Downside risk aversion, fixed income exposure, and the value premium puzzle

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ABSTRACT

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Key words: downside risk, semi-variance, interest rates, fixed income, value premium, asset pricing, behavioral finance

JEL: G11, G12

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ABSTRACT

The value premium substantially reduces for downside risk averse investors with a substantial fixed income exposure. Growth stocks are attractive to these investors because they offer a good hedge against a bad bond performance. This result holds for evaluation horizons of around one year. Our findings cast doubt on the practical relevance of the value premium for institutional investors such as insurance companies and pension funds, and reiterates the importance of the choice of the relevant test portfolio, risk measure and investment horizon in empirical tests of market efficiency and equilibrium.

The value premium refers to stocks which have a high fundamental value relative to their market value (value stocks) earning higher average stock returns than stocks with a relatively low fundamental value (growth stocks). This finding manifests itself in several forms. For example, stocks of firms that rank high on earnings-to-price ratio (E/P; Basu, 1977, 1983, Jaffe, Keim and Westerfield, 1989), debt-equity ratio (D/E; Bhandari, 1988), dividend-to-price ratio (D/P; Keim, 1983), cash flow-to-price ratio (C/P; Chan, Hamao, and Lakonishok, 1991, Lakonishok, Shleifer and Vishny, 1994), and ratio of book value of common equity to market value of common equity (B/M; Rosenberg, Reid and Lanstein, 1985, De Bondt and Thaler, 1987) perform historically substantially better than firms that rank low on these measures.[1] Moreover, Fama and French (1992, 1993) show that the CAPM (Sharpe, 1964, Lintner 1965, Mossin, 1966) cannot explain the value premium, since value stocks have higher average returns than growth stocks, but do not have higher equity betas.[2]

Furthermore, the effects do not seem to be the result of data mining, as suggested by Black (1993) and Lo and Mackinlay (1990), and are manifested in multiple countries and sub-periods.[3] Thus, there seems to be convincing and robust evidence that

[1] See Chan and Lakonishok (2004) and Lettau and Wachter (2007) for a recent update of this evidence.

[2] Fama and French (1993) document two common factors in the returns of stocks sorted on size and B/M that are unrelated to the market return (SMB and HML). Fama and French (1996) show that these size and value factors explain the strategies based on E/P, B/M, five-year sales growth, and three to five year past returns documented by De Bondt and Thaler (1985). In addition, Fama and French (1995) find that the SMB and HML factors can partly be traced to common factors in the earnings and sales of firms.

[3] For example, Chan, Hamao and Lakonishok (1991) find a value effect in the Japanese stock market ,Dimson, Nagel and Quigley (2003) in the UK market. Also, Capaul, Rowley and Sharpe (1993), Fama and French (1998, 2006a) and Griffin (2002) provide further international evidence. In addition, Davis (1994), Davis, Fama and French (2000) show a value premium for the pre-1963 period. Barber and Lyon (1997) find a value premium using financial firms only, while Kim (1997) finds a value premium after correcting for the possible selection biases of Compustat data. Furthermore, Basu (1983), Jaffe, Keim and Westerfield (1989) and Fama and French (1992) find that the value premium to be different from the size premium documented by Banz (1981).

investors can enhance their portfolios by overweighting value stocks and underweighting growth stocks.[4] This evidence constitutes a major challenge to advocates of market efficiency and passive investment strategies.

This study challenges the evidence for the value premium by questioning three maintained assumptions in the empirical tests. First, these studies generally compare the performance of value and growth portfolios relative to an *all equity market portfolio*. However, a substantial part of an investor's portfolio is likely to be tied up in fixed-income instruments, or assets that are highly correlated to fixed-income instruments. For instance, consumer loans and mortgages represent claims to residential real estate, consumer durables and human capital, household assets that constitute an important part of the total portfolio of many investors. Figure 1 shows that large institutional investors like insurance companies and pension funds invest heavily in fixed income instruments. In principle, this concern can be addressed by adding fixed income assets to the benchmark or market portfolio. For instance, Stambaugh (1982) and Shanken (1987) found that for beta, industry and size sorted portfolios inferences about the CAPM are independent of the inclusion of bonds in the market index. Still, they did not include value sorted portfolios in the analysis and also pointed out that inferences about asset pricing theory critically depend on the test assets included. However, the inclusion of bond returns in the benchmark portfolio can have substantial effects on the especially value sorted portfolios as bond returns and its predictors correlate less with growth stocks than with value stocks and tend to predict better growth returns if bonds are expected to perform relatively bad (see among others Baker and Wurgler, 2008, and Koijen, Lustig and Van Niewerburgh, 2008).

[Insert Figure 1 about here]

Second, studies of the value premium tend to assume, either implicitly or explicitly, that investors equate *risk* with *variance*. A well-known limitation of variance is that it places the same weight on upward and downward deviations. However, already in his seminal work on the mean-variance portfolio theory Markowitz (1959) suggested that investors are only concerned with losses and that semi-variance may be a better measure of risk than variance. In fact, in his Nobel Lecture Markowitz (1991,

[4] Although Loughran (1997) suggest that the value premium is less important for money managers, since; (i) it is only present in the smallest firms which represent 6% of the total market value, (ii) is driven by a January seasonal for large firms, and (iii) exceptionally low returns on small young growth stocks outside January, which are hard to short. However, Fama and French (2006a) find that a value premium is present in both small and large firm portfolios sorted on E/P and in international value sorted portfolios of stocks. Moreover, the bad performance of small growth stocks in the B/M sort are mainly due to bad performance of small firms with negative earnings.

p. 476) points out that: "*Semi-variance seems more plausible than variance as a measure of risk, since it is concerned only with adverse deviations*." This conjecture is supported by numerous psychological works on the way people perceive and deal with risk, ranging from students to business managers and professional investors. For instance, in their review on many of these studies Slovic (1972) and Libby and Fishburn (1977) conclude that variance seems to be a bad descriptive measure of managerial risk preferences. Instead, a model that trades off expected return with risk defined by below target return (like semi-variance) seems the most appropriate. Moreover, Cooley (1977) finds that institutional investors are mainly concerned with downside risk. Kahneman and Tversky (1979) and Tversky and Kahneman (1991, 1992) show that people care disproportionably more about losses than gains, a finding they term loss aversion. Furthermore, Ang, Chen and Xing (2006) show the relevance of systematic downside risk for the cross-section of stock returns. In fact, results reported by Petkova and Zhang (2005) suggest that downside risk aversion may especially have a large influence on value sorted portfolios if an investor's portfolio is also subject to a substantial fixed income exposure. Their results show that value stocks have a higher downside beta than growth stocks with respect to variables known to predict bond returns (as for example documented by Keim and Stambaugh, 1986 and Fama and French, 1989). Interestingly, downside risk aversion may also help to explain why a substantial fraction of investable wealth is invested in fixed income instruments, despite the sizeable equity premium (see Benartzi and Thaler, 1995, Barberis and Huang, 2001, Barberis, Huang and Santos, 2001, and Berkelaar, Kouwenberg and Post, 2005).[5]

Third, most studies rely on *monthly returns* to calculate the systematic risk of value stocks. However, the investment horizon of most investors is likely to exceed one month. Bernartzi and Thaler (1995) argue that an annual evaluation period is most appropriate because most financial reporting takes place on an annual basis (e.g. financial statements, tax files, update retirement accounts). Interestingly, Campbell and Viceira (2005) show that the variance and correlation structure of real returns can change dramatically across investment horizons. For example, they find that mean-reversion in stock returns decreases the volatility per period of real stock returns at long horizons, while reinvestment risk increases the volatility per period of real T-bill returns.

We will study the sensitivity of the value premium to these maintained assumptions. To examine the role of fixed income exposure, we consider various hypothetical mixtures of equity and fixed income as well as the actual fixed income exposures of institutional investors. To account for downside risk, we use the mean-

[5] In fact, Barberis and Huang (2001) show that the value premium naturally emerges in an economy in which investors are; (i) loss averse, (ii) less risk averse after gains and more risk averse after losses, and (iii) care about fluctuations in the outcomes of each asset held (instead fluctuations in their portfolio). By contrast, we will study the importance of the value premium for rational investors that only care about downside fluctuations in their portfolio, while having a certain fixed income exposure.

semi-variance criterion (see for example, Mao, 1970, and Hogan and Warren, 1972), as well as non-parametric stochastic dominance criteria, and compare its performance with the classical mean-variance criterion (see for example, Markowitz, 1959). Finally, to study the effect of the investment horizons we consider horizons varying from one month to two years.

Table I gives a first illustration of our findings. Panel A shows the returns in the three worst years for equities: 1973, 1974 and 2002, years during which the stock market plummeted by more than 22%. A risk-averse all equity investor would want to hedge against such losses by holding stocks that perform relatively well during such years. However, growth stocks performed worse than value stocks during these critical years; the HML return in 1973, 1974 and 2002 was 11.7% on average. This demonstrates the difficulty of rationalizing the value premium for a risk-averse all equity investor. Panel B shows the returns in the three worst years for bonds: 1969, 1979 and 1980, years during which bonds lost more than 10% of their real value. Stocks generally performed well during these years, limiting the losses for investors who mix stocks and bonds, and illustrating the advantages of diversification over asset classes. Interestingly, growth stocks performed substantially better than value stocks did during these years; the average HML return over 1969, 1979 and 1980 was -11.3%. Clearly, growth stocks offer a better hedge against a bad bond performance than value stocks.

[Insert Table I about here]

This study will show that the value premium is severely reduced for investors with substantial bond exposures (larger than about 60%), an aversion to downside risk, and an medium evaluation horizon (of around one year). For 60-90% fixed income exposure the spread in CAPM alpha between value and growth stocks is reduced from 6.4% to 5.4%-3.4%. Furthermore, the assumption that investors care only about downside risk reduces the value premium again by about two percent to 1.6% and becomes statistically insignificant. These results hold for evaluation horizons of six to 18 months, while the value premium is unaffected for shorter evaluation horizons. The results are robust to a number of factors, such as the use of actual portfolio weights of institutional investors, the use of the relevant data sets and sorting procedure, and the precise specification of the downside risk measure.

These findings cast doubt on the practical relevance of the value premium for investors with a substantial fixed income exposure. In fact, growth stocks are attractive because they offer a better hedge against a bad bond performance than value stocks do. Our findings also have a number of other interesting implications. First, our results demonstrate the effect of non-normal asset returns and the need to include risk measures that differ from variance. Levy and Markowitz (1979) report that the mean-variance criterion generally gives a good approximation for general expected utility maximizers. By contrast, we demonstrate that the mean-variance criterion and the mean-semi-variance criterion give very different results for value sorted portfolios. Second, the significant effect of adding fixed income instruments to the analysis contrasts with the robustness reported by Stambaugh (1982) and Shanken (1987) and reiterates the importance of Roll's (1977) critique and the choice of the relevant test portfolio. Third, our results reveal the importance of the investment horizon used to study portfolio efficiency.

The remainder of this paper is structured as follows. Section I introduces preliminary notation, assumptions and concepts. Section II and Section III subsequently discuss our empirical methodology and data set, respectively. Next, Section IV discusses the test results and the robustness with respect to the data set and methodology. Finally, Section V gives concluding remarks and suggestions for further research.

I. Theoretical framework

It is hard to find assets that provide riskless long-term real returns. For example, even one-month T-bills yielded real returns of less than -3% in 1974 and 1979 due to unexpectedly high inflation. Nowadays, Treasury Inflation-Protected Securities (TIPS) promise riskless real yields-to-maturity. However, such instruments have been introduced in the US as late as 1997 and were not available during the largest part of our sample period (1963-2007). Also, the TIPS market remains relatively illiquid in terms of outstanding amounts and trading activity. For this reason, we analyze portfolio efficiency without a riskless asset.

We consider a simple single-period, portfolio-based model of investment in a perfect capital market. The investment universe consists of N risky assets. The returns to the risky assets are denoted by $\boldsymbol{x} \equiv (x_1 \ldots x_N)^{\mathrm{T}}$ and are treated as random variables with joint cumulative distribution function $G : P^N \to [0,1]$, where the domain $P \subset \Re$ is nonempty, closed and convex.[6] Investors may diversify between the assets, and the portfolio possibilities are represented by the polyhedron $\Lambda \equiv \{\boldsymbol{\lambda} \in \Re^N : \mathbf{1}_N^{\mathrm{T}} \boldsymbol{\lambda} = 1\}$. The evaluated portfolio is denoted by $\boldsymbol{\tau} \in \Lambda$.

Investors choose investment portfolios to maximize the expected value of an increasing and concave utility function $u : P \to \Re$ that is defined over the return of their

[6] Throughout the text, we will use $\Re^N$ for an N-dimensional Euclidean space, and $\Re_-^N$ and $\Re_+^N$ denote the negative and positive orthants. To distinguish between vectors and scalars, we use a bold font for vectors and a regular font for scalars. Further, all vectors are column vectors and we use $\boldsymbol{x}^{\mathrm{T}}$ for the transpose of $\boldsymbol{x}$. Finally, $\mathbf{0}_N$ and $\mathbf{1}_N$ denote a (1xN) zero vector and a (1xN) unity vector.

portfolios. The mean-variance investor can be represented by the following standardized, one-parameter, quadratic utility function:[7]

$$u_{MV}(x,\theta) = (1-\theta E[\mathbf{x}^{\mathrm{T}}\boldsymbol{\tau}])x + 0.5\theta x^2 \tag{1}$$

with $\theta \le 0$ for the risk aversion parameter. The utility function for the downside risk averter, or mean-semi-variance investor, is quadratic for losses and linear for gains: [8]

$$u_{MS}(x,\theta) = (1-\theta E[(\mathbf{x}^{\mathrm{T}}\boldsymbol{\tau})1[\mathbf{x}^{\mathrm{T}}\boldsymbol{\tau} \le 0]])x + 0.5\theta 1[x \le 0]x^2 \tag{2}$$

with $\theta \le 0$.

Under the above assumptions, the investor's optimization problem can be summarized as

$$\begin{aligned} &\max_{\boldsymbol{\lambda}\in\Lambda} \int u(\mathbf{x}^{\mathrm{T}}\boldsymbol{\lambda})dG(\mathbf{x}) \quad u \in \{u_{MV}, u_{MS}\} \\ &s.t. \quad \mathbf{1}_N^{\mathrm{T}}\boldsymbol{\lambda} = 1 \end{aligned} \tag{3}$$

The evaluated portfolio $\boldsymbol{\tau} \in \Lambda$ is efficient or the optimal solution for some utility function u if and only if the first-order optimality condition applies:

$$E[u'(\mathbf{x}^{\mathrm{T}}\boldsymbol{\tau},\theta)\mathbf{x}] = \gamma \mathbf{1}_N \tag{4}$$

where γ is the shadow price of the budget restriction $\mathbf{1}_N^{\mathrm{T}}\boldsymbol{\lambda} = 1$ or the shadow price of not having a riskless asset available for lending and borrowing. A negative shadow price implies that the investor would like to invest in a riskless asset (riskless lending) if such an asset were available; a positive shadow price implies that riskless borrowing is desired.

Violations of the optimality condition or "alphas" are defined as

$$\boldsymbol{\alpha}(\theta,\gamma) \equiv E[u'(\mathbf{x}^{\mathrm{T}}\boldsymbol{\tau},\theta)\mathbf{x}] - \gamma \mathbf{1}_N \tag{5}$$

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[7] This utility function is standardized such that $u_{MV}(0,\theta) = 0$ and $E[u'_{MV}(\mathbf{x}^{\mathrm{T}}\boldsymbol{\tau},\theta)] = 1$. Maximizing the expectation of this utility function is equivalent to maximizing a trade-off between mean $E[x]$ and variance $Var[x] = E[x^2] - E[x]^2$: $E[u_{MV}(x,\theta)] = \{1-\theta E[\mathbf{x}^{\mathrm{T}}\boldsymbol{\tau}] + 0.5\theta E[x]\}E[x] + 0.5\theta Var[x]$.

[8] The variable $1[x \le 0]$ is a dummy variable that takes the value 1 if $x \le 0$ and else 0. The utility function is standardized such that $u_{MS}(0,\theta) = 0$ and $E[u'_{MS}(\mathbf{x}^{\mathrm{T}}\boldsymbol{\tau},\theta)] = 1$. Maximizing the expectation of this utility function is equivalent to maximizing a trade-off between mean and semi-variance $SVar[x] = E[x^2 1[x \le 0]] / \Pr[x \le 0]$: $E[u_{MS}(x,\theta)] = \{1-\theta E[\mathbf{x}^{\mathrm{T}}\boldsymbol{\tau}1[\mathbf{x}^{\mathrm{T}}\boldsymbol{\tau} \le 0]]\}E[x] + 0.5\theta \Pr[x \le 0]SVar[x]$.

Efficiency occurs if and only if $\boldsymbol{\alpha}(\theta,\gamma)=\mathbf{0}_N$. If $\alpha_i(\theta,\gamma)>0$, asset i is underweighted and its weight in the portfolio should be increased relative to τ_i in order to achieve efficiency. Similarly, if $\alpha_i(\theta,\gamma)<0$, the asset is overweighed and its weight in the portfolio should be decreased.

We may further reformulate the optimality condition as the following trade-off between mean return and "beta" or systematic risk of the evaluated portfolio:

$$E[\boldsymbol{x}]=\gamma\mathbf{1}_N+\rho(\theta)\boldsymbol{\beta}(\theta) \tag{6}$$

with

$$\rho(\theta)\equiv -Cov[u'(\boldsymbol{x}^{\mathrm{T}}\boldsymbol{\tau},\theta),(\boldsymbol{x}^{\mathrm{T}}\boldsymbol{\tau})] \tag{7}$$

$$\boldsymbol{\beta}(\theta)\equiv\frac{Cov[u'(\boldsymbol{x}^{\mathrm{T}}\boldsymbol{\tau},\theta),\boldsymbol{x}]}{Cov[u'(\boldsymbol{x}^{\mathrm{T}}\boldsymbol{\tau},\theta),(\boldsymbol{x}^{\mathrm{T}}\boldsymbol{\tau})]} \tag{8}$$

The variable $\rho(\theta)$ is the risk premium for every unit of beta risk. Due to risk aversion ($\theta\leq 0$), marginal utility is a decreasing function of the portfolio return and hence the risk premium is positive, that is, $\rho(\theta)\geq 0$.

In the case of mean-variance investors, we obtain the following expressions for the risk premium and the betas:

$$\rho_{MV}(\theta)=-\theta Var[\boldsymbol{x}^{\mathrm{T}}\boldsymbol{\tau}] \tag{9}$$

$$\boldsymbol{\beta}_{MV}(\theta)=\frac{Cov[\boldsymbol{x},\boldsymbol{x}^{\mathrm{T}}\boldsymbol{\tau}]}{Var[\boldsymbol{x}^{\mathrm{T}}\boldsymbol{\tau}]} \tag{10}$$

In case of downside risk averters, the following expressions apply

$$\rho_{MS}(\theta)=-\theta Cov[(\boldsymbol{x}^{\mathrm{T}}\boldsymbol{\tau}),(\boldsymbol{x}^{\mathrm{T}}\boldsymbol{\tau})1(\boldsymbol{x}^{\mathrm{T}}\boldsymbol{\tau}\leq 0)] \tag{11}$$

$$\boldsymbol{\beta}_{MS}(\theta)=\frac{Cov[\boldsymbol{x},(\boldsymbol{x}^{\mathrm{T}}\boldsymbol{\tau})1(\boldsymbol{x}^{\mathrm{T}}\boldsymbol{\tau}\leq 0)]}{Cov[(\boldsymbol{x}^{\mathrm{T}}\boldsymbol{\tau}),(\boldsymbol{x}^{\mathrm{T}}\boldsymbol{\tau})1(\boldsymbol{x}^{\mathrm{T}}\boldsymbol{\tau}\leq 0)]} \tag{12}$$

The above analysis applies for every single-period, portfolio-oriented model of investment in a perfect capital market; every investor's portfolio needs to be efficient according to the efficiency criterion associated with his or her preferences over money.

The model can also be generalized to an equilibrium model of capital markets. In representative investor models, capital market equilibrium can be described by the optimization problem of a single, representative investor. In these models, the value-weighted market portfolio is the optimal solution for the representative investor. Equation (4) becomes the equilibrium condition with τ equal to the relative market capitalization of the assets and $u(x)$ equal to the utility function of the representative investor. The representative investor's marginal utility function $u'(x)$ then represents a "pricing kernel" and the alphas represent "pricing errors" or deviations from equilibrium. For the mean-variance specification, the equilibrium model is equivalent to Black's (1972) zero-beta model with no lending and borrowing at the riskless rate of interest, and for the mean-semi-variance specification, we obtain a zero-beta variant to the equilibrium model by Hogan and Warren (1974) and Bawa and Lindenberg (1977).

However, we stress the need to be cautious with market portfolio efficiency tests, because reliable information about the market value of all capital assets currently is not available due to, for example, measurement problems for non-traded assets such as human capital and the problem of "double-counting" multiple financial claims on the same underlying assets (see Roll, 1977).

II. Empirical methodology

In practice, we cannot directly gauge portfolio efficiency, because the return distribution of the assets (G) is unknown. However, we can estimate the return distribution using time-series return observations and employ statistical tests to determine if efficiency is violated to a significant degree. Throughout the text, we will represent the observations by $\boldsymbol{x}_t \equiv (x_{1t} \cdots x_{Nt})^{\mathrm{T}}$, $t = 1, \cdots, T$. Using the observations, we can construct the following empirical alphas:

$$\hat{\boldsymbol{\alpha}}(\theta, \gamma) \equiv T^{-1} \sum_{t=1}^{T} u'(\mathbf{x}_t^{\mathrm{T}} \boldsymbol{\tau}, \theta) \mathbf{x}_t - \gamma \mathbf{1}_N \tag{13}$$

In the spirit of the Generalized Method of Moments (Hansen, 1982), we can use the following aggregate procedure to test efficiency:

$$JT \equiv \min_{\theta, \gamma} T \hat{\boldsymbol{\alpha}}(\theta, \gamma)^{\mathrm{T}} \mathbf{W} \hat{\boldsymbol{\alpha}}(\theta, \gamma) \tag{14}$$

with $\mathbf{W}$ for an appropriately chosen weighting matrix. The JT-statistic thus selects the risk aversion parameter θ and the shadow price γ that minimize a weighted average of the squares and cross-terms of the alphas.[9]

In this study, we will follow the recommendations of Cochrane (2001) and employ an one-stage GMM procedure with the identity matrix as weighting matrix, i.e. $\mathbf{W} = \mathbf{I}_N$. In this case, minimizing the JT statistic is equivalent to maximizing the R-squared of a cross-sectional regression between sample means and sample second moments and the estimation is almost similar to the classical cross-sectional Fama and MacBeth (1973) procedure. Use of the identity matrix as weighting matrix instead of the "optimal weighing matrix", or the empirical covariance matrix of the first-stage alphas, allows the comparison of our non-nested models and avoids the empirical pitfall of maximizing the volatility of the alphas instead of truly minimizing the alphas. However, we stress that using another common pre-specified weighting matrix, namely the inverse of the sample second moment matrix of returns proposed by Hansen and Jagannathan (1997), yields similar conclusions.[10]

In addition to the R-squared, we also report the p-values of each alpha. These p-values require the empirical covariance matrix of the alphas, which may be poorly estimated in our analysis. This is caused by the large number of moments relative to the number of time series observation, making the estimates of this matrix possibly unstable. Instead, we compute the p-values by means of 1,499 bootstrap draws of the current sample and calculate the standard errors of the alphas over these bootstrap realizations.[11]

Although, the R-squared is intuitive, it has one potential weakness as model comparison criterion. It gives equal weight to each alpha, even though some assets are more volatile than others. To surmount this statistical shortcoming, we follow Campbell and Vuolteenaho (2004) and also compute the following composite test-statistic:

$$CV \equiv \hat{\alpha}(\theta,\gamma)^{\mathrm{T}} \hat{\mathbf{\Omega}}^{-1} \hat{\alpha}(\theta,\gamma) \tag{15}$$

Where CV is the Campbell and Vuolteenaho test statistic, $\hat{\alpha}(\theta,\gamma)$ are the estimated alphas for value sorted portfolios, and $\hat{\mathbf{\Omega}}$ is a diagonal matrix with estimated return volatilities on the main diagonal. The CV-test statistic places less weight on more volatile observations, yet allows a clean model comparison, since it employs the same weighting matrix for different models. In addition, it provides us with a test on the joint

[9] See Cochrane (2001) and Jagannathan and Wang (2002) for the efficacy of the GMM procedure, as well as a comparison and equivalence between different GMM, cross-sectional and time series regressions approaches.

[10] These results are not tabulated, yet available form the authors upon request.

[11] However, bootstrapping the t-values or the asymptotic p-value yields similar conclusions. More details are available from the authors upon request.

equality of all value-sorted-portfolio-alphas to zero.[12] Like Campbell and Vuolteenaho (2004), we avoid using a freely estimated variance-covariance matrix of test asset returns for $\hat{\Omega}$, since the inverse of this matrix may be poorly behaved with a large number of test assets relative to time-series observations. The p-values for the *CV*-test statistic are produced by bootstrapping 1,499 observations from the sample in which the test asset returns are adjusted to yield alphas equal to zero, given the original parameter estimates.

The above methodology assumes serially independently and identically distributed (IID) returns and does not condition on the state-of-the-world. Some studies provide evidence in favor of time-varying risk and time-varying risk aversion, and propose conditional asset pricing models that explain the value premium (see among others, Jagannathan and Wang, 1996, Lettau and Ludvigson, 2001b, Lustig and Van Nieuwerburgh, 2005, Petkova and Zhang, 2005, and Santos and Veronesi, 2006). This conditional risk based approach typically measures risk as the covariance of returns with marginal utility of consumption or returns. Stocks are risky if they pay out less in bad times (in which the marginal utility is high), and vice versa for good times.

Unfortunately, conditional models entail several problems. There is little theoretical guidance for selecting the appropriate specification and the results can be very sensitive to specification errors (see for example, Ghysels, 1998). Furthermore, the models may lack statistical power due to the use of additional free parameters. There is also no guarantee that the model is consistent with risk aversion and no-arbitrage in all states of the world (see for example, Wang and Zhang, 2004). Moreover, if a conditional approach captures the value premium, it is explained by the co-variation of value and growth with a scaled version of the market return. For example, Lettau and Ludvinson (2001b) argue that value stocks earn higher returns than growth stocks since the value stocks have a higher correlation with consumption growth and the market risk premium in bad times, characterized by a high level of their aggregate consumption-to-wealth ratio. However, as pointed out by Lewellen and Nagel (2006), conditional models are unlikely to explain the value premium for two major reasons. First, the co-variation between the conditional expected return on the market and the conditional market betas of value and growth stocks is not high enough, and often has the wrong sign.

[12] Another possible test statistic, provided by Cochrane (2001, p. 204), is:

$$T\hat{\alpha}(\theta,\gamma)^{\mathrm{T}}[(\boldsymbol{I}_N - \boldsymbol{d}(\boldsymbol{d}^{\mathrm{T}}\boldsymbol{W}\boldsymbol{d})^{-1}\boldsymbol{d}^{\mathrm{T}}\boldsymbol{W})\hat{\boldsymbol{S}}(\boldsymbol{I}_N - \boldsymbol{d}(\boldsymbol{d}^{\mathrm{T}}\boldsymbol{W}\boldsymbol{d})^{-1}\boldsymbol{d}^{\mathrm{T}}\boldsymbol{W})^{\mathrm{T}}]^{-1}\hat{\alpha}(\theta,\gamma)$$

where $\boldsymbol{d}$ contains the derivatives of the moment conditions with respect to the parameters, $\boldsymbol{W} = \boldsymbol{I}_N$, and $\hat{\boldsymbol{S}}$ is the estimated empirical covariance matrix of the alphas that is singular and hence has to be pseudo-inverted. Assuming that the time-series observations are serially independently and identically distributed (IID) random draws, this test statistic obeys an asymptotic chi-squared distribution with (N-2) degrees of freedom. However, this test statistic has two serious drawbacks for our analysis. First, $\hat{\boldsymbol{S}}$ may be unstable. Second, this statistic is not comparable across different models, since the squared alphas are weighted differently over various models (i.e. $\hat{\boldsymbol{S}}$ is different for the different models).

Second, the betas of value stocks increase in bad times, but by too little to generate significant unconditional alphas, a finding also shown by Petkova and Zhang (2005). In fact, the analysis of Lewellen and Nagel (2006) reveals that time variation in risk or risk premia should have a relatively small impact on cross-sectional asset pricing tests.

Still, the unconditional approach with a mixed market proxy, as employed in this study, may partly capture possible time variation in the risk premium and/or risk loadings of value and growth stocks. For example, Baker and Wurgler (2008) and Koijen, Lustig and Van Niewerburgh (2008) show that growth stocks correlate less with nominal bond returns and its predictors. Similarly, the results reported by Fama and French (1989), Ferson and Harvey (1999), Petkova and Zhang (2005) and Petkova (2006) suggest that the variables related to good times and a relatively good performance of growth stocks over value stocks, are also closely linked to a bad performance of fixed income instruments. And precisely these periods could generally be classified as bad times in which marginal utility is higher, especially for an investor who invests substantial amounts of his portfolio in fixed income. We will explore this link in more detail in Section IV.G.

III. Data

We consider yearly real returns on stocks and bonds.[13] As discussed in Benartzi and Thaler (1995, p.83), one year is a plausible choice for the investor's evaluation period, because "*individual investors file taxes annually, receive their most comprehensive reports from their brokers, mutual funds, and retirement accounts once a year, and institutional investors also take the annual reports most seriously*." Another reason for focusing on annual returns rather than higher-frequency returns is that higher-frequency returns are affected by heteroskedasticity and serial correlation to a significant degree. These statistical problems cast doubt on the use of statistical procedures which assume serially IID returns (such as the procedure described in Section II). Heteroskedasticity and serial correlation also have an important economic effect, because investors with an annual investment horizon want to be protected especially from a series of monthly losses that translate into annual losses. For these reasons, annual returns seem the most appropriate choice. Still, we will also use monthly returns to investigate the monthly return dynamics that determine the shape of the higher frequency return distributions. Moreover, we will also test our findings for a range of other return frequencies ranging from monthly to bi-annual returns.

Our sample starts in 1963 and ends in 2007 (45 annual observations). There are two reasons for starting in 1963 and omitting the pre-1963 data. First, prior to 1963, the Compustat database is affected by survivorship bias caused by the back-filling procedure excluding delisted firms, which typically are less successful (Kothari,

[13] However, the results are not materially affected by using nominal returns. The nominal results are available from the author upon request.

Shanken and Sloan, 1995). Further, from June 1962, AMEX-listed stocks are added to the CRSP database, which includes only NYSE-listed stocks before this month. Since AMEX stocks generally are smaller than NYSE stocks, the relative number of small caps in the analysis increases from June 1962. Since the value effect is most pronounced in the small-cap segment, the post-June-1962 data set is most challenging.

The investment universe of stocks is proxied by ten value weighted portfolios constructed on B/M. We choose ten portfolios rather than a larger number, because this guarantees a minimum number of stocks in every portfolio while still having substantial variation in returns on value sorted portfolios. We will demonstrate the robustness of our results to the benchmark set by using portfolios sorted on E/P and C/P, as well as portfolios constructed at the intersection of two groups formed on market capitalization of equity, or size, and three groups formed on B/M.[14] Furthermore, in the spirit of Fama and French (1993) we will employ a high-minus-low hedge portfolio that buys the highest two value portfolios and shorts the lowest two, to summarize the value effects.

Following Dittmar (2002), we complete the investment universe by adding a portfolio consisting of one-month Treasury bills, which has a relatively low return and beta. Incorporating the moment condition for this portfolio in our estimation procedure enforces the shadow price to lie near the real one-month Treasury bill rate, thereby preventing extreme negative shadow prices and extremely high risk premia.

The stock market portfolio is proxied by the CRSP all-share index, a value-weighted average of common stocks listed on NYSE, AMEX, and NASDAQ. The bond index is defined as the average of the Long Term Government bond index (LTG), Long Term Corporate bond index (LTC) and Intermediate Term Government bond index (ITG) maintained by Ibbotson Associates.[15] We will also analyze the robustness of our findings with respect to using this particular index. Bond data is obtained from Ibbotson Associates, Consumer Price Index inflation data from the U.S. department of Labor and the stock portfolio data from Kenneth French's online data library.

Table II shows some descriptive statistics for our data set. Particularly puzzling are the low returns on growth stocks. The lowest two value sorted stock portfolio earned an average annual real return of 6.84% (6.22% and 7.46%), 5.92% less than the 12.76% (11.86% and 13.65%) for the two highest value sorted portfolio. At first sight, it seems difficult to explain away this premium with risk because growth stocks actually have

[14] In these sorts, stocks with negative B/M, E/P or C/P are excluded. These stocks typically have high returns and high market betas. However, this exclusion is unlikely to influence our results, because it only involves a small number of firms that have a relatively low market cap (see Jaffe, Keim and Westerfield, 1989, and Fama and French, 1992).

[15] These bond indices are constructed as follows; the LTG index includes U.S. government bonds with remaining maturity closest to 20 years or longer, the LTC index includes nearly all U.S. Aaa or Aa rated corporate bonds with an average maturity of approximately 20 years, and the ITG index includes U.S. government bonds with a remaining maturity closest to 5 years or longer.

almost the same standard deviation as value stocks. However, as suggested in Table I, growth stocks provide the best hedge during bad bond market years.

[Insert Table II about here]

IV. Empirical results

This section discusses our empirical findings. Section A first discusses the main results for the ten B/M sorted stock portfolios and the one-month Treasury bills, using annual returns. Next, we will analyze the robustness of our findings with respect to the use of actual portfolio weights for four types of institutional investors (section B), the choice of the stock portfolios (Section C), the return frequency (Section D), the bond index (Section E), and the choice of parameterization (Section F). Finally, we will link our findings to the literature on time-varying risk (Section G).

A. Main results

Table III summarizes our main results. Panel A shows the mean-variance results for an annual investment horizon. Consistent with existing evidence, the mean-variance model gives a poor fit for the all equity index, with an alpha of –4.32% (p-value = 0.02) for the growth portfolio and an alpha of 3.47% (p-value = 0.04) for the value portfolio. The presence of a value premium is captured by the alpha of the VMG hedge portfolio; its alpha is substantial (6.42%) and significantly different from zero (p-value = 0.00). Moreover, the overall R-squared is 47% and the p-value of the *CV*-test is 0.02.

Using a market proxy with a substantial fraction invested in bonds helps to improve the fit. When bonds represent 60% of the portfolio, the growth stock alpha falls to -3.32% (p-value = 0.11), the value stock alpha falls to 2.86% (p-value = 0.08), and the alpha of the value premium portfolio (VMG) becomes 5.41% (p-value = 0.04). The overall R-squared increases to 63% and the *CV*-test statistic falls to 0.113. Moreover, when bonds represent 90% of the portfolio, the growth stock alpha falls to -0.98% (p-value = 0.67), the value stock alpha falls to 2.09% (p-value = 0.25), and the VMG alpha falls to 3.38% (p-value = 0.22). The overall R-squared increases further to 82% and the *CV*-test statistic falls to 0.059 with an associated p-value of 0.49. Still, some portfolios may have a negative alpha for a mean-variance 90% bond investor. For instance, the alpha of the second lowest B/M portfolio is -1.97% with an associated p-value of 0.09.[16]

As shown in Panel B, the results further improve for the mean-semi-variance criterion. In line with the findings of Ang, Chen and Xing (2006) the value premium remains present for an mean-semi-variance all equity investor, witnessing for example

[16] Note that the Tbill portfolio is slightly mispriced. However, restricting the alpha of the Tbill portfolio to equal zero does not materially affect our results. Still, we choose to present to current results since we do not want to impose restrictions on the shadow price that are not warranted.

the VMG alpha of 5.47% (p-value=0.03). However, with 60% invested in bonds, the growth stock alpha falls to -2.77% (p-value = 0.27), the value stock alpha falls to 2.89% (p-value = 0.18), and the alpha of the value premium portfolio (VMG) falls to 4.59% (p-value = 0.12). The overall R-squared becomes 70% and the *CV*-test p-value 0.36. When bonds represent 90% of the portfolio, the growth stock alpha falls to -0.37% (p-value = 0.89), the value stock alpha falls to 1.37% (p-value = 0.54), and the alpha of the value premium portfolio (VMG) falls to 1.56% (p-value = 0.60). The overall R-squared increases further to 95% and the *CV*-test statistic falls to 0.012 with an associated p-value of 0.99.

[Insert Table III about here]

Figure 2 illustrates the same pattern using the alphas of the VMG hedge portfolio, the R-squared, and *CV*-test p-value. Clearly, the VMG alpha critically depends on the percentage bonds included in the market portfolio. But the choice between the mean-variance and the mean-semi-variance efficiency criterion has important consequences as well. Roughly, for portfolios in which bonds constitute 60% or more of the portfolio, the value premium is severely reduced, and for the mean-semi-variance model portfolios in which bonds constitute 80 to 90% of the portfolio it approaches zero.

[Insert Figure 2 about here]

Figure 3 further illustrates our findings by means of mean-beta plots for mean-variance and mean-semi-variance investors who invest either 0% or 80% in bonds (and hence 100% or 20% in equity). The mean-beta line shows the fitted expected return for various values of (downside) beta. The fitted returns are computed using the estimated parameter values for either the mean-variance or mean-semi-variance model specification. The dots show the time-series averages of the returns on the 10 sorted portfolios on increasing values of B/M (in that order, G= growth, V= value) and the one-month Treasury bill (Tbill), given their (downside) beta. If the portfolios are in line with a given investor's mean-variance or mean-semi-variance preferences, the dots should lie on the straight mean-beta line.

The upper two figures show the results for the all equity investors. Clearly, the returns on the B/M sorted portfolios are difficult to reconcile with these investor's preferences. Most notably, the value portfolios have a higher return than the growth portfolio, while its (downside) beta is similar. By contrast, the lower left figure shows that the 10 B/M sorted portfolios align more with the preferences of mean-variance investors who invests 80% of his wealth in bonds. Portfolios with a higher return generally have a higher beta (although the second lowest B/M portfolio still seems rather “anomalous”).[17] The results improve further for the mean-semi-variance investor (see lower right figure), for which all 10 portfolios lie almost on the mean-beta line.

[Insert Figure 3 about here]

Hence, the value premium is severely reduced for downside risk averters holding relatively low to intermediate fractions of their portfolios in equities. As discussed in the introduction, for many institutional investors, this is representative of their actual equity exposure during our sample period (1963-2007). For example, at the beginning of 2007, US life insurance companies had \$1,365bn invested in corporate equities and \$149bn in mutual fund shares. The combined amount of \$1,514bn represents roughly 32% of the total financial assets of \$4,685 bn, which consist primarily of money-market fund shares (\$179bn) and credit-market instruments (\$2,829bn). Moreover, during most of the sample period (1963-2007), the investment in equity was substantially smaller than in 2002. For example, in 1963, equities represented just 5% of the financial assets held by life-insurers.[18]

B. Using institutional investor’s portfolio weights

The results in the previous section assume a certain fixed and constant distribution of portfolio weights between equity and bonds. Although, this distribution may be representative for many investors, we check the robustness of our results to the portfolios of groups of actual investors with time varying bond/equity exposures. To accomplish this we pick four large groups of institutional investors who invested in both equities and bonds over the entire sample period, i.e. life insurance companies (life ins), property-casualty insurance companies (other ins), private pension funds (priv. pen), and state and local government employee retirement funds (state ret), and infer their portfolio composition from the Federal Reserve Board’s Flow of Funds Accounts.[19] Like the analysis in the previous section, we assume that each institutional investor type divided her money between the CRSP all-share equity index and the equal weighted bond index. We compute the annual fractions invested in equities as the sum of the amounts outstanding in corporate equities and equity mutual funds, divided by the

[17] In addition, as will be shown in Section F, the mean-variance investors investing 80% of their wealth in bonds are violating the basic regularity condition of non-satiation. In fact, the utility function is decreasing on a large part of the observed return range, casting doubt on the economic meaning of the mean-variance results. For example, violations of non-satiation can lead to the non-existence of a general equilibrium in the mean-variance CAPM without a riskless asset (see Nielsen, 1990) and violate the no-arbitrage condition (Harrison and Kreps, 1979).

[18] See www.federalreserve.gov, the Federal Reserve Board “Flow of Funds Quarterly Summary Report”.

[19] The relevant data can be found in tables L.116 till L.119 of the Flow of Funds Accounts of the United States.

total financial assets minus miscellaneous assets, reported at the end of last quarter of the previous year.[20]

Table IV summarizes the results for the four institutional investor types, as well as for the all equity investor. Panel A shows the mean-variance results. Consistent with the results in the previous section, adding a substantial fraction of bonds to the portfolio decreases the value premium and helps to improve the fit. Most notably, for life insurance companies (who invested on average 85% in bonds) the growth stock alpha falls to -2.14% (p-value = 0.35), the value stock alpha falls to 2.21% (p-value = 0.24), and the alpha of VMG hedge portfolio falls to 4.39% (p-value = 0.11). The overall R-squared increases to 73% and the *CV*-test p-value to 0.27. However, the mean-variance investor still has some outperformance possibilities, since the alpha of the second lowest B/M portfolio is -2.29% with an associated p-value of 0.03. Similar results are obtained for the other insurance companies, who invest on average 76% in bonds. By contrast, private pension funds and state retirement fund, who have invested a relatively low fraction of their portfolio in bonds (on average 39% and 63% respectively), display only a slight increase in the fit and decrease in the alpha of the value, growth and VMG hedge portfolios.

As shown in Panel B, the results for the mean-semi-variance criterion show a further decrease in the value premium for the institutional investors with the highest fixed income exposure, confirming the earlier findings. Most notably, for life insurance companies, the growth stock alpha falls to -1.35% (p-value = 0.61), the value stock alpha falls to 1.80% (p-value = 0.42), and the alpha of the value premium portfolio (VMG) falls to 2.80% (p-value = 0.36). The overall R-squared becomes 88%, and the *CV*-test p-value becomes 0.96. Moreover, the alpha of the second lowest B/M portfolio now reduces to -1.05% with an associated p-value of 0.45. In sum we find that the value premium becomes smaller for retirement investors and becomes insignificant for insurance investors which have larger fixed income exposures.

[Insert Table IV about here]

C. Choice of stock portfolios

We may ask if our results are specific to the B/M sorted portfolios. To check that our results also hold for other value measures we rerun our analysis using 10 E/P and C/P sorted portfolios. Figure 4 shows the results, using the alphas of the VMG hedge portfolio (that buys the top two value deciles and shorts the bottom two), the R-squared, and *CV*-test statistic. Clearly, the sub-figures on the left show that the E/P based VMG alpha substantially falls and the R-squared substantially rises for the mean-variance investor who invest substantial amounts in bonds. For example, the VMG alpha falls

[20] In addition, for other insurance companies we subtract trade receivables from the reported total financial assets. However, the miscellaneous assets and trade receivables categories are generally negligible and have therefore almost no impact on our results.

from 6.56% (p-value = 0.01) for an all equity investor, to 4.57% (p-value = 0.10) for an investor who invests 60% in bonds, to 1.44% (p-value = 0.58) for an investor who invests 90% in bonds. The results further improve for the mean-semi-variance investor. For 90% invested in bonds the VMG alpha decreases to 0.26% (p-value = 0.93).

[Insert Figure 4 about here]

Roughly similar results are obtained if the 10 C/P ratio sorted portfolios are used (see the right sub-figures). Here the mean-semi-variance assumption is more important than the percentage invested in bonds. The rise in the R-squared and fall in the VMG alpha are relatively small for the mean-variance investor. For example, the VMG alpha falls from 5.50% (p-value = 0.01) for an all equity investor, to 4.89% (p-value = 0.03) for an investor who 60% invests in bonds, to 3.87% (p-value = 0.10) for an investor who 90% invests in bonds. Similarly, its *CV*-test p-value rises to 0.09, only marginally insignificant at a 5% level. By contrast, the results for the mean-semi-variance investor are in line with the other value measures. For 60% invested in bonds the VMG alpha decreases to 3.51% (p-value = 0.18) and for 90% invested in bonds the VMG alpha decreases further to 1.30% (p-value = 0.62). Moreover, the R-squared increases substantially from 57% to 86% for the 90% bond mean-semi-variance investor.

Given the evidence of a larger value premium in the small cap segment (see for example Fama and French, 1992, and Loughran, 1997), we may ask if our results also hold for the six double-sorted portfolios formed on size and B/M. Figure 5 contains the results. Shown are the HML hedge portfolio of Fama and French (1993) that buys the highest and shorts the lowest B/M portfolios in both size segments, the corresponding portfolio for the big cap (BV-BG) and small cap (SV-SG) segment, the R-squared and the *CV*-test p-value.

[Insert Figure 5 about here]

Again, some intriguing results appear. The alpha of the HML hedge portfolio falls from 7.45% (p-value = 0.00) for a mean-variance all equity investor, to 5.95% and 2.58% (p-value = 0.01 and 0.34) for a mean-variance investor who invests 60% or 90% in bonds, to 5.75% and 0.66% (p-value = 0.04 and 0.83) for a mean-semi-variance investor who invests 60% or 90% in bonds. Similarly, the R-squared goodness of fit measure increases from 42%, to 77%, and the *CV*-test p-value increases from 0.01, to 0.70. However, some unreported, but anomalous results remain. For instance, for the mean-variance-90%-bond investor the alpha of the small value portfolio equals 4.44% (p-value = 0.04). Similarly, the alpha of the big growth stocks actually increases to -3.49% (p-value = 0.05). By contrast, the mean-semi-variance-90%-bond model has a better performance; the alpha of small value stock portfolio falls to 2.91% (p-value = 0.19), and of the big growth portfolio to -1.92% (p-value = 0.37).

These results hold both in the big and small cap segments. In the big cap segment the value premium falls from 4.79% (p-value = 0.02) for a mean-variance all equity investor, to 2.75% (p-value = 0.30) for a mean-variance-80%-bond investor, to 1.48% (p-value = 0.63) for a mean-semi-variance-80%-bond investor. In the small cap segment the alpha of the SV-SG portfolio goes from 10.12% (p-value = 0.000) for a mean-variance all equity investor, to 5.14% (p-value = 0.12) for a mean-variance-80%-bond investor, to 5.12% (p-value = 0.17) for a mean-semi-variance-80%-bond investor. As before, the best fit is achieved for the mean-semi-variance investor who invests roughly between the 60% and 90% in bonds. In fact, for the mean-semi-variance investor with 90% invested in bonds the alpha of the BV-BG portfolio just equals 0.14% (p-value = 0.94), while the alpha of the SV-SG portfolio equals 2.33% (p-value = 0.67), a reduction of respectively 97% and 77% compared to the classical mean-variance all equity investor. Overall, the results are very similar to those obtained with the 10 B/M sorted stock portfolios. These findings show that our results are robust with respect to the value definition of the cross-section, and hold in the small cap segment as well.

D. Choice of return frequency

Following Benartzi and Thaler (1995), our analysis relies on annual returns. To analyze if our results are affected by the return frequency, we rerun our analysis using monthly, quarterly, semi-annual, 1.5 yearly, and bi-annual real returns. Figure 6 shows the results. The sub-figures show the annualized alphas of the VMG hedge portfolio for the various evaluation horizons. Adding bonds to the portfolio has little impact on the value premium for horizons up to a quarter. Similarly, for a semi-annual horizon the value premium is practically unchanged for the mean-variance investor. By contrast, for the semi-annual mean-semi-variance investor the annualized alpha of the VMG portfolio is reduced from 6.33% (p-value = 0.00), to 3.17% (p-value = 0.26) for a 90% bond investor. A similar pattern is found in the (unreported) R-squared; it increases from 43% for a mean-variance all equity investor, to 84% for the mean-semi-variance-90%-bond investor. The 1.5 yearly evaluation horizon yield similar results as the semi-annual results; the alpha of the VMG hedge portfolio for the mean-variance investor is largely unchanged for various percentages invested in bonds, while it substantially decreases for the mean-semi-variance investor. By contrast, the bi-annual horizon gives some different findings. Although, the alpha of the VMG hedge portfolio decreases for investors who invest substantial percentages in fixed income, the effect of downside risk aversion over an aversion to variance is absent for an investor who invest roughly 80% or more in fixed income. Moreover, unreported results reveal that the bi-annual horizon yields significant alphas of roughly 2.50% to 3.00% for the one- and two-but-highest

B/M portfolios, for both the mean-variance and the mean-semi-variance investor who invests 80% or 90% in bonds.

Hence, generally the alphas decrease for mean-variance investor with an annual evaluation horizon, and for mean-semi-variance investor with investment horizons ranging between 6 and 18 months. For shorter investment horizons (1-3 months), the value premium remains large and significant, irrespective of the composition of the benchmark portfolio. Consequently, similar to a term-structure of the risk-return trade-off (see Campbell and Viceira, 2005), there is a close connection between the investment horizon and the value premium for investor with a substantial fixed income exposure.

[Insert Figure 6 about here]

The striking differences for different investment horizons are presumably caused by the different shapes of the return distribution for monthly returns and other lower frequency returns. For example, losses on the 20/80 mixed portfolio occur roughly in 35% of the months but in 30% of the years.[21] Without pretending to forward the correct dynamic specification for monthly returns, it is insightful to consider the following regression model with four betas:

$$\begin{aligned} x_{it} &= \alpha_i + \beta_i^- \mathbf{x}_t^{\mathrm{T}} \boldsymbol{\tau} 1(\mathbf{x}_t^{\mathrm{T}} \boldsymbol{\tau} \leq 0) + \beta_i^+ \mathbf{x}_t^{\mathrm{T}} \boldsymbol{\tau} 1(\mathbf{x}_t^{\mathrm{T}} \boldsymbol{\tau} > 0) \\ &\quad + \sum_{l=1}^{L} \beta_{-l,i}^- \mathbf{x}_{t-1}^{\mathrm{T}} \boldsymbol{\tau} 1(\mathbf{x}_{t-1}^{\mathrm{T}} \boldsymbol{\tau} \leq 0) + \beta_{-l,i}^+ \mathbf{x}_{t-1}^{\mathrm{T}} \boldsymbol{\tau} 1(\mathbf{x}_{t-1}^{\mathrm{T}} \boldsymbol{\tau} > 0) + \varepsilon_{it} \end{aligned} \tag{16}$$

This model includes separate betas for downside market movements (β_i^- and $\beta_{-l,i}^-$) and upside market movements (β_i^+ and $\beta_{-l,i}^+$). In case of a symmetric response to market movements, the upside and downside betas will be identical. Also, the model includes separate betas for the instantaneous response (β_i^- and β_i^+) and lagged responses ($\beta_{-l,i}^-$ and $\beta_{-l,i}^+$). If returns are serially IID, then the lagged betas will be zero. If there is a significant lagged response, then the long-term market exposure will differ from the short-term exposure.

We estimate equation (16) using OLS regression analysis for the monthly returns to the 10 B/M sorted portfolios relative to the CRSP all equity index and relative to the bond index. We estimate the model with no lags and with lagged betas up to a quarter, half year, year, and 18 months. Table V summarizes our estimation results.

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[21] Also, the monthly returns are affected by heteroskedasticity and serial correlation to a significant degree. These statistical problems cast doubt on the use of statistical procedures which assume serially IID returns (such as the procedure described in Section II) as well as the representativeness of the monthly return distribution for annual returns.

[Insert Table V about here]

For the equity index, three results are noteworthy. First, growth stocks are as risky as value stocks on a monthly basis. For example, the instantaneous downside equity beta for growth (G) and value (V) stocks both equal 1.02. Second, unlike the higher B/M portfolios, the lower B/M stocks are significantly affected by lagged downside market movements for lags up to one year. Most notably, for growth stocks, the lagged effects increase to total (instantaneous plus lagged) annual downside beta to 1.19, while the downside beta of value stocks remains largely unaltered. Hence, the lagged effects make growth stocks riskier than value stocks. Third, the downside and upside equity betas are roughly equal, reducing the potential explanatory role for downside risk aversion.

Interestingly, the results change substantially if we replace the equity index with the bond index. On a monthly basis the growth stocks are still as risky as value stocks. For example, the instantaneous downside bond beta for growth stocks and value stocks both equal 0.54. However, the lagged upside and downside exposures to the bond index are stronger than to the equity index, especially for the higher B/M portfolios. These lagged responses increase the long-term downside beta of value stocks relative to growth stocks, hence enhancing the potential role for downside risk aversion in the long run. Most notably, for value stocks, the lagged effects increase to total annual downside beta to 1.46, while that of growth stocks only increase to 1.15. Hence, on an annual basis the lagged responses make value stocks riskier than growth stocks, meaning that growth stocks provide a better hedge against interest rate risk than value stocks do. Third, the systematic risk is asymmetric; the downside bond betas are larger than the upside bond betas.

In brief, the monthly returns of value stocks exhibit a strong lagged response to downside bond movements that makes these stocks less effective as a hedge against bond risk than growth stocks. These results show that a naïve application to monthly returns overlooks the strong dynamic patterns of monthly returns and reinforce our argument in favor of using lower frequency returns such as annual returns.

E. Choice of bond index

The equal weighted bond index we employed so far may actually be a bad proxy for the fixed income exposure of an investor. For example, many institutional investors invest heavily in various fixed income instruments, but some invest mainly in corporate bonds, loans and mortgages, while others invested mainly in government bonds. We may therefore ask if our results also apply if stocks are mixed with one of these other fixed income instruments. Unfortunately, we do not have reliable data on loans and mortgages, which often are not traded securities, available. However, we have the individual components of our equally weighted bond index. We therefore rerun our analysis using either the Long Term Corporate bond index (LTC), the Intermediate Term Government bond index (ITG), or the Long Term Government bond index (LTG).[22] The results for these bond indices are strikingly similar to the results obtained with the equally weighted bond index, as shown in Figure 7; we again clearly see the substantial decrease in the alpha of the VMG hedge portfolio. Similarly, the (unreported) R-squared reveals a substantial increase in explanatory power and *CV*-test p-value related to increasing bond exposure and downside risk.

[Insert Figure 7 about here]

F. Choice of parameterization

Although the mean-semi-variance model improves significantly upon the mean-variance model, we may ask if it gives the best possible description of the preferences of investors who mix bonds and stocks. That is, other types of utility functions may yield an even better description, as for example investors like positive skewness (Cooley, 1977), and dislike large possible losses and behave extremely risk averse in the face of these possible ruin losses (Libby and Fishburn, 1977, and Laughhunn, Payne and Crum, 1980). To answer this question we identify the utility function that gives the best possible fit in terms of the R-squared, while imposing the restrictions of risk aversion and skewness preference. For this purpose, we use respectively the Third-order Stochastic Dominance (TSD) efficiency tests introduced by Post (2003) and further developed by Post and Versijp (2007).

Figure 8 shows the results for the TSD investors, as compared to the mean-variance and mean-semi-variance investors. Clearly, the alpha of the VMG hedge portfolio and the R-squared of the TSD investor coincide tremendously with the test statistics of the mean-semi-variance investor.[23] For example, the overall R-squared for the TSD-80%-bond investor only slightly increases from 86% to 88%. Figure 9 further illustrates these results by means of the estimated kernel and mean-beta plots for the mean-variance, mean-semi-variance and TSD investors who invest 80% in bonds (and 20% in equity). The optimal marginal utility function for the TSD investors is remarkably similar to that of the mean-semi-variance model on the observed return range; both are risk neutral for gains and have a similar risk aversion for losses.[24]

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[22] Moreover, the results are not materially affected by the use of different weights for the equal weighted bond portfolio. We also find that adding other bond indices, such as high yield bonds or one-month and one-year Treasury bills, does not affect the results and give similar outcomes. These results are available from the author upon request.

[23] However, note that the CV-test p-value is substantially lower for the TSD investor as compared to the MS investor, caused by substantial increase in degrees of freedom for the TSD investor.

[24] Moreover, roughly similar results are obtained with the risk-averse utility function of best fit (hence omitting the skewness preference restriction), tested by means of a Second-order Stochastic Dominance (SSD) efficiency test.

Overall, these results confirm the goodness of the mean-semi-variance model; the model comes close to the model of best fit. By contrast, the marginal utility function implied by the mean-variance model has a serious problem; it becomes very negative in the domain of gains, hence severely violating non-satiation and hence the no-arbitrage condition (see Harrison and Kreps, 1979), thereby casting doubt on the meaning of the mean-variance model. In fact, unreported results reveal that the results for the mean-variance model deteriorate substantially if we impose utility to be weakly increasing. For example, a mean-variance 80% bond investor has an alpha of the VML hedge portfolio of 5.29% and a R-squared of 47% (compared to 4.32% and 75% if utility is allowed to be decreasing). By contrast, the results for the mean-semi-variance model are unaffected, since they never violate non-satiation. This makes the case for downside risk aversion as factor driving our results even stronger.

[Insert Figure 8 about here]

[Insert Figure 9 about here]

In addition, we may ask if semi-variance only outperforms the mean-variance model because it captures preference for systematic higher-order risk moments, like co-skewness (see Harvey and Siddique, 2000) and co-kurtosis (see Dittmar, 2002), and properly including the preference for these higher-order risk moments would wipe out the superiority of the mean-semi-variance model. To answer this question one could extend the investor's quadratic utility function given in (1) to a cubic or quartic utility function, in the spirit of Harvey and Siddique (2000) and Dittmar (2002). However, it follows from the theoretical analysis of Tsiang (1972) that a quadratic function gives a good approximation for any continuously differentiable concave utility function over the typical sample range of asset returns, and that higher-order polynomials are unlikely to improve the fit. Indeed, in typical asset pricing tests cubic and quartic utility terms hardly improve the fit if risk aversion is imposed (see for instance Dittmar, 2002, Section III.D). Hence, for a *risk-averse* utility maximizer higher-order return moments can at most be of minor importance.[25]

G. Relation with time-varying risk explanation

Several papers forward time varying risk and risk premia as an explanation of the value premium puzzle. These paper find that the (Consumption) CAPM can explain the value premium substantially better if the market return or consumption growth is scaled by a condition variable that summarizes macroeconomic conditions (see for example Jagannathan and Wang, 1996, Lettau and Ludvigson, 2001b, Lustig and Van

[25] By contrast, for a *non-risk-averse* utility maximizer the first-order optimality condition (4) will not be sufficient to ensure optimality. In fact, such an investor generally likes to hold a less diversified portfolio than the benchmark portfolio employed in this study.

Nieuwerburgh, 2005, Santos and Veronesi, 2006). These conditional models typically measure risk as the covariance of returns with marginal utility of consumption or returns. They argue that value stocks earn higher returns than growth stocks, because they become riskier in bad periods times, in which the marginal utility and hence price of risk are high, and vice versa for good times.[26] Remarkably, the results reported by, among others, Fama and French (1989), Ferson and Harvey (1999), Petkova and Zhang (2005) and Petkova (2006) suggests that the variables related to good times (in which growth stocks are expected to perform good relative to value stocks) are also closely linked to a bad expected bond performance. For example, Petkova and Zhang (2005) show that the betas of value (growth) stocks tend to co-vary positively (negatively) with the expected equity premium, meaning that value stocks have higher betas in bad times (in which the expected equity premium is high) and growth stocks have higher betas in good times (in which the expected market risk premium is low). However, the variables known to predict these good times (i.e. low aggregate dividend yield, low term spread, low default spread, and high short-term interest rate) also tend to predict low bond returns, and vice versa (see for example, Keim and Stambaugh, 1986, and Fama and French, 1989). Similarly, Ferson and Harvey (1999) show that growth stocks generally have lower sensitivities to lagged values of the term spread than value stocks, and Petkova (2006) finds that growth stocks load higher on shocks to the aggregate dividend yield and lower on shocks to the term spread and default spread. If low bond returns coincide with these conditional variables then this could mean that the unconditional approach with a mixed market proxy, as employed in this study, implicitly captures (part of) the time-variation in the risk premium and/or risk loadings of value and growth stocks.[27]

To get a first insight into this relationship we compute the average values for seven well-known conditioning variables for the worst, middle and best 33% of real annual bond returns. Table VI shows the data details and results. Clearly, in the years in which bonds have a bad performance (and growth stocks a good performance), most conditioning variables indicate expected good times, and hence a low price of risk. The term spread (Term), default spread (Def), and aggregate consumption-to-wealth ratio (*cay*) of Lettau and Ludvigson (2001a) are lower in the worst 33% of bond performance years as compared to the middle and best 33%. A similar signal comes from the change in the 3-months Treasury bill yield (Δ3mTbill); it is higher in the worst than in the middle or best bond years. By contrast, mixed signals are provided by the housing-collateral ratio (*mymo*) of Lustig and Van Nieuwerburgh (2005), the labor-income-to-

[26] However, see, Daniel and Titman (2006), Lewellen and Nagel (2006), Lewellen, Nagel and Shanken (2007), and Phalippou (2008) for findings that seem at odds with these conditional models.

[27] Moreover, the results reported by Petkova and Zhang (2005) suggest that the sensitivities to these predictive variables also create asymmetry in the treatment of risk. More specific, their results show that growth stocks have a lower downside beta with respect to the expected equity market return (predicted by the four variables known to predict bond returns) than value stocks, and a higher upside beta, also in absolute terms.

consumption ratio (s^w) of Santos and Veronesi (2006) and an opposite signal comes from the aggregate dividend yield on the S&P 500 (D/P). Although *mymo* and s^w are higher in the worst 33% of bond performance years than in the best 33% (suggesting better times in the worst bond years as compared to the best bond years), *mymo* is even higher in the middle 33% of bond performance years while s^w reaches it lowest values in that years. Moreover, D/P on average reaches its lowest values in the middle 33% bond performance years, and it suggests that the worst 33% of bond performance years were happening when we expected worse times than in the best 33% of years.[28]

Hence, in years in which our bond index have the poorest performance most conditioning variables indicate that we actually are in an expected good state of the world in which, according to the conditional models, the market price of risk is low and growth stocks are expected to perform relatively well. This suggests that the inclusion of bond returns in the investment portfolio captures part of the time-varying risk patterns in value sorted stocks advocated by the conditional models.

[Insert Table VI about here]

V. Concluding remarks

Downside risk aversion may explain why a substantial fraction of investable wealth is invested in fixed income instruments, such as bills, bonds and loans. This study shows that the same phenomenon can also explain the value premium for investors with a substantial fixed income exposure. Despite the sizeable value premium relative to an equity index, growth stocks are attractive to especially downside-risk-averse investors because they offer a better hedge against a bad bond performance. These results hold for evaluation horizons of around one year, while the value premium is unaffected for quarterly or monthly evaluation horizons. Our findings are robust to a number of factors, like the use of actual portfolio weights of institutional investors, the use of other value sorts and data sets, and the use of other preference specification tests. These findings cast doubt on the practical relevance of the value premium for institutional investors such as life-insurance companies, banks and pension funds who generally invest heavily in fixed income instruments.

Related to our results, Ferguson and Shockley (2003) show that the size and B/M effects may actually results from the use of an equity only market proxy. Betas computed against an all equity index understate true beta's and these errors are increasing with a firm's relative degree of leverage and distress, which heavily correlate with size and B/M. Hence, the CAPM may actually be efficient relative to size and B/M

[28] However, it should be noted that the predictive power of D/P for equity returns seems to be very weak to absent, especially in the last two decades (see Goyal and Welch, 2003).

sorted portfolios and including the right debt proxy in the market proxy should reveal this. Our results are suggestive of this model; the CAPM seems more efficient against size and B/M portfolios if more debt is included. However, in addition to the results of Ferguson and Shockley, we show that an aversion to downside risk in combination with the evaluation horizon have important consequences for the value premium as well.

This study complements many recent studies that try to explain the value premium. In fact, several reasons for the value premium have been postulated. First, stock risks are multidimensional, and the higher average returns on value stocks are compensation for risk. That is, value proxies for a risk factor in returns (see for example Fama and French, 1993, and Lewellen, 1999). Second, value might capture biases in investor expectations, and provide information about security mispricing. Growth stocks tend to be firms that have strong fundamentals like earnings and sales, while the opposite holds for value stocks. Investors might overreact to past performance and naively extrapolate it, resulting in stock prices that are too high for growth stocks and too low for value stocks (see for example De Bondt and Thaler, 1987, Lakonishok, Shleifer and Vishny, 1994, La Porta, 1996, and Griffin and Lemmon, 2002, for supportive evidence). However, irrespective of the reason for the value premium, we ask if the value premium can be exploited by (institutional) investors who; (i) invest substantial amounts in fixed income, (ii) are disproportionably more sensitive to losses than to gains, and (iii) evaluate portfolios frequently, as can be explained based on behavioral and institutional arguments.

Our findings also have a number of other interesting implications. First, our results demonstrate the effect of non-normal asset returns and the need to include risk measures that differ from the variance. Levy and Markowitz (1979) report that the mean-variance criterion generally gives a good approximation for general expected utility maximizers. By contrast, we demonstrate that the mean-variance criterion and the mean-semi-variance criterion give very different results using value sorted data sets. Presumably, the mean-variance criterion is unable to capture downside risk aversion. Tsiang (1972) demonstrates that the quadratic utility function associated with mean-variance analysis is likely to give a good approximation for any (continuously differentiable) concave utility function over the typical sample range, and that higher-order polynomials are unlikely to improve the fit. Interestingly, this argument does not apply to mean-semi-variance analysis, because the quadratic-linear utility function is not continuously differentiable and generally can not be approximated with high precision by a quadratic function. This limitation pleads for combining the mean-variance efficiency criterion with alternative efficiency criteria, including the mean-semi-variance efficiency criterion and the general stochastic dominance efficiency criteria.

Second, the significant effect of adding fixed income instruments to the analysis reiterates the importance of Roll's (1977) critique; the uncertainty regarding the composition of the market portfolio and the sensitivity of the results regarding the market proxy call for caution when interpreting market portfolio efficiency tests. In this respect, our results contrast with those reported in Stambaugh (1982), who reports that adding bonds among other assets to the stock market portfolio does not materially affect the conclusions regarding the CAPM.[29] At least three differences between our study and that of Stambaugh can explain our markedly different conclusion. First, Stambaugh considers industry portfolios rather than portfolios formed on size and B/M and hence he did not explicitly analyze the value premium puzzle. Second, the earlier study focuses on the mean-variance criterion and the CAPM, while we show that the mean-semi-variance criterion and the associated equilibrium model perform much better for investors with fixed income exposure. Third, Stambaugh uses monthly returns rather than annual returns. In fact, for monthly returns we observe no effects if fixed income instruments are added to the investment portfolio. However, as shown in this study, monthly return give an incomplete view of the annual return distribution due to strong dynamic effects, especially for value stocks; they show a stronger exposure to lagged downside bond movements than growth stocks, making these stocks less effective as a hedge against bond risk than growth stocks are.

Our findings suggest several avenues for future research. First, there is a lot known about the characteristics of value and growth stocks. For instance, a large part of the value premium returns occurs around earnings announcement dates (see La Porta, Lakonishok, Shleifer and Vishny, 1997), and, ex post, stocks with a high growth in income before extraordinary items have a low B/M (see Chan, Karceski and Lakonishok, 2003). Moreover, Anderson and Garcia-Feijóo (2006) find that the value effect is closely related to firm-specific growth in capital expenditures. Growth firms tend to have accelerated investment prior to classification year, while value stocks tend to have slowed investments.[30] Future research may exploit how these characteristics relate to our findings. That is how do they relate to the different fixed income sensitivities of value sorted stocks?

Second, our analysis is performed in a CAPM-like world, in which investors judge investments by the contribution to the expected return and (semi-) variance of their portfolio. However, several studies model other worlds, in which varying sources

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[29] Shanken (1987) reports similar results for an equity only proxy versus an multivariate proxy that adds long term government bonds.

[30] Moreover, Fama and French (1995) show that the firms with high B/M have persistently low earnings and reinvestments five years before and after the measurement of B/M, and Fama and French (2006b) find that value firms grow less rapidly than growth firms and are less profitable one to three years ahead. Furthermore, Chen and Zhang (1998) find that value stocks are characterized by a high financial risk, high earnings uncertainty and many dividend cuts. In addition, Dechow, Sloan and Soliman (2004) find that growth stocks have cash flows of longer duration than growth stocks. In a similar spirit, Campbell and Vuolteenaho (2004) find that growth stocks are more sensitive to discount rate shocks, and less sensitive to cash flow news than value stocks, and Campbell, Polk and Vuolteenaho (2007) find that these effects are determined by the cash flow fundamentals of growth and value companies. The cash flows of growth stocks are particularly sensitive to temporally movements in aggregate stock prices (driven by changes in the equity premium), while the cash flows of value stocks are particularly sensitive to permanent movements in aggregate stock prices (driven by market wide shocks to cash flows).

of (market-wide) risk are priced differently. Subsequently, these studies show how value stocks may be riskier than growth, since value co-varies more with the higher priced sources of risk (see for example Campbell and Vuolteenaho, 2004, Yogo, 2006, and Lettau and Wachter, 2007).[31] Future work may relate these models to our findings, that is why do growth stocks have lower (lagged) fixed income sensitivities?

[31] More specific, Campbell and Vuolteenaho (2004) introduce an asset pricing model in which investors care about permanent cash flow driven movements and about temporary discount rate driven movements in the aggregate stock market. In their model the expected return on a stock is determined by its beta with market cash flow changes that earn a high premium, and by its beta with market discount rates that earn a low premium. In a similar spirit, Lettau and Wachter (2007) develop a model in which investor's perceived risk of a firm's dividends depends on their average duration, and shocks to aggregate dividends are priced, but shocks to the discount rate are not. By contrast, Yogo (2006) develops a model in which durable and non-durable consumption are non-separable, durable consumption is more pro-cyclical, and investors want to hedge against durable consumption growth risk. For an overview of many other models, see Table 1 of Daniel and Titman (2006).

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Table I Returns during 'bad years'

The table shows annual real returns of portfolios designed to capture the value premium defined as the Value Minus Growth (VMG) portfolio. This hedge portfolio buys the two top deciles and shorts the two bottom deciles of the ten stock portfolios formed on book-to-market equity ratio (B/M), earnings-to-price ratio (E/P), and cash flow-to-price ratio (C/P). Further the HML hedge portfolio as defined by Fama and French (1993) is also included. The equity market portfolio is defined as the CRSP all equity index and the bond index is an average of Intermediate Term Government Bond index, Long Term Government Bond index and Long Term Corporate Bond index. Panel A shows the returns during the three years when the equity market experienced the largest negative returns; Panel B shows the returns during the three worst years for bonds. The sample period is from 1963 to 2007 (45 annual observations). Equity data are from Kenneth French's website, bond data is from Ibbotson Associates and inflation data is from the U.S. Department of Labor website (www.bls.gov/cpi).

Panel A: Worst years for equities

Year	VMG(B/M)	VMG(E/P)	VMG(C/P)	HML	Equity	Bonds
1974	3.9	2.2	10.7	8.9	-35.6	-8.5
1973	10.9	1.3	1.2	16.4	-25.7	-7.2
2002	-3.6	17.6	6.7	10.0	-22.8	12.8
Avg	3.7	7.1	6.2	11.7	-28.0	-0.9

Panel B: Worst years for bonds

Year	VMG(B/M)	VMG(E/P)	VMG(C/P)	HML	Equity	Bonds
1979	9.8	5.2	16.5	-2.1	9.2	-12.6
1980	-20.6	-19.3	-9.4	-22.3	19.2	-11.4
1969	-20.8	-26.0	-27.2	-9.4	-16.0	-10.2
Avg	-10.5	-13.4	-6.7	-11.3	4.1	-11.4

Table II Descriptive statistics

The table shows descriptive statistics for the annual real returns for the 10 stock portfolios formed on increasing values (in that order) of the book-to-market ratio of common equity (G= growth, V= value), the equity market portfolio (CRSP all equity index), the equally weighted bond index (consisting of the Long Term Government bonds index (LTG), the Long Term Corporate bonds index (LTC) and the Intermediate Term Government bonds index (ITG)), and the one-month T-bill portfolio. The sample period is from 1963 to 2007 (45 annual observations). Equity data are from Kenneth French's website, bond data is from Ibbotson Associates and inflation data is from the U.S. Department of Labor website (www.bls.gov/cpi).

	Avg	Stdev	Skew	Kurt	Min	Max
G	6.22	19.89	-0.05	-0.38	-40.02	52.24
2	7.46	16.89	-0.40	-0.39	-33.58	36.03
3	7.75	16.11	-0.44	-0.38	-31.91	36.10
4	8.22	16.99	-0.18	0.02	-35.97	46.36
5	7.86	16.00	-0.39	-0.27	-29.88	37.97
6	9.05	15.40	-0.31	-0.42	-29.96	36.86
7	10.68	17.63	-0.32	-0.31	-30.25	42.47
8	10.89	16.98	-0.16	-0.19	-28.88	53.02
9	11.86	17.94	-0.62	-0.08	-33.99	44.61
V	13.65	21.24	-0.50	-0.21	-33.14	55.89
Equity	7.44	16.27	-0.60	-0.34	-35.55	32.07
Bonds	3.29	9.69	0.65	0.35	-12.62	32.38
LTG	3.44	11.04	0.58	0.55	-15.88	37.46
LTC	3.42	11.56	0.66	0.01	-14.10	35.34
ITG	2.97	6.99	0.62	0.36	-8.62	24.48
Tbill	1.30	2.29	0.18	-0.20	-3.39	6.58

Table III Main test results

The table shows the test results for the mean-variance investor (Panel A) and mean-semi-variance investor (Panel B) for various percentages invested in the bond index (%) and the remainder invested in the CRSP all-share index. The bond index is an equal weighted index consisting of the Long Term Government bond index, the Long Term Corporate bond index and the Intermediate Term Government bond index. Shown are the alphas for 6 of the 10 stock portfolios formed on increasing values (in that order) of the book-to-market ratio of common equity (G= growth, V= value), the one-month T-bill portfolio, and the portfolio buying the highest two book-to-market portfolios and shorting the lowest two (Value minus Growth, VMG), the R-squared, and the Campbell-Vuolteenaho weighted alpha statistic (*CV*-test). Asterisks are used to indicate if an estimated parameter or test statistic deviates from zero at a significance level of 10% (*), 5% (**) or 1% (***). The corresponding p-values are computed by bootstrapping the standard errors (alphas) and the test statistic (CV-test). The sample period is from 1963 to 2007 (45 annual observations). Equity data are from Kenneth French's website, bond data is from Ibbotson Associates and inflation data is from the U.S. Department of Labor website (www.bls.gov/cpi).

Panel A: mean-variance efficiency

% bonds	α_G	α_2	α_3	α_8	α_9	α_V	α_{Tbill}	α_{VMG}	R^2 (%)	*CV*-test
0	-4.32**	-2.24**	-1.66	2.33**	2.81**	3.47**	-0.82	6.42***	47	0.156**
20	-4.15**	-2.25***	-1.68	2.25**	2.73**	3.34**	-0.54	6.24***	51	0.148**
40	-3.87**	-2.26**	-1.71	2.12**	2.60**	3.15*	-0.17	5.94**	56	0.134**
60	-3.32	-2.24**	-1.74	1.89*	2.39*	2.86*	0.32	5.41**	63	0.113*
80	-2.11	-2.13*	-1.74	1.44	2.01	2.39	0.82	4.32	75	0.078
90	-0.98	-1.97*	-1.70	1.06	1.71	2.09	0.84	3.38	82	0.059
100	0.70	-1.65	-1.56	0.56	1.37	1.87	0.18	2.10	86	0.048

Panel B: mean-semi-variance efficiency

% bonds	α_G	α_2	α_3	α_8	α_9	α_V	α_{Tbill}	α_{VMG}	R^2 (%)	*CV*-test
0	-3.98**	-2.21**	-1.69*	2.53**	2.05	2.7	-0.28	5.47**	57	0.134
20	-3.70*	-2.11*	-1.70*	2.32*	1.97	2.68	0.05	5.23*	61	0.122
40	-3.25	-1.96	-1.68	1.99	1.89	2.72	0.43	4.91*	66	0.107
60	-2.77	-1.67	-1.54	1.48	1.85	2.89	0.74	4.59	70	0.091
80	-1.79	-1.13	-1.07	0.58	1.12	2.09	1.22	3.06	86	0.039
90	-0.37	-0.68	-0.61	-0.05	0.69	1.37	0.92	1.56	95	0.012
100	1.44	-0.18	-0.10	-0.63	0.38	0.76	-0.64	-0.06	96	0.010

Table IV Test results for portfolios of institutional investors

The table shows the test results for the mean-variance investor (Panel A) and mean-semi-variance investor (Panel B) for the portfolios of four types of institutional investors. The institutional investor portfolios are constructed using the quarterly assets holdings data (equity and fixed income), measured at the end of the fourth quarter of 1962 till 2007, taken from the "Flow of Funds Accounts of the United States" from the Federal Reserve Board (www.federalreserve.gov). The bond index is an equal weighted index consisting of the Long Term Government bond index, the Long Term Corporate bond index and the Intermediate Term Government bond index. Shown are the 6 alphas of the 10 stock portfolios formed on increasing values (in that order) of the book-to-market ratio of common equity (G= growth, V= value), the one-month T-bill portfolio, and the portfolio buying the highest two book-to-market portfolios and shorting the lowest two (Value minus Growth, VMG), the R-squared, and the Campbell-Voulteenaho weighted alpha statistic (*CV*-test). Asterisks are used to indicate if an estimated parameter or test statistic deviates from zero at a significance level of 10% (*), 5% (**) or 1% (***). The corresponding p-values are computed by bootstrapping the standard errors (alpha's) and the test statistic (CV-test). The sample period is from 1963 to 2007 (45 annual observations). Equity data are from Kenneth French's website, bond data is from Ibbotson Associates and inflation data is from the U.S. Department of Labor website (www.bls.gov/cpi).

Panel A: mean-variance efficiency

Inst. inv.	α_G	α_2	α_3	α_8	α_9	α_V	α_{Tbill}	α_{VMG}	R^2 (%)	*CV*-test
All equity	-4.32**	-2.24**	-1.66*	2.33**	2.81**	3.47**	-0.82	6.42***	47	0.156**
Life ins.	-2.14	-2.29**	-1.99*	1.83	2.14	2.21	0.67	4.39	73	0.088
Other ins.	-2.64	-2.18**	-1.66	1.46	1.91	2.37	0.77	4.55*	74	0.081
Priv. pen.	-4.01**	-2.33***	-1.76*	2.34**	2.70**	3.16*	-0.46	6.10**	52	0.145**
State ret.	-3.69*	-2.44***	-2.03**	2.63**	2.87**	3.00*	-0.49	6.00***	52	0.148**

Panel B: mean-semi-variance efficiency

Inst. inv.	α_G	α_2	α_3	α_8	α_9	α_V	α_{Tbill}	α_{VMG}	R^2 (%)	*CV*-test
All equity	-3.98*	-2.21**	-1.69*	2.53**	2.05	2.70	-0.28	5.47**	57	0.133
Life ins.	-1.35	-1.05	-1.20	0.50	1.39	1.80	1.23	2.80	88	0.035
Other ins.	-2.37	-1.30	-1.20	0.76	1.13	2.30	1.13	3.55	82	0.051
Priv. pen.	-3.71*	-2.11*	-1.68*	2.26*	1.90	2.76	0.07	5.24*	61	0.121
State ret.	-3.36	-1.98*	-1.59	2.07*	1.85	2.19	0.50	4.70*	69	0.097

Table V Dynamics of monthly returns

The table shows the estimation results for the regression model $x_{it} = \alpha_i + \beta_i^- \mathbf{x}_t^{\mathrm{T}} \boldsymbol{\tau} 1(\mathbf{x}_t^{\mathrm{T}} \boldsymbol{\tau} \le 0) + \beta_i^+ \mathbf{x}_t^{\mathrm{T}} \boldsymbol{\tau} 1(\mathbf{x}_t^{\mathrm{T}} \boldsymbol{\tau} > 0) + \sum_{l=1}^{L} (\beta_{-l,i}^- \mathbf{x}_{t-l}^{\mathrm{T}} \boldsymbol{\tau} 1(\mathbf{x}_{t-l}^{\mathrm{T}} \boldsymbol{\tau} \le 0) + \beta_{-l,i}^+ \mathbf{x}_{t-l}^{\mathrm{T}} \boldsymbol{\tau} 1(\mathbf{x}_{t-l}^{\mathrm{T}} \boldsymbol{\tau} > 0)) + \varepsilon_{it}$ where β_i^- is an instantaneous downside beta, β_i^+ is an instantaneous upside beta, $\beta_{-l,i}^-$ is a lagged downside beta of lag l and $\beta_{-l,i}^+$ is a lagged upside beta of lag l. We estimate the regression model using OLS regression analysis for the monthly real returns to the 10 stock portfolios formed on increasing values (in that order) of the book-to-market ratio of common equity (G= growth, V= value) relative to either the CRSP all equity index (Panel A) or the equal weighted bond index consisting of the Long Term Government bond index, the Long Term Corporate bond index and the Intermediate Term Government bond index (Panel B). We estimate the model with L = 0, L = 3, L = 6, L = 12, and L = 18. For the model with no lags (L = 0) asterisks are used to indicate if the estimated downside beta or upside beta deviates from zero at a significance level of 10% (*), 5% (**) or 1% (***). For the model with lagged betas (L > 0), the asterisk are used to indicate of the Wald-test on the joint significance of the *lagged* downside or upside betas. The sample period is from 1963 to 2007 (540 monthly observations). Equity data are from Kenneth French's website, bond data is from Ibbotson Associates and inflation data is from the U.S. Department of Labor website (www.bls.gov/cpi).

Panel A: Exposure to equity index

	β_i^-	$\sum_{l=0}^{3} \beta_{-l,i}^-$	$\sum_{l=0}^{6} \beta_{-l,i}^-$	$\sum_{l=0}^{12} \beta_{-l,i}^-$	$\sum_{l=0}^{18} \beta_{-l,i}^-$	β_i^+	$\sum_{l=0}^{3} \beta_{-l,i}^+$	$\sum_{l=0}^{6} \beta_{-l,i}^+$	$\sum_{l=0}^{12} \beta_{-l,i}^+$	$\sum_{l=0}^{18} \beta_{-l,i}^+$
G	1.02***	1.07	1.06	1.19**	1.21	1.17***	1.18	1.16	1.22	1.21
2	1.00***	0.98	0.97	0.91*	0.97*	1.07***	1.11	1.12	1.15*	1.17*
3	1.02***	0.95	0.90	0.82**	0.85**	1.01***	1.04	1.07	0.96	0.97
4	0.96***	0.99	0.94**	0.87***	0.96**	0.99***	0.92	0.93	1.02	1.03
5	0.91***	0.87	0.84	0.78*	0.82	0.89***	0.83	0.94	0.94	0.99
6	0.88***	0.88	0.85	0.85	0.84	0.91***	0.87	0.89	0.79	0.79
7	0.79***	0.77**	0.75*	0.76	0.77	0.94***	0.95	1.03	1.02	0.97
8	0.81***	0.78	0.74	0.66	0.60	0.87***	0.86	0.93*	0.86	0.77
9	0.92***	0.91	0.94	0.89	0.88	0.90***	0.90	0.86	0.86	0.95
V	1.02***	1.11	1.07	0.96	0.91	0.95***	1.13*	1.11	1.01	1.11

Panel B: Exposure to bond index

	β_i^-	$\sum_{l=0}^{3} \beta_{-l,i}^-$	$\sum_{l=0}^{6} \beta_{-l,i}^-$	$\sum_{l=0}^{12} \beta_{-l,i}^-$	$\sum_{l=0}^{18} \beta_{-l,i}^-$	β_i^+	$\sum_{l=0}^{3} \beta_{-l,i}^+$	$\sum_{l=0}^{6} \beta_{-l,i}^+$	$\sum_{l=0}^{12} \beta_{-l,i}^+$	$\sum_{l=0}^{18} \beta_{-l,i}^+$
G	0.54**	1.14*	1.50	1.15*	1.27**	0.48***	0.88	1.06	1.02	1.17
2	0.49***	0.93	1.32	1.10*	1.17*	0.59***	1.08*	1.29	1.28	1.40
3	0.45***	0.90*	1.33**	1.11*	1.07*	0.59***	1.02	1.41*	1.28	1.28
4	0.44***	0.80**	1.26**	1.07**	1.10*	0.57***	1.00	1.37*	1.33	1.35
5	0.49***	0.86**	1.25**	1.22**	1.19**	0.49***	0.86	1.17	1.13	1.10
6	0.51***	0.93*	1.34**	1.23*	1.17*	0.60***	0.97	1.23	1.08	1.14
7	0.49***	1.02**	1.40**	1.36**	1.14*	0.59***	1.06**	1.26**	1.15	0.97
8	0.56***	0.99*	1.37**	1.22	0.94	0.53***	0.81	1.09	0.89	0.68
9	0.46***	0.98*	1.33*	1.23	0.99	0.57***	0.96	1.23	1.07	1.04
V	0.54***	1.14**	1.59**	1.46*	1.32*	0.43***	0.99**	1.37*	1.22	1.24

Table VI Conditioning and bad bond returns

The table shows average values (in %) of well-known conditioning variables for the worst, middle and best 33% of real annual bond returns (Bonds), as well as the expected conditioning effect in expected good times relative to expected bad times (Expectation). The bond index is an equal weighted index consisting of the Long Term Government bond index, the Long Term Corporate bond index and the Intermediate Term Government bond index. The reported conditioning variables are; the change in the 3-months Treasury bill yield (Δ 3mTbill), the term spread (Term; 10 years government bond yield minus the 3-months Treasury bill rate), the default spread (Def; Moody's Baa rated corporate bond yield minus the Aaa rated corporate bond yield), the aggregate dividend yield (D/P; dividends accruing to S&P over past year divided by price at beginning of the current year), the aggregate consumption-to-wealth ratio (*cay*) of Lettau and Ludvigson (2001a), the housing-collateral ratio (*mymo*) of Lustig and Van Nieuwerburgh (2005), and the labor-income-to-consumption ratio (s^w) of Santos and Veronesi (2006). The values of *cay*, *mymo* and s^w are computed at the last quarter of the previous year. The other values are in real time. Bond data is from Ibbotson Associates, inflation data is from the U.S. Department of Labor website (www.bls.gov/cpi), Term, Def; and Δ 3mTbill are from the St. Louis Fed: Economic Database (http://research.stlouisfed.org/fred2), Aggr. D/P is from Shiller's website and Yahoo Finance, *cay* is from Ludvigson's website, m*ymo* is from Van Nieuwerburgh's website, and s^w is computed from U.S. Department of Commerce, Bureau of Economic Analysis (www.bea.gov). The sample period is from 1963 to 2007 (45 annual observations).

	Bonds	Δ3mTbill	Term	Def	D/P	*cay*	*mymo*	s^w
Expectation		Higher	Lower	Lower	Lower	Lower	Higher	Higher
Worst bond years	-6.83	0.89	0.44	0.94	3.44	-0.62	-1.30	92.99
Middle bond years	2.33	-0.33	1.51	1.01	2.73	-0.05	5.41	87.61
Best bond years	14.36	-0.41	2.04	1.13	3.13	0.57	-3.10	88.71

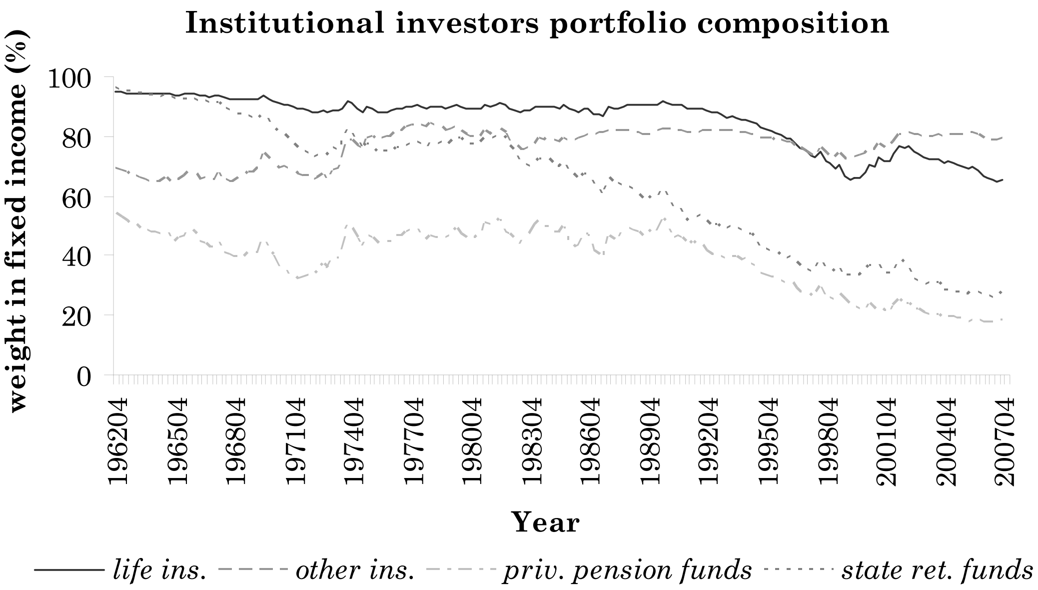

Figure 1: Institutional investor's portfolio compositions. The figure shows the investment in fixed income instruments as a percentage of the total financial assets for various categories of institutional investors: life insurance companies ("life ins."), property-casualty insurance companies ("other ins."), private pension funds ("priv. pension funds"), and state and local government employee retirement funds ("state ret. funds"). The results are based on quarterly assets holdings, measured at the end of the fourth quarter of 1962 till 2007. The data are taken from the "Flow of Funds Accounts of the United States" from the Federal Reserve Board; www.federalreserve.gov.

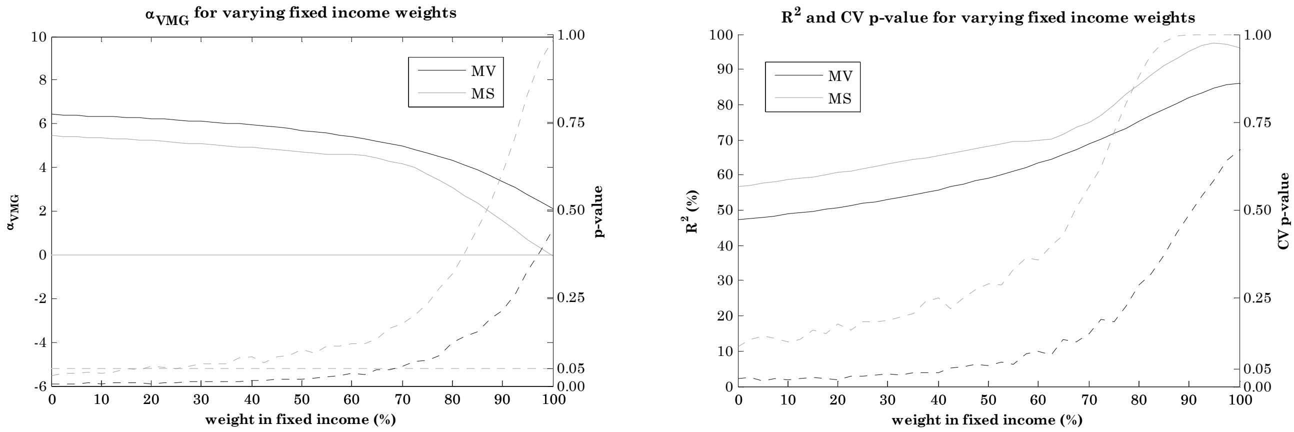

Figure 2: Results book-to-market sorted decile portfolios. The figure shows the test results for the mean-variance investor (MV; black line) and mean-semi-variance investor (MS; grey line) for various percentages invested in the bond index (%) and the remainder invested in the CRSP all-share index. The bond index is an equal weighted index consisting of the Long Term Government bond index, the Long Term Corporate bond index and the Intermediate Term Government bond index. The tested stock portfolios are ten portfolios formed on formed on increasing values (in that order) of the book-to-market ratio of common equity. Shown in the left subfigure are the alphas (solid lines) and bootstrapped p-values (dashed lines) for the portfolio buying the highest two decile portfolios and shorting the lowest two (VMG). The right subfigure shows the R-squared (R^2, solid lines), and the bootstrapped p-values of the Campbell-Vuolteenaho weighted alpha statistic (*CV* p-value, dashed lines). The sample period is from 1963 to 2007 (45 annual observations). Equity data are from Kenneth French's website, bond data is from Ibbotson Associates and inflation data is from the U.S. Department of Labor website (www.bls.gov/cpi).

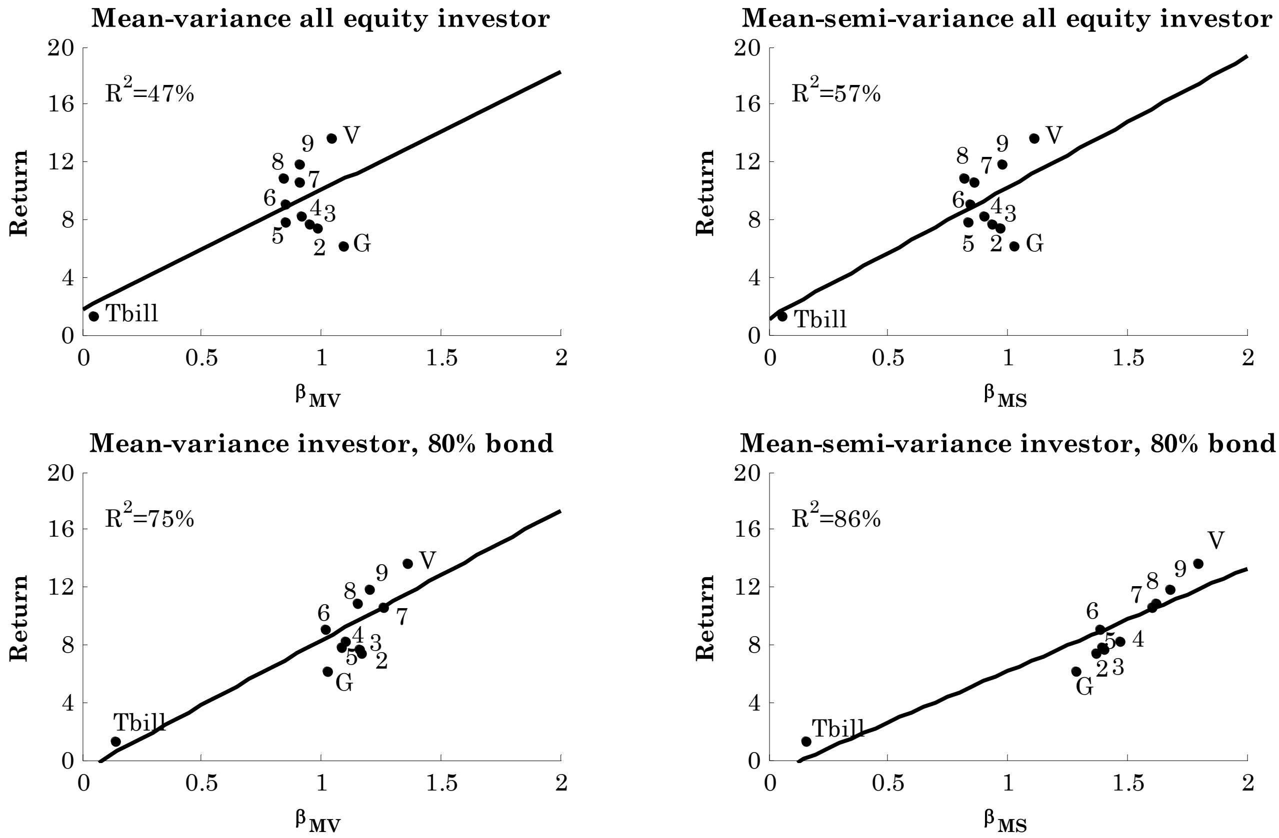

Figure 3: Return-beta plots of book-to-market sorted decile portfolios. The figure illustrates the mean-variance test results for the 10 stock portfolios formed on increasing values (in that order) of the book-to-market ratio of common equity (G= growth, V= value), and the long the one-month T-bill portfolio (Tbill). Results are shown for the mean-variance criterion and the mean-semi-variance criterion and for various mixtures of the CRSP all-share index and the bond index. The results are based on annual real returns from 1963 to 2007 (45 annual return observations).

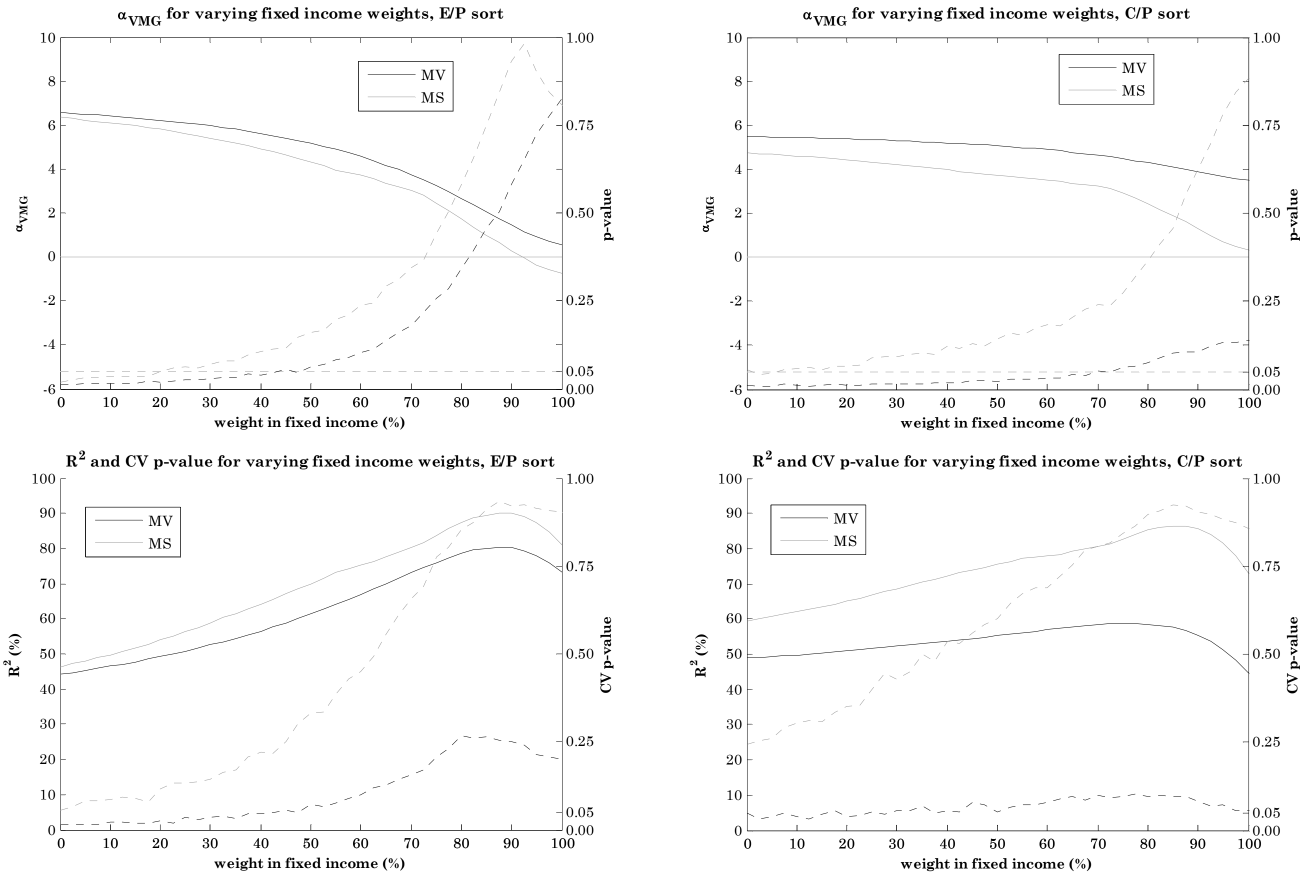

Figure 4: Results earnings-to-price and cash flow-to-price sorted decile portfolios. The figure shows the test results for the mean-variance investor (MV; black line) and mean-semi-variance investor (MS; grey line) for various percentages invested in the bond index (%) and the remainder invested in the CRSP all-share index. The bond index is an equal weighted index consisting of the Long Term Government bond index, the Long Term Corporate bond index and the Intermediate Term Government bond index. The tested stock portfolios are ten portfolios formed on formed on increasing values (in that order) of earnings-to-price (left subfigures) or cash flow-to-price (right subfigures). Shown in the top subfigures are the alphas (solid lines) and bootstrapped p-values (dashed lines) for the portfolio buying the highest two decile portfolios and shorting the lowest two (VMG). The bottom two subfigures show the R-squared (R^2, solid lines), and the bootstrapped p-values of the Campbell-Vuolteenaho weighted alpha statistic (*CV* p-value, dashed lines). The sample period is from 1963 to 2007 (45 annual observations). Equity data are from Kenneth French's website, bond data is from Ibbotson Associates and inflation data is from the U.S. Department of Labor website (www.bls.gov/cpi).

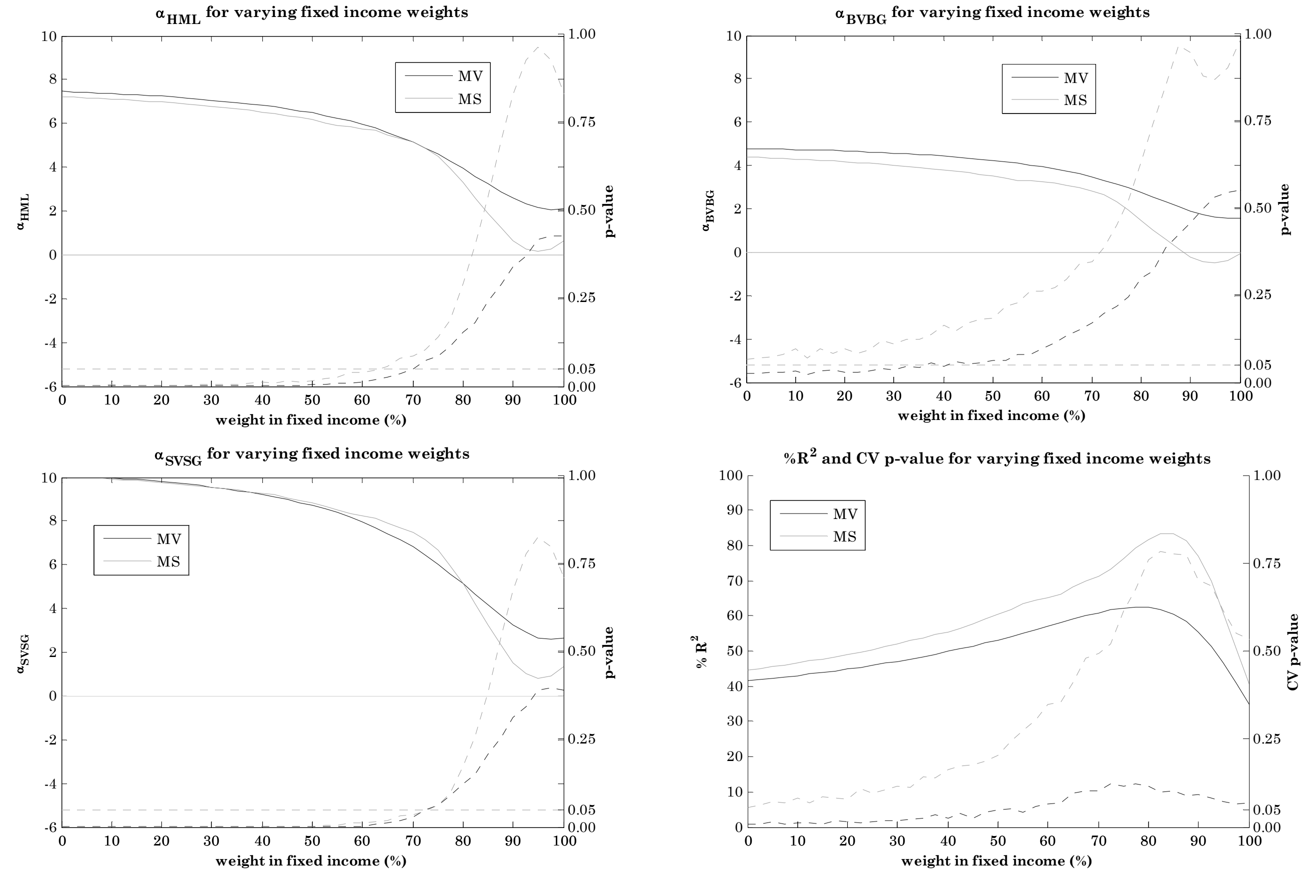

Figure 5: Results six size and book-to-market sorted portfolios. The figure shows the test results for the mean-variance investor (MV; black line) and mean-semi-variance investor (MS; grey line) for various percentages invested in the bond index (%) and the remainder invested in the CRSP all-share index. The bond index is an equal weighted index consisting of the Long Term Government bond index, the Long Term Corporate bond index and the Intermediate Term Government bond index. The tested stock portfolios are the six Fama and French portfolios formed on market capitalization of equity and book-to-market equity ratio (SG=small growth, SN=small neutral, SV=small value, BG=big growth, BN=big neutral and BV=big value). Shown are the alphas (solid lines) and bootstrapped p-values (dashed lines) for the portfolio that captures the value premium (HML), constructed as 1/2(SV+BV)-1/2 (SG + BG), the counterpart of this portfolio in the small cap segment (SVSG; SV-SG), the counterpart of this portfolio in the big cap segment (BVBG; BV-BG), the R-squared (R^2, solid lines), and the bootstrapped p-values of the Campbell-Vuolteenaho weighted alpha statistic (*CV* p-value, dashed lines). The sample period is from 1963 to 2007 (45 annual observations). Equity data are from Kenneth French's website, bond data is from Ibbotson Associates and inflation data is from the U.S. Department of Labor website (www.bls.gov/cpi).

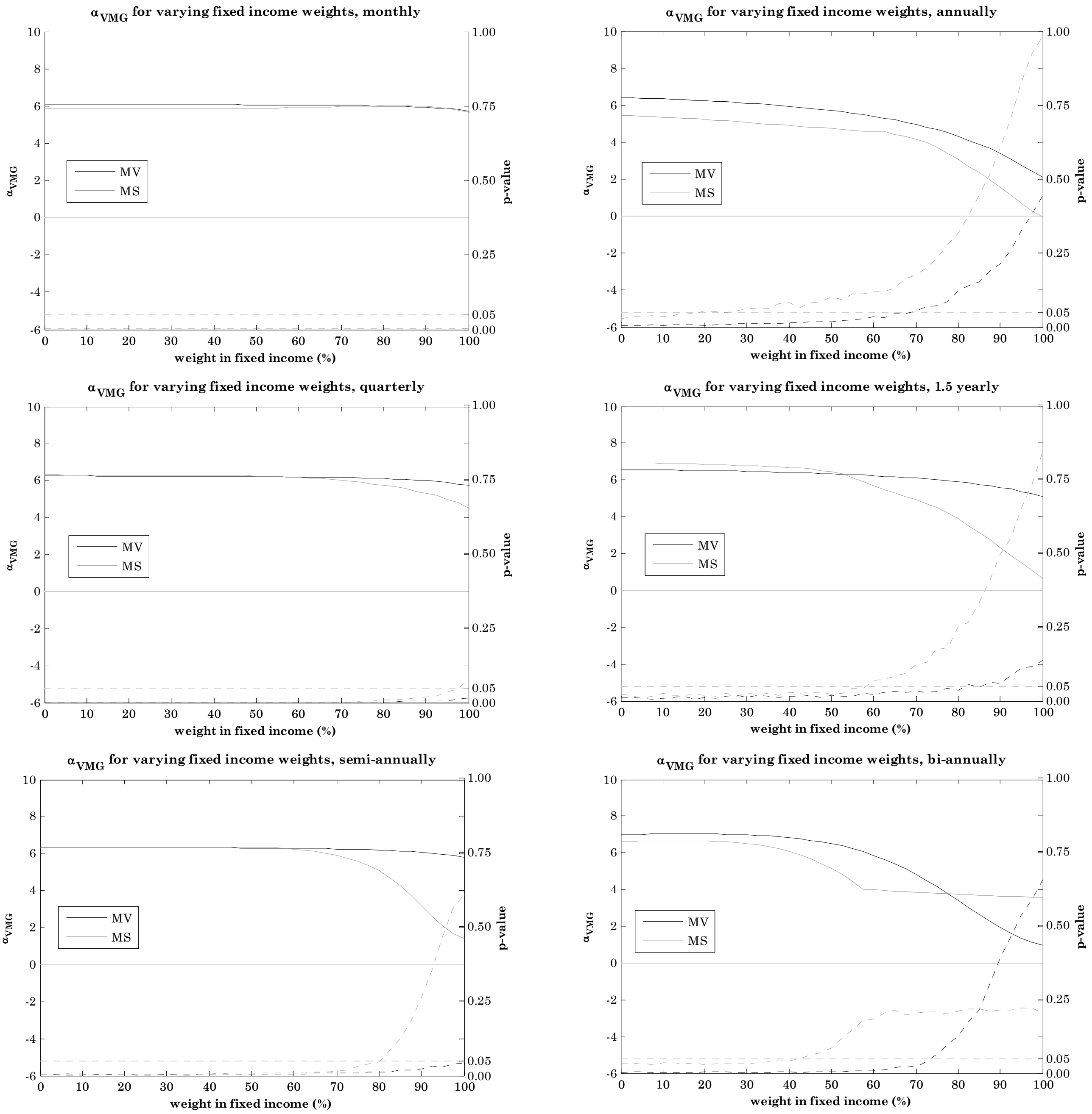

Figure 6: Effect return frequency. The figure shows the test results for the mean-variance investor (MV; black line) and mean-semi-variance investor (MS; grey line) for a 1-month, 3-months, 6-months, 12-months, 18-months and 24-months investment horizon for various percentages invested in the bond index (%) and the remainder invested in the CRSP all-share index. The bond index is an equal weighted index consisting of the Long Term Government bond index, the Long Term Corporate bond index and the Intermediate Term Government bond index. Shown are, for each investment horizon, the alphas (solid lines) and bootstrapped p-values (dashed lines) for the portfolio buying the highest two book-to-market decile portfolios and shorting the lowest two (VMG). The sample period is from 1963 to 2007 (45 annual observations). Equity data are from Kenneth French's website, bond data is from Ibbotson Associates and inflation data is from the U.S. Department of Labor website (www.bls.gov/cpi).

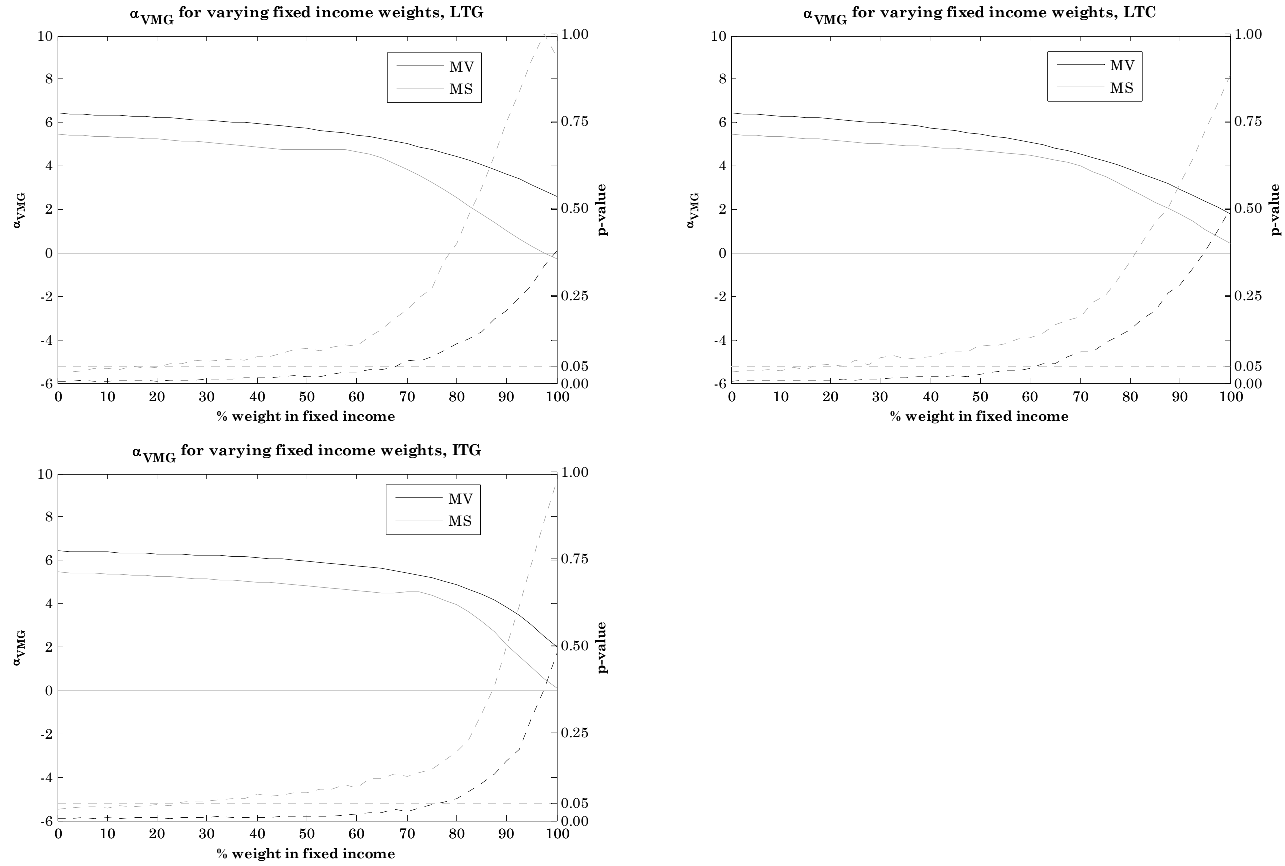

Figure 7: Robustness to the bond index. The figure shows the test results for the mean-variance investor (MV; black line) and mean-semi-variance investor (MS; grey line) for various percentages invested a particular bond index (%) and the remainder invested in the CRSP all-share index. LTG denotes the long-term government bond index, ITG the intermediate-term government bond index, and LTC the long-term corporate bond index. The tested stock portfolios are ten portfolios formed on formed on increasing values (in that order) of the book-to-market ratio of common equity. Shown are the alphas (solid lines) and bootstrapped p-values (dashed lines) for the portfolio buying the highest two decile portfolios and shorting the lowest two (VMG). The sample period is from 1963 to 2007 (45 annual observations). Equity data are from Kenneth French's website, bond data is from Ibbotson Associates and inflation data is from the U.S. Department of Labor website (www.bls.gov/cpi).

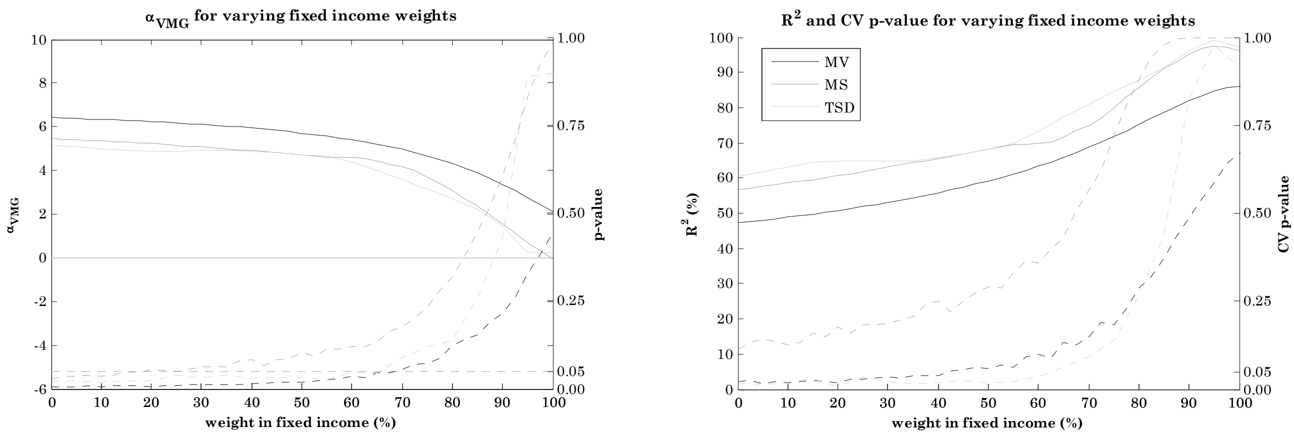

Figure 8: Third-order Stochastic Dominance results. The figure shows the test results for Third-order Stochastic Dominance (TSD) investor (light grey line), compared to the test results of the mean-variance investor (MV; back line) and mean-semi-variance investor (MS; dark grey line) for various percentages invested in the bond index (%) and the remainder invested in the CRSP all-share index. The bond index is an equal weighted index consisting of the Long Term Government bond index, the Long Term Corporate bond index and the Intermediate Term Government bond index. Shown are the alphas (solid lines) and bootstrapped p-values (dashed lines) for the portfolio buying the highest two book-to-market decile portfolios and shorting the lowest two (VMG), R-squared (R^2, solid lines), and the bootstrapped p-values of the Campbell-Vuolteenaho weighted alpha statistic (*CV* p-value, dashed lines). The sample period is from 1963 to 2007 (45 annual observations). Equity data are from Kenneth French's website, bond data is from Ibbotson Associates and inflation data is from the U.S. Department of Labor website (www.bls.gov/cpi).

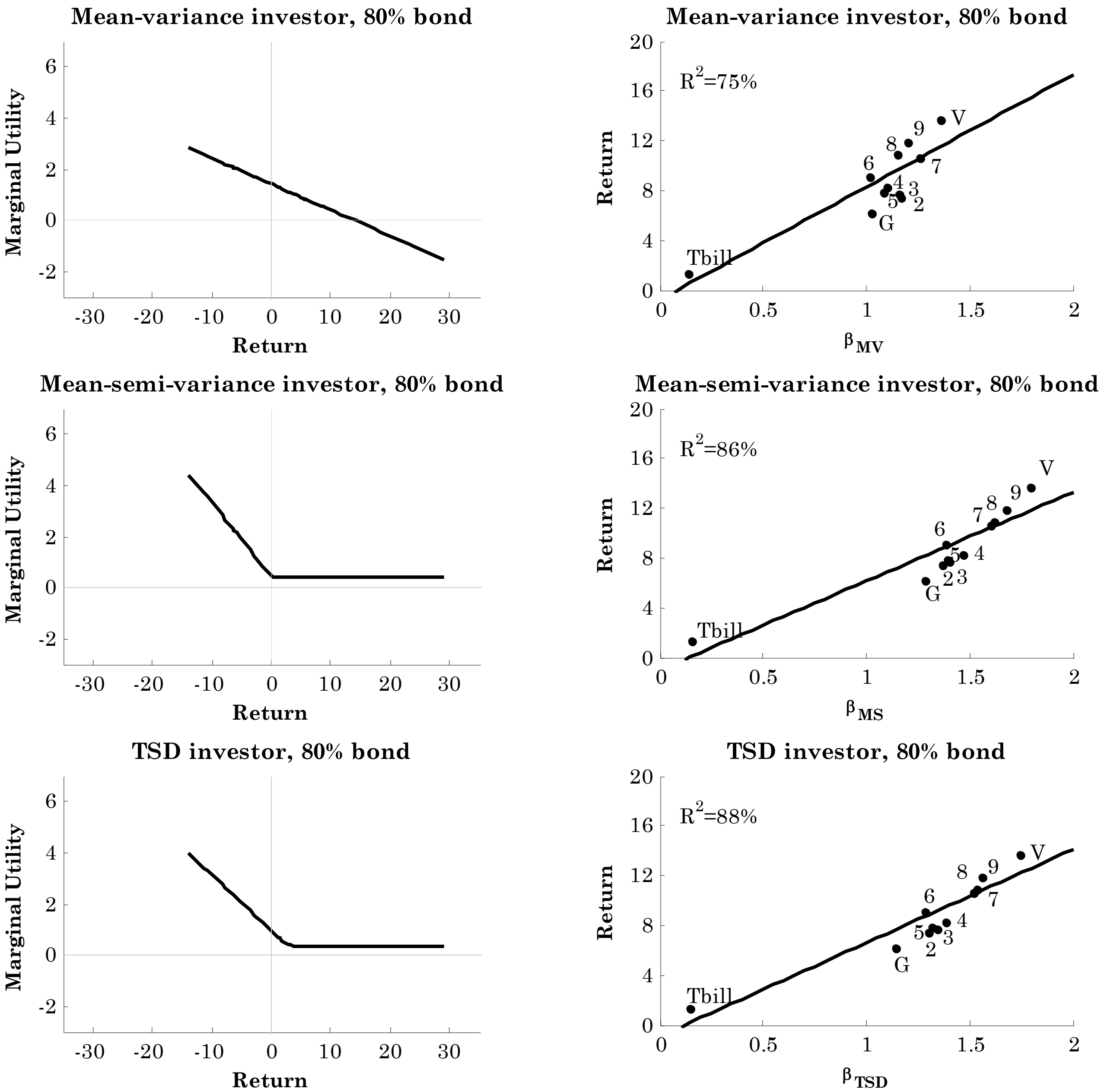

Figure 9: Kernel and return-beta plots of book-to-market sorted decile portfolios. The figure shows the estimated kernels and expected versus realized return relationships for the 10 stock portfolios formed on increasing values (in that order) of the book-to-market ratio of common equity (G= growth, V= value), and the one-month T-bill portfolio (Tbill). Results are shown for the mean-variance criterion, the mean-semi-variance criterion, and the third-order stochastic dominance (TSD) criterion. For the all cases, the evaluated portfolio is a mixture of 20% invested in bonds and 80% in equities. The equity index is proxied by the CRSP all-share index, and the bond index is proxied by the equal weighted combination of the Long Term Government bond index, the Long Term Corporate bond index and the Intermediate Term Government bond index. The results are based on annual real returns from 1963 to 2007 (45 annual observations).