ASSESSING PORTFOLIO PERFORMANCE USING ASSET PRICING KERNELS

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Abstract

The Stochastic Discount Factor (SDF) representation or asset pricing kernel approach provides a general and convenient framework to price various financial assets. We use this general asset pricing framework to derive a conditional asset pricing kernel that accounts efficiently for time variation in expected returns and risk. Our model is suitable to perform unconditional evaluations of fixed-weight strategies and (un)conditional evaluations of dynamic strategies. We develop the appropriate empirical framework for the estimation of the performance measures and their associated tests using the GMM of Hansen (1982). We examine the performance of Canadian equity mutual funds over the period, November 1989 through December 1999. The results indicate that there is evidence of abnormal unconditional performance and that performance deteriorates and becomes negative using the conditional asset pricing kernel model. Moreover, the performance statistics are weakly sensitive to changes in the level of relative risk aversion of the uninformed investor.

Keywords: SDF, (un)conditional models, mutual fund returns, performance measures, generalized method of moments

JEL Classification: G11, G12

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1. Introduction

Most previous studies on portfolio performance evaluation use equilibrium-based asset pricing models (such as the CAPM and the APT) to estimate the risk-adjusted performance of actively managed portfolios. These performance metrics are obtained by comparing the portfolio's average excess return to the one implied by the selected model for the same level of risk. This approach uses the (un)conditional forms of these models and assumes that they are well specified. However, evidence against the empirical validity of these models (priced anomalies) is mounting. In addition, these models fail to deliver reliable measures of performance and they can generate misleading inferences. This is caused essentially by problems related to estimation bias due to the presence of timing information (Dybvig and Ross, 1985; Admati and Ross, 1985; and Grinblatt and Titman, 1989) and to the choice and efficiency of benchmarks where rankings can change with different benchmarks (Roll, 1977, 1978). These problems led to the development of an asset pricing model-free measure to assess portfolio performance.

This alternative methodology relies on the general asset pricing framework (GAPF) based on the stochastic discount factor (SDF) representation for asset prices. According to Harrison and Kreps (1979), this methodology requires weaker market conditions of either the law of one price or no arbitrage conditions. The GAPF implies that any gross return discounted by a market-wide random variable has a constant conditional expectation. The GAPF nests all common (un)conditional asset pricing models (such as the CAPM, APT, ICAPM, Multifactor Models, CCAPM, or Option Models) depending on the specification of the stochastic discount factor. Moreover, the GAPF allows for an integration of the role of conditioning information with different structures (Hansen and Richard, 1987).

The GAP framework initially was applied to portfolio performance evaluation by Grinblatt and Titman (1989) via their positive period weighting measure (PPWM) where the SDF is the marginal utility of the return on an efficient portfolio. Subsequently, this methodology is applied and further developed by Glosten and Jagannathan (1994), Grinblatt and Titman (1994), Chen and Knez (1996), Kryzanowski and Lalancette (1996), Bansal and Harvey (1996), He et al. (1999), Goldbaum (1999), Dahlquist and Soderlind (1999), and Farnsworth et al. (2002).

In this paper, we introduce a conditional asset pricing kernel adapted to performance evaluation. It efficiently accounts for time variation in expected returns and risk. This stochastic discount factor or SDF depends on some parameters and on the returns on an efficient portfolio, and satisfies some regularity conditions. This approach has the advantage of not being dependent on any asset pricing model or any distributional assumptions. The proposed SDF is efficient by construction, given that it prices all the benchmarks and assets. Further, the multiplicative structure of conditioning information is explored and applied. This framework is suitable for performing unconditional evaluations of fixed-weight strategies and (un)conditional evaluations of dynamic strategies.

At the empirical level, we develop the appropriate framework for the estimation of the performance measures. More importantly, we advocate the use of a flexible estimation methodology using the (un)conditional Generalized Method of Moments (GMM) of Hansen (1982). We construct the empirical performance measures and their associated tests, and use this methodology to assess the performance of a set of Canadian equity mutual funds over the period, November 1989 through December 1999. We also test the sensitivity of the performance measures to changes in the level of relative risk aversion of the uninformed investor.

The remainder of the paper is organized as follows: Section 2 presents the general asset pricing framework. In section 3, we derive the asset pricing kernel in the presence of time-varying returns. We conduct a (un)conditional portfolio performance evaluation using the developed normalized pricing operator in section 4. In section 5, we develop and explain the econometric methodology and the construction of the tests. Section 6 introduces the sample and the data used herein. Section 7 presents and discusses the main empirical results. Finally, section 8 summarizes the findings and discusses their implications.

2. General Asset Pricing Framework (GAPF)

The fundamental theorem in asset pricing theory states that the price of a security is determined by the conditional expectations of its discounted future payoffs in frictionless markets. The stochastic discount factor (SDF) is a random variable that reflects the fundamental economy-wide sources of risk.[1] The basic asset pricing equation is written as:

(1) $$P_{i,t} = E_t(M_{t+1} X_{i,t+1}), \quad \text{all } i = 1,\ldots,N$$

The conditional expectation is defined with respect to the sub-sigma field on the set of states of nature, Ω_t, which represents the information available to investors at time t. $P_{i,t}$ is the price of asset i at time t, $X_{i,t+1}$ is the payoff of asset i at time $t+1$, and M_{t+1} is the stochastic discount factor or the pricing kernel.[2] The prices, payoffs and discount factors can be real or nominal. We generally assume that the asset payoffs have finite second moments. As shown by Luttmer (1996), (1) becomes an inequality when transaction costs or any other market frictions are introduced.

If a riskless asset with a unit payoff exists, then its price is equal to the conditional mean of the pricing kernel:

(2) $$E_t(M_{t+1}) = P_{f,t} = \frac{1}{R_{f,t+1}}$$

When the security payoff is a gross return, the price is one. Then equation (1) is equivalent to:

(3) $$E_t(M_{t+1} R_{i,t+1}) = 1, \quad \text{all } i = 1,\ldots,N$$

where $R_{i,t+1}$ represents a gross return (payoff divided by price) on asset i at time $t+1$.

If we define $r_{i,t+1} \equiv R_{i,t+1} - R_{f,t+1}$ as an excess return, it will have a zero price. The pricing equation then becomes:

(4) $$E_t(M_{t+1} r_{i,t+1}) = 0, \quad \text{all } i = 1,\ldots,N$$

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[1] It is a generalization of the standard discount factor under uncertainty. It is stochastic because it varies across the states of nature.

[2] The SDF has various other names. It is often called the intertemporal marginal rate of substitution in the consumption-based model, the equivalent martingale measure for allowing the change of measure from the

The SDF representation integrates both the absolute and the relative pricing approaches and has several advantages. First, it is general and convenient for pricing stocks, bonds, derivatives and real assets. Second, the SDF representation is simple and flexible in that it nests all asset pricing models by introducing explicit assumptions on the functional form of the pricing kernel and on the payoff distributions.[3] Third, the SDF representation leads to a reliable analysis of passively and actively managed portfolios by avoiding the limitations of the traditional models by providing robust measures. Fourth, by construction, the SDF representation offers a suitable framework when performing econometric tests of such models using the GMM approach of Hansen (1982). Fifth, the SDF representation accommodates conditioning information and exploits its implications and the predictions of the underlying model in a simple way.

Kan and Zhou (1999) identify an empirical flaw associated with the SDF methodology when the asset returns are generated by a linear factor structure. They argue that the SDF methodology ignores the full dynamics of asset returns (does not incorporate the data generating process in the moment conditions), and that some noisy or unsystematic factors may satisfy the SDF equation. Specifically, Kan and Zhou show that under such assumptions, the model parameters (risk premiums) are poorly estimated (less efficient compared to those estimated with classical regression methods), and that the power of the specification tests is significantly reduced due to the misspecification of the second moment matrix of the moment conditions. The evidence on this last problem is corroborated in Kan and Zhang (1999) for GMM tests of SDF models with useless factors. Jagannathan and Wang (2000) and Cochrane (2000) contradict these results by demonstrating that the GMM/SDF estimation is as efficient as the traditional time-series and cross-sectional regressions asymptotically and in finite samples.

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actual or objective probabilities to the risk-neutral probabilities, or the state price density when the Arrow-Debreu or state-contingent price is scaled by the associated state probability.

[3] These models include the CAPM of Sharpe (1964), the APT of Ross (1976), the CCAPM of Lucas (1978) and Breeden (1979), the ICAPM of Merton (1973), the multifactor models of Chen, Roll, and Ross (1986) and Fama and French (1993), and the Nonlinear APM of Hansen and Singleton (1982).

3. Time-Varying Returns and Asset Pricing Kernels

When investment opportunities are time-varying, the stochastic discount factors or the period weights can be interpreted as the conditional marginal utilities of an investor with isoelastic preferences described by a power utility function that exhibits constant relative risk aversion (CRRA) given by:

$$U(W_t) = \frac{1}{1-\gamma} W_t^{1-\gamma}$$

where W_t is the level of wealth at *t*, and γ is the relative risk aversion coefficient.

In a single-period model, the uninformed investor who holds the benchmark portfolio (the risky asset) maximizes the conditional expectation of the utility of his terminal wealth:

(5) $$E[U(W_{t+1}) \mid \Omega_t]$$

The conditional expectation is based upon the information set Ω_t.

The investor with such preferences decides on the fraction α_t of wealth to allocate to the risky asset (the benchmark portfolio). Any remaining wealth is invested in a riskless security. The return on wealth is given by:

(6)

$$R_{w,t+1} = \alpha_t R_{b,t+1} + (1-\alpha_t) R_{f,t+1} = \alpha_t (R_{b,t+1} - R_{f,t+1}) + R_{f,t+1} = \alpha_t r_{b,t+1} + R_{f,t+1}$$

where:

$R_{b,t+1}$: the gross return on the benchmark portfolio from *t* to *t* +1;

$r_{b,t+1}$: the excess return on the benchmark portfolio from *t* to *t* +1;

$R_{f,t+1}$: the gross risk-free rate from *t* to *t* +1 but is known one period in advance at time *t*; and

α_t: is the proportion of total wealth invested in the benchmark portfolio.

The optimal risky asset allocation (portfolio policy) is no longer a constant parameter when asset returns are predictable. Fama and French (1988, 1989), Ferson and Harvey (1991), Bekaert and Hodrick (1992), Schwert (1989), and Kandel and Stambaugh (1996), among others, document evidence of significant return predictability for long and short horizons, where the means and variances of asset returns are time-varying and depend on some key variables (such as lagged returns, dividend yield, term structure variables, and interest rate variables). Moreover, more recent papers by Brennan et al. (1997), Campbell and Viceira (1999), Brandt (1999), Barberis (2000), and Aït-Sahalia and Brandt (2001) invoke different assumptions on the intertemporal preferences of investors and on stock return dynamics. They show that the optimal portfolio weight is a function of the state variable(s) that forecast the expected returns when stock returns are predictable. It follows that the optimal portfolio weight is a *random variable measurable with respect to the set of state or conditioning variables and consistent with a conditional Euler equation*:[4]

(7) $$\alpha_t \equiv \alpha(\Omega_t)$$

Thus, considering a constant optimal portfolio weight when returns are predictable affects the construction of any measure based on this variable, and distorts inferences related to the use of such a measure. In addition, the functional form and the parameterization of the optimal portfolio allocation depend on the relationship between asset returns and the predicting variables. Brandt (1999) conducts a standard non-parametric estimation of the time-varying portfolio choice using four conditioning variables (dividend yield, default premium, term premium, and lagged excess return).

Assuming initial wealth at time t is equals to one, the conditional optimization problem as in Brandt (1999), Ferson and Siegel (2001), and Aït-Sahalia and Brandt (2001) for the uninformed investor is:

(8) $$\alpha_t^* = \arg\max_{\alpha_t} E[U(\alpha_t r_{b,t+1} + R_{f,t+1}) \mid \Omega_t]$$

The first order condition gives:

(9) $$E[U'(\alpha_t r_{b,t+1} + R_{f,t+1}) r_{b,t+1} \mid \Omega_t] = E[(\alpha_t r_{b,t+1} + R_{f,t+1})^{-\gamma} r_{b,t+1} \mid \Omega_t] = 0$$

This is a conditional Euler equation. Now define, $M_{t+1}^c \equiv (\alpha_t r_{b,t+1} + R_{f,t+1})^{-\gamma}$.

It is a strictly positive conditional stochastic discount factor (or conditional marginal utility) consistent with the no-arbitrage principle. This ensures that, if a particular fund has a higher positive payoff than another fund, then it must have a higher positive

[4] Ingersoll (1987) shows that with mean-variance preferences the optimal risky asset allocation is a nonlinear function of the first and second conditional moments of asset returns.

performance. Grinblatt and Titman (1989) and Chen and Knez (1996) stress the importance of this positivity property in providing reliable performance measures.[5,6]

We can normalize M^c_{t+1} such that: (10) $Q^c_{t+1} \equiv \frac{M^c_{t+1}}{E_t(M^c_{t+1})} = M^c_{t+1} R_{f,t+1}$. Then $E_t(Q^c_{t+1}) = 1$. This scaling is more convenient and is consistent with the original derivation of the PPWM of Grinblatt and Titman (1989) and Cumby and Glen (1990). The new conditional normalized pricing kernel plays a central role in the construction of the portfolio performance measure.

The unconditional normalized pricing kernel is given by:

(11) $Q^u_{t+1} \equiv \frac{M^u_{t+1}}{E(M^u_{t+1})} = M^u_{t+1} R_{f,t+1}$, where α is a constant parameter.

Let λ^i_{t+1}, $i = (u,c)$, be the (un)conditional portfolio performance measure depending on the use of the appropriate stochastic discount factor. It is an admissible positive performance measure with respect to the Chen and Knez (1996) definition.[7] Specifically:

(12) $\lambda^u_{t+1} = E(Q^u_{t+1} r_{y,t+1}) = E(r_{y,t+1}) + \mathrm{Cov}(Q^u_{t+1}, r_{y,t+1})$, such that $E(Q^u_{t+1} r_{b,t+1}) = 0$ and $E(Q^u_{t+1}) = 1$.

(13) $\lambda^c_{t+1} = E_t(Q^c_{t+1} r_{y,t+1}) = E_t(r_{y,t+1}) + \mathrm{Cov}_t(Q^c_{t+1}, r_{y,t+1})$, such that $E_t(Q^c_{t+1} r_{b,t+1}) = 0$ and $E_t(Q^c_{t+1}) = 1$.

In equations (12) and (13), $r_{y,t+1}$ is the excess return on any particular portfolio *y*.

It follows that the expected performance measure reflects an average value plus an adjustment for the riskiness of the portfolio measured by the covariance of its excess return with the appropriate normalized pricing kernel. Specifically:

[5] In this sense, the traditional Jensen alpha is implied by the CAPM pricing kernel when the positivity condition is not satisfied everywhere (Dybvig and Ross, 1985).

[6] In general, when the pricing kernel can be negative with certain positive probability, a truncation is adopted. The truncation provides a similar representation for an option on a payoff with a zero strike price.

[7] According to Chen and Knez (1996), a performance measure is admissible when it satisfies four minimal conditions: it assigns zero performance to each portfolio in the defined reference set, and it is linear, continuous, and nontrivial.

(14) $$Q_{t+1}^{u} \equiv \frac{(\alpha r_{b,t+1} + R_{f,t+1})^{-\gamma}}{E[(\alpha r_{b,t+1} + R_{f,t+1})^{-\gamma}]},$$

(15) $$Q_{t+1}^{c} \equiv \frac{(\alpha_t r_{b,t+1} + R_{f,,t+1})^{-\gamma}}{E_t[(\alpha_t r_{b,t+1} + R_{f,t+1})^{-\gamma}]}, \; \alpha_t \equiv \alpha(\Omega_t)$$

The condition $E_t(Q_{t+1}^{c} r_{b,t+1}) = 0$, or equivalently $E_t(Q_{t+1}^{c} R_{b,t+1}) = R_{f,t+1}$, guarantees that the benchmark portfolio is efficient for the uniformed investor. In the case where $R_{b,t+1}$ is a vector of gross returns on *K* efficient benchmark portfolios, the condition becomes: $E_t(Q_{t+1}^{c} R_{b,t+1}) = R_{f,t+1} 1_K$, where 1_K is a *K*-vector of ones. This condition guarantees that the benchmark portfolios are efficient for uninformed investors. The restriction on the conditional mean of the pricing kernel ensures correct pricing of the risk-free asset.

4. Performance Evaluation of Passively and Actively Managed Portfolios

4.1 Unconditional Framework

When uninformed investors do not incorporate public information, the portfolio weights are fixed or constant. The gross return on such a portfolio is:
$R_{p,t+1} = w' R_{1,t+1}$, with $w' 1_N = 1$, R_1 is a *N*-vector of gross security returns, and 1_N is a *N*-vector of ones. We assume that the portfolio weights *w* are chosen one period before. The corresponding unconditional performance measure is:

(16) $\lambda_{t+1}^{u} = E(Q_{t+1}^{u} r_{p,t+1}) = E(Q_{t+1}^{u} R_{p,t+1}) - R_{f,t+1} = 0$, where $E(Q_{t+1}^{u}) = 1$ and $E(Q_{t+1}^{u} r_{b,t+1}) = 0$.

$$\lambda_{t+1}^{u} = E(Q_{t+1}^{u} R_{p,t+1}) - R_{f,t+1} = w' E(Q_{t+1}^{u} R_{1,t+1}) - R_{f,t+1} = w' R_{f,t+1} 1_N - R_{f,t+1} = 0$$

$$Q_{t+1}^{u} \equiv Q(r_{b,t+1}, \alpha)$$

It follows that the risk-adjusted return on the passive portfolio held by the uninformed investor is equal to the risk-free rate.

The unconditional normalized pricing kernel (the PPWM) is able to price any asset or portfolio whose returns are attainable from all possible linear combinations of the original N assets (fixed-weight trading strategies). It will not price correctly any returns outside this defined return space.

The parameters of Q^u_{t+1} are chosen such that $E(Q^u_{t+1} r_{b,t+1}) = 0$. If $r_{b,t+1}$ is of dimension K, then $E(Q^u_{t+1} r_{b,t+1}) = 0_K$ and $E(Q^u_{t+1}) = 1$. Informed investors, such as possibly some mutual fund managers, trade based on some private information or signals implying non-constant weights for their portfolios.[8,9] The gross return on the actively managed portfolio is:

$$R_{a,t+1} = w(\Omega^a_t)' R_{1,t+1}, \text{ with } w(\Omega^a_t)' 1_N = 1$$

where Ω^p and Ω^a represent public and private information sets, respectively.

The unconditional performance measure is given by:

$$(17) \qquad \lambda^u_{t+1} = E(Q^u_{t+1} r_{a,t+1}) = E(Q^u_{t+1} R_{a,t+1}) - R_{f,t+1} = E(w(\Omega^a_t)' Q^u_{t+1} R_{1,t+1}) - R_{f,t+1}$$

When informed investors optimally exploit their private information or signals, this measure is expected to be strictly positive. According to Chen and Knez (1996), this measure reflects the price of the information and the manager's skills in using it. Conversely, inferior performance is related to the non-optimal use of the private information.

4.2 Conditional Framework

When uninformed investors use publicly known information in constructing their portfolios, the weights are a function of the information variables. The gross return is given by:

$$R_{p,t+1} = w(\Omega^p_t)' R_{1,t+1}, \text{ with } w(\Omega^p_t)' 1_N = 1, \text{ and } \Omega^p_t \subset \Omega^a_t$$

The conditional SDF prices the portfolio such that:

$$(18) \qquad \lambda^c_{t+1} = E_t(Q^c_{t+1} r_{p,t+1}) = E_t(Q^c_{t+1} R_{p,t+1}) - R_{f,t+1} = 0$$

$$\lambda^c_{t+1} = E_t(w(\Omega^p_t)' Q^c_{t+1} R_{1,t+1}) - R_{f,t+1}$$

$$= w(\Omega^p_t)' E_t(Q^c_{t+1} R_{1,t+1}) - R_{f,t+1} = w(\Omega^p_t)' R_{f,t+1} 1_N - R_{f,t+1} = 0$$

[8] The information may either concern individual stocks and/or the overall market.
[9] There is no restriction on the weight function. It may be nonlinear including any option-like trading strategies (Merton, 1981; and Glosten and Jagannathan, 1994).

$$Q_{t+1}^{c} \equiv Q(r_{b,t+1}, \Omega_t^p, \alpha)$$

Consistent with the semi-strong form of the efficient market hypothesis, this neutral performance reflects the fact that the use of publicly known information will not produce any superior risk-adjusted returns.

4.3 Model of Conditioning Information

We define $Z_t \in \Omega_t^p$ where Z_t is a L-vector of conditioning variables containing unity as its first element. These conditional expectations can be analyzed in two different ways. First, we can create general managed portfolios, and then examine the implications for the unconditional expectations as in Cochrane (1996). Second, as in Glosten and Jagannathan (1994), we can explicitly specify or approximate the conditional moments by incorporating the time-variation into the expected asset returns and volatilities.[10] This latter approach has the disadvantage of being sensitive to any misspecification in the conditional moments. Also, it can lead to estimation problems given the increase in the number of parameters to be estimated compared to the number of available observations. Consequently, we focus on the first approach using different models of conditioning information to characterize the managed portfolios.

Hansen and Singleton (1982) and Hansen and Richard (1987) propose including the conditioning information by scaling the original returns by the instruments.[11] This simple multiplicative approach implies linear trading strategies.[12] Moreover, it allows one to uncover an additional implication of the conditional SDF model that is not captured by the simple application of the law of iterated expectations. This approach does not require the specification of the conditional moments. Moreover, we can interpret these scaled returns as payoffs to managed portfolios or conditional assets. In effect, an

[10] It can be semi- or non-parametric.

[11] Bekaert and Liu (1999) propose to integrate conditioning information into the conditional pricing kernel model by determining the optimal scaling factor or the functional form of the conditioning information. These authors argue that the multiplicative model is not necessarily optimal in terms of exploiting the conditioning information and in providing the greatest lower bound. However, at the empirical level, this approach has a notable limitation in that the optimal scaling factor depends on the first and second conditional moments of the distribution of asset returns leading to an increasing number of parameters to be estimated and different parameterization of the conditional asset pricing kernel. All of this leads to the need to estimate a complex system of equations.

[12] It has become a commonly used approach in the asset pricing literature.

investor whose trading strategy is based on the value of Z_{lt}, where $l = 1,...,L$, will put Z_{lt} dollars into the asset.[13] The investor will receive $Z_{lt}R_{t+1}$ dollars at the end of the period, and each period the investor's portfolio is rebalanced according to the value of the instrument. Hence, the payoff space is expanded to *NL* dimensions to represent the number of trading strategies available to uninformed investors.[14]

The conditional performance measure can be written as:

(19) $$\lambda_{t+1}^{c} = E_t(Q_{t+1}^{c} R_{1,t+1}) \otimes Z_t - R_{f,t+1} 1_N \otimes Z_t = 0$$

(20) $$E_t(Q_{t+1}^{c}) Z_t = Z_t$$

Assuming stationarity and applying the law of iterated expectations, we have:

(21) $$E[Q_{t+1}^{c}(R_{1,t+1} \otimes Z_t)] = E(R_{f,t+1} 1_N \otimes Z_t)$$

(22) $$E(Q_{t+1}^{c} Z_t) = E(Z_t)$$

where $\otimes$ is the Kronecker product obtained by multiplying every asset return by every instrument. These two conditions ensure that the conditional mean of the pricing kernel is one, and that these managed portfolios are correctly priced.

The conditional normalized pricing kernel is able to price any asset or portfolio whose returns are attainable from dynamic trading strategies of the original *N* assets (i.e., asset returns scaled with the instruments) with respect to the defined conditioning information set. The conditional normalized pricing kernel will not price correctly any returns outside this expanded return space.

The conditional performance for the actively managed portfolio is given by:

(23) $$\lambda_{t+1}^{c} = E_t(Q_{t+1}^{c} r_{a,t+1}) = E_t(Q_{t+1}^{c} R_{a,t+1}) - R_{f,t+1}$$

This conditional test determines whether the private information or signal contains useful information beyond that available publicly, and whether or not this information has been used profitably.

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[13] The expected (average) price of this trading strategy is equal to the expected (average) value of the chosen instrument.

[14] The intuition underlying the multiplicative approach is closely related to the evidence of returns predictability, where some prespecified variables predict asset returns. Such evidence potentially improves the risk-return tradeoffs available to uninformed investors (this is in comparison to the time-invariant risk-return tradeoff). Bekaert and Hodrick (1992), Cochrane (1996), and Bekaert and Liu (1999) show that scaling the original returns by the appropriate instruments improves or sharpens the Hansen-Jagannathan lower bound on the pricing kernel when we account for conditioning information.

Furthermore, the *unconditional evaluation of dynamic performance* that is implied by the conditional normalized pricing kernel is obtained by the simple application of the law of iterated expectations on the conditional model as in Ferson and Schadt (1996) and Dahlquist and Soderlind (1999). The parametrization of the conditional normalized pricing kernel differs from the one associated with the conditional evaluation and is consistent with these two moment conditions:

(24) $$E(Q^c_{t+1}R_{1,t+1}) = R_{f,t+1}1_N$$

(25) $$E(Q^c_{t+1}) = 1$$

$$Q^c_{t+1} \equiv Q(r_{b,t+1}, \Omega^p_t, \alpha)$$

5. Econometric Methodology and Construction of the Tests

In this section we lay out the empirical framework for the estimation of the performance measures and for the tests of the different hypotheses and specifications using Hansen's (1982) generalized method of moments (GMM).[15] We also examine and discuss important issues associated with the estimation procedure and the optimal weighting matrix (distance matrix).

5.1 The General Methodology

To assess the performance of actively managed portfolios such as mutual funds, two methods are available and both rely on the GMM approach. The first or two-step method first estimates the appropriate normalized pricing kernel, and then measures the risk-adjusted fund performance by multiplying the gross fund return by the estimated pricing kernel and subtracting off the gross return on the risk-free asset. The performance estimates obtained in the second step do not account for the sampling errors resulting from the first-step estimation, and consequently are not fully efficient but are consistent (Chen and Knez, 1996). The second or one-step method jointly and simultaneously

[15] This general and flexible technique has become the common approach to estimate and test asset pricing models that imply conditional moment restrictions, even in the presence of nonstandard distributional assumptions. It is an alternative to the maximum likelihood approach with no requirement to specify the law of motion of the underlying variables. Cochrane (2000) provides a comprehensive exposition of the relationship between the two techniques.

estimates the normalized pricing kernel parameters and the performance measures. The estimates so obtained are more efficient than those from the two-step method, but require more moment conditions especially when all the funds are included in the evaluation. Hence, the joint estimation is conducted herein for each individual fund and in a multivariate framework where all the cross-equation correlations are incorporated. By construction (using excess returns), this estimation accounts for the restriction on the mean of the normalized (un)conditional pricing kernels.[16] Dahlquist and Soderlind (1999) and Farnsworth et al. (2002) note the importance of accounting for this restriction in order to obtain reliable estimates.

5.2 The GMM General Framework

We present and outline the general steps and expressions leading to the estimation of the performance measures under the GMM approach. Our focus is mainly related to the general case of conditional GMM estimation relevant for the conditional evaluation of dynamic trading-based portfolios. The unconditional GMM estimation is applied to both the unconditional evaluation of dynamic trading and the fixed-weight trading-based portfolios. It is trivially obtained as a special case from the general one.

Let $\theta \equiv (\alpha\ \gamma)'$ be the vector of unknown parameters to be estimated. Our model implies the following conditional moment restriction:

(26) $$E_t[Q^c(r_{b,t+1}, Z_t, \theta_0) r_{p,t+1}] = 0_N$$

such that $E_t[Q^c(r_{b,t+1}, Z_t, \theta_0)] = 1$.

Now define $u^c_{t+1} = Q^c(r_{b,t+1}, Z_t, \theta) r_{p,t+1} \equiv u(r_{b,t+1}, r_{p,t+1}, Z_t, \theta)$ as a N-vector of residuals or pricing errors, that depend on the set of unknown parameters, the excess returns on the benchmark portfolio(s), the conditioning variables, and the excess returns on passive trading strategy-based portfolios (eventually excess returns on individual assets).

We assume that the dimension of the benchmark excess return is K, and that the dimension of the conditioning variables (including a constant) is L. Then, the dimension of the vector of unknown parameters is (KL+1).

[16] The mean of the normalized pricing kernel is equal to one and the mean of the non normalized asset pricing kernel is equal to the inverse of the gross return on the risk-free asset.

We then have:

(27) $$E_t[u(r_{b,t+1}, r_{p,t+1}, Z_t, \theta_0)] = E[u(r_{b,t+1}, r_{p,t+1}, Z_t, \theta_0)] = 0_N$$

Define $h(r_{b,t+1}, r_{p,t+1}, Z_t, \theta) = u^c_{t+1} \otimes Z_t = u(r_{b,t+1}, r_{p,t+1}, Z_t, \theta) \otimes Z_t$. Our conditional and unconditional (by using the law of iterated expectations) moment restrictions can be written as:[17]

(28) $$E_t[h(r_{b,t+1}, r_{p,t+1}, Z_t, \theta_0)] = E[h(r_{b,t+1}, r_{p,t+1}, Z_t, \theta_0)] = 0_{NL}\text{, and}$$

(29) $$E_t[Q^c(r_{b,t+1}, Z_t, \theta_0)Z_t - Z_t] = E[Q^c(r_{b,t+1}, Z_t, \theta_0)Z_t - Z_t] = 0_L$$

The GMM estimation exploits these moment restrictions by setting their sample analogues equal to zero. This is feasible only when the number of linearly independent moment conditions is equal to the number of unknown parameters (i.e., the model is identified).[18] If the number of moment conditions exceeds the number of unknown parameters (the model is overidentified), then the GMM estimation is performed by setting (*KL*+1) linear combinations of the *NL* moment conditions equal to zero. When an additional moment condition is considered,[19] the number of moments increases to *L*(*N*+1) and the number of parameters remains unchanged. Similarly, when the estimation of the performance measures is completed in one step, the number of moment conditions (*L*(*N*+1)) and the number of unknown parameters (*KL*+2) is augmented.

Define:

(30) $$g_0(\theta) = E[h(r_{b,t+1}, r_{p,t+1}, Z_t, \theta)]$$

Since this does not depend on *t*, it implies that g_0 has a zero at $\theta = \theta_0$. By the law of large numbers (through the stationarity assumption), the sample mean of $h(r_{b,t+1}, r_{p,t+1}, Z_t, \theta)$ converges to its population mean, or:

$$g_T(\theta) \xrightarrow{p} g_0(\theta)$$

---

[17] Some technical assumptions are required for the consistency (strict stationarity and ergodicity of the process underlying the observable variables) and for the identification of the model (*h* has a nonsingular population conditional (unconditional) covariance matrix and the conditional and unconditional expectations of the first derivatives of *h* have a full raw rank). See Hansen (1982) and Gallant and White (1988) for more details.

[18] In this case, we can use the traditional method of moments.

[19] Koenker and Machado (1999) derive restrictions on the growth rate of the number of moment conditions to ensure the validity of the conventional asymptotic inference for the GMM estimation. In effect, these restrictions affect the estimation of the optimal weighting matrix.

where: (31) $$g_T(\theta) = \frac{1}{T}\sum_{t=1}^{T} h(r_{b,t+1}, r_{p,t+1}, Z_t, \theta)$$

For large values of *T*, the vector $g_T(\theta)$ should be close to zero when evaluated at $\theta = \theta_0$. Following Hansen (1982), the GMM estimator of θ_0 is obtained by selecting $\hat{\theta}_T$ to minimize the sample quadratic form J_T given by:

(32) $$J_T(\theta) \equiv g_T(\theta)' W_T g_T(\theta)$$

where W_T is a symmetrical and nonsingular positive semi-definite $NL \times NL$ weighting matrix, which may depend on the sample and converges in probability to a positive definite (nonrandom) limit W. The weighing matrix underlines the importance of each moment condition in the estimation.

Hansen (1982) shows that under some regularity conditions, the GMM estimator $\hat{\theta}_T$ is consistent and asymptotically normal for any fixed W.[20] It has an asymptotic variance-covariance matrix that depends on the limiting weighting matrix. Furthermore, this estimator is asymptotically efficient in that it has the smallest variance-covariance matrix in the class of estimators that minimize the quadratic form for fixed W, when W is chosen to be a consistent estimate of the inverse of the variance-covariance matrix of the orthogonality conditions.

The general asymptotic variance-covariance matrix of the estimator of θ_0 is given by:

(33) $$\text{Cov}(\hat{\theta}_T) = (D_0' W D_0)^{-1} (D_0' W S_0 W D_0)(D_0' W D_0)^{-1}$$

where:

(34) $D_0 = E\left(\frac{\partial u(r_{b,t+1}, r_{p,t+1}, Z_t, \theta_0)}{\partial \theta'} \otimes Z_t \right)$ represents the expectation of the $NL \times (KL+1)$ matrix of first-derivatives. S_0 is the asymptotic variance-covariance matrix of $g_T(\theta_0)$ which is defined as: (35) $S_0 = \sum_{j=-\infty}^{+\infty} E[h(r_{b,t+1}, r_{p,t+1}, Z_t, \theta_0) h(r_{b,t-j+1}, r_{p,t-j+1}, Z_{t-j}, \theta_0)']$.

When the model is overidentified, (*NL*>*KL*+1), (*KL*+1) restrictions are used in the estimation, and the remaining "free" restrictions ((*N*-*K*)*L*-1) are used to assess and test the goodness of fit of the model (i.e., as a test of the overidentifying restrictions). Let $J_T(\hat{\theta}_T)$ be the minimized value of the sample quadratic form.[21] When the optimal weighting matrix (inverse of the variance-covariance matrix of the orthogonality conditions) is used, $TJ_T(\hat{\theta}_T)$ has an asymptotic standard central chi-square distribution with ((*N*-*K*)*L*-1) degrees of freedom equal to the number of orthogonality conditions minus the number of parameters to be estimated. This is the well-known Hansen J_T-statistic. This estimation can handle the assumption that the vector of disturbances exhibits non-normality, conditional heteroskedasticity, and/or serial correlation even with unknown form.

5.3 The Estimation Procedure and the Optimal Weighting Matrix

The estimates of the portfolio performance measure are obtained from minimizing the GMM criterion function constructed from a set of moment conditions. This requires a consistent estimate of the weighting matrix that is a general function of the true parameters (at least in the efficient case). The dominant approach in the literature is the iterative procedure[22] suggested by Ferson and Foerster (1994).

Hansen (1982) proves that the GMM estimator is asymptotically efficient when the weighting matrix is chosen to be the inverse of the variance-covariance matrix of the moment conditions.[23] Specifically:

(36) $$W^* = S_0^{-1}$$

where S_0 is the positive definite spectral density at frequency zero or long run variance-covariance matrix of $h(r_{b,t+1}, r_{p,t+1}, Z_t, \theta_0)$.

---

[20] Also, see Gallant and White (1988) for the general theory of these estimators.

[21] Jagannathan and Wang (1996) show that *T* times the minimized GMM criterion function is asymptotically distributed as a weighted sum of central chi-squared random variables.

[22] It consists of updating the weighting matrix based on a previous step estimation of the parameters, and then updating the estimator. This is repeated until convergence for a prespecified criterion and for a large number of steps. Ferson and Foerster (1994) and Cochrane (1996) find that this iterative approach has better small sample properties than the two-step procedure, and is robust to small variations in the model specifications.

[23] The choice of the weighting matrix only affects the efficiency of the GMM estimator. Newey (1993) shows that the estimator's consistency only depends on the correct specification of the residuals and the information or conditioning variables.

In this case, the asymptotic variance-covariance matrix of the estimator is given by:

(37) $$\text{Cov}(\hat{\theta}_T) = (D_0' S_0^{-1} D_0)^{-1}$$

This variance-covariance matrix is unknown and should be replaced by a consistent sample estimate. The consistent sample estimate of the variance-covariance matrix is a function of consistent sample estimates of D_0 and S_0 that are given by $\hat{D}_T$ and $\hat{S}_T$, respectively.

A consistent sample estimate of D_0 is obtained by replacing the expectation operator with the sample average operator, and replacing θ_0 with $\hat{\theta}_T$ to get:

(38) $$\hat{D}_T = \frac{1}{T}\sum_{t=1}^{T} \frac{\partial u(r_{b,t+1}, r_{p,t+1}, Z_t, \hat{\theta}_T)}{\partial \theta'} \otimes Z_t$$

A robust and consistent sample estimate of S_0 is obtained by using an estimator of the spectral density at zero frequency to $h(r_{b,t+1}, r_{p,t+1}, Z_t, \hat{\theta}_T)$. This GMM efficient estimation of portfolio performance measures is the most frequently used approach, and is used in Chen and Knez (1996), Kryzanowski et al. (1997), Dahlquist and Soderlind (1999), and Farnsworth et al. (2002).

To estimate the optimal weighing matrix and to calculate the asymptotic standard errors for the GMM estimates, a consistent estimate of the empirical variance-covariance matrix of the moments is required. This variance-covariance matrix is defined as the zero-frequency spectral density of the pricing errors vector $h(r_{b,t+1}, r_{p,t+1}, Z_t, \theta_0)$. From this perspective, a consistent estimate of this spectral density is used to construct a heteroskedastic and autocorrelation consistent (HAC) or robust variance-covariance matrix in the presence of heteroskedasticity and autocorrelation of unknown forms.[24]

Newey and West (1987a) propose the (modified) Bartlett kernel to construct a robust estimator for the variance-covariance matrix.[25] Chen and Knez (1996), Kryzanowski et al. (1997), Dahlquist and Soderlind (1999), and Farnsworth et al. (2002)

[24] Priestly (1981) provides an overview discussion of the estimation of spectral density functions.
[25] The higher-order sample autocovariances are downweighted (linear declining weights), and those with order exceeding a certain parameter inclusively receive zero weight.

construct robust t-statistics using this method in their estimation of the performance measures.

6. Sample and Data

6.1 Mutual Fund Returns

The sample of mutual funds is drawn from the Financial Post mutual fund database. The sample consists of 95 Canadian equity funds that have no more than 5% of their values missing over the period from November 30, 1989, through December 31, 1999. The 122 monthly returns for each fund are calculated using the monthly changes in the net asset value per share, and are adjusted for capital gains and dividend payments. Since the sample only includes surviving funds, a survivorship bias in favor of better performance exists in the results obtained below. Estimates of this survivorship bias will be assessed in future research.

A preliminary process (screening rules) to select the sample of funds is conducted to achieve consistency with the construction of the stochastic discount factor. In effect, the restrictions on the fund type are closely related to the type of securities (and essentially the benchmark variables) used to estimate the SDF.

As in most previous studies (Chen and Knez, 1996; Ferson and Schadt, 1996; Kryzanowski et al., 1997; and Farnsworth et al., 2002), we use only equity funds for the tests of abnormal performance. In effect, we cannot price or evaluate the performance of other types of funds with an equity based-asset pricing kernel.

Table 1 presents some summary statistics on these funds. Panel A gives statistics on the cross-sectional distribution of the 95 mutual funds. The average annual fund returns vary from –3.08% (Cambridge Growth of Sagit Investment Management) to 18.03% (AIC Advantage of AIC Limited) with a mean of 9.86%. The fund annual volatilities or standard deviations range from 6.00% (Canadian Protected of Guardian Timing Services) to 31.05% (Cambridge Special Equity of Sagit Investment Management). Over the same sample, the average annual TSE 300 index return is 11.17% and market volatility is 14.53%.

[Please insert table 1 about here.]

In panel B of table 1, portfolios of funds grouped by investment objectives are obtained from equally weighted portfolios using the 95 funds in the sample. The funds fall into six investment objective categories: aggressive growth (27 funds), growth (50 funds), growth and income (12 funds), income (3 funds), balanced (1 fund), and specialty (2 funds). The highest mean return is found in the group of aggressive growth funds and the lowest mean return is found within the group of growth and income funds (if we exclude the one balanced fund). As expected, aggressive growth (specialty) funds have the highest (lowest) unconditional volatility of 13.39% (11.02%). The first-order autocorrelations of the fund returns are greater than 0.1 for 30 of the 95 funds.

6.2 Information Variables

A set of six instrumental variables is selected based on evidence of their predictive power in studies of stock return predictability. All the data series are drawn from Statistics Canada's CANSIM database. We consider the lagged values of the following variables:

(i) DY is the dividend yield of the TSE 300 index (Fama and French, 1988, Ferson and Schadt, 1996, Kryzanowski et al., 1997, Christopherson et al., 1997, and Farnsworth et al., 2001).

(ii) TB1 and TB3 are respectively the Canadian one-month and three-month T-Bill rates (Fama and Schwert, 1977; and Ferson and Korajczyk, 1995).

(iii) RISK is the risk premium as measured by the yield spread between the long-term corporate (McLeod, Young, Weir bond index) and long-term government of Canada bonds (Chen, Roll, and Ross, 1986; Kryzanowski and Zhang, 1992; and Kryzanowski and Koutoulas, 1996).

(iv) TERM is the slope of the term structure as measured by the yield spread between long-tem government of Canada bonds and the one period lagged three-month Treasury bill rate (Ferson and Harvey, 1991; and Chen and Knez, 1996).

(v) TSEX-EW, TSEX-VW and TSE300X are the equally-weighted, value-weighted, and the TSE 300 index excess returns respectively (Harvey, 1989).

(vi) DUMJ is a dummy variable for the month of January (Ferson and Schadt, 1996; Kryzanowski et al., 1997; and Farnsworth et al., 2002).

Descriptive statistics and autocorrelations, and a correlation analysis of these variables are provided in panels A and B of table 2, respectively. The correlations between all the instruments range from –0.82 to 0.84.

[Please insert table 2 about here.]

In the empirical estimation of the performance measures, we restrict the use of the information variables to one or two (DY and/or TB1). These two variables account for most of the time variation in mutual fund excess returns as explained in the next section.

6.3 Predictability of Mutual Fund Excess Returns

In order to motivate the implementation of the conditional methodology, we conduct a predictability analysis of two groups of portfolios of mutual fund (excess) returns. The first group includes six equally-weighted portfolios of funds constructed using individual fund returns within each investment objective. The second group is composed of six size-weighted portfolios of funds constructed using the individual fund returns and the corresponding total net asset values within each investment objective. Time-series regressions of these portfolios of funds excess (of one-month Treasury bill rate) returns on a set of five instruments (the lagged values of the dividend yield, the risk premium, the slope of the term structure, the one-month Treasury bill rate, and the dummy variable for the month of January) are performed. The predictive power of the instruments is assessed using the Wald test proposed by Newey and West (1987b).

The results reported in table 3 indicate significant levels of predictability for the equally-weighted and size-weighted portfolios of funds excess returns. The null hypothesis that all the slope coefficients associated with the selected instruments are zeros, is largely rejected. The evidence of high predictability in the stocks composing the funds in the portfolios may explain these patterns. These figures are higher than the ones obtained with the portfolios of funds returns and with the passive portfolio excess returns (results not reported). Furthermore, the coefficients associated with the dividend yield on the TSE 300 index and the yield on the one-month Treasury bill are significant for most of the portfolios (results not reported). These findings provide strong support for undertaking a conditional performance analysis where the use of the conditional asset pricing kernel eliminates the predictability (based on the set of predetermined information variables) in the mutual fund excess returns.

[Please insert table 3 about here.]

6.4 Passive Strategies

Passive or basis (reference) assets must reflect the investment opportunities set of investors and portfolio managers. In the empirical implementation of the performance measures, the type and the number of assets to be considered are important issues. In effect, assets included must be consistent with the type of funds (essentially equity) under consideration. We construct ten size-based portfolios representing passive buy and hold strategies (stock market). All the stocks on the TSE/Western monthly database are considered. In a first step, we compute the market value of each stock by multiplying the December-end price by the number of shares outstanding. The stocks are ranked on the basis of their market values at the end of the previous year. Ten decile portfolios are then formed each year with an approximately equal number of securities in each portfolio. The securities with the smallest capitalization are placed in portfolio one (see Kryzanowski et al. (1997) for a similar construction).

Panels A and B in table 4 provide descriptive statistics and autocorrelations and the correlation matrix for these ten portfolios, respectively. The annualized average returns on the size portfolios range from 1.27% (sixth portfolio) to 58.58% (first portfolio). All the series indicate a low degree of persistence where all the first-order autocorrelations are less than 0.236.

[Please insert table 4 about here.]

6.5 Benchmark Assets

Three proxies of the benchmark asset are retained; namely, the TSE 300, TSE equally-weighted, and TSE value-weighted indices. This permits us to test the sensitivity of the performance statistics with respect to the selected benchmarks.

6.6 Optimal Risky Asset Allocation Specifications

In a conditional setting, the optimal risky asset allocation (the uninformed investor portfolio's policy) is a function of the conditional moments of asset returns. With the assumption that these conditional moments are linear in the state variables that predict the stock returns, a linear structure is retained (Aït-Sahalia and Brandt, 2001). Hence two linear specifications are adopted and integrated into the construction of the performance measures; namely: [26]

(39) $$\alpha_t = Z_t'\alpha$$

where α is a vector of unknown parameters, and Z_t is a vector of instruments (including a constant) with a dimension equal to two or three depending on the retained variables (DY only or DY and TB1). When unconditional evaluation is conducted, the uninformed investor's portfolio policy is a constant.

7. Empirical Results on Performance

We use the (un)conditional pricing kernel models to assess the risk-adjusted performance of the 95 equity funds under consideration. In particular, we determine the average and the median performance of all funds, its sign and significance, its total and per group of funds variability, and its sensitivity to the procedure for forming portfolios of funds and to the selected benchmark portfolio. We place emphasis on the use of two portfolio formation procedures: an equally weighted and a size or value-weighted structure. Size is defined as the total net asset value of the fund.

We examine the performance of two groups of portfolios of funds. The first group includes six equally-weighted portfolios of funds constructed using individual fund

[26] Aït-Sahalia and Brandt (2001) use a single linear index to characterize the relationship between the portfolio weight and the state variables.

returns within each investment objective. The second group is composed of six size-weighted portfolios of funds constructed using the individual fund returns and the corresponding total net asset values within each investment objective.

Finally, we address the issue of the sensitivity of the performance metrics to changes in the level of relative risk aversion of the uninformed investor.

7.1 Implementation and Estimation Issues

The (un)conditional estimation of the asset pricing kernel parameters and performance measures is conducted simultaneously. This one-step method is superior and more efficient that the two-step method, although Farnsworth et al. (2002) demonstrate that both approaches yield the same numerical results. Considering the limited number of observations, the joint estimation uses subgroups of individual funds (one to eight) in addition to the ten size-based passive strategies. This has the advantage of controlling for the number of moment conditions in order to minimize computational problems.

7.2 Unconditional Performance Evaluation

Table 5 reports the performance results for the twelve equally weighted and size-weighted portfolios of mutual funds using the three benchmark variables. Panel A shows that all equally-weighted portfolios (except the income, balanced, and the specialty ones) have consistently positive and significant abnormal performance. The average lambda is 0.0762% per month, and the growth/income funds contribute the most with a highly significant lambda of 0.2591% using the value-weighted TSE index as a benchmark. The performance of the balanced and specialty portfolios is negative but not significant (except when using the equally-weighted TSE index as a benchmark). The same analyses conducted on the six size-weighted portfolios of funds (panel B) produces comparable and more significant results. The lambdas of the aggressive growth (27 funds) and growth (50 funds) portfolios are highly significant and are 0.2463% and 0.2626%, respectively. The overall average lambda is 0.1282% per month. An equally-weighted formation of portfolios of funds appears to underestimate unconditional performance.

[Please insert table 5 about here.]

The performance of individual funds is summarized in table 6 (panels A and B) for the two portfolio performance formation procedures. The results indicate that the equally-weighted portfolios of performances based on the value-weighted TSE index as a benchmark have a positive mean and median lambda (0.1931% and 0.1778%, respectively) with an average p-value of 27.55%. In addition, the aggressive growth, growth, growth/income, and income portfolios exhibit positive but not significant abnormal performance. The aggregate significance levels must be interpreted with care since they are averages of individual levels. Moreover, the lambdas are symmetrically distributed with fat tails.

These results differ from those reported for U.S. funds (Chen and Knez, 1996; Ferson and Schadt, 1996; and Farnsworth et al., 2002), and are consistent with the evidence in Kryzanowski et al. (1997) where the unconditional average Jensen alpha is positive but not significant over the period 1981-1988 and for all fund groups.

When the individual fund performances are weighted by the total net asset value of the fund, the average lambda increases and becomes less insignificant (0.2224% at the level of 22.46%) using the value-weighted TSE index. This performance improvement is obtained for the aggressive growth, growth, income, and specialty portfolios. These observations are confirmed when the two other benchmarks are used.

[Please insert table 6 about here.]

To better understand the sources of this positive average performance, we examine the distribution of the p-values for all funds and per fund group (all based on heteroskedasticity and autocorrelation consistent t-statistics) for the three benchmarks. Based on table 7, almost 43% of the funds have p-values less than 5%, and only three funds exhibit significant negative performance using the value-weighted TSE index as the benchmark. There is a predominance of funds with good performance across all fund groups except for the sole balanced fund that has a negative but non-significant lambda. These figures increase using the equally-weighted TSE index as the benchmark. Six funds have negative and significant lambdas, and 43 funds have positive and significant lambdas. These differences are essentially caused by the performance of some growth/income funds. Moreover, the p-values based on the Bonferroni inequality indicate that the positive extreme t-statistics are significant for all funds and across all fund groups with the exception of the balanced fund.[27] This rejects the joint hypothesis of zero lambdas. However, the conservative p-value corresponding to the minimum t-statistic for all funds, using the TSE 300 and the value-weighted TSE indices, are 0.577 and 0.458, respectively.

[Please insert table 7 about here.]

Overall, this positive significant unconditional performance may reflect the presence of private and/or public information correlated with future returns. A conditional performance evaluation controlling for the effects of public information is necessary to better assess the performance of fund managers.

7.3 Conditional Performance Evaluation

The conditional model is estimated under two specifications for the conditioning structure. First, we consider only the dividend yield on the TSE 300 index in the construction of the conditional performance measures. Second, the information set consists of the dividend yield and the yield on the one-month T-bill. This approach is useful for examining the sensitivity of the performance measures to the conditional specification. Moreover, we provide Wald tests (Newey and West, 1987b) on the coefficients of the time-varying alpha in order to assess the validity of the conditional approach.

7.3.1. Conditioning with the Dividend Yield Only

When the conditional asset pricing kernel model is used with one instrumental variable (the dividend yield), the average performance of 0.0710% weakens but remains positive and significant for the equally-weighted portfolios of mutual funds for the value-weighted TSE index if we exclude the balanced and the specialty portfolios (see panel A in table 8). This is explained by the significant decrease in the performance of the growth, growth/income and income portfolios. In contrast, the performance of the

[27] It uses the maximum or the minimum one-tailed p-value from the t-statistic distribution for all funds and fund groups multiplied by the corresponding number of funds.

aggressive growth portfolio increases and becomes more significant (0.2715%). The unique balanced (Industrial Pension of Mackenzie Financial Corporation) maintains its negative and non-significant lambda (-0.0127%). This result is robust to the use of the second benchmark. The performance analyses using the size-weighted portfolios of funds reveal a clear deterioration of the average performance (0.0465%) (see panel B). This is explained by the low performance of the aggressive growth portfolio, and the surprisingly negative lambda of the growth/income portfolio. Overall, the conditional model has more impact on the size-weighted portfolios than on the equally-weighted portfolios.

[Please insert table 8 about here.]

The previous conclusions are corroborated by examining the performance of individual funds. Based on table 9, the average fund performance is negatively affected using the conditional model. In addition, the distribution of the lambdas becomes less symmetric and with less observations in the tails. These results differ from the empirical evidence for U.S. funds reported in Chen and Knez (1996) and Ferson and Schadt (1996) that the inclusion of public information positively impacts the performance statistics. The changes in the point estimates of performance from the unconditional to conditional frameworks reported herein are parallel to the ones observed in Bansal and Harvey (1996) and Kryzanowski et al. (1997).

[Please insert table 9 about here.]

The most notable source of the deteriorating conditional lambdas is the poor performance of the individual growth and growth/income funds. Overall 42 (15) funds have negative (significantly negative) lambdas using the value-weighted TSE index as a benchmark. The number of funds with positive and significant performance decreases from 42 to 38. Moreover, all the Bonferroni p-values, corresponding to the extreme t-statistics (maximum and minimum) reject the null hypothesis of joint zero lambdas (see table 10, panels A and B).

[Please insert table 10 about here.]

7.3.2. Conditioning with the Dividend Yield and Yield on the One-Month T-Bill

The information set now is extended to two instrumental variables by adding the yield on the one-month T-bill to the set with the dividend yield. Based on the results reported in table 11 (panels A and B), the performance values become negative but non significant, except for the income and specialty portfolios where the lambda is negative and significant, and for the aggressive growth group which exhibits decreased positive performance. The average lambda for the equally-weighted portfolios of funds is –0.1159% using the value-weighted TSE index as a benchmark. Moreover, the Wald tests based on the methodology of Newey and West (1987b) validate the conditional approach. The Wald statistics reject the null hypothesis of no time variation in the optimal allocation of risky assets for all portfolios. These figures are verified using the size-weighted portfolios of funds, where the average size-weighted lambda is –0.1312%.

[Please insert table 11 about here.]

Based on panels A and B of table 12, the performance of the individual funds and portfolios of performances support the previous conclusions obtained from the portfolios of funds. The distribution of the conditional lambdas is now asymmetric with less extreme observations compared to the unconditional and one instrument based conditional lambdas.

[Please insert table 12 about here.]

Based on table 13 (panels A and B), the number of funds with significant negative lambdas increases to 36. This compares to 3 and 15 funds using the unconditional and one instrument based conditional estimations. The number of significant positive lambdas decreases to 16. This is less than half of the number (38) obtained with the unconditional asset pricing kernel model. These figures are caused by the negative performance of aggressive growth, growth, and growth/income funds. Moreover, the Bonferroni test is significant for all fund groups except for the maximum t-statistic associated with the income group (3 funds). This rejects the joint null hypothesis of zero conditional lambdas.

[Please insert table 13 about here.]

The overall results indicate that when public information, such as the dividend yield and the yield on one-month T-bills, are integrated into the construction of the asset pricing kernel and the performance measures, it becomes more difficult for the fund managers to realize excess returns. This leads to poorer fund performance. This partially confirms the theoretical conclusions of Chen and Knez (1996) who advocate that the performance results can change in either direction in the presence of conditioning information, due to an infinity of admissible (un)conditional stochastic discount factors.

7.4 Performance and Relative Risk Aversion

We also test the sensitivity of the performance measures to changes in the level of the relative risk aversion of the uninformed investor using the twelve equally-weighted and value-weighted portfolios of funds under the (un)conditional specifications. We seek an answer to the question, how is the ability of fund managers to realize excess returns related to the changes in the risk preferences of uninformed investors? These preferences are important since they affect the construction of the benchmark model and are expected to impact performance. To this end, we estimate the unconditional and the two conditional measures for various levels of the relative risk aversion coefficient, and we examine potential patterns or associations between the two variables.

The results for the unconditional tests are reported in table 14. They suggest that the performance metrics are decreasing in the coefficient of relative risk aversion. The average performance for the equally-weighted portfolios of funds (panel A) is 0.088% with gamma equal to 3, 0.087% with gamma equal to 4, 0.085% with gamma equal to 5, and 0.083% with gamma equal to 7 when the TSE 300 index is used as the benchmark. However, this negative association is reversed for the two main portfolios, the aggressive growth and the growth portfolios using the equally weighted and the value weighted TSE indices. These patterns persist using the size-weighted portfolios of mutual funds (panel B). Overall, we may conclude that unconditional performance is sensitive to changes in the level of relative risk aversion, and this association depends on the selected benchmark. This could be explained by the correlation between the use of public and/or private information and the changes in the risk attitudes of the uninformed investor.

[Please insert table 14 about here.]

The results based on the conditional model with one instrumental variable (the dividend yield on the TSE 300 index) are presented in table 15 (panels A and B). They show, on average, a weak positive link between lambda and gamma. This is especially the case for the size-weighted growth portfolio. Its performance improves from 0.108% when gamma is equal to 3, to 0.116% when gamma is equal to 7, when the value-weighted TSE index is used as the benchmark. The only major exceptions are the equally-weighted and size-weighted aggressive growth portfolios. Their performances deteriorate, as the uninformed investor becomes more risk averse. It seems that a conditional framework with one instrumental variable impacts the nature of the relationship between fund performance and relative risk aversion, and has little effect on the aggressive growth style managers.

[Please insert table 15 about here.]

To test the robustness of this last conclusion, we use the extended conditional model with two instrumental variables. The results reported in table 16 are consistent for the aggressive growth portfolios showing a negative association. In contrast, the performance of the growth portfolios indicate weak sensitivity to changes in gamma. These two empirical observations suggest that there is a weak negative average link between conditional performance and relative risk aversion.

[Please insert table 16 about here.]

It is difficult to make unambiguous statements about the direction of the sensitivity of performance to changes in the relative risk aversion of the uninformed investor based on the results for all these models. However, the risk-adjusted performance of aggressive growth oriented managers is negatively related to changes in the risk preferences of uninformed investors.

8. Conclusion

In this paper we use the general asset-pricing framework (SDF representation) to derive a conditional asset-pricing kernel that is relevant for evaluating the performance of actively managed portfolios. Our approach takes into consideration the predictability of asset returns and accounts for conditioning information. Hence, three performance measures are constructed and are related respectively to the unconditional evaluation of fixed-weight strategies, unconditional evaluation of dynamic strategies, and conditional evaluation of dynamic strategies.

We develop the appropriate empirical framework to estimate and implement the proposed performance measures and their associated tests by using the GMM method. We assess the risk-adjusted performance of a sample of 95 Canadian equity mutual funds by applying the developed models. The results indicate that there is evidence of abnormal unconditional performance, and that on average the conditional performance is negative. Significant negative performance is found for the growth, growth/income, income, and specialty portfolios. The aggressive growth and the balanced portfolios exhibit positive but non-significant lambdas.

The tests of the sensitivity of the performance measures to changes in the relative risk aversion of the uninformed investor reveal a weak link between the two variables. Aggressive growth managers are exceptions, and their risk-adjusted performance deteriorates, as the uninformed investor becomes more risk averse.

Our approach may be extended and improved in two ways. The first way is to examine potential relationships between the performance measures and some business cycle indicators or variables. This may differentiate and improve the active portfolio management process during periods of expansions and recessions. Second, at an econometric level, the (unfeasible) full efficient conditional GMM estimation, which is based on general interactions between functions of conditioning variables and pricing errors, can be conducted (feasible) using nonparametric estimates for the optimal set of instruments as suggested in Newey (1993).

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Table1: Summary Statistics for the Mutual Funds

This table reports the summary statistics for the mutual fund returns using monthly data from November 1989 to December 1999, a total of 122 observations. Panel A provides the statistics on the distribution of the mean, standard deviation, minimum, maximum, skewness, and kurtosis for the sample of 95 equity mutual funds. Panel B gives the number of funds per category, the average and the standard deviation of returns for the equally-weighted portfolios of funds grouped by investment objective.

Panel A: Individual Mutual Funds

Statistics	Mean Return	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis
Mean	0.008	0.041	-0.180	0.123	-0.695	4.105
Std. Dev.	0.003	0.010	0.034	0.059	0.603	1.884
Minimum	-0.003	0.017	-0.238	0.060	-1.562	0.305
1%	-0.001	0.026	-0.232	0.062	-1.514	0.356
2.5%	0.001	0.028	-0.227	0.065	-1.476	0.967
5%	0.004	0.032	-0.218	0.072	-1.401	1.298
10%	0.006	0.033	-0.208	0.078	-1.231	1.714
25%	0.007	0.037	-0.200	0.091	-1.048	2.900
Median	0.008	0.040	-0.188	0.109	-0.870	4.192
75%	0.009	0.042	-0.167	0.130	-0.518	5.089
90%	0.011	0.049	-0.146	0.158	0.097	6.014
95%	0.014	0.057	-0.115	0.267	0.462	7.225
97.5%	0.014	0.067	-0.084	0.314	0.732	8.308
99%	0.015	0.077	-0.051	0.370	1.350	9.675
Maximum	0.015	0.090	-0.046	0.393	2.054	10.434

Panel B: Investment Objective Portfolios

Objective	N	Mean Return	Std. Dev.
Aggressive Growth	27	0.008	0.039
Growth	50	0.008	0.036
Growth and Income	12	0.008	0.033
Income	3	0.008	0.034
Balanced	1	0.006	0.034
Specialty	2	0.009	0.032

Table 2: Summary Statistics for the Instrumental Variables

This table reports the summary statistics for the monthly returns of the instrumental variables. TSEEWX is the equally-weighted TSE index return less the 1-month Treasury bill rate. TSEVWX is the value-weighted TSE index return less the 1-month Treasury bill rate. TSE300X is the TSE 300 index return less the 1-month Treasury bill rate. DY is the dividend yield on the TSE 300 index. TERM is the yield spread between the long-term government of Canada bonds and the one period lagged 3-month Treasury bill rate (percentage points per month). RISK represents the yield spread between the long-term corporate bond (McLeod, Young, Weir bond index) and the long-term government of Canada bond (percentage points per month). TB1 is the 1-month Treasury bill rate (percentage points per month). TB3 is the 3-month Treasury bill rate (percentage points per month). Panel A provides information on the mean, median, standard deviation, minimum, maximum, skewness, kurtosis, and autocorrelation coefficients of order 1, 3, 6, and 12. Panel B presents the correlation matrix. The data cover the period from November 1989 to December 1999, for a total of 122 observations.

Panel A: Descriptive Statistics and Autocorrelations

Portfolios	Mean	Median	Std. Dev.	Min.	Max.	Skew.	Kurt.	ρ_1	ρ_3	ρ_6	ρ_{12}
TSEEWX	0.013	0.010	0.063	-0.215	0.367	1.110	10.849	0.203	0.119	0.058	-0.115
TSEVWX	0.011	0.011	0.041	-0.192	0.0411	-0.787	6.686	0.063	0.026	0.043	-0.037
TSE300X	0.004	0.007	0.042	-0.205	0.116	-0.889	6.826	0.066	0.006	0.050	-0.122
DY	0.204	0.191	0.062	0.109	0.338	0.385	1.952	0.976	0.928	0.856	0.682
TERM	0.130	0.138	0.001	-0.245	0.148	-0.743	2.942	0.920	0.793	0.630	0.244
RISK	0.072	0.0733	0.000	0.038	0.103	-0.163	1.839	0.948	0.837	0.721	0.619
TB1	0.514	0.415	0.002	0.212	1.143	1.161	3.449	0.966	0.883	0.747	0.438
TB3	0.528	0.441	0.002	0.228	1.138	1.171	3.510	0.963	0.882	0.738	0.420

Panel B: Correlation Matrix

Variables	TSEEWX	TSEVWX	TSE300X	DY	TERM	RISK	TB1	TB3
TSEEWX	1.000	0.720	0.702	-0.100	0.116	0.068	-0.181	-0.195
TSEVWX		1.000	0.991	-0.276	0.122	-0.054	-0.254	-0.266
TSE300X			1.000	-0.245	0.113	-0.033	-0.233	-0.245
DY				1.000	-0.493	0.666	0.841	0.833
TERM					1.000	-0.447	-0.825	-0.810
RISK						1.000	0.557	0.540
TB1							1.000	0.996
TB3								1.000

Table 3: Mutual Fund Excess Return Predictability

This table reports statistics on the mutual fund return predictability based on time series predictive regressions of two groups of portfolios of mutual fund excess returns on five lagged instrumental variables (dividend yield, risk premium, slope of the term structure, one-month Treasury bill rate, and dummy variable for January). The first group includes six equally-weighted portfolios of funds constructed using individual fund returns within each investment objective (EWAG, EWG, EWGI, EWI, EWBL, and EWSP). The second group is composed of six size-weighted portfolios of funds constructed using the individual fund returns and the corresponding total net asset values within each investment objective (SWAG, SWG, SWGI, SWI, SWBL, and SWSP). The estimation is conducted using the GMM method. The χ^2 column presents the Newey and West (1987b) tests of the hypothesis that all the slope coefficients are zeros. The next column includes the corresponding p-value. The data cover the period from November 1989 to December 1999, for a total of 122 observations.

Fund Portfolio	Number of Funds	χ^2	p-value
EWAG	27	15.343	0.009
EWG	50	16.467	0.006
EWGI	12	17.531	0.004
EWI	3	14.633	0.012
EWBL	1	26.828	0.000
EWSP	2	19.726	0.001
SWAG	27	15.268	0.009
SWG	50	16.250	0.006
SWGI	12	16.978	0.005
SWI	3	13.018	0.023
SWBL	1	26.828	0.000
SWSP	2	26.410	0.000

Table 4: Summary Statistics for the Passive Portfolios

This table reports the summary statistics for the monthly returns of the size-sorted portfolios using all TSE stocks. Ten size-sorted stock portfolios are formed according to size deciles on the basis of the market value of equity outstanding at the end of the previous year. The securities with the smallest capitalizations are placed in P1. Panel A provides information on the mean, median, standard deviation, minimum, maximum, skewness, kurtosis, and autocorrelation coefficients of order 1, 3, 6, and 12. Panel B presents the correlation matrix. The data cover the period from November 1989 to December 1999, for a total of 122 observations.

Panel A: Descriptive Statistics and Autocorrelations

Portfolios	Mean	Median	Std. Dev.	Min.	Max.	Skew.	Kurt.	ρ_1	ρ_3	ρ_6	ρ_{12}
P1	0.049	0.033	0.115	-0.181	0.705	1.767	10.756	0.228	0.070	-0.103	0.111
P2	0.014	0.012	0.076	-0.258	0.297	0.158	4.825	0.222	0.079	-0.070	-0.018
P3	0.008	0.007	0.065	-0.207	0.181	0.021	3.723	0.236	0.141	0.038	-0.018
P4	0.008	0.008	0.064	-0.250	0.263	0.161	6.373	0.225	0.070	-0.062	0.042
P5	0.005	0.008	0.065	-0.230	0.396	1.164	14.139	0.111	-0.037	-0.087	-0.032
P6	0.001	0.006	0.055	-0.271	0.142	-1.033	7.022	0.136	0.118	0.059	-0.087
P7	0.001	0.002	0.046	-0.216	0.103	-0.899	6.101	0.062	0.054	-0.008	-0.088
P8	0.004	0.004	0.044	-0.200	0.114	-0.940	6.222	0.109	0.052	0.026	-0.166
P9	0.004	0.003	0.044	-0.181	0.106	-0.629	4.822	0.063	0.036	0.023	-0.129
P10	0.009	0.009	0.040	-0.190	0.085	-1.009	6.604	-0.036	-0.018	0.048	-0.067

Panel B: Correlation Matrix

Portfolios	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
P1	1.000	0.670	0.655	0.627	0.595	0.655	0.555	0.455	0.458	0.398
P2		1.000	0.892	0.867	0.681	0.843	0.784	0.708	0.675	0.593
P3			1.000	0.830	0.670	0.837	0.780	0.718	0.692	0.622
P4				1.000	0.652	0.837	0.799	0.732	0.698	0.634
P5					1.000	0.752	0.743	0.675	0.697	0.652
P6						1.000	0.900	0.874	0.825	0.774
P7							1.000	0.886	0.884	0.811
P8								1.000	0.925	0.840
P9									1.000	0.883
P10										1.000

Table 5: Portfolios of Funds Performance Measures using the Unconditional Pricing Kernel (GMM Estimation)

This table reports the performance measures per investment objective using the unconditional pricing kernel for the three selected benchmarks. Simultaneous system estimation, including the ten size-based passive strategies, is conducted using the GMM method. Panel A (B) provides information on the performance of six equally (size)-weighted portfolios of mutual funds. The twelve portfolios of funds are: The aggressive growth portfolio is an equally (size)-weighted portfolio of 27 funds, the growth portfolio is an equally (size)-weighted portfolio of 50 funds, the growth/income portfolio is an equally (size)-weighted portfolio of 12 funds, the income portfolio is an equally (size)-weighted portfolio of 3 funds, the balanced portfolio represents the only balanced fund, and the specialty portfolio is an equally (size)-weighted portfolio of 2 funds. All represents the average of all the statistics of each of the six portfolios. Information related to the estimated performance, the t-statistics, the p-values, and the J-statistic (using the Bartlett kernel) is provided in the table. Size is defined as the total net asset value of the fund. TSE 300 is the TSE 300 index, TSEEW is the equally-weighted TSE index, and TSEVW is the value-weighted TSE index. The J-Statistic is the minimized value of the sample quadratic form constructed using the moment conditions and the optimal weighting matrix. Monthly data is used from November 1989 to December 1999, a total of 122 observations per portfolio of funds.

Panel A: Equally-Weighted Portfolios of Mutual Funds

Benchmark Variable		**TSE 300**			**TSEEW**			**TSEVW**	
Fund Group	Lambda	t(Lambda)	p-value	Lambda	t(Lambda)	p-value	Lambda	t(Lambda)	p-value
Aggressive Growth	0.0019	2.504	0.012	0.0023	2.803	0.005	0.0018	2.410	0.016
Growth	0.0021	3.272	0.001	0.0027	3.722	0.000	0.0021	3.257	0.001
Growth/Income	0.0027	3.604	0.000	0.0025	3.238	0.001	0.0026	3.556	0.000
Income	0.0015	1.603	0.109	0.0012	1.279	0.201	0.0014	1.540	0.124
Balanced	-0.0008	-0.477	0.633	-0.0042	-2.514	0.012	-0.0010	-0.582	0.561
Specialty	-0.0022	-1.229	0.219	-0.0044	-2.610	0.009	-0.0024	-1.329	0.184
All	0.0009	1.546	0.163	0.0000	0.986	0.038	0.0008	1.475	0.148
J-Statistic	0.1506			0.1505			0.1505		

Panel B: Size-Weighted Portfolios of Mutual Funds

Benchmark Variable		**TSE 300**			**TSEEW**			**TSEVW**	
Fund Group	Lambda	t(Lambda)	p-value	Lambda	t(Lambda)	p-value	Lambda	t(Lambda)	p-value
Aggressive Growth	0.0026	3.223	0.001	0.0030	3.492	0.001	0.0025	3.145	0.002
Growth	0.0027	3.780	0.000	0.0030	3.933	0.000	0.0026	3.768	0.000
Growth/Income	0.0019	2.750	0.006	0.0018	2.395	0.017	0.0018	2.662	0.008
Income	0.0019	1.979	0.048	0.0018	1.785	0.074	0.0018	1.912	0.056
Balanced	-0.0008	-0.477	0.633	-0.0042	-2.514	0.012	-0.0010	-0.582	0.561
Specialty	0.0000	0.019	0.985	-0.0010	-0.911	0.362	-0.0001	-0.056	0.955
All	0.0014	1.879	0.279	0.0007	1.363	0.078	0.0013	1.808	0.264
J-Statistic	0.1506			0.1505			0.1505		

Table 6: Individual Fund Performance Measures using the Unconditional Pricing Kernel (GMM Estimation)

This table reports summary statistics of performance per investment objective based on individual fund performances using the unconditional pricing kernel, for the three benchmark variables. Simultaneous GMM system estimation is conducted using a subset of the individual funds in addition to the ten size-based passive strategies. Panel A (B) presents information on equally (size)-weighted portfolios of individual fund performances per investment objective. The constructed portfolios are: The aggressive growth portfolio is an equally (size)-weighted portfolio of the performances of 27 individual funds, the growth portfolio is an equally (size)-weighted portfolio of the performances of 50 individual funds, the growth/income portfolio ia an equally (size)-weighted portfolio of the performances of 12 individual funds, the income portfolio is an equally (size)-weighted portfolio of the performances of 3 individual funds, the balanced portfolio represents the performance of the only balanced fund, and the specialty portfolio is an equally (size)-weighted portfolio of the performances of 2 individual funds. All represents the equally (size)-weighted portfolio of the performance of all individual funds. Information related to the estimated performance (average, median, standard deviation, mean p-value, skewness, kurtosis) and the J-Statistic (using the Bartlett kernel) is provided in the table. The J-Statistic is the minimized value of the sample quadratic form constructed using the moment conditions and the optimal weighting matrix. Size is defined as the total net asset value of the fund. TSE 300 is the TSE 300 index, TSEEW is the equally-weighted TSE index, and TSEVW is the value-weighted TSE index. Monthly data is used from November 1989 to December 1999, a total of 122 observations per fund.

Panel A: Equally-Weighted Portfolios of Individual Mutual Fund Performances

Benchmark Variable		**TSE 300**						**TSEEW**						**TSEVW**					
Fund Group	**N**	Mean Lambda	Median Lambda	Stdev.	Mean p-val	Skew.	Kurt.	Mean Lambda	Median Lambda	Stdev.	Mean p-val	Skew.	Kurt.	Mean Lambda	Median Lambda	Stdev.	Mean p-val	Skew.	Kurt.
Aggressive Growth	27	0.0019	0.0017	0.004	0.263	-0.99	2.66	0.0023	0.0035	0.005	0.239	-1.79	6.35	0.0018	0.0018	0.004	0.258	-1.17	3.34
Growth	50	0.0021	0.0019	0.003	0.288	0.30	4.39	0.0027	0.0023	0.003	0.166	0.79	2.68	0.0021	0.0019	0.003	0.285	0.33	4.14
Growth/Income	12	0.0027	0.0020	0.005	0.204	1.31	4.38	0.0025	0.0031	0.006	0.036	-0.23	2.08	0.0026	0.0019	0.005	0.190	1.30	4.37
Income	3	0.0015	0.0004	0.002	0.509	1.73	na	0.0012	-0.0005	0.003	0.388	1.72	na	0.0014	0.0004	0.002	0.542	1.71	na
Balanced	1	-0.0008	-0.0008	na	0.633	na	na	-0.0042	-0.0042	na	0.012	na	na	-0.0010	-0.0010	na	0.563	na	na
Specialty	2	-0.0022	-0.0022	0.000	0.275	na	na	-0.0044	-0.0044	0.002	0.035	na	na	-0.0024	-0.0024	0.000	0.242	na	na
All	95	0.0020	0.0017	0.004	0.281	0.14	4.25	0.0023	0.0023	0.004	0.173	-0.90	5.17	0.0019	0.0018	0.004	0.275	0.00	4.62
Mean J-Stat		0.1506						0.1505						0.1505					

Panel B: Size-Weighted Portfolios of Individual Mutual Fund Performances

Benchmark Variable		**TSE 300**			**TSEEW**			**TSEVW**		
Fund Group	**N**	Mean Lambda	Mean t(Lambda)	Mean p-val	Mean Lambda	Mean t(Lambda)	Mean p-val	Mean Lambda	Mean t(Lambda)	Mean p-val
Aggressive Growth	27	0.0024	1.950	0.204	0.0030	2.220	0.218	0.0023	1.934	0.198
Growth	50	0.0025	2.284	0.218	0.0028	2.449	0.143	0.0024	2.279	0.213
Growth/Income	12	0.0019	1.273	0.292	0.0018	1.220	0.027	0.0018	1.230	0.268
Income	3	0.0019	1.479	0.426	0.0019	1.394	0.331	0.0018	1.421	0.450
Balanced	1	-0.0008	-0.478	0.633	-0.0042	-2.517	0.012	-0.0010	-0.579	0.563
Specialty	2	-0.0021	-1.337	0.212	-0.0039	-2.555	0.023	-0.0023	-1.433	0.183
All	95	0.0023	1.993	0.231	0.0026	2.123	0.154	0.0022	1.978	0.225
Mean J-Stat		0.1506			0.1505			0.1505		

Table 7: Summary Statistics for the Unconditional Pricing Kernel based Performance Estimates for the Six Fund Groups based on Individual Fund Performances

This table presents summary statistics for the unconditional performance measures per fund group and for all funds. Panel A presents these results using the TSE 300 index as the benchmark. Panel B presents these results using the equally-weighted TSE index as the benchmark. Panel C presents these results using the value-weighted TSE index as the benchmark. N is the number funds in each group. All the p-values are based on a GMM estimation using the Bartlett kernel. Information related to the funds with significant (5% level) performance and with positive significant performance is provided in the table. The Bonferroni p-values are the minimum and the maximum one-tailed p-values from the t-distribution across all of the funds and all of the fund groups, multiplied by the defined number of funds.

Panel A: TSE 300 Index

Fund Group	N	Max p	Min p	Percent of funds with p < 5%	Number of funds with lambda > 0 and p < 5%	Bonferroni p-value (Min. t)	Bonferroni p-value (Max. t)
Aggressive Growth	27	0.894	0.000	48.15%	11	0.245	0.000
Growth	50	0.980	0.000	42.00%	21	1.000	0.000
Growth/Income	12	0.984	0.000	41.67%	4	0.073	0.000
Income	3	0.812	0.000	33.33%	1	na	0.005
Balanced	1	0.633	0.633	0.00%	0	na	0.316
Specialty	2	0.437	0.114	0.00%	0	0.057	na
All	95	0.984	0.000	42.11%	37	0.577	0.000

Panel B: Equally-Weighted TSE Index

Fund Group	N	Max p	Min p	Percent of funds with p < 5%	Number of funds with lambda > 0 and p < 5%	Bonferroni p-value (Min. t)	Bonferroni p-value (Max. t)
Aggressive Growth	27	0.947	0.000	48.15%	12	0.012	0.000
Growth	50	0.971	0.000	46.00%	22	1.000	0.000
Growth/Income	12	0.283	0.000	83.33%	8	0.000	0.000
Income	3	0.740	0.000	33.33%	1	0.635	0.000
Balanced	1	0.012	0.012	100.00%	0	0.006	na
Specialty	2	0.065	0.004	50.00%	0	0.004	na
All	95	0.971	0.000	51.58%	43	0.001	0.000

Panel C: Equally-Weighted TSE Index

Fund Group	N	Max p	Min p	Percent of funds with p < 5%	Number of funds with lambda > 0 and p < 5%	Bonferroni p-value (Min. t)	Bonferroni p-value (Max. t)
Aggressive Growth	27	0.931	0.000	48.15%	11	0.237	0.000
Growth	50	0.948	0.000	42.00%	21	1.000	0.000
Growth/Income	12	0.866	0.000	50.00%	5	0.058	0.000
Income	3	0.824	0.000	33.33%	1	na	0.006
Balanced	1	0.563	0.563	0.00%	0	0.281	na
Specialty	2	0.392	0.092	0.00%	0	0.092	na
All	95	0.948	0.000	43.16%	38	0.458	0.000

Table 8: Portfolios of Funds Performance Measures using the Conditional Pricing Kernel One Instrumental Variable (DY) and GMM Estimation

This table reports the performance measures per investment objective using the conditional pricing kernel for the two selected benchmarks (TSE 300 and value-weighted TSE indexes). Only the dividend yield (DY) is used as a instrumental variable. Simultaneous system estimation, including the ten size-based passive strategies, is conducted using the GMM method. Panel A (B) provides information on the performance of six equally (size)-weighted portfolios of mutual funds. The twelve portfolios of funds are: The aggressive growth portfolio is an equally (size)-weighted portfolio of 27 funds, the growth portfolio is an equally (size)-weighted portfolio of 50 funds, the growth/income is an equally (size)-weighted portfolio of 12 funds, the income portfolio is an equally (size)-weighted portfolio of 3 funds, the balanced portfolio represents the only balanced fund, and the specialty portfolio is an equally (size)-weighted portfolio of 2 funds. All represents the average of all the statistics of the twelve portfolios. Information related to the estimated performance, the t-statistics, the p-values, and the J-statistic (using the Bartlett kernel) is provided in the table. The J-Statistic is the minimized value of the sample quadratic form constructed using the moment conditions and the optimal weighting matrix. Size is defined as the total net asset value of the fund. TSE 300 is the TSE 300 index and TSEVW is the value-weighted TSE index. Monthly data is used from November 1989 to December 1999, a total of 122 observations per portfolio of funds.

Panel A: Equally-Weighted Portfolios of Mutual Funds

Benchmark Variable	**TSE 300**				**TSEVW**			
Fund Group	Lambda	t(Lambda)	p-value	J-Stat	Lambda	t(Lambda)	p-value	J-Stat
Aggressive Growth	0.0031	5.669	0.000	0.1791	0.0028	5.182	0.000	0.1789
Growth	0.0010	2.264	0.024	0.1792	0.0009	2.056	0.040	0.1791
Growth/Income	0.0015	3.050	0.002	0.1794	0.0013	2.638	0.008	0.1793
Income	-0.0006	-0.938	0.348	0.1792	-0.0008	-1.139	0.255	0.1791
Balanced	-0.0002	-0.261	0.794	0.1797	-0.0001	-0.161	0.872	0.1797
Specialty	0.0004	0.322	0.748	0.1790	0.0002	0.139	0.889	0.1788
All	0.0009	1.684	0.319	0.1792	0.0007	1.453	0.344	0.1792

Panel B: Size-Weighted Portfolios of Mutual Funds

Benchmark Variable	**TSE 300**				**TSEVW**			
Fund Group	Lambda	t(Lambda)	p-value	J-Stat	Lambda	t(Lambda)	p-value	J-Stat
Aggressive Growth	0.0029	5.079	0.000	0.1793	0.0025	4.396	0.000	0.1791
Growth	0.0013	2.907	0.004	0.1792	0.0011	2.541	0.011	0.1791
Growth/Income	0.0000	0.067	0.947	0.1800	-0.0001	-0.261	0.794	0.1799
Income	-0.0004	-0.532	0.595	0.1791	-0.0005	-0.770	0.442	0.1790
Balanced	-0.0002	-0.261	0.794	0.1797	-0.0001	-0.162	0.872	0.1797
Specialty	0.0002	0.232	0.817	0.1789	-0.0001	-0.064	0.949	0.1788
All	0.0006	1.249	0.526	0.1794	0.0005	0.947	0.511	0.1793

Table 9: Individual Fund Performance Measures using the Conditional Pricing Kernel One Instrumental Variable (DY) and GMM Estimation

This table reports summary statistics of performance per investment objective based on individual fund performances, using the conditional pricing kernel, for the two selected benchmarks. Only the dividend yield (DY) is used as a instrumental variable. Simultaneous GMM system estimation is conducted using a subset of the individual funds (one to eight) and the ten size-based passive strategies. Panel A (B) presents equally (size)-weighted portfolios of individual fund performances per investment objective. The constructed twelve portfolios are: The aggressive growth portfolio is an equally (size)-weighted portfolio of the performances of 27 individual funds, the growth portfolio is an equally (size)-weighted portfolio of the performances of 50 individual funds, the growth/income portfolio is an equally (size)-weighted portfolio of the performances of 12 individual funds, the income portfolio is an equally (size)-weighted portfolio of the performances of 3 individual funds, the balanced portfolio represents the performance of the only balanced fund, and the specialty portfolio is an equally (size)-weighted portfolio of the performances of 2 individual funds. All represents the equally (size)-weighted portfolio of the performance of all individual funds. Information related to the estimated performance (average, median, standard deviation, mean p-value, skewness, and kurtosis) and the J-Statistic (using the Bartlett kernel) is provided in the table. The J-Statistic is the minimized value of the sample quadratic form constructed using the moment conditions and the optimal weighting matrix. Size is defined as the total net asset value of the fund. TSE 300 is the TSE 300 index and TSEVW is the value-weighted TSE index. Monthly data is used from November 1989 to December 1999, a total of 122 observations per fund.

Panel A: Equally-Weighted Portfolios of Individual Mutual Fund Performances

Benchmark Variable		TSE 300							TSEVW						
Fund Group	**N**	Mean Lambda	Median Lambda	Stdev.	Mean p-val	Skew.	Kurt.	Mean J-Stat	Mean Lambda	Median Lambda	Stdev.	Mean p-val	Skew.	Kurt.	Mean J-Stat
Aggressive Growth	27	0.0030	0.0022	0.003	0.152	0.81	0.91	0.1801	0.0027	0.0022	0.003	0.158	0.70	0.74	0.1808
Growth	50	0.0010	0.0009	0.003	0.224	-0.05	0.49	0.1798	0.0008	0.0009	0.003	0.210	-0.20	0.36	0.1792
Growth/Income	12	0.0017	0.0007	0.006	0.114	1.83	4.68	0.1797	0.0015	0.0007	0.006	0.118	1.75	4.48	0.1803
Income	3	-0.0009	-0.0009	0.002	0.266	0.15	na	0.1797	-0.0011	-0.0010	0.002	0.321	-0.09	na	0.1787
Balanced	1	-0.0002	-0.0002	na	0.796	na	na	0.1797	-0.0001	-0.0001	na	0.872	na	na	0.1797
Specialty	2	0.0019	0.0019	0.002	0.291	na	na	0.1808	0.0018	0.0018	0.002	0.390	na	na	0.1808
All	95	0.0016	0.0015	0.003	0.198	1.06	3.54	0.1799	0.0014	0.0015	0.003	0.198	0.95	3.30	0.1805

Panel B: Size-Weighted Portfolios of Individual Mutual Fund Performances

Benchmark Variable		TSE 300				TSEVW			
Fund Group	**N**	Mean Lambda	Mean t(Lambda)	Mean p-val	Mean J-Stat	Mean Lambda	Mean t(Lambda)	Mean p-val	Mean J-Stat
Aggressive Growth	27	0.0026	2.392	0.185	0.1799	0.0023	2.214	0.179	0.1804
Growth	50	0.0013	1.623	0.205	0.1796	0.0012	1.541	0.182	0.1788
Growth/Income	12	0.0002	-0.302	0.169	0.1797	0.0001	-0.444	0.175	0.1799
Income	3	-0.0006	-0.700	0.294	0.1795	-0.0008	-0.964	0.375	0.1776
Balanced	1	-0.0002	-0.258	0.796	0.1797	-0.0001	-0.161	0.872	0.1797
Specialty	2	0.0014	0.988	0.339	0.1812	0.0013	0.777	0.491	0.1814
All	95	0.0015	1.526	0.204	0.1797	0.0013	1.405	0.195	0.1799

Table 10: Summary Statistics for the Conditional Pricing Kernel based Performance Estimates for the Six Fund Groups based on Individual Fund Performances with One Instrumental Variable (DY)

This table presents summary statistics for the conditional performance measures per fund group and for all funds. The dividend yield (DY) is used as a instrumental variable. Panel A (B) presents the results using the TSE 300 index (value-weighted TSE index) as the benchmark. N is the number of individual funds within each group. All the p-values are based on a GMM estimation using the Bartlett kernel. Information related to the funds with significant (5% level) performance and with positive significant performance is provided in the table. The Bonferroni p-values are the minimum and the maximum one-tailed p-values from the t-distribution across all of the funds and all of the fund groups, multiplied by the defined number of funds.

Panel A: TSE 300 Index

Fund Group	N	Max p	Min p	Percent of funds with p < 5%	Number of funds with lambda > 0 and p < 5%	Bonferroni p-value (Min. t)	Bonferroni p-value (Max. t)
Aggressive Growth	27	0.938	0.000	62.96%	16	0.000	0.000
Growth	50	0.959	0.000	60.00%	22	0.000	0.000
Growth/Income	12	0.715	0.000	75.00%	6	0.000	0.000
Income	3	0.439	0.000	33.33%	0	0.001	0.537
Balanced	1	0.796	0.796	0.00%	0	0.398	na
Specialty	2	0.415	0.168	0.00%	0	na	0.168
All	95	0.959	0.000	60.00%	44	0.000	0.000

Panel B: Value-Weighted TSE Index

Fund Group	N	Max p	Min p	Percent of funds with p < 5%	Number of funds with lambda > 0 and p < 5%	Bonferroni p-value (Min. t)	Bonferroni p-value (Max. t)
Aggressive Growth	27	0.904	0.000	55.56%	14	0.000	0.000
Growth	50	0.912	0.000	62.00%	22	0.000	0.000
Growth/Income	12	0.655	0.000	83.33%	6	0.000	0.000
Income	3	0.574	0.000	33.33%	0	0.000	0.861
Balanced	1	0.872	0.872	0.00%	0	0.436	na
Specialty	2	0.648	0.133	0.00%	0	na	0.132
All	95	0.912	0.000	60.00%	42	0.000	0.000

Table 11: Portfolios of Funds Performance Measures using the Conditional Pricing Kernel Two Instrumental Variables (DY and TB1) and GMM Estimation

This table reports the performance measures per investment objective using the conditional pricing kernel for the two selected benchmarks (TSE 300 and TSE value-weighted indexes). The dividend yield (DY) and the yield on the one-month T-bill (TB1) are used as instrumental variables. Simultaneous system estimation, including the ten size-based passive strategies, is conducted using the GMM method. Panel A (B) provides information on the performance estimates of six equally (size)-weighted portfolios of mutual funds. The twelve portfolios of funds are: The aggressive growth portfolio is an equally (size)-weighted portfolio of 27 funds, the growth portfolio is an equally (size)-weighted portfolio of 50 funds, the growth/income portfolio is an equally (size)-weighted portfolio of 12 funds, the income portfolio is an equally (size)-weighted portfolio of 3 funds, the balanced portfolio represents the only balanced fund, and the specialty portfolio is an equally (size)-weighted portfolio of 2 funds. All represents the average of all the statistics of each of the six portfolios. Information related to the estimated performance, the t-statistics, the p-values, and the J-statistic (using the Bartlett kernel) is provided in the table. Wald corresponds to the p-value based on the Newey and West (1987b) Wald test of the marginal significance of the two conditioning variables. The J-Statistic is the minimized value of the sample quadratic form constructed using the moment conditions and the optimal weighting matrix. Size is defined as the total net asset value of the fund. TSE 300 is the TSE 300 index and TSEVW is the value-weighted TSE index. Monthly data is used from November 1989 to December 1999, a total of 122 observations per portfolio of funds.

Panel A: Equally-Weighted Portfolios of Mutual Funds

Benchmark Variable			**TSE 300**					**TSEVW**		
Fund Group	Lambda	t(Lambda)	p-value	Wald	J-Stat	Lambda	t(Lambda)	p-value	Wald	J-Stat
Aggressive Growth	0.0003	0.764	0.445	0.000	0.1826	0.0001	0.139	0.890	0.000	0.1811
Growth	-0.0009	-1.653	0.099	0.000	0.1818	-0.0007	-1.500	0.134	0.000	0.1797
Growth/Income	-0.0008	-1.435	0.152	0.000	0.1828	-0.0005	-0.959	0.338	0.000	0.1804
Income	-0.0024	-3.965	0.000	0.000	0.1827	-0.0021	-3.407	0.001	0.000	0.1801
Balanced	0.0018	2.306	0.021	0.000	0.1864	0.0008	0.951	0.342	0.000	0.1857
Specialty	-0.0053	-4.460	0.000	0.000	0.1897	-0.0044	-3.643	0.000	0.000	0.1896
All	-0.0012	-1.407	0.119	0.000	0.1843	-0.0012	-1.403	0.284	0.000	0.1828

Panel B: Size-Weighted Portfolios of Mutual Funds

Benchmark Variable			**TSE 300**					**TSEVW**		
Fund Group	Lambda	t(Lambda)	p-value	Wald	J-Stat	Lambda	t(Lambda)	p-value	Wald	J-Stat
Aggressive Growth	0.0011	2.672	0.008	0.000	0.1829	0.0008	1.994	0.046	0.000	0.1814
Growth	-0.0005	-0.987	0.324	0.000	0.1819	-0.0002	-0.495	0.621	0.000	0.1804
Growth/Income	-0.0010	-1.580	0.114	0.000	0.1826	-0.0008	-1.420	0.156	0.000	0.1804
Income	-0.0028	-4.415	0.000	0.000	0.1824	-0.0025	-3.968	0.000	0.000	0.1798
Balanced	0.0018	2.306	0.021	0.000	0.1864	0.0008	0.951	0.342	0.000	0.1857
Specialty	-0.0060	-7.442	0.000	0.000	0.1880	-0.0059	-7.386	0.000	0.000	0.1871
All	-0.0012	-1.574	0.078	0.000	0.1840	-0.0013	-1.721	0.194	0.000	0.1825

Table 12: Individual Fund Performance Measures using the Conditional Pricing Kernel Two Instrumental Variables (DY and TB1) and GMM Estimation

This table reports summary statistics of performance per investment objective based on individual fund performances, using the conditional pricing kernel, for the two selected benchmarks. The dividend yield (DY) and the yield on the one-month T-bill (TB1) are used as instrumental variables. Simultaneous GMM system estimation is conducted using a subset of the individual funds (one to eight) and the ten size-based passive strategies. Panel A (B) presents equally (size)-weighted portfolios of individual fund performances per investment objective. The constructed twelve portfolios are: The aggressive growth portfolio is an equally (size)-weighted portfolio of the performances of 27 individual funds, the growth portfolio is an equally (size)-weighted portfolio of the performances of 50 individual funds, the growth/income portfolio is an equally (size)-weighted portfolio of the performances of 12 individual funds, the income portfolio is an equally (size)-weighted portfolio of the performances of 3 individual funds, the balanced portfolio represents the performance of the only balanced fund, and the specialty portfolio is an equally (size)-weighted portfolio of the performances of 2 individual funds. All represents the equally (size)-weighted portfolio of the performance of all individual funds. Information related to the estimated performance (average, median, standard deviation, mean p-value, skewness, and kurtosis) and the J-Statistic (using the Bartlett kernel) is provided in the table. Wald corresponds to the p-value based on the Newey and West (1987b) Wald test of the marginal significance of the two conditioning variables. The J-Statistic is the minimized value of the sample quadratic form constructed using the moment conditions and the optimal weighting matrix. Size is defined as the total net asset value of the fund. TSE 300 is the TSE 300 index and TSEVW is the value-weighted TSE index. Monthly data is used from November 1989 to December 1999, a total of 122 observations per fund.

Panel A: Equally-Weighted Portfolios of Individual Mutual Fund Performances

Benchmark Variable		TSE 300								TSEVW							
Fund Group	**N**	Mean Lambda	Median Lambda	Stdev.	Mean p-val	Skew.	Kurt.	Mean Wald	Mean J-Stat	Mean Lambda	Median Lambda	Stdev.	Mean p-val	Skew.	Kurt.	Mean Wald	Mean J-Stat
Aggressive Growth	27	0.0011	0.0009	0.004	0.165	-0.04	0.42	0.000	0.1852	0.0009	0.0005	0.004	0.179	-0.17	0.77	0.000	0.1838
Growth	50	-0.0010	-0.0012	0.002	0.170	0.90	1.80	0.000	0.1844	-0.0009	-0.0011	0.002	0.171	0.80	1.75	0.000	0.1828
Growth/Income	12	-0.0010	-0.0016	0.004	0.201	2.40	7.50	0.000	0.1850	-0.0009	-0.0016	0.004	0.168	2.61	8.29	0.000	0.1830
Income	3	-0.0034	-0.0034	0.003	0.134	0.14	na	0.000	0.1847	-0.0032	-0.0037	0.003	0.315	0.81	na	0.000	0.1835
Balanced	1	0.0018	0.0018	na	0.021	na	na	0.000	0.1864	0.0008	0.0008	na	0.342	na	na	0.000	0.1857
Specialty	2	-0.0029	-0.0029	0.000	0.069	na	na	0.000	0.1885	-0.0022	-0.0022	0.001	0.250	na	na	0.000	0.1873
All	95	-0.0005	-0.0007	0.003	0.168	1.02	2.08	0.000	0.1848	-0.0005	-0.0009	0.003	0.181	0.99	2.65	0.000	0.1833

Panel B: Size-Weighted Portfolios of Individual Mutual Fund Performances

Benchmark Variable		TSE 300					TSEVW				
Fund Group	**N**	Mean Lambda	Mean t(Lambda)	Mean p-val	Mean Wald	Mean J-Stat	Mean Lambda	Mean t(Lambda)	Mean p-val	Mean Wald	Mean J-Stat
Aggressive Growth	27	0.0014	1.392	0.154	0.000	0.1855	0.0012	1.170	0.148	0.000	0.1840
Growth	50	-0.0006	-0.147	0.149	0.000	0.1847	-0.0005	-0.222	0.143	0.000	0.1831
Growth/Income	12	-0.0012	-1.529	0.258	0.000	0.1844	-0.0012	-1.520	0.210	0.000	0.1824
Income	3	-0.0037	-4.490	0.122	0.000	0.1845	-0.0035	-4.531	0.287	0.000	0.1834
Balanced	1	0.0018	2.317	0.021	0.000	0.1864	0.0008	0.951	0.342	0.000	0.1857
Specialty	2	-0.0028	-3.306	0.042	0.000	0.1879	-0.0025	-3.247	0.153	0.000	0.1865
All	95	-0.0002	-0.042	0.159	0.000	0.1849	-0.0002	-0.153	0.158	0.000	0.1833

Table 13: Summary Statistics for the Conditional Pricing Kernel based Performance Estimates for the Six Fund Groups based on Individual Fund Performances with Two Instrumental Variables (DY and TB1)

This table presents summary statistics for the conditional performance measures per fund group and for all funds. The dividend yield (DY) and the yield on the one-month T-bill (TB1) are used as instrumental variables. Panel A (B) presents the results using the TSE 300 index (value-weighted TSE index) as the benchmark. N is the number of individual funds within each group. All the p-values are based on a GMM estimation using the Bartlett kernel. Information related to the funds with significant (5% level) performance and with positive significant performance is provided in the table. The Bonferroni p-values are the minimum and the maximum one-tailed p-values from the t-distribution across all of the funds and all of the fund groups, multiplied by the defined number of funds.

Panel A: TSE 300 Index

Fund Group	N	Max p	Min p	Percent of funds with p < 5%	Number of funds with lambda > 0 and p < 5%	Bonferroni p-value (Min. t)	Bonferroni p-value (Max. t)
Aggressive Growth	27	0.858	0.000	55.56%	11	0.000	0.000
Growth	50	0.971	0.000	58.00%	8	0.000	0.000
Growth/Income	12	0.978	0.000	66.67%	1	0.000	0.000
Income	3	0.402	0.000	66.67%	0	0.000	0.603
Balanced	1	0.021	0.021	100.00%	1	na	0.010
Specialty	2	0.138	0.000	50.00%	0	0.000	na
All	95	0.978	0.000	58.95%	21	0.000	0.000

Panel B: Value-Weighted TSE Index

Fund Group	N	Max p	Min p	Percent of funds with p < 5%	Number of funds with lambda > 0 and p < 5%	Bonferroni p-value (Min. t)	Bonferroni p-value (Max. t)
Aggressive Growth	27	0.869	0.000	48.15%	8	0.000	0.000
Growth	50	0.934	0.000	58.00%	7	0.000	0.000
Growth/Income	12	0.787	0.000	58.33%	1	0.000	0.000
Income	3	0.944	0.000	66.67%	0	0.000	na
Balanced	1	0.342	0.342	0.00%	0	na	0.829
Specialty	2	0.500	0.000	50.00%	0	0.000	na
All	95	0.944	0.000	54.74%	16	0.000	0.000

Table 14: Unconditional Performance and Relative Risk Aversion

This table reports the performance measures per investment objective for various levels of the relative risk aversion (RRA) coefficient (Gamma) using the unconditional pricing kernel for the three selected benchmarks. Simultaneous system estimation, including the ten size-based passive strategies, is conducted using the GMM method. Panel A (B) provides information on the performance estimates of six equally (size)-weighted portfolios of mutual funds. The twelve portfolios of funds are: The aggressive growth portfolio is an equally (size)-weighted portfolio of 27 funds, the growth portfolio is an equally (size)-weighted portfolio of 50 funds, the growth/income portfolio is an equally (size)-weighted portfolio of 12 funds, the income portfolio is an equally (size)-weighted portfolio of 3 funds, the balanced portfolio represents the only balanced fund, and the specialty portfolio is an equally (size)-weighted portfolio of 2 funds. All represents the average of all the statistics of the six portfolios. Information related to the estimated performance, the p-values, and the J-statistic (using the Bartlett kernel) is provided in the table. TSE 300 is the TSE 300 index, TSEEW is the equally-weighted TSE index, and TSEVW is the value-weighted TSE index. The J-Statistic is the minimized value of the sample quadratic form constructed using the moment conditions and the optimal weighting matrix. Monthly data is used from November 1989 to December 1999, a total of 122 observations per portfolio of funds.

Panel A: Equally-Weighted Portfolios of Mutual Funds

Benchmark Variable	**TSE 300**								**TSEEW**								**TSEVW**							
RRA Coefficient (Gamma)	**3**		**4**		**5**		**7**		**3**		**4**		**5**		**7**		**3**		**4**		**5**		**7**	
Fund Group	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val
Aggressive Growth	0.00190	0.01	0.00188	0.01	0.00187	0.01	0.00184	0.01	0.00223	0.01	0.00227	0.01	0.00230	0.00	0.00232	0.00	0.00223	0.01	0.00227	0.01	0.00230	0.00	0.00232	0.00
Growth	0.00216	0.00	0.00214	0.00	0.00212	0.00	0.00210	0.00	0.00261	0.00	0.00265	0.00	0.00268	0.00	0.00269	0.00	0.00261	0.00	0.00265	0.00	0.00268	0.00	0.00269	0.00
Growth/Income	0.00270	0.00	0.00268	0.00	0.00265	0.00	0.00261	0.00	0.00259	0.00	0.00253	0.00	0.00248	0.00	0.00240	0.00	0.00259	0.00	0.00253	0.00	0.00248	0.00	0.00240	0.00
Income	0.00153	0.11	0.00151	0.11	0.00149	0.11	0.00145	0.12	0.00130	0.19	0.00124	0.20	0.00120	0.22	0.00113	0.24	0.00130	0.19	0.00124	0.20	0.00120	0.22	0.00113	0.24
Balanced	-0.00078	0.64	-0.00079	0.63	-0.00080	0.63	-0.00081	0.62	-0.00377	0.02	-0.00423	0.01	-0.00455	0.01	-0.00495	0.00	-0.00377	0.02	-0.00423	0.01	-0.00455	0.01	-0.00495	0.00
Specialty	-0.00224	0.22	-0.00223	0.22	-0.00222	0.22	-0.00219	0.22	-0.00415	0.01	-0.00436	0.01	-0.00447	0.01	-0.00456	0.01	-0.00415	0.01	-0.00436	0.01	-0.00447	0.01	-0.00456	0.01
All	0.00088	0.16	0.00087	0.16	0.00085	0.16	0.00083	0.16	0.00013	0.04	0.00002	0.04	-0.00006	0.04	-0.00016	0.04	0.00013	0.04	0.00002	0.04	-0.00006	0.04	-0.00016	0.04
J-Statistic	0.1506		0.1506		0.1505		0.1505		0.1512		0.1505		0.1500		0.1490		0.1512		0.1505		0.1500		0.1490	

Panel B: Size-Weighted Portfolios of Mutual Funds

Benchmark Variable	**TSE 300**								**TSEEW**								**TSEVW**							
RRA Coefficient (Gamma)	**3**		**4**		**5**		**7**		**3**		**4**		**5**		**7**		**3**		**4**		**5**		**7**	
Fund Group	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val
Aggressive Growth	0.00259	0.00	0.00257	0.00	0.00254	0.00	0.00251	0.00	0.00293	0.00	0.00297	0.00	0.00299	0.00	0.00301	0.00	0.00293	0.00	0.00297	0.00	0.00299	0.00	0.00301	0.00
Growth	0.00273	0.00	0.00270	0.00	0.00267	0.00	0.00263	0.00	0.00300	0.00	0.00301	0.00	0.00300	0.00	0.00298	0.00	0.00300	0.00	0.00301	0.00	0.00300	0.00	0.00298	0.00
Growth/Income	0.00195	0.01	0.00192	0.01	0.00190	0.01	0.00186	0.01	0.00180	0.01	0.00175	0.02	0.00171	0.02	0.00165	0.02	0.00180	0.01	0.00175	0.02	0.00171	0.02	0.00165	0.02
Income	0.00193	0.05	0.00190	0.05	0.00187	0.05	0.00184	0.05	0.00183	0.07	0.00178	0.07	0.00175	0.08	0.00168	0.09	0.00183	0.07	0.00178	0.07	0.00175	0.08	0.00168	0.09
Balanced	-0.00078	0.64	-0.00079	0.63	-0.00080	0.63	-0.00081	0.62	-0.00377	0.02	-0.00423	0.01	-0.00455	0.01	-0.00495	0.00	-0.00377	0.02	-0.00423	0.01	-0.00455	0.01	-0.00495	0.00
Specialty	0.00003	0.98	0.00002	0.99	0.00002	0.99	0.00002	0.99	-0.00094	0.42	-0.00103	0.36	-0.00107	0.34	-0.00109	0.31	-0.00094	0.42	-0.00103	0.36	-0.00107	0.34	-0.00109	0.31
All	0.00141	0.28	0.00139	0.28	0.00137	0.28	0.00134	0.28	0.00081	0.09	0.00071	0.08	0.00064	0.07	0.00055	0.07	0.00081	0.09	0.00071	0.08	0.00064	0.07	0.00055	0.07
J-Statistic	0.1506		0.1506		0.1505		0.1505		0.1512		0.1505		0.1500		0.1490		0.1512		0.1505		0.1500		0.1490	

Table 15: Conditional Performance (One Instrumental Variable DY) and Relative Risk Aversion

This table reports the performance measures per investment objective for various levels of the relative risk aversion coefficient (Gamma) using the conditional pricing kernel with the dividend yield (DY) as a instrumental variable and for the two selected benchmarks. Simultaneous system estimation, including the ten size-based passive strategies, is conducted using the GMM method. Panel A (B) presents information on the performance of six equally (size)-weighted portfolios of mutual funds. The twelve portfolios of funds are: The aggressive growth portfolio is an equally (size)-weighted portfolio of 27 funds, the growth portfolio is an equally (size)-weighted portfolio of 50 funds, the growth/income portfolio is an equally (size)-weighted portfolio of 12 funds, the income portfolio is an equally (size)-weighted portfolio of 3 funds, the balanced portfolio represents the only balanced fund, and the specialty portfolio is an equally (size)-weighted portfolio of 2 funds. All represents the average of all the statistics of the six portfolios. Information related to the estimated performance, the p-values, and the J-statistic (using the Bartlett kernel) is provided in the table. TSE 300 is the TSE 300 index and TSEVW is the value-weighted TSE index. The J-Statistic is the minimized value of the sample quadratic form constructed using the moment conditions and the optimal weighting matrix. Monthly data is used from November 1989 to December 1999, a total of 122 observations per portfolio of funds.

Panel A: Equally-Weighted Portfolios of Mutual Funds

Benchmark Variable	**TSE 300**								**TSEVW**							
RRA Coefficient (Gamma)	**3**		**4**		**5**		**7**		**3**		**4**		**5**		**7**	
Fund Group	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val
Aggressive Growth	0.00326	0.00	0.00308	0.00	0.00305	0.00	0.00306	0.00	0.00273	0.00	0.00279	0.00	0.00270	0.00	0.00269	0.00
Growth	0.00111	0.01	0.00101	0.02	0.00106	0.02	0.00111	0.01	0.00094	0.04	0.00092	0.04	0.00091	0.04	0.00095	0.03
Growth/Income	0.00146	0.00	0.00148	0.00	0.00149	0.00	0.00148	0.00	0.00128	0.01	0.00129	0.01	0.00129	0.01	0.00129	0.01
Income	-0.00073	0.30	-0.00065	0.35	-0.00059	0.39	-0.00053	0.43	-0.00087	0.21	-0.00078	0.26	-0.00071	0.29	-0.00063	0.34
Balanced	-0.00025	0.76	-0.00021	0.79	-0.00034	0.67	-0.00020	0.80	-0.00034	0.67	-0.00013	0.87	-0.00001	0.99	0.00012	0.87
Specialty	0.00025	0.84	0.00040	0.75	0.00050	0.68	0.00062	0.61	0.00001	0.99	0.00017	0.89	0.00028	0.82	0.00042	0.72
All	0.00085	0.32	0.00085	0.32	0.00086	0.29	0.00092	0.31	0.00062	0.32	0.00071	0.34	0.00074	0.36	0.00081	0.33
J-Statistic	0.1794		0.1792		0.1791		0.1790		0.1794		0.1792		0.1790		0.1787	

Panel B: Size-Weighted Portfolios of Mutual Funds

Benchmark Variable	**TSE 300**								**TSEVW**							
RRA Coefficient (Gamma)	**3**		**4**		**5**		**7**		**3**		**4**		**5**		**7**	
Fund Group	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val
Aggressive Growth	0.00294	0.00	0.00289	0.00	0.00283	0.00	0.00269	0.00	0.00261	0.00	0.00251	0.00	0.00244	0.00	0.00232	0.00
Growth	0.00122	0.01	0.00129	0.00	0.00131	0.00	0.00132	0.00	0.00108	0.02	0.00113	0.01	0.00114	0.01	0.00116	0.01
Growth/Income	0.00000	0.99	0.00003	0.95	0.00006	0.91	0.00005	0.92	-0.00017	0.74	-0.00013	0.79	-0.00011	0.83	-0.00006	0.90
Income	-0.00044	0.54	-0.00037	0.59	-0.00033	0.63	-0.00028	0.68	-0.00060	0.39	-0.00053	0.44	-0.00048	0.48	-0.00042	0.53
Balanced	-0.00025	0.76	-0.00021	0.79	-0.00034	0.67	-0.00020	0.80	-0.00034	0.67	-0.00013	0.87	-0.00001	0.99	0.00012	0.87
Specialty	0.00015	0.88	0.00022	0.82	0.00027	0.77	0.00033	0.72	-0.00013	0.89	-0.00006	0.95	-0.00001	0.99	0.00007	0.94
All	0.00060	0.53	0.00064	0.53	0.00063	0.50	0.00065	0.52	0.00041	0.45	0.00047	0.51	0.00050	0.55	0.00053	0.54
J-Statistic	0.1795		0.1794		0.1793		0.1791		0.1795		0.1793		0.1791		0.1788	

Table 16: Conditional Performance (Two Instrumental Variables DY and TB1) and Relative Risk Aversion

This table reports the performance measures per investment objective for various levels of the relative risk aversion coefficient (Gamma) using the conditional pricing kernel with the dividend yield (DY) and the yield on the one-month T-bill (TB1) as instrumental variables and for the two selected benchmarks. Simultaneous system estimation, including the ten size-based passive strategies, is conducted using the GMM method. Panel A (B) presents information on the performance estimates of six equally (size)-weighted portfolios of mutual funds. The twelve portfolios of funds are: The aggressive growth portfolio is an equally (size)-weighted portfolio of 27 funds, the growth portfolio is an equally (size)-weighted portfolio of 50 funds, the growth/income portfolio is an equally (size)-weighted portfolio of 12 funds, the income portfolio is an equally (size)-weighted portfolio of 3 funds, the balanced portfolio represents the only balanced fund, and the specialty portfolio is an equally (size)-weighted portfolio of 2 funds. All represents the average of all the statistics of the six portfolios. Information related to the estimated performance, the p-values, and the J-statistic (using the Bartlett kernel) is provided in the table. The J-Statistic is the minimized value of the sample quadratic form constructed using the moment conditions and the optimal weighting matrix. TSE 300 is the TSE 300 index and TSEVW is the value-weighted TSE index. Monthly data is used from November 1989 to December 1999, a total of 122 observations per portfolio of funds.

Panel A: Equally-Weighted Portfolios of Mutual Funds

Benchmark Variable	**TSE 300**								**TSEVW**							
RRA Coefficient (Gamma)	**3**		**4**		**5**		**7**		**3**		**4**		**5**		**7**	
Fund Group	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val
Aggressive Growth	0.00040	0.31	0.00030	0.44	0.00022	0.56	0.00021	0.58	0.00012	0.76	0.00006	0.89	0.00002	0.95	0.00000	0.99
Growth	-0.00089	0.11	-0.00090	0.10	-0.00089	0.10	-0.00085	0.11	-0.00073	0.15	-0.00075	0.13	-0.00075	0.13	-0.00074	0.12
Growth/Income	-0.00079	0.17	-0.00082	0.15	-0.00082	0.15	-0.00080	0.15	-0.00049	0.37	-0.00052	0.34	-0.00053	0.32	-0.00054	0.31
Income	-0.00245	0.00	-0.00240	0.00	-0.00237	0.00	-0.00233	0.00	-0.00216	0.00	-0.00214	0.00	-0.00213	0.00	-0.00212	0.00
Balanced	0.00193	0.01	0.00178	0.02	0.00165	0.03	0.00148	0.05	0.00094	0.24	0.00077	0.34	0.00060	0.46	0.00040	0.62
Specialty	-0.00426	0.00	-0.00525	0.00	-0.00552	0.00	-0.00562	0.00	-0.00323	0.01	-0.00437	0.00	-0.00477	0.00	-0.00505	0.00
All	-0.00101	0.10	-0.00122	0.12	-0.00129	0.14	-0.00132	0.15	-0.00093	0.26	-0.00116	0.28	-0.00126	0.31	-0.00134	0.34
J-Statistic	0.1865		0.1843		0.1830		0.1815		0.1847		0.1828		0.1816		0.1802	

Panel B: Size-Weighted Portfolios of Mutual Funds

Benchmark Variable	**TSE 300**								**TSEVW**							
RRA Coefficient (Gamma)	**3**		**4**		**5**		**7**		**3**		**4**		**5**		**7**	
Fund Group	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val	Lambda	p-val
Aggressive Growth	0.00119	0.00	0.00110	0.01	0.00105	0.01	0.00100	0.01	0.00090	0.03	0.00082	0.05	0.00078	0.06	0.00074	0.07
Growth	-0.00054	0.32	-0.00053	0.32	-0.00051	0.34	-0.00046	0.38	-0.00023	0.64	-0.00024	0.62	-0.00024	0.61	-0.00023	0.62
Growth/Income	-0.00097	0.11	-0.00096	0.11	-0.00095	0.12	-0.00094	0.12	-0.00080	0.16	-0.00080	0.16	-0.00080	0.15	-0.00080	0.15
Income	-0.00287	0.00	-0.00281	0.00	-0.00278	0.00	-0.00272	0.00	-0.00257	0.00	-0.00255	0.00	-0.00253	0.00	-0.00250	0.00
Balanced	0.00193	0.01	0.00178	0.02	0.00165	0.03	0.00148	0.05	0.00094	0.24	0.00077	0.34	0.00060	0.46	0.00040	0.62
Specialty	-0.00585	0.00	-0.00602	0.00	-0.00603	0.00	-0.00596	0.00	-0.00567	0.00	-0.00588	0.00	-0.00592	0.00	-0.00590	0.00
All	-0.00118	0.07	-0.00124	0.08	-0.00126	0.08	-0.00127	0.09	-0.00124	0.18	-0.00131	0.19	-0.00135	0.21	-0.00138	0.24
J-Statistic	0.1861		0.1840		0.1828		0.1813		0.1843		0.1825		0.1813		0.1799	