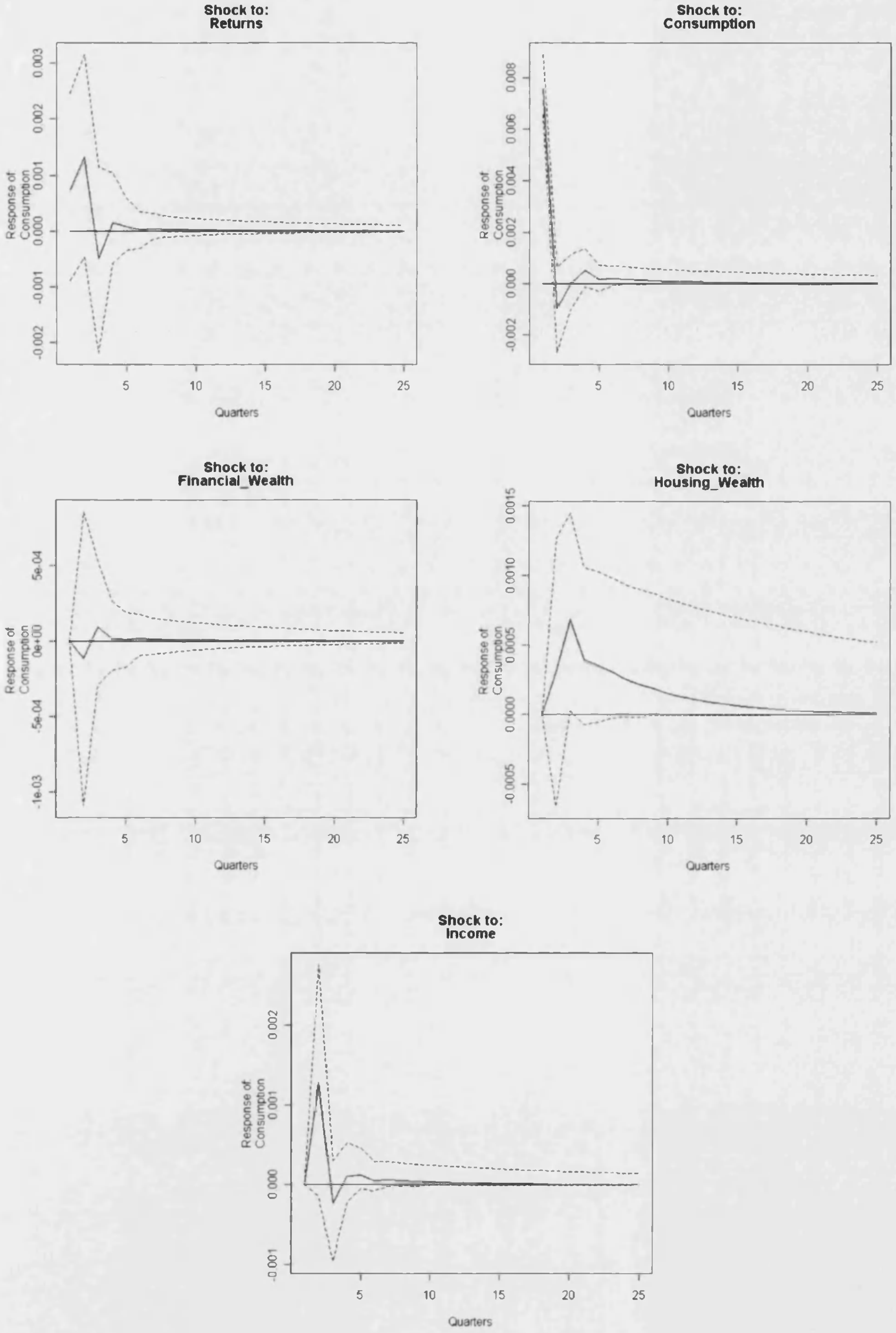

Figure 9: Impulse-response functions of consumption.

The figure depicts the impulse-response functions of consumption based on the Vector Auto-Regression (VAR) model estimated in equation (14).

5 Conclusion

This paper uses the representative consumer's budget constraint to derive an equilibrium relation between the trend deviations among consumption, (dis)aggregate wealth and labor income (summarized by the variable *cday*) and expected future asset returns, and explores the predictive power of the empirical counterpart of these trend deviations ($\widehat{cday}$) for future asset returns.

The main finding of the paper is that $\widehat{cday}$ has high predictive power for future market returns and it performs better than a variable like $\widehat{cay}$ suggested by Lettau and Ludvigson (2001), which does not take into account the issue of the disaggregation of wealth. I show that the superior forecasting power of *cday* is due to: (*i*) its ability to track the changes in the composition of asset wealth and the specificities of the different assets; and (*ii*) the coefficients converge faster to the "long-run equilibrium" parameters. Therefore, disaggregating asset wealth into its main components (financial and housing wealth) is important and helps providing better forecasts for future asset returns: if consumption is above its trend relationship, then agents expect higher financial asset returns and/or higher housing asset returns.

Using data for the United Kingdom, I also show that financial wealth effects are significantly different from housing wealth effects. Unlike Lettau and Ludvigson (2001, 2004), who argue that asset wealth fluctuations are largely transitory, the results suggest that, while substantial fluctuations in financial assets need not indeed be associated with large subsequent movements in consumption, fluctuations in housing assets are very important due to their persistence. An important implication is that governments and central banks need to pay special attention to the behavior of housing markets (and to a smaller extent to the behavior of financial markets) when defining macroeconomic stabilizing policies.

This work is, however, only a first approach to the subject and has, therefore, some limitations. First, this approach does not correspond to a more structural representation of the economy in which the consumer's preferences and the production side are formalized. Lantz and Sartre (2001) address partially this question, showing that consumption does not react directly to wealth changes, but instead both consumption and wealth react to changes in productivity. Second, the formulation ignores labor income risk and its importance in the context of forecasting asset returns, an issue that has been dealt recently by Julliard (2004). Third, the specification implicitly assumes that agents consume a single good. In contrast, Yogo (2006), Piazzesi *et al.*(2007) and Lustig and Van Nieuwervurgh (2005) present models in which agents care about the composition of a consumption basket that includes housing services.

Finally, this work is just a starting point for future research. A potentiality to analyze in the future is the role of financial deregulation/liberalization. Bayoumi (1993) and Caporale and Williams (1997), among others, point out the importance of these processes for the credit expansion and the elimination of liquidity restrictions that they provide; Bonser-Neal and Dewenter (1999) emphasize the effects of level of development of financial markets on the savings rate; and Bekaert *et al.*(2005) emphasize their importance for economic growth. Therefore, it would be important to approach the importance of these processes on the magnitude of wealth effects, an aspect that is analyzed in a recent work of Boone *et al.*(2001) and what are their implications for forecasting asset returns. Second, it would be also important to analyze the importance of the concentrated nature of the wealth and its impact on the dynamics of wealth distribution. Finally, although literature emphasizes the role played by wealth on non-durable consumption expenditure, it would also be interesting to analyze its role on durables consumption expenditure.

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Appendix

A Data Description

Consumption

Consumption is defined as total consumption (ZAKV) less consumption of durable (UTIB) and semi-durable goods (UTIR). Data are quarterly, seasonally adjusted at an annual rate, measured in millions of pounds (2001 prices), in per capita and expressed in the logarithmic form. Series comprises the period 1963:1 - 2003:4. The source is Office for National Statistics (ONS).

Wealth

Aggregate wealth is defined as the net worth of households and nonprofit organizations, this is, the sum of financial wealth and housing wealth. Data are quarterly, seasonally adjusted at an annual rate, measured in millions of pounds (2001 prices), in per capita terms and expressed in the logarithmic form. Series comprises the period 1975:1 - 2004:1. The sources of information are: Fernandez-Corugedo *et al.* (2003), for the period 1975:1 - 1986:4; Office for National Statistics (ONS), for the period 1987:1 - 2004:1.

Financial wealth

Financial wealth is defined as the net financial wealth of households and nonprofit organizations (NZEA). Data are quarterly, seasonally adjusted at an annual rate, measured in millions of pounds (2001 prices), in per capita terms and expressed in the logarithmic form. Series comprises the period 1970:1 - 2004:1. The sources of information are: Fernandez-Corugedo *et al.* (2003), for the period 1970:1 - 1986:4; Office for National Statistics (ONS), for the period 1987:1 - 2004:1.

Housing wealth

Housing wealth is defined as the housing wealth of households and nonprofit organizations and is computed as the sum of tangible assets in the form of residential buildings adjusted by changes in house prices (CGRI), the dwellings (of private sector) of gross fixed capital formation (GGAG) and Council house sales (CTCS). Data are quarterly, seasonally adjusted at an annual rate, measured in millions of pounds (2001 prices), in per capita terms and expressed in the logarithmic form. Series comprises the period 1975:1 - 2004:1. The sources of information are: Fernandez-Corugedo *et al.* (2003), for the period 1975:1 - 1986:4; Office for National Statistics (ONS), for the period 1987:1 - 2004:1. For data on house prices, the sources of information are: Office of the Deputy Prime Minister (ODPM), Halifax Plc and the Nationwide Building Society.

After-tax labor income

After-tax labor income is defined as the sum of wages and salaries (ROYJ), social benefits (GZVX), self employment (ROYH), other benefits (RPQK + RPHS + RPHT - ROYS - GZVX + AIIV), employers social contributions (ROYK) less social contributions (AIIV) and taxes. Taxes are defined as (taxes on income (RPHS) and other taxes (RPHT)) x ((wages and salaries (ROYJ) + self employment (ROYH)) / (wages and salaries (ROYJ) + self employment (ROYH) + other income (ROYL - ROYT + NRJN - ROYH)). Data are quarterly, measured in millions of pounds (2001 prices), in per capita terms and expressed in the logarithmic form. Series comprises the period 1974:3 - 2003:4. The sources of information are: Fernandez-Corugedo *et al.* (2003), for the period 1974:3 - 1986:4; Office for National Statistics (ONS), for the period 1987:1 - 2003:4.

Population

Population is defined as mid-year estimates of resident population of the United Kingdom (DYAY) in millions. Original data are available as an annual series. The data are interpolated to quarterly frequencies, computing the annual population growth rate and the applying the average quarterly population growth rate every quarter. Series comprises the period 1946:4 - 2003:4. The source of information is Office for National Statistics (ONS).

Price deflator

The nominal consumption, wealth, financial wealth, housing wealth, labor income and interest rates were deflated by the All Items-Retail Prices Index (CHAW) (January 13 1987 = 100). Data are quarterly. Series comprises the period 1947:4 - 2004:4. The source of information is Office for National Statistics (ONS).

Inflation rate

Inflation rate was computed from price deflator. Data are quarterly. Series comprises the period 1947:3 - 2004:4. The source of information is Office for National Statistics (ONS).

Interest rate ("Risk-free rate")

Risk-free rate is defined as the quarterly real yield rate of 3-month Treasury Bills (AJRP). Original data are available as an annual series. Quarterly data are computed applying the average quarterly real yield rate every quarter. Series comprises the period 1972:1 - 2004:4. The source of information is Office for National Statistics (ONS).

Asset returns

Asset returns were computed using the MSCI - UK Total Return Index for the UK, which measure the market performance, including price performance and income from dividend payments. I use the index which includes gross dividends, this is, approximating the maximum possible dividend reinvestment. The amount reinvested is the dividend distributed to individuals resident in the country of the company, but does not include tax credits. Series comprises the period 1970:1 - 2004:4. The source of information is Morgan Stanley Capital International (MSCI).

B Tests of the Existence of Unit Roots and Cointegration

Table B1:

Phillips-Perron unit root tests to the variables' cointegration order (levels).

The Phillips-Perron unit root test has been applied to the variables in levels included in $\hat{cday}_t$.

Symbols * and ** denote rejection of the null hypothesis at a significance level of 1 and 5%, respectively.

Newey-West (1987) bandwith selection. Critical values suggested by MacKinnon (1996).

		Critical values	
	Phillips-Perron t-Statistic	5% Level	1% Level
c_t	-1.83	-3.46	-4.06
f_t	-3.03	-3.46	-4.06
u_t	-1.76	-3.46	-4.06
y_t	-2.60	-3.46	-4.06

Table B2:

Phillips-Perron unit root tests to the variables' cointegration order (first-differences).

The Phillips-Perron unit root test has been applied to the variables in first-differences included in $\widehat{cday}_t$. Symbols * and ** denote rejection of the null hypothesis at a significance level of 1 and 5%, respectively. Newey-West (1987) bandwith selection. Critical values suggested by MacKinnon (1996).

		Critical values	
	Phillips-Perron t-Statistic	5% Level	1% Level
Δc_t	-11.06*	-2.89	-3.50
Δf_t	-10.81*	-2.89	-3.50
Δu_t	-3.09**	-2.89	-3.50
Δy_t	-10.41*	-2.89	-3.50

Table B3:

Test of cointegration using the methodology of Engle and Granger (1987).

The test of cointegration using the methodology of Engle and Granger (1987) has been applied to $\widehat{cday}_t$ and $\widehat{cay}_t$. Symbols * and ** denote rejection of the null hypothesis at a significance level of 1 and 5%, respectively. Newey-West (1987) bandwith selection. Critical values suggested by MacKinnon (1996).

		Critical values	
	Phillips-Perron t-Statistic	5% Level	1% Level
$\widehat{cday}_t$	-5.47*	-2.89	-3.50
$\widehat{cay}_t$	-4.50*	-2.89	-3.50

C Assessing Uncertainty

To assess uncertainty in the regression results in Table 10, I report 95 percent confidence intervals for the estimated slope coefficients constructed via Monte Carlo integration by drawing from the posterior distribution of the estimated VAR coefficients. I proceed as follows:

1. I draw covariance matrices $\grave{\Sigma}$ from the inverse Wishart with parameters $(n\hat{\Sigma})^{-1}$ and $n-m$.
2. Conditional on $\grave{\Sigma}$, I draw a vector of coefficients for the VAR, $\grave{\beta}$, from $\grave{\beta} \sim N(\hat{\beta}, \grave{\Sigma} \otimes (X'X)^{-1})$.
3. I repeat this procedure 50,000 times and construct the median and slope OLS coefficients associated to the VAR, and the 95 percent confidence intervals from the Monte Carlo iterations.

Chapter II

Wealth Shocks and Risk Aversion

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Abstract

Modern literature departs from time-separable constant relative risk aversion preferences to explain asset pricing facts. This deviation typically implies that wealth shocks generate transitory variations in agents' relative risk aversion and, possibly, portfolio re-allocations over time.

I empirically analyze this relationship using U.S. macroeconomic data and find evidence for time-variation in portfolio shares that is consistent with counter-cyclical risk aversion. These results suggest, therefore, that wealth-dependent, habit-formation or loss and disappointment aversion utility functions are a good description of preferences.

Controlling for observed *versus* expected asset returns, I also show that: (*i*) wealth effects are significant (although temporary) and there is no evidence of inertia contrary to Brunnermeier and Nagel (2006); and (*ii*) the consumption-wealth ratio (Lettau and Ludvigson, 2001), the labor income risk (Julliard, 2004), and the labor income-consumption ratio (Santos and Veronesi, 2006) partially explain changes in the risky asset share.

Keywords: wealth, risk aversion.

JEL classification: E21, G11, E44.

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1 Introduction

Time-separable utility functions with constant relative risk aversion (CRRA) are commonly used in macroeconomics and asset pricing. An important implication of this kind of preferences is that shocks to an agent's wealth leave his relative risk aversion (RRA) unchanged. A growing number of studies have recently explored alternative preferences that allow wealth shocks to generate transitory effects on relative risk aversion. The ways by which these effects take place include: (*i*) habit-formation preferences;[1] (*ii*) agents may care about relative social status or have direct preferences over wealth;[2] and (*iii*) agents may have loss or disappointment aversion preferences.[3]

These modifications are appealing because they help to explain the counter-cyclicality of risk premia in asset markets and they seem plausible from a psychological perspective. However, whilst researchers have typically focused on time-variation in risk premium, the models also imply time-variation on portfolio shares, an implication that has not yet been put into a rigorous empirical test.[4]

Moreover and despite the apparent agreement regarding the counter-cyclical pattern of risk aversion (Cochrane, 1997; Guvenen, 2004), the empirical evidence on the relationship between wealth shocks and relative risk aversion is not consensual and the analysis has mostly been centered on the unconditional equity premium (instead of time-variation in risk aversion) using household level data.[5] Brunnermeier and Nagel (2006) provide the first test to the assumption of constant relative risk aversion, but conclude that wealth shocks do not prompt households to change the allocation of their financial wealth between risky and riskless assets.

Whilst representing an important result, the estimates of wealth effects on asset allocation based on household level data are likely to be under-estimated due to the poor coverage at the top-level of wealth

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[1] Consumers may look at changes in wealth as isolated shocks with persistent effects (Campbell, 1998). Campbell and Cochrane (1999) suggest that agents are more risk averse during troughs and that a positive wealth shock leads to a transitory decrease in relative risk aversion. These effects largely depend on how quickly habit adjusts (Dunn and Singleton, 1986; Abel, 1990; Boldrin *et al.*, 1995; Heaton, 1995).

[2] In this case, wealth has consumption characteristics due to, for example, the social status that it provides and directly affects portfolio decisions (Robson, 1992; Bakshi and Chen, 1996; St-Amour, 2005). Carroll (1997) emphasizes the accumulation of wealth as an end by itself. Cole *et al.* (1992, 1995) and Corneo and Jeanne (1999) focus instead on the role of wealth as determining status, a ranking mechanism that determines the allocation of non-marketed goods.

[3] See, for example, Kahneman and Tversky (1979), Gul (1991), Tversky and Kahneman (1991), Barberis *et al.* (2001), Fielding and Stracca (2003), and Routledge and Zin (2003).

[4] Cox *et al.* (1985) and Lo and Wang (2001) suggest that portfolios that contain dynamic hedging strategies against unfavorable shifts in the state variable are qualitatively similar to those obtained under time-varying investment sets, and result in time-varying portfolio shares.

[5] See, for example, Friend and Blume (1975), Cohn et al (1975), Blake (1996), Morin and Fernandez Suarez (1983) and Guiso and Paiella (2001).

distribution where the exposure to risky assets is largest. On the other hand, the majority of works on portfolio composition share a common weakness: as they rely on cross sectional data, the effects of time-variation of asset prices, expected returns and volatility are not taken into account.[6]

In this paper, I test the assumption of constant relative risk aversion using U.S. quarterly data for the period 1953:4 - 2004:4. I use macroeconomic data to look at the relationship between unexpected wealth variation and changes of the risky asset allocation in aggregate portfolios. The results show that the risky asset share exhibits a cyclical behavior and it is significantly (and positively) affected by wealth shocks. There is, therefore, evidence suggesting that risk aversion is counter-cylical and supporting the existence of preferences that depart from the assumption of constant relative risk aversion.[7] This is in accordance with cross-sectional evidence on portfolios which shows that: stockholders are: (*i*) wealthier (Poterba, 2000; Ait-Sahalia *et al.*, 2004; Reynard, 2004); (*ii*) have a larger elasticity of inter-temporal substitution (Vissing-Jorgensen, 2002; Guvenen, 2006); and (*iii*) have a lower degree of risk aversion (Mankiw and Zeldes, 1991; Attanasio *et al.*, 2002; Brav *et al.*, 2002). By its turn, a fall of the share of housing wealth tends to be associated with positive unexpected wealth variation, which highlights the possibility of the use of housing assets as an hedge against unfavorable states.[8]

I then show that the relationship that one observes between wealth shocks and changes in the portfolio composition does not reflect possible price effects, that is, changes in the price of financial assets, housing assets or the relative price of assets are not responsible for the time-variation of the risky asset share. Additionally, there is some weak evidence suggesting that housing returns or holding gains on housing assets (but not financial returns or holding gains in corporate equities) play a role in wealth allocation. This asymmetric behavior may be related with agents looking at changes in financial returns as transitory and perceiving changes in housing returns as persistent. Despite this, the empirical findings are still robust to asset return effects and confirm that wealth shocks are important determinants of agents' risk aversion.

One potential drawback of the previous results is that time varying portfolio shares may be simply reflecting time-variation in the expectations about future returns and/or in the volatility of returns. In

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[6] Heaton and Lucas (2000) and Guiso *et al.* (2003) show that, conditional on stock market participation, the cross-sectional relationship between the risky asset share and the level of wealth is essentially flat. Vissing-Jorgensen (2002) and Paiella (2005) emphasize the importance of participation costs as determining risky asset allocation.

[7] Cochrane (1997) and Guvenen (2004) also suggest that risk aversion is counter-cyclical, based on the counter-cyclicality of excess returns. Melino and Yian (2003) and Gordon and St-Amour (2000, 2004) emphasize the role of direct preferences over wealth to achieve the same conclusion.

[8] Cocco (2000) analyzes the benefits of housing as a hedge against income shocks. Englund *et al.* (2002) and Iacoviello and Ortalo-Magné (2003) show the importance of housing as a hedge against the risk of financial portfolios. Sinai and Souleles (2005) point out its benefits as a hedge against rent risk.

fact, at the time of wealth shocks, future returns on assets can only be predicted and the mapping of the risk aversion to the risky asset share is only valid when those effects are taken into account and correctly identified. Therefore, I control for changes in expected asset returns and in the volatility of asset returns. The empirical findings suggest that some proxies developed by the literature on asset pricing to capture time-variation in expected returns, such as the consumption-wealth ratio (Lettau and Ludvigson, 2001), the labor income risk (Julliard, 2004) and the labor income-consumption ratio (Santos and Veronesi, 2006), partially explain the changes observed in risky asset allocation. However, the estimations show that wealth shocks remain significant and are responsible for the bulk of the variation, consistent with preferences that deviate from the assumption of constant relative risk aversion.

Considering a variety of wealth definitions, it is shown that, although significant, wealth effects on asset allocation are mainly temporary: the explanatory power of wealth shocks quickly falls over horizons of three quarters, therefore, providing evidence against the existence of long-run effects on asset composition. Additionally and contrary to the findings of Brunnermeier and Nagel (2006), there is weak evidence of inertia or slow adjustment in asset allocation, as agents quickly rebalance the composition of their portfolios following to wealth shocks.

Finally, as a robustness check of the previous results, I analyze the importance of wealth effects on asset allocation in a Bayesian framework. I estimate a reduced-form Vector Autoregressive Model (VAR) and show that: (*i*) lagged changes in wealth do not explain the changes in the risky asset share, suggesting that wealth effects on asset allocation are transitory and there is no inertia on asset allocation; (*ii*) lagged returns do not forecast future returns, but the consumption-wealth ratio, *cay*, contains important predictive power, consistent with the findings of Lettau and Ludvigson (2001). Using a Markov Chain Monte Carlo algorithm to compute the error bands of the impulse-response functions to an aggregate wealth shock, I show that unexpected wealth variation has a positive (although temporary) effect on the risky asset share, agents quickly rebalance their portfolios, and the effect erodes over the next four quarters.

The paper is organized as follows. Section 2 presents the theoretical and econometric approach. Section 3 describes the data, estimates the wealth effects on portfolio allocation and checks the robustness of the results. In Section 4, I control for the effects of expected returns on asset allocation. In Section 5, I address the issues of long-run wealth effects and inertia. In Section 6, I present a reduced-form VAR and analyze the importance of wealth effects on asset allocation in a more structural framework. Finally, in Section 7, I conclude and discuss the implications of the findings.

2 Theory and Econometric Approach

2.1 Wealth Effects on Asset Allocation

Consider the optimal portfolio choice of an investor with habit-formation preferences and continuous time.[9] Assume, as in Campbell and Cochrane (1999), that agents have power utility with additive habit, that is,

$$U(C) = E\int_0^\infty e^{-\delta t}\frac{(C_t - X_t)^{1-\gamma}}{1-\gamma}dt, \tag{1}$$

which converges to a log-utility function for $\gamma = 1$.[10] Following Sundaresan (1989), Constantinides (1990) and Ingersoll (1992), X_t, the habit level, is internal, and depends on past consumption according to the following law

$$X_t = b\int_0^t e^{-a(t-s)}C_s ds + e^{-at}X_0, \tag{2}$$

with $b > 0$. Current consumption at the habit level increases X_t at a rate of b, while the impact of past consumption depreciates at a rate of a.

The investor chooses consumption, C_t, and the share of wealth invested in risky assets, α_t, to maximize expected utility, subject to

$$dW_t = (\mu_{p,t}W_t - C_t)dt + \sigma_{p,t}W_t dZ_t, \tag{3}$$

where $\mu_{p,t} := r_t^f + \alpha_t(\mu_t - r_t^f)$ is the expected instantaneous return on wealth, $\sigma_{p,t}$ is the instantaneous volatility of the return on wealth, r_t^f is the instantaneous return on the risk-free asset, and μ_t is the drift of the risky asset return process. The wealth process is driven by a deterministic component $(\mu_{p,t}W_t - C_t)dt$ and a stochastic component that contains a one-dimensional Brownian motion Z_t, and $\mu_{p,t}$ and $\sigma_{p,t}$ depend on the agent's portfolio choice, i.e. α_t, and, possibly, Z_t (time-varying investment opportunities).

Following Schroder and Skiadas (2002), it is possible to derive an isomorphism between optimal portfolio selection of an agent with habit formation preferences ($b > 0$) and an agent without habit formation ($X_0 = 0$ and $b = 0$). In the case of constant risk-free rate, the habit-utility agent's investment in the risky asset, α_t, is[11]

$$\alpha_t = (1 - \frac{X_t}{W_t}\frac{1}{r + (a - b)})\hat{\alpha}_t, \tag{4}$$

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[9] In this Subsection, I follow Brunnermeier and Nagel (2006).

[10] An utility function with multiplicative habit of the form $U(C) = E\int_0^\infty e^{-\delta t}\frac{(C_t/X_t)^{1-\gamma}}{1-\gamma}dt$ does not exhibit time-varying risk aversion.

[11] Shore and White (2003) derive a tractable relationship in an external habit setting.

where $\hat{\alpha}_t$ is the corresponding risky asset share for an agent without habit. With constant investment opportunities, i.e. constant expected risky asset return and volatility, $\hat{\alpha}_t$ would be constant. In contrast, an agent with habit preferences invests the first $\frac{X_t}{r^f+(a-b)}$ dollars in the risk-free asset in order to secure a minimum consumption equal to future expected habit. Only then, a constant fraction of the surplus wealth will be invested in the risky asset.

In Appendix B, it is shown that the log risky asset share, i.e. $\rho_t := log(\alpha_t)$, follows the process

$$d\rho_t = (\frac{\hat{\alpha}_t}{\alpha_t} - 1)\left\{\left[\mu_{w,t} - \mu_{x,t} - \frac{\hat{\alpha}_t}{2\alpha_t}\sigma^2_{p,t}\right] dt + \sigma_{p,t} dZ_t\right\}, \tag{5}$$

where $w_t := \log(W_t)$, $x_t := \log(X_t)$, and $\mu_{w,t}$ and $\mu_{x,t}$ are the instantaneous drifts of the w_t and x_t processes. Since surplus wealth rises when the agent receives a positive wealth shock, one could intuitively infer that this leads to an increase in the optimal portfolio share of the risky asset. That is, everything else equal, an unexpected wealth shock of 1 percent increases the fraction invested in the risky asset, ρ_t, by $(\frac{\hat{\alpha}_t}{\alpha_t} - 1)$ percent. However, this shift in asset allocation is not permanent: over time, as the habit catches up with the new wealth level (i.e. $\mu_{x,t} > \mu_{w,t}$), the risky asset share mean-reverts, and the initial impact of the unexpected wealth shock erodes. Consequently, one can not say *a priori* what is the direction of the effects of unexpected wealth variation on the share of risky assets, and this work aims at providing more light about it.

2.2 Econometric Specification

I use the approximate discrete-time counterpart to Equation (5) to estimate the impact of wealth shocks on portfolio composition. Wealth shocks are computed in two ways. First, I use the standard set of Box-Jenkins selection procedures to determine the best fitting for wealth growth and then use the residuals, ε_t, as a proxy for unexpected wealth variation. In this case, among the models considered, the Akaike information, the Schwarz and the Hanan-Quinn criteria suggest that the data-generating process that fits better wealth growth is the ARMA(2,3) model. I hence restrict the attention to the ARIMA(2,1,3) specification for wealth. Appendix C describes in detail the computation of the wealth shock, ε_t.[12] Second, I estimate a reduced form cointegrated vector auto-regressive model (VAR) for consumption growth, Δc_t, wealth growth, Δw_t, and labor income growth, Δy_t and then use the residuals of the equation for wealth growth, ξ^w_t, as a proxy for wealth shocks.[13]

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[12] I also use a Kalman filter to extract the innovation component of the wealth growth process and use it as a proxy for unexpected wealth variation. The results, however, do not change significantly.

[13] I also estimate the VAR without imposing cointegration, but the results do not change significantly.

The starting point for the econometric specification is, therefore,

$$\Delta\rho_t = \delta_0 + \delta_1\varepsilon_t + u_t, \tag{6}$$

where $\Delta\rho_t := \rho_t - \rho_{t-1}$ denotes the first-difference in the log portfolio share of risky assets, ε_t is an unexpected wealth shock at time t, and u_t is a random disturbance uncorrelated with ε_t.

In the second case, I specify the following cointegrated vector auto-regressive model (VAR) for consumption growth, Δc_t, wealth growth, Δw_t, and labor income growth, Δy_t:

$$\Delta\mathbf{X}_t = \theta + \gamma_t\beta_t'\mathbf{X}_{t-1} + \Gamma(L)\Delta\mathbf{X}_{t-1} + \xi_t, \tag{7}$$

where $\mathbf{X}_t = (c_t, w_t, y_t)$ is the vector of consumption, aggregate wealth, and labor income, $\gamma_t = (\gamma_c, \gamma_w, \gamma_y)'$ is a (4×1) vector, $\beta_t = (1, -\beta_w, -\beta_y)'$ is the vector of estimated cointegration coefficients, $\Gamma(L)$ is a finite-order distributed lag operator, $\xi_t = (\xi_t^c, \xi_t^w, \xi_t^y)$ is a vector of disturbance terms and θ is a vector of constants. Thus, γ_t is the short-run adjustment vector telling us how the variables react to the last period's cointegrating error while returning to long-term equilibrium after a deviation; β_t measures the long-run elasticities of one variable respective to another; and the term $\beta_t'\mathbf{X}_{t-1}$ measures the cointegrating residual. Following Campbell and Shiller (1988), for small perturbations around the steady state, the variables included in the VAR should capture most of the relevant information for wealth changes. Therefore, the residuals of the equation for wealth growth, ξ_t^w, shall be a good proxy for wealth shocks and I regress:

$$\Delta\rho_t = \delta_0 + \delta_1\xi_t^w + u_t. \tag{8}$$

Equations (6) and (8) shall provide a robust test to the assumption of constant relative risk aversion: if wealth shocks are important determinants of transitory risk aversion, the coefficient will be significant and this will a piece of evidence supporting preferences that depart from that assumption.[14]

3 Wealth Effects and Asset Allocation

3.1 Data

The main data sources are the Flow of Funds Accounts provided by Federal Reserve System and BEA of U.S. Department of Commerce. In Appendix A, I present a detailed discussion of data.

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[14] To address the measurement error problem and the potential correlation between the wealth shock proxy and the disturbance term, I estimate a two-stage least-squares regression using instrumental variables. Whilst some precision is lost with the use of this estimation, the results are still robust and point in the direction of the significant wealth effects on asset alllocation.

In the estimations, I use quarterly, seasonally adjusted data for U.S., variables are measured at 2000 prices and expressed in the logarithmic form of per capita terms, and the sample period is 1953:4 - 2004:4.

The definition of consumption includes nondurable consumption goods and services. Data on income includes only after-tax labor income. Aggregate wealth corresponds to the net worth of households and nonprofit organizations, that is, the sum of housing wealth and financial wealth.

Housing wealth (or home equity) is defined as the value of real estate held by households minus home mortgages. Financial wealth is defined as the sum of financial assets (deposits, credit market instruments, corporate equities, mutual fund shares, security credit, life insurance reserves, pension fund reserves, equity in noncorporate business, and miscellaneous assets) minus financial liabilities (credit market instruments excluding home mortgages, security credit, trade payables, and deferred and unpaid life insurance premiums). Original data on wealth correspond to the end-period values. Therefore, I lag once the data, so that the observation of wealth in t corresponds to the value at the beginning of the period $t+1$.

I start by defining ρ_t^1 as the log share of financial wealth in total wealth and ρ_t^2 as the log of the share of housing wealth in total wealth. Then, I consider risky asset holdings as the stock market wealth - that is, the sum of the value of corporate equities, directly and indirectly held - and denote by ρ_t^3 the log share of risky assets in financial wealth. This is the preferred proxy for agent's risk aversion. In addition, I consider two measures of risky asset holdings: (*i*) one that includes only risky asset direct holdings, ρ_t^4; and (*ii*) another that includes only indirect holdings, ρ_t^5. In both cases, the risky asset share is computed as ratios of financial wealth.[15]

Figure 1 shows the evolution of the composition of wealth: while the share of housing wealth exhibits a counter-cyclical pattern, the other portfolio shares fall during recessions and increase in expansions. This evidence suggests that housing is an hedge against unfavorable wealth shifts and that risk aversion is counter-cyclical.

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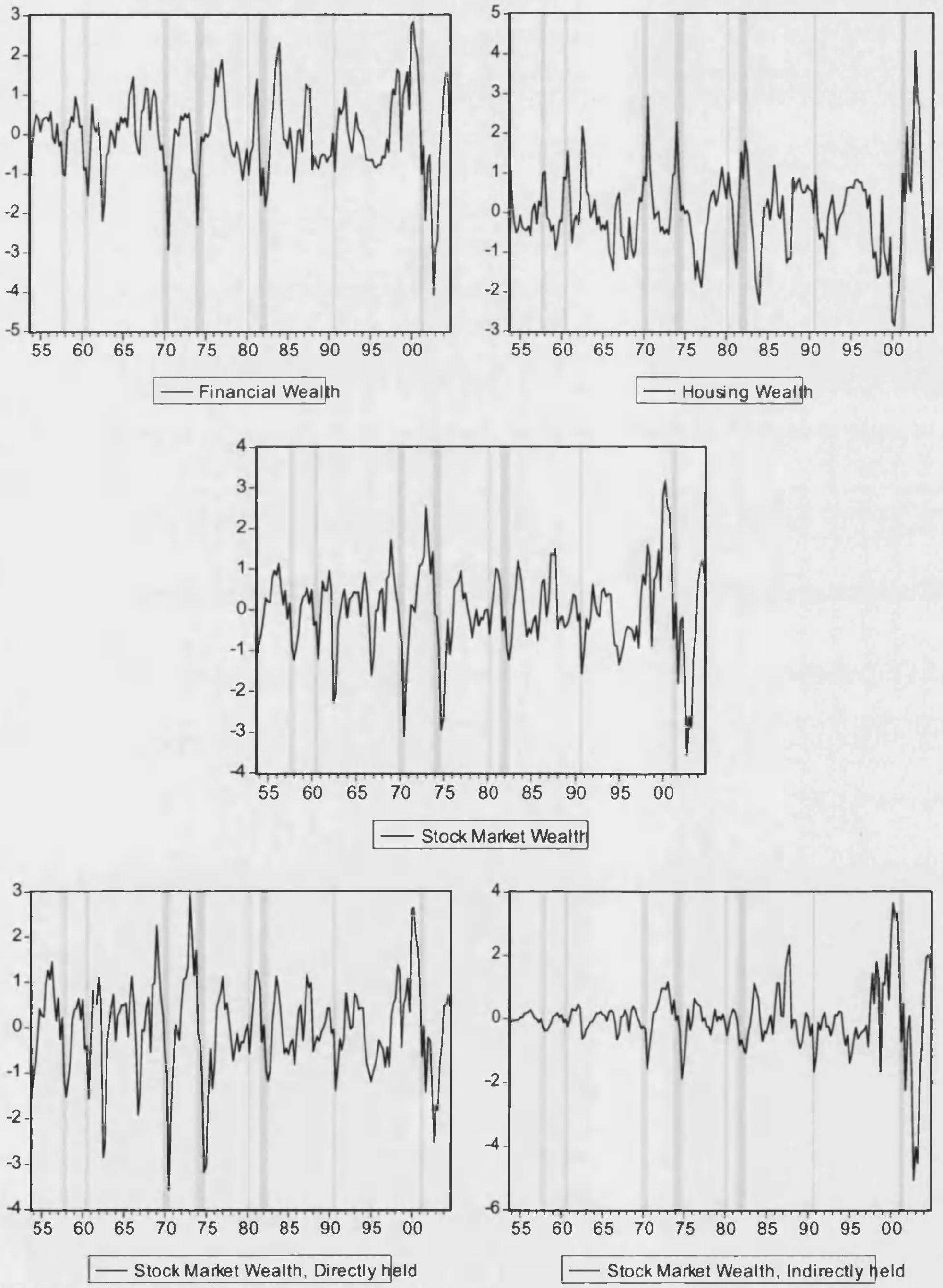
[15] The estimation results do not change significantly when different measures of consumption (including durable goods) are used or when the risky asset share is measured as a ratio of total wealth.

Figure 1: Evolution of the composition of wealth.

The picture depicts the evolution of the shares of financial and housing wealth in total wealth and the shares of stock market wealth and its components in financial wealth. All series are detrended using the Hodrick-Prescott (1997) filter and normalized to standard deviations of unity. The sample period is 1953:4 to 2004:4. Shaded areas denote NBER recessions.



3.2 Empirical Evidence

The starting points for the estimation of wealth effects on portfolio composition are equation (6) - where wealth shocks are computed using the residuals of the estimated data-generating process for wealth growth - and equation (8) - where they are computed as the residuals of the wealth growth equation in a reduced vector auto-regression model (VAR).

Tables 1 and 2 show a summary of the results. The estimated coefficient on the wealth shock (respectively, ε_t and ξ_t^w) is positive and significant and is very similar in both specifications. When the dependent variable is the change in the ratio of stock market wealth to financial wealth, i.e. the favourite definition of risky asset share, $\Delta\rho_t^3$, the coefficient associated with the wealth shock is large and positive (respectively, 2.682 and 2.210 in Tables 1 and 2): an unexpected shock of 1% in aggregate wealth leads to an increase of the share of risky assets by, respectively, 2.682% and 2.210%. The $\bar{R}^2$ are also large (respectively, 0.69 and 0.54), showing that wealth shocks are important determinants of risk aversion. When the definition of risky asset share is split into directly versus indirectly held risky risky assets, $\Delta\rho_t^4$ and $\Delta\rho_t^5$, it can be seen that wealth effects are stronger in the first case: both the coefficient on wealth shocks and the $\bar{R}^2$ are larger in magnitude. This is consistent with agents that do not trade some categories of assets (such as mutual or pension funds). The only exception to the positive effect of wealth shocks is the share of housing wealth, given that the coefficient is negative. This empirical finding is important and suggests that housing is an hedge against unexpected wealth variation: in face of a positive wealth shock, the relative risk aversion falls and the agent reduces the share of housing assets.

Table 1: Wealth effects in asset allocation - wealth shocks from single equation.

	Financial Wealth $\Delta\rho_t^1$	Housing Wealth $\Delta\rho_t^2$	Stock Market Wealth $\Delta\rho_t^3$	Stock Market Wealth, Directly. held $\Delta\rho_t^4$	Stock Market Wealth, Indirectly held $\Delta\rho_t^5$
Constant	-0.000	0.000	0.004	0.000	0.013*
	(-0.238)	(0.219)	(1.563)	(0.128)	(4.645)
ε_t	0.16*	-0.770*	2.682*	2.810*	2.292*
	(7.278)	(-7.412)	(21.291)	(11.910)	(10.264)
$\bar{R}^2$	[0.41]	[0.45]	[0.69]	[0.68]	[0.57]

Symbols *, **, *** represent, respectively, significance level of 1%, 5% and 10%.

Newey and West (1987) corrected t-statistics appear in parenthesis.

The sample period is 1953:4 to 2004:4.

Table 2: Wealth effects in asset allocation: wealth shocks from VAR system.

	Financial Wealth $\Delta\rho_t^1$	Housing Wealth $\Delta\rho_t^2$	Stock Market Wealth $\Delta\rho_t^3$	Stock Market Wealth Directly held $\Delta\rho_t^4$	Stock Market Wealth Indirectly held $\Delta\rho_t^5$
Constant	-0.000	0.000	0.004	0.000	0.013*
	(-0.210)	(0.190)	(1.045)	(0.117)	(3.908)
ξ_t^w	0.143*	-0.690*	2.210*	2.301*	1.979*
	(8.516)	(-8.454)	(11.632)	(12.066)	(10.115)
$\bar{R}^2$	[0.38]	[0.41]	[0.54]	[0.53]	[0.49]

Symbols *, **, *** represent, respectively, significance level of 1%, 5% and 10%.

Newey and West (1987) corrected t-statistics appear in parenthesis.

The sample period is 1953:4 to 2004:4.

3.3 Robustness Analysis

3.3.1 Price Effects

While the previous regressions suggest that wealth shocks affect portfolio composition, one could argue that this is just reflecting possible changes in the price of corporate equities, or housing prices or both. Therefore, I control for possible price effects and consider the log change of price of financial assets, Δp_t^f, and the log change of relative price of financial to housing assets, $\Delta\left(\frac{p_t^f}{p_t^u}\right)$ as possible explanatory variables.

Financial prices are measured using the Standard & Poor's (S&P 500) Composite Index. Housing prices are measured using two sources: (a) the Price Index of New One-Family Houses sold including the Value of Lot provided by the U.S. Census since 1963:1; and (b) the House Price Index computed by the Office of Federal Housing Enterprise Oversight (OFHEO) since 1975:1.

The results are summarized in Tables 3 and 4. For simplicity, only the results that use the Census Housing Price Index are reported, although the regressions with the OFHEO Housing Price Index corroborate the major findings. The evidence of price effects is very weak: only a few coefficients are statistically significant and their inclusion does not significantly change the $\bar{R}^2$ statistic. Nevertheless, the signs are consistent with an increase in risky asset share, i.e. an increase in the price of financial assets or in the relative price of financial to housing assets is associated with an increase in the share of risky assets and a decrease in the share of housing assets.

Table 3: Asset allocation and financial price effects.

	Financial Wealth	Housing Wealth	Stock Market Wealth	Stock Market Wealth Directly held	Stock Market Wealth Indirectly held
	$\Delta\rho_t^1$	$\Delta\rho_t^2$	$\Delta\rho_t^3$	$\Delta\rho_t^4$	$\Delta\rho_t^5$
Constant	-0.000	0.000	0.003	-0.001	0.013*
	(-0.301)	(0.272)	(1.156)	(-0.248)	(4.638)
ε_t	0.159*	-0.769*	2.671*	2.795*	2.285*
	(7.357)	(-7.489)	(11.522)	(12.019)	(10.243)
Δp_t^f	0.002	-0.006	0.045	0.057**	0.025
	(0.339)	(-0.296)	(1.596)	(2.024)	(0.718)
$\bar{R}^2$	[0.40]	[0.44]	[0.69]	[0.68]	[0.57]

Symbols *, **, *** represent, respectively, significance level of 1%, 5% and 10%.

Newey and West (1987) corrected t-statistics appear in parenthesis.

The sample period is 1953:4 to 2004:4.

Table 4: Asset allocation and relative price of assets (Census).

	Financial Wealth	Housing Wealth	Stock Market Wealth	Stock Market Wealth Directly held	Stock Market Wealth Indirectly held
	$\Delta\rho_t^1$	$\Delta\rho_t^2$	$\Delta\rho_t^3$	$\Delta\rho_t^4$	$\Delta\rho_t^5$
Constant	-0.000	0.001	0.001	-0.003	0.010*
	(-0.651)	(0.636)	(0.373)	(-0.911)	(3.382)
ε_t	0.155*	-0.750*	2.567*	2.693*	2.262*
	(6.268)	(-6.394)	(10.418)	(10.928)	(9.217)
$\Delta\frac{p_t^f}{p_t^u}$	0.001	-0.006	0.039	0.048***	0.033
	(0.251)	(-0.224)	(12.54)	(1.634)	(0.776)
$\bar{R}^2$	[0.38]	[0.43]	[0.67]	[0.66]	[0.57]

Symbols *, **, *** represent, respectively, significance level of 1%, 5% and 10%.

Newey and West (1987) corrected t-statistics appear in parenthesis.

The sample period is 1963:2 to 2004:4.

3.3.2 Asset Return Effects

Another channel that may affect portfolio composition is through asset returns. The previous findings may be capturing changes in asset returns instead of the effects of wealth shocks *per se.* I, therefore, add returns on financial assets, r_t, and returns on housing assets, r_t^u, as explanatory variables. The results are summarized in Tables 5 and 6 and Appendix A presents the computation of returns. Whilst financial returns do not play any role in wealth allocation, there is weak evidence suggesting that housing returns are important. This asymmetric behavior may be related with agents looking at changes in financial returns as transitory and perceiving changes in housing returns as persistent.

Table 5: Asset Allocation and returns on financial assets.

	Financial Wealth $\Delta\rho_t^1$	Housing Wealth $\Delta\rho_t^2$	Stock Market Wealth $\Delta\rho_t^3$	Stock Market Wealth Directly held $\Delta\rho_t^4$	Stock Market Wealth Indirectly held $\Delta\rho_t^5$
Constant	-0.000	0.000	0.003	-0.000	0.013
	(-0.295)	(0.263)	(1.263)	(-0.134)	(4.724)
ε_t	0.160*	-0.770*	2.680*	2.806*	2.291*
	(7.252)	(-7.386)	(11.569)	(12.096)	(10.234)
r_t	0.001	-0.005	0.030	0.042	0.005
	(0.337)	(-0.277)	(1.220)	(1.617)	(0.199)
$\bar{R}^2$	[0.41]	[0.44]	[0.69]	[0.68]	[0.57]

Symbols *, **, *** represent, respectively, significance level of 1%, 5% and 10%.

Newey and West (1987) corrected t-statistics appear in parenthesis.

The sample period is 1953:4 to 2004:4.

Table 6: Asset allocation and housing returns.

	Financial Wealth $\Delta\rho_t^1$	Housing Wealth $\Delta\rho_t^2$	Stock Market Wealth $\Delta\rho_t^3$	Stock Market Wealth Directly held $\Delta\rho_t^4$	Stock Market Wealth Indirectly held $\Delta\rho_t^5$
Constant	0.001**	-0.006**	0.005	0.002	0.017*
	(2.158)	(-2.008)	(1.058)	(0.301)	(3.693)
ε_t	0.168*	-0.807*	2.689*	2.817*	2.316*
	(8.347)	(-8.492)	(11.218)	(11.651)	(10.106)
r_t^u	-0.073*	0.318**	-0.056	-0.060	-0.211
	(-2.616)	(2.403)	(-0.287)	(-0.278)	(-1.114)
$\bar{R}^2$	[0.44]	[0.47]	[0.69]	[0.68]	[0.57]

Symbols *, **, *** represent, respectively, significance level of 1%, 5% and 10%.

Newey and West (1987) corrected t-statistics appear in parenthesis.

The sample period is 1953:4 to 2004:4.

3.3.3 Holding Gains and Net Acquisitions of Assets

In this Subsection, I test for other potential sources of variation in portfolio composition. In particular, I control for the effects of holding gains and net acquisition of assets which may be driving the changes in the risky asset allocation.

Holding gains are calculated as the change in amount outstanding less net purchases during the period and the effects of holding gains in corporate equities, $\Delta(\textit{stock gains})_t$, and holding gains in real estate, $\Delta(\textit{housing gains})_t$ are shown in Tables 7 and 8. Consistent with the previous findings, the results suggest that stock gains have no effect on portfolio allocation, but housing gains are important. This duality may be associated with the beliefs that stock gains are transitory and housing gains are persistent. Despite this, the coefficient associated with wealth shocks, ε_t, and the $\bar{R}^2$ statistic do not change significantly, further reinforcing that these are important determinants of asset allocation.

As a final robustness check, I test the impact of the net acquisition of corporate equities, $\Delta(\textit{stock purchases})_t$, and the net acquisition of mortgages, $\Delta(\textit{mortgages})_t$, and include them as explanatory variables in different specifications. The results are summarized in Tables 9 and 10: whilst there is evidence suggesting that net acquisition of corporate equities prompt agents to increase the proportion of wealth invested in risky assets, net acquisition of mortgages has no effect on asset allocation.

Table 7: Asset allocation and holding gains in corporate equities.

	Financial Wealth $\Delta\rho_t^1$	Housing Wealth $\Delta\rho_t^2$	Stock Market Wealth $\Delta\rho_t^3$	Stock Market Wealth Directly held $\Delta\rho_t^4$	Stock Market Wealth Indirectly held $\Delta\rho_t^5$
Constant	-0.000	0.000	0.004	-0.000	0.013*
	(-0.330)	(0.310)	(1.225)	(-0.103)	(4.669)
ε_t	0.160*	-0.771*	2.685*	2.810*	2.292*
	(7.187)	(-7.314)	(11.588)	(12.162)	(10.230)
$\Delta(stock\ gains)_t$	0.000	-0.001	0.002	0.003	-0.000
	(0.663)	(-0.594)	(0.966)	(1.550)	(-0.087)
$\bar{R}^2$	[0.41]	[0.44]	[0.69]	[0.68]	[0.57]

Symbols *, **, *** represent, respectively, significance level of 1%, 5% and 10%.

Newey and West (1987) corrected t-statistics appear in parenthesis.

The sample period is 1953:4 to 2004:4.

Table 8: Asset allocation and holding gains in real estate.

	Financial Wealth $\Delta\rho_t^1$	Housing Wealth $\Delta\rho_t^2$	Stock Market Wealth $\Delta\rho_t^3$	Stock Market Wealth Directly held $\Delta\rho_t^4$	Stock Market Wealth Indirectly held $\Delta\rho_t^5$
Constant	0.000*	-0.005*	0.009*	-0.011*	0.021*
	(2.882)	(-2.724)	(2.603)	(-3.007)	(5.884)
ε_t	0.164*	-0.787*	2.698*	2.831*	2.315*
	(7.902)	(-7.985)	(11.218)	(12.082)	(10.097)
$\Delta(housing\ gains)_t$	-0.003*	0.014*	-0.013**	-0.017*	-0.020*
	(-4.192)	(4.048)	(-2.059)	(-2.526)	(-2.746)
$\bar{R}^2$	[0.46]	[0.49]	[0.69]	[0.72]	[0.58]

Symbols *, **, *** represent, respectively, significance level of 1%, 5% and 10%.

Newey and West (1987) corrected t-statistics appear in parenthesis.

The sample period is 1953:4 to 2004:4.

Table 9: Asset allocation and net acquisition of corporate equities.

	Financial Wealth $\Delta\rho_t^1$	Housing Wealth $\Delta\rho_t^2$	Stock Market Wealth $\Delta\rho_t^3$	Stock Market Wealth Directly held $\Delta\rho_t^4$	Stock Market Wealth Indirectly held $\Delta\rho_t^5$
Constant	0.000	-0.000	0.006**	0.002	0.015*
	(0.278)	(-0.243)	(-1.913)	(0.617)	(5.579)
ε_t	0.161*	-0.777*	2.697*	2.824*	2.311*
	(7.461)	(-7.507)	(11.454)	(11.901)	(10.325)
$\Delta(stock\ purchases)_t$	0.002*	-0.009**	0.021**	0.021**	0.026*
	(2.585)	(-2.433)	(2.118)	(1.956)	(2.670)
$\bar{R}^2$	[0.42]	[0.46]	[0.70]	[0.69]	[0.59]

Symbols *, **, *** represent, respectively, significance level of 1%, 5% and 10%.

Newey and West (1987) corrected t-statistics appear in parenthesis.

The sample period is 1953:4 to 2004:4.

Table 10: Asset allocation and net acquisition of mortgages.

	Financial Wealth $\Delta\rho_t^1$	Housing Wealth $\Delta\rho_t^2$	Stock Market Wealth $\Delta\rho_t^3$	Stock Market Wealth Directly held $\Delta\rho_t^4$	Stock Market Wealth Indirectly held $\Delta\rho_t^5$
Constant	-0.000	0.001	0.004	-0.000	0.013*
	(-0.506)	(0.491)	(1.223)	(-0.038)	(4.504)
ε_t	0.161*	-0.773*	2.684*	2.813*	2.292*
	(7.346)	(-7.475)	(11.474)	(11.911)	(10.309)
$\Delta mortgage_t$	0.004	-0.017	0.011	-0.018	0.001
	(1.434)	(-1.475)	(0.371)	(-0.644)	(-0.023)
$\bar{R}^2$	[0.41]	[0.45]	[0.69]	[0.68]	[0.57]

Symbols *, **, *** represent, respectively, significance level of 1%, 5% and 10%.

Newey and West (1987) corrected t-statistics appear in parenthesis.

The sample period is 1953:4 to 2004:4.

4 Expected Returns and Asset Allocation

One potential drawback of the previous analysis is that it neglects the possibility of time-variation in the expectations about future returns and in the volatility of returns. Moreover, at the time of wealth shocks, future returns on assets are not observable and, therefore, can only be predicted. Following Friend and Blume (1975), the optimal investment in risky assets can be approximated by the following formula:

$$\rho_t = \log \frac{E(r_t - r_t^f)}{\sigma_t^2} - \log \gamma, \tag{9}$$

where ρ_t is the log share of wealth invested in risky assets, γ is Pratt's measure of relative risk aversion,[16] r_t and σ_t^2 denote, respectively, the return and the variance of the return on the portfolio of risky assets, and r^f is the risk-free interest rate. Given estimates of ρ_t and the market price for risk, $\frac{E(r_t - r_t^f)}{\sigma_t^2}$, this equation can be used to estimate the coefficient of relative risk aversion. It, therefore, shows that time-varying expected returns or volatility of returns may generate transitory variation in portfolio composition.

I address the issue of time-variation in expected returns using numerous empirical proxies developed in the literature, namely: the consumption-wealth ratio (Lettau and Ludvigson, 2001), the labor income-consumption ratio (Santos and Veronesi, 2006), the labor income risk (Julliard, 2004), the composition risk (Piazzesi *et al.*, 2007), and the housing collateral ratio (Lustig and Van Nieuwerburgh, 2005). The results show that the ARCH or GARCH specifications do not fit well the wealth growth process, so it does not capture the time-variation in the volatility of returns. Consequently, the analysis will be focusing on the effects of time-varying expected returns.

4.1 Consumption-Wealth Ratio

Lettau and Ludvigson (2001) show that fluctuations in the consumption-wealth ratio, *cay*, summarize changes in expected returns and can be used for predicting stock returns. Investors want to maintain a flat consumption path over time and will attempt to "smooth out" transitory movements in their asset wealth arising from time-variation in asset returns.

In order to capture the effect of changes in expected returns, I include *cay* as an explanatory variable for risky asset allocation. I estimate *cay* as: $cay_t := c_t - 0.42w_t - 0.65y_t$. Table 11 presents a summary of the results. It can be seen that the coefficient associated to *cay* is always significant: an increase of 1% in *cay* generates an increase of 0.349% in the share of stock market wealth. This is consistent with the idea

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[16] It can be interpreted as the wealth elasticity of the marginal utility of wealth, i.e. $\gamma := -W_t \frac{U''(W_t)}{U'(W_t)}$.

that investors increase their exposition to risk when they expect higher returns. Note, however, that the coefficients associated to wealth shocks, as well as the $\bar{R}^2$, are not significantly different from those obtained in previous regressions. The results suggest, therefore, that changes in risky asset allocation are only partially explained by changes in expected returns.

Table 11: Asset allocation and consumption-wealth ratio.

	Financial Wealth $\Delta\rho_t^1$	Housing Wealth $\Delta\rho_t^2$	Stock Market Wealth $\Delta\rho_t^3$	Stock Market Wealth Directly held $\Delta\rho_t^4$	Stock Market Wealth Indirectly held $\Delta\rho_t^5$
Constant	0.000	-0.002	0.008**	0.004	0.0168*
	(1.107)	(-1.275)	(2.336)	(1.077)	(5.095)
ε_t	0.166*	-0.800*	2.735*	2.858*	2.336*
	(7.367)	(-7.442)	(11.864)	(12.260)	(10.678)
cay_t	0.035*	-0.167*	0.294*	0.270**	0.245**
	(3.280)	(-3.492)	(2.737)	(2.351)	(2.180)
$\bar{R}^2$	[0.43]	[0.47]	[0.70]	[0.69]	[0.58]

Symbols *, **, *** represent, respectively, significance level of 1%, 5% and 10%.

Newey and West (1987) corrected t-statistics appear in parenthesis.

The sample period is 1953:4 to 2004:4.

4.2 Labor Income-Consumption Ratio

Santos and Veronesi (2006) propose a model in which investors' income has two sources, wages and dividends, growing stochastically over time. As the fraction of consumption funded by the endowment flow of labor income - i.e. labor income-consumption ratio, lc - fluctuates, the relationship between stock returns and consumption growth varies, thereby generating changes in the risk premia that investors require to hold stocks.

In Table 12, I include lc as an explanatory variable of risky asset allocation. The coefficient associated to lc is small in magnitude and is not significant in most of the regressions, although the sign is consistent with the predictions of the theory: an increase of 1% in lc - or a fall in the fraction of consumption funded by dividends - leads to a decrease of the risky asset share of 0.103%. Moreover, as the coefficients associated to wealth shocks, as well as the $\bar{R}^2$, do not change significantly relative to the previous regressions, the results show that wealth shocks are responsible for most of the variation in portfolio composition.

Table 12: Asset allocation and labor income-consumption ratio.

	Financial Wealth $\Delta\rho_t^1$	Housing Wealth $\Delta\rho_t^2$	Stock Market Wealth $\Delta\rho_t^3$	Stock Market Wealth Directly held $\Delta\rho_t^4$	Stock Market Wealth Indirectly held $\Delta\rho_t^5$
Constant	0.000	-0.001	0.008**	0.004	0.015*
	(0.311)	(-0.276)	(2.371)	(1.026)	(4.584)
ε_t	0.160*	-0.769*	2.678*	2.807*	2.290*
	(7.031)	(-7.202)	(11.563)	(11.989)	(10.253)
lc_t	-0.006	0.024	-0.103**	-0.086***	-0.046
	(-0.800)	(0.699)	(-2.164)	(-1.664)	(-0.942)
$\bar{R}^2$	[0.41]	[0.45]	[0.69]	[0.68]	[0.57]

Symbols *, **, *** represent, respectively, significance level of 1%, 5% and 10%.

Newey and West (1987) corrected t-statistics appear in parenthesis.

The sample period is 1953:4 to 2004:4.

4.3 Labor Income Risk

Julliard (2004) uses the representative consumer's budget constraint to derive an equilibrium relation between future labor income growth rates, lr, and expected future asset returns. The author shows that expectations of high (low) future labor income growth are associated with lower (higher) stock market excess returns.

In order to capture the effect of labor income risk, lr is added as an explanatory variable of portfolio composition. The results, summarized in Table 13, show that labor income risk is a source of variation of risk aversion: the coefficient associated to lr is significant in the regressions with the share of stock market wealth, $\Delta\rho_t^3$, and the share of directly held risky assets, $\Delta\rho_t^4$, as the dependent variables. The coefficients are negative (respectively, -0.704 and -0.806), consistent with a high lr representing a state of the world in which returns on asset wealth are low, because agents expect to have abundance of resources in the future to finance consumption. As before, the coefficients associated to wealth shocks and the $\bar{R}^2$ statistics remain basically unchanged, therefore, suggesting that wealth shocks are important determinants of changes in aggregate portfolio shares.

Table 13: Asset allocation and labor income risk.

	Financial Wealth $\Delta\rho_t^1$	Housing Wealth $\Delta\rho_t^2$	Stock Market Wealth $\Delta\rho_t^3$	Stock Market Wealth Directly held $\Delta\rho_t^4$	Stock Market Wealth Indirectly held $\Delta\rho_t^5$
Constant	0.000	-0.001	0.004	0.001	0.014*
	(0.516)	(-0.551)	(1.506)	(0.418)	(4.609)
ε_t	0.139*	-0.685*	2.872*	3.020*	2.371*
	(6.286)	(-6.150)	(10.224)	(10.635)	(8.592)
lr_t	-0.014	0.058	-0.663**	-0.765**	-0.331
	(-0.459)	(0.411)	(-1.981)	(-2.223)	(-0.879)
$\bar{R}^2$	[0.32]	[0.36]	[0.68]	[0.68]	[0.54]

Symbols *, **, *** represent, respectively, significance level of 1%, 5% and 10%.

Newey and West (1987) corrected t-statistics appear in parenthesis.

The sample period is 1953:4 to 2000:4.

4.4 Non-Separability of Preferences

Yogo (2006) shows that when utility is nonseparable in nondurable and durable consumption and the elasticity of substitution between the two consumption goods is sufficiently high, marginal utility rises when durable consumption falls.[17] Stock returns are unexpectedly low at business cycle troughs, when durable consumption falls sharply, helping to explain the countercyclical variation in the equity premium. Piazzesi *et al.* (2007) explicitly model housing both as an asset and a consumption good. Nonseparable preferences describe households' concern with composition risk, that is, fluctuations of the relative share of non-housing in their consumption basket, φ, the housing share can be used to forecast returns on stocks.

The importance of nondurability of preferences in generating transitory risk aversion is tested in Table 14. It suggests that composition risk does not play a role in asset allocation: the coefficient associated to φ is not significant and is small in magnitude in most of the regressions and the $\bar{R}^2$ statistics remain unchanged.

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[17] Pakos (2003) argues that the falling price of durables raised real income and increased the consumption of durables, i.e. preferences are non-homothetic. On the other hand, Dunn and Singleton (1986) and Eichenbaum and Hansen (1990) report evidence against separabilility of preferences, but conclude that introducing durables does not help in reducing the pricing errors for stocks.

Table 14: Asset allocation and composition risk.

	Financial Wealth $\Delta\rho_t^1$	Housing Wealth $\Delta\rho_t^2$	Stock Market Wealth $\Delta\rho_t^3$	Stock Market Wealth Directly held $\Delta\rho_t^4$	Stock Market Wealth Indirectly held $\Delta\rho_t^5$
Constant	-0.019***	0.084**	0.030	-0.001	0.097
	(-1.913)	(1.980)	(0.318)	(-0.008)	(0.969)
ε_t	0.159*	-0.767*	2.683*	2.810*	2.295*
	(7.234)	(-7.381)	(11.423)	(11.874)	(10.221)
φ_t	-0.091***	0.412**	0.131	-0.006	0.411
	(-1.912)	(1.979)	(0.278)	(-0.012)	(0.837)
$\bar{R}^2$	[0.42]	[0.46]	[0.69]	[0.68]	[0.57]

Symbols *, **, *** represent, respectively, significance level of 1%, 5% and 10%.

Newey and West (1987) corrected t-statistics appear in parenthesis.

The sample period is 1953:4 to 2004:4.

4.5 Housing Collateral Ratio

Lustig and Van Nieuwerburgh (2005) show that the ratio of housing wealth to human wealth shifts the conditional distribution of asset prices and consumption growth and helps predicting stock returns. There are two main channels that transmit shocks originated in the housing market to the risk premia in asset markets: (*i*) when housing prices fall, collateral is destroyed and households are more exposed to idiosyncratic income risk; (*ii*) households want to hedge against rental price shocks or composition shocks when the utility function is nonseparable in nondurable consumption and housing services. Housing provides, therefore, utility and collateral services.

The aggregate stock of housing collateral is measured using the value of residential fixed assets (structures), $hvfa$. The housing collateral ratio, $myfa$, is then computed as the deviation from the cointegration relationship between the value of the aggregate housing stock and the aggregate labor income (both when the coefficient associated with income, ϖ, is restricted to be equal to -1 and when it is freely estimated) and added as an explanatory variable. Appendix A provides a detailed description.

Tables 15 and 16 present a summary of the results and show that $myfa$ is not an important determinant of risk aversion, as the estimated coefficients are not significant. In addition, the coefficients associated to wealth shocks remain significant and the $\bar{R}^2$ are similar to those previously found.

Table 15: Asset allocation and housing collateral ratio (ϖ=−1).

	Financial Wealth $\Delta\rho_t^1$	Housing Wealth $\Delta\rho_t^2$	Stock Market Wealth $\Delta\rho_t^3$	Stock Market Wealth Directly held $\Delta\rho_t^4$	Stock Market Wealth Indirectly held $\Delta\rho_t^5$
Constant	-0.000	0.000	0.004	0.000	0.013*
	(-0.253)	(0.232)	(1.412)	(0.130)	(4.713)
ε_t	0.159*	-0.765*	2.677*	2.804*	2.287*
	(7.132)	(-7.278)	(11.422)	(11.868)	(10.220)
$myfa_t$	-0.003*	0.012*	-0.012	-0.015	-0.013
	(-2.791)	(2.848)	(-1.112)	(-1.189)	(-1.386)
$\bar{R}^2$	[0.43]	[0.47]	[0.69]	[0.68]	[0.57]

Symbols *, **, *** represent, respectively, significance level of 1%, 5% and 10%.

Newey and West (1987) corrected t-statistics in parenthesis. The sample period is 1954:1 to 2004:4.

Table 16: Asset allocation and housing collateral ratio (ϖ is freely estimated).

	Financial Wealth $\Delta\rho_t^1$	Housing Wealth $\Delta\rho_t^2$	Stock Market Wealth $\Delta\rho_t^3$	Stock Market Wealth Directly held $\Delta\rho_t^4$	Stock Market Wealth Indirectly held $\Delta\rho_t^5$
Constant	-0.000	0.000	0.004	0.000	0.013*
	(-0.253)	(0.232)	(1.412)	(0.130)	(4.713)
ε_t	0.159*	-0.765*	2.677*	2.804*	2.287*
	(7.132)	(-7.278)	(11.421)	(11.868)	(10.220)
$myfa_t$	-0.013*	0.055*	-0.053	-0.066	-0.057
	(-2.791)	(2.848)	(-1.112)	(-1.189)	(-1.386)
$\bar{R}^2$	[0.43]	[0.47]	[0.69]	[0.68]	[0.57]

Symbols *, **, *** represent, respectively, significance level of 1%, 5% and 10%.

Newey and West (1987) corrected t-statistics in parenthesis. The sample period is 1954:1 to 2004:4.

5 Long-Run Effects and Inertia in Asset Allocation

In this Section, I look at the long-run effects of wealth shocks and explore the issue of inertia in asset allocation. The previous regressions suggest that there are important wealth effects on asset allocation, but they do not allow us to distinguish between short-run and long-run effects. This distinction is important because we may want to know whether unexpected wealth variation is better characterized as producing transitory effects on portfolio composition or as generating persistent effects on asset allocation.

To assess the long-run effects of wealth shocks, I regress the following specification:

$$\sum_{h=0}^{H} \Delta \rho_{t+h} = \beta_0 + \beta_1 \varepsilon_t + u_t, \tag{10}$$

where H represents the number of quarters and the results.

On the other hand, inertia may also play some role on asset allocation. Changes in wealth may accrue first in the form of riskless, liquid assets such as checking accounts. Additionally, adjustment costs (transaction costs or cognitive costs), limited attention or a belief that changes are transitory may be important. Finally, capital gains and losses on risky assets may have a direct impact on utility (as in loss aversion preferences or narrow framing of risks) or on beliefs about future returns (trend-chasing). In these circumstances, agents will gradually adjust their portfolio composition, implying that the previous regressions using contemporaneous wealth shocks and risky asset holdings are downward biased.

To address the issue of inertia in asset allocation, I include the lag of the change in the portfolio share, $\Delta \rho_{t-1}$, as an explanatory variable and regress the following specification:

$$\sum_{h=0}^{H} \Delta \rho_{t+h} = \beta_0 + \beta_1 \varepsilon_t + \beta_2 \Delta \rho_{t-1} + u_t, \tag{11}$$

where H represents the number of quarters. If inertia results from adjustment costs that are traded off against the benefits of rebalancing, then there could be inertia in the short run, but the share of stock holdings should revert to its optimal level in the long run. On the other hand, if investors chase returns, i.e. increase their exposure to risky assets following a positive wealth shock, then long-run effects would exceed short-run effects.

Table 17 shows that the effects of wealth shocks on the allocation between financial and housing assets are mainly transitory: in the case of the share of financial wealth, $\Delta \rho_t^1$, the $\bar{R}^2$ falls from 0.41 to 0.15 after 2 quarters and wealth shocks explain only 6% of the changes in portfolio composition over the next 3 quarters. Moreover, in the face of a positive wealth shock, agents reduce the share of housing assets, that is, housing is an important hedge against unexpected wealth variation. Table 18 confirms these findings: the effects of wealth shocks are transitory and in the case of the preferred definition of risky asset holdings, $\Delta\rho_t^3$, the $\bar{R}^2$ falls from 0.69 to 0.18 over the next 3 quarters.

By its turn, Tables 19 and 20 suggest that there is very weak evidence of inertia in asset allocation, as agents strongly rebalance their portfolios following a wealth shock: the coefficient associated to the lag of the portfolio share, $\Delta\rho_{t-1}$, is not statistically significant and its magnitude is very close to zero in most of the regressions. This goes against the findings of Brunnermeier and Nagel (2006) who argue that there are important inertia effects at the microeconomic level due to the failure of households to rebalance following capital gains and losses.

These results, therefore, show that the estimates of the wealth effects on asset allocation based on household level data are likely to be under-estimated: due to the poor coverage at the top-level of wealth distribution, where the exposure to risky assets is largest, a large component of the variation of wealth is not captured at the microeconomic level and, as a consequence, the estimates tend to be biased towards rejecting the existence of wealth effects. The use of macroeconomic data avoids this problem and the empirical findings clearly indicate that the risky asset share exhibits a cyclical behavior, whilst housing is an hedge against unexpected wealth variation.

Table 17: Long-run effects of wealth shocks on asset allocation - financial and housing wealth.

	Horizon H			
Regressor	0	1	2	3
	Panel A: Financial Wealth, $\sum_{h=0}^{H}\Delta\rho_{t+h}^1$			
ε_t	0.160*	0.141*	0.145*	0.139*
	(7.278)	(4.742)	(3.776)	(3.135)
$\bar{R}^2$	[0.41]	[0.15]	[0.09]	[0.06]
	Panel B: Housing Wealth, $\sum_{h=0}^{H}\Delta\rho_{t+h}^2$			
ε_t	-0.770*	-0.686*	-0.686*	-0.673*
	(-7.412)	(-4.923)	(-3.791)	(-3.133)
$\bar{R}^2$	[0.45]	[0.16]	[0.10]	[0.07]

Symbols *, ** and *** represent significance at a 1%, 5% and 10% level, respectively.

Newey and West (1987) corrected t-statistics appear in parenthesis.

The sample period is 1953:4 to 2004:4.

Table 18: Long-run effects of wealth shocks on asset allocation - stock market wealth.

	Horizon H			
Regressor	0	1	2	3
Panel A: Stock Market Wealth, $\sum_{h=0}^{H} \Delta\rho_{t+h}^{3}$				
ε_t	2.682*	2.693*	2.724*	2.780*
	(21.291)	(7.052)	(6.014)	(5.495)
$\bar{R}^2$	[0.69]	[0.33]	[0.22]	[0.18]
Panel B: Stock Market Wealth, directly held, $\sum_{h=0}^{H} \Delta\rho_{t+h}^{4}$				
ε_t	2.810*	2.770*	2.815*	2.906*
	(11.910)	(6.964)	(5.907)	(5.310)
$\bar{R}^2$	[0.68]	[0.31]	[0.21]	[0.17]
Panel C: Stock Market Wealth, indirectly held, $\sum_{h=0}^{H} \Delta\rho_{t+h}^{5}$				
ε_t	2.292*	2.369*	2.413*	2.380*
	(10.264)	(7.073)	(6.096)	(5.746)
$\bar{R}^2$	[0.57]	[0.29]	[0.21]	[0.16]

Symbols *, ** and *** represent significance at a 1%, 5% and 10% level, respectively.

Newey and West (1987) corrected t-statistics appear in parenthesis.

The sample period is 1953:4 to 2004:4.

Table 19: Inertia in asset allocation: financial and housing wealth.

	Horizon H			
Regressor	0	1	2	3
	Panel A: Financial Wealth, $\sum_{h=0}^{H} \Delta\rho^1_{t+h}$			
Constant	-0.000	-0.000	-0.000	-0.000
	(-0.280)	(-0.210)	(-0.305)	(-0.438)
ε_t	0.1604*	0.142*	0.146*	0.140*
	(11.983)	(6.064)	(4.722)	(3.748)
$\Delta\rho^1_{t-1}$	0.098***	0.168***	0.195	0.243
	(1.817)	(1.766)	(1.559)	(1.607)
$\bar{R}^2$	[0.41]	[0.16]	[0.10]	[0.07]
	Panel B: Housing Wealth, $\sum_{h=0}^{H} \Delta\rho^2_{t+h}$			
Constant	0.000	0.000	0.001	0.001
	(0.222)	(0.139)	(0.171)	(0.221)
ε_t	-0.772*	-0.689*	-0.690*	-0.678*
	(-7.430)	(-5.074)	(-3.902)	(-3.247)
$\Delta\rho^2_{t-1}$	0.080	0.163	0.202	0.270
	(1.584)	(1.453)	(1.229)	(1.400)
$\bar{R}^2$	[0.45]	[0.17]	[0.11]	[0.08]

Symbols *, ** and *** represent significance at a 1%, 5% and 10% level, respectively.

Newey and West (1987) corrected t-statistics appear in parenthesis. The sample period is 1953:4 to 2004:4.

Table 20: Inertia in asset allocation: stock market wealth.

	Horizon H			
Regressor	0	1	2	3
Panel A: Stock Market Wealth, $\sum_{h=0}^{H} \Delta\rho^3_{t+h}$				
Constant	0.004	0.008	0.012	0.016
	(1.358)	(1.274)	(1.191)	(1.169)
ε_t	2.681*	2.693*	2.725*	2.781*
	(11.681)	(7.032)	(5.982)	(5.455)
$\Delta\rho^3_{t-1}$	0.054***	0.000	-0.023	-0.043
	(1.598)	(0.005)	(-0.172)	(-0.318)
$\bar{R}^2$	[0.69]	[0.32]	[0.22]	[0.17]
Panel B: Stock Market Wealth, Directly held, $\sum_{h=0}^{H} \Delta\rho^4_{t+h}$				
Constant	0.000	0.001	0.002	0.001
	(0.140)	(0.208)	(0.198)	(0.150)
ε_t	2.806*	2.769*	2.816*	2.907*
	(20.849)	(9.587)	(7.433)	(6.488)
$\Delta\rho^4_{t-1}$	0.040	0.009	-0.007	-0.006
	(1.000)	(0.105)	(-0.065)	(-0.047)
$\bar{R}^2$	[0.68]	[0.31]	[0.21]	[0.16]
Panel C: Stock Market Wealth, Indirectly held, $\sum_{h=0}^{H} \Delta\rho^5_{t+h}$				
Constant	0.012*	0.027*	0.041*	0.054*
	(4.365)	(4.324)	(4.138)	(4.182)
ε_t	2.300*	2.367*	2.405	2.370*
	(10.526)	(7.058)	(5.985)	(5.607)
$\Delta\rho^5_{t-1}$	0.068***	-0.017	-0.064	-0.082
	(1.817)	(-0.184)	(-0.462)	(-0.667)
$\bar{R}^2$	[0.58]	[0.29]	[0.21]	[0.16]

Symbols *, ** and *** represent significance at a 1%, 5% and 10% level, respectively.

Newey and West (1987) corrected t-statistics appear in parenthesis. The sample period is 1953:4 to 2004:4.

6 Asset Allocation in a VAR Framework: a Skeptical Look

As a robustness check of the previous results, I analyze the importance of wealth effects on asset allocation in a more structural framework. I estimate the following Vector Autoregressive Model (VAR)

$$\mathbf{X}_t = \theta + B(L)\mathbf{X}_{t-1} + \mathbf{\Psi}\mathbf{Z}_{t-1} + \Upsilon_t, \tag{12}$$

where $X_t = (\Delta\rho_t, \Delta w_t, \Delta c_t, \Delta y_t, r_t)$ is the vector of the change of share of risky assets in financial wealth, wealth growth, consumption growth, income growth, and real returns on financial assets, $B(L)$ is a finite-order distributed lag operator, $Z_{t-1} = (cay_{t-1}, d_{t-1} - p_{t-1}, RREL_{t-1}, DEF1_{t-1}, DEF2_{t-1}, TRM_{t-1})$ is a vector of exogenous variables including the consumption-wealth ratio, *cay*, the dividend yield, the relative bill rate, the default rates (the Moody's BAA corporate bond rate minus the AAA corporate bond rate and the Moody's BAA corporate bond yield minus the 10-year Treasury bond yield) and the term spread (the 10-year Treasury bond yield minus the 3-month Treasury bond yield), $\mathbf{\Psi}$ is a matrix of coefficients associated with Z_{t-1}, Υ_t is a vector of error terms, and θ is a vector of constants.[18]

Using the VAR in specification (12), I assess the effect of a wealth shock.[19] Under a diffuse prior, the posterior distribution of the estimated VAR can be factorized as the product of an inverse Wishart and, conditional on the covariance matrix, a multivariate normal distribution

$$\beta|_\Sigma \sim N(\overset{\wedge}{\beta}, \Sigma \otimes (X'X)^{-1})$$

$$\Sigma^{-1} \sim Wishart((n\overset{\wedge}{\Sigma})^{-1}, n-m)$$

where β is the vector of VAR coefficients, Σ is the covariance matrix of the residuals, the variables with a hat denote the corresponding estimates, X is the matrix of regressors, n is the sample size and m is the number of estimated parameters (Zellner, 1971; Schervish, 1995; Bauwens *et al.*, 1999).[20] I compute 50,000 draws from the posterior distribution of the VAR coefficients and report 95 percent confidence intervals from the Monte Carlo iterations. The procedure is described in Appendix E.

Table 21 summarizes the results and shows that: (*i*) lagged changes in wealth do not explain the changes in the risky asset share, suggesting that wealth effects on asset allocation are transitory and there is no inertia on asset allocation; and (*ii*) lagged returns do not forecast future returns, but *cay* contains important predictive power, consistent with the findings of Lettau and Ludvigson (2001). Figure 2 shows the impulse-response functions to a wealth shock. Consistently, wealth shocks have a

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[18] The selected optimal lag length is 1, in accordance with findings from Akaike and Schwarz tests.

[19] The Granger Causality tests with 4 lags clearly indicate that causality runs one-way from wealth shocks to asset allocation.

[20] This result is exact under normality and the Jeffrey's prior $f(\beta, \Sigma) \infty |\Sigma|^{-(p+1)/2}$ (where p is the number of left hand side variables), but can also be obtained as an asymptotic approximation around the posterior MLE.

positive (although temporary) effect on the risky asset share. Following a shock, agents rebalance their portfolios, wealth mean-reverts and the effect erodes over the next four quarters.

Table 21: Stock market wealth: estimates from vector-autoregressions (VAR).

	Equation				
Dependent variable	$\Delta\rho_t$	Δw_t	Δc_t	Δy_t	r_t
$\Delta\rho_{t-1}$	0.047	-0.013	0.006	0.018	-0.372**
	(1.240)	(-0.623)	(0.716)	(0.967)	(-2.060)
Δw_{t-1}	-0.180	0.022	-0.031	-0.090	1.227**
	(-1.434)	(0.325)	(-1.096)	(-1.457)	(2.071)
Δc_{t-1}	-0.137	0.165	0.179*	0.464*	0.451
	(-0.425)	(0.962)	(2.478)	(2.935)	(0.296)
Δy_{t-1}	-0.070	0.134	0.077**	-0.120	-0.244
	(-0.443)	(1.589)	(2.177)	(-1.548)	(-0.326)
r_{t-1}	0.721*	0.221*	0.015*	0.020**	-0.065
	(42.451)	(24.471)	(3.923)	(2.372)	(-0.808)
Constant	-0.067**	0.003	0.015**	-0.013	0.137
	(-2.110)	(0.202)	(2.118)	(-0.839)	(0.905)
cay_{t-1}	0.018	-0.043	-0.076*	-0.037	1.260*
	(0.205)	(-0.930)	(-3.868)	(-0.866)	(3.047)
$d_{t-1} - p_{t-1}$	-1.262***	0.124	0.251***	-0.362	-1.823
	(-1.908)	(0.353)	(1.693)	(-1.114)	(0.582)
$RREL_{t-1}$	-0.075	0.249*	-0.019	-0.049	-1.514**
	(-0.493)	(3.072)	(-0.562)	(-0.650)	(-2.104)
$DEF1_{t-1}$	0.477	-0.315	-0.170	-0.311	-0.099
	(0.582)	(-0.720)	(-0.924)	(-0.773)	(0.025)
$DEF2_{t-1}$	-0.173	0.193	0.021	0.076	-0.688
	(-0.422)	(0.880)	(0.230)	(0.379)	(-0.353)
TRM_{t-1}	0.017	0.126***	0.099*	0.069	-0.556
	(0.132)	(1.851)	(3.432)	(1.092)	(-0.916)
$\bar{R}^2$	[0.93]	[0.80]	[0.25]	[0.11]	[0.09]

This table reports the estimated coefficients from vector-autoregressions (VAR).

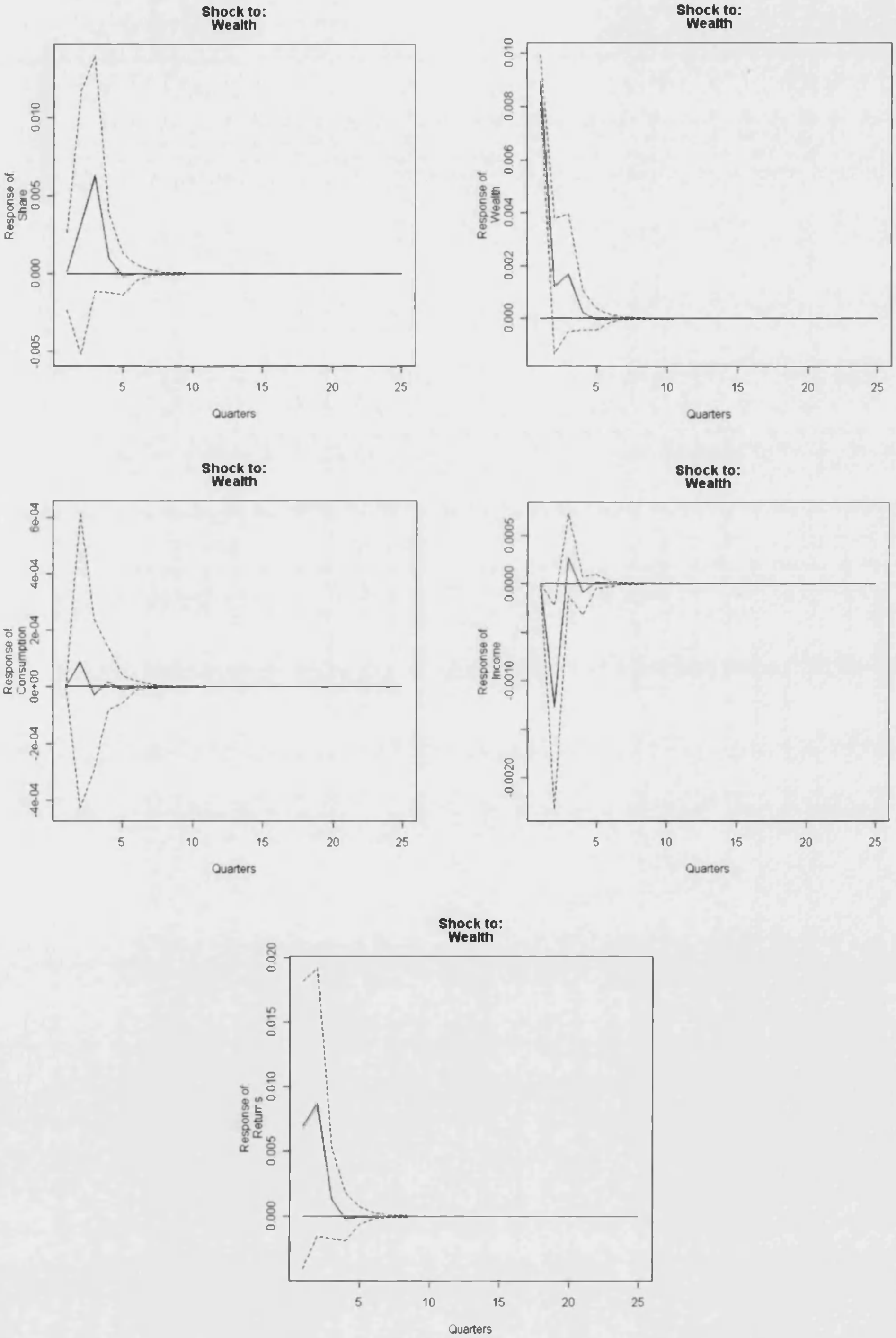
Symbols *, **, *** represent, respectively, significance level of 1%, 5% and 10%.

Newey-West (1987) corrected t-statistics appear in parenthesis. The sample period is 1953:4 to 2004:4.

Figure 2: Impulse-response functions to an aggregate wealth's shock.

The picture depicts the response to a one standard-deviation shock to aggregate wealth.

95% confidence intervals computed using the Markov chain Monte Carlo algorithm.



7 Conclusion

This paper tests the assumption of constant relative risk aversion using U.S. quarterly data for the period 1953:4 - 2004:4. I use macroeconomic data to analyze the role of wealth shocks in generating transitory changes in portfolio composition.

The main finding is that the risky asset share exhibits a cyclical behavior and, unlike Brunnermeier and Nagel (2006), it is significantly (and positively) affected by wealth shocks. There is, therefore, evidence suggesting that risk aversion is countercyclical and supporting the existence of preferences that depart from the assumption of constant relative risk aversion such as habit-formation or wealth-dependent utility functions. Additionally, it is shown that the share of housing wealth in portfolio falls when the agent is faced with a positive wealth shock, i.e. housing is a hedge against unexpected wealth variation.

Looking at the composition of risky asset holdings, the results suggest that wealth effects are slightly stronger for direct holdings than for indirect holdings. This is in accordance with the findings of Samuelson and Zeckhauser (1988), Ameriks and Zeldes (2004), Agnew *et al.* (2003) and Huberman and Sengmueller (2004), who show that a substantial fraction of agents do not trade at all in some categories of assets such as retirement accounts.

Controlling for changes in expected asset returns, it is shown that consumption-wealth ratio (Lettau and Ludvigson, 2001), the labor income risk (Julliard, 2004) and the labor income-consumption ratio (Santos and Veronesi, 2006) partially explain the changes in risky asset allocation. Nevertheless, wealth shocks remain important determinants of risk aversion.

Finally, considering a variety of wealth definitions, the empirical findings suggest that, although significant, wealth effects on asset allocation are mainly temporary as agents quickly rebalance the portfolio composition. In fact, and contrary to Brunnermeier and Nagel (2006), there is weak evidence of inertia or slow adjustment in asset allocation.

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Appendix

A Data Description

Consumption

Consumption is defined as the expenditure in non-durable consumption goods and services. Data are quarterly, seasonally adjusted at an annual rate, measured in billions of dollars (2000 prices), in per capita terms and expressed in the logarithmic form. Series comprises the period 1947:1-2005:4. The source is U.S. Department of Commerce, Bureau of Economic Analysis, NIPA Table 2.3.5.

Aggregate Wealth

Aggregate wealth is defined as the net worth of households and nonprofit organizations. Data are quarterly, seasonally adjusted at an annual rate, measured in billions of dollars (2000 prices), in per capita terms and expressed in the logarithmic form. Series comprises the period 1952:2-2006:1. The source of information is Board of Governors of Federal Reserve System, Flow of Funds Accounts, Table B.100, line 41 (series FL152090005.Q).

Stock market Wealth

Stock market wealth is defined as the sum of value of stocks, directly and indirectly held, namely: (a) stocks held by households – direct property (line 23 of Table B.100 - series FL153064105.Q); (b) stocks held by private pension funds (line 12 of Table L.118 - series FL573064105.Q); (c) stocks held by state and local government retirement funds (line 13 of Table L.119 - series FL223064105.Q); (d) stocks held by federal government retirement funds (line 6 of Table L. 120 - series FL343064105.Q); (e) stocks held by property-casualty insurance companies (line 10 of Table L.116 - series FL513064003.Q); (f) stocks held by closed-end funds (line 6 of Table L.123 - series FL553064103.Q); (g) stocks held by exchange-traded funds (line 12 of Table L.123 - series FL563064103.Q); (h) stocks held by mutual funds (line 9 of Table L.122 - series FL653064000.Q); and (i) stocks held by life insurance companies (line 12 of Table L.117 - series FL543064105.Q), multiplied by the ratio of reserves of life insurance companies (lines 17 and 18 of Table L.117 - series FL543140003.Q and series FL543150005.Q) to the total final assets of life insurance companies (line 1 of Table L.117 - series FL544090005.Q). This definition follows Davis e Palumbo (2001). Data are quarterly, seasonally adjusted at an annual rate, measured in billions of dollars (2000 prices), in per capita terms and expressed in the logarithmic form. Series comprises the period 1952:2-2006:1. The source of information is Board of Governors of Federal Reserve System, Flow of Funds Accounts.

Stock Market wealth, Directly Held

Stock market wealth (directly held) is defined as the sum of value of stocks held by households (line 23 of Table B.100 - series FL153064105.Q). Data are quarterly, seasonally adjusted at an annual rate, measured in billions of dollars (2000 prices), in per capita terms and expressed in the logarithmic form. Series comprises the period 1952:2-2006:1. The source of information is Board of Governors of Federal Reserve System, Flow of Funds Accounts.

Stock Market Wealth, Indirectly Held

Stock market wealth (indirectly held) is defined as the sum of value of: (a) stocks held by private pension funds (line 12 of Table L.118 - series FL573064105.Q); (b) stocks held by state and local government retirement funds (line 13 of Table L.119 - series FL223064105.Q); (c) stocks held by federal government retirement funds (line 6 of Table L. 120 - series FL343064105.Q); (d) stocks held by property-casualty insurance companies (line 10 of Table L.116 - series FL513064003.Q); (e) stocks held by closed-end funds (line 6 of Table L.123 - series FL553064103.Q); (f) stocks held by exchange-traded funds (line 12 of Table L.123 - series FL563064103.Q); (g) stocks held by mutual funds (line 9 of Table L.122 - series FL653064000.Q); and (h) stocks held by life insurance companies (line 12 of Table L.117 - series FL543064105.Q), multiplied by the ratio of reserves of life insurance companies (lines 17 and 18 of Table L.117 - series FL543140003.Q and series FL543150005.Q) to the total final assets of life insurance companies (line 1 of Table L.117 - series FL544090005.Q). Data are quarterly, seasonally adjusted at an annual rate, measured in billions of dollars (2000 prices), in per capita terms and expressed in the logarithmic form. Series comprises the period 1952:2-2006:1. The source of information is Board of Governors of Federal Reserve System, Flow of Funds Accounts.

Non-Stock Market Wealth

Non-Stock market wealth is defined as the difference between aggregate net wealth, held by households and nonprofit organizations (line 41 of Table B.100 - series FL152090005.Q) and stock market wealth (see previous definition). This definition follows Davis e Palumbo (2001). Data are quarterly, seasonally adjusted at an annual rate, measured in billions of dollars (2000 prices), in per capita terms and expressed in the logarithmic form. Series comprises the period 1952:2-2006:1. The source of information is Board of Governors of Federal Reserve System, Flow of Funds Accounts.

After-Tax Labor Income

After-tax labor income is defined as the sum of wage and salary disbursements (line 3), personal current transfer receipts (line 16) and employer contributions for employee pension and insurance funds (line 7) minus personal contributions for government social insurance (line 24), employer contributions for government social insurance (line 8) and taxes. Taxes are defined as: [(wage and salary disbursements (line 3)) / (wage and salary disbursements (line 3)+ proprietor' income with inventory valuation and capital consumption adjustments (line 9) + rental income of persons with capital consumption adjustment (line 12) + personal dividend income (line 15) + personal interest income (line 14))] * (personal current taxes (line 25)). Data are quarterly, seasonally adjusted at annual rates, measured in billions of dollars (2000 prices), in per capita terms and expressed in the logarithmic form. Series comprises the period 1947:1-2005:4. The source of information is U.S. Department of Commerce, Bureau of Economic Analysis, NIPA Table 2.1..

Financial Returns

The proxy chosen for the market return is the value weighted CRSP (CRSP-VW) market return index. The CRSP index includes NYSE, AMEX and NASDAQ, and should provide a better proxy for market returns than the Standard & Poor (S&P) index since it is a much broader measure. Data are quarterly, deflated by the personal consumption chain-weighted index (2000=100) and expressed in the logarithmic form. Series comprises the period 1947:2-2004:4. The source of information is Robert Shiller's web site.

Housing Returns

In computing housing returns, I follow Lustig and Van Nieuwerburgh (2006). I construct data on the log change in the value of the aggregate housing stock (Δp_{t+1}^h) and the log change in the dividend payments on the aggregate housing stock (Δd_{t+1}^h). The aggregate housing stock is measured as the value of residential real estate of the household sector (Flow of Funds Accounts, Board of Governors of Federal Reserve System, line 4 of Table B.100, series FL155035015.Q). The dividend on aggregate housing is measured as housing services consumption (U.S. Department of Commerce, Bureau of Economic Analysis, NIPA Table 2.3.5., line 14). I construct a log price index p^h by fixing the 1952:1 observation to 0, and using the log change in prices in each quarter. Likewise, we choose an initial log dividend level, and construct the dividend index using log dividend growth. The log dividend price ratio $d^h - p^h$ is the difference of the log dividend and the log price index. The initial dividend index level is chosen to match the mean log dividend price ratio to the one on stocks (-4.6155) (in the model the mean dividend price ratios are the same on all assets). I use the Campbell-Shiller decomposition:

$$r_t^h = k + \Delta d_t^h + (d_{t-1}^h - p_{t-1}^h) - v(d_t^h - p_t^h).$$

where υ and k are Campbell Shiller linearization constants. In the model, these constants must be the same for all assets (financial wealth, housing wealth and human wealth). I use stock market data to pin down υ and k: $\upsilon := \frac{1}{1+\overline{d^a-p^a}} = 0.9906$ and $k := -\log(\upsilon) - (1-\upsilon)\log(\upsilon^{-1}-1) = 0.0534$. Data are quarterly, deflated by the personal consumption chain-weighted index (2000=100) and expressed in the logarithmic form. Series comprises the period 1952:2-2005:4.

Human Capital Returns

In computing human capital returns, I follow Lustig and Van Nieuwerburgh (2006). The authors use a standard single-agent model and impute the residual of consumption growth innovations that cannot be attributed to either news about financial asset returns or future labor income growth to news about expected future returns on human wealth. This accounting procedure only depends on the agent's willingness to substitute consumption over time, not her consumption risk preferences. The benchmark calibration sets the intertemporal elasticity of substitution to 0.28, a compromise between the estimates of Hall (1988) at the macroeconomic level - close to 0 - and the estimates of Browning, Hansen and Heckman (2000) at the microeconomic level - around 0.5. Data are quarterly, deflated by the personal consumption chain-weighted index (2000=100) and expressed in the logarithmic form. Series comprises the period 1952:1-2002:4.

Housing Collateral

Aggregate stock of housing collateral is computed using the current cost of net stock of owner-occupied and tenant-occupied residential fixed assets for non-farm persons (NIPA Fixed Asset Table 2.1., line 59). It includes 1-4 units and 5+ units and is the sum of new units, additions and alterations, major replacements and mobile homes. The real value of the stock is calculated with a perpetual inventory method and a geometric depreciation pattern (Katz and Herman, 1997). Depreciation rates are estimated on the basis of resale prices of used assets and are 1.1% per annum for 1-4 units and 1.4% per annum for 5+ structures. The net stock corresponds to the stock after taking into account depreciation. The current cost or replacement cost values the real stock refers to market prices. Original data are annual and are converted to a quarterly frequency using data for residential fixed investment (NIPA Table 1.1.5., line 11). Data comprises the period 1947:1 - 2004:4. The source of information is U.S. Department of Commerce, Bureau of Economic Analysis.

Following Lustig and Van Nieuwerburgh (2005), I measure the aggregate stock of housing collateral using the value of residential fixed assets (structures), $hvfa$. Table A.1 reports the results of the vector error correction estimation of the cointegration coefficients:

$$\begin{bmatrix} \Delta hvfa_t \\ \Delta y_t \end{bmatrix} = \alpha\left[hvfa_t + \varpi y_t + \vartheta t + \chi\right] + \sum_{k=1}^{K} D_k \begin{bmatrix} \Delta hvfa_{t-k} \\ \Delta y_{t-k} \end{bmatrix} + \eta_t.$$

The housing collateral ratio, $myfa$, is measured as the deviation from the cointegration relationship between the value of the aggregate housing stock (collateralizable wealth) and the aggregate labor income (noncollateralizable wealth), i.e.: $myfa_t = \log(hvfa_t) + \hat{\varpi}\log(y_t) + \hat{\vartheta} t + \hat{\chi}$. I also estimate the cointegrating relationship while imposing the restriction $\varpi = -1$.

Table A1: Housing collateral ratio: coefficients of myfa_t.

Housing Wealth Measure: Fixed Assets, fa		
ϖ	ϑ	χ
Unrestricted		
-0.224	-0.004	-7.386
(-0.595)	(-1.970)	
Restricted		
-1	-0.019	-32.923
	(-2.375)	

Symbols *, **, *** represent, respectively, significance level of 1%, 5% and 10%.

Newey and West (1987) corrected t-statistics appear in parenthesis.

The sample period is 1953:4 to 2004:4.

Population

Population was defined by dividing aggregate real disposable income (line 35) by per capita disposable income (line 37). Data are quarterly. Series comprises the period 1946:1-2005:4. The source of information is U.S. Department of Commerce, Bureau of Economic Analysis, NIPA Table 2.1.

Price Deflator

The nominal wealth, after-tax income, consumption, and interest rates were deflated by the personal consumption expenditure chain-type price deflator (2000=100), seasonally adjusted. Data are quarterly. Series comprises the period 1947:1-2005:4. The source of information is U.S. Department of Commerce, Bureau of Economic Analysis, NIPA Table 2.3.4., line 1.

Inflation Rate

Inflation rate was computed from price deflator. Data are quarterly. Series comprises the period 1947:2-2005:4. The source of information is U.S. Department of Commerce, Bureau of Economic Analysis, NIPA Table 2.3.4, line 1.

Interest Rate ("Risk-Free Rate")

Risk-free rate is defined as the 3-month U.S. Treasury bills real interest rate. Original data are monthly and are converted to a quarterly frequency by computing the simple arithmetic average of three consecutive months. Additionally, real interest rates are computed as the difference between nominal interest rates and the inflation rate. The 3-month U.S. Treasury bills real interest rate' series comprises the period 1947:2-2005:4, and the source of information is the H.15 publication of the Board of Governors of the Federal Reserve System.

B Derivation of the Risky Asset Share

The dynamics of the linear habit presented in Equation (2) can be written as a differential equation as:

$$dXt = (bC_t - aX_t)\,dt, \tag{13}$$

and the wealth dynamics (Equation (3)) becomes:

$$\frac{dW_t}{W_t} = \left[(r + \alpha_t(\mu_t - r)) - \frac{C_t}{W_t}\right] dt + \sigma_{p,t} dZ_t. \tag{14}$$

Both differential equations involve the consumption term of the agent.

Following Schroder and Skiadas (2002), the agent's consumption can be written in terms of the consumption of an agent without habit. Let $\hat{C}_t/\hat{W}_t$ be the consumption-wealth ratio of an agent without habit. If expected returns are not time-varying, $\hat{C}_t/\hat{W}_t$ is constant. The optimal consumption-wealth ratio of an agent with habit is given by

$$\frac{C_t}{W_t} = \frac{X_t}{W_t} + \left(\frac{r + a - b - \frac{X_t}{W_t}}{r + a - b + 1}\right)\frac{\hat{C}_t}{\hat{W}_t} = f\left(\frac{X_t}{W_t}, \frac{\hat{C}_t}{\hat{W}_t}\right), \tag{15}$$

and is a function of X_t/W_t.

Replacing the drift term of the wealth differential equation with $\mu_W(\alpha_t, \frac{X_t}{W_t}, \frac{\hat{C}_t}{\hat{W}_t}\mu_t) := r + \alpha_t(\mu_t - r) - f(\frac{X_t}{W_t}, \frac{\hat{C}_t}{\hat{W}_t})$, defining $w_t := \log(W_t)$, and applying Ito's lemma, one obtains

$$dw_t = \mu_w\left(\alpha_t, \frac{X_t}{W_t}, \frac{\hat{C}_t}{\hat{W}_t}, \mu_t\right) dt - \sigma_{p,t} dZ_t, \tag{16}$$

where $\mu_w\left(\alpha_t, \frac{X_t}{W_t}, \frac{\hat{C}_t}{\hat{W}_t}, \mu_t\right) := \mu_W\left(\alpha_t, \frac{X_t}{W_t}, \frac{\hat{C}_t}{\hat{W}_t}, \mu_t\right) - \frac{1}{2}\sigma_{p,t}^2$.

Similarly, substituting consumption out of the dX equation yields:

$$dX_t = \left(bW_t f(\frac{X_t}{W_t}, \frac{\hat{C}_t}{\hat{W}_t}) - aX_t\right) dt. \tag{17}$$

Applying Ito's lemma to $x_t := \log(X_t)$, one obtains:

$$dx_t = \left(b\frac{f(\frac{X_t}{W_t}, \frac{\hat{C}_t}{\hat{W}_t})}{\frac{X_t}{W_t}} - a\right) dt =: \mu_x\left(\frac{X_t}{W_t}, \frac{\hat{C}_t}{\hat{W}_t}\right) dt. \tag{18}$$

Defining $y_t := \log\left(\frac{X_t}{W_t}\right) = x_t - w_t$, it follows that:

$$dy_t = \left(\mu_x\left(\frac{X_t}{W_t}, \frac{\hat{C}_t}{\hat{W}_t}\right) - \mu_w\left(\alpha_t, \frac{X_t}{W_t}, \frac{\hat{C}_t}{\hat{W}_t}, \mu_t\right)\right) dt - \sigma_{p,t} dZ_t. \tag{19}$$

Equation (4) can now be written as:

$$\alpha_t = \left(1 - \frac{e^{y_t}}{r + a - b}\right)\hat{\alpha}_t. \tag{20}$$

Applying Ito's lemma again, one gets:

$$d\alpha_t = -\hat{\alpha}_t \frac{e^{y_t}}{r + a - b}\left(dy_t + \frac{1}{2}\sigma_{p,t}^2\right). \tag{21}$$

Using $1 - \frac{\alpha_t}{\hat{\alpha}_t} = \frac{e^{y_t}}{r+a-b}$,

$$d\alpha_t = -\left(\hat{\alpha}_t - \alpha_t\right)\left(dy_t + \frac{1}{2}\sigma_{p,t}^2\right) = \left(\hat{\alpha}_t - \alpha_t\right)\left[dw_t - dx_t - \frac{1}{2}\sigma_{p,t}^2\right] \tag{22}$$

$$= \left(\hat{\alpha}_t - \alpha_t\right)\left\{\left[\mu_w\left(\alpha_t, \frac{X_t}{W_t}, \frac{\hat{C}_t}{\hat{W}_t}, \mu_t\right) - \mu_x\left(\frac{X_t}{W_t}, \frac{\hat{C}_t}{\hat{W}_t}\right) - \frac{1}{2}\sigma_{p,t}^2\right] dt + \sigma_{p,t} dZ_t\right\}. \tag{23}$$

Finally, defining $\rho_t := log(\alpha_t)$, and from Ito's lemma, Equation (5) can be written as:

$$d\rho_t = \left(\frac{\hat{\alpha}_t}{\alpha_t} - 1\right)\left\{\left[\mu_w\left(\alpha_t, \frac{X_t}{W_t}, \frac{\hat{C}_t}{\hat{W}_t}, \mu_t\right) - \mu_x\left(\frac{X_t}{W_t}, \frac{\hat{C}_t}{\hat{W}_t}\right) - \frac{1}{2}\sigma_{p,t}^2 - \frac{1}{2}\left(\frac{\hat{\alpha}_t - \alpha_t}{\alpha_t}\right)\sigma_{p,t}^2\right] dt + \sigma_{p,t} dZ_t\right\} \tag{24}$$

$$= \left(\frac{\hat{\alpha}_t}{\alpha_t} - 1\right) \left\{ \left[\mu_w \left(\alpha_t, \frac{X_t}{W_t}, \frac{\hat{C}_t}{\hat{W}_t}, \mu_t \right) - \mu_x \left(\frac{X_t}{W_t}, \frac{\hat{C}_t}{\hat{W}_t} \right) - \frac{\hat{\alpha}_t}{2\alpha_t} \sigma_{p,t}^2 \right] dt + \sigma_{p,t} dZ_t \right\}. \tag{25}$$

C Estimation of Wealth Shocks

In order to model the wealth process, I experimented with several specifications in the ARIMA class, and performed the standard set of Box-Jenkins selection procedures. In particular, among the models considered, ARMA(2,3) process fits well to first differences of log wealth and hence I restricted attention to the ARIMA(2,1,3) specification for log wealth. Thus, the fitted wealth specification is:

$$\Delta w_t = \mu_w + \nu_1 \Delta w_{t-1} + \nu_2 \Delta w_{t-2} + \eta_t + \vartheta_1 \eta_{t-1} + \vartheta_2 \eta_{t-2} + \vartheta_3 \eta_{t-3}$$

where η_t is the time t innovation, ν's are auto-regressive coefficients and ϑ's are moving average coefficients. The estimated coefficients are reported in Table C.1.

Table C1: Estimated wealth process.

$\hat{\mu}_w$	$\hat{\nu}_1$	$\hat{\nu}_2$	$\hat{\vartheta}_1$	$\hat{\vartheta}_2$	$\hat{\vartheta}_3$
0.006	0.379	-0.896	-0.320	0.943	0.110
(0.0016)	(0.0336)	(0.0371)	(0.0868)	(0.0394)	(0.0817)

Newey-West standard errors appear in parenthesis.

D Human Wealth

Julliard (2004) points out that claims on non-traded labor income represent roughly two thirds of overall wealth in the major industrialized countries. Following Roll (1977)'s critique, the literature has recognized the importance of human wealth returns as part of the market return (Shiller, 1995; Campbell, 1996; Jagannathan and Wang, 1996).

If labor income was riskless, then human wealth, H_t, would be considered as a riskless asset. Additionally, since human wealth is non-tradeable, the optimal portfolio shares, α_t and $\hat{\alpha}_t$, would be the shares of risky assets in total wealth including human wealth (Campbell and Viceira, 2002). Denoting non-human wealth by W_t, and defining $\alpha_{N,t}$ as the share of risky assets in non-human wealth, then:

$$\alpha_{N,t} W_t = \alpha_t (W_t + H_t). \tag{26}$$

With $\rho_{N,t} := \log(\alpha_{N,t})$, it is possible to derive:

$$d\rho_{N,t} = d\rho_t + d\log(Wt + Ht) - d\log(Wt). \tag{27}$$

Using Ito's Lemma, one obtains

$$d\rho_{N,t} = d\rho_t + \psi_t dt - \theta_t \sigma_{p,t} dZ_t, \tag{28}$$

where $\theta_t := \frac{H_t}{W_t + H_t}$, and ψ_t is a time-varying drift term. Therefore, even though a positive shock to non-human wealth ($dZ_t > 0$) leads to $d\rho_t > 0$, it is not clear that $d\rho_{N,t} > 0$, because there is a countervailing effect ($-\theta_t \sigma_{p,t} dZ_t < 0$). Consequently, the wealth shock should be interacted with θ_t, which is related to the human wealth/total wealth ratio H_t/W_t. Human wealth is approximated to current labor income, Y_t, times a (growing) annuity factor, A, as it is not directly observable, i.e. $\theta_t \approx a_0 + a_1 (y_t - w_t) + log(A)$, where y_t is the log labor income. Table D.1 summarizes the estimations for which income growth is included as an explanatory variable, suggesting that it is not an important determinant of portfolio composition.

On the other hand, if labor income is risky but uncorrelated with risky asset returns, the direction of the effect would be the same but smaller in magnitude. By its turn, if labor income is positively correlated with asset returns, the effects of labor income can go in the opposite direction and the effects of wealth shocks could be amplified rather than dampened. As a robustness check, I replace income growth by income shocks - proxied by the residuals of the labor income growth equation from the reduced-form vector auto-regression model (VAR) - as an explanatory variable. Table D.2 shows that the coefficients associated to income shocks are small in magnitude and not significant. Therefore, the risky labor income story does not change the previous results.

Table D.1: Asset allocation and human wealth.

	Financial Wealth $\Delta\rho_t^1$	Home Wealth $\Delta\rho_t^2$	Stock Market Wealth $\Delta\rho_t^3$	Stock Market Wealth Directly held $\Delta\rho_t^4$	Stock Market Wealth Indirectly held $\Delta\rho_t^5$
Constant	0.000	-0.000	0.005	0.001	0.014*
	(0.206)	(-0.256)	(1.394)	(0.238)	(4.551)
ε_t	0.163*	-0.785*	2.697*	2.819*	2.305*
	(7.547)	(-7.697)	(11.747)	(12.102)	(10.349)
Δy_t	-0.028	0.135	-0.134	-0.089	-0.121
	(-1.031)	(1.098)	(-0.443)	(-0.268)	(-0.419)
$\bar{R}^2$	[0.41]	[0.45]	[0.69]	[0.68]	[0.57]

Symbols *, **, *** represent, respectively, significance level of 1%, 5% and 10%.

Newey and West (1987) corrected t-statistics appear in parenthesis.

The sample period is 1953:4 to 2004:4.

Table D.2: Asset allocation and income risk - labor income shocks from VAR system.

	Financial Wealth $\Delta\rho_t^1$	Home Wealth $\Delta\rho_t^2$	Stock Market Wealth $\Delta\rho_t^3$	Stock Market Wealth Directly held $\Delta\rho_t^4$	Stock Market Wealth Indirectly held $\Delta\rho_t^5$
Constant	-0.000	0.000	0.004	0.000	0.013*
	(-0.238)	(0.220)	(1.405)	(0.129)	(4.689)
ε_t	0.158*	-0.761*	2.663*	2.790*	2.272*
	(7.327)	(-7.476)	(11.409)	(11.798)	(10.091)
ξ_t^y	0.026	-0.117	0.255	0.269	0.265
	(0.894)	(-0.930)	(0.819)	(0.746)	(0.953)
$\bar{R}^2$	[0.41]	[0.45]	[0.69]	[0.68]	[0.57]

Symbols *, **, *** represent, respectively, significance level of 1%, 5% and 10%.

Newey and West (1987) corrected t-statistics appear in parenthesis.

The sample period is 1953:4 to 2004:4.

Finally, Table D.3 estimates the role of human capital returns on asset allocation, following the computation described in Appendix A. The results show that returns on human capital are not important determinants of the changes in portfolio composition: the coefficients are small in magnitude and not significant.

Table D.3: Asset allocation and returns on human capital.

	Financial Wealth $\Delta\rho_t^1$	Home Wealth $\Delta\rho_t^2$	Stock Market Wealth $\Delta\rho_t^3$	Stock Market Wealth Directly held $\Delta\rho_t^4$	Stock Market Wealth Indirectly held $\Delta\rho_t^5$
Constant	-0.000	0.000	0.003	-0.017*	0.011*
	(-0.129)	(0.050)	(0.882)	(-4.709)	(3.875)
ε_t	0.160*	-0.776*	2.693*	2.844*	2.275*
	(7.094)	(-7.260)	(11.280)	(12.227)	(9.994)
r_t^h	0.006	-0.005	0.462	0.224	0.606**
	(0.215)	(-0.039)	(1.614)	(0.777)	(2.336)
$\bar{R}^2$	[0.41]	[0.45]	[0.69]	[0.72]	[0.58]

Symbols *, **, *** represent, respectively, significance level of 1%, 5% and 10%.

Newey and West (1987) corrected t-statistics appear in parenthesis.

The sample period is 1953:4 to 2002:4.

E Assessing Uncertainty

To assess uncertainty in the regression results in Table 21, I report 95 percent confidence intervals for the estimated slope coefficients constructed via Monte Carlo integration by drawing from the posterior distribution of the estimated VAR coefficients. I proceed as follows:

1. I draw covariance matrices $\grave{\Sigma}$ from the inverse Wishart with parameters $(n\hat{\Sigma})^{-1}$ and $n-m$.

2. Conditional on $\grave{\Sigma}$, I draw a vector of coefficients for the VAR, $\grave{\beta}$, from $\grave{\beta} \sim N(\hat{\beta}, \grave{\Sigma} \otimes (X'X)^{-1})$.

3. I repeat this procedure 50,000 times and construct the median and slope OLS coefficients associated to the VAR, and the 95 percent confidence intervals from the Monte Carlo iterations.

Chapter III

Monetary Policy and Housing Prices

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Abstract

According to popular wisdom, recent run ups in housing prices have been caused by lower interest rates, and increased credit availability. This paper investigates empirically the link between interest rate movements and residential housing prices in the U.S. and the U.K. using a Structural Vector Autoregression approach. We find that monetary policy contractions have a large and negative impact on housing prices. Moreover, the reaction of housing prices to interest rate shocks is extremely slow: monetary policy shocks cause almost negligible movements during the first few quarters following the shock, but their effect becomes large later on and reaches its maximum impact after about 10 quarters. Using different sub-samples, we also show that the magnitude of the effects has fallen over time. On the contrary, the effect of monetary policy shocks on stock markets is small and very fast.

Keywords: housing prices, monetary policy, structural VARs.

JEL classification: E37, E52.

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1 Introduction

According to popular wisdom, the recent dramatic run ups in housing prices have been caused by market-wide low interest rates, the increased availability of credit, or even money illusion.[1]

There is a growing literature on the implications of housing wealth for asset returns' predictability. Yogo (2006) and Piazzesi *et al.* (2007) emphasize the role of nonseparability of preferences in explaining the countercyclical variation in the equity premium. Lustig and Van Nieuwerburgh (2005) show that the ratio of housing wealth to human wealth (the housing collateral ratio) shifts the conditional distribution of asset prices and consumption growth and, therefore, predicts returns on stocks. Sousa (2007) argues that the composition of wealth is important not only because of its impact on consumption but also because it has implications for the predictability of asset returns. Gomes *et al.* (2007) show that the demand for durable goods is more cyclical than that for nondurable goods and services and that, in consequence, the cash flow and stock returns of durable-good producers are exposed to higher systematic risk.

On the other hand, the fundamental restructuring of the housing finance system, from a regulated system dominated by savings, loans and mutual savings banks to a relatively unregulated system dominated by mortgage bankers and brokers, the process of mortgage securitization, and a greater competitiveness in the primary mortgage market have led to a reduction in volatility of residential investment. The housing finance system is now integrated with the broader capital markets in the sense that "mortgage rates move in response to changes in other capital market rates, and mortgage funds are readily available at going market rates" (Hendershott and Shiling, 1989). As a result, the transmission of monetary policy to residential investment has changed and a tightening of monetary policy is now less likely to result in nonprice rationing of mortgage credit.

Given the prominent importance of housing wealth in household portfolios (housing wealth is the largest component of household balance sheets), there might exist a potentially important link between monetary policy, housing prices and consumption. In this paper we focus our attention in investigating the empirical validity of a link between monetary policy and housing prices.

Despite the empirical importance of understanding housing over the business cycle and the intense debates regarding housing prices, the effect of monetary policy on housing prices has not been fully

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[1] Brunnermeier and Julliard (2007) show that a reduction in inflation can fuel housing prices if people suffer from money illusion. Investors who decide whether to rent or buy a house by simply comparing monthly rent and mortgage payments do not take into account the fact that inflation lowers future real mortgage costs. The authors decompose the price-rent ratio into a rational component and an implied mispricing and find that inflation and nominal interest rates explain a large share of the time-series variation of the mispricing.

explored. McCarthy and Peach (2002) show that the eventual magnitude of the response of residential investment to a given change in monetary policy is similar to what it has been in the past. Chirinko *et al.* (2004) study the interrelationship between stock prices, house prices, and real activity, focusing on the determination of the role that asset prices play in formulating monetary policy. Iacoviello and Minetti (2003) document the role that the housing market plays in creating a credit channel for monetary policy. Iacoviello (2005) offers reduced-form Vector Autoregression (VAR) evidence based on detrended house prices but mostly emphasizes the monetary policy-house price to consumption channel from a theoretical model that analyses the two-way interaction between house prices and output. The author finds that policy shocks have a significant effect on house prices. Iacoviello and Neri (2007) analyze the contribution of the housing market to business fluctuations and show that: (*i*) a large fraction of the upward trend in real housing prices over the last 40 years can be accounted for by slow technological progress in the housing sector; (*ii*) residential investment and housing prices are very sensitive to monetary policy and housing demand shocks; and (*iii*) the wealth effects from housing on consumption are positive and significant. Similarly, Aoki *et al.* (2004) argue that there is a collateral transmission mechanism to consumption but do not condition on monetary policy. More recently, Del Negro and Otrok (2007) try to disentangle the relative importance of the common component in OFHEO house price movements from local (state- or region-specific) shocks and find that whilst historically movements in house prices were mainly driven by the local component, the increase in house prices in the recent period (2001-2005) is mainly a national phenomenon. The authors find the impact of policy shocks on house prices to be small in comparison with the magnitude of recent fluctuations. Fratantoni and Schuh (2003) also study the effects of monetary policy on regions in the U.S. and find that the response of housing investment to monetary policy varies by region.

As with housing prices, the link between monetary policy and stock markets has not been generally explored. Rigobon and Sack (2002, 2003) report a significant response of the stock market to interest rate surprises using an heteroskedasticity-based estimator to correct for possible simultaneity bias, an approach subsequently extended by Craine and Martin (2003). Bernanke and Kuttner (2005) analyze the impact of changes in the monetary policy on equity prices, with the objectives of both measuring the average reaction of the stock market and understanding the economic sources of that reaction. The authors find that, on average, a hypothetical unanticipated 25-basis-point cut in the Federal funds rate target is associated with about a 1% increase in broad stock indexes. Adapting a methodology due to Campbell and Ammer (1993) - who use a VAR to calculate revisions in expectations of future interest rates, dividends, and excess returns -, the authors find that the effects of unanticipated monetary policy actions on expected excess returns account for the largest part of the response of stock prices. Goto and Valkanov (2000) use a somewhat different VAR-based method to focus on the covariance between inflation and stock returns. Both Patelis (1997) and Goto and Valkanov (2000) relied on policy shocks derived from identified VARs, however, rather than futures-based surprises. Boyd *et al.* (2005) also consider the linkage between policy and stock prices, but their analysis focuses on market's response to employment news, rather than to monetary policy directly.

In this paper, we pay close attention to different identification schemes and focus on the empirical evidence linking monetary policy to housing prices. Specifically, we analyze evidence both from the U.S. and the U.K., at both monthly and quarterly frequency, and experiment with a large number of identification schemes to shed light on the question of interest. Based on this analysis, we ask how housing markets in general, and housing prices in particular, are affected by monetary policy shocks. To the extent that we find a link between monetary shocks and housing prices, we then ask how large are these effects and for how long do they persist. Additionally, we look at the effects of monetary policy shocks on stock markets. Our goal is to analyze whether monetary policy has an impact on housing and stock markets, and, if so, whether the magnitude of the reaction is similar or exhibits asymmetry.

Our main findings are robust to different identification schemes, they hold for both countries separately and tend to be broadly similar for both monthly and quarterly specifications, allowing us to be confident with regards to the conclusions. We find that monetary policy contractions (positive interest rate shocks) have a large and significantly negative impact on real housing prices. Nevertheless, the reaction of housing prices to interest rate shocks is extremely slow: monetary policy shocks cause almost negligible movements in housing prices during the first few quarters following the shock, but their effect becomes large later and reaches its maximum impact after about 10 quarters. Using different sub-samples, we also show that although important, the magnitude of the effects of monetary policy on housing prices has fallen over time, particularly, since the eighties, a feature that may be associated with the restructuring of the housing finance system and the broadening of financial instruments associated to the housing markets. This is in accordance with the "Great Moderation", this is, the substantial decline in macroeconomic volatility observed over the past twenty years. On the other hand, monetary policy shocks do not seem to cause a significant impact on stock markets: the magnitude of the effects is small and not persistent, as the reaction of the markets is very fast.

The remainder of the paper is organized as follows. In Section 2, we present the empirical methodology. In Section 3 we describe the two different data sets for the U.S. and the U.K. and, in Section 4, we discuss the results. Section 5 concludes.

2 Empirical Methodology

2.1 Estimation

Consider the following structural VAR (S-VAR)

$$\underbrace{\Gamma(L)}_{n\times n}\underbrace{X_t}_{n\times 1} = \Gamma_0 X_t + \Gamma_1 X_{t-1} + ... = c + \varepsilon_t \text{ where } \varepsilon_t | X_s, s < t \sim N(\underline{0}, \Lambda) \tag{1}$$

where $\Gamma(L)$ is a matrix valued polynomial in positive powers of the lag operator L, n is the number of variables in the system, and ε_t (the fundamental economic shocks) that span the space of innovations to X_t. That is, in the "reduced form"

$$\Gamma_0^{-1}\Gamma(L) X_t = B(L) X_t = a + v_t \sim N(\underline{0}, \Sigma)$$

where $\Sigma := \Gamma_0^{-1}\Lambda\left(\Gamma_0^{-1}\right)'$, the vector $v_t = \Gamma_0^{-1}\varepsilon_t$ contains the innovations of X_t, and Γ_0 pins down the contemporaneous relations among the variables in the system. In what follows we use the normalization $\Lambda = I$.

To be able to identify the structural monetary shocks we need at least $(n-1)n/2$ linearly independent restrictions. With enough restrictions in the Γ_0 matrix and no restrictions in the matrix of coefficients on the lagged variables, the estimation of the model is numerically simple since the log-likelihood will be

$$\begin{aligned} l(B, a, \Gamma_0) &= -\frac{T}{2} + \log|\Gamma_0| - \frac{1}{2} trace\left[S(B, a)\Gamma_0'\Gamma_0\right] \\ \text{where } S(B, a) &= \sum_{t=1}^{T}(B(L)X_t - a)(B(L)X_t - a)' \end{aligned}$$

and the maximum-likelihood estimator of B and a can be found simply doing OLS equation-by-equation regardless of the value of Γ_0. Integrating $l(B, a, \Gamma_0)$ (or the posterior with conjugate priors) with respect to (B, a) the marginal log probability density function of Γ_0 is proportional to

$$-\frac{T-k}{2}\log(2\pi) + (T-k)\log|\Gamma_0| - \frac{1}{2} trace\left[S\left(\hat{B}_{OLS}, \hat{a}_{OLS}\right)\Gamma_0'\Gamma_0\right]. \tag{2}$$

If we take the classical approach instead and maximize $l(B, a, \Gamma_0)$ for $(B(L), a)$ holding Γ_0 fixed, we have the same expression with T rather than $T-k$ multiplying the first terms. We follow the common approach of using $|\Gamma_0|^k$ as an improper prior, so that the concentrated likelihood and the marginal posterior coincide. The last expression can be maximized with respect to Γ_0 to obtain the maximum-likelihood estimator, and a consistent estimate of the asymptotic variance of these parameters can be constructed from the Hessian evaluated at the estimated parameter values.

Note that the normalization of $\Sigma = I$ gives us the problem that changing the sign of a row of Γ_0 leaves the value of the likelihood unchanged. This is not an issue for the point estimates (as they can be flipped) but it's problematic when drawing from the posterior distribution of the reduced-form VAR and then estimating Γ_0. If we do not plan to make draws directly from (2), this problem can be solved with the following alternative normalization:

1. $\Sigma = \Lambda$ where Λ is a diagonal matrix
2. the diagonal elements of Γ_0 are all equal to 1.

In this case, the concentrated likelihood is proportional to

$$-\frac{T}{2}\log\left|\Gamma_0^{-1}\Lambda\left(\Gamma_0'\right)^{-1}\right| + \frac{1}{2}trace\left[S\left(\hat{B}_{OLS},\hat{a}_{OLS}\right)\left(\Gamma_0'\Lambda^{-1}\Gamma_0\right)\right] \tag{3}$$

The impulse-response function to a one standard-deviation shock under this normalization is:

$$B(L)^{-1}\Gamma_0^{-1}\Lambda^{\frac{1}{2}}.$$

The integrated log likelihood with respect to B and a is proportional to

$$p(\Gamma_0) = (T-k)\log|\Gamma_0| - \frac{1}{2}trace\left[S\left(\hat{B}_{OLS},\hat{a}_{OLS}\right)\Gamma_0'\Gamma_0\right] \tag{4}$$

where $S(B,a) = \sum_{t=1}^{T}(B(L)X_t - a)(B(L)X_t - a)'$. If we use the improper prior, $|\Gamma_0|^k$, the first term becomes multiplied by T and the expression is equivalent to the maximized likelihood with respect to B and a. We use these approaches in order to have identity of the maximum-likelihood estimator and the Bayesian posterior mode as in Sims and Zha (1999).

In this setting, the key issue in identifying monetary policy shocks is the choice of identification restrictions in the Γ_0 matrix. We report results based on three identification strategies commonly used in the empirical S-VAR literature.

2.2 Identification

2.2.1 Recursive Partial Identification

In our first identification scheme, we follow Christiano *et al.* (2005) and assume that the variables in X_t can be separated into 3 groups: (*i*) a subset of n_1 variables, X_{1t}, whose contemporaneous values appear in the policy function and do not respond contemporaneously to the policy shocks; (*ii*) a subset of n_2 variables, X_{2t}, that respond contemporaneously to the monetary policy shocks and whose values appear in the policy function only with a lag; and (*iii*) the policy variable itself in the form of a short term interest rate, i_t.[2] We include in our system the same variables as in Christiano *et al.* (2005) but also add housing market variables among the X_{1t} variables, that is, we allow the monetary policy authority to react contemporaneously to changes in the housing market. We also include the stock market index in X_{2t}. The recursive assumptions can be summarized by $X_t = [X_{1t}', \ i_t, \ X_{2t}']'$ and

$$\Gamma_0 = \begin{bmatrix} \underbrace{\gamma_{11}}_{n_1 \times n_1} & \underbrace{0}_{n_1 \times 1} & \underbrace{0}_{n_1 \times n_2} \\ \underbrace{\gamma_{21}}_{1 \times n_1} & \underbrace{\gamma_{22}}_{1 \times 1} & \underbrace{0}_{1 \times n_2} \\ \underbrace{\gamma_{31}}_{n_2 \times n_1} & \underbrace{\gamma_{32}}_{n_2 \times 1} & \underbrace{\gamma_{33}}_{n_2 \times n_2} \end{bmatrix}.$$

The two upper blocks of zeros correspond, respectively, to the assumptions that the variables in X_1 do not respond to the monetary policy shock either directly or indirectly. This approach delivers a correct identification of the monetary policy shock but not of the other shocks in the system.

Suppose that the monetary policy rule equation is in the S-VAR and that (*i*) only the policy instrument (the appropriate short-term interest rate) responds contemporaneously to monetary policy shocks (i.e. only the row of Γ_0^{-1} corresponding to the policy equation has a non-zero coefficient associated with the monetary policy shock), and (*ii*) the policy functions follows some kind of Taylor rule

$$i_t = \phi_\pi \pi_t + \phi_y y_t + \phi_h h_t + \phi_z z_t + lags + \varepsilon_t^{mp}$$

where π_t, y_t and h_t are respectively measure of inflation, output gap and housing price movements, and z_t are other variables in the information set of the central bank. Then, we have that:

1. ε_t^{mp} is identified and structural since the row of Γ_0 corresponding to the policy equation is linearly independent from the other rows;

2. since the other variables do not react immediately to the monetary policy shock, π, y and h are predetermined so OLS in the policy equation is consistent;

3. since ε_t^{mp} is identified regardless of the ordering restrictions among the non-policy variables, to get consistent impulse-responses to a monetary policy shock we can put arbitrary $0s$ in the non-policy blocks of Γ_0 to obtain $(n-1)\,n/2$ linearly independent restrictions, and the impulse-response function of ε_t^{mp} will be correct (and invariant to the choice of $0s$).

This result can be generalized to a setting in where some variables - for example, the stock market index - also react contemporaneously to the monetary policy *but* enter the policy function only as lagged values (Christiano *et al.*, 1999).

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[2] We also experimented using a monetary aggregate as the policy variable.

The impulse-response functions will be given by:

$$B(L)^{-1}\Gamma_0^{-1} \tag{5}$$

To make Γ_0 invertible, we add arbitrary zero restrictions in the non-policy blocks to obtain a total of $(n-1)\,n/2$ linearly independent restrictions - therefore delivering an exactly identified system. The identification of the monetary policy shocks, as well as the shape of the impulse-response function following a monetary policy shock are, by construction, independent from the choice of these additional restrictions.

To assess uncertainty regarding the impulse-response functions, we follow Sims and Zha (1999) and construct confidence bands by drawing from the Normal-Inverse-Wishart posterior distribution of $B(L)$ and Σ

$$\begin{aligned} \beta|_{\Sigma} &\sim N\left(\hat{\beta}, \Sigma \otimes (X'X)^{-1}\right) \\ \Sigma^{-1} &\sim \text{Wishart}\left(\left(T\hat{\Sigma}\right)^{-1}, T-m\right) \end{aligned}$$

where β is the vector of regression coefficients in the VAR system, Σ is the covariance matrix of the residuals, the variables with a hat denote the corresponding maximum-likelihood estimates, X is the matrix of regressors, T is the sample size and m is the number of estimated parameters per equation (see Zellner, 1971; Schervish, 1995; and Bawens *et al.,* 1999).[3] Note that the use of this Bayesian approach allows us to draw inference that is robust to the presence of non-stationary behavior in the variables, since the posterior will have an asymptotically Gaussian shape even in the presence of unit roots (Kim, 1994).

2.2.2 Fully Simultaneous Systems

In addition to the recursive identification scheme mentioned above, we also estimate two structural VAR models in which we relax the assumptions that: (*i*) some of the variables are predetermined with respect to monetary policy and that (*ii*) the monetary policy reacts only to variables that are predetermined with respect to the monetary policy shock. The two structural VAR approaches we use build on the models of Sims and Zha (2006a) and of Leeper and Zha (2003)[4] to which we add the housing sector.

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[3] This result is exact under normality and the Jeffreys' prior $f(\beta, \Sigma) \propto |\Sigma|^{-(p+1)/2}$ (where p is the number of right hand side variables), but can also be obtained, under mild regularity conditions, as an asymptotic approximation around the posterior MLE. The Jeffreys' prior formulates the idea of "lack of prejudice" on the space of distribution for the data, and is also flat over the space of the βs and remains flat under reparameterization.

[4] The identification scheme used in this paper is also used, with the addition of a Markov switching structure, in Sims and Zha (2006b).

Sims and Zha (2006a) Sims and Zha (2006a) abandon two potentially unsatisfactory assumptions of the Christiano *et al.* (2005) type of identification scheme seen before: (*i*) they do not assume that the central bank reacts only to variables that are predetermined relative to policy shocks; and most importantly (*ii*) they assume that there are no predetermined variables with respect to ε^{mp} (this implies that we cannot do OLS – nor IV – to identify the policy shocks). This is particularly appealing, especially with quarterly frequency data (their approach is also motivated by a structural model of the economy).

In order to reach identification, we postulate the following money demand function

$$M_t - P_t - Y_t = b_1 i_t + \text{lagged}\,(X_t) + \sigma_M \varepsilon_t^M$$

where M_t is the log monetary aggregate, P_t is the log aggregate price index, Y_t is the log GDP, ε_t^M is the money demand shock and σ_M is its standard deviation (the coefficients on this variables are restricted to unity). We also assume that the monetary policy function can be expressed as

$$i_t = \phi_M M_t + \phi_{Pcm} Pcm_t + \phi_H H_t + \text{lagged}\,(X_t) + \sigma \varepsilon_t^{mp}$$

where Pcm_t is the log price index for crude materials and H_t is the log housing price index. Note that in this case the policy function does not contain contemporaneous values of the aggregate price level and output. We also experimented excluding the contemporaneous housing price index on the right hand side of the last equation. In recognition of the fact that the price of crude materials, Pcm_t, is determined in markets characterized by a continuous auction structure, we allow this variable to react contemporaneously to all the variables in the system. The other variables included in the system – the log producer price index of intermediate goods, Pim_t, the aggregate log GDP deflator, P, the log average hourly real wage, W, log real GDP, Y, and the log housing price index, H – are not predetermined relative to the monetary policy shocks but it is assumed that the policy shock can influence them contemporaneously through its effect on the price of crude materials. The remaining part of the Γ_0 concerning these variables is normalized to have an upper triangular structure, and this normalization is irrelevant for the identification of monetary policy shocks.

In this specification we proxy their variables with $X_t =$ [log PPI Crude, nominal $M2$, Fed Funds rate, log Deflator, log real GDP, log Wage, log PPI Commodities, log Census HPI]$'$. As in Sims and Zha (2006a), we do not assume that P and Y are predetermined relative to ε_t^{mp} (what Christiano *et al.* (2005) do to reach identification) but instead limit the channels by which monetary policy shocks can affect P and Y. In particular, we partition the data such that $X_t = [X_{1t}', X_{2t}']'$ where

$$X_{1t} = \begin{bmatrix} Pcm_t \\ M_t \\ i_t \end{bmatrix}; \; X_{2t} = \begin{bmatrix} Pim_t \\ P_t \\ W_t \\ Y_t \\ H_t \end{bmatrix}.$$

The identifying restriction on the matrix of contemporaneous effects, Γ_0, is

$$\begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} & \gamma_{14} & \gamma_{15} & \gamma_{16} & \gamma_{17} & \gamma_{18} \\ 0 & \gamma_{22} & \gamma_{23} & 0 & -\gamma_{22} & 0 & -\gamma_{22} & 0 \\ \gamma_{31} & \gamma_{32} & \gamma_{33} & 0 & 0 & 0 & 0 & 0 \\ \gamma_{41} & 0 & 0 & \gamma_{44} & \gamma_{45} & \gamma_{46} & \gamma_{47} & \gamma_{48} \\ \gamma_{51} & 0 & 0 & 0 & \gamma_{55} & \gamma_{56} & \gamma_{57} & \gamma_{58} \\ \gamma_{61} & 0 & 0 & 0 & 0 & \gamma_{66} & \gamma_{67} & \gamma_{68} \\ \gamma_{71} & 0 & 0 & 0 & 0 & 0 & \gamma_{77} & \gamma_{78} \\ \gamma_{81} & 0 & 0 & 0 & 0 & 0 & 0 & \gamma_{88} \end{bmatrix} \begin{bmatrix} Pcm_t \\ M_t \\ i_t \\ Pim_t \\ P_t \\ W_t \\ Y_t \\ H_t \end{bmatrix} \tag{6}$$

where the second and third rows correspond to the correspond, respectively, to the money demand and policy rule equation (and the second and third elements of ε_t correspond to ε_t^M and ε_t^{mp}). The zeros in the subcolumn starting at $(4,2)$ correspond to the assumption that monetary policy shocks have only an indirect contemporaneous effect on the X_{2t} variables.

This one again is a partially identified S-VAR (the last 5 equations are linearly dependent) where correct impulse-response functions to monetary policy shocks can be constructed independently from where we put the zero restrictions in the last 5 equations. It is therefore straightforward to enrich this setting for our purpose adding housing price index and a set of housing supply cost shifters among the X_2 variables since these are unlikely to respond directly to monetary policy shocks at time t.

Leeper and Zha (2003) In the same spirit, but somehow less restrictive, is the identification scheme of Leeper and Zha (2003). In this setting, the economy is divided into 3 sectors: a financial, a monetary and a production sector. The financial sector – summarized by commodity prices index, Pcm – reacts contemporaneously to all new information. The monetary sector, that allows for simultaneous effects, comprises: (*i*) "money demand" that links money reserves, M, with the short term interest rate, i, GDP, Y, and the GDP deflator, P; and (*ii*) "money supply," where monetary policy is assumed to react only to commodity prices (since they are observed in real time), money reserves and the interest rate (since the other data are not observed in real time by the central bank).

The production sector consists of log real GDP, Y, unemployment rate, U, the GDP deflator, P, and – in our case – the housing price index, H. This sector does react contemporaneously to the financial sector but not directly to the monetary sector. The orthogonalization within this sector is irrelevant to identify monetary policy shocks correctly. The identification can be summarized in the following table where "+" indicates non-zero elements and we added a triangular orthogonalization for the production sector that is irrelevant for the identification of monetary policy shocks.

	Sector:						
	Financial	M Policy	M Demand	Prod Y	Prod P	Prod U	Prod HPI
Pcm	+	+					
M	+	+	+				
i	+	+	+				
Y	+		+	+	+	+	+
P	+		+		+	+	+
U	+					+	+
H	+						+

Both fully simultaneous identification schemes considered deliver overidentification. This implies that the estimates of Γ_0 are obtained via numerical maximization of the integrated likelihood (2) and that confidence bands for the impulse-response functions in equation (5) should be constructed by drawing jointly from the posterior distribution of $B(L)$ and Γ_0 (see Sims and Zha, 1999). This task is complicated by the fact that equation (2) is not in the form of any standard probability density function, implying that we cannot draw Γ_0 from it directly to make inference. We solve this problem by: (*i*) taking draws for Γ_0 using an importance sampling approach that combines the posterior distribution in equation (2) with the asymptotic distribution of Γ_0; and (*ii*) drawing $B(L)$ from its posterior distribution conditional on Γ_0. Confidence bands are then constructed from the weighted percentiles of the impulse-response functions drawn in this fashion. This Monte Carlo approach is explained in detail in the Appendix.

3 Data Description

This section provides a summary description of the data employed in the empirical analysis. A detailed description is provided in Section A of the Appendix. All the variables are in natural logarithms unless stated otherwise.

3.1 U.S. Data

For the recursive partial identification scheme we use the following variables. The variables in X_{1t} – the ones predetermined with respect to monetary policy innovations – are the Census housing price index (or the median sales price of new houses sold for monthly data), housing starts, the producers' price index for materials and components for construction, the producers' price index for intermediate materials, supplies and components, real gross domestic product, real consumption excluding housing services, the CPI excluding food, shelter and energy, real investment excluding residential investment, the real wage, and labor productivity. The variables in X_{2t} – the ones allowed to react contemporaneously to monetary policy shocks – are real profits, the growth rate of M2 and the S&P500 Index. As measure of the monetary policy instrument we use the Federal Funds rate denoted by i_t.

For the two fully simultaneous identification schemes considered we follow the data choice of Sims and Zha (2006a) and of Leeper and Zha (2003) to which we add the housing sector.[5]

For the first specification we use federal funds rate, the CPI excluding food, shelter and energy, real gross domestic product, the real wage, the producers' price index for all commodities, the Census housing price index (or the median sales price of new houses sold for monthly data), the producers' price index for crude materials and M2.

For the second specification we use: real gross domestic product, the CPI excluding food, shelter and energy, the unemployment rate, and the Census housing price index (or the median sales price of new houses sold for monthly data), M2, the Federal Funds rate and the commodity prices.

The data are available over the samples 1967:3-2006:3 and 1967:1-2006:9, at the quarterly and monthly frequency respectively.

3.2 U.K. Data

There are some minor differences in the variable choice for the UK analysis. We use the 3-month short term interest rate on gilts instead of the Federal Funds rate, the FTSE index rather than the S&P 500 index and there are some differences in producer price indices. A detailed description is provided in Section A of the Appendix. A crucial difference relative to the U.S. arises from the sample periods. For the quarterly frequency specifications, they start either in 1963:2 for the recursive partial identification scheme and 1982:4 for the simultaneous system specifications. For the monthly data, on the other hand, the period is restricted to start from 1991 due to data limitations in the housing market variables.

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[5] Some of the variables in these specifications are therefore different from the ones used in the recursive identification scheme.

4 Results

4.1 U.S. Data

4.1.1 Recursive Partial Identification

The impulse-response functions of all variables in X_t are displayed in Figure 1 for quarterly data. The solid line corresponds to the point estimate and the dashed lines indicate the 95 percent posterior confidence intervals.

The results suggest that after a restrictive monetary policy shock, the housing sector reacts in the following way. First, housing prices fall after a lag of around three quarters, and the effect is maximized after about 10 quarters. Moreover, housing prices remain at a lower level for at least four years. Second, housing starts also fall but the response is much faster and much less persistent - the shock is not statistically significant after about 5 quarters. Third, producer price indexes of materials for construction and intermediate materials fall, but the responses are not statistically significant.

The response of the other variables in the system (output, consumption, investment, inflation, real profits, and real wages) to a monetary policy contraction are largely consistent with the findings in Christiano *et al.* (2005). Additionally, we show that the impact of monetary policy on the stock market is small and very quick.

We repeat the same analysis for monthly data and the results are reported in Figure 2. Broadly speaking, the qualitative changes (a persistent fall in housing prices and starts) are the same as in the quarterly specification. Quantitatively, the monetary policy shock exerts its maximum impact on housing prices earlier than in the quarterly specification. Specifically, the maximum effect is reached after about 18 months, whereas in the quarterly specification this is reached after 10 quarters.

We also use different sub-samples and show that the magnitude of the effect of monetary policy shocks on housing markets has fallen over time: when we restrict the analysis to the period after 1983:1, we find that the monetary policy shocks have become less important and that their effects are less persistent.[6] These findings are in accordance with the age of "Great Moderation".

The strategy for estimating the parameters of the model focuses on the portion of fluctuations in the data that is caused by a monetary policy shock. It is, therefore, natural to ask how large that component is. With this question in mind, Table 1 reports variance decompositions, and displays the percentage of variance of the k-step-ahead forecast error in the elements of X_t due to monetary policy shocks, for k = 1, 4, 8 and 20 using quarterly data. Notice that policy shocks account for only a small fraction of inflation. On the other hand, monetary policy shocks are responsible for a substantial

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[6] Results available upon request.

fraction of the variation in the housing market variables.

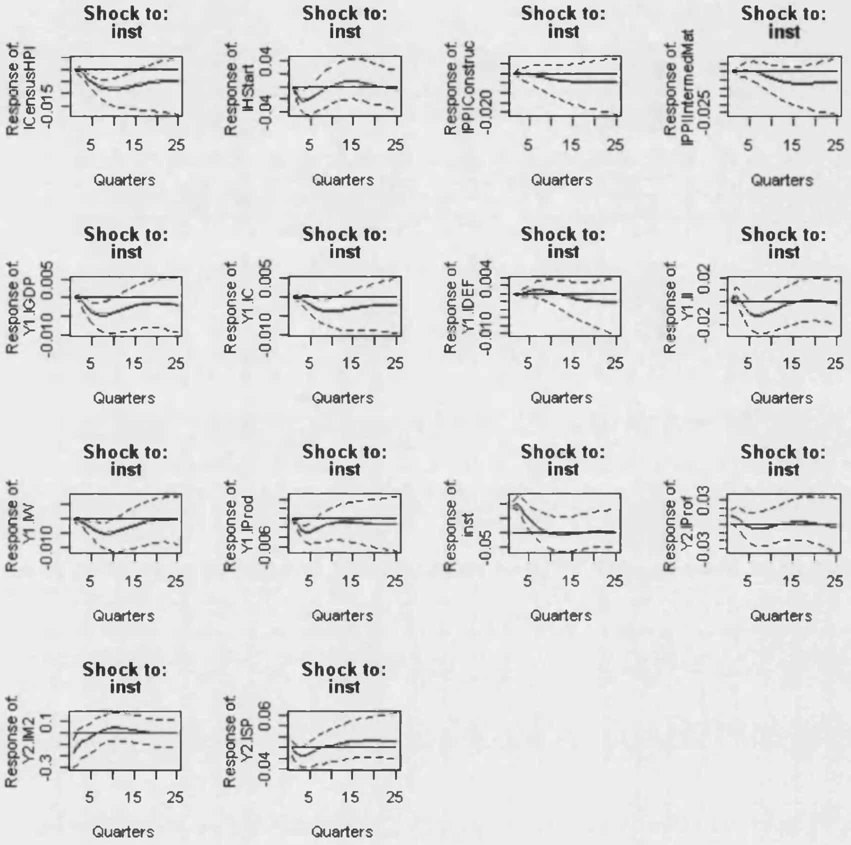

Figure 1: *Christiano et al. (2005) identification, US quarterly data. inst =FedFunds rate. Responses to a monetary policy contraction.* 95% *confidence bands based on 10000 draws.*

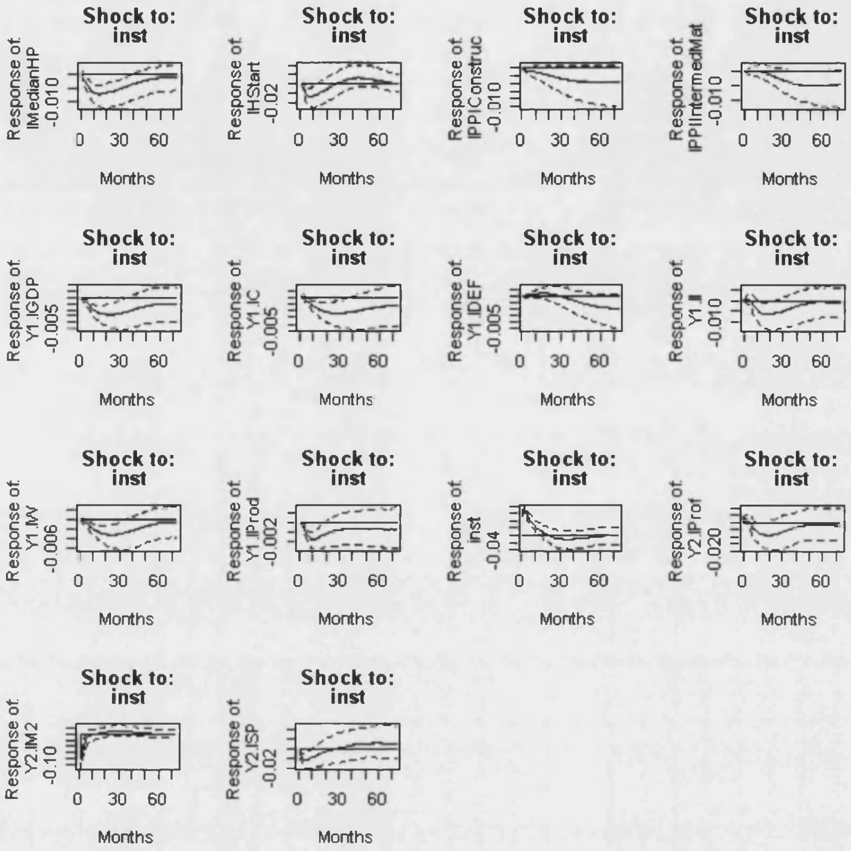

Figure 2: *Christiano et al. (2005) identification, US monthly data. inst =FedFunds rate. Responses to a monetary policy contraction. 95% confidence bands based on 1000 draws.*

Table 1: Percentage variance due to monetary policy shocks.

	1 Quarter Ahead	4 Quarters Ahead	8 Quarters Ahead	20 Quarters Ahead
Housing price index	0.6	5.0	5.2	3.5
Housing starts	2.8	15.2	22.2	19.5
PPI for construction	0.4	3.0	5.3	15.9
PPI for intermediate materials	2.8	1.9	5.1	6.5
GDP	0.0	1.6	1.4	1.5
Consumption	0.0	4.1	3.7	2.4
Deflator	0.4	0.4	1.2	1.4
Investment	3.1	0.7	1.2	1.2
Real wage	0.1	1.9	3.1	2.4
Productivity	0.2	3.5	5.0	5.5
Fed Funds rate	89.5	55.0	34.7	22.0
Real profits	0.0	0.4	3.2	4.7
M2 growth	0.0	0.1	0.5	1.0
Stock price index	0.0	7.1	8.3	12.7

4.1.2 Fully Simultaneous Systems

Sims and Zha (2006a) The Sims and Zha (2006a) identification results for the quarterly frequency data are reported in Figure 3. It shows that a monetary contraction produces an initial interest rate rise and a money stock decline. Output and wages decline by a statistically significant amount peaking as before at around 10 quarters.

Housing prices are substantially impacted by the increase in the interest rate: housing prices fall, peaking at around 15 quarters and the effect of the monetary policy shock is very persistent. Relative to the results from the previous specification, the impact of monetary shocks on housing prices are similar but slightly more persistent in this case. These results are in line with Sims and Zha (2006a). However, our findings deliver a substantial price puzzle, as prices increase following a monetary policy contraction and remain higher for almost 20 quarters.

We repeat the same analysis for monthly data and the results are reported in Figure 4. The persistent fall in housing prices and the price puzzle also emerge using data at monthly frequency.

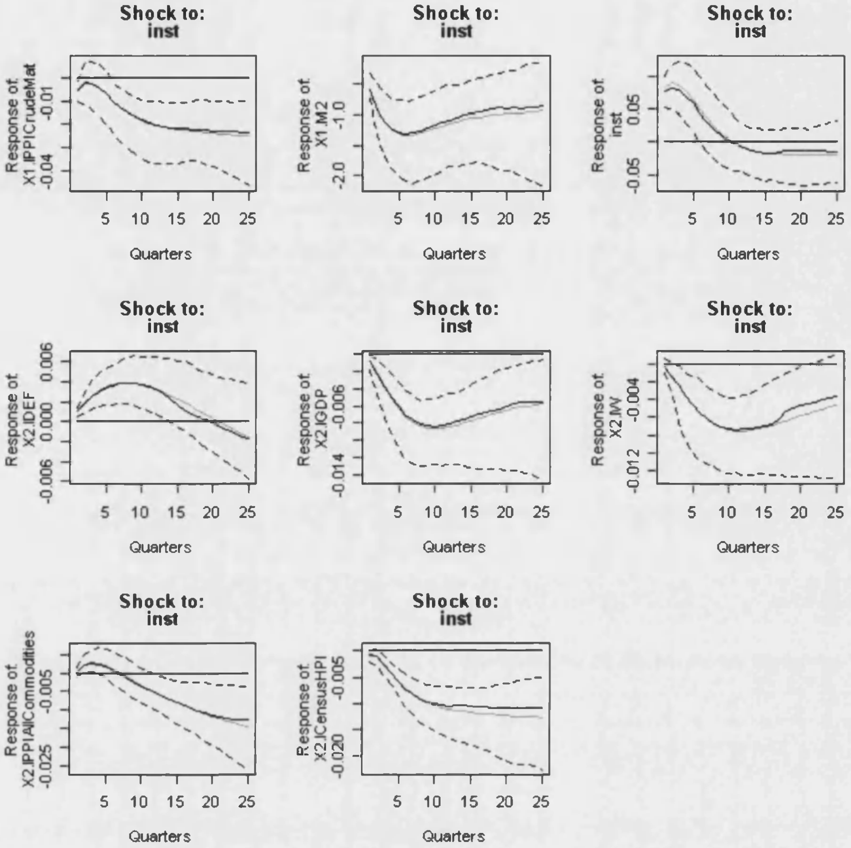

Figure 3: *Sims and Zha (1996, 2005) identification, US quarterly data. inst =FedFunds rate. Responses to a monetary policy contraction.* 90% *confidence bands based on 30000 draws with strict rejection for* $\tilde{\Gamma}_0$ *and weighted quantiles.*

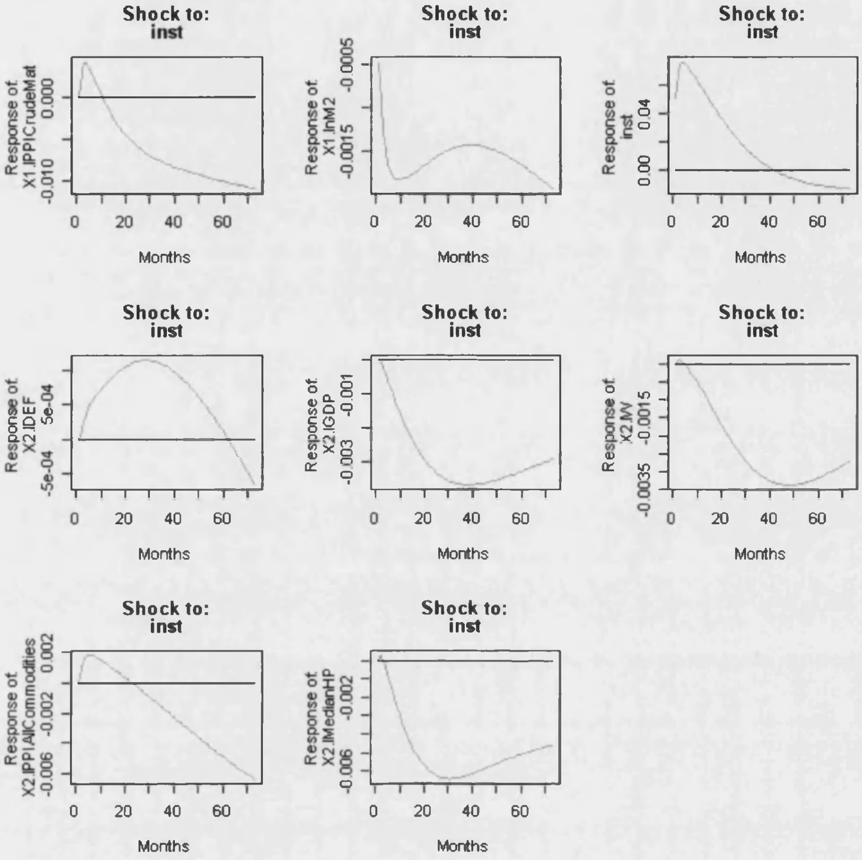

Figure 4: *Sims and Zha (1996, 2005) identification, US monthly data. inst =FedFunds rate. Responses to a monetary policy contraction.*

We also report the estimated contemporaneous coefficients along with 95 percent equal-tailed probability intervals for the two behavioral equations of interest where quarterly data are used. Those equations are money demand

$$\underset{(0.77,1.54)}{1.20}\ M_t + \underset{(5.31,11.27)}{8.65}\ i_t \ \underset{(-0.76,-1.54)}{-1.20}\ Y_t \ \underset{(-0.76,-1.54)}{-1.20}\ P_t = \varepsilon_t^M,$$

and monetary policy

$$\underset{(-8.86,-1.16)}{-5.19}\ PPICrude_t \ \underset{(-1.27,-0.25)}{-0.80}\ M_t + \underset{(0.70,9.65)}{6.01}\ i_t = \varepsilon_t^{mp}$$

Money demand has reasonable economic interpretations as the interest elasticity of demand is negative. Monetary policy responds strongly to the money stock: disturbances that raise the money stock induce the Fed to increase the federal funds rate. The estimates also seem to suggest the Fed reacts substantially to information contained in commodity prices.

Leeper and Zha (2003) We next report the results based Leeper and Zha (2003). Figure 5 displays the responses to an exogenous monetary policy expansion when we use quarterly data, whilst Figure 6 shows the responses at monthly frequency. A monetary policy expansion lowers the funds rate initially and immediately increases the money stock and commodity prices, both of which continue to decline smoothly over the 25-quarter horizon.

The effects of monetary policy on housing prices are significant. A monetary policy expansion increases housing prices with the effect peaking at around 8 quarters; then, housing prices start declining and go back to their initial level. After a brief delay, output falls and stays lower, while unemployment rises. Twelve quarters after the exogenous action, both output and unemployment are likely to differ from their initial levels. Contrary to the findings of Leeper and Zha (2003), our results suggest that prices do not decline and do not go back to their initial level: consumer prices adjust very slowly and will remain at a higher level 15 quarters ahead.

The response of the interest rate to an exogenous policy expansion also shows that the initial liquidity effect lasts about six quarters. However, after this period, the funds rate revert and goes up and remains persistently at a higher level even 25 quarters ahead. This is the shape of the path of the short-term nominal interest rate following a monetary expansion that Friedman (1968) and Cagan (1974) describe as a short-lived liquidity effect followed by income and expected inflation effects. After five years the increases in inflation and the federal funds rate are roughly of the same size, as one might anticipate if expected inflation is the dominant source of fluctuations in nominal rates over long periods. The responses in the figures suggest that the Fed should raise the funds rate only briefly in order to higher lower persistently. Because lower inflation is ultimately associated with a lower funds rate, the Fed must begin to reduce the rate within about a year and an half, and then keep it lower.

For the monthly specification (Figure 6) we reach the same conclusions: housing prices increase after a monetary expansion.

Table 2 reports the estimate of contemporaneous coefficient matrix when we use quarterly data. As can be seen from the "M Policy" column, the policy rule shows a much larger contemporaneous coefficient on i than on M, implying that the Federal Reserve pays much more attention to the interest rate than the money stock.

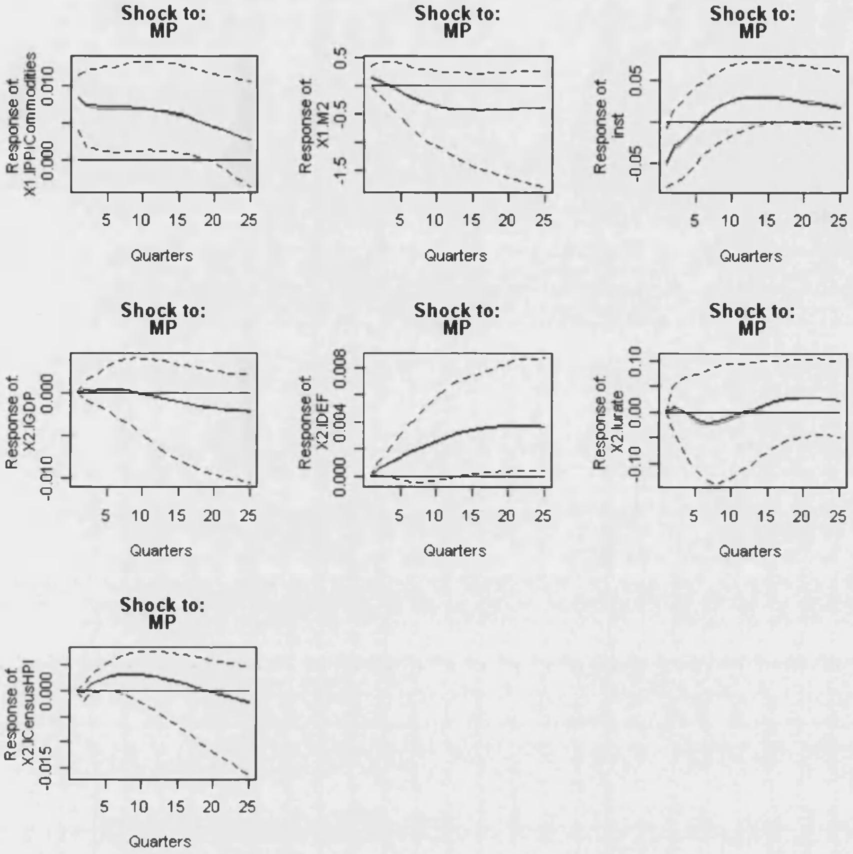

Figure 5: *Leeper and Zha (2003) identification, US quarterly data. inst =FedFunds rate. Responses to a monetary policy expansion.* 90% *confidence bands based on 30000 draws with strict rejection for* $\tilde{\Gamma}_0$ *and weighted quantiles.*

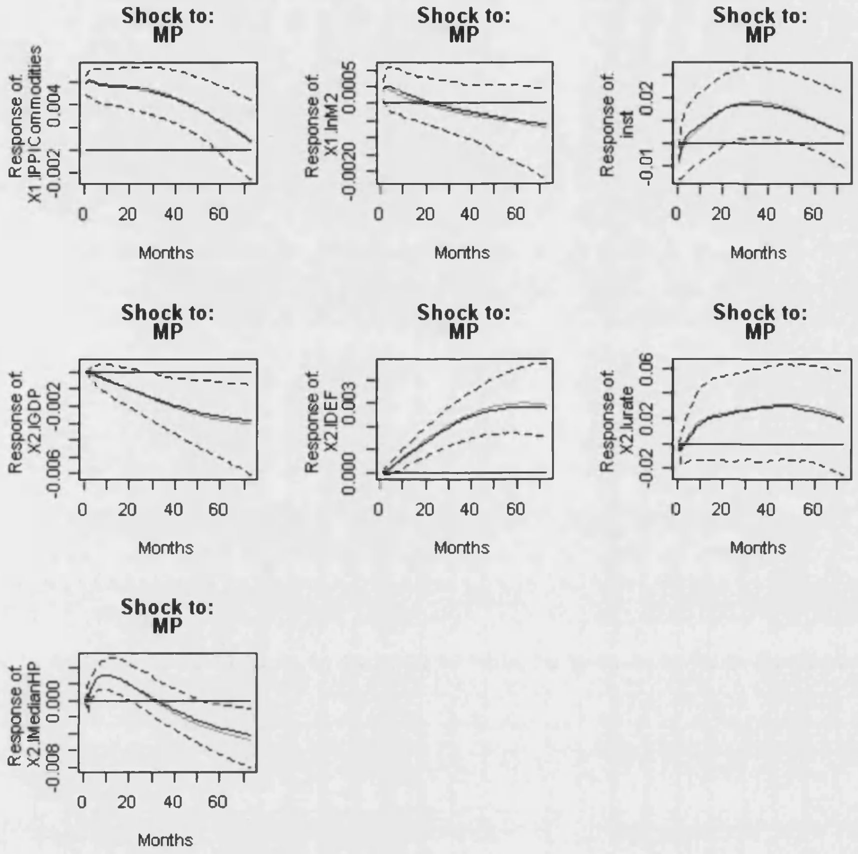

Figure 6: *Leeper and Zha (2003) identification, US monthly data. inst =FedFunds rate. Responses to a monetary policy expansion.* 90% *confidence bands based on 15000 draws with strict rejection for* $\tilde{\Gamma}_0$ *and weighted quantiles.*

Table 2: Contemporaneous coefficient matrix.

	Sector:						
	Financial	M Policy	M Demand	Prod Y	Prod P	Prod U	Prod HPI
Pcm	49.34	72.80	0.00	0.00	0.00	0.00	0.00
M	-0.01	0.31	1.60	0.00	0.00	0.00	0.00
i	7.75	-6.91	4.60	0.00	0.00	0.00	0.00
Y	3.05	0.00	-18.35	141.10	30.45	72.23	-14.59
P	-76.61	0.00	164.09	0.00	370.47	99.01	66.68
U	1.40	0.00	0.00	0.00	0.00	4.29	0.48
H	-5.54	0.00	0.00	0.00	0.00	0.00	91.82

4.2 U.K. Data

4.2.1 Recursive Partial Identification

The impulse-response functions of all variables in X_t are displayed in Figures 7 (quarterly data) and 8 (monthly data). The solid line corresponds to the point estimate and the dashed lines indicate the 95 percent confidence intervals.

The results suggest that after a restrictive monetary policy shock housing prices fall, reaching their maximum drop after about 10 quarters, and remain at a lower level for almost 25 quarters. These results are in line with our findings for the U.S. and point towards the substantially persistent response of housing prices conditional on a monetary policy shock. On the other hand, the impact of monetary policy on the stock market is smaller in magnitude and the effect is less persistent as the stock market reacts faster than the housing market.

When we use monthly data we also find a negative effect on housing prices and a shortening of the monetary policy shock impact. Using different sub-samples, we show that the magnitude of the effects of monetary policy shocks has fallen over time and became less persistent in accordance to the decrease of macroeconomic volatility observed over the past twenty years.[7]

We then look at the portion of fluctuations in the data that is caused by a monetary policy shock. Table 3 reports variance decompositions, and displays the percentage of variance of the k-step-ahead forecast error in the elements of X_t due to monetary policy shocks, for $k = 1$, 4, 8 and 20 using quarterly data. Policy shocks account for only a small fraction of inflation and stock prices. On the

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[7] Results available upon request.

other hand, policy shocks are responsible for a substantial fraction of the variation in the housing prices and investment.

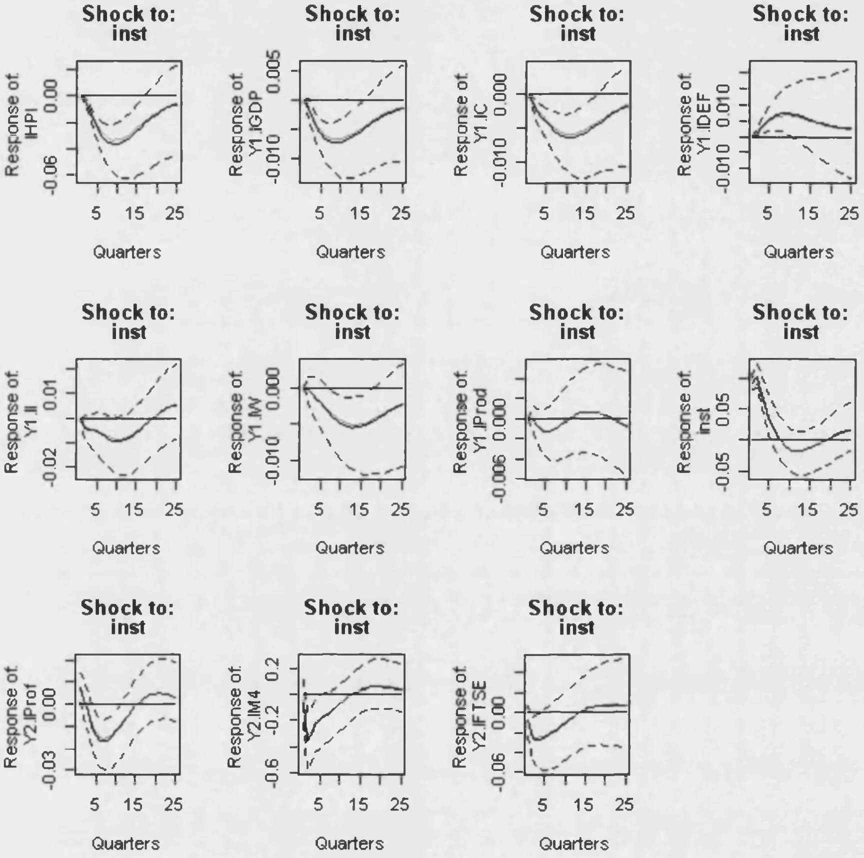

Figure 7: *Christiano et al. (2005) identification, UK quarterly data. inst =FedFunds rate. Responses to a monetary policy contraction.* 95% *confidence bands based on 10000 draws.*

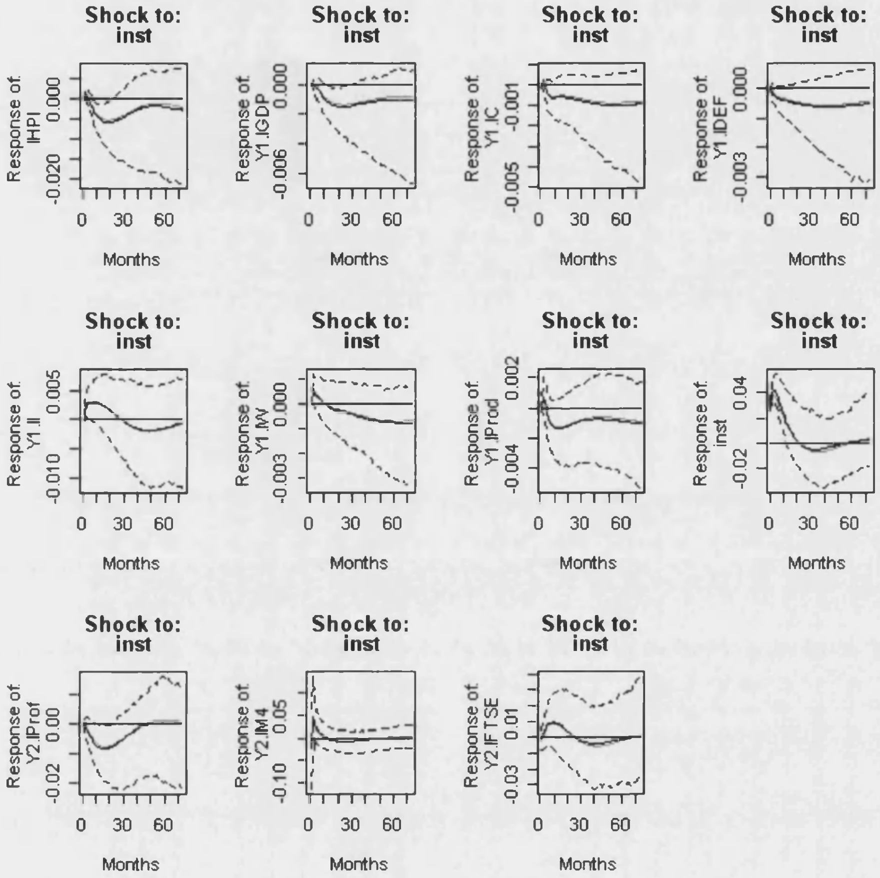

Figure 8: *Christiano et al. (2005) identification, UK monthly data. inst =FedFunds rate. Responses to a monetary policy contraction.* 95% *confidence bands based on 1000 draws.*

Table 3: Percentage variance due to monetary policy shocks.

	1 Quarter Ahead	4 Quarters Ahead	8 Quarters Ahead	20 Quarters Ahead
Housing price index	1.7	1.4	7.4	12.2
GDP	1.4	0.9	0.8	0.9
Consumption	1.7	1.6	3.2	5.5
Deflator	3.4	5.9	5.8	5.1
Investment	4.8	8.6	12.5	14.7
Real wage	0.6	8.9	9.0	6.8
Productivity	0.0	1.3	1.7	4.7
Interest rate	86.5	68.1	52.5	41.5
Real profits	0.0	0.5	1.6	2.0
M2 growth	0.0	0.6	2.4	3.8
Stock price index	0.0	2.1	3.1	2.9

4.2.2 Fully Simultaneous Systems

Sims and Zha (2006a) The Sims and Zha (2006a) identification (Figure 9) shows that a monetary contraction generates substantial effects on housing prices: housing prices fall significantly with the effect peaking at around 12 quarters. Moreover, the effects are very persistent, as housing prices remain below their initial level for more than 25 quarters. These results are comparable with the main conclusions from the U.S. and suggest a strong negative link between monetary policy shocks and housing prices. For the monthly specification (Figure 10) we reach the similar conclusions.

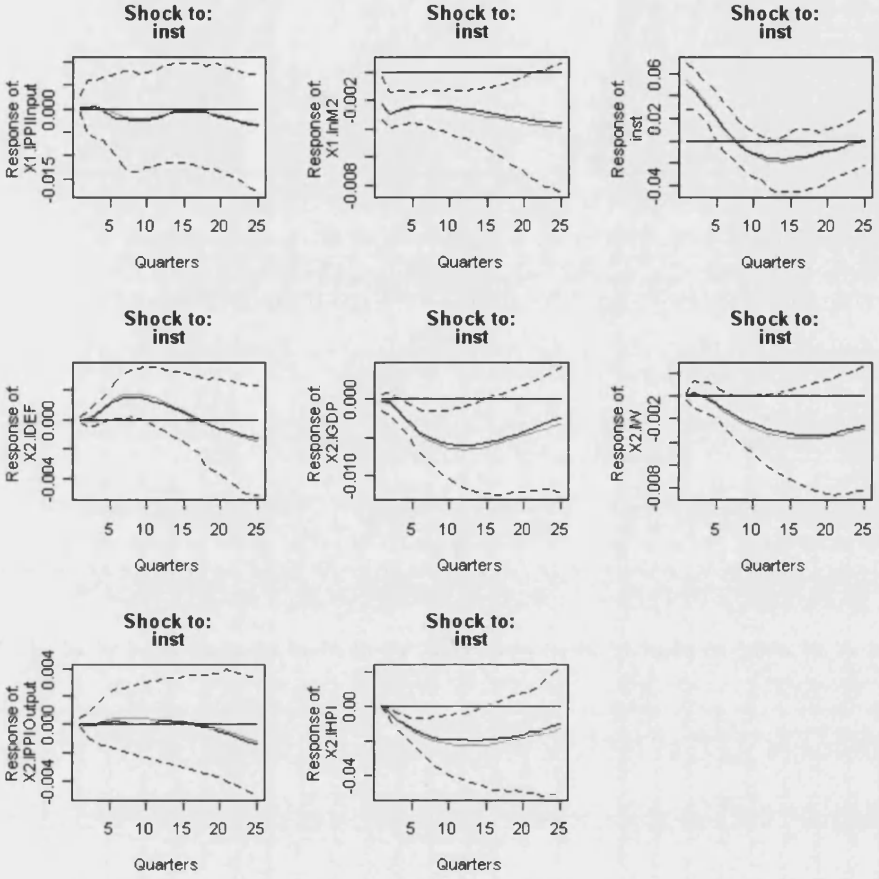

Figure 9: *Sims and Zha (1996, 2005) identification, UK quarterly data. inst =FedFunds rate. Responses to a monetary policy contraction.* 90% *confidence bands based on 30000 draws with strict rejection for* $\tilde{\Gamma}_0$ *and weighted quantiles.*

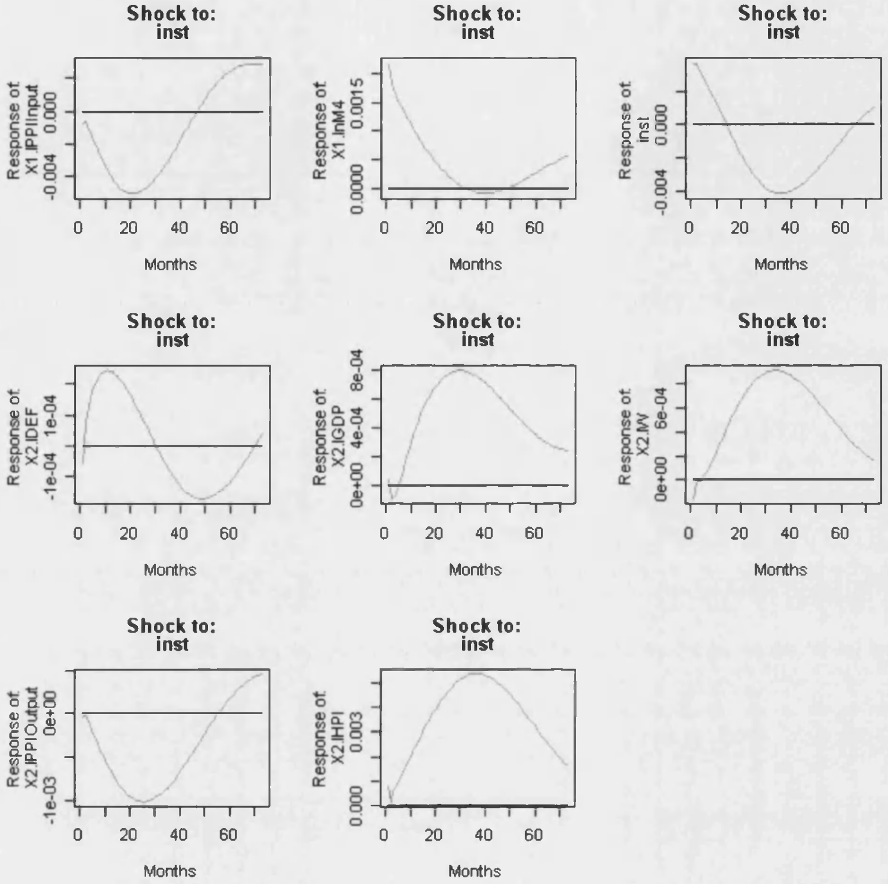

Figure 10: *Sims and Zha (1996, 2005) identification, UK monthly data. inst =FedFunds rate. Responses to a monetary policy expansion.*

For the two behavioral equations of interest - money demand and monetary policy rule -, we report estimated contemporaneous coefficients along with 95 percent equal-tailed probability intervals when quarterly data are used:

$$\underset{(115.75,186.64)}{158.71}\ M_t + \underset{(-0.02,11.73)}{5.32}\ i_t \ \underset{(-115.75,-186.64)}{-158.71}\ Y_t \ \underset{(-115.75,-186.64)}{-158.71}\ P_t = \varepsilon_t^M$$

$$\underset{(-22.36,4.86)}{-9.18}\ PPIInput_t \ \underset{(-288.60,36.10)}{-171.96}\ M_t + \underset{(4.32,16.63)}{11.81}\ i_t = \varepsilon_t^{mp}$$

As before, the interest elasticity of money demand is negative and monetary policy responds strongly to the money stock. Consequently, perturbations that raise the money stock induce the Bank of England to increase the interest rate. In contrast with the behaviour of the Fed, the results suggest that the Bank of England does not react much to information contained in commodity prices.

Leeper and Zha (2003) The results of the Leeper and Zha (2003) identification scheme for the UK (quarterly data) are shown in Figure 11. The expansion lowers the funds rate initially and immediately increases the money stock and input prices, both of which continue to decline smoothly over the 25-quarters horizon. After a brief delay, output falls and stays lower, while unemployment rises and they remain at levels different from the initial ones for almost 25 quarters. In line with the findings of Leeper and Zha (2003), our results suggest that prices adjust very gradually: the effect on prices peaks after 10 quarters and prices remain at a higher level after 25 quarters. The effects of monetary policy on housing prices are weaker as the results suggest that monetary policy does not immediately impact on housing prices. The response of the interest rate to an exogenous policy expansion also shows that the initial liquidity effect lasts about five quarters. However, after this period, the interest rate goes up and returns to its initial level. For the monthly specification (Figure 12) we reach the same conclusions: housing prices fall after a monetary contraction.

Table 4 reports the estimate of contemporaneous coefficient matrix using quarterly data. Interestingly and in contrast with the U.S., the "M Policy" column shows that the policy rule has a much larger contemporaneous coefficient on M than on i, implying that the Bank of England pays much more attention to the money stock than the interest rate.

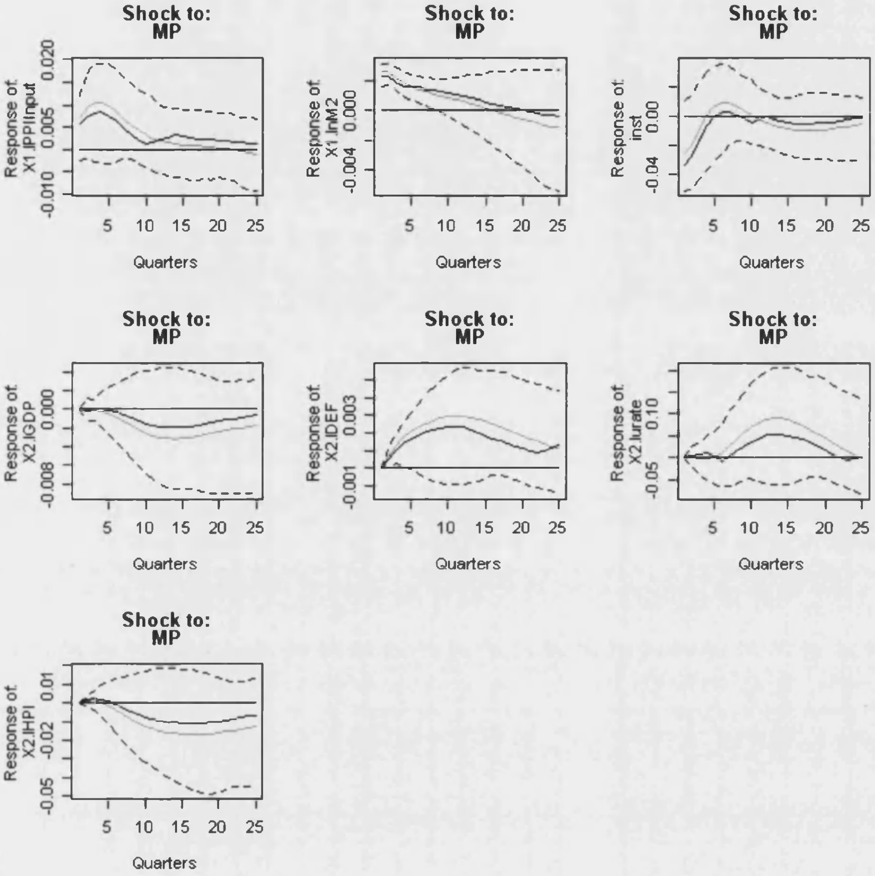

Figure 11: Leeper and Zha (2003) *identification, UK quarterly data. inst =FedFunds rate. Responses to a monetary policy expansion.* 90% *confidence bands based on 30000 draws with strict rejection for* $\tilde{\Gamma}_0$ *and weighted quantiles.*

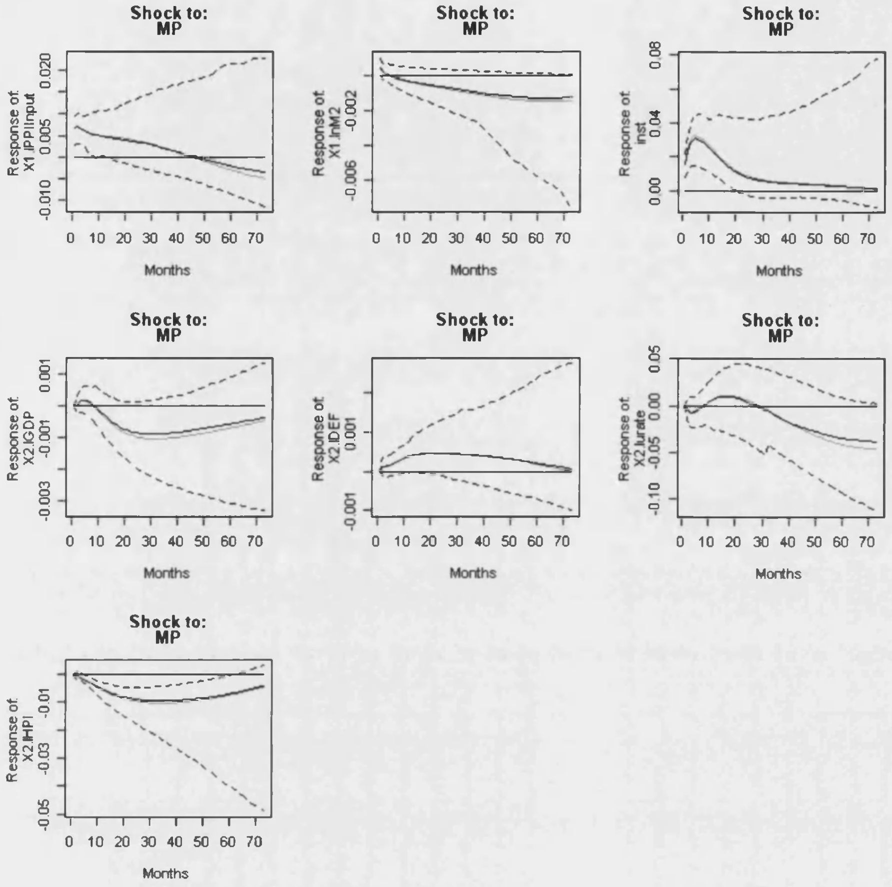

Figure 12: Leeper and Zha (2003) *identification, UK monthly data. inst =FedFunds rate. Responses to a monetary policy contraction.* 90% *confidence bands based on 15000 draws with strict rejection for* $\tilde{\Gamma}_0$ *and weighted quantiles.*

Table 4: Contemporaneous coefficient matrix.

	Sector:						
	Financial	M Policy	M Demand	Prod Y	Prod P	Prod U	Prod HPI
$PPIInput$	57.31	28.89	0.00	0.00	0.00	0.00	0.00
M	-154.08	235.15	122.20	0.00	0.00	0.00	0.00
i	-0.05	-6.71	12.63	0.00	0.00	0.00	0.00
Y	63.80	0.00	-27.97	170.91	73.08	35.76	-38.01
P	-4.67	0.00	-71.10	0.00	368.67	-35.84	95.60
U	0.65	0.00	0.00	0.00	0.00	7.66	0.07
H	19.67	0.00	0.00	0.00	0.00	0.00	87.90

5 Conclusion

In this paper we investigate whether a link between monetary policy shocks and housing prices exists in the data. We analyze evidence both from the U.S. and the U.K., at both monthly and quarterly frequency, and experiment with a large number of identification schemes to shed light on this question. In most specifications we find that housing prices are negatively affected by monetary policy contractions and this effect tends to be very persistent. To the extent that data are available, we find that housing starts also tend to be negatively affected by monetary policy but they react much faster. We also find that in more recent times there has been a substantial reduction in the reaction time of housing prices to interest rate shocks in the UK, consistent with the view of a structural change in the mortgage market.

Additionally, we show that monetary policy shocks do not seem to play an important role in the fluctuations of the stock markets: the impact of the shocks is rather small in magnitude and tends to disappear very quickly.

The results also show important different behaviours in the policies followed by the Fed and the Bank of England: (*i*) whilst the Fed seems to react substantially to changes in the commodity prices, the Bank of England does not seem to attribute an important role to fluctuations in these prices; and (*ii*) whilst the Fed seems to pay a lot of attention to the interest rate, the focus of the Bank of England seems to go in the direction of the money stock.

We think that these findings can be useful when constructing models to better understand the aggregate implications of housing market dynamics. Generating a highly persistent response of house prices and a quick answer of stock prices to monetary policy may prove to be a challenge in quantitative models of the housing and stock market fluctuations.

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Appendix

A Detailed Data Description

A.1 U.S. Data

Housing Sector

Housing prices are measured using two sources: (*a*) the Price Index of New One-Family Houses sold including the Value of Lot provided by the U.S. Census, an index based on houses sold in 1996, available for the period 1963:1-2006:3; and (*b*) the House Price Index computed by the Office of Federal Housing Enterprise Oversight (OFHEO), available for the period 1975:1-2006:3. Data are quarterly, seasonally adjusted.

Other Housing Market Indicators are provided by the U.S. Census. We use the Median Sales Price of New Homes Sold including land and the New Privately Owned Housing Units Started. The data for the Median Sales Price of New Homes Sold including land are: (*i*) quarterly, seasonally adjusted using Census X12 ARIMA, and comprise the period 1963:1-2006:3; and (*ii*) monthly, seasonally adjusted using Census X12 ARIMA, and comprise the period January 1963-November 2006. The data for the New Privately Owned Housing Units Started are: (*i*) quarterly (computed by the sum of corresponding monthly values), seasonally adjusted and comprise the period 1959:1-2006:4; and (*ii*) monthly, seasonally adjusted and comprise the period January 1959-December 2006.

GDP

The source is Bureau of Economic Analysis, NIPA Table 1.1.5, line 1. Data for GDP are: (*i*) quarterly, seasonally adjusted , and comprise the period 1947:1-2006:3; and (*ii*) monthly, seasonally adjusted , linearly interpolated from quarterly series and comprise the period March 1947-September 2006.

Consumption

The source is Bureau of Economic Analysis, NIPA Tables 2.3.5 and 2.6. Consumption is defined as: (*a*) the expenditure in non-durable consumption goods (line 6) and services (line 13) excluding housing services (line 14); and (*b*) the expenditure in non-durable consumption goods (line 3) and services (line 4). Data are: (*i*) quarterly, seasonally adjusted , and comprise the period 1947:1-2006:3; and (*ii*) monthly, seasonally adjusted , and comprise the period January 1959-November 2006.

Price Deflator

All variables were deflated by the CPI, All items less food, shelter, and energy (U.S. city average, 1982-1984=100) ("CUSR0000SA0L12E"). Data are: (*i*) quarterly (computed from monthly series by using end-of-period values), seasonally adjusted , and comprise the period 1967:1-2006:4; (*ii*) monthly, seasonally adjusted, and comprise the period January 1967-December 2006. The source is the Bureau of Labor Statistics.

Investment

The source is Bureau of Economic Analysis, NIPA Table 1.1.5. Investment is defined as the gross private domestic investment (line 6) excluding residential investment (line 11). Data are: (*i*) quarterly, seasonally adjusted , and comprise the period 1947:1-2006:3; and (*ii*) monthly, seasonally adjusted , linearly interpolated from quarterly series and comprise the period March 1947-September 2006.

Wages

The source is Bureau of Economic Analysis, NIPA Tables 2.1 and 2.6. Wages are defined as the sum of wages and salary disbursements (line 3). Data are: (*i*) quarterly, seasonally adjusted , and comprise the period 1947:1-2006:3; and (*ii*) monthly, seasonally adjusted , and comprise the period January 1959-November 2006.

Productivity

Productivity is defined as the Nonfarm Business Output Per Hour Index (1992=100) ("PRS85006093"). Data are: (*i*) quarterly, seasonally adjusted , and comprise the period 1947:1-2006:3; and (*ii*) monthly, seasonally adjusted , linearly interpolated from quarterly series and comprise the period March 1947-September 2006. The source is the Bureau of Labor Statistics.

Profits

The source is Bureau of Economic Analysis, NIPA Table 1.14. Profits are defined as the profits before tax without IVA and CCAdj ("A446RC1", line 32). Data are: (*i*) quarterly, seasonally adjusted, and comprise the period 1947:1-2006:3; and (*ii*) monthly, seasonally adjusted , linearly interpolated from quarterly series and comprise the period March 1947-September 2006.

Monetary Aggregate

Monetary Aggregate corresponds to M2. Data are: (*i*) quarterly, seasonally adjusted , and comprise the period 1960:1-2006:3; and (*ii*) monthly, seasonally adjusted , and comprise the period January 1959-December 2006. The sources are the OECD, Main Economic Indicators (series "USA.MABMM201.STSA") and the Board of Governors of the Federal Reserve System, Release H6.

Stock Market Index

Stock Market Index corresponds to S&P 500 Composite Price Index (close price adjusted for dividends and splits). Data are: (*i*) quarterly (computed from monthly series by using end-of-period values), and comprise the period 1950:1-2006:4; and (*ii*) monthly and comprise the period January 1950-December 2006.

Short-Run Interest Rate

Short-Run Interest Rate is defined as the Federal Funds effective rate. Data are: (*i*) quarterly (computed from monthly series by using the compounded rate), and comprise, respectively, the periods 1957:2-2006:4 and (*ii*) monthly and comprise, respectively, the periods July 1957-December 2006. The source is the Board of Governors of the Federal Reserve System, Release H15 (series "RIFSPFF_N.M" and "RIFSGFSM03_N.M").

Producer Price Indexes

Producer Price Indexes include: (*a*) the producers' price index, Materials and components for construction (1982=100) (series "WPUSOP2200"); (*b*) the producers' price index, All commodities (1982=100) (series "WPU00000000"); (*c*) the producers' price index, Crude materials (stage of processing), (1982=100) (series "WPUSOP1000"); (*d*) the producers' price index, Intermediate materials, supplies and components (1982=100) (series "WPUSOP2000"). Data are: (*i*) quarterly (computed from monthly series by using end-of-period values), and comprise the period 1947:1-2006:4; and (*ii*) monthly and comprise the period January 1947-December 2006. All series are seasonally adjusted using Census X12 ARIMA. The source is the Bureau of Labor Statistics.

Unemployment Rate

Unemployment rate is defined as the civilian unemployment rate (16 and over) (series "LNS14000000"). Data are: (*i*) quarterly (computed from monthly series by using end-of-period values), seasonally adjusted and comprise the period 1948:1-2006:4; and (*ii*) monthly, seasonally adjusted and comprise the period January 1948-December 2006. The source is the Bureau of Labor Statistics, Current Population Survey.

A.2 U.K. Data

Housing Prices

Housing prices are measured using two sources: (*a*) the Mix-Adjusted House Price Index (Feb 2002 = 100) provided by the Office of the Deputy Prime Minister (ODPM), seasonally adjusted , and available for the period 1968:2-2006:2 and January 2002-August 2006; and (*b*) the All-Houses Price Index (1952Q4 = 100 and 1993Q1=100) computed by the Nationwide Building Society, seasonally adjusted using Census X12 ARIMA, and available for the period 1952:4-2006:3 and January 1991-September 2006.

Housing Market Indicators

Other Housing Market Indicators are provided by the Office for National Statistics (ONS), Release ET, Table 5.4 and include the number (in thousands) of Housing Starts in the Private Sector in Great Britain (series "FCAB"). The data are quarterly, seasonally adjusted using Census X12 ARIMA, and comprise the period 1947:1-2005:3.

GDP

Data for GDP are: (*i*) quarterly, seasonally adjusted , and comprise the period 1955:1-2006:3; and (*ii*) monthly, seasonally adjusted , linearly interpolated from quarterly series and comprise the period March 1955-September 2006. The source is the Office for National Statistics, Release UKEA, Table A1 (series "YBHA").

Consumption

The source is the Office for National Statistics, Release CT, Tables 0.GS.CS, SER.CS and NDG.CS. Consumption is defined as the expenditure in non-durable consumption goods and services excluding housing services, actual rentals paid by tenants and imputed rentals for housing, i.e. UTIJ-[LLKE-(UTZI+ZWUQ)]+UTIN-(BMBT-GBFJ), where: "UTIJ" is expenditure in non-durable goods, "LLKE" is expenditure in housing, water, electricity, gas and other fuels, "UTZI" is expenditure in water supply, "ZWUZQ" is expenditure in electricity, gas and other fuels, "UTIN" is expenditure in consumption services, "BMBT" is expenditure in actual rentals paid by tenants, and "GBFJ" is expenditure in imputed rentals for housing. Data are: (*i*) quarterly, seasonally adjusted , and comprise the period 1963:1-2006:3; and (*ii*) monthly, seasonally adjusted , and linearly interpolated from quarterly series and comprise the period March 1963-September 2006.

Price Deflator

The source is the Office for National Statistics, Release MDS, Table 18.1. All variables were deflated by the Retail Price Index, excluding housing (January 1987=100) (series "CHAZ"). Data are: (*i*) quarterly, seasonally adjusted using Census X12 ARIMA, and comprise the period 1947:3-2006:4; (*ii*) monthly, seasonally adjusted using Census X12 ARIMA, and comprise the period July 1947-December 2006.

Investment

The source is the Office for National Statistics, Release MD (Table 1.10) and Release ETAS (Table 2.7). Investment is defined as total gross fixed capital formation (series "NPQX") excluding gross fixed capital formation in dwellings by private sector (series "DFDF") and gross fixed capital formation by general government (series "NNBF"). Data are: (*i*) quarterly, seasonally adjusted , and comprise the period 1955:1-2006:1; and (*ii*) monthly, seasonally adjusted , linearly interpolated from quarterly series and comprise the period March 1955-March 2006.

Wages

Wages correspond to UK average monthly wages (2000=100). Data are: (*i*) quarterly, seasonally adjusted , and comprise the period 1963:1-2006:1; and (*ii*) monthly, seasonally adjusted, and comprise the period January 1963-September 2006. The source is Datastream, based on IMF, International Financial Statistics.

Productivity

The source is the Office for National Statistics, Release PRDY (Table 1) and Release MDS (Table 7.2). Productivity is defined as: (*a*) the Index of Output per worker of the whole economy (2003=100) (series "A4YM") for quarterly data; (*b*) the Index of Output per filled job in Manufacturing Industries for monthly data (2003=100) (series "LNNX"). Data are: (*i*) quarterly, seasonally adjusted , and comprise the period 1959:3-2006:3; and (*ii*) monthly, seasonally adjusted , and comprise the period September 1984-September 2006.

Profits

The source is the Office for National Statistics, Release UKEA, Tables X1 and X8. Profits are defined as the sum of gross trading profits of private non-financial corporations both non UKs (series "CAED") and UK continental shelf companies (series "CAGD") and financial corporations (series

"RITQ"). Data are: (*i*) quarterly, seasonally adjusted , and comprise the period 1955:1-2006:3; and (*ii*) monthly, seasonally adjusted , linearly interpolated from quarterly series and comprise the period March 1955-September 2006.

Monetary Aggregate

The source is the Office for National Statistics, Release MD, Table 17.5. Monetary Aggregate corresponds to: (*a*) M2 (series "VQWU"); and (*b*) M4 (series "AUYN"). Data are: (*i*) quarterly, seasonally adjusted , and comprise the periods 1982:3-2006:3 (for M2) and 1963:1-2006:3 (for M4); and (*ii*) monthly, seasonally adjusted , and comprise the period June 1982-September 2006.

Stock Market Index

Stock Market Index corresponds to the FTSE-All Shares Index (1962:2=100 or 1962 April=100). Data are: (*i*) quarterly, and comprise the period 1962:2-2006:3; and (*ii*) monthly and comprise the period March 1962-May 2006. The source is Datastream.

Short-Run Interest Rate

Short-Run Interest Rate is defined as the 3-month Treasury bills rate discount basis (series "UK3MTHINE"). Data are: (*i*) quarterly, and comprise the period 1957:1-2006:3; and (*ii*) monthly and comprise the period January 1957-October 2006. The source is Datastream, based on ONS.

Producer Price Indexes

The source is the Office for National Statistics, Release ETAS, Table 3.3. Producer Price Indexes include: (*a*) the producers' price index, Input prices (materials and fuel) of all manufacturing (2000=100) (series "RNNK"); (*b*) the producers' price index, Output of manufactured products (2000=100) (series "PLLU"). Data are: (*i*) quarterly and comprise the period 1974:1-2006:4; and (*ii*) monthly and comprise the period January 1974-December 2006. All series are seasonally adjusted using Census X12 ARIMA.

Unemployment Rate

The source is the Office for National Statistics, Labor Market Statistics. Unemployment rate is defined as the UK unemployment rate among all aged 16 and over (series "MGSX"). Data are: (*i*) quarterly, seasonally adjusted and comprise the period 1971:1-2006:4; and (*ii*) monthly, seasonally adjusted and comprise the period February 1971-December 2006.

B Assessing Posterior Uncertainty in Fully Simultaneous S-VAR

In the S-VAR setting considered, the impulse-response functions are given by

$$B(L)^{-1}\Gamma_0^{-1}$$

This implies that to assess posterior uncertainty regarding the impulse-response function we need joint draws for both $B(L)$ and Γ_0.

Since equation (2) is not in the form of any standard probability density function we cannot draw Γ_0 from it directly to make inference. Nevertheless, if we take a second order expansion of equation (2) around its peak we get the usual Gaussian approximation to the asymptotic distribution of the elements in Γ_0. Since this is not the true form of the posterior probability density function, we cannot use it directly to produce a Monte Carlo sample. A possible approach is importance sampling, in which we draw from the Gaussian approximation, but weigh the draws by the ratio of (2) to the probability density function from which we draw. The weighted sample cumulative density function then approximates the cumulative density function corresponding to (2).

Note also that the distribution of $B(L)$, given Γ_0, is the usual normal distribution

$$vec(B(L))|\Gamma_0 \sim N\left(vec\left(\hat{B}_{OLS}\right), \Gamma_0^{-1}\left(\Gamma_0^{-1}\right)' \otimes \left(X'X\right)^{-1}\right). \tag{7}$$

So we can take joint draws using the following simple algorithm: (*i*) draw Γ_0 using importance sampling (2); and (*ii*) draw $vec(B(L))$ using equation (7).

Confidence bands for the impulse-response function are then constructed from the weighted percentiles of the Monte Carlo sample where the weights used are the importance sampling weights.

B.1 Algorithm for Drawing from the Posterior Distribution

The method used is a mixed Monte Carlo/importance sampling approach.

Denote with $\hat{H}$ the numerical Hessian from the *minimization* routine at the point estimate and $\hat{\Gamma}_0$ the maximum-likelihood estimator.

The algorithm is the following:

1. Check that all the coefficients on the main diagonal of $\hat{\Gamma}_0$ are positive. If they are not, flip the sign of the rows that have a negative coefficient on the main diagonal (that is, our point estimates are normalized to have positive elements on the main diagonal).

2. Set $i = 0$.

3. Drawn $vech\left(\tilde{\Gamma}_0\right)$ from a normal $N\left(vech\left(\hat{\Gamma}_0\right), \hat{V}\right)$, where $\hat{V} = \hat{H}^{-1}$ and $vech\left(.\right)$ vectorizes the unconstrained elements of a matrix. That is, this step draws from the asymptotic distribution of Γ_0.

   There are 3 possible options to handle draws in which some of the diagonal elements of $\tilde{\Gamma}_0$ are not positive:

   (a) if some of the diagonal entries of $\tilde{\Gamma}_0$ are not positive, reject the draw and go back to 2. to take another draw (this is what is also done in the Sims and Zha (2006a)).

   (b) reject the draw if and only if one of the negative entries on the main diagonal is more than "alpha" standard deviations away from the maximum-likelihood estimator.

   (c) accept the draw and continue.

4. Compute and store the importance sampling weight

$$m_i = \exp \begin{bmatrix} T \log \left|\det\left(\tilde{\Gamma}_0\right)\right| - \frac{1}{2} trace\left(S\left(\hat{B}_{OLS}, \hat{a}_{OLS}\right)\tilde{\Gamma}_0'\tilde{\Gamma}_0\right) \\ -\log\left|\hat{V}\right|^{-\frac{1}{2}} + .5\left(vech\left(\tilde{\Gamma}_0\right) - vech\left(\hat{\Gamma}_0\right)\right)' \hat{V}^{-1}\left(vech\left(\tilde{\Gamma}_0\right) - vech\left(\hat{\Gamma}_0\right)\right) \\ -SCFT \end{bmatrix}$$

   where $SCFT$ is a scale factor that prevents overflow/underflow (a good choice for it is normally the value of the likelihood at its peak).[8]

5. Draw $vec\left(\tilde{B}\left(L\right)\right)$ from a normal $N\left(vec\left(\hat{B}_{OLS}\right), \tilde{\Gamma}_0^{-1}\left(\tilde{\Gamma}_0^{-1}\right)' \otimes \left(X'X\right)^{-1}\right)$ to get a draw for $\tilde{B}\left(L\right)$.

6. Compute the impulse-response function and store it in a multidimensional array.

7. If $i < \#draws$, set $i = i + 1$ and go back to 3.

The stored draws of the impulse-response function, jointly with the importance sampling weights, are used to construct confidence bands from their percentiles. Moreover, the draws of $\tilde{\Gamma}_0$ are stored to construct posterior confidence interval for these parameters from the posterior (weighted) quantiles.

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[8] Confidence bands constructed using unweighted quantiles are asymptotically justified (due to the asymptotic Gaussianity), and are good to give a quick look at the shape of the impulse-response function using a small number of draws. The unweighted approach should be used with caution since: (*i*) it is likely to produce unrealistically tight bands in the presence of multiple local maxima; and (*ii*) will not capture asymmetries of the confidence bands (what are important in detecting whether and impulse-response function is significantly different from zero).

Normalized weights that sum up to 1 are simply constructed as:

$$w_i = \frac{m_i}{\sum_i^{\#draws} m_i}.$$

When the number of draws is sufficiently large for the procedure outlined above to deliver accurate inference, the plot of the normalized weights should ideally show that none of them is too far from zero – that is, one single draw should not receive 90% of the weight.[9]

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[9] When the importance sampling performs too poorly (due to the variability in the weights), we can replace that part of the algorithm with the random walk Metropolis Markov-Chain Monte Carlo of Waggoner and Zha (1997), using also their approach to handle switch in the sign of the rows of Γ_0 (that is, use a normalization for each draw that minimizes the distance of Γ_0 from the maximum likelihood estimate).

Chapter IV

Risks for the Long-Run and the Cross-Section of Asset Returns

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Abstract

This paper combines Epstein-Zin preferences and the consumer's budget constraint to derive a relationship where the importance of the risks for the long-run can help explaining the cross-section of average returns.

We find that when consumption growth, the consumption-wealth ratio and its first-differences are used as conditioning information for the Consumption Capital Asset Pricing Model (C-CAPM), the resulting linear factor model explains a large fraction of the variation in observed average returns across the Fama and French (25) portfolios and prices correctly the small growth portfolio.

The model captures: (*i*) the preference of investors for a smooth path for consumption as implied by the intertemporal budget constraint; and (*ii*) the low intertemporal elasticity of substitution and the high risk aversion, which imply that agents demand large equity risk premia because they fear a reduction in future economic prospects. Moreover, the implied stochastic discount factor exhibits a business cycle pattern, and the model developed clearly outperforms the standard C-CAPM with power utility.

Keywords: Epstein-Zin preferences, intertemporal budget constraint, expected returns, consumption capital asset pricing.

JEL classification: E21, E24, G12.

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1 Introduction

The natural economic explanation for differences in expected returns across assets is differences in risk. Lucas (1978) and Breeden (1979) argue that the risk premium on an asset is determined by its ability to insure against consumption fluctuations and Sharpe (1964) and Lintner (1965) show that the exposure of asset returns to movements in aggregate consumption explains cross-sectional differences in risk premia.

Identifying the economic sources of risks remains, however, an important economic issue because differences in the covariance of returns and contemporaneous consumption growth across portfolios have not proved to be sufficient to justify the differences in expected returns observed in the U.S. stock market (Mankiw and Shapiro, 1986; Breeden *et al.*, 1989; Campbell, 1996; Cochrane, 1996; Lettau and Ludvigson, 2001b). Additionally, Hansen and Singleton (1982) - for the consumption-based models -, and Fama and French (1992) - for the CAPM -, show that these models have considerable difficulty in supporting the differences in a cross-section of asset returns.

The empirical failure of the canonical consumption-based asset pricing model has spawned a large literature that addresses its shortcomings: inefficiencies of financial markets (Fama (1970, 1991, 1998), Fama and French (1996), Farmer and Lo (1999)); the rational response of agents to time-varying investment opportunities driven by variation in risk aversion (Sundaresan (1989), Constantinides (1990), Campbell and Cochrane (1999)) or in the joint distribution of consumption and asset returns (Duffee (2005), Santos and Veronesi (2006)) have been offered as explanations for why differences in expected returns are not due to differences in risk to consumption. In addition, several papers tried to shed more light on this question and many economically motivated variables have been developed to capture time-variation in expected returns and document long-term predictability.[1]

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[1] See, for example, Fama and French (1988), Campbell and Shiller (1988), Poterba and Summers (1988), Richards (1995), Lettau and Ludvigson (2001a, 2004). Lettau and Ludvigson (2001a) show that the transitory deviation from the common trend in consumption, aggregate wealth and labor income, *cay*, is a strong predictor of asset returns, as long as the expected return to human capital and consumption growth are not too volatile. Fernandez-Corugedo *et al.* (2003) use the same approach but incorporate the relative price of durable goods, whilst Julliard (2004) shows that the expected changes in labor income are important because of their ability to track time varying risk premia. The nonseparability between consumption and leisure in on the basis of the work of Wei (2005), who argue that human capital risk can generate sufficient variation in the agent's risk attitude to produce equity returns and bond yields with properties close to the observed in the data. Whilst the last two papers emphasize the role of human capital, others have focused on the importance of the housing market instead. Yogo (2006) and Piazzesi *et al.* (2007) emphasize the role of nonseparability of preferences in explaining the countercyclical variation in the equity premium. Pakos (2003) argues that there is an important non-homotheticity in preferences. In the same spirit, Lustig and Van Nieuwerburgh (2005) show that the ratio of housing wealth to human wealth (the housing collateral ratio) shifts the conditional distribution of asset prices and

Within the representative agent representation, two main lines of investigation have been successfully explored. The first approach introduces time-varying risk-aversion in preferences and is based on the external habit model of Campbell and Cochrane (1999), which was designed to show that equilibrium asset prices can match the data in a world without predictability in cash-flows, that is, where dividend growth and aggregate consumption are *i.i.d.*.[2] The second approach is based on the concept of long-run risk (Epstein and Zin, 1991; Bansal and Yaron, 2004), and introduces predictability in aggregate consumption growth, as a result of the persistency of the shocks to cash-flows.[3] Low-frequency movements, and time-varying uncertainty in aggregate consumption growth are the key channels for understanding asset prices.

The model of the long-run risk of Bansal and Yaron (2004) has two major features. First, it relies on Epstein and Zin (1989) preferences, which allows for a separation between the intertemporal elasticity of substitution and risk aversion. Second, it models consumption and dividend growth as containing a small persistent expected growth component, and fluctuating volatility, which captures time-varying economic uncertainty. The authors show that an intertemporal elasticity of substitution greater than 1 is critical for capturing the observed negative correlation between consumption volatility and price-dividend ratios. The results show that risks related to varying growth prospects and fluctuating economic uncertainty can quantitatively justify many of the observed features of asset market data.

The present work combines Epstein-Zin preferences, the intertemporal budget constraint and the homogeneity property of the Bellman equation to derive a relationship that highlights the role of risks for the long-run in predicting U.S. quarterly stock market returns and explaining the cross-sectional variation of average returns. We explore this relationship, and show that it outperforms most of the asset pricing models developed in the literature and show that the implied stochastic discount factor

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consumption growth and, therefore, predicts returns on stocks.

[2] Abel (1990), Constantinides (1990), Ferson and Constantinides (1991), Abel (1999) are among the early contributions to the literature on habit-formation models. On the other hand, Menzly *et al.* (2004) and Wachter (2006) provide more recent approaches to the topic. Chen and Ludvigson (2007) estimate the habit process for a class of external habit models. Sousa (2007) tests the CRRA assumption using macroeconomic data, and shows that the representative agent may have habit-formation preferences.

[3] Bansal *et al.* (2005) suggest that changes in expectations about the entire path of future cash flows can account for the puzzling differences in risk premia across book-to-market, momentum, and size-sorted portfolios. Hansen *et al.* (2006), Parker and Julliard (2005) and Malloy *et al.* (2005) measure long-run risk based on leads and long-run impulse responses of consumption growth. Bansal *et al.* (2006) estimate the long-run risk model, Piazzesi and Schneider (2006) study its implications for the yield curve, Bansal *et al.* (2005) and Yang (2007) study the implications for the cross-section of equity portfolios, and Benzoni *et al.* (2005) for credit spreads. Bekaert *et al.* (2005) estimate both long-run risk and external habit models. Bansal *et al.* (2007) estimate and examine the empirical plausibility of the habit-formation model and the long-run risk model.

can be expressed as a function of the consumption growth, C_{t+1}/C_t, the consumption-aggregate wealth ratio, *cay*, and its first-differences, Δcay.

We find that: (*i*) risks for the long-run are important determinants of both real returns and asset returns over a Treasury bill rate; and (*ii*) when risks for the long-run are used as conditioning information for the Consumption Capital Asset Pricing Model (C-CAPM), the resulting linear factor model explains a large fraction of the variation in observed average returns across the 25 Fama and French portfolios and prices correctly the small growth portfolio. The model is able to explain between 44 and 50 percent of the cross-sectional variation of asset returns, and clearly outperforms the standard C-CAPM with power utility. Additionally, it rivals the Fama and French (1993) three-factor model, the Lettau and Ludvigson (2001b) three-factor model, and the Parker and Julliard (2005) ultimate consumption risk model in explaining the cross-section of expected returns.

The main novelty of the paper is that it allows us to estimate simultaneously the intertemporal elasticity of substitution and the risk aversion by using the consumption-aggregate wealth ratio, *cay*, or the market return, R^m, to recover the return on aggregate wealth. In this sense, the model provides a more informative summary of the representative agent's characteristics than most of the optimal choice models developed in the literature of asset pricing.

We show that the intertemporal elasticity of substitution is relatively small (ranging from 0.034 and 0.41), consistent with the findings of Hall (1988) and Campbell (1999) at the macroeconomic level - close to 0 - and Browning, Hansen and Heckman (2000) at the microeconomic level - around 0.5. Additionally, it questions the findings of Hansen and Singleton (1982), Attanasio and Weber (1989), Guvenen (2001), Vissing-Jorgensen (2002) and, more recently, Bansal and Yaron (2004), who argue that the intertemporal elasticity of substitution is well over 1. We also show that the coefficient of risk aversion is relatively high: the point estimates range from 91.089 and 96.114. Mehra and Prescott (1985) argue that a reasonable upper bound for risk aversion is around 10. In this sense, our estimate for risk aversion is high.

The success of the model in predicting asset returns and explaining the cross-sectional variation of expected excess returns is due to its ability to track time varying equilibrium risk premia. The model captures: (*i*) the preference of investors for a smooth path for consumption as implied by the intertemporal budget constraint; and (*ii*) the separation between a low intertemporal elasticity of substitution and a high risk aversion, implying that agents demand large equity risk premia because they fear that a reduction in economic prospects or a rise in economic uncertainty will lower asset prices. The risks for the long-run are, therefore, important determinants of the risk premium and explain a substantial fraction of the cross-sectional variation that one observes in expected returns in the Fama-French portfolios.

The results are robust to different measures of consumption - nondurable goods consumption *versus* total consumption - and to different sample sizes. Moreover, the implied stochastic discount factor of the model that combines Epstein-Zin preferences with *cay* exhibits a clear business cycle pattern, contrary to the C-CAPM specification: consumption falls around recessions, so that the stochastic discount factor is highest right before and at the start of recessions.

The paper is organized as follows. Section 2 presents the theoretical approach and how we combine the Epstein-Zin preferences with the intertemporal budget constraint to derive the stochastic discount factor. Section 3 describes the data, and Section 4 presents the estimation methodology. Section 5 presents the results of the regressions, and Section 6 compares the performance of the model with other different linear asset pricing specifications. Finally, in Section 7, we conclude and discuss the implications of the findings.

2 Epstein-Zin Preferences and the Intertemporal Budget Constraint

Consider a representative agent economy in which wealth is tradable. Defining W_t as time t aggregate wealth (human capital plus asset wealth), C_t as time t consumption and $R_{w,t+1}$ as the return on aggregate wealth between period t and $t+1$, the consumer's budget constraint can be written as[4]

$$W_{t+1} = (1 + R_{t+1})(W_t - C_t) \quad \forall t \tag{1}$$

where W_t is total wealth and $R_{w,t}$ is the return on wealth, that is,

$$R_{t+1} := \left(1 - \sum_{i=1}^{N} w_{it}\right) R^f + \sum_{i=1}^{N} w_{it} R_{it+1} = R^f + \sum_{i=1}^{N} w_{it}\left(R_{it+1} - R^f\right) \tag{2}$$

where w_i is the wealth share invested in the ith risky asset and R^f is the risk-free rate.

With Epstein and Zin (1989, 1991) preferences, the optimal value of the utility, V, at time t will be a function of the wealth W_t and takes the form

$$V(W_t) \equiv \max_{\{C,w\}} \left\{ (1-\delta) C_t^{\frac{1-\gamma}{\theta}} + \delta \left(E_t \left[V(W_{t+1})^{1-\gamma} \right] \right)^{\frac{1}{\theta}} \right\}^{\frac{\theta}{1-\gamma}} \tag{3}$$

where C_t is the consumption, δ is the rate of time preference, γ is the relative risk aversion, ψ is the intertemporal elasticity of substitution, E_t is the rational expectation operator, and $\theta := \frac{1-\gamma}{1-1/\psi}$.

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[4] Labor income does not appear explicitly in this equation because of the assumption that the market value of tradable human capital is included in aggregate wealth.

By homogeneity, $V(W_t) \equiv \phi_t W_t$ for some ϕ_t and, given the structure of the problem, consumption is also proportional to W_t, that is $C_t = \varphi_t W_t$.

The first-order condition for C_t can be written as:

$$\delta E_t\left[\phi_{t+1}^{1-\gamma}R_{t+1}^{1-\gamma}\right]^{\frac{1}{\theta}} = (1-\delta)\left(\frac{\varphi_t}{1-\varphi_t}\right)^{\frac{1-\gamma}{\theta}-1}. \tag{4}$$

Using homogeneity, equation(3) becomes:

$$\begin{aligned}\phi_t &= \max\left\{(1-\delta)\left(\frac{C_t}{W_t}\right)^{\frac{1-\gamma}{\theta}} + \delta\left(E_t\left[\phi_{t+1}^{1-\gamma}R_{t+1}^{1-\gamma}\right]\right)^{\frac{1}{\theta}}\left(1-\frac{C_t}{W_t}\right)^{\frac{1-\gamma}{\theta}}\right\}^{\frac{\theta}{1-\gamma}} \\ &= (1-\delta)^{\frac{\theta}{1-\gamma}}\left(\frac{C_t}{W_t}\right)^{1-\frac{\theta}{1-\gamma}}.\end{aligned}$$

Plugging the solution for ϕ_t in the first-order condition (4), one can derive the Euler equation for the return on wealth:

$$1 = E_t\left[\delta^\theta\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{\theta}{\psi}}R_{t+1}^\theta\right] \quad \forall t. \tag{5}$$

The first-order condition for w_{it} can be written as:

$$E_t\left[\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{\theta}{\psi}}R_{t+1}^{\theta-1}R_{it+1}\right] = E_t\left[\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{\theta}{\psi}}R_{t+1}^{\theta-1}\right]R^f \quad \forall t, i. \tag{6}$$

From the Euler equation (5) and the definition of return on wealth (2), we have:

$$1 = E_t\left[\delta^\theta\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{\theta}{\psi}}R_{t+1}^{\theta-1}\left(R^f + \sum_{i=1}^{N} w_{it}\left(R_{it+1}-R^f\right)\right)\right] \quad \forall t.$$

Using (6), the equilibrium risk free rate is such that:

$$1/R^f = E_t\left[\delta^\theta\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{\theta}{\psi}}R_{t+1}^{\theta-1}\right] \quad \forall t.$$

Finally, multiplying both sides of (6) by δ^θ and using the last result to remove R^f, the Euler equation for any risky asset i becomes:

$$E_t\left[\delta^\theta\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{\theta}{\psi}}R_{t+1}^{\theta-1}R_{it+1}\right] = 1 \quad \forall t, i. \tag{7}$$

From equation (1), one obtains

$$R_{t+1}^{-1} = \frac{W_t}{W_{t+1}} - \frac{C_t}{W_{t+1}} = \frac{C_t}{C_{t+1}}\left(\frac{W_t}{C_t}\frac{C_{t+1}}{W_{t+1}} - \frac{C_{t+1}}{W_{t+1}}\right)$$

and consequently,

$$R_{t+1}^{\theta-1} = e^{(\theta-1)\Delta c_{t+1}}\left[e^{\Delta cw_{t+1}} - e^{cw_{t+1}}\right]^{1-\theta}$$

where $cw_t := \log(C_t/W_t)$.

Putting the last result into equation (7), we have

$$E_t \left\{ \left(\frac{C_{t+1}}{C_t} \right)^{-\gamma} \left[e^{\Delta cw_{t+1}} - e^{cw_{t+1}} \right]^{1-\theta} \left(R_{it+1} - R^f \right) \right\} = 0$$

where the stochastic discount factor, m_t, is:[5]

$$m_{t+1} = \left(\frac{C_{t+1}}{C_t} \right)^{-\gamma} \left[e^{\Delta cw_{t+1}} - e^{cw_{t+1}} \right]^{1-\frac{1-\gamma}{1-1/\psi}}. \tag{8}$$

In order to estimate the last equation, we need a proxy for cw. Following Lettau and Ludvigson (2001a):

$$cw_t \approx \kappa + cay_t.$$

Alternatively, Campbell (1996) and Jagannathan and Wang (1996) assume that labor income (Y_t) can be thought of as the dividend on human capital (H_t). In this context, and under the assumption that the steady state human capital-labor income ratio is constant ($Y/H = \rho_h^{-1} - 1$, where $0 < \rho_h < 1$), one can follow Julliard (2004) and use the following expression

$$cw_t \approx \kappa + cay_t - (1 - \omega)\, lr_t$$

where $lr_t := \psi(L)\epsilon_t = E_t \sum_{i=1}^{\infty} \rho_h^{i-1} \Delta y_{t+i}$ and ω is the share of asset wealth in total wealth.[6] On the other hand, if the return on total wealth is proxied by the return on the market (as Epstein and Zin (1989, 1991) originally suggested), the stochastic discount factor can be written as:

$$\begin{aligned} m_{t+1} &= \left(\frac{C_{t+1}}{C_t} \right)^{-\frac{\theta}{\psi}} R_{M,t+1}^{\theta-1} = \left(\frac{C_{t+1}}{C_t} \right)^{-\frac{1-\gamma}{\psi-1}} R_{M,t+1}^{\frac{1-\gamma}{1-1/\psi}-1} \\ &= \left(\frac{C_{t+1}}{C_t} \right)^{-\frac{1-\gamma}{\psi-1}} R_{M,t+1}^{\frac{-\gamma+1/\psi}{1-1/\psi}}. \end{aligned} \tag{9}$$

3 Data

In the estimations, we use quarterly, seasonally adjusted data for U.S., variables are measured at 2000 prices and expressed in the logarithmic form of per capita terms, and the sample period is 1952:1 - 2005:4.

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[5] Appendices B and C provide the derivation of the stochastic discount factor.

[6] The author assumes that y_t follows an ARIMA process with innovations indicated by ϵ_t. If a good measure for the returns on human capital was available, then the expression for cw_t would be:

$$cw_t \approx \kappa + cay_t - (1 - \omega)\, E_t \sum_{i=1}^{\infty} \rho_h^{i-1} (\Delta y_{t+i} - r_{h,t+i}).$$

The proxy chosen for the market return is the value weighted CRSP (CRSP-VW) market return index. We use the quarterly returns on the 25 Fama and French (1992) portfolios $\{R_{i,t+1}\}_{i=1}^{25}$ and construct excess returns as these returns less the return on a 3-month Treasury Bill (the "risk-free" rate), $R^f_{t,t+1}$. The returns of these portfolios have a large dispersion in average returns that is relatively stable in sub-samples and have been used extensively to evaluate asset pricing models. Moreover, they are designed to focus on two features of average returns: the size effect - firms with small market value have, on average, higher returns - and the value premium - firms with high book values relative to market equity have, on average, higher returns.

Therefore, the 25 Fama-French portfolios are the intersections of five portfolios formed on size (market equity) and five portfolios formed on the ratio of book equity to market equity. Data on portfolio returns are available monthly from July 1926 to December 2006. A portfolio is denoted by the rank of its market equity and then the rank of its book-to-market ratio so that portfolio 15 is the smallest quintile of stocks by market equity and the largest quintile of stocks by book-to-market. To match the frequency of consumption data, we cumulate returns to a quarterly frequency, so that $R_{i,t+1}$ represents the return on portfolio i during the quarter $t+1$. All returns are deflated by the same deflator as consumption.

For consumption, we use (chain-weighted) personal consumption expenditures on nondurable goods. We make the standard "end-of-period" timing assumption that consumption during quarter t takes place at the end of the quarter, so that $Cov[m_{t+1}, R^e_{i,t+1}]$ is calculated using NIPA consumption in $t+1$ relative to t and returns during $t+1$.[7] For income, we include only labor income. Original data on wealth correspond to the end-period values. Therefore, we lag once the data, so that the observation of wealth in t corresponds to the value at the beginning of the period $t+1$.

The main data sources are the Flow of Funds Accounts provided by Federal Reserve System and BEA of U.S. Department of Commerce. The time series of cay_t is taken from Sidney Ludvigson's homepage. In Appendix A, we present a detailed discussion of data.

4 Estimation Methodology

We estimate the parameters μ, γ, α, κ, ψ in the expression for the stochastic discount factor

$$m_t := \left(\frac{C_{t+1}}{C_t}\right)^{-\gamma} \left[e^{\Delta cay_{t+1}} - e^{\kappa + cay_{t+1}}\right]^{1-\frac{1-\gamma}{1-1/\psi}},$$

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[7] Under this convention the entire period that C_t covers is contained in the information set of the agent before $R^e_{i,t+1}$. The alternative timing convention, used by Campbell (1999), for example, is that consumption occurs at the beginning of the period, so that, using NIPA dates, one aligns m_{t+2} with $R^e_{i,t+1}$.

by GMM, using the 26 × 1 empirical moment function

$$g\left(\mathrm{R}_t^e, \frac{C_{t+1}}{C_t}, \Delta cay_{t+1}, cay_{t+1}; \mu, \gamma, \alpha, \kappa, \psi\right) = \left[\begin{array}{c} \mathrm{R}_t^e - \alpha 1_{25} + \dfrac{(m_t - \mu)\,\mathrm{R}_t^e}{\mu} \\ m_t - \mu \end{array}\right], \tag{10}$$

where R_t^e is the 25 × 1 vector whose ith element is the excess return, $R_{it+1} - R_{t+1}^f$.

Equation (10) implies that the moment function satisfies the 26 moment restrictions

$$E_t\left\{\left(\frac{C_{t+1}}{C_t}\right)^{-\gamma}\left[e^{\Delta cay_{t+1}} - e^{\kappa + cay_{t+1}}\right]^{1-\frac{1-\gamma}{1-1/\psi}}\left(R_{it+1} - R_{t+1}^f\right)\right\} = 0,$$

or

$$E\left[g\left(\mathrm{R}_t^e, \frac{C_{t+1}}{C_t}, \Delta cay_{t+1}, cay_{t+1}; \mu, \gamma, \alpha, \kappa, \psi\right)\right] = 0. \tag{11}$$

at the true parameter values.

It is worth making two points about this approach to estimation. First, we base estimation on equation (11) even though this choice means having to include the additional moment $E[m_t - \mu] = 0$ because this allows different models to be evaluated using a similar criterion. For any stochastic discount factor, the differences between the empirical and theoretical moments are pricing errors: the extent to which the expected return predicted by the model does not equal the observed average excess return.[8] Therefore, the units of these errors are independent of the choice of stochastic discount factor. Second, by including the parameter α rather than imposing $\alpha = 0$, we analyze the ability of the models to explain both the equity premium and the cross section of expected stock returns. Because of our choice, α is in units of expected return and, consequently, measures the extent to which the model underpredicts the excess returns of all Fama-French portfolios by the same amount, that is, the extent to which the model has an equity premium puzzle.[9]

We report estimates from GMM with a pre-specified weighting matrix. The pre-specified weighting matrix is a diagonal matrix that places weight one on the first 25 moments and very large weight on the last moment.[10] This estimator has three advantages over efficient GMM (iterated to convergence).

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[8] These are errors in expected return. However, since they are all scaled by the mean of the stochastic discount factor, they are proportional to the pricing errors.

[9] As Parker and Julliard (2005) point out, if we omitted α, then we might incorrectly conclude that the model was only weakly related to expected returns across portfolios when in fact it was "merely" not consistent with the average excess return of all portfolios. In fact, many potential explanations of the equity premium - such as limited participation, differential taxation of stocks and bonds, liquidity demand for Treasury bills, and changing regulation of asset markets - can be consistent with consumption risk pricing the expected returns among stocks, but not between stocks and Treasury bills.

[10] Following Yogo (2006), we choose the weight of the last moment to be large enough so that variation in the weight does not change the parameter estimates. This ensures that our findings are not due to misestimating the mean of the stochastic discount factor.

First, these estimates match the mean of the stochastic discount factor and minimize the sum of squared pricing errors on the Fama-French portfolios, giving each portfolio equal weight. Thus it forces the model to try to explain the size effect and the value premium. Efficient GMM, on the other hand, minimizes the sum of squared pricing errors on weighted combinations of the portfolios, first-order conditioning on linear combinations of returns that have low variance and, therefore, ignoring the value premium or size effect or both if they are "hard" to price.[11] Second, measures of fit and specification tests are more comparable across different models than for efficient GMM, because GMM with a pre-specified weighting matrix tries to price the same portfolios (Cochrane 2001, chap. 11). Finally, GMM with a pre-specified weighting matrix has superior small-sample properties (Ferson and Foerster 1994; Hansen, Heaton, and Yaron 1996; Ahn and Gadarowski 1999).[12]

5 Risks for the Long Run and the Cross-Section of Asset Returns

This section asks whether risks for the long-run explain the cross-sectional variation in expected returns on different portfolios of stocks. First, are the risks for the long-run economically significant - do they explain a large share of the variance of average returns? Second, are risks for the long-run statistically significant? Third, can we combine Epstein-Zin preferences and the intertemporal budget constraint to obtain estimates of the intertemporal elasticity of substitution and the risk aversion that reconcile the empirical evidence at the micro and macroeconomic level?

Our estimates provide two additional pieces of information about the model. First, we estimate both the risk aversion and the elasticity of intertemporal substitution of the representative investor. These are structural parameters and should be consistent with behavior under risk in other economic environments. Second, our estimates of α measure the extent to which the risks for the long-run of different portfolios are consistent with the average excess return on all portfolios.

We estimate the model (11) using the stochastic discount factor expressed in (8) and also perform the estimation using the stochastic discount factor expressed in (9). Both models are estimated by GMM using a pre-specified weighting matrix and are compared with other asset pricing models, namely, the standard C-CAPM and the ultimate consumption risk by Parker and Julliard (2005).[13]

Table 1 presents the cross-sectional asset pricing results using the "end-of-period" timing convention

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[11] Efficient GMM normally prices unusual combinations of portfolios, with extreme long and short positions.

[12] We follow Jagannathan and Wang (1996) and Hansen and Jagannathan (1997) in the estimation of the model by GMM using the pre-specified weighting matrix.

[13] We follow the authors and assume that the number of quarters ahead, S, is equal to 11.

for consumption growth that aligns $\left(\frac{C_{t+2}}{C_{t+1}}\right)^{-\gamma}$ with $R^e_{i,t+1}$. The definition of consumption includes only nondurable consumption goods and the sample size is 1952:1 to 2005:4.

Panel A shows the results of the estimation of the standard C-CAPM with power utility. It shows that this model performs poorly in several ways. First, contemporaneous consumption risk is not an economically significant determinant of the cross section of expected returns. Column 1 displays the percentage of the variation in average returns explained by the fitted model, given by the cross-sectional R^2.[14] The model explains only 25 percent of the cross-sectional variation in average returns.

Panel B refers to the ultimate consumption risk model from Parker and Julliard (2005). The model explains a large part of the variation in average returns, delivering a cross-sectional R^2 of 60 percent, the highest among the asset pricing models considered. Additionally, all parameters are statistically significant. However, the model delivers a point estimate for the coefficient of risk aversion of 31.913 and it does not allow us to obtain an estimate of the intertemporal elasticity of substitution.

Panel C provides a summary of the results combining Epstein-Zin preferences and the intertemporal budget constraint, that is, using *cay* to recover the return on wealth. The model explains 50 percent of the cross-sectional variation in average returns. All the parameters are statistically significant. Additionally, it delivers an estimate for the coefficient of risk aversion of 91.089. Mehra and Prescott (1985) argue that a reasonable upper bound for risk aversion is around 10. In this sense, our estimate for risk aversion is high. The model also provides an estimate for the intertemporal elasticity of substitution of 0.41, consistent with the findings of Hall (1988) and Campbell (1999) at the macroeconomic level - close to 0 - and Browning, Hansen and Heckman (2000) at the microeconomic level - around 0.5. It goes against the empirical evidence of Hansen and Singleton (1982), Attanasio and Weber (1989), Guvenen (2001), Vissing-Jorgensen (2002) and Bansal and Yaron (2004), who argue that the intertemporal elasticity of substitution is well over 1.

Finally, Panel D shows the estimates of the model that combines Epstein-Zin preferences with the use of the market return R^m to recover the return on wealth. It can be seen that the model explains 44 percent of the cross-sectional variation in average returns. All the parameters are statistically significant. As with the previous model, the estimate for the coefficient of risk aversion is also high (96.114) and the estimate for the intertemporal elasticity of substitution is also well below 1 (0.034).

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[14] This measure of fit follows Jagannathan and Wang (1996) and is given by: $R^2 = 1 - \frac{Var_c\left(E_T\left[R^e_{i,t}\right] - \hat{R}^e_i\right)}{Var_c\left(E_T\left[R^e_i\right]\right)}$, where $E_T\left[.\right]$ is the time series average operator, Var_c denotes a cross-sectional variance, $\hat{R}^e_i$ is the fitted average return of asset i.

Table 1: Cross-sectional asset pricing results.

R^2	α	γ	ψ	κ	μ
		Panel A: Standard C-CAPM			
0.25	-0.017*	97.436*			0.886*
	(0.001)	(20.804)			(0.028)
		Panel B: Ultimate Consumption Risk with constant R^f ($S = 11$)			
0.60	-0.012*	31.913*			0.352*
	(0.003)	(6.332)			(0.045)
		Panel C: Epstein-Zin with *cay*			
0.50	-0.034*	91.089*	0.410*	-4.468*	1.962*
	(0.005)	(19.358)	(0.080)	(0.359)	(0.000)
		Panel D: Epstein-Zin with R^m			
0.44	-0.035*	96.114*	0.034*		0.906*
	(0.006)	(17.700)	(0.010)		(0.029)

The table reports the estimated GMM coefficients of the different asset pricing models.
GMM uses an identity matrix except that the weight on the last moment is large.
Covariance matrices are calculated using the Newey-West (1987) procedure with 4 lags.
Symbols *, **, *** represent, respectively, significance level of 1%, 5% and 10%.
Standard errors are reported in parentheses and significance levels in brackets.
The sample period is 1952:1 to 2005:4.

Figure 1 plots the predicted and average returns of different portfolios for the standard C-CAPM, the ultimate consumption risk model and the models that are based on the Epstein-Zin preferences. In each panel, the horizontal distance between a portfolio and the 45^o line is the extent to which the expected return based on the fitted model (on the horizontal axis) differs from the observed average return (on the vertical axis). All models, besides the standard C-CAPM, do quite well at fitting expected returns. In fact, all the models outperform the standard C-CAPM, reducing the pricing errors for the majority of the 25 portfolios considered. Moreover, the models with Epstein-Zin preferences generally perform better than the C-CAPM in pricing the small firms. This is an important feature of the results given the well documented inability of linear factor models to price the small growth portfolio (i.e. the lowest quintile in both size and book-to-market equity).[15] The failure in explaining the average return of portfolio 11 is generally justified invoking market frictions not considered by linear factor models and

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[15] Yogo (2006), coherently with our estimation, finds that the portfolio 11 is an outlier for all the models considered.

frictionless equilibrium models.[16] Our models instead price better this portfolio.

Table 2 provides a summary of the results using total consumption in place of nondurable consumption. Ait-Sahalia *et al.* (2004) argue that the consumption risk of equity is understated by NIPA nondurable goods because it contains many necessities and few luxury goods. The usual concern with using total consumption is that it contains expenditures on durable goods instead of the theoretically desired stock of durable goods. However, expenditures and stocks are cointegrated and, therefore, the long-term movement in expenditures following an innovation to equity returns also measures the long-term movement in consumption flows.

The table shows that using total consumption risk in place of nondurable consumption risk leads to broadly similar conclusions. Ultimate consumption risk delivers the highest cross-sectional R^2 (75 percent), being followed by the models with Epstein-Zin preferences (40 and 35 percent). All models outperform the standard C-CAPM. Moreover, the estimates of the coefficient of risk aversion are lower: a point estimate of 54.448 when we use Epstein-Zin preferences and cay_t to recover the return on wealth, and 59.438 when Epstein-Zin references are combined with the market return to recover the return on wealth. The estimates of the intertemporal elasticity of substitution are also consistent with the previous findings: Panel C suggests a value of 0.45, whilst Panel D highlights an estimate of 0.042. All the coefficients are statistically significant.

Finally, Table 3 shows the results using nondurable consumption and the original Fama-French data based on a sample of returns for the period 1963:3 to 2003:3, a starting period set that matches that of Lettau and Ludvigson (2001b). In this subperiod, the pattern of coefficients and fit tell a similar story, except that the models with Epstein-Zin preferences do even better by reaching a cross-sectional R^2 very similar to the one of Parker and Julliard (2005) - 61 percent in the model with cay and 58 percent in the model with R^m, which compare to 64 percent in the ultimate consumption risk model. The estimates of the coefficient of risk aversion are very high: a point estimate of 107.964 when we use Epstein-Zin preferences and cay_t to recover the return on wealth, and 113.757 when Epstein-Zin references are combined with the market return to recover the return on wealth. The estimates of the intertemporal elasticity of substitution are consistent with the previous findings: Panel C suggests a value of 0.26, whilst Panel D highlights an estimate of 0.024. All the coefficients are significant.

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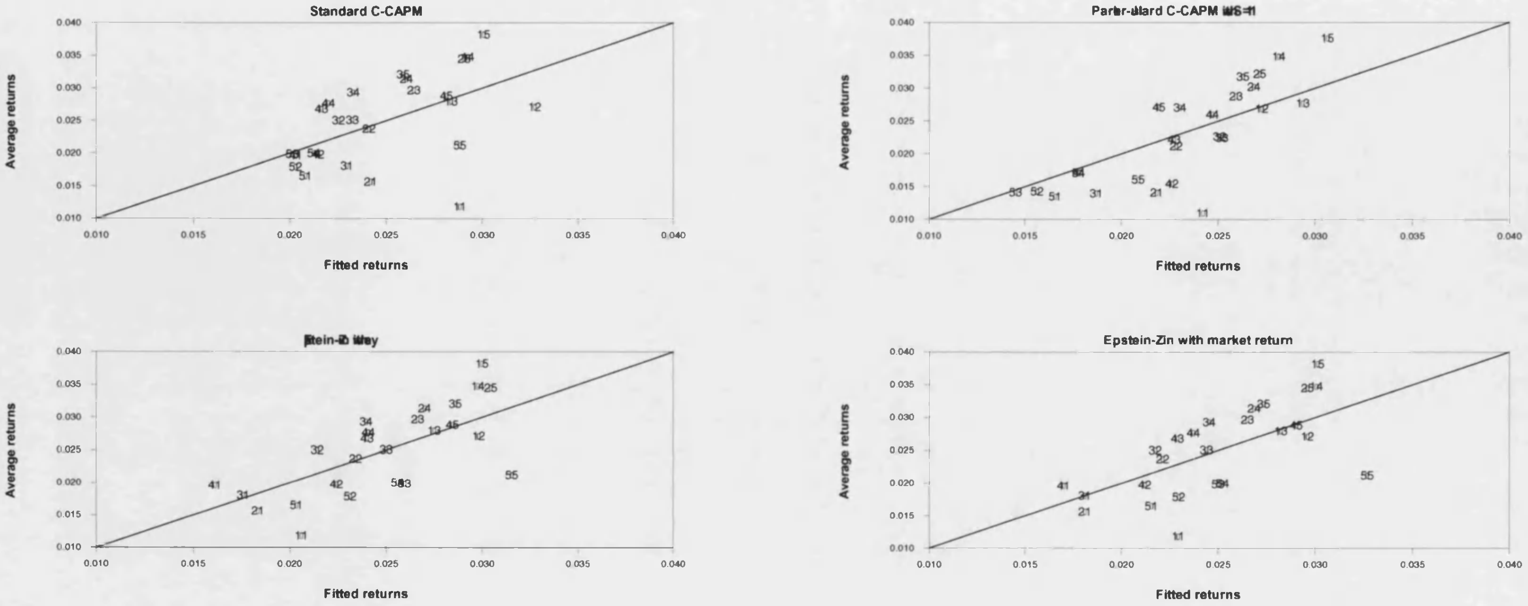
[16] D'Avolio (2002) and Lamont and Thaler (2003) document limits to arbitrage, due to short-sale constraints, for the types of stocks that are generally characterized as small growth.

Figure 1: Fitted returns and average returns among different asset pricing models.



All returns are quarterly rates. Fitted values are based on the model estimates.

Each portfolio is denoted by the rank of its market equity and then the rank of its ratio of book value to market value.

The sample period is 1952:1 to 2005:4.

Table 2: Cross-sectional asset pricing results using total consumption.

R^2	α	γ	ψ	κ	μ
	Panel A: Standard C-CAPM				
0.26	-0.024*	68.097*			0.772*
	(0.002)	(16.809)			(0.019)
	Panel B: Ultimate Consumption Risk with constant R^f ($S = 11$)				
0.75	-0.0181*	37.413*			0.165*
	(0.001)	(6.520)			(0.030)
	Panel C: Epstein-Zin with *cay*				
0.40	-0.036*	54.448*	0.450*	-3.751*	2.287*
	(0.005)	(18.730)	(0.128)	(0.415)	(0.000)
	Panel D: Epstein-Zin with R^m				
0.35	-0.036*	59.438*	0.042**		0.795*
	(0.006)	(17.038)	(0.019)		(0.030)

The table reports the estimated GMM coefficients of the different asset pricing models.
GMM uses an identity matrix except that the weight on the last moment is large.
Covariance matrices are calculated using the Newey-West (1987) procedure with 4 lags.
Symbols *, **, *** represent, respectively, significance level of 1%, 5% and 10%.
Standard errors are reported in parentheses and significance levels in brackets.
The sample period is 1952:1 to 2005:4.

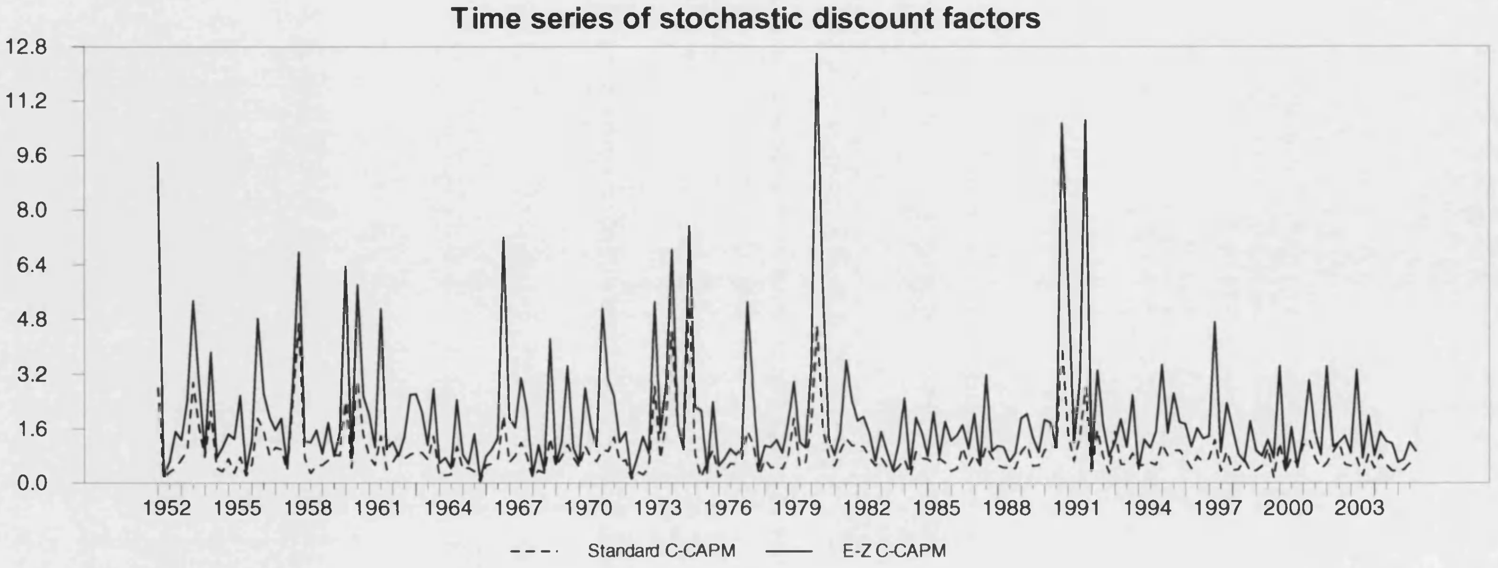
Table 3: Cross-sectional asset pricing results using original Fama-French start date: 1963:3-2003:3.

R^2	α	γ	ψ	κ	μ
	Panel A: Standard C-CAPM				
0.47	-0.016*	116.904*			0.879*
	(0.001)	(21.059)			(0.041)
	Panel B: Ultimate Consumption Risk with constant R^f ($S = 11$)				
0.64	-0.010*	27.020*			0.390
	(0.004)	(7.264)			(0.064)
	Panel C: Epstein-Zin with *cay*				
0.61	-0.029*	107.964*	0.260*	-3.854*	1.985*
	(0.006)	(20.801)	(0.092)	(0.497)	(0.000)
	Panel D: Epstein-Zin with R^m				
0.58	-0.031*	113.757*	0.024*		0.880*
	(0.007)	(18.098)	(0.008)		(0.035)

The table reports the estimated GMM coefficients of the different asset pricing models.
GMM uses an identity matrix except that the weight on the last moment is large.
Covariance matrices are calculated using the Newey-West (1987) procedure with 4 lags.
Symbols *, **, *** represent, respectively, significance level of 1%, 5% and 10%.
Standard errors are reported in parentheses and significance levels in brackets.
The sample period is 1952:1 to 2005:4.

Figure 2 displays the estimated stochastic discount factors of the standard C-CAPM and the model that combines Epstein-Zin preferences with *cay* to recover the return on wealth. While consumption growth at the C-CAPM has little visible business cycle pattern, with Epstein-Zin preferences and *cay* the series is clearly related to the business cycle. Consumption falls around recessions, so that the stochastic discount factor is highest right before and at the start of recessions. Therefore, our model captures: (*i*) the link among consumption, aggregate wealth, and labor income that comes from the intertemporal budget constraint and, consequently, the fact that investors try to "smooth out" transitory movements in their asset wealth arising from time variation in expected returns; and (*ii*) the separation between a low intertemporal elasticity of substitution and a high risk aversion, implying that agents demand large equity risk premia because they fear that a reduction in economic prospects or a rise in economic uncertainty will lower asset prices. The long-run risk is, in consequence, an important determinant of the risk premium and helps explaining a substantial fraction of the cross-sectional variation in expected returns in the Fama-French portfolios.

Figure 2: Stochastic discount factors of the standard C-CAPM and the model with Epstein-Zin preferences and *cay*.



Shaded areas are NBER recessions.

6 Comparison with Other Linear Factor Models

In this section, we compare the performance of different linear asset pricing models. Explaining the cross-section of expected stock returns has been proven to be a hard task for most of the existing asset pricing models. The capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965) has virtually no power to explain the cross section of average returns on assets sorted by size and book-to-market ratios (Fama and French (1992, 1993), Lettau and Ludvigson (2001b)).

The consumption CAPM (C-CAPM), first developed by Rubinstein (1976) and Breeden (1979), addressed the criticism of Merton (1973) (that the static CAPM failed to account for the intertemporal hedging component of asset demand) and Roll (1977) (that the market return cannot be proxied by an index of common stocks), but has been disappointing empirically, performing little better than the static CAPM in explaining the cross section of average asset returns (Mankiw and Shapiro (1986), Breeden, Gibbons, and Litzenberger (1989), Campbell (1996), Cochrane (1996), Lettau and Ludvigson (2001b), Yogo (2006) and Parker and Julliard (2005)).

Fama and French (1992, 1993) show that a three-factor model explains a large fraction of the cross-sectional variation in expected returns in the FF portfolios. The factors are the excess return on the market (denoted R^m), and the two excess returns capturing the value and size premia: the excess return on a portfolio containing stocks of firms with high ratios of book value to market equity relative to a portfolio of firms with low book value to market equity ("high minus low" denoted HML), and the excess return on a portfolio containing stocks of small firms relative to a portfolio of large firms ("small minus big" denoted SMB).

Lettau and Ludvigson (2001a) argue that the budget constraint of the representative household implies that consumption, income, and asset wealth should be cointegrated and then show that the deviation of these variables from their long-run relationship (the error correction term in the three variables vector autoregression) is a good predictor of market returns. Lettau and Ludvigson (2001b) shows that this variable, denoted by cay_t, consumption growth ($\Delta \ln C_{t+1}$), and their interaction provide a three-factor model that does as well in explaining the cross section of expected returns as the Fama-French three-factor model.

Parker and Julliard (2005) make the ultimate consumption risk into a linear model comparable to these models, following Lettau and Ludvigson (2001a) and applying a first-order log-linear approximation to the utility function.

In our case, the Epstein-Zin preferences are combined with the intertemporal budget constraint and using the homogeneity of the Bellman equation we show that one can derive a relationship between excess returns, consumption growth, the consumption-wealth ratio, cay, and its first-differences, Δcay.

Each of five models above says that the expected return on any portfolio is the weighted sum of the covariance of the return and each factor. Denote the vector of factors by f_{t+1}, so

$$f_{t+1} = (cay_t, \Delta \ln C_{t+1}, cay_t \Delta \ln C_{t+1})\prime$$

in the Lettau-Ludvigson model,

$$f_{t+1} = (R^m_{t+1}, SMB_{t+1}, HML_{t+1})\prime$$

in the Fama-French model,

$$f_{t+1} = (R^f_{t+1} \ln \frac{C_{t+1}}{C_t}, R^f_{t+1}, 0)\prime$$

in the standard C-CAPM model,

$$f_{t+1} = (R^f_{t+1,t+1+S} \ln \frac{C_{t+1+S}}{C_t}, R^f_{t+1,t+1+S}, 0)\prime$$

in the ultimate consumption risk model, and

$$f_{t+1} = (\frac{C_{t+1}}{C_t}, \Delta cay_{t+1}, cay_{t+1})\prime$$

in our model that combines Epstein-Zin preferences with *cay* to recover the return on wealth.

Let $b = (b_1, b_2, b_3)'$ be the vector of coefficients on the factors. Following Yogo (2006), we estimate the Fama-French and Lettau-Ludvigson models by GMM, using the 28×1 empirical moment function

$$g(\mathbf{R}^e_t, f_{t+1}; \alpha, \mu, \mathbf{b}) = \begin{bmatrix} \mathbf{R}^e_t - \alpha \mathbf{1}_{25} + \mathbf{R}^e_t (f_t - \mu)'\mathbf{b} \\ f_t - \mu \end{bmatrix},$$

where μ now denotes a 3×1 parameter vector. Under the null that the model prices expected returns, the theoretical moment restriction

$$E\left[g(\mathbf{R}^e_t, f_{t+1}; \alpha, \mu, \mathbf{b})\right] = 0$$

holds for the true $(\alpha', \mu', \mathbf{b}') \in \mathbb{R}^7$. As in our basic estimation, the difference between a fitted moment and zero is a measure of the mispricing of an expected return, and we include an intercept that allows all excess returns to be mispriced by a common amount.[17]

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[17] As a pre-specified weighting matrix, we use an identity matrix, resetting the diagonal entries for the moments $E[f_t - \mu] = 0$ to very large numbers so that the point estimates are identical to those from the Fama and MacBeth (1973) procedure.

Table 4 presents the results of the estimation using the longest sample in which data for all five models are available. Panel A reports the fit, estimated intercept and coefficients for the standard C-CAPM with power utility. Panel B reports the same statistics for the Fama-French three-factor model. Panel C summarizes the results for the Lettau-Ludvigson three-factor model. Finally, Panels D and E report, respectively, the results for the ultimate consumption risk model with constant risk-free rate, R^f, and $S = 11$, and for the model that combines Epstein-Zin preferences with *cay*.[18]

An important point of Table 4 is that although the highest cross-sectional R^2 is delivered by the Fama-French three-factor model - the model explains 72 percent of the cross-sectional variation of the excess returns -, the specification that combines Epstein-Zin preferences with *cay* to recover the return on wealth fits expected returns nearly as well, with a cross-sectional R^2 of 63 percent. Moreover, the explanatory power of the ultimate consumption risk and the Lettau-Ludvigson models are also economically significant, fitting 59 and 53 percent of the variation in expected returns. Consistent with the previous findings, the standard C-CAPM performs poorly as the cross-sectional R^2 reaches just 18 percent. On the other hand, the ultimate consumption risk implies lower levels of the estimated intercept, whilst the other models perform less well on this dimension. Also, in all models the factors are statistically significant.

Figure 3 graphs the pricing errors for each portfolio, for the five main models. All models besides the standard C-CAPM do quite well at fitting expected returns.

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[18] For all models, the covariance matrices are calculated using the Newey-West procedure with four lags.

Table 4: Comparison of affine factor models of expected returns.

R^2	α	b_1	b_2	b_3
	A. Standard C-CAPM			
0.18	0.021*	0.004*		
	(0.006)	(0.003)		
	B. Fama-French Three-Factor Model			
0.72	0.034*	-0.009*	0.409*	1.364*
	(0.012)	(0.014)	(0.418)	(0.384)
	C. Lettau-Ludvigson *cay* Model			
0.53	0.035*	-0.002*	0.000*	0.000*
	(0.008)	(0.003)	(0.003)	(0.000)
	D. Ultimate Consumption Risk with constant R^f ($S = 11$).			
0.59	0.014*	0.029*		
	(0.008)	(0.009)		
	E. Epstein-Zin with *cay*			
0.63	0.039*	0.006*	0.002*	0.004*
	(0.007)	(0.002)	(0.004)	(0.001)

The table reports the estimated GMM coefficients of the different asset pricing models.

GMM uses an identity matrix except that the weight on the last moment is large.

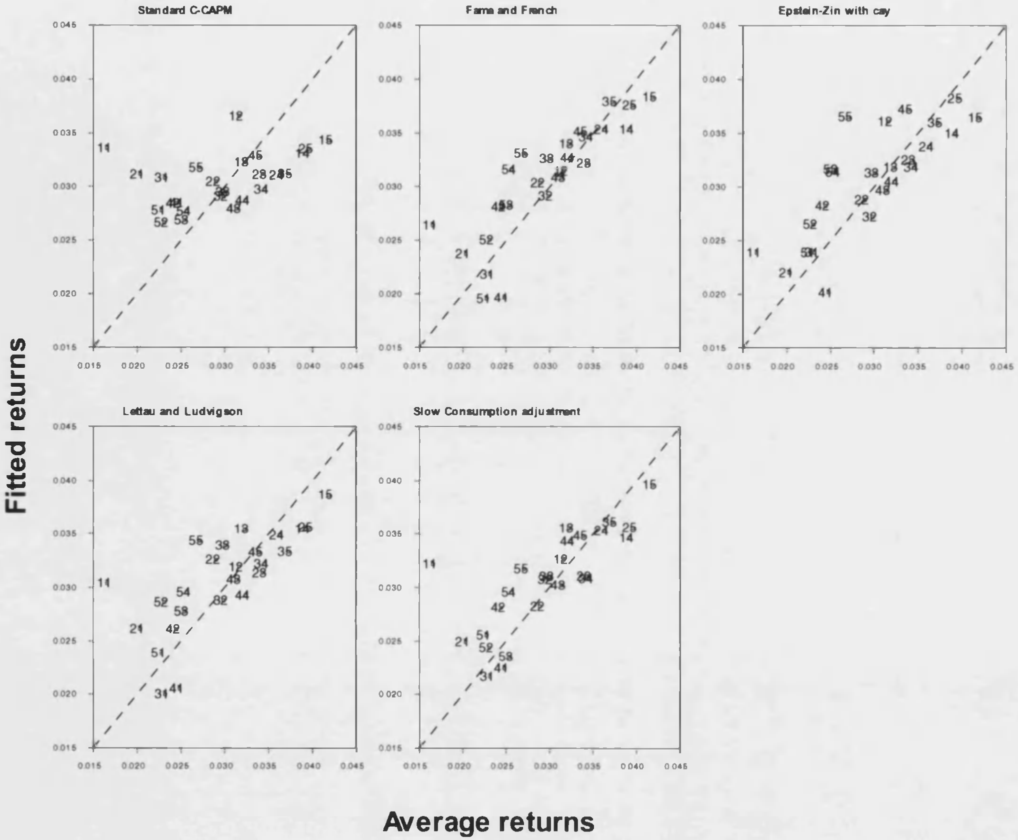
Covariance matrices are calculated using the Newey-West (1987) procedure with 4 lags.

Symbols *, **, *** represent, respectively, significance level of 1%, 5% and 10%.

Standard errors are reported in parentheses and significance levels in brackets.

The sample period is 1952:1 to 2005:4.

Figure 3: Comparison of affine factor models of expected returns.



a, Standard C-CAPM; *b*, Fama-French three-factor model;

c, Model with Epstein-Zin preferences and *cay*; *d*, Lettau-Ludvigson *cay* model; *e*, Ultimate Consumption Risk, $S = 11$.

All returns are quarterly rates. Fitted values are based on the model estimates.

Each portfolio is denoted by the rank of its market equity and then the rank of its ratio of book value to market value.

The sample period is 1952:1 to 2005:4.

7 Conclusion

This paper uses the representative consumer's budget constraint, combines it with Epstein-Zin preferences and the homogeneity of the Bellman Equation and derives a relationship between expected excess returns, consumption growth, the consumption-aggregate wealth ratio, cay, and the first-order differences of this ratio, Δcay. We then explore this relationship to check whether it carries relevant information to predict future asset returns and explain the cross-section of average asset returns, and show that it outperforms most of the asset pricing models developed in the literature.

Additionally, our model allows us to directly estimate both the intertemporal elasticity of substitution and the coefficient of risk aversion. We show that the intertemporal elasticity of substitution is relatively small (ranging from 0.034 and 0.41), consistent with the findings of Hall (1988) and Campbell (1999) at the macroeconomic level - close to 0 - and Browning, Hansen and Heckman (2000) at the microeconomic level - around 0.5. On the other hand, the model delivers an estimate for the coefficient of risk aversion that is relatively high: the point estimates range from 91.089 and 96.114.

When we use the consumption growth, cay and Δcay as conditioning variables for the Consumption-Capital Asset Pricing model (C-CAPM), we obtain a linear factor model that rivals the Fama and French (1993) three-factor model, the Lettau and Ludvigson (2001b) three-factor model, and the Parker and Julliard (2005) ultimate consumption risk model in explaining the cross-section of expected returns of the Fama and French size and book-to-market portfolios. Moreover, the conditional factor model proposed prices correctly the small growth portfolio and performs well in explaining the cross-section of expected returns for a wide range of portfolio data sets.

The success of the model in predicting asset returns and explaining the cross-sectional variation of expected excess returns is due to its ability to track time varying equilibrium risk premia. The model: (i) captures the fact that investors try to "smooth out" transitory movements in their asset wealth arising from time variation in expected returns; and (ii) shows that agents with low intertemporal elasticity of substitution and high risk aversion demand large equity risk premia because they fear that a reduction in economic prospects or a rise in economic uncertainty will lower asset prices. The risks for the long-run are, therefore, important determinants of the risk premium and explain a substantial fraction of the cross-sectional variation that one observes in expected returns in the Fama-French portfolios.

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Appendix

A Detailed Data Description

Consumption

Consumption is defined either as the total personal consumption expenditure or the expenditure in non-durable consumption goods. Data are quarterly, seasonally adjusted at an annual rate, measured in billions of dollars (2000 prices), in per capita terms and expressed in the logarithmic form. Series comprises the period 1947:1-2007:1. The source is U.S. Department of Commerce, Bureau of Economic Analysis, NIPA Table 2.3.5.

Aggregate Wealth

Aggregate wealth is defined as the net worth of households and nonprofit organizations. Data are quarterly, seasonally adjusted at an annual rate, measured in billions of dollars (2000 prices), in per capita terms and expressed in the logarithmic form. Series comprises the period 1952:2-2007:1. The source of information is Board of Governors of Federal Reserve System, Flow of Funds Accounts, Table B.100, line 41 (series FL152090005.Q).

After-tax Labor Income

After-tax labor income is defined as the sum of wage and salary disbursements (line 3), personal current transfer receipts (line 16) and employer contributions for employee pension and insurance funds (line 7) minus personal contributions for government social insurance (line 24), employer contributions for government social insurance (line 8) and taxes. Taxes are defined as: [(wage and salary disbursements (line 3)) / (wage and salary disbursements (line 3)+ proprietor' income with inventory valuation and capital consumption adjustments (line 9) + rental income of persons with capital consumption adjustment (line 12) + personal dividend income (line 15) + personal interest income (line 14))] * (personal current taxes (line 25)). Data are quarterly, seasonally adjusted at annual rates, measured in billions of dollars (2000 prices), in per capita terms and expressed in the logarithmic form. Series comprises the period 1947:1-2007:1. The source of information is U.S. Department of Commerce, Bureau of Economic Analysis, NIPA Table 2.1.

Consumption-Aggregate Wealth Ratio, cay

The consumption-aggregate wealth ratio is computed as the demeaned time series of *cay*, based on a DLS procedure that includes 8 leads and lags. Series comprises the period 1951:4-2005:4.The time series of *cay* is taken from Sidney Ludvigson's homepage.(*http://www.econ.nyu.edu/user/ludvigsons*).

Financial Returns

The proxy chosen for the market return is the value weighted CRSP (CRSP-VW) market return index. The CRSP index includes NYSE, AMEX and NASDAQ, and should provide a better proxy for market returns than the Standard & Poor (S&P) index since it is a much broader measure. Data are quarterly, deflated by the personal consumption chain-weighted index (2000=100) and expressed in the logarithmic form. Series comprises the period 1926:3-2006:4. The source of information is Robert Shiller's web site.

Asset Portfolios

The Fama-French 25 portfolios are the intersections of 5 portfolios formed on size (market equity, ME) and 5 portfolios formed on the ratio of book equity to market equity (B/M). Each portfolio is denoted by the rank of its ME and then the rank of its B/M, so that the portfolio 15 belongs to the smallest quintile of stocks by ME and the largest quintile of stocks by B/M. To match the frequency of labor income and consumption data, returns are converted to a quarterly frequency, so that $R^e_{i,t+1}$ represents the excess return on portfolio i during the quarter $t+1$. Portfolios formed on cash-flow price ratios, dividend price ratios and earning price ratios are formed grouping assets according to the decile they belong to. The ten industry portfolios are constructed assigning each NYSE, AMEX, and NASDAQ stock to an industry portfolio at the end of June of year τ based on its four-digit SIC code at that time. Returns from July of τ to June of $\tau+1$ are then computed. Series comprises the period 1926:3-2006:4. The source of information is Kenneth French's home page (*http://mba.tuck.dartmouth.edu/pages/faculty/ken.french*).

Population

Population was defined by dividing aggregate real disposable income (line 35) by per capita disposable income (line 37). Data are quarterly. Series comprises the period 1946:1-2001:4. The source of information is U.S. Department of Commerce, Bureau of Economic Analysis, NIPA Table 2.1.

Price Deflator

The nominal wealth, after-tax income, consumption, and interest rates were deflated by the personal consumption expenditure chain-type price deflator (2000=100) or the implied price deflator according to the definition of consumption, seasonally adjusted. Data are quarterly. Series comprises the period 1947:1-2007:1. The source of information is U.S. Department of Commerce, Bureau of Economic Analysis, NIPA Table 2.3.4., line 1.

Inflation Rate

Inflation rate was computed from price deflator. Data are quarterly. Series comprises the period 1947:2-2007:1. The source of information is U.S. Department of Commerce, Bureau of Economic Analysis, NIPA Table 2.3.4, line 1.

Interest Rate ("Risk-Free Rate")

Risk-free rate is defined as the 3-month U.S. Treasury bills real interest rate. Original data are monthly and are converted to a quarterly frequency by computing the simple arithmetic average of three consecutive months. Additionally, real interest rates are computed as the difference between nominal interest rates and the inflation rate. The 3-month U.S. Treasury bills real interest rate' series comprises the period 1934:1-2006:4, and the source of information is the H.15 publication of the Board of Governors of the Federal Reserve System.

B Combining Epstein-Zin Preferences with the Intertemporal Budget Constraint

With Epstein-Zin preferences, the utility function is defined recursively as

$$U_t = \left\{ (1-\delta) C_t^{\frac{1-\gamma}{\theta}} + \delta \left(E_t \left[U_{t+1}^{1-\gamma} \right] \right)^{\frac{1}{\theta}} \right\}^{\frac{\theta}{1-\gamma}}, \tag{12}$$

where C_t is the consumption, δ is the rate of time preference, γ is the relative risk aversion, $\theta := \frac{1-\gamma}{1-1/\psi}$, ψ is the intertemporal elasticity of substitution,and E_t is the rational expectation operator.

The budget constraint is

$$W_{t+1} = R_{t+1} \left(W_t - C_t \right) \quad \forall t,$$

where W is total wealth and R_t is the return on wealth, that is,

$$R_{t+1} := \left(1 - \sum_{i=1}^{N} w_{it} \right) R^f + \sum_{i=1}^{N} w_{it} R_{it+1} = R^f + \sum_{i=1}^{N} w_{it} \left(R_{it+1} - R^f \right), \tag{13}$$

where w_i is the wealth share invested in the i^{th} risky asset and R^f is the risk-free rate.

The recursive structure of the utility function makes it straightforward to write down the Bellman equation, despite its non-linearity. The optimal value of the utility, V, at time t will be a function of the wealth W_t. From equation (12), we have that the Bellman equation takes the form:

$$V(W_t) \equiv \max_{\{C,w\}} \left\{ (1-\delta) C_t^{\frac{1-\gamma}{\theta}} + \delta \left(E_t \left[V(W_{t+1})^{1-\gamma} \right] \right)^{\frac{1}{\theta}} \right\}^{\frac{\theta}{1-\gamma}}.$$

By homogeneity,

$$V(W_t) \equiv \phi_t W_t$$

for some ϕ_t. Therefore, the first-order condition C_t will be

$$\begin{aligned} (1-\delta) C_t^{\frac{1-\gamma}{\theta}-1} &= \delta \left(E_t \left[V(W_{t+1})^{1-\gamma} \right] \right)^{\frac{1}{\theta}-1} E_t \left[V(W_{t+1})^{-\gamma} \phi_{t+1} R_{t+1} \right] \\ &= \delta \left(E_t \left[\phi_{t+1}^{1-\gamma} W_{t+1}^{1-\gamma} \right] \right)^{\frac{1}{\theta}-1} E_t \left[\phi_{t+1}^{1-\gamma} W_{t+1}^{-\gamma} R_{t+1} \right] \\ &= \delta E_t \left[\phi_{t+1}^{1-\gamma} R_{t+1}^{1-\gamma} \right]^{\frac{1}{\theta}} (W_t - C_t)^{\frac{1-\gamma}{\theta}-1}. \end{aligned} \tag{14}$$

where we simplified terms before writing the first line and used the budget constraint to substitute out W_{t+1} in the last line.

Given the structure of the problem, consumption is also proportional to W_t, that is $C_t = \omega_t W_t$. Therefore the last equation can be rewritten as

$$\begin{gathered} (1-\delta)\,\omega_t^{\frac{1-\gamma}{\theta}-1} = \delta E_t \left[\phi_{t+1}^{1-\gamma} R_{t+1}^{1-\gamma} \right]^{\frac{1}{\theta}} (1-\omega_t)^{\frac{1-\gamma}{\theta}-1} \\ \rightarrow \delta E_t \left[\phi_{t+1}^{1-\gamma} R_{t+1}^{1-\gamma} \right]^{\frac{1}{\theta}} = (1-\delta) \left(\frac{\omega_t}{1-\omega_t} \right)^{\frac{1-\gamma}{\theta}-1}. \end{gathered} \tag{15}$$

We can now rewrite the Bellman equation using homogeneity and the last result as

$$\begin{aligned} \phi_t &= \max \left\{ (1-\delta) \left(\frac{C_t}{W_t} \right)^{\frac{1-\gamma}{\theta}} + \delta \left(E_t \left[\phi_{t+1}^{1-\gamma} R_{t+1}^{1-\gamma} \right] \right)^{\frac{1}{\theta}} \left(1 - \frac{C_t}{W_t} \right)^{\frac{1-\gamma}{\theta}} \right\}^{\frac{\theta}{1-\gamma}} \\ &= \max \left\{ (1-\delta)\,\omega_t^{\frac{1-\gamma}{\theta}} + \delta \left(E_t \left[\phi_{t+1}^{1-\gamma} R_{t+1}^{1-\gamma} \right] \right)^{\frac{1}{\theta}} (1-\omega_t)^{\frac{1-\gamma}{\theta}} \right\}^{\frac{\theta}{1-\gamma}} \\ &= (1-\delta)^{\frac{\theta}{1-\gamma}} \left\{ \omega_t^{\frac{1-\gamma}{\theta}} + \left(\frac{\omega_t}{1-\omega_t} \right)^{\frac{1-\gamma}{\theta}-1} (1-\omega_t)^{\frac{1-\gamma}{\theta}} \right\}^{\frac{\theta}{1-\gamma}} \\ &= (1-\delta)^{\frac{\theta}{1-\gamma}}\, \omega_t^{1-\frac{\theta}{1-\gamma}} = (1-\delta)^{\frac{\theta}{1-\gamma}} \left(\frac{C_t}{W_t} \right)^{1-\frac{\theta}{1-\gamma}} \end{aligned}$$

where the budget constraint is used to replace W_{t+1} in the first line, and in the third line the max operator is removed since $\delta E_t \left[\phi_{t+1}^{1-\gamma} R_{t+1}^{1-\gamma} \right]^{\frac{1}{\theta}}$ is replaced with its value coming from the first-order condition (15). Plugging the solution for ϕ_t in the first-order condition (14) we can derive the Euler equation for the return on wealth

$$\begin{aligned}
1 &= \frac{\delta}{1-\delta} E_t \left[\phi_{t+1}^{1-\gamma} R_{t+1}^{1-\gamma}\right]^{\frac{1}{\theta}} \left(\frac{W_t}{C_t} - 1\right)^{\frac{1-\gamma}{\theta}-1} = \delta E_t \left[\left(\frac{C_{t+1}}{W_{t+1}}\right)^{1-\gamma-\theta} R_{t+1}^{1-\gamma}\right]^{\frac{1}{\theta}} \left(\frac{W_t}{C_t} - 1\right)^{\frac{1-\gamma}{\theta}-1} \\
&= \delta E_t \left[\left(\frac{C_{t+1}}{W_{t+1}}\right)^{1-\gamma-\theta} \left(\frac{W_t}{C_t} - 1\right)^{1-\gamma-\theta} R_{t+1}^{1-\gamma}\right]^{\frac{1}{\theta}} \\
&= \delta E_t \left\{\left[\frac{C_{t+1}}{C_t}\left(\frac{W_t - C_t}{W_{t+1}}\right)\right]^{1-\gamma-\theta} R_{t+1}^{1-\gamma}\right\}^{\frac{1}{\theta}} = \delta E_t \left\{\left[\frac{C_{t+1}}{C_t} R_{t+1}^{-1}\right]^{1-\gamma-\theta} R_{t+1}^{1-\gamma}\right\}^{\frac{1}{\theta}}
\end{aligned}$$

$$\rightarrow 1 = E_t \left[\delta^{\theta} \left(\frac{C_{t+1}}{C_t}\right)^{-\frac{\theta}{\psi}} R_{t+1}^{\theta}\right] \quad \forall t. \tag{16}$$

The first-order condition for w_{it} is

$$\begin{aligned}
E_t \left[\phi_{t+1}^{1-\gamma} R_{t+1}^{-\gamma} \left(W_t - C_t\right)^{-\gamma} \left(R_{it+1} - R^f\right)\right] &= 0 \\
E_t \left[\left(\frac{C_{t+1}}{W_{t+1}}\right)^{1-\gamma-\theta} R_{t+1}^{-\gamma} \left(R_{it+1} - R^f\right)\right] &= 0 \\
E_t \left[\left(\frac{C_{t+1}}{W_{t+1}}\right)^{1-\gamma-\theta} \left(\frac{W_t}{C_t} - 1\right)^{1-\gamma-\theta} R_{t+1}^{-\gamma} \left(R_{it+1} - R^f\right)\right] &= 0 \\
E_t \left\{\left[\frac{C_{t+1}}{C_t} R_{t+1}^{-1}\right]^{1-\gamma-\theta} R_{t+1}^{-\gamma} \left(R_{it+1} - R^f\right)\right\} &= 0 \\
E_t \left[\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{\theta}{\psi}} R_{t+1}^{\theta-1} \left(R_{it+1} - R^f\right)\right] &= 0
\end{aligned}$$

$$\therefore E_t \left[\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{\theta}{\psi}} R_{t+1}^{\theta-1} R_{it+1}\right] = E_t \left[\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{\theta}{\psi}} R_{t+1}^{\theta-1}\right] R^f \quad \forall t, i \tag{17}$$

where in the fourth line the budget constraint is used to substitute out W_{t+1}. From the Euler equation (16) and the definition of return on wealth (13) we have

$$1 = E_t \left[\delta^{\theta} \left(\frac{C_{t+1}}{C_t}\right)^{-\frac{\theta}{\psi}} R_{t+1}^{\theta-1} \left(R^f + \sum_{i=1}^{N} w_{it} \left(R_{it+1} - R^f\right)\right)\right] \quad \forall t$$

and using (17) to substitute out $E_t \left\{\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{\theta}{\psi}} R_{t+1}^{\theta-1} R_{it+1}\right\}$ and simplifying we have that the equilibrium risk free rate is such that:

$$1/R^f = E_t \left[\delta^{\theta} \left(\frac{C_{t+1}}{C_t}\right)^{-\frac{\theta}{\psi}} R_{t+1}^{\theta-1}\right] \quad \forall t.$$

Multiplying both sides of (17) by δ^{θ} and using the last result to remove R^f, we have the Euler equation for any risky asset i:

$$E_t\left[\delta^{\theta}\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{\theta}{\psi}} R_{t+1}^{\theta-1} R_{it+1}\right] = 1 \quad \forall t, i.$$

C From the Intertemporal Budget Constraint to the Stochastic Discount Factor

Following Campbell (1996) and Jagannathan and Wang (1996), labor income (Y_t) can be thought of as the dividend on human capital (H_t). Under this assumption, the return to human capital can be defined as:

$$1 + R_{h,t+1} = \frac{H_{t+1} + Y_{t+1}}{H_t}. \tag{18}$$

Under the assumption that the steady state human capital-labor income ratio is constant ($Y/H = \rho_h^{-1} - 1$, where $0 < \rho_h < 1$), this relation can be log-linearized around the steady state to get

$$r_{h,t+1} = (1 - \rho_h)k_h + \rho_h(h_{t+1} - y_{t+1}) - (h_t - y_t) + \Delta y_{t+1} \tag{19}$$

where $r := log(1 + R)$, $h := logH$, $y := logY$, k_h is a constant of no interest, and the variables without time subscript are evaluated at their steady state value. Assuming that $\lim_{i\to\infty} \rho_h^i(h_{t+i} - y_{t+i}) = 0$, the log human capital income ratio can be rewritten as a linear combination of future labor income growth and future returns on human capital:

$$h_t - y_t = \sum_{i=1}^{\infty} \rho_h^{i-1}(\Delta y_{t+i} - r_{h,t+i}) + k_h. \tag{20}$$

Equation (20) tells us that the log human capital to labor income ration ratio has to be equal to the discounted sum of future labor income growth and human capital returns. Moreover, this equation is similar, both in structure and interpretation, to the relation between the log dividend-price ratio and future returns and dividends derived by Campbell and Shiller (1988): taking time t conditional expectation of both sides, when the log human capital to labor income ratio is high, agents should expect high future labor income growth or low human capital returns.[19]

Defining W_t as aggregate wealth (given by human capital plus asset holdings), C_t as consumption, and $R_{w,t+1}$ as the return on aggregate wealth between period t and $t + 1$, the consumer's budget

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[19] Campbell and Shiller (1988), defining the log return of an asset as $r_t = log(P_t + D_t) - logP_{t-1}$, (where P and D are, respectively, price and dividend of the asset) derive the relation $d_t - p_t = E_t \sum_{i=1} \rho^{i-1}(r_{t+i} - \Delta d_{t+i}) + k_d$ where $d := \log d$ and $p := \log P$.

constraint can be written as:[20]

$$W_{t+1} = (1 + R_{w,t+1})\,(W_t - C_t)\,. \tag{21}$$

Campbell and Mankiw (1989) show that, under the assumption that the consumption-aggregate wealth is stationary and that $\lim_{i\to\infty} \rho_w^i (c_{t+i} - w_{t+i}) = 0$, where $\rho_w := (W - C)/W < 1$, equation (21) can be approximated by Taylor expansion obtaining

$$c_t - w_t = \sum_{i=1}^{\infty} \rho_w^i r_{w,t+i} - \sum_{i=1}^{\infty} \rho_w^i \Delta c_{t+i} + k_w \tag{22}$$

where $c := logC$, $w := logW$, and k_w is a constant. The aggregate return on wealth can be decomposed as

$$R_{w,t+1} = \omega_t R_{a,t+1} + (1 - \omega_t) R_{h,t+1} \tag{23}$$

where ω_t is a time varying coefficient and $R_{a,t+1}$ is the return on asset wealth. Campbell (1996) shows that we can approximate this last expression as

$$r_{w,t} = \omega r_{a,t} + (1 - \omega) r_{h,t} + k_r \tag{24}$$

where k_r is a constant, ω is the mean of ω_t and $r_{w,t}$ is the log return on asset wealth. Moreover, we can approximate the log total wealth as

$$w_t = \omega a_t + (1 - \omega) h_t + k_a \tag{25}$$

where a_t is the log asset wealth and k_a is a constant.

Replacing equation (20), (24), and (25) into (22), we get

$$c_t - \omega a_t - (1 - \omega)(y_t + \sum_{i=1}^{\infty} \rho_h^{i-1} \Delta y_{t+i}) =$$

$$= \sum_{i=1}^{\infty} \rho_w^i (\omega r_{a,t+i} - \Delta c_{t+i}) + (1 - \omega) \sum_{i=1}^{\infty} (\rho_w^i - \rho_h^{i-1}) r_{h,t+i} + k. \tag{26}$$

where k is a constant. This equation holds ex-post as a direct consequence of agent's budget constraint, but it also has to hold ex-ante. Taking time t conditional expectation of both sides, we have that

$$\underbrace{c_t - \omega a_t - (1 - \omega) y_t}_{cay_t} - (1 - \omega) \underbrace{E_t \sum_{i=1}^{\infty} \rho_h^{i-1} \Delta y_{t+i}}_{lr_t} = E_t \sum_{i=1}^{\infty} \rho_w^i (\omega r_{a,t+i} - \Delta c_{t+i}) + \eta_t + k$$

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[20] Labor income does not appear explicitly in this equation because of the assumption that the market value of tradable human capital is included in aggregate wealth.

where: $lr_t := E_t\sum_{i=1}^{\infty}\rho_h^{i-1}\Delta y_{t+i}$ represent the expected growth in future labor income, this is, the labor income risk;[21] $\eta_t := (1-\omega)\sum^{\infty}(\rho_w^i - \rho_h^{i-1})r_{h,t+i}$ is a stationary component; and, following Lettau and Ludvigson (2001a, 2001b), $cay_t := c_t - \omega a_t - (1-\omega)y_t$.

From the intertemporal budget constraint

$$\begin{aligned} R_{t+1}^{-1} &= \frac{W_t}{W_{t+1}} - \frac{C_t}{W_{t+1}} = \frac{C_t}{C_{t+1}}\left(\frac{W_t}{C_t}\frac{C_{t+1}}{W_{t+1}} - \frac{C_{t+1}}{W_{t+1}}\right) \\ \therefore\quad & R_{t+1}^{\theta-1} = e^{(\theta-1)\Delta c_{t+1}}\left[e^{\Delta cw_{t+1}} - e^{cw_{t+1}}\right]^{1-\theta} \end{aligned}$$

where $cw_t := \log(C_t/W_t)$.

Putting the last result into the euler equation we have

$$E_t\left\{\left(\frac{C_{t+1}}{C_t}\right)^{-\gamma}\left[e^{\Delta cw_{t+1}} - e^{cw_{t+1}}\right]^{1-\theta}\left(R_{it+1} - R^f\right)\right\} = 0$$

where the stochastic discount factor is

$$M_{t+1} \propto \left(\frac{C_{t+1}}{C_t}\right)^{-\gamma}\left[e^{\Delta cw_{t+1}} - e^{cw_{t+1}}\right]^{1-\frac{1-\gamma}{1-1/\psi}}$$

or to estimate this we need a proxy for cw .If we follow Lettau and Ludvigson (2001a), we have:

$$cw_t \approx \kappa + cay_t.$$

Alternatively, we have the complete expression (with $Y/H =: \rho_h^{-1} - 1$, where $0 < \rho_h < 1$):

$$cw_t \approx \kappa + cay_t - (1-\omega)\,E_t\sum_{i=1}^{\infty}\rho_h^{i-1}(\Delta y_{t+i} - r_{h,t+i}).$$

If we use the return on the market to proxy for the return on total wealth (as Epstein and Zin (1989, 1991) originally suggested) we have:

$$\begin{aligned} M_{t+1} &= \left(\frac{C_{t+1}}{C_t}\right)^{-\frac{\theta}{\psi}} R_{M,t+1}^{\theta-1} = \left(\frac{C_{t+1}}{C_t}\right)^{-\frac{1-\gamma}{\psi-1}} R_{M,t+1}^{\frac{1-\gamma}{1-1/\psi}-1} \\ &= \left(\frac{C_{t+1}}{C_t}\right)^{-\frac{1-\gamma}{\psi-1}} R_{M,t+1}^{\frac{-\gamma+1/\psi}{1-1/\psi}}. \end{aligned}$$

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[21] Following Campbell and Shiller (1988) and approximating the log return on human capital as $r_{h,t+1} = r + (E_{t+1} - E_t)\sum_{i=1}^{\infty}\rho_h^{i-1}\Delta y_{t+i}$, we have from equation (20) that the log human capital will depend only (disregarding constant terms) on current and future expected labor income

$$h_t = y_t + E_t\sum_{i=1}^{\infty}\rho_h^{i-1}\Delta y_{t+i},$$

therefore the human capital wealth level will vary as expectations of future labor income change.

Chapter V

Expectations, Shocks, and Asset Returns

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October 30, 2007

Abstract

I use the consumer's budget constraint to derive a relationship between stock market returns, the residuals of the trend relationship among consumption, aggregate wealth, and labour income, *cay*, and three major sources of risk: future changes in the housing consumption share, *cr*, future labour income growth, *lr*, and future consumption growth, *lrc*.

Then, I model the joint dynamics of changes in housing consumption share, consumption growth, wealth growth, income growth, asset returns, consumption-wealth ratio and dividend-price ratio, and show that asset returns largely reflect expectations about long-run risk. On the other hand, unexpected shocks play a negligible role in the context of forecasting future returns.

Combining the intertemporal budget constraint and the forecasting properties of an informative Vector-Autogression (VAR), one can, therefore, generate the predictability of many economically motivated variables developed in the literature on asset pricing, and accommodate the implications of a wide class of optimal models of consumer behaviour without imposing a functional form on preferences.

Keywords: expectations, shocks, asset returns, wealth, income, consumption, housing share.

JEL classification: E21, E44, D12.

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1 Introduction

Differences in expected returns across assets are naturally explained by differences in risk and the risk premium is generally considered as reflecting the ability of an asset to insure against consumption fluctuations (Lucas (1978), Breeden (1979), Sharpe (1964), Lintner (1965)).

Despite this, differences in the covariance of returns and contemporaneous consumption growth across portfolios have not proved to be sufficient to justify the differences in expected returns observed in the U.S. stock market (Mankiw and Shapiro, 1986; Breeden *et al.*, 1989; Campbell, 1996; Cochrane, 1996; Lettau and Ludvigson, 2001b). Additionally, Hansen and Singleton (1982) - for the consumption-based models -, and Fama and French (1992) - for the CAPM -, show that these models have considerable difficulty in supporting the differences in a cross-section of asset returns.

As a result, the identification of the economic sources of risks is still an important issue. According to canonical macroeconomic theory, aggregate consumption reflects the optimal choices of a representative consumer and can be explained by changes in the risk-free rate of return and in the information about current wealth, future income, and future rates of return. Whilst this theory is supported by the unpredictability of consumption growth, several studies have shown that predictable movements in aggregate consumption growth are almost uncorrelated with the risk-free rate of return and are significantly correlated with predictable changes in income, therefore, questioning its validity.[1] Parker and Preston (2005) use household-level data to measure the relative importance of new information, the real interest rate, the preference for consumption, and precautionary saving in explaining fluctuations in aggregate consumption growth and find that precautionary savings play an important role in consumption fluctuations.[2,3] By its turn and in the spirit of Brainard *et al.* (1991),[4] Parker and Julliard (2005) measure the risk of a portfolio by its ultimate risk to consumption, defined as the covariance of its return and consumption growth over the quarter of the return and many following quarters and show that it is able to explain cross-section of asset returns.[5]

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[1] See Flavin (1981), Shiller (1982), Hall (1988), Campbell and Deaton (1989), and Campbell and Mankiw (1989).

[2] Nelson (1994), Cochrane (1991), and Attanasio and Davis (1996) reject complete consumption insurance in the U.S. and Rios-Rull (1994), Krusell and Smith (1998) and Gourinchas (2000) study precautionary saving in model economies.

[3] See, for example, Baxter and Jermann (1999), Basu and Kimball (2000), and Ogaki and Reinhart (1998). Carroll (1997) argues that incomplete markets are an important source of bias, whilst Attanasio and Weber (1995) finds that labor supply is an important shifter of the preference for consumption.

[4] These authors show that the longer the horizon of the investor, the better the CCAPM performs relative to the CAPM.

[5] The authors show that this can provide the correct measure of risk under several extant explanations of slow consumption adjustment, such as some models of: (*a*) measurement error in consumption; (*b*) costs of adjusting consumption; (*c*) nonseparability of the marginal utility of consumption from factors such as labor supply or housing stock, which themselves are constrained to adjust slowly; or (*d*) constraints on information flow or calculation so that household behavior

The literature in asset pricing has, therefore, largely concluded that differences in expected returns are not due to differences in risk to consumption, but instead arise from inefficiencies of financial markets, time variation in effective risk aversion (Sundaresan, 1989; Constantinides, 1990; Campbell and Cochrane, 1999), in the joint distribution of consumption and asset returns or quite different models of economic behavior. In addition, several papers tried to shed more light on this question and many economically motivated variables have been developed to capture time-variation in expected returns and document long-term predictability.[6] Lettau and Ludvigson (2001a) show that the transitory deviation from the common trend in consumption, aggregate wealth and labor income, *cay*, is a strong predictor of asset returns, as long as the expected return to human capital and consumption growth are not too volatile. Fernandez-Corugedo *et al.* (2003) use the same approach but incorporate the relative price of durable goods, whilst Julliard (2004) shows that the expected changes in labor income are important because of their ability to track time varying risk premia. The nonseparability between consumption and leisure in on the basis of the work of Wei (2005), who argues that human capital risk can generate sufficient variation in the agent's risk attitude to produce equity returns and bond yields with properties close to the observed in the data. Whilst the last two papers emphasize the role of human capital, others have focused on the importance of the housing market instead. Yogo (2006) and Piazzesi *et al.* (2007) emphasize the role of nonseparability of preferences in explaining the countercyclical variation in the equity premium.[7] In the same spirit, Lustig and Van Nieuwerburgh (2005) show that the ratio of housing wealth to human wealth (the housing collateral ratio) shifts the conditional distribution of asset prices and consumption growth and, therefore, predicts returns on stocks.

More recently, the focus has been directed towards the importance of long-term risk. Abel (1999) and Bansal and Yaron (2004) show that differences in risk compensation on assets mirror differences in the exposure of assets' cash flows to consumption. Bansal *et al.* (2005) suggest that changes in expectations about the entire path of future cash flows provide very valuable information about systematic risks in asset returns.

Given the current state of the literature, one can ask the following questions: What are the major sources of risk that explain asset returns? What is the importance of long-term risk? Are we able to generate the predictability of asset returns without relying on a specific description of preferences?

In this paper, I use the consumer's budget constraint to derive a relationship between stock market returns, the residuals of the trend relationship among consumption, aggregate wealth, and labour in-

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is "near-rational".

[6] See, for example, Fama and French (1988), Campbell and Shiller (1988), Poterba and Summers (1988), Richards (1995), Lettau and Ludvigson (2001a, 2004).

[7] Pakos (2003) argues that there is an important non-homotheticity in preferences.

come, *cay*, and three major sources of risk: future changes in the housing consumption share, *cr*, future labour income growth, *lr*, and future consumption growth, *lrc*.

Then, I model the joint dynamics of changes in housing consumption share, consumption growth, wealth growth, income growth, asset returns, consumption-wealth ratio and dividend-price ratio using a Vector-Autoregression (VAR) framework, and obtain measures of expected and unexpected long-run changes in the major determinants of asset returns. I find that: (*i*) *cay*, expected *lr*, *cr*, *lrc* and ex-ante long-run expected real returns, *lrret*, strongly forecast future ex-post asset returns; (*ii*) unexpected *lrc* and unexpected *lrret* contain some predictive power for ex-post asset returns; (*iii*) unexpected *lr* and unexpected *cr* do not predict future ex-post asset returns.

Moreover, this work suggests that agents' expectations about long-run risk are important and that asset returns largely reflect that information. The results show that expectations of high future labor income, expectations of high future consumption growth, and expectations of low housing consumption share are associated with lower stock market returns, and low labor income growth expectations, low consumption growth expectations and high housing consumption share expectations are associated with higher than average real returns. Therefore, the success of *lr*, *cr*, and *lrc* as predictors of asset returns seems to be due to their ability to track risk premia. On the other hand, shocks to long-run expectations seem to play a negligible role as its forecasting power for asset returns is, in general, very low.

The framework presented is sufficiently flexible to accommodate the implications of a wide class of optimal models of consumer behaviour. Its advantage lies on the fact that it does not impose any functional form on preferences. It, therefore, shows that one can use the intertemporal budget constraint and the forecasting properties of an informative VAR to generate the predictability of many empirical proxies developed in the literature on asset pricing.

The paper is organized as follows. Section 2 presents the theoretical and econometric approach. Section 3 describes the data and presents the estimation results of the forecasting regressions. Finally, in Section 4, I conclude and discuss the implications of the findings.

2 Theory and Econometric Approach

2.1 Deriving the Major Determinants of Asset Returns

Following Campbell (1996) and Jagannathan and Wang (1996), labor income, Y_t, can be thought of as the dividend on human capital, H_t. Under this assumption, the return to human capital can be defined as:

$$1 + R_{h,t+1} = \frac{H_{t+1} + Y_{t+1}}{H_t}. \tag{1}$$

Under the assumption that the steady state human capital-labor income ratio is constant ($Y/H = \rho_h^{-1} - 1$, where $0 < \rho_h < 1$),[8] this relation can be log-linearized around the steady state to get

$$r_{h,t+1} = (1 - \rho_h)k_h + \rho_h(h_{t+1} - y_{t+1}) - (h_t - y_t) + \Delta y_{t+1}, \tag{2}$$

where $r := log(1 + R)$, $h := logH$, $y := logY$, k_h is a constant of no interest, and the variables without time subscript are evaluated at their steady state value. Assuming that $\lim_{i \to \infty} \rho_h^i (h_{t+i} - y_{t+i}) = 0$, the log human capital income ratio can be rewritten as a linear combination of future labor income growth and future returns on human capital:

$$h_t - y_t = \sum_{i=1}^{\infty} \rho_h^{i-1} (\Delta y_{t+i} - r_{h,t+i}) + k_h. \tag{3}$$

Equation (3) shows that the log human capital to labor income ration ratio has to be equal to the discounted sum of future labor income growth and human capital returns. Moreover, this equation is similar, both in structure and interpretation, to the relation between the log dividend-price ratio and future returns and dividends derived by Campbell and Shiller (1988): taking time t conditional expectation of both sides, when the log human capital to labor income ratio is high, agents should expect high future labor income growth or low human capital returns.[9]

Defining W_t as aggregate wealth (given by human capital plus asset holdings), C_t as non-housing consumption, U_t as consumption of housing services, P_t^U as relative price of consumption of housing services, S_t as non-housing consumption share,[10] and $R_{w,t+1}$ as the return on aggregate wealth between period t and $t + 1$, the consumer's budget constraint can be written as:[11]

$$W_{t+1} = (1 + R_{w,t+1}) \left(W_t - C_t - P_t^U U_t\right) = (1 + R_{w,t+1}) \left(W_t - \frac{C_t}{S_t}\right). \tag{4}$$

Campbell and Mankiw (1989) show that, under the assumption that the consumption-aggregate wealth is stationary and that $\lim_{i \to \infty} \rho_w^i (c_{t+i} - w_{t+i}) = 0$, where $\rho_w := (W - C)/W < 1$, equation (4) can be approximated by Taylor expansion obtaining

$$c_t - s_t - w_t = \sum_{i=1}^{\infty} \rho_w^i r_{w,t+i} + \sum_{i=1}^{\infty} \rho_w^i \Delta s_{t+i} - \sum_{i=1}^{\infty} \rho_w^i \Delta c_{t+i} + k_w, \tag{5}$$

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[8] Baxter and Jermann (1997) calibrate $Y/H = 4.5\%$ implying $\rho_h = 0.955$. In this paper, I set $\rho_w = \rho_h = 0.95$, although results do not significantly change for different values.

[9] Campbell and Shiller (1988), defining the log return of an asset as $r_t = log(P_t + D_t) - logP_{t-1}$, (where P and D are, respectively, price and dividend of the asset), derive the relation $d_t - p_t = E_t \sum_{i=1} \rho^{i-1} (r_{t+i} - \Delta d_{t+i}) + k_d$ where $d := \log D$ and $p := \log P$.

[10] This is, $S_t := \frac{C_t}{C_t + P_t^U U_t}$.

[11] Labor income does not appear explicitly in this equation because of the assumption that the market value of tradable human capital is included in aggregate wealth.

where $c := logC$, $s := logS$, $w := logW$, and k_w is a constant. The aggregate return on wealth can be decomposed as

$$R_{w,t+1} = \omega_t R_{a,t+1} + (1-\omega_t) R_{h,t+1}, \tag{6}$$

where ω_t is a time varying coefficient and $R_{a,t+1}$ is the return on asset wealth. Campbell (1996) shows that the last expression can be approximated as

$$r_{w,t} = \omega r_{a,t} + (1-\omega) r_{h,t} + k_r, \tag{7}$$

where k_r is a constant, ω is the mean of ω_t and $r_{w,t}$ is the log return on asset wealth. Moreover, the log total wealth can be approximated as

$$w_t = \omega a_t + (1-\omega) h_t + k_a, \tag{8}$$

where a_t is the log asset wealth and k_a is a constant.

Replacing equation (3), (7) and (8) into (5), one gets

$$\begin{aligned} c_t - s_t - \omega a_t - (1-\omega)\Big(y_t + \sum_{i=1}^{\infty} \rho_h^{i-1} \Delta y_{t+i}\Big) - \sum_{i=1}^{\infty} \rho_w^{i} \Delta s_{t+i} + \sum_{i=1}^{\infty} \rho_w^{i} \Delta c_{t+i} = \\ = \omega \sum_{i=1}^{\infty} \rho_w^{i} r_{a,t+i} + (1-\omega) \sum_{i=1}^{\infty} (\rho_w^{i} - \rho_h^{i-1}) r_{h,t+i} + k, \end{aligned} \tag{9}$$

where k is a constant. This equation holds ex-post as a direct consequence of agent's budget constraint, but it also has to hold ex-ante. Taking time t conditional expectation of both sides, we have that

$$\begin{aligned} \underbrace{c_t - s_t - \omega a_t - (1-\omega) y_t}_{cay_t} - (1-\omega) \underbrace{E_t \sum_{i=1}^{\infty} \rho_h^{i-1} \Delta y_{t+i}}_{lr_t} - \underbrace{E_t \sum_{i=1}^{\infty} \rho_w^{i} \Delta s_{t+i}}_{cr_t} + \underbrace{E_t \sum_{i=1}^{\infty} \rho_w^{i} \Delta c_{t+i}}_{lrc_t} = \\ = \omega E_t \sum_{i=1}^{\infty} \rho_w^{i} r_{a,t+i} + \eta_t + k, \end{aligned} \tag{10}$$

where: $lr_t := E_t \sum_{i=1}^{\infty} \rho_h^{i-1} \Delta y_{t+i}$ represents the expected growth in future labor income, this is, the labor income risk;[12] $cr_t := E_t \sum_{i=1}^{\infty} \rho_w^{i} \Delta s_{t+i}$ represents the discounted expected change in the share of non-housing consumption in total consumption, this is, the composition risk; $lrc_t := E_t \sum_{i=1}^{\infty} \rho_w^{i-1} \Delta c_{t+i}$

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[12] Following Campbell and Shiller (1988) and approximating the log return on human capital as $r_{h,t+1} = r + (E_{t+1} - E_t) \sum_{i=1}^{\infty} \rho_h^{i-1} \Delta y_{t+i}$, we have from equation (3) that the log human capital will depend only (disregarding constant terms) on current and future expected labor income $h_t = y_t + E_t \sum_{i=1}^{\infty} \rho_h^{i-1} \Delta y_{t+i}$, therefore the human capital wealth level will vary as expectations of future labor income change.

represents the discounted expected growth in future consumption, that is, the long-run consumption risk; $\eta_t := (1-\omega)\sum_{i=1}^{\infty}(\rho_w^i - \rho_h^{i-1})r_{h,t+i}$ is a stationary component; and, following Lettau and Ludvigson (2001a, 2001b), $cay_t := c_t - s_t - \omega a_t - (1-\omega)y_t$.

When the left hand side of equation (10) is high, consumers expect high future returns on market wealth. The lr_t term measures the contribution of future labor income growth to the state variable h_t, therefore capturing the expected long run wealth effect of current and past labor income shocks: if agents expect their labor income to grow in the future (high lr_t), the equilibrium return on asset wealth will be lower. One interpretation is that high lr_t represents a state of the world in which agents expect to have abundance of resources in the future, therefore, low returns on asset wealth are feared less. The cr_t term measures the contribution of future changes in non-housing expenditure share, therefore, capturing the composition risk, this is the degree of separability of consumer's preferences: if preferences are separable, nondurable consumption and housing will be substitutes, and agents can easily "smooth out" any transitory movement in their asset wealth arising from time variation in expected return; if, however, preferences are non-separable, nondurable consumption and housing will be complements, agents will not be able to "smooth out" exogenous shocks and, therefore, this term will contain valuable information about future asset returns. The lrc_t term measures the contribution of future consumption growth. Parker and Julliard (2005) measure risk by the covariance of an asset's return and consumption growth cumulated over many quarters (the ultimate consumption risk), rather than the contemporaneous covariance of an asset's return and consumption growth. I follow the same idea and measure the long-run consumption risk as the expected present value of changes in consumption growth. Finally, equation (10) shows that the consumption-wealth ratio, cay_t, will also be a good proxy for market expectations of future asset returns, $r_{a,t+i}$.[13] Based on equation (10), cay_t, lr_t, cr_t, and lrc_t should carry relevant information about market expectations of future asset returns, $r_{a,t+i}$, and I test the forecasting power of these proxies developed by Lettau and Ludvigson (2001a), Julliard (2004), Piazzesi *et al.* (2007) and Parker and Julliard (2005).

2.2 Econometric Specification

In this section, I propose a method for analyzing the driving sources of risk and their predictive power for asset returns. In the *first stage*, I follow Campbell (1996) and Campbell and Shiller (1987,

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[13] It can be shown that $c_t - s_t$ corresponds to the definition of consumption of nondurable goods and services *including* housing services. Denote by c_t^{ND}, the log consumption of nondurable goods and services *including* housing services, c_t, the log consumption of nondurable goods and services *excluding* housing services, and u_t, the log consumption of housing services. We can write: $c_t - s_t = log(C_t) - log(S_t) = log(C_t) - log(\frac{C_t}{C_t + P_t^U U_t}) = log(Ct + P_t^U U_t) = \log(C_t^{ND}) = c_t^{ND}$.

1988) and use a Vector Auto-Regression (VAR) model to represent the law of motion for the state vector, exploiting the restrictions imposed by the cointegration of consumption, wealth and labor income (Lettau and Ludvigson, 2001a). Once the VAR is estimated, it is possible to compute long-run measures of the major variables determining asset returns as well as their innovations. In the *second stage*, I use the standard way to analyze the predictive power for asset returns, that is, regressing the one-period ex-post real return, r_t, on the long-run measures computed before and known at the beginning of period t. If the coefficients on these variables are significant, then they are considered as good proxies for future asset returns.

This approach has some potential advantages over the standard approach. First, it is able to detect long-lived deviations of the major determinants of asset returns, avoiding the low power of single-period returns regressions (Shiller, 1984; Summers, 1986). Second, it does not rely on an optimal behavior model - only on the intertemporal budget constraint - and, therefore, it avoids the need of imposing a functional form on preferences.

Although this methodology is based on the estimation of a VAR, it properly accounts for the extra information that market participants have. This is so because returns are included as one variable in the VAR, enabling the generation of forecasts of consumption, non-housing consumption share, income, wealth, and returns. Moreover, although it is not possible to observe everything that market participants do, returns are observed and summarize the market's relevant information.

The $N \times 1$ state vector z_t used in the first stage of the estimation procedure is given by $z'_t = (\Delta s_t, \Delta w_t, \Delta c_t, \Delta y_t, r_t, cay_t, d_t - p_t)$, and includes non-housing consumption share growth, wealth growth, consumption growth, labor income growth, real returns on financial assets, consumption-aggregate wealth ratio, and the dividend yield. The dynamics of the state vector are described by a Vector Auto-Regressive Model (VAR):

$$z_t = Az_{t-1} + \xi_t, \tag{11}$$

where $A(L)$ is a finite-order distributed lag operator, and ξ_t is a vector of error terms with innovation covariance matrix $E[\xi\xi'] = \Sigma$.[14] The dimensions of Σ and A are $N \times N$, whilst the dimensions of ξ and z are $N \times T$.

The vector z_t has the useful property that to forecast it ahead k periods given the information set Ω_t, one can simply multiply z_t by the k^{th} power of the matrix A, that is, $E_t[z_{t+k}|\Omega_t] = A_t^k z_t$. It is

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[14] The selected optimal lag length is 1, in accordance with findings from Akaike and Schwarz tests. However, the results are not sensible to different lag lengths.

possible, therefore, to define

$$cr_t = E_t \sum_{i=1}^{\infty} \rho_w^i \Delta s_{t+i} = e_1' A(I - \rho_w A)^{-1} z_t \tag{12}$$

$$lr_t = E_t \sum_{i=1}^{\infty} \rho_h^{i-1} \Delta y_{t+i} = e_4' A(I - \rho_h A)^{-1} z_t \tag{13}$$

$$lrc_t = E_t \sum_{i=1}^{\infty} \rho_w^i \Delta c_{t+i} = e_3' A(I - \rho_w A)^{-1} z_t \tag{14}$$

$$lrdp_t = E_t \sum_{i=1}^{\infty} \rho_w^i (d_{t+i} - p_{t+i}) = e_7' A(I - \rho_w A)^{-1} z_t \tag{15}$$

$$lrret_t = E_t \sum_{i=1}^{\infty} \rho_w^i r_{t+i} = e_5' A(I - \rho_w A)^{-1} z_t, \tag{16}$$

where e_k is the k^{th} column of an identity matrix of the same dimension as A. I estimate A from the VAR in specification (11) and Appendix B reports a summary of the coefficient estimates.

After the estimation of the VAR, it is possible to extract the current innovations of the variables of major interest in the model and to use them to compute a measure of the long-run innovations, therefore, building proxies for long-run unexpected changes in the housing share, in labor income growth, in consumption growth, in the price-dividend ratio and in ex-ante asset returns, that is:

$$cr_t = (\Delta s)_{t,\infty} = (E_t - E_{t-1}) \sum_{i=1}^{\infty} \rho_w^i \Delta s_{t+i} = e_1' A(I - \rho_w A)^{-1} \boldsymbol{\xi}_t \tag{17}$$

$$lr_t = (\Delta y)_{t,\infty} = (E_t - E_{t-1}) \sum_{i=1}^{\infty} \rho_h^{i-1} \Delta y_{t+i} = e_4' A(I - \rho_h A)^{-1} \boldsymbol{\xi}_t \tag{18}$$

$$lrc_t = (\Delta c)_{t,\infty} = (E_t - E_{t-1}) \sum_{i=1}^{\infty} \rho_w^i \Delta c_{t+i} = e_3' A(I - \rho_w A)^{-1} \boldsymbol{\xi}_t \tag{19}$$

$$lrdp_t = (dp)_{t,\infty} = (E_t - E_{t-1}) \sum_{i=1}^{\infty} \rho_w^i (d_{t+i} - p_{t+i}) = e_7' A(I - \rho_w A)^{-1} \boldsymbol{\xi}_t \tag{20}$$

$$lrret_t = (r)_{t,\infty} = (E_t - E_{t-1}) \sum_{i=1}^{\infty} \rho_w^i r_{t+i} = e_5' A(I - \rho_w A)^{-1} \boldsymbol{\xi}_t, \tag{21}$$

where the subscript t, ∞ denotes current and future innovations. As a final step, the forecasting power of these proxies is estimated in single equation regressions.

3 Expected Changes, Unexpected Shocks, and Asset Returns

3.1 Data

In the estimations, I use quarterly, seasonally adjusted data for U.S., variables are measured at 2000 prices and expressed in the logarithmic form of per capita terms, and the sample period is 1954:1 - 2004:1. The main data sources are the Flow of Funds Accounts provided by Board of Governors of Federal Reserve System and Bureau of Economic Analysis of U.S. Department of Commerce. In Appendix A, I present a detailed discussion of data.

The definition of consumption includes nondurable consumption goods and services. Data on income includes only labor income. The definition of total wealth corresponds to the net worth of households and nonprofit organizations, this is, the sum of housing wealth and financial wealth. Housing wealth (or home equity) is defined as the value of real estate held by households minus home mortgages. Original data on wealth correspond to the end-period values. Therefore, I lag once the data, so that the observation of wealth in t corresponds to the value at the beginning of the period $t+1$. Finally, asset returns are measured using the value weighted CRSP (CRSP-VW) market return index.

Figure 1 plots the time series of $\widehat{cay}_t$, $\widehat{cr}_t$, $\widehat{lr}_t$, $\widehat{lrc}_t$, $\widehat{lrdp}_t$, $\widehat{lrret}_t$ (based on the expected forecasts generated by the VAR) and the real return, r_t.[15] It shows a multitude of episodes during which sharp increases in these proxies precede large reductions in the real return and it displays interesting business cycle patterns: (*i*) $\widehat{cay}_t$ increases in recessions and falls in expansions; and (*ii*) $\widehat{cr}_t$, $\widehat{lr}_t$, and $\widehat{lrc}_t$ fall in recessions and increase in expansions. It also shows that $\widehat{lrdp}_t$ does not seem to be a good predictor of future returns, and this may be the result of its high persistence. Finally, the pattern of $\widehat{lrret}_t$, that is, the proxy for the ex-ante expected long-run returns captures relatively well the pattern of the ex-post returns, which suggests that, for small perturbations around the steady state, the variables included in the VAR should capture most of the relevant information for the asset returns.

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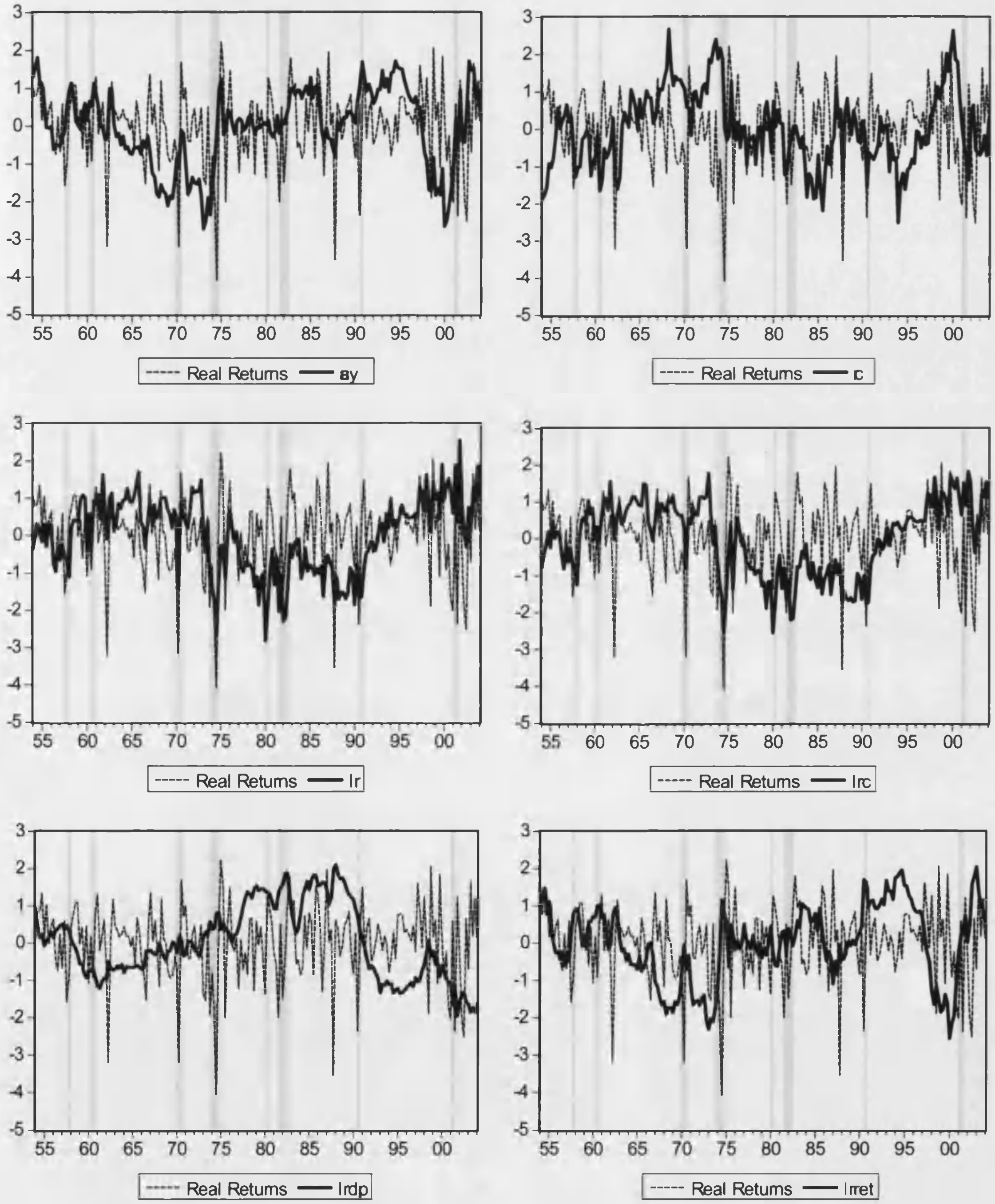
[15] Real returns are constructed as the difference between the CRSP-VW market return index and the inflation rate. The time series are standardized to have unit variance and smoothed to facilitate the reading.

Figure 1: Time series of *cay*, *lr*, *cr*, *lrc*, *lrdp*, *lrret* and real returns.

All series are normalized to standard deviations.

The sample period is 1954:1 to 2004:1. Shaded areas denote NBER recessions.



3.2 Consumption-Wealth Ratio

I examine the relative predictive power of $\widehat{cay}_t, \widehat{lr}_t, \widehat{cr}_t, \widehat{lrc}_t, \widehat{lrdp}_t, \widehat{lrret}_t$ for real returns over horizons spanning 1 to 4 quarters. In the estimation of the regressions of real returns, the dependent variable is the H-period log real return on the CRSP-VW Index, $r_{t+1} + .. + r_{t+H}$. For each regression - with the exceptions of *cay* and *cday* in Table 1 -, the tables report the estimates from OLS regressions based on the expected long-run forecasts (Panel A) and on the unexpected long-run deviations (Panel B) and all equations include lag returns as a regressor.

Lettau and Ludvigson (2001a) show that fluctuations in the consumption-aggregate wealth ratio, *cay*, summarize changes in expected returns and can be used for predicting stock returns. Investors want to maintain a flat consumption path over time and will attempt to "smooth out" transitory movements in their asset wealth arising from time variation in asset returns. When excess returns are, for example, expected to be higher in the future, forward-looking investors will react by increasing consumption out of current asset wealth and labor income, allowing consumption to rise above its common trend with those variables. More recently, Sousa (2007) shows that fluctuations in the consumption-(dis)aggregate wealth ratio, *cday*, have superior forecasting power due to its ability to track the changes in the composition of asset wealth (financial versus housing wealth) and the faster rate of convergence of the coefficients to the "long-run equilibrium" parameters.

I analyze the forecasting power of *cay* and *cday* for real returns. I estimate *cay* as $cay_t := c_t - 0.42w_t - 0.65y_t$ and *cday* as $cday_t := c_t - 0.29f_t - 0.17u_t - 0.60y_t$, where c_t, y_t, w_t, f_t and u_t represent, respectively, nondurable consumption of goods and services, labor income, aggregate asset wealth, financial wealth and housing wealth.[16]

Table 1 reports a summary of the results. Panel A shows that $\widehat{cay}$ has a significant forecasting power for future real returns, particularly at 3 and 4 quarters horizons, with the $\bar{R}^2$ statistic reaching 0.30, consistent with Lettau and Ludvigson (2001a). In accordance with Sousa (2007), Panel B shows that $\widehat{cday}$ performs better: the coefficient estimates are larger in magnitude and, for the same horizons, the $\bar{R}^2$ statistic ranges between 0.25 and 0.30. This suggests that the disaggregation of wealth into its main components is an important issue in the context of forecasting future asset returns.[17]

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[16] I estimate cay_t and $cday_t$ using dynamic OLS with 4 lags and leads.

[17] The predictive impact of $\widehat{cday}$ on future returns is economically larger than that of $\widehat{cay}$: in the one-period ahead regressions, the point estimate of the coefficient on $\widehat{cday}$ is about 1.549 for real returns and only 1.164 in the case of $\widehat{cay}$. Thus, a one-standard-deviation increase in $\widehat{cday}$ (standard deviation is 0.019) leads to, approximately, a 82.07 basis points rise in the expected real return on value weighted CRSP index, this is, a 3.32% increase at an annual rate. On the other hand, $\widehat{cay}$ itself has a standard deviation of about 0.023, implying that a one-standard-deviation increase in $\widehat{cay}$ leads to, approximately, a 50 basis points rise in the expected real return on value weighted CRSP index, this is, a 2.02% increase

Table 1: Forecasting real returns using *cay* and *cday*.

Regressor	Forecast Horizon H 1	2	3	4
Panel A: Real Returns, using $\widehat{cay}$				
cay_{t-1}	1.164*	2.325*	3.381*	4.329*
(t-stat)	(4.554)	(4.466)	(4.560)	(4.944)
$\bar{R}^2$	[0.08]	[0.16]	[0.24]	[0.30]
Panel B: Real Returns, using $\widehat{cday}$				
$cday_{t-1}$	1.549*	3.055*	4.360*	5.434*
(t-stat)	(4.978)	(4.868)	(4.975)	(5.271)
$\bar{R}^2$	[0.10]	[0.18]	[0.25]	[0.30]

Symbols *, ** and *** represent significance at a 1%, 5% and 10% level, respectively.

Newey-West (1987) corrected t-statistics appear in parenthesis.

The sample period is 1954:1 to 2004:1.

3.3 Long-Run Changes in the Composition of Consumption

In the standard model, investors' concern with consumption risk implies that stock prices move with the business cycle. In recessions, investors expect higher future consumption and try to sell stocks today to increase current consumption. This intertemporal substitution mechanism drives down stock prices in bad times.

Yogo (2006) shows that when utility is nonseparable in nondurable and durable consumption and the elasticity of substitution between the two consumption goods is sufficiently high, marginal utility rises when durable consumption falls.[18] Stock returns are unexpectedly low at business cycle troughs, when durable consumption falls sharply, and this helps to explain the countercyclical variation in the equity premium. Piazzesi *et al.* (2007) consider a consumption-based asset pricing model where housing is explicitly modelled both as an asset and as a consumption good. Nonseparable preferences describe households' concern with composition risk, that is, fluctuations of the relative share of non-housing in their consumption basket and the model predicts that the housing share can be used to forecast returns on stocks. Finally, Lustig and Van Nieuwerburgh (2005) show that in a model with housing collateral, the ratio of housing wealth to human wealth shifts the conditional distribution of asset prices

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at an annual rate.

[18] Dunn and Singleton (1986) and Eichenbaum and Hansen (1990) report evidence against separabilility of preferences, but they conclude that introducing durables does not help in reducing the pricing errors for stocks.

and consumption growth and, therefore, predicts returns on stocks. The authors consider two main channels that transmit shocks originated in the housing market to the risk premia in the asset market: (*i*) when housing prices decrease, collateral is destroyed and households are more exposed to idiosyncratic labor income risk; and (*ii*) households want to hedge against rental price shocks or consumption basket composition shocks when the utility function is nonseparable in nondurable consumption and housing services.

I analyze the forecasting power of the housing share for asset returns. However, instead of imposing nonseparability of preferences, as in the works mentioned above, I use the intertemporal budget constraint to derive a relationship between the present discount value of changes in housing share, cr, and asset returns. Moreover, while the focus of previous literature is on the forecasting power of the housing share, I focus instead in the long-run changes of the housing share. Finally, with the VAR estimated in Section 2.2, I estimate and compare the forecasting power of expected and unexpected changes in housing share.

Table 2 presents a summary of the results. Panel A shows that expected changes in the housing share strongly forecast future real returns, with the $\bar{R}^2$ statistic ranging from 0.09 to 0.23. In contrast, Panel B shows that unexpected growth has only a small predictive power (the $\bar{R}^2$ statistic ranges between 0.01 and 0.02). In both regressions, the coefficient associated to cr is negative, consistent with the fact that a high cr represents a state of the world in which returns on asset wealth are low.

This suggests that while expected changes in the long-run housing share are an important determinant of real returns, unexpected changes do not play an important role in the context of forecasting asset returns, in accordance with the findings of Lustig and Van Nieuwerburgh (2005) and Piazzesi *et al.* (2007). The reason lies in the observation that housing share is a macroeconomic variable with a high degree of persistent and, therefore, its changes can largely be forecasted by consumers. As a result, unexpected changes in the long-run composition risk play a negligible role in forecasting asset returns.

Table 2: Forecasting real returns using *cr*.

	Forecast Horizon H			
Regressor	1	2	3	4
	Panel A: Expected Changes			
cr_{t-1}	-17.308*	-32.280*	-43.503*	-55.694*
(t-stat)	(-3.918)	(-4.036)	(-4.193)	(-4.595)
$\bar{R}^2$	[0.09]	[0.15]	[0.18]	[0.23]
	Panel B: Unexpected Changes			
cr_{t-1}	-16.906***	-27.621***	-28.088	-33.344
(t-stat)	(-1.695)	(-1.875)	(-1.536)	(-1.550)
$\bar{R}^2$	[0.02]	[0.02]	[0.01]	[0.01]

Symbols *, ** and *** represent significance at a 1%, 5% and 10% level, respectively.

Newey-West (1987) corrected t-statistics appear in parenthesis.

The sample period is 1954:1 to 2004:1.

3.4 Long-Run Labor Income Growth

Julliard (2004) uses the representative consumer's budget constraint to derive an equilibrium relation between expected future labor income growth rates - summarized by the variable lr - and expected future asset returns. The author shows that expectations of high (low) future labor income growth are associated with lower (higher) stock market excess returns. These results are consistent with the fact that high lr represents a state of the world in which agents expect to have abundance of resources in the future to finance consumption, therefore low returns on asset wealth are feared less and lower equilibrium risk premia are required.

In order to model the labor income process, the author experimented with several specifications in the ARIMA class, and performed the standard set of Box-Jenkins selection procedures.[19] In the present paper, I use a different methodology in that expected and unexpected labor income growth rates are computed directly from the VAR estimated in Section 2.2.

Table 3 presents a summary of the results describing the forecasting power of lr: Panel A considers the expected long-run growth as the major explanatory variable, while Panel B includes only the unexpected long-run shocks. In both regressions, the coefficient associated to lr is negative, consistent with the fact that a high lr represents a state of the world in which returns on asset wealth are low. Moreover, it can be seen that, consistently with Julliard (2004), expected growth has a significant

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[19] In particular, the ARIMA(0,1,2) specification for log income fits well the data.

forecasting power for future real returns, with the $\bar{R}^2$ statistic ranging from 0.01 to 0.07. In contrast, Panel B shows that unexpected growth has no predictive power. In sum, expected long-run labor income growth is an important determinant of real returns, while unexpected changes do not play a significant role in the context of forecasting asset returns.

Table 3: Forecasting real returns using *lr*.

	Forecast Horizon H			
Regressor	1	2	3	4
	Panel A: Expected Changes			
lr_{t-1}	-1.818**	-3.484**	-5.452*	-7.251*
(t-stat)	(-2.279)	(-2.266)	(-2.632)	(-2.882)
$\bar{R}^2$	[0.01]	[0.03]	[0.05]	[0.07]
	Panel B: Unexpected Changes			
lr_{t-1}	-1.650	-2.588	-6.236	-12.717*
(t-stat)	(-0.648)	(-0.676)	(-1.394)	(-2.852)
$\bar{R}^2$	[0.00]	[0.00]	[0.00]	[0.03]

Symbols *, ** and *** represent significance at a 1%, 5% and 10% level, respectively.

Newey-West (1987) corrected *t*-statistics appear in parenthesis.

The sample period is 1954:1 to 2004:1.

3.5 Long-Run Consumption Growth

Bansal *et al.* (2005) show that asset prices reflect the discounted value of cash flows and that return news reflect revisions in expectations about the entire path of future cash flows and discount rates. Changes in expectations of cash flows are important ingredients determining asset return news. Systematic risks in cash flows therefore should have some bearing on the risk compensation of assets. In particular, assets whose cash flows have higher aggregate consumption risks should also carry a higher risk premium. This intuition is also captured in the consumption-based models presented in Abel (1999) and Bansal and Yaron (2004), who show that differences in risk compensation on assets mirror differences in the exposure of assets' cash flows to consumption. Economic risks in cash flows provide very valuable information about systematic risks in asset returns.

By its turn, Parker and Julliard (2005) study the Fama and French size and book-to-market portfolios and reevaluate the central insight of the consumption capital asset pricing model that an asset's expected return is determined by its equilibrium risk to consumption. Rather than measuring the risk of a portfolio by the contemporaneous covariance of its return and consumption growth, the authors measure the risk of a portfolio by its ultimate risk to consumption, defined as the covariance of its return and consumption growth over the quarter of the return and many following quarters.

The present work is based on a similar argument: instead of looking at the forecasting power of current consumption's growth for asset returns, the focus is on the long-run consumption growth, lrc. Using the VAR estimated in Section 2.2, I compute the expected and the unexpected long-run consumption growth and then use them as explanatory variables for future returns.

Table 4 presents a summary of the results: Panel A includes the expected changes as the major explanatory variable, while Panel B includes the unexpected changes. It can be seen that the coefficient associated to lrc is negative in both regressions, consistent with the fact that a high lrc represents a state of the world in which returns on asset wealth are low. This also implies that consumers try to hedge future fluctuations in consumption by investing in the stock markets, that is, stocks are used as an hedging device against negative future consumption shocks. The results are, therefore, in line with the findings of Parker and Julliard (2005).

Table 4: Forecasting real returns using *lrc*.

	Forecast Horizon H			
Regressor	1	2	3	4
Panel A: Expected Changes				
lrc_{t-1}	-2.009*	-3.957*	-5.950*	-7.897*
(t-stat)	(-2.795)	(-2.877)	(-3.202)	(-3.399)
$\bar{R}^2$	[0.03]	[0.05]	[0.08]	[0.11]
Panel B: Unexpected Changes				
lrc_{t-1}	-4.593***	-7.662	-13.640*	-24.252*
(t-stat)	(-1.692)	(-1.621)	(-2.475)	(-4.090)
$\bar{R}^2$	[0.01]	[0.01]	[0.03]	[0.09]

Symbols *, ** and *** represent significance at a 1%, 5% and 10% level, respectively.

Newey-West (1987)] corrected t-statistics appear in parenthesis.

The sample period is 1954:1 to 2004:1.

3.6 Long-Run Dividend-Price Ratio

Shiller (1984), Campbell and Shiller (1998), and Fama and French (1988) all find that the ratios of price to dividends or earnings have predictive power for excess returns. Lamont (1998) finds that the ratio of dividend to earnings has forecasting power at quarterly horizons. Campbell (1991) and Hodrick (1992) find that the relative T-bill rate (the 30-day T-bill rate minus its 12-month moving average) predicts returns, and Fama and French (1989) study the forecasting power of the term spread (the 10-year Treasury bond yield minus the 1-year Treasury bond yield) and the default spread (the difference between the BAA and AAA corporate bond rates). Lamont (1998) argues that the dividend payout ratio should be a potentially potent predictor of excess returns, a result of the fact that high dividends typically forecast high returns whereas high earnings typically forecast low returns. On the other hand, Lettau and Ludvigson (2001a) show that these predictors do not convey significant information about future asset returns.

I use the VAR estimated in Section 2.2 to build measures of the long-run dividend-price ratio, *lrdp*, and test its forecasting power over different horizon spans. Table 5 presents a summary of the results and shows that the long-run dividend to price ratio does not contain explanatory power for real returns in accordance with the findings of Lettau and Ludvigson (2001a). Empirically, this result can be explained by the poor dynamics (and huge persistence) of *lrdp*, which does not enable it to match the fluctuations that characterize asset returns.

Table 5: Forecasting real returns using *lrdp*.

	Forecast Horizon H			
Regressor	1	2	3	4
Panel A: Expected Changes				
$lrdp_{t-1}$	0.123	0.242	0.325	0.381
(t-stat)	(1.086)	(1.102)	(1.047)	(0.995)
$\bar{R}^2$	[0.00]	[0.00]	[0.00]	[0.00]
Panel B: Unexpected Changes				
$lrdp_{t-1}$	0.335	1.409	1.669	1.419
(t-stat)	(0.463)	(1.299)	(1.430)	(1.044)
$\bar{R}^2$	[0.00]	[0.00]	[0.00]	[0.00]

Symbols *, ** and *** represent significance at a 1%, 5% and 10% level, respectively.

Newey-West (1987) corrected t-statistics appear in parenthesis.

The sample period is 1954:1 to 2004:1.

3.7 Long-Run Asset Returns

Most of the literature on asset pricing aimed at building proxies of asset returns measure the forecasting power relating these proxies with ex-post realized asset returns. Favero (2005) tries to highlight the differences between ex-ante expected returns and ex-post realized returns. The author derives a proxy for the long-run expected returns using a VAR that includes asset returns, *cay*, consumption growth and asset returns. After realization, the VAR is re-estimated each point in time and projected forward for a long-horizon, so that long-run expected returns are computed.

I compute a proxy for the expected and unexpected long-run asset returns, *lrret*, using the VAR estimated in Section 2.2. While the focus of Favero (2005) is on assessing the differences between those proxies and the predictive power of *cay*, I aim at analyzing to which extent asset returns reflect expectations about future returns and the importance of unexpected shocks.

Table 6 presents a summary of the results. Panel A shows that expected ex-ante long-run real returns strongly forecast future ex-post real returns, with the $\bar{R}^2$ statistic ranging from 0.07 to 0.28. Panel B shows that ex-ante unexpected shocks to long-run real returns also have some predictive power (the $\bar{R}^2$ statistic ranges between 0.01 and 0.05). This suggests that both expected and unexpected long-run asset returns are important determinants of ex-post real returns. Moreover, expectations about future returns represent only a small component of the behaviour of observed asset returns and other forces drive this variable.

Table 6: Long-run horizon regressions using *lrret*.

Regressor	Forecast Horizon H			
	1	2	3	4
Panel A: Expected Changes				
$lrret_{t-1}$	0.128*	0.257*	0.377*	0.486*
(t-stat]	(4.463)	(4.356)	(4.414)	(4.745)
$\bar{R}^2$	[0.07]	[0.14]	[0.21]	[0.28]
Panel B: Unexpected Changes				
$lrret_{t-1}$	0.176	0.289***	0.493**	0.720*
(t-stat]	(1.628)	(1.841)	(2.218)	(2.546)
$\bar{R}^2$	[0.01]	[0.01]	[0.03]	[0.05]

Symbols *, ** and *** represent significance at a 1%, 5% and 10% level, respectively.

Newey-West (1987) corrected t-statistics appear in parenthesis.

The sample period is 1954:1 to 2004:1.

4 Conclusion

This paper uses the representative consumer's budget constraint to derive an equilibrium relation between the trend deviations among consumption, aggregate wealth and labor income, *cay*, expected future changes in the housing consumption share, *cr*, expected future labor income growth, *lr*, expected future consumption growth, *lrc*, and expected future asset returns, and explores the predictive power of these variables for future asset returns.

The novelty of the paper is in the methodology. Instead of relying on a model of consumer behaviour that explicitly assumes a functional form for preferences, I use the intertemporal budget constraint to derive the major determinants of asset returns. Then, I explore the forecasting properties of an informative VAR to build proxies for the long-run determinants of asset returns. Finally, the forecasting power of these proxies for future asset returns is assessed and this is used as a way of indirectly testing the assumptions about preferences considered in many optimal models of consumer behaviour.

Using the VAR, I compute measures of expected and unexpected long-run changes of the major determinants of asset returns and find that: (*i*) *cay*, *cday*, expected future labor income growth, expected future changes in the composition of consumption, expected future consumption growth, expected changes in ex-ante long-run real returns strongly forecast future asset returns; (*ii*) unexpected long-run consumption growth and unexpected changes in ex-ante long-run real returns contain some predictive power for asset returns; (*iii*) unexpected future labor income growth and unexpected changes in the housing share do not predict future asset returns; and (*iv*) neither expected nor unexpected changes in the dividend-price ratio forecast asset returns.

Additionally, it is shown that expectations about long-run risk are important determinants of asset returns: expectations of high (low) future labour income growth, expectations of high (low) future consumption growth, and expectations of high (low) non-housing consumption share are associated with lower (higher) than average stock market returns. The empirical proxies *cay*, *cday*, *cr*, *lr*, and *lrc* are able to track the risk premium and this explains their success as predictors of asset returns. On the other hand, shocks to long-run expectations play a negligible role in what concerns forecasting future returns.

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Appendix

A Data Description

Consumption

Consumption is defined as the expenditure in non-durable consumption goods and services. Data are quarterly, seasonally adjusted at an annual rate, measured in billions of dollars (2000 prices), in per capita terms and expressed in the logarithmic form. Series comprises the period 1947:1-2005:4. The source is U.S. Department of Commerce, Bureau of Economic Analysis, NIPA Table 2.3.5.

Aggregate Wealth

Aggregate wealth is defined as the net worth of households and nonprofit organizations. Data are quarterly, seasonally adjusted at an annual rate, measured in billions of dollars (2000 prices), in per capita terms and expressed in the logarithmic form. Series comprises the period 1952:2-2006:1. The source of information is Board of Governors of Federal Reserve System, Flow of Funds Accounts, Table B.100, line 41 (series FL152090005.Q).

After-Tax Labor Income

After-tax labor income is defined as the sum of wage and salary disbursements (line 3), personal current transfer receipts (line 16) and employer contributions for employee pension and insurance funds (line 7) minus personal contributions for government social insurance (line 24), employer contributions for government social insurance (line 8) and taxes. Taxes are defined as: [(wage and salary disbursements (line 3)] / (wage and salary disbursements (line 3)+ proprietor' income with inventory valuation and capital consumption adjustments (line 9) + rental income of persons with capital consumption adjustment (line 12) + personal dividend income (line 15) + personal interest income (line 14))] * (personal current taxes (line 25)]. Data are quarterly, seasonally adjusted at annual rates, measured in billions of dollars (2000 prices), in per capita terms and expressed in the logarithmic form. Series comprises the period 1947:1-2005:4. The source of information is U.S. Department of Commerce, Bureau of Economic Analysis, NIPA Table 2.1..

Asset Returns

The proxy chosen for the market return is the value weighted CRSP (CRSP-VW) market return index. The CRSP index includes NYSE, AMEX and NASDAQ, and should provide a better proxy for market returns than the Standard & Poor (S&P) index since it is a much broader measure. Data are quarterly, deflated by the personal consumption chain-weighted index (2000=100) and expressed in the logarithmic form. Series comprises the period 1947:2-2004:4. The source of information is Robert Shiller's web site: *http://www.econ.yale.edu/~shiller/data.htm.*

Population

Population was defined by dividing aggregate real disposable income (line 35) by per capita disposable income (line 37). Data are quarterly. Series comprises the period 1946:1-2005:4. The source of information is U.S. Department of Commerce, Bureau of Economic Analysis, NIPA Table 2.1.

Price Deflator

The nominal wealth, after-tax income, consumption, and interest rates were deflated by the personal consumption expenditure chain-type price deflator (2000=100), seasonally adjusted. Data are quarterly. Series comprises the period 1947:1-2005:4. The source of information is U.S. Department of Commerce, Bureau of Economic Analysis, NIPA Table 2.3.4., line 1.

Inflation Rate

Inflation rate was computed from price deflator. Data are quarterly. Series comprises the period 1947:2-2005:4. The source of information is U.S. Department of Commerce, Bureau of Economic Analysis, NIPA Table 2.3.4, line 1.

Interest Rate ("Risk-Free Rate")

Risk-free rate is defined as the 3-month U.S. Treasury bills real interest rate. Original data are monthly and are converted to a quarterly frequency by computing the simple arithmetic average of three consecutive months. Additionally, real interest rates are computed as the difference between nominal interest rates and the inflation rate. The 3-month U.S. Treasury bills real interest rate' series comprises the period 1947:2-2005:4, and the source of information is the H.15 publication of the Board of Governors of the Federal Reserve System.

B Vector-Autoregression (VAR) Estimation

Table B1: Estimates from Vector-Autoregressions (VAR).

	Equation						
Dependent variable	Δs_t	Δw_t	Δc_t	Δy_t	r_t	cay_t	$d_t - p_t$
Δs_{t-1}	0.443*	-1.886*	-0.670**	-0.916	-8.303	0.717	0.039
	(5.889)	(-2.818)	(-2.319)	(-1.474)	(-1.376)	(1.422)	(0.660)
Δw_{t-1}	-0.000	-0.019	-0.009	-0.038	0.146	0.024	0.002
	(-0.063)	(-0.556)	(-0.585)	(-1.192)	(0.477)	(0.929)	(0.577)
Δc_{t-1}	-0.059*	0.585*	0.280*	0.583*	1.138	-0.345**	0.002
	(-2.712)	(3.010)	(3.329)	(3.228)	(0.649)	(-2.355)	(0.130)
Δy_{t-1}	0.017***	0.132	0.080**	-0.111	-0.577	0.096	0.006
	(1.799)	(1.580)	(2.213)	(-1.428)	(-0.766)	(1.532)	(0.822)
r_{t-1}	0.001	0.212*	0.011*	0.020*	-0.045	-0.091*	0.001
	(1.002)	(25.924)	(3.247)	(2.666)	(-0.606)	(-14.743)	(1.284)
cay_{t-1}	-0.007***	-0.036	-0.026***	-0.024	1.153*	1.004*	-0.008*
	(-1.830)	(-1.137)	(-1.930)	(-0.821)	(4.040)	(42.182)	(-2.982)
$d_{t-1} - p_{t-1}$	-0.003	0.055**	-0.075*	-0.048***	-0.667*	-0.067*	1.005*
	(-1.034)	(1.955)	(-6.199)	(-1.853)	(-2.631)	(-3.165)	(408.095)
$\bar{R}^2$	[0.16]	[0.80]	[0.20]	[0.08]	[0.07]	[0.91]	[0.91]

This table reports the estimated coefficients from Vector-Autoregressions (VAR).

Symbols *, **, *** represent, respectively, significance level of 1%, 5% and 10%.

Newey-West (1987) corrected t-statistics appear in parenthesis.

The sample period is 1953:4 to 2004:4.

C Notation: Current and Long-Run Innovations

Table C1: Notation - current and long-run innovations.

Label	*Definition*	*Expression*
	Current Innovations	
$(\Delta s)_t$	$\Delta s_t - E_{t-1}[\Delta s_t]$	$e_1'\boldsymbol{\xi}_t$
$(\Delta y)_t$	$\Delta y_t - E_{t-1}[\Delta y_t]$	$e_4'\boldsymbol{\xi}_t$
$(\Delta c)_t$	$\Delta c_t - E_{t-1}[\Delta c_t]$	$e_3'\boldsymbol{\xi}_t$
$(dp)_t$	$(d_t - p_t) - E_{t-1}[d_t - p_t]$	$e_7'\boldsymbol{\xi}$
$(r)_t$	$r_t - E_{t-1}[r_t]$	$e_5'\boldsymbol{\xi}_t$
	Long-Run Innovations	
$(\Delta s)_{t,\infty}$	$(E_t - E_{t-1})\sum_{i=1}^{\infty}\rho_w^i \Delta s_{t+i}$	$e_1'A(I-\rho_w A)^{-1}\boldsymbol{\xi}_t$
$(\Delta y)_{t,\infty}$	$(E_t - E_{t-1})\sum_{i=1}^{\infty}\rho_h^{i-1} \Delta y_{t+i}$	$e_4'A(I-\rho_h A)^{-1}\boldsymbol{\xi}_t$
$(\Delta c)_{t,\infty}$	$(E_t - E_{t-1})\sum_{i=1}^{\infty}\rho_w^i \Delta c_{t+i}$	$e_3'A(I-\rho_w A)^{-1}\boldsymbol{\xi}_t$
$(dp)_{t,\infty}$	$(E_t - E_{t-1})\sum_{i=1}^{\infty}\rho_w^i (d_{t+i} - p_{t+i})$	$e_7'A(I-\rho_w A)^{-1}\boldsymbol{\xi}_t$
$(r)_{t,\infty}$	$(E_t - E_{t-1})\sum_{i=1}^{\infty}\rho_w^i r_{t+i}$	$e_5'A(I-\rho_w A)^{-1}\boldsymbol{\xi}_t$

The subscript t denotes current innovations.

The subscript t, ∞ denotes current and future innovations.

General Conclusion

This dissertation analyzes the linkages between consumption, housing and financial wealth, asset returns, and monetary policy.

In Chapter I, I use the representative consumer's budget constraint to derive an equilibrium relation between the trend deviations among consumption, (dis)aggregate wealth and labor income, *cday*, and expected future asset returns, and explore its predictive power.

The main finding is that *cday* has high predictive power for future market returns and it performs better than a variable like *cay* suggested by Lettau and Ludvigson (2001), which does not take into account the issue of the wealth composition. I show that the superior forecasting power of *cday* is due to: (*i*) its ability to track the changes in the composition of asset wealth and the characteristics of the different assets; and (*ii*) the faster rate of convergence of the coefficients to the "long-run equilibrium" parameters.

In Chapter II, I test the assumption of constant relative risk aversion and, using macroeconomic data, analyze the role played by wealth shocks as generating transitory variation in portfolio composition. I show that the risky asset share exhibits a cyclical behavior and, unlike Brunnermeier and Nagel (2006), it is significantly (and positively) affected by wealth shocks. There is, therefore, evidence suggesting that risk aversion is countercyclical and supporting the existence of preferences, such as habit-formation or wealth-dependent utility functions. Additionally, it is shown that the share of housing wealth in portfolio falls when the agent is faced with a positive wealth shock, i.e. housing is a hedge against unexpected wealth variation.

In Chapter III, I investigate whether there is a link between monetary policy shocks and housing prices. Using data at different frequencies, and experimenting with a large number of identification schemes, I find that housing prices are negatively affected by monetary policy contractions and that this effect tends to be very persistent. I also show that monetary policy shocks do not seem to play an important role in the fluctuations of the stock markets: the impact of the shocks is rather small in magnitude and tends to disappear very quickly. Moreover, I provide evidence suggesting the Fed and the Bank of England exhibit important differences in the way they conduct the monetary policy: (*i*) whilst the Fed seems to react substantially to changes in the commodity prices, the Bank of England does not attribute an important role to fluctuations in these prices; and (*ii*) whilst the Fed seems to pay a lot of attention to the interest rate, the focus of the Bank of England points in the direction of the money stock.

In Chapter IV, I use the representative consumer's budget constraint, combine it with Epstein-Zin preferences and the homogeneity of the Bellman Equation, and derive a relationship between expected excess returns, consumption growth, the consumption-aggregate wealth ratio, *cay*, and the first-order differences of this ratio, Δcay. I then explore this relationship to check whether it carries relevant information to cross-sectional variation of asset returns, and show that it outperforms most of the asset pricing models developed in the literature. Additionally, I show that the intertemporal elasticity of substitution is relatively small and that coefficient of risk aversion is relatively high.

The success of the model is that it captures: (*i*) the fact that investors try to "smooth out" transitory movements in their asset wealth arising from time-variation in expected returns; and (*ii*) the large equity risk premia demanded by agents when they fear a rise in economic uncertainty or a reduction in economic prospects.

Finally, in Chapter V, I derive an equilibrium relation between the trend deviations among consumption, aggregate wealth and labor income, *cay*, expected future changes in the housing consumption share, *cr*, expected future labor income growth, *lr*, expected future consumption growth, *lrc*, and expected future asset returns. Instead of relying on a model of consumer behavior that explicitly assumes a functional form for preferences, I use the intertemporal budget constraint to derive the major determinants of asset returns. Then, I explore the forecasting properties of an informative VAR to build proxies for the long-run determinants of asset returns, and find that: (*i*) *cay*, *cday*, expected future labor income growth, expected future changes in the composition of consumption, expected future consumption growth, expected changes in ex-ante long-run real returns strongly forecast future asset returns; (*ii*) unexpected long-run consumption growth and unexpected changes in ex-ante long-run real returns contain some predictive power for asset returns; (*iii*) unexpected future labor income growth and unexpected changes in the housing share do not predict future asset returns; and (*iv*) neither expected nor unexpected changes in the dividend price-dividend ratio forecast asset returns.

Additionally, expectations of high future labor income, expectations of high future consumption growth, and expectations of high non-housing consumption share are associated with lower stock market returns, whilst low labor income growth expectations, low consumption growth expectations and low non-housing consumption share expectations are associated with higher than average real returns. Consequently, the success of *lr*, *cr*, and *lrc* as predictors of asset returns seems to be due to their ability to track risk premia. On the other hand, shocks to long-run expectations play a negligible role as their forecasting power for returns is, in general, very low.