PRICING KERNEL MEASURES OF CANADIAN FUND PERFORMANCE

Mohamed A. Ayadi

A Thesis

in

The John Molson School of Business

Presented in Partial Fulfillment of the Requirements
for the Degree of Doctor of Philosophy at
Concordia University
Montreal, Quebec, Canada

October 2003

0-612-85267-9

ABSTRACT

PRICING KERNEL MEASURES OF CANADIAN FUND PERFORMANCE

Mohamed A. Ayadi, Ph.D.
Concordia University, 2003

The dissertation consists of four essays that address several issues related to the performance of Canadian equity and fixed-income mutual funds.

In the first essay, a general asset pricing framework is used to derive a conditional asset pricing kernel that accounts efficiently for time variation in expected returns and risk, and is suitable to perform (un)conditional evaluations of passive and dynamic investment strategies. The abnormal unconditional performance of Canadian equity mutual funds over the period 1989-1999 becomes negative with conditioning. The performance statistics are weakly sensitive to changes in the level of relative risk aversion of the uninformed investor. The reversal in the size-based performance results with limited information conditioning is alleviated somewhat with an expansion of the conditioning set. Estimates of survivorship bias due to the elimination of funds with shorter lives, which range from 36 to 58 basis points per year, are stable across performance models but differ across groupings by fund objective.

In the second essay, we examine the sensitivity of various measures of portfolio performance using various return-based linear benchmark models in both their unconditional and conditional versions for a sample of Canadian equity mutual funds. In a departure from the current literature, performance inferences are based on tests that incorporate the contemporaneous cross-correlations across fund returns. The performance inferences are sensitive to the choice of the linear benchmark model. Conditioning has a more pronounced impact on absolute than on relative performance inferences. Risk-adjusted performance is related with the age and size of a fund and its management fees, and to a lesser extent with the fund's management expense ratio. These identified relationships suggest important differences and similarities between the

availability of scale economies and levels of competition in the Canadian versus the American and European mutual fund industries.

In the third essay, we use higher-order moment and nonlinear asset pricing kernel models to estimate the risk-adjusted performance of a sample of Canadian equity mutual funds. (Un)conditional frameworks are developed that are suitable to perform evaluations of fixed-weight and dynamic strategies. The results show that the weak unconditional performance becomes positive and significant with nonlinear and conditional kernel-based benchmarks. A restriction on the mean of the asset-pricing kernel not only affects the performance statistics and inferences but also reverses and mitigates the conditioning information-based size effect. The findings on the relationship between fund performance and fund characteristics suggest that risk-adjusted performance is related to the age and size of the fund and to a lesser extent to the fund load structure but is unrelated to management fees.

In the fourth essay, we presents new evidence on the performance of Canadian fixed-income funds using various linear single- and multi-factor benchmark models based on a sample of Canadian fixed-income mutual funds over the period, 1985-2000. Frameworks are developed that are suitable to perform evaluations of fixed-weight and dynamic strategies. The results show evidence of negative performance, which improves with partial conditioning. The performance measures are weakly sensitive to the return generating process. Tests that do not incorporate the contemporaneous cross-correlations in the returns among individual funds consistently alter and reverse the conditioning information-based performance inferences and the large fund effect. The stock market factor not only improves the performance statistics but also preserves the single factor-based superior performance of large funds. The findings on the relationship between fund performance and fund characteristics suggest that risk-adjusted performance is related with the fund age, management expense ratio, and load structure, and to a lesser extent with fund size and management fees. These identified relationships suggest important differences and similarities on the economics of the Canadian versus the American and European fixed-income mutual fund industries. Estimates of survivorship bias, which are less than 15 basis points per year, are stable across performance models but differ across fund objective groups.

Acknowledgements

No words can express my gratitude enough toward my supervisor, Dr. Lawrence Kryzanowski, for his guidance, encouragement, and support. He has read this thesis and its previous drafts uncountable times and has continuously provided invaluable suggestions to me. I would not have achieved what I have achieved now without his generous support and advice through all the years of my graduate studies at Concordia University.

I would like to thank the other members of my dissertation committee: Dr. Lorne Switzer and Dr. Simon Lalancette for their helpful suggestions. Both of them have provided valuable insights and encouragement in writing this thesis.

While attending Concordia University, I have been fortunate to be surrounded by its outstanding faculty and classmates. I have learned a lot from them about how to access various problems in finance and econometrics. I would like to thank Dr. James McIntosh, Dr. Pierre Perron, and Dr. Jerome Detemple. Also thanks to my colleagues, Hatem Ben-Ameur, Zhongzhe He, and Skander Lazrak, at Concordia University.

The support from my colleagues and especially the Dean of the Faculty of Business, Dr. Martin Kusy, at Brock University facilitated the completion of the dissertation process.

I would like to thank my parents for their love and support. They gave me a life and made me what I am. Also, they have always given me encouragement and done whatever they can.

Finally, I would like to thank my wife, Sonia, for her continuous love and emotional support over the past three years. Special dedication also to my daughter Emna, who has been with me at the end of the thesis process. Her smile always let me forget all the distress during some difficult periods.

TABLE OF CONTENTS

LIST OF TABLES

CHAPTER 1

INTRODUCTION

Portfolio management has become an increasingly important industry in Canada as well as in many countries across the world. Measuring and evaluating the performance of actively managed portfolios have received significant interest in the academic literature and practical world during the last thirty years. Four important issues of particular interest are first, the identification of the appropriate return generating process to adjust for risk and to estimate normal or passive benchmark performance. This issue is closely related to developments and advances in the asset pricing literature. Hence, most papers in the literature use classical asset pricing models such as the CAPM, the APT and multifactor models, the CCAPM, or the ICAPM to develop performance statistics and tests. The validity of these metrics is largely dependent on that of the underlying models. Alternative approaches stem from the general asset pricing framework or the stochastic discount factor representation of asset prices. This methodology requires weaker market conditions of either the law of one price or no arbitrage conditions. Of the few papers that use this flexible framework, most of them apply existing asset pricing kernels that are not adapted to performance evaluation where negative realizations are possible.

Second, there is a growing body of research examining the role of conditioning information in the construction of the performance statistics and tests, and on the impact of information conditioning on performance inferences. Classical measures of investment performance are unreliable since they are unconditional. They confuse the inherent time-variation in the expected returns and risks of funds with the possibility of superior abilities of portfolio managers. A conditional performance evaluation asserts that any managed portfolio strategy that can be replicated using publicly available information should not be deemed to be superior performance. Only managers who correctly and efficiently use private information have superior abilities. This conditional approach is suitable to accommodate the complex portfolio and individual assets dynamics, and is consistent with the semi-strong version of market efficiency.

Third, several studies attempt to unravel the determinants of fund performance. The few studies of non-U.S. funds obtain findings that differ somewhat from those for U.S. funds. Fund attributes or properties examined as potential determinants of fund performance in this rapidly evolving literature include fund size, age, fees, trading activity, flows, and past returns. However, these studies typically do not examine the robustness of their results to the potential nonlinearities in the fund payoffs, choice of performance evaluation model, market index benchmark, or conditioning information.

Fourth, the last fifteen years have witnessed an important growth of fixed-income assets and funds. This has increased interest in fixed-income funds, which to-date has received a relatively small amount of research interest in the literature compared to equity funds. However, not all of the aforementioned issues are addressed for fixed-income funds. Hence, there is still a debate about the appropriate benchmark model for fixed-income fund returns ranging from the single- to the multi-factor specifications. Other unresolved issues are related to the role of conditioning information, the potential determinants of performance, and the robustness of the obtained relationship between performance and several fund attributes or characteristics. Finally, there is no rigorous and comprehensive assessment of the impact of survivorship bias on the performance of fixed-income funds, and its properties with respect to performance models and fund objective groupings.

The dissertation consists of four chapters that address several issues related to the performance of Canadian equity and fixed-income mutual funds.

The second chapter, "Portfolio Performance Measurement using APM-Free Kernel Models", assesses the performance of Canadian equity mutual funds over the period 1989-1999. We use the general asset pricing framework or GAPF based on the stochastic discount factor or SDF representation of asset prices to derive a conditional asset pricing kernel that accounts efficiently for time variation in expected returns and risk. The proposed SDF is efficient by construction and is differentiated from most existing SDF models because it has a unique structure that reflects nonlinear interdependence between its unconditional and conditional versions due to the time-variability in the optimal risky asset allocation. We develop frameworks that are suitable for performing unconditional evaluations of fixed-weight and dynamic strategies. The empirical performance measures and their associated tests are constructed and tested within the appropriate empirical framework. We advocate the use of a flexible estimation methodology using the (un)conditional Generalized Method of Moments or GMM of Hansen (1982). We also test the sensitivity of the performance measures to changes in the level of the relative risk aversion of the uninformed investor, and estimate survivorship bias and its sensitivity to the choice of the performance measurement model using an additional sample of non-surviving Canadian equity mutual funds.

The empirical results show that the unconditional risk-adjusted performance of fund managers is positive and that conditioning information negatively impacts the performance statistics and inferences. With limited conditioning, the performance statistics based on all individual funds are higher than those based on portfolios of the funds, and the superior performance switches from large funds to small funds. An expansion of the conditioning information set seems to alleviate the impact of the conditional pricing kernel on the size-based statistics. The performance statistics and inferences are only weakly sensitive to changes in the level of relative risk aversion of the uninformed investor. Finally, the survivorship bias due to the elimination of funds with shorter lives is important for the performance of Canadian equity mutual funds. This importance is similar to that estimated for U.S. and European funds. While survivorship bias is reasonably stable across performance models, it differs materially across funds grouped by their investment objectives.

The third chapter, "Linear Performance Measurement Models and Fund Characteristics", examines the sensitivity of various (un)conditional measures of portfolio performance using various return-based linear benchmark models for a sample of Canadian equity mutual funds over the period, 1989-1999. Our approach departs from the current literature, by assessing the performance inferences based on tests that incorporate the contemporaneous cross-correlations across fund returns using equal- and size-weighted portfolios of funds grouped by investment objective. Several (un)conditional stock selection and market timing models are proposed and estimated using the flexible and robust Generalized Method of Moments or GMM of Hansen (1982). We also attempt to unravel the determinants of fund performance based on various fund attributes or characteristics, and to examine the robustness of our results to the choice of performance evaluation model or market index benchmark. Empirical evidence shows that the measured selection performance of fund managers improves as the conditional benchmark becomes multifactor. Managers of Canadian mutual funds exhibit pervasive negative market-timing ability, and controlling for conditioning information somewhat alleviates the pervasiveness of the negative market-timing inferences. The non-parametric performance rankings tests indicate that all of the measures are quite strongly related or concordant, and suggest that conditioning has a more pronounced impact on absolute than on relative performance inferences. Risk-adjusted performance is related with the age and size of a fund and its management fees, and to a lesser extent with the fund's management expense ratio. These identified relationships suggest important differences and similarities between the availability of scale economies and levels of competition in the Canadian versus the American and European mutual fund industries.

In the fourth chapter, "Portfolio Performance Measurement using Higher-Order Moment and Nonlinear Asset Pricing Kernel Models", we use higher-order moment and nonlinear asset pricing kernel models to estimate the risk-adjusted performance of a sample of Canadian equity mutual funds over the period, 1989-1999. These models jointly accommodate the conditional pricing of portfolios with linear and nonlinear payoffs and have not yet been tested in the context of (un)conditional performance evaluation. The importance of the restriction on the mean of the asset pricing kernel for performance evaluation is tested. We relate nonlinear performance statistics to several fund characteristics or attributes such as fund type, age, size, and management fees and expenses, and to examine the robustness of these relations for Canadian equity mutual funds. We develop the appropriate framework for the estimation of the SDF-based performance measures and the relationship between fund performance and fund characteristics. The flexible (un)conditional Generalized Method of Moments (GMM) of Hansen (1982) is used to estimate the various models. The empirical results show weak unconditional performance, which becomes positive and significant with nonlinear and conditional kernel-based benchmarks. The additional restriction on the mean of the asset pricing kernel not only affects the performance statistics and inferences but also reverses and mitigates the conditioning information-based performance superiority of large over small funds (so-called "large fund effect" herein). Finally, the findings on the relationship between fund performance and fund characteristics suggest that risk-adjusted performance is related to the age and size of the fund and to a lesser extent to the fund load structure but is unrelated to management fees.

The fifth chapter, "Performance of Canadian Fixed-Income Mutual Funds", examines the performance of Canadian fixed-income mutual funds over the period 1985-2000. We use various single- and multi-factor linear benchmark models and develop frameworks that are suitable to perform evaluations of fixed-weight and dynamic strategies. The selected benchmark models seem appropriate to span the movements in the expected returns of bonds and to accommodate the unique features of bond returns. We also address two important issues largely ignored in the literature. First, a comprehensive analysis of the survivorship bias inherent in large samples of fixed-income mutual funds. In particular, we study its impact and properties with respect to risk-adjusted performance, benchmark model, and fund investment objectives. Second, we examine the determinants of fixed-income fund performance and robustness based on linear (un)conditional benchmark models. Fund attributes or properties as potential determinants of fund performance include fund size, age, fees, trading activity, flows, and past returns. The empirical tests show evidence of underperformance. The performance measures are weakly sensitive to the return generating process, and partial conditioning positively impacts the performance statistics and inferences. Tests that do not incorporate the contemporaneous cross-correlations in the returns among individual funds consistently alter and reverse the conditioning information-based performance inferences and the large fund effect. The stock market factor is useful for evaluating the conditional performance of Canadian fixed-income funds. Its inclusion not only improves the performance statistics but also preserves the single factor-based superior performance of large funds. The estimates of survivorship bias, which are less than 15 basis points per year, are similar to that estimated for European funds but lower than the U.S. estimates. Our estimates are stable across performance models but differ across fund objective groupings. The findings on the relationship between fund performance and fund characteristics suggest that risk-adjusted performance is related with the age of the fund, management expense ratio, and load structure, and to a lesser extent with fund size and management fees. These identified relationships suggest important differences and similarities on the economics of the Canadian versus the American and European fixed-income mutual fund industries.

Finally, some concluding remarks and directions for future research are presented in the sixth chapter.

CHAPTER 2

PORTFOLIO PERFORMANCE MEASUREMENT USING APM-FREE KERNEL MODELS

2.1 Introduction

Most previous studies of 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 that implied by the selected model for the same level of risk. Evidence against the empirical validity of these models in the form of priced anomalies is mounting. These models also fail to deliver reliable measures of performance and sometimes 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 the chosen benchmarks where rankings can change with the use of 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 or GAPF based on the stochastic discount factor or SDF representation of 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).

Grinblatt and Titman (1989) initially apply the GAP framework to portfolio performance evaluation via their positive period weighting measure or 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). Most of these papers use existing asset pricing kernels that are not adapted to performance evaluation when realizations may be negative, adopt simple linear conditioning information integration between the unconditional and conditional pricing kernels, and/or employ unconditional average returns.

Thus, given these limitations in the literature, this paper has two major objectives. The first major objective is to introduce a conditional asset-pricing kernel adapted to performance evaluation that efficiently accounts for the time variation in expected returns and risk, and not to rely on the linear information scaling used in most SDF-based performance tests reported in the literature. This 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. The proposed SDF is further differentiated from most existing SDF models because it has a unique structure that reflects nonlinear interdependence between its unconditional and conditional versions caused essentially by the time-variability in the optimal risky asset allocation. The framework also is suitable for performing unconditional evaluations of fixed-weight strategies and (un)conditional evaluations of dynamic strategies.

The second major objective is to develop the appropriate empirical framework for the estimation of the performance measures. We advocate the use of a flexible estimation methodology using the (un)conditional Generalized Method of Moments or 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 1989-1999. We also test the sensitivity of the performance measures to changes in the level of the relative risk aversion of the uninformed investor, and estimate the survivorship bias and its sensitivity to the choice of the performance measurement model.

The first major finding is that the measured unconditional performance of fund managers is positive. The performance statistics deteriorate with conditioning, which suggests that the time-variation in the conditional risky asset allocation used herein appears to have a greater impact on conditional performance than the common linear information scaling applied in most SDF-based performance tests. While the unconditional performance estimates are similar when the averages of the individual fund performances are compared against the average performances of the portfolios of all funds, the tests of significance for the latter are more reliable since the latter reflect the contemporaneous correlations in the returns among the individual funds. With limited conditioning, the performance statistics based on all individual funds are higher than those based on portfolios of the funds, and the superior performance switches from large funds to small funds. These results may be due to an increased nonlinearity in the risk adjustment for the limited conditional pricing kernel. Furthermore, an expansion of the conditioning information set seems to alleviate the impact of the conditional pricing kernel on the size-based statistics.

The second major finding is that performance statistics and inferences are only weakly sensitive to changes in the level of relative risk aversion of the uninformed investor. This indicates that the pricing kernel-based performance measure is reasonably robust over a certain range of investor preferences.

The third major finding is that survivorship bias due to the elimination of funds with shorter lives is important for the performance of Canadian equity mutual funds. This importance is similar to that estimated for U.S. and European funds. While survivorship bias is reasonably stable across performance models, it differs materially across funds grouped by their investment objectives.

The remainder of the paper is organized as follows: Section two presents the general asset-pricing framework. In section three, 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 four. In section five, we develop and explain the econometric methodology and the construction of the tests. Section six introduces the sample and the data used herein. Section seven presents and discusses the main empirical results. Finally, section eight summarizes the findings and discusses their implications.

2.2 General Asset Pricing Framework or 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 or SDF is a random variable that reflects the fundamental economy-wide sources of risk.[1] The basic asset pricing equation is written as:

$$P_{i,t} = E_t(M_{t+1} X_{i,t+1}), \quad \text{all } i = 1,\ldots,N \tag{2.1}$$

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, and the general assumption is that the asset payoffs have finite second moments. As shown by

---

[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 such as the intertemporal marginal rate of substitution in the consumption-based model, the equivalent martingale measure for allowing the change of measure from the 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.

Luttmer (1996), (2.1) 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:

$$E_t(M_{t+1}) = P_{f,t} = \frac{1}{R_{f,t+1}} \tag{2.2}$$

When the security payoff is a gross return, the price is one. Then equation (2.1) is equivalent to:

$$E_t(M_{t+1}R_{i,t+1}) = 1, \quad \text{all } i = 1,\ldots,N \tag{2.3}$$

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

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

$$E_t(M_{t+1}r_{i,t+1}) = 0, \quad \text{all } i = 1,\ldots,N \tag{2.4}$$

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

[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).

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 in that it 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 (specifically risk premiums) are poorly estimated in that they are 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.

2.3 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:

$$(2.5) \qquad E[U(W_{t+1}) \mid \Omega_t]$$

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 and any remaining wealth is invested in a risk-free security. The return on wealth is given by:

$$(2.6) \qquad R_{w,t+1} = \alpha_t R_{b,t+1} + (1-\alpha_t) R_{f,t+1} = \alpha_t (R_{b,t+1} - R_{f,t+1}) + R_{f,t+1} = \alpha_t r_{b,t+1} + R_{f,t+1}$$

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 $t+1$ that 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 or 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 is consistent with a conditional Euler equation:[4]

$$\alpha_t \equiv \alpha(\Omega_t) \tag{2.7}$$

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 equals one, the conditional optimization problem as in Brandt (1999), Ferson and Siegel (2001), and Aït-Sahalia and Brandt (2001) for the uninformed investor is:

$$\alpha_t^* = \arg\max_{\alpha_t} E[U(\alpha_t r_{b,t+1} + R_{f,t+1}) \mid \Omega_t] \tag{2.8}$$

The first order condition gives:

$$E[U'(\alpha_t r_{b,t+1} + R_{f,t+1}) r_{b,t+1} \mid \Omega_t] = E[(\alpha_t r_{b,t+1} + R_{f,t+1})^{-\gamma} r_{b,t+1} \mid \Omega_t] = 0 \tag{2.9}$$

This is a conditional Euler equation.

Now define, $M_{t+1}^c \equiv (\alpha_t r_{b,t+1} + R_{f,t+1})^{-\gamma}$, which is a strictly positive conditional stochastic discount factor consistent with the no-arbitrage principle. This ensures that, if a particular fund

[4] See the appendix 2.1 for a proof that the optimal risky asset allocation is a nonlinear function of the first and second conditional moments of asset returns.

has a higher positive payoff than another fund, then it must have a higher positive performance. Grinblatt and Titman (1989) and Chen and Knez (1996) stress the importance of this positivity property in providing reliable performance measures.[5,6]

M^c_{t+1} can be normalized such that: (2.10) $Q^c_{t+1} \equiv \dfrac{M^c_{t+1}}{E_t(M^c_{t+1})} = M^c_{t+1} R_{f,t+1}$. 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:

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

Let λ^i_t, $i = (u,c)$, be the (un)conditional portfolio performance measure depending on the use of the appropriate SDF. It is an admissible positive performance measure with respect to the Chen and Knez (1996) definition.[7] Specifically:

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

(2.13) $\lambda^c_t = E_t(Q^c_{t+1} r_{y,t+1}) = E_t(r_{y,t+1}) + \mathrm{Cov}_t(Q^c_{t+1}, r_{y,t+1})$, such that $E_t(Q^c_{t+1} r_{b,t+1}) = 0$ and $E_t(Q^c_{t+1}) = 1$. In equations (2.12) and (2.13), $r_{y,t+1}$ is the excess return on any particular portfolio y.

---

[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.

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:

$$Q_{t+1}^{u} \equiv \frac{(\alpha r_{b,t+1} + R_{f,t+1})^{-\gamma}}{E[(\alpha r_{b,t+1} + R_{f,t+1})^{-\gamma}]} \tag{2.14}$$

$$Q_{t+1}^{c} \equiv \frac{(\alpha_t r_{b,t+1} + R_{f,,t+1})^{-\gamma}}{E_t[(\alpha_t r_{b,t+1} + R_{f,t+1})^{-\gamma}]},\ \alpha_t \equiv \alpha(\Omega_t) \tag{2.15}$$

The condition that guarantees that the benchmark portfolio is efficient for the uniformed investor is that $E_t(Q_{t+1}^{c} r_{b,t+1}) = 0$, or equivalently $E_t(Q_{t+1}^{c} R_{b,t+1}) = R_{f,t+1}$. 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.

2.4 Performance Evaluation of Passively and Actively Managed Portfolios

2.4.1 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:

$$\lambda_t^{u} = E(Q_{t+1}^{u} r_{p,t+1}) = E(Q_{t+1}^{u} R_{p,t+1}) - R_{f,t+1} = 0 \tag{2.16}$$

where $E(Q^u_{t+1}) = 1$ and $E(Q^u_{t+1} r_{b,t+1}) = 0$.

$$\lambda^u_t = E(Q^u_{t+1} R_{p,t+1}) - R_{f,t+1} = w' E(Q^u_{t+1} R_{1,t+1}) - R_{f,t+1} = w' R_{f,t+1} 1_N - R_{f,t+1} = 0$$

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

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 or the PPWM is able to price any asset or portfolio whose returns are attainable from all possible linear combinations of the original N assets or fixed-weight trading strategies. It does 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 an actively managed portfolio is given by:

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

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

The unconditional performance measure is given by:

$$\lambda^u_t = E(Q^u_{t+1} r_{a,t+1}) = E(Q^u_{t+1} R_{a,t+1}) - R_{f,t+1} = E(w(\Omega^a_t)' Q^u_{t+1} R_{1,t+1}) - R_{f,t+1} \tag{2.17}$$

When informed investors optimally exploit their private information or signals, this measure is expected to be strictly positive.

---

[8] The information may either concern individual stocks and/or the overall market.

2.4.2 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:

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

The conditional SDF prices the portfolio such that:

$$\lambda_t^c = E_t(Q_{t+1}^c r_{p,t+1}) = E_t(Q_{t+1}^c R_{p,t+1}) - R_{f,t+1} = 0 \tag{2.18}$$

$$\lambda_t^c = E_t(w(\Omega_t^p)'Q_{t+1}^c R_{1,t+1}) - R_{f,t+1}$$

$$= w(\Omega_t^p)'E_t(Q_{t+1}^c R_{1,t+1}) - R_{f,t+1} = w(\Omega_t^p)'R_{f,t+1}1_N - R_{f,t+1} = 0$$

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

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

To model the conditioning information, 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 either of two different ways. First, we can create general managed portfolios, and then examine the implications for the unconditional expectations as in Cochrane (1996). Alternatively, 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. This latter approach has the disadvantage of being sensitive to any misspecification in the conditional moments, and 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.

---

[9] There is no restriction on the weight function. It may be nonlinear including any option-like trading

Hansen and Singleton (1982) and Hansen and Richard (1987) propose including the conditioning information by scaling the original returns by the instruments.[10] This simple multiplicative approach implies linear trading strategies and does not require the specification of the conditional moments.[11] This approach 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. These scaled returns can be interpreted as payoffs to managed portfolios or conditional assets. In effect, an investor whose trading strategy is based on the value of Z_{lt}, where $l = 1,...,L$, will put Z_{lt} dollars into the asset.[12] 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.[13]

The conditional performance measure can be written as:

$$\lambda_t^c = E_t(Q_{t+1}^c R_{1,t+1}) \otimes Z_t - R_{f,t+1} 1_N \otimes Z_t = 0 \tag{2.19}$$

$$E_t(Q_{t+1}^c) Z_t = Z_t \tag{2.20}$$

Assuming stationarity and applying the law of iterated expectations yields:

---

strategies (Merton, 1981; and Glosten and Jagannathan, 1994).

[10] Bekaert and Liu (1999) propose that the conditioning information be integrated 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.

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

[12] The expected or average price of this trading strategy is equal to the expected or average value of the chosen instrument.

[13] 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, unlike 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.

(2.21) $$E[Q^c_{t+1}(R_{1,t+1} \otimes Z_t)] = E(R_{f,t+1} 1_N \otimes Z_t)$$

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

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 only 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 performance for the actively managed portfolio is given by:

(2.23) $$\lambda^c_t = E_t(Q^c_{t+1} r_{a,t+1}) = E_t(Q^c_{t+1} R_{a,t+1}) - R_{f,t+1}$$

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.

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 parameterization of the conditional normalized pricing kernel differs from the one associated with the conditional evaluation and is consistent with the following two moment conditions:

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

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

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

2.5 Econometric Methodology and Construction of the Tests

In this section, 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) is detailed.[14] Important issues associated with the estimation procedure and the optimal weighting or distance matrix also are dealt with.

2.5.1 The General Methodology

Two estimation methods are available for assessing the performance of actively managed portfolios such as mutual funds using a GMM system approach. The two-step method first estimates the appropriate normalized pricing kernel using a system of moment equations including only passively managed portfolios, and then measures the risk-adjusted fund performance by multiplying the gross fund return by the estimated or fitted 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 consistent but not fully efficient (Chen and Knez, 1996). The one-step method jointly and simultaneously estimates the normalized pricing kernel parameters and the performance measures by augmenting the number of moment conditions in the initial system with the actively managed fund(s) or portfolio(s) of funds. 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.

In this paper, a one-step estimation is conducted using the excess returns for each individual fund or portfolio of funds and the set of passive portfolios.[15] This multivariate framework

[14] 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.
[15] Farnsworth et al. (2002) show that the performance estimates and associated standard errors are invariant to the number of actively managed individual funds or portfolios of funds in the GMM system. Thus, a

incorporates all of the cross-equation correlations. By construction, 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.

The general steps and expressions leading primarily to the general case of conditional GMM estimation relevant for the conditional evaluation of dynamic trading-based portfolios are now presented. The unconditional GMM estimation is trivially obtained as a special case from the general one.

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

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

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

Now define $u_{t+1}^c = Q^c(r_{b,t+1}, Z_t, \theta) r_{p,t+1} \equiv u(r_{b,t+1}, r_{p,t+1}, Z_t, \theta)$ 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.

Assume that the dimensions of the benchmark excess return and the conditioning variables are K and L, respectively. Then, the dimension of the vector of unknown parameters is (KL+1). We then have:

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

---

system, which is estimated simultaneously for each fund or portfolio of funds with the passive portfolios, is equivalent to an extended system with several funds or portfolios of funds. Such a system setup limits the number of moment conditions and controls the saturation ratios in the estimation.

[16] The means of the normalized and non normalized pricing kernels are equal to one and the inverse of the gross return on the risk-free asset, respectively.

Define $h(r_{b,t+1}, r_{p,t+1}, Z_t, \theta) = u_{t+1}^c \otimes Z_t = u(r_{b,t+1}, r_{p,t+1}, Z_t, \theta) \otimes Z_t$. Our conditional and unconditional moment restrictions can be written as:[17]

$$(2.28) \qquad E_t[h(r_{b,t+1}, r_{p,t+1}, Z_t, \theta_0)] = E[h(r_{b,t+1}, r_{p,t+1}, Z_t, \theta_0)] = 0_{NL}, \text{ and}$$

$$(2.29) \qquad E_t[Q^c(r_{b,t+1}, Z_t, \theta_0)Z_t - Z_t] = E[Q^c(r_{b,t+1}, Z_t, \theta_0)Z_t - Z_t] = 0_L$$

Because the model is overidentified, the GMM system is estimated by setting the (KL+1) linear combinations of the NL moment conditions equal to zero. When an additional moment condition is considered,[18] the number of moments increases to $L(N+1)$ and the number of parameters remains unchanged. Similarly, when the system 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:

$$(2.30) \qquad g_0(\theta) = E[h(r_{b,t+1}, r_{p,t+1}, Z_t, \theta)]$$

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 given by:

$$(2.31) \qquad g_T(\theta) = \frac{1}{T}\sum_{t=1}^{T} h(r_{b,t+1}, r_{p,t+1}, Z_t, \theta)$$

[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. The variable h must have a nonsingular population conditional or unconditional covariance matrix, and the conditional and unconditional expectations of the first derivatives of h must have a full raw rank. See Hansen (1982) and Gallant and White (1988) for more details.

[18] 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.

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 is obtained by selecting $\hat{\theta}_T$ that minimizes the sample quadratic form J_T that is given by:[19]

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

where W_T is a symmetrical and nonsingular positive semi-definite $NL \times NL$ weighting matrix.

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

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

where:

(2.34) $D_0 = E\left(\dfrac{\partial u(r_{b,t+1}, r_{p,t+1}, Z_t, \theta_0)}{\partial \theta'} \otimes Z_t \right)$ 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:

(2.35) $$S_0 = \sum_{j=-\infty}^{+\infty} E[h(r_{b,t+1}, r_{p,t+1}, Z_t, \theta_0) h(r_{b,t-j+1}, r_{p,t-j+1}, Z_{t-j}, \theta_0)']$$

When the model is overidentified, the remaining "free" restrictions ((*N*-*K*)*L*-1) are used to assess and test the goodness of fit of the model or as a test of the overidentifying restrictions. Let $J_T(\hat{\theta}_T)$ be the minimized value of the sample quadratic form.[20] When the optimal weighting matrix or the 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. This is the well-known Hansen J_T-statistic. This estimation can handle the assumption

[19] Under some regularity conditions, Hansen (1982) shows that the GMM estimator is consistent and asymptotically normal for any fixed weighting matrix.

that the vector of disturbances exhibits non-normality, conditional heteroskedasticity, and/or serial correlation even with unknown form.

2.5.2 The Estimation Procedure and the Optimal Weighting Matrix

The estimates of the portfolio performance measure are obtained by minimizing the GMM criterion function constructed from a set of moment conditions in the system. 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 suggested by Ferson and Foerster (1994).[21]

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.[22] Specifically, S_0 is the positive definite spectral density at frequency zero or long run variance-covariance matrix of $h(r_{b,t+1}, r_{p,t+1}, Z_t, \theta_0)$. In this case, the asymptotic variance-covariance matrix of the estimator is given by:

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

This variance-covariance matrix is unknown and should be replaced by a consistent sample estimate, which 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.

---

[20] 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.
[21] This 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.
[22] 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.

Replacing the expectation operator with the sample average operator, and replacing θ_0 with $\hat{\theta}_T$ gives a consistent sample estimate of D_0 given by:

$$\hat{D}_T = \frac{1}{T}\sum_{t=1}^{T}\frac{\partial u(r_{b,t+1}, r_{p,t+1}, Z_t, \hat{\theta}_T)}{\partial \theta'} \otimes Z_t \tag{2.37}$$

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 $h(r_{b,t+1}, r_{p,t+1}, Z_t, \theta_0)$. A consistent estimate of this spectral density is used herein to construct a heteroskedastic and autocorrelation consistent (HAC) or robust variance-covariance matrix in the presence of heteroskedasticity and autocorrelation of unknown forms (Priestly, 1981). Chen and Knez (1996), Kryzanowski et al. (1997), Dahlquist and Soderlind (1999), and Farnsworth et al. (2002) construct robust t-statistics for their estimates of performance by using the modified Bartlett kernel proposed by Newey and West (1987a) to construct a robust estimator for the variance-covariance matrix.[23]

[23] The higher-order sample autocovariances are downweighted or linear declining weights, and those with order exceeding a certain parameter receive zero weight.

2.6 Sample and Data

2.6.1 Mutual Fund and Benchmark Returns

The initial mutual fund sample, which is drawn from the Financial Post mutual fund database, consists of 95 Canadian equity funds with 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 given by the monthly changes in the net asset value per share, and are adjusted for capital gains and dividend payments. As in most previous studies (Chen and Knez, 1996; Ferson and Schadt, 1996; Kryzanowski et al., 1997; and Farnsworth et al., 2002), only equity funds are used for the tests of abnormal performance since an equity-based asset pricing kernel cannot price or be used to evaluate the performance of non-equity funds. To be able to test the sensitivity of the performance statistics with respect to the selected benchmark, two benchmark proxies are used herein; namely, the 300 and value-weighted TSE indices. We use an additional sample of terminated and start-up funds over the studied period to estimate the impact of survivorship bias on fund performance, and to assess the impact of performance sensitivity across performance metrics and benchmark models.

Table A1 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% for Cambridge Growth of Sagit Investment Management to 18.03% for AIC Advantage of AIC Limited, and have a cross-sectional mean of 9.86%. The fund annual volatilities or standard deviations range from 6.00% for Canadian Protected of Guardian Timing Services to 31.05% for Cambridge Special Equity of Sagit Investment Management. Over the same sample, the annual average mean and volatility of the TSE 300 index return are 11.17% and 14.53%, respectively.

[Please insert table A1 about here.]

In panel B of table A1, portfolios of funds grouped by investment objectives are obtained from equal-weighted portfolios using the 95 funds in the sample. The number of funds in each of six investment objective categories is 27 aggressive growth funds, 50 growth funds, 12 growth and income funds, 3 income funds, 1 balanced fund, and 2 specialty funds. Among the groups with at least five funds, the highest and lowest mean returns occur in the group of aggressive growth funds and the group of growth and income funds, respectively. The first-order autocorrelations of the fund returns are greater than 0.1 for 30 of the 95 funds.

2.6.2 Information Variables

A set of six instrumental variables is selected based on evidence of their predictive power in studies of stock return predictability. Data for each of these variables are drawn from Statistics Canada's CANSIM database. The set includes DY or the dividend yield of the TSE 300 index (Fama and French, 1988, Ferson and Schadt, 1996, Kryzanowski et al., 1997, Christopherson et al., 1998, and Farnsworth et al., 2002); TB1 and TB3 or the Canadian one- and three-month T-bill rates, respectively (Fama and Schwert, 1977; and Ferson and Korajczyk, 1995); RISK or the risk premium as measured by the yield spread between long corporates (McLeod, Young, Weir bond index) and long Canadas (Chen, Roll, and Ross, 1986; Kryzanowski and Zhang, 1992; and Kryzanowski and Koutoulas, 1996); TERM or the slope of the term structure as measured by the yield spread between long Canadas and the one period lagged three-month Treasury bill rate (Ferson and Harvey, 1991; and Chen and Knez, 1996); TSEVWX and TSE300X are the value-weighted and the TSE 300 index excess returns, respectively (Harvey, 1989); and 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 such as autocorrelations, and the correlation matrix for these variables are provided in panels A and B of table A2, respectively. The correlations between these instruments range from -0.825 to 0.841. Since two variables account for most of the time variation in mutual fund excess returns, subsequent empirical analysis only uses DY or DY and TB1 in the estimation of the performance measures.

[Please insert table A2 about here.]

2.6.3 Predictability of Mutual Fund Excess Returns

To motivate the implementation of the conditional methodology, we conduct a predictability analysis of two groups of six portfolios of mutual fund excess returns. The groups are equal- and size-weighted portfolios of funds using the individual fund returns within each investment objective. Time-series regressions of the excess returns of these portfolios of funds on a set of five instruments consisting of 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 panel D of table A1 indicate significant levels of predictability for the equal- and size-weighted portfolios of funds. 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 also are higher than the unreported ones obtained with the portfolios of funds returns and with the passive portfolio excess returns. Furthermore, the unreported 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. These findings provide strong support for undertaking a conditional performance analysis where the use of the conditional asset-pricing kernel eliminates the predictability in the mutual fund excess returns based on the set of predetermined information variables.

2.6.4 Passive Strategies

Passive or basis or 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 stock market strategies considering all the stocks on the TSE/Western monthly database. 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, as in Kryzanowski et al. (1997).

Panels A and C in table A2 provide descriptive statistics such as autocorrelations and the correlation matrix for these ten portfolios, respectively. The annualized average returns on the size portfolios range from 1.27% for portfolio six to 58.58% for portfolio one. All the series indicate a low degree of persistence since all of the first-order autocorrelations are less than 0.236.

2.6.5 Optimal Risky Asset Allocation Specifications

In a conditional setting, the optimal risky asset allocation of the uninformed investor is a function of the conditional moments of asset returns. We assume that these conditional moments are linear in the state variables. Hence two linear specifications are adopted and integrated into the construction of the performance measures; namely:[24]

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

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

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 if the set of conditioning variables includes DY only or both DY and TB1. When an unconditional evaluation is conducted, the uninformed investor's portfolio policy is a constant.

2.7 Empirical Performance Results

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 variability in total and per group of funds, and its sensitivity to the procedure for forming portfolios of funds and to the selected benchmark portfolio.[25]

We address two important issues related to risk-adjusted performance measurement. First, we examine the sensitivity of the performance metrics to changes in the level of relative risk aversion of the uninformed investor. Second, we estimate the survivorship bias and its sensitivity across performance metrics and benchmark models by using an additional sample of terminated and start-up funds over the studied period.

2.7.1 Evaluation of Unconditional Performance

The performance results for the major equal- and size-weighted portfolios of mutual funds using the two benchmark variables are summarized in table A3. Panel A shows that all equal-weighted portfolios have consistently positive and significant abnormal performance. The lambda of a portfolio of all funds is 0.1933% per month, and the growth/income fund group contributes

[25] Equal- and size-weighted portfolios of funds based on the investment objectives and for all funds are constructed. These portfolios provide insights on potential size effects associated with performance and are interpreted as funds-of-funds. They represent diversified investments that do not suffer from the most common criticism of funds-of funds that they add an extra layer of costs. Other constructions could be based on industry or geographic sector investment themes.

the most with a highly significant lambda of 0.2591% using the value-weighted TSE index as a benchmark. The same analyses conducted on the size-weighted portfolios of funds (panel B) produces comparable and more significant results. The lambdas of the 27 aggressive growth fund and the 50 growth fund portfolios are a highly significant 0.2463% and 0.2626%, respectively. The lambda of a size-weighted portfolio of all funds is 0.2438% per month. An equal-weighted portfolio of funds appears to underestimate unconditional performance.

[Please insert table A3 about here.]

The performance of individual funds is summarized in panels A and D of table A4 for the two portfolio performance formation procedures. The results indicate that the equal-weighted portfolios of performances based on the value-weighted TSE index as a benchmark have a positive mean and median lambda of 0.1931% and 0.1778%, respectively (average p-value of 0.275). The aggressive growth, growth, and growth/income portfolios exhibit not significant but positive abnormal performance. However, these aggregate significance levels must be interpreted with care since they are averages of individual levels, and 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).

When the individual fund performances are weighted by the total net asset values of the funds, the average lambda increases to 0.2224% and becomes less insignificant (average p-value of 0.225) using the value-weighted TSE index. This performance improvement is obtained for the aggressive growth and growth portfolios, and confirmed when the other benchmark is used.

The comparison between these individual performance averages and the performance of portfolios of all funds suggests similar inferences with comparable lambda point estimates and consistent superior performance of large funds across the two benchmark variables. However, the p-values associated with the performance of portfolios of funds are superior and more reliable than those obtained from averaging the individual statistics.

[Please insert table A4 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 for the two benchmarks using heteroskedasticity and autocorrelation consistent t-statistics. Based on table A5, 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. A predominance of funds with good performance exists across all major fund groups. The p-values based on the Bonferroni inequality indicate that the positive extreme t-statistics are significant for all funds and across all major fund groups.[26] This rejects the joint hypothesis of zero lambdas. However, the conservative p-values corresponding to the minimum t-statistic for all funds are 0.577 and 0.458 using the TSE 300 and the value-weighted TSE indices, respectively.

[Please insert table A5 about here.]

Overall, this positive and 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 our sample of fund managers.

2.7.2 Evaluation of Conditional Performance

The conditional model is estimated using two specifications for the conditioning structure in order to assess the sensitivity of the performance measures to the conditional specification. The first considers only the dividend yield on the TSE 300 index, while the second considers both the

[26] This test 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.

dividend yield and the yield on the one-month T-bill. To assess the validity of the conditional approach, Wald tests (Newey and West, 1987b) are conducted on the coefficients of the time-varying alpha.

2.7.2.1 Conditioning with the Dividend Yield Only

When the conditional asset pricing kernel model with DY as the only instrumental variable is used, the performance of an equal-weighted portfolio of all funds is 0.1371% is weaker but still significant using the value-weighted TSE index (see panel C in table A3). This could be explained by the significant decrease in the performance of the growth, and growth/income portfolios. In contrast, the performance of the aggressive growth portfolio increases to 0.2785% and becomes more significant. The performance analyses using the size-weighted portfolios of funds reveal a clear deterioration of the performance to 0.1209% (see panel D of table A3). 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 equal-weighted portfolios.

Examining the performance of individual funds further supports the previous conclusions. Based on table A4, the average fund performance is affected negatively using the conditional model. 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) who report that the inclusion of public information positively impacts their performance statistics. The changes in the point estimates of performance from the unconditional to conditional frameworks reported herein are consistent with those observed in Bansal and Harvey (1996) and Kryzanowski et al. (1997).

With the conditional model, the performance statistics based on all individual funds are higher than those of the portfolios of all funds. This result could be explained by the increasing nonlinearity in the risk adjustment with the conditional pricing kernel. The superior performance switches from large funds to small funds confirming the differential impact of conditioning information on size-weighted portfolios. The most notable source of the deterioration in the conditional lambdas is the poor performance of the individual growth and growth/income funds. Overall 42 and 15 funds have negative and significantly negative lambdas, respectively, using the value-weighted TSE index as the benchmark. The number of funds with positive and significant performance decreases from 42 to 38. Moreover, all of the Bonferroni p-values, which correspond to the extreme maximum and minimum t-statistics reject the null hypothesis of joint zero lambdas (see panels C and D of table 2.5).

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

Based on the results reported in table A3 (panels E and F), the performance values become negative but not significant when the information set is expanded to two instruments, except for the aggressive growth group which exhibits decreased positive performance. The lambda for the equal-weighted portfolios of all funds is -0.0573% using the value-weighted TSE index as the benchmark. The Wald tests validate the conditional approach in that 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 lambda of the aggregate portfolio is -0.0129%.

Based on panels C and F of table A4, the performance of the individual funds and portfolios of performances support the conclusions reached previously for the portfolios of funds. The distribution of the conditional lambdas is now asymmetric with less extreme observations compared to the unconditional and conditional lambdas based on one instrument.

With the full conditional model, the differences between the averages of individual fund performances and the performances of portfolios of funds are more pronounced with a consistent superior performance of large funds across the two benchmark variables. The extension of the conditioning information set seems to alleviate the impact of the conditional pricing kernel on the size-based statistics.

Based on panels E and F of table A5, the number of funds with significant negative lambdas is 36 compared to 3 and 15 funds using the unconditional and conditional with one-instrument estimations. The number of significant and positive lambdas decreases to 16, which is less than half of the number obtained with the unconditional asset pricing kernel model. These figures are caused by the negative performance of the aggressive growth, growth, and growth/income funds. Moreover, the Bonferroni test is significant for all major fund groups. This rejects the joint null hypothesis of zero conditional lambdas.

The overall results indicate that fund managers experience greater difficulty in realizing excess returns 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. This finding partially confirms the theoretical conclusions of Chen and Knez (1996) who advocate that performance results can change in either direction in the presence of conditioning information, due to an infinity of admissible (un)conditional stochastic discount factors.

2.7.3 Performance and Relative Risk Aversion

We now test the sensitivity of the performance measures to changes in the level of the relative risk aversion of the uninformed investor using the sets of equal- 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 may affect measured performance.

The results for the unconditional tests, which are reported in panels A and B of table A6, suggest that the performance metrics are decreasing in the coefficient of relative risk aversion.

The performance for the equal-weighted portfolios of all funds (panel A) is 0.2017% with a gamma equal to 3, 0.1994% with a gamma equal to 4, 0.1975% with a gamma equal to 5, and 0.1964% with a gamma equal to 6 when the TSE 300 index is used as the benchmark. However, this negative association is consistent across all portfolios of funds, the two benchmark variables, and the two portfolio formation procedures. Thus, the unconditional performance is negatively but weakly sensitive to changes in the level of relative risk aversion. This could be explained by implied investment/risk restrictions due to changes in the risk attitudes of the uninformed investor.

[Please insert table A6 about here.]

The results for the conditional model with one instrumental variable DY are presented in panels C and D of table A6. On average, they show a weak positive link between lambda and gamma, especially for the size-weighted growth portfolio. When the value-weighted TSE index is used as the benchmark, its performance improves from 0.1082% when gamma is equal to 3, to 0.1153% when gamma is equal to 6. The only major exceptions are the equal- and size-weighted aggressive growth portfolios, whose performances deteriorate as the uninformed investor becomes more risk averse. A conditional framework with one instrumental variable affects the nature of the relationship between fund performance and relative risk aversion, but has little effect on the measured performance of the aggressive growth and growth style managers.

To test the robustness of this last conclusion, we use the extended conditional model with two instrumental variables. The results reported in panels E and F of table A6 are consistent (negative) for the aggressive growth portfolios. In contrast, the performances of the growth portfolios indicate weak sensitivity to changes in gamma. These two empirical observations suggest that a weak negative average link exists between conditional performance and relative risk aversion.

Nevertheless, it is difficult to make unambiguous statements about the direction of the sensitivity of performance inferences 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.

2.7.4 Survivorship Bias and Risk-Adjusted Performance

The original sample of mutual funds includes only funds that existed or survived over the full studied period. This sampling procedure produces a survivorship bias that is likely to overstate measured performance. This bias is inherent in the majority of the papers published on performance measurement (Jensen, 1968; Lehmann and Modest, 1987; Grinblatt and Titman, 1994; Ferson and Schadt, 1996; and Kryzanowski et al., 1997).[27] Recent attempts to address this issue use various approaches. Grinblatt and Titman (1989) and Wermers (1997) examine the effect of survivorship on a database of stock holdings and estimate the survivorship bias to be 20 basis points per year. Malkiel (1995) obtains a greater value of 1.4 percent per year for survivorship bias over the ten-year period 1981-1991. Brown and Goetzmann (1995) estimate a survivorship bias of 80 basis points over a 10-year period for a sample of mutual funds. Elton et al. (1996) argue that the size of this bias is a function of the number of years in the study. They find that the bias varies between 25.4 basis points per year to 71.9 basis points per year for a 14-year sample using several benchmark models and reinvestment assumptions. These conclusions are partially confirmed by Carhart et al. (2002) where the survivorship bias is an increasing function of the time-length of the sample. They find a survivorship bias equal to 43 basis points for a five-year sample, and that the bias ranges from 17 basis points for a one year sample to one percent per year for samples longer than fifteen years. However, the size of the bias is robust to the underlying performance model.

Thus, our objective in this section is to estimate the survivorship bias for Canadian equity mutual funds, and then to examine the impact of survivorship bias on the measured performance across fund investment objective and chosen performance measurement model. Survivorship bias is estimated as the difference between the risk-adjusted performances of the size-weighted portfolios of all surviving and non-surviving funds, and of surviving funds only.

For this purpose, we track monthly returns and total net asset values of funds that have existed, started up and terminated over the studied period of November 1989 through December 1999. Five size-weighted portfolios of aggressive growth, growth, growth/income, income, and all funds are then constructed using all of the funds as long as they have at least one monthly return. For instance, the aggressive growth and growth portfolios consist of 41 and 114 funds including 14 and 64 end-of-period dead funds, respectively. The growth/income portfolio has 24 funds where 50% of the funds are terminated by period end. These figures represent the maximum number of funds in each portfolio since the composition of each portfolio changes over time depending on the existence and termination of each fund.

Based on the results reported in panels A, B, and C of table A7, the estimate of the survivorship bias varies somewhat across the various benchmarks and the performance measurement models. The survivorship bias ranges from 36 basis points per year using the conditional asset pricing kernel with one instrumental variable (DY) to 58 basis points per year with the unconditional model. The survivorship bias differs across fund objective groups in that it is more pronounced for the growth/income and growth groups at 119 and 49 basis points per year, respectively, than for the aggressive and income groups where it is 15 and nearly zero basis points per year, respectively. These results are robust to the benchmark model. These bias estimates and properties differ from those of Elton et al. (1996), and parallel the findings of Carhart (1997) and Carhart et al. (2002) for U.S. equity mutual funds. Furthermore, the risk-

[27] Most of these studies completely ignore this selection bias or argue that this bias has a limited and insignificant impact on their conclusions.

adjusted performances of these extended size-weighted portfolios deteriorates and are negative when conditioning information is integrated into the estimation. This is consistent with our original conclusions that do not account for the survivorship bias.

[Please insert table A7 about here.]

2.8 Conclusion

This paper uses the general asset-pricing or SDF framework to derive an asset-pricing kernel that is relevant for evaluating the performance of actively managed portfolios. Our approach reflects the predictability of asset returns and accounts for conditioning information. Three performance measures are constructed and are related to the unconditional evaluation of fixed-weight strategies, and unconditional and conditional evaluations of dynamic strategies. The appropriate empirical framework to estimate and implement the proposed performance measures and their associated tests using the GMM method is developed.

The developed models are used to assess the risk-adjusted performance of a sample of 95 Canadian equity mutual funds with and without the addition of shorter-lived funds. The empirical evidence indicates abnormal unconditional performance, and that conditional performance is negative on average. Significant negative performance is found for the growth and growth/income, and income portfolios of fund, and positive but not significant performance is found for the aggressive growth portfolios of funds. Survivorship bias is material as it ranges from 36 to 58 basis points per year for the total sample. While survivorship bias is reasonably stable across performance models, it differs materially across fund objective groups.

Performance inferences are weakly related to changes in the relative risk aversion of the uninformed investor for all but the aggressive growth grouping of funds. Risk-adjusted performance deteriorates as the uninformed investor becomes more risk averse.

Our approach may be extended in two ways. The first extension is to examine potential relationships between the performance measures and some business cycle indicators or variables to better determine if the performance of active portfolio management differs during periods of expansion and contraction. The second extension is to conduct the unfeasible fully efficient conditional GMM estimation, which is based on general interactions between functions of conditioning variables and pricing errors, using nonparametric estimates for the optimal set of instruments as suggested in Newey (1993).

CHAPTER 3

LINEAR PERFORMANCE MEASUREMENT MODELS AND FUND CHARACTERISTICS

3.1 Introduction

The evidence for the sensitivity of measured portfolio performance to the choice of the benchmark model is mixed. Lehmann and Modest (1987) find that measured performance is very sensitive to the choice of the return generating process and to the estimation procedure for the CAPM- and APT-based benchmark models.[28] Kryzanowski et al. (1994, 1998) identify a benchmark invariancy problem using various conditional intertemporal or multi-factor asset pricing models for Canadian mutual funds. Performance inferences are sensitive to various features involved in the construction of the benchmark models, such as number of factors, nonsynchronous trading adjustment, and firm sizes used for the factor extraction. In contrast, Farnsworth et al. (2002) and Blake et al. (1993) find robust performance inferences for several stochastic discount factor models for U.S. equity funds and for various bond-based benchmark models for U.S. bond funds, respectively. The performance inferences reported in these papers typically are based on tests that do not incorporate the contemporaneous cross-correlations across individual fund returns.

Other studies attempt to unravel the determinants of fund performance. The few studies of non-U.S. funds obtain findings that differ somewhat from those for U.S. funds.[29] Fund attributes or properties examined as potential determinants of fund performance in this rapidly evolving literature include fund size, age, fees, trading activity, flows, and past returns. Furthermore, these

[28] Also, see Coggin et al. (1993) and Grinblatt and Titman (1994).
[29] The evidence for U.S. funds includes Ippolito (1989), Elton et al. (1993), Gruber (1996), Carhart (1997), Sirri and Tufano (1998), Zheng (1999), Berk and Green (2002), and Chen et al. (2003). The evidence for non-U.S. (European) funds includes Dahlquist et al. (2000) and Otten and Bams (2002).

studies typically do not examine the robustness of their results to the choice of performance evaluation model or market index benchmark.

Thus, given these deficiencies in the literature, this paper has two major objectives. The first major objective is to provide new and robust tests of the sensitivity of performance inferences based on the family of (un)conditional linear benchmark models for Canadian equity mutual funds. These CAPM and four-index benchmark models are estimated using the flexible and robust Generalized Method of Moments or GMM of Hansen (1982). This paper is the first to examine a full conditional multi-index model.[30] To deal with inference problems caused by returns of individual funds being contemporaneously correlated that have plagued most previous tests, the performance inferences drawn herein are based on equal- and size-weighted portfolios of funds grouped by investment objective.

The second major objective is to examine the robustness of the relation between performance differentials across fund groups and the differences in fund characteristics or attributes for Canadian equity mutual funds. Of specific interest is whether the determinants of fund performance are robust even if the performance inferences themselves are not across the class of linear performance benchmark models studied herein, and what the estimated relations imply about economies of scale and the level of competition in the Canadian mutual fund industry.

The first major finding is that the measured selection performance of fund managers improves as the conditional benchmark becomes multifactor. The performance inferences for the stock selection skills by fund managers are not positive and are weakly positive for the extended conditional CAPM and the full conditional multifactor model, respectively.

The second major finding is that managers of Canadian mutual funds exhibit pervasive negative market-timing ability, and that controlling for conditioning information somewhat

[30] Zheng (1999) uses a partial conditional three-index model. Subsequent to the initial draft of our paper, Lynch et al. (2002) assess the performance of individual funds using both a partial and full conditional multi-index model where they argue that dividend yield by itself is sufficient as a conditioning variable to describe movements in the business cycle.

alleviates the pervasiveness of the negative market-timing inferences. The evidence strongly suggests that the widely used unconditional timing models of Treynor and Mazuy (1966) and Henriksson and Merton (1981) are not appropriate for measuring the timing ability of managers of Canadian mutual funds.

The third major finding is that the performance rankings across all of the performance measurement models are significantly and quite strongly related or concordant. Furthermore, the level of concordance across the rankings using various performance measurement metrics is weakened by partial and not by full conditioning, and is relatively unchanged after the incorporation of a market-timing adjustment or by the particular choice of one from a number of reasonably representative market index benchmarks. Thus, full model conditioning appears to have a much greater impact on absolute rather than on relative portfolio performance inferences.

The fourth major finding is that the determinants of Canadian equity mutual funds is a mix of that identified for U.S. and European funds, and reflects the different market structure that exists in the Canadian mutual fund industry. Four of these significant determinants of the performance of Canadian equity mutual funds are robust across the various linear performance models evaluated herein. These determinants are the age, size, management fee, and to a lesser extent the management expense ratio of each fund. Two of the identified relationships provide information about the economics of the mutual fund industry in Canada. First, the positive relation between performance and fund size suggests the presence of scale economies in the Canadian mutual fund industry. This is consistent with the evidence found for funds only in Europe (Otten and Bams, 2002) with the exception of Sweden (Dahlquist et al., 2000). Second, the weakly negative relation between performance and the management expense ratio suggests a weak level of competition in the Canadian mutual fund industry. This finding is consistent with that reported by Elton et al. (1993) and Carhart (1997) for U.S. funds, and not with that reported by Ippolito (1989) and Otten and Bams (2002) for U.S. and European funds, respectively.

The remainder of the paper is organized as follows: In section two, the sample of funds and data used in the empirical tests reported herein are discussed. In section three, the econometric methodology and the construction of the tests are developed. In section four, the various benchmark models are presented and the estimates of risk-adjusted portfolio performance results for our sample of mutual funds are presented and analyzed. In section five, the empirical results from the market-timing-adjusted models and from the performance ranking tests are reported and assessed. In section six, the relationship between risk-adjusted performance and several fund characteristics is examined. Finally, section seven concludes the paper.

3.2 Sample and Data

The sample consists of 95 Canadian equity funds from the Financial Post mutual fund database with no more than 5% of their values missing over the period from November 1989 through December 1999. This selection screen imparts a survivorship bias in the results presented herein in favor of better performance. The 122 monthly returns for each fund are calculated using the monthly changes in the net asset value per share or NAVPS, and are adjusted for capital gains and dividend payments. To facilitate comparison with previous studies, only equity funds are examined.

Some summary statistics on these funds are presented in table A1. Panel A reports statistics on the cross-sectional distribution of the 95 mutual funds. The average annual fund returns vary from -3.08% for Cambridge Growth of Sagit Investment Management to 18.03% for AIC Advantage of AIC Limited, and the grand mean is 9.86%. The annual standard deviations range from 6.00% for Canadian Protected of Guardian Timing Services to 31.05% for Cambridge Special Equity of Sagit Investment Management. The corresponding average annual TSE 300 index return and volatility are 11.17% and 14.53%, respectively.

Summary statistics are provided in panel B of table A1 for equal-weighted portfolios of funds grouped by the six major investment objectives. If the one balanced fund is ignored, the highest and lowest mean returns occur for the aggressive growth grouping of 27 funds and the growth and income grouping of 12 funds. The aggressive growth and specialty funds exhibit the highest and lowest unconditional volatilities of 13.39% and 11.02%, respectively. The first-order autocorrelations of the fund returns are greater than 0.1 for 30 of the 95 funds.

3.3 Econometric Methodology

3.3.1 The Estimation Method and Construction of the Tests

The GMM method is used to estimate the risk-adjusted performance, assess timing ability, and examine the relationship between fund performance and fund attributes.[31] Not only does the GMM allow for an easy integration of conditioning information but it uses a robust estimator for the variance-covariance matrix to construct p-values that are robust to serial correlation and conditional heteroskedasticity. This is true even with arbitrary forms, using different kernel functions such as the modified Bartlett kernel in Newey and West (1987a), the Parzen kernel in Gallant (1987), or the quadratic spectral kernel in Andrews (1991).

For the (un)conditional linear models, the performance measures of stock selection and market timing abilities are estimated using time-series regressions for *each* fund or *each* portfolio of funds. The vector of residuals is defined as:

(3.1) $$\varepsilon_{p,t+1} = r_{p,t+1} - \alpha_p - \Gamma' X$$

[31] 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. GMM 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.

where $r_{p,t+1}$ is the fund or portfolio of funds p excess return between t and $t+1$, α_p is the risk-adjusted performance, Γ is a vector of the coefficients with dimension equal to J, and X is a vector of independent variables whose dimension is model specific. The total number of parameters to be estimated is (J+1) for *each* fund or *each* portfolio of funds. The models imply that:

(3.2) $$E(\varepsilon_{p,t+1} \mid F_t) = 0 \text{ for all } p \text{ and } t$$

For the unconditional tests, $F_t = \{1, X_1\}$, where X_1 corresponds to the vector of the original regressors in the model. When conditioning information is introduced, $F_t = \{1, X_2\}$, where X_2 includes the original regressors augmented by their cross-products with the instrumental variables. For the case of the conditional CAPM with time-varying alphas and betas, four instrumental variables are added to $F_t = \{1, X_2, z\}$. Assuming a dimension n_1 for F_t, the orthogonality conditions are constructed using:

(3.3) $$E(\varepsilon_{p,t+1} \otimes F_t) = 0_{n_1} \text{ for all } p \text{ and } t$$

3.3.2 The Estimation Procedures

The estimates of the portfolio performance measures are obtained from minimizing the GMM criterion function constructed from the set of moment conditions using time-series regression normal equations. This requires a consistent estimate of the weighting matrix. 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.[32] This GMM efficient estimation of portfolio performance is used in Chen and Knez (1996), Kryzanowski et al. (1997), and Farnsworth et al. (2002).

Several restrictions on the parameter estimates are tested under the GMM framework based on the Wald test developed by Newey and West (1987b). Let $g(.)$ be a known vector of functions with dimension of v, less or equal to the dimension of the vector of parameters, and $G_0 \equiv \partial g(.)/\partial\theta$ be the Jacobian of $g(.)$ evaluated at θ_0 and assumed to have a rank of v. Then, the restriction $g(\theta_0) = 0$ is tested using the Wald statistic, based on the unrestricted GMM estimator θ_T^u. It has the following construction:

(3.4)
$$\Delta_T \equiv T \times g(\theta_T^u)'(G_T V_T^{-1} G_T')^{-1} g(\theta_T^u)$$

where θ is the vector of unknown parameters and V_T^{-1} is a consistent estimator of the asymptotic variance-covariance matrix of the unconstrained estimator constructed using the optimal weighting matrix.

3.3.3 Information Variables, Benchmark Assets, and Factors

For the conditional models, five instrumental variables are selected initially based on their predictive power uncovered in studies of stock return predictability.[33] The variables, which are drawn from Statistics Canada's CANSIM database, are the lagged values of DY or the dividend yield of the TSE 300 index (Fama and French, 1988; Ferson and Schadt, 1996; Kryzanowski et al., 1997; Christopherson et al., 1998; and Farnsworth et al., 2002), TB1 or the one-month Treasury bill rate (Ferson and Schadt, 1996; and Farnsworth et al., 2002), RISK or the risk premium as measured by the yield spread between the long-term corporate McLeod, Young, Weir

[32] 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.

[33] Time-series predictive regressions of the excess returns for the six equal-weighted portfolios based on investment objectives and the six size- or NAV-weighted portfolios of funds on the five instruments provide strong support for conducting a conditional performance analysis. The unreported coefficient estimates for the dividend yield and T-bill yield variables are significant for most of the portfolios. The null hypothesis, that all the slope coefficients associated with the selected instruments are zeros, is largely rejected.

bond index and long-term government of Canada bonds (Chen, Roll, and Ross, 1986; Kryzanowski and Zhang, 1992; and Koutoulas and Kryzanowski, 1996), TERM or 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), and DUMJ or a dummy variable for the month of January (Ferson and Schadt, 1996; Kryzanowski et al., 1997; and Farnsworth et al., 2002). To allow for a simple interpretation of the estimated coefficients, the variables are demeaned in some of the models, as in Ferson and Schadt (1996).

Descriptive statistics and autocorrelations, and a correlation analysis of these variables are provided in panels A and B of table A2, respectively. The correlations between all the instruments range from -0.825 to 0.841.

The TSE 300 and value-weighted TSE are used as proxies of the market benchmark for the CAPM models. The five indexes used in the multifactor model are obtained from BARRA for the small-cap stock portfolio, the growth stock portfolio, and the value stock portfolio. The TSE 35 index is used as a proxy for the large-cap stock portfolio and is obtained from the TSE Review. The Scotia Canada Universe bond index obtained from Datastream is used as a proxy for the aggregate bond index since it includes all marketable corporate and government bonds. Ten size-based portfolios are formed from all the stocks on the CFMRC to represent passive buy and hold stock strategies. As reported in panel A of table A2, all the return series for these ten portfolios display a low degree of persistence with no first-order autocorrelation exceeding 0.236.

3.4 Portfolio Performance Using Various Linear Benchmark Models

3.4.1 Empirical Issues

Most of the previous research on performance measurement assesses the performance statistics and inferences using individual funds and averaging their individual performances. This approach produces unreliable and biased results since it very likely that the individual estimated alphas are correlated within fund groups. In this case, the basic assumption of independence underlying any statistical test is violated. In addition, the average significance levels are meaningless. In this paper, we use an alternative robust approach that is based on the performance of two types of portfolios of funds. The first type includes four equal-weighted portfolios of funds constructed using individual fund returns within each investment objective. The second type is composed of four size-weighted portfolios of funds constructed using the individual fund returns and the corresponding total net asset values within each investment objective. Our approach does not suffer from the limitation of the testing methods based on individual performances and represents an innovation of the paper.

3.4.2 The Unconditional CAPM

The traditional CAPM is widely used as the benchmark model to measure risk-adjusted portfolio performance (e.g., see Jensen, 1968, 1969). Dybvig and Ingersoll (1982) show that the single market beta representation or traditional CAPM is equivalent to a stochastic discount factor model where the pricing kernel is a linear function of the efficient market portfolio return.[34] The assumption that the systematic risk of the portfolio is stationary over the evaluation period is not tenable when the portfolio manager is timing the market by adjusting her exposure to the movements in the market return (Grinblatt and Titman, 1989) or when the portfolio manager uses

[34] These two representations are equivalent and unique up to the addition of a random variable that is orthogonal to the asset return into the discount factor specification. Moreover, the parameters of the single beta model are related to the SDF representation coefficients.

derivatives securities that alter the characteristics or the return distribution of the portfolio under management (Admati and Ross, 1985; and Dybvig and Ross, 1985).[35]

The risk-adjusted performance of managed portfolios, α_p, then is given by:

$$r_{p,t+1} = \alpha_p + \beta_p r_{m,t+1} + \varepsilon_{p,t+1}, \quad t = 0,\ldots,T-1, \quad p = 1,\ldots,N \tag{3.5}$$

$$E(\varepsilon_{p,t+1}) = E(r_{m,t+1}\varepsilon_{p,t+1}) = 0$$

where β_p is the sensitivity of the excess return on the fund to the excess return on the market portfolio, $r_{m,t+1}$ is the excess return on the benchmark portfolio m between t and $t+1$, and $\varepsilon_{p,t+1}$ is the random error of fund p in month $t+1$.

The results reported in panels A and B of table A8 for the four equal-weighted portfolios of funds exhibit no significant performance. The alpha of the portfolio of all funds is -0.1411% per month (p-value of 0.19). The only exception is for the equal-weighted growth portfolio of 50 funds that has a significant alpha of -0.1594% (p-value of 0.05). The alpha of the size-weighted portfolio of all funds is higher with -0.1128% but it is not significant, and only the size-weighted portfolio of 12 growth/income funds has a significant negative alpha of -0.1827% per month (p-value of 0.01). Both of the portfolios with significant alphas also have relatively high estimated unconditional betas of 0.844 and 0.769, respectively.[36] The size-weighted aggressive growth and growth portfolios outperform the equal-weighted portfolios using the two market benchmarks. The betas of these two size-weighted portfolios of 0.840 and 0.861 are higher than the 0.832 and 0.844 estimates, respectively, using their corresponding equal-weighted portfolios. This result is consistent using portfolios of all funds. All of the adjusted R^2 are relatively high exceeding 80%.

[Please insert table A8 about here.]

[35] The CAPM-implied SDF may take negative values in some states of nature implying negative performance measures for superior managers (Dybvig and Ingersoll, 1982).
[36] The unreported empirical distribution of the individual fund alphas has a slight negative skewness with fat tails.

An examination of the distribution of the p-values of the performance for all funds and per fund group that are reported in table A9 shows that only 24% of the funds have negative and significant alphas, and no fund has a positive and significant alpha when the value-weighted TSE index is used as the benchmark. The Bonferroni p-values tend to confirm these results. The negative extreme t-statistics are significant only for the growth and growth/income fund groups rejecting the hypothesis that all alphas are zeros.

[Please insert table A9 about here.]

The overall results are similar to those reported by Ferson and Schadt (1996) for U.S. mutual funds, are consistent with those reported by Dahlquist et al. (2000) for Swedish equity mutual funds, and are somewhat consistent with those reported by Kryzanowski et al. (1997) for Canadian mutual funds for the period 1981-1988. Although these unconditional CAPM-based performance statistics do not lead to any serious inferences about the ability of fund managers, they are useful for comparison purposes with the other models reported below.

3.4.3 The Conditional CAPM

In the conditional CAPM, the positive and linear relationship between the conditional expected return and market risk premium for a fund p is given by:

$$E_t(r_{p,t+1}) = \beta_{p,t} E_t(r_{m,t+1}) \tag{3.6}$$

Most previous tests of asset pricing and portfolio performance implicitly or explicitly assume linear conditional expectations in conditioning information.[37] The main conditioning variables are the lagged values of the four conditioning variables discussed above.

[37] Examples include Harvey (1989), Cochrane (1996), Chen and Knez (1996), Ferson and Schadt (1996), Kryzanowski et al. (1997), Christopherson et al. (1998) and Aït-Sahalia and Brandt (2001). Harvey (2001) provides sufficient conditions on the data distribution to form expectations linear in the conditioning information.

3.4.3.1 Conditional CAPM with Time-Varying Betas

Ferson and Schadt (1996) argue that a conditional CAPM specification is appropriate to estimate the abnormal performance of mutual funds when the expected returns and risk vary with changing economic conditions. The conditional beta in their framework has the following linear reaction function:

(3.7)
$$\beta_{p,t} = b_{p0} + b_p' z_t$$

The intercept coefficient b_{p0} is the unconditional mean of the conditional beta. The vector of slope coefficients b_p' measures the response of the conditional beta to movements in the innovations in the conditioning variables, $z_t = Z_t - E(Z_t)$. The conditional performance measure, α_p^c is implied by the following equation:

(3.8)
$$r_{p,t+1} = \alpha_p^c + b_{p0} r_{m,t+1} + b_p'(z_t r_{m,t+1}) + \varepsilon_{p,t+1},\ \ t = 0,\ldots,T-1,\ \ p = 1,\ldots,N$$

$$E(r_{m,t+1}\varepsilon_{p,t+1}) = E(z_t^l r_{m,t+1}\varepsilon_{p,t+1}) = E(\varepsilon_{p,t+1}) = 0,\ \ l = 1,\ldots,L$$

This model is an unconditional multi-factor model where the additional factors are the products of the market portfolio and the lagged information variables. These factors are interpreted as returns to self-financing dynamic strategies obtained by purchasing z_t units of the market portfolio by borrowing at the risk-free rate.

The conditional alpha is estimated as the intercept of the extended regression model and the average beta is obtained from the estimated coefficient associated with the benchmark excess return. The performance and risk results for the equal- and size-weighted portfolios of funds are presented in panels C and D of table A8. They are marginally better than the unconditional statistics. Most portfolios now have negative but not significant performance. For example, the alpha of the equal-weighted portfolio of all funds is -0.1261% (p-value of 0.19) using the value-weighted TSE index as the benchmark. This is below the average monthly management fees of

0.1442% suggesting neutral performance. However, the growth and growth/income portfolios have negative and significant performance, and their alpha point estimates are weaker than most of the fund portfolios.[38] This evidence is somewhat consistent with the results of Ferson and Schadt (1996) who find that the inclusion of conditioning information impacts their performance statistics away from inferior performance. Their argument holds if the covariance between the conditional beta and the excess return on the benchmark portfolio or $\mathrm{Cov}(r_m, b_p z)$ is negative.[39] However, this result contrasts with that of Christopherson et al. (1998, table 1) for the conditional performance of U.S. pension fund managers. The superior performance of size-weighted portfolios compared to their equal-weighted counterparts suggests that partial conditioning preserves the unconditional-based large fund effect. Moreover, the beta coefficients are slightly lower for most of the portfolios under the conditional methodology. This suggests that unconditional betas may be biased, and that fund managers could be revising their portfolios to changing economic conditions.

The Wald test conducted on the marginal contribution of the conditioning variables produces mixed results that vary with the benchmark variable. It rejects the null hypothesis of fixed betas using the TSE 300 index as the benchmark for all portfolios except the equal-weighted aggressive growth portfolio (average p-value of 0.26). With the value-weighted TSE index as the benchmark, the constant conditional betas hypothesis cannot be rejected for most portfolios except the two growth/income portfolios.[40]

[38] The unreported analysis of the individual fund performances and risks results in similar inferences. There are 53 and 51 funds with a conditional alpha higher than the unconditional estimate using the TSE 300 index and value-weighted TSE indices as benchmarks, respectively. The distribution of the alphas is still negatively skewed with more observations in the tails compared to the normal distribution and conditioning information decreases the fund risk sensitivities.

[39] In this case, the unconditional Jensen alpha is negatively biased.

[40] With the same benchmark variable and using the 5% (10%) significance level, the hypothesis of fixed betas is rejected for 17 (18) of 27 aggressive growth funds, 32 (36) of 50 growth funds, and 5 (7) of 12 growth/income funds. Similar figures are obtained in the performance tests reported by Dahlquist et al. (2000) for Swedish equity mutual funds.

The examination of the p-value distributions in panels C and D of table A9 indicates that more funds have significant performance compared to the unconditional tests. There are two funds (one aggressive growth and one growth oriented) with positive and significant alphas using the value-weighted TSE index as the benchmark. In addition, the Bonferroni conservative p-values are significant only for the minimum extreme t-statistics, rejecting the joint hypothesis of zero alphas against the alternative that at least one alpha is negative.

The overall results indicate that a partial conditional approach is superior to models with constant betas, conditioning information positively impacts the inferences, and fund managers do not possess enough skills to display positive risk-adjusted performance. This conclusion is somewhat parallel to that obtained by Ferson and Schadt (1996) given their positive but non significant conditional alphas.

3.4.3.2 Conditional CAPM with Time-Varying Alphas and Betas

Christopherson et al. (1998) advocate the use of a full conditioning model. If the portfolio manager possesses private information, the portfolio weights are conditionally correlated with future returns. In turn, the conditional alpha depends on this conditional covariance where the dependence is approximated by the following linear function:

$$\alpha^c_{p,t} = \alpha_{p0} + \alpha'_p z_t \tag{3.9}$$

This conditional equation can be modified as follows:

$$r_{p,t+1} = \alpha_{p0} + \alpha'_p z_t + b_{p0} r_{m,t+1} + b'_p (z_t r_{m,t+1}) + \varepsilon_{p,t+1},\ \ t = 0,\dots,T-1,\ p = 1,\dots,N \tag{3.10}$$

$$E(z^l_t \varepsilon_{p,t+1}) = E(r_{m,t+1}\varepsilon_{p,t+1}) = E(z^l_t r_{m,t+1}\varepsilon_{p,t+1}) = E(\varepsilon_{p,t+1}) = 0,\ \ l = 1,\dots,L$$

Coefficient restriction tests are performed on the validity of the conditional alpha, beta, and joint alpha/beta structures.

In the above full conditional CAPM model with time-varying alphas and betas, the alphas also are a function of the four conditioning variables. The validity of this extended specification is tested through Wald tests on the alpha, beta, and on their joint structures (i.e., W1, W2, and W3, respectively). The results for the equal- and size-weighted portfolios of funds, which are presented in panels E and F of table A8, seem to validate this full conditioning approach.[41] All of the Wald tests are significant using the TSE 300 index as the benchmark. However, the performance statistics are comparable to those reported earlier for the time-varying beta only conditional model. The conditional alphas are -0.1260% and -0.1008% based on the equal- and size-weighted portfolios of all funds, respectively, with the value-weighted TSE index as the benchmark. Except for the aggressive growth and aggregate portfolios, the other portfolios of funds exhibit negative and highly significant alphas. With full conditioning, the large fund effect is confirmed. Thus, unlike Christopherson et al. (1998), the inclusion of conditioning information only has a limited and mixed impact on our risk-adjusted performance inferences.[42]

To better understand the source of this performance, we examine the distributions of the p-values adjusted for serial correlation and heteroskedasticity that are reported in panels E and F of table A9. The number of funds with negative and significant alphas is higher at 35, and is due essentially to the growth and growth/income groups. The number of funds with positive and significant alphas remains the same at two compared to that for the conditional beta model with the value-weighted TSE index as the benchmark but higher than that implied by the model with constant alphas and betas. In addition, the Bonferroni p-values are all significant, except for the minimum t-statistics associated with the growth/income and income groups. This rejects the joint hypothesis of zero alphas.

---

[41] This evidence is further confirmed when the same test on the conditioning structure rejects the null hypotheses of fixed alphas and betas for 61 funds and 65 funds, respectively, at the 10% level using the value-weighted TSE index as the benchmark.

[42] Similar inferences are drawn from the unreported individual fund performances and risk estimates where the performances of 58 (57) funds are slightly poorer (better) than those for the previous partial conditional (unconditional) model. The distribution of the conditional alpha is less asymmetric, but still negative with

The performance based on the extended conditional CAPM model tends to confirm the absence of any stock selection skills by fund managers. This conclusion does depend on the assumption that this model represents the appropriate return generating process driving mutual fund returns. We assess the robustness and the stability of these performance inferences using a four-index model next.

3.4.4 The Unconditional Four-Index Model

Elton, Gruber, and Blake (1996) propose the use of a four-index model as a benchmark to estimate the risk-adjusted performance of mutual funds. This methodology is closely related to the return-style analysis of Sharpe (1992, 1995),[43] where the performance of a fund is measured relative to a benchmark that consists of four portfolios that capture the investment style of the manager. The model is similar to the three-factor model of Fama and French (1993, 1995, 1996), the four-factor model of Carhart (1997), and the characteristics based performance model of Daniel et al. (1997). Gruber (1996), Elton et al. (1999), and Gruber (2001) find that this model outperforms the single factor model and is useful in explaining the behavior of U.S. mutual fund returns.

The four-index model is based on the following unconditional specification:

$$r_{p,t+1} = \alpha_p + \beta_{p,m} r_{m,t+1} + \beta_{p,SL} r_{SL,t+1} + \beta_{p,GV} r_{GV,t+1} + \beta_{p,B} r_{B,t+1} + v_{p,t+1}, \tag{3.11}$$

$$t = 0, \ldots, T-1, \; p = 1, \ldots, N$$

$$E(r_{m,t+1} v_{p,t+1}) = E(r_{SL,t+1} v_{p,t+1}) = E(r_{GV,t+1} v_{p,t+1}) = E(r_{B,t+1} v_{p,t+1}) = E(v_{p,t+1}) = 0$$

where $r_{p,t+1}$ is the excess return on fund p in month $t+1$, $r_{SL,t+1}$ is the return differential between small- and large-cap stock portfolios in month $t+1$, $r_{GV,t+1}$ is the return differential between

---

fewer observations in the tails. The distribution of betas is still negatively skewed with fat tails. The tests also indicate an incremental increase in the explanatory power of the regressions.

[43] Sharpe develops an asset class factor model. It imposes restrictions on the model coefficients to be non negative and to sum to one. The fitted portfolio can be interpreted as a portfolio of the different benchmarks

growth and value stock portfolios, and $r_{B,t+1}$ is the excess on an aggregate bond index representing corporate and government bonds in month $t+1$ or the bond index total return minus the one-month Treasury bill rate. The beta coefficients $\beta_{p,k}$, $k = \{m, SL, GV, B\}$ measure the sensitivities of the excess returns of fund p to the four factors in the equation, and α_p is the unconditional risk-adjusted performance.

The performance and risk estimates for equal- and size-weighted portfolios of funds are presented in table A10. The alphas for the equal- and size-weighted portfolios of all funds are -0.0164% and 0.0053%, respectively. All of the portfolios have non-significant performances except for the size-weighted portfolio of growth/income funds which has a negative alpha. All of the portfolios have positive weightings or betas on the smallness index, and negative weightings on the growth-value index with the exception of the aggressive growth portfolios.[44] This surprising result for the growth and growth/income portfolios tends to question the validity of the assumed return structure or fund self-classification.

[Please insert table A10 about here.]

This realized performance is analyzed further by examining the distribution of the p-values associated with the individual alphas in panel G of table A9. 12 funds have negative and significant alphas, and only seven have significant positive alphas. Since the computed Bonferroni p-values are significant for the minimum and the maximum t-statistics at the 0% and 9% levels, respectively, the joint null hypothesis of zero for the four index-based alphas is not supported by the data. The evidence for this model seems to indicate that fund mangers do outperform the benchmark when we consider management fees. Although this model provides a

with short-selling restrictions. The drawback of this style analysis is that it does not capture dynamic strategies.

[44] Based on an examination of the weightings or betas of the individual funds, the average size index beta of 0.25 indicates that the average fund tends to hold stocks that are essentially smaller than the average stock in the TSE 300 index.

good description of the returns of U.S. mutual funds (Elton et al. 1993; and Gruber, 2001), such is not the case for the Canadian mutual fund returns.

3.4.5 The Conditional Four-Index Models

3.4.5.1 Conditional Four-Index Model with Time-Varying Betas

The conditional version of this multifactor model with time-varying beta coefficients is given by:

$$(3.12) \quad r_{p,t+1} = \alpha_p^c + \beta_{p,m}(z_t) r_{m,t+1} + \beta_{p,SL}(z_t) r_{SL,t+1} + \beta_{p,GV}(z_t) r_{GV,t+1} + \beta_{p,B}(z_t) r_{B,t+1} + v_{p,t+1},$$

$$t = 0,\dots,T-1,\ p = 1,\dots,N$$

The following linear multiplicative information structures are assumed:

$$\beta_{p,m}(z_t) = b_{p,m,0} + b'_{p,m} z_t$$

$$\beta_{p,SL}(z_t) = b_{p,SL,0} + b'_{p,SL} z_t$$

$$\beta_{p,GV}(z_t) = b_{p,GV,0} + b'_{p,GV} z_t$$

$$\beta_{p,B}(z_t) = b_{p,B,0} + b'_{p,B} z_t$$

where $b_{p,m,0}, b_{p,SL,0}, b_{p,GV,0}$, and $b_{p,B,0}$ are average conditional betas, and $b'_{p,m}, b'_{p,SL}, b'_{p,GV}$, and $b'_{p,B}$ are vectors of beta-response coefficients with respect to the four factors to innovations in the conditioning variables, and α_p^c measures the conditional risk-adjusted performance. The estimation is subject to the regularity conditions given by:

$$E(r_{k,t+1} v_{p,t+1}) = E(z_t^l r_{k,t+1} v_{p,t+1}) = E(v_{p,t+1}) = 0$$

$$k = \{m, SL, GV, B\} \text{ and } l = 1,\dots,L$$

This conditional model is designed to capture non-linearities with a multiplicative structure, which are implied by dynamic portfolio strategies that combine the four factors with the set of conditioning information variables.

The performance and risk statistics for the equal- and size-weighted portfolios of funds are presented in table A10. The equal- and size-weighted average alphas increase to 0.0285% and 0.0469%, respectively, from -0.0164% and 0.0053% for the unconditional model due to the relatively good performances of the aggressive growth and growth portfolios. This conditional estimation confirms the superior performance of large funds observed with the unconditional statistics. The beta estimates are similar to those for the unconditional model with positive weightings on the size index for all portfolios, and negative weightings on the growth-value index with the exception of the aggressive growth and aggregate portfolios. This result is corroborated by the Wald tests, which cannot reject the joint time-variation in all index sensitivity coefficients. Based on individual factor tests, the time-variation in the market, size, and bond index sensitivity coefficients are rejected for only a few of the equal-weighted portfolios of funds, but not for the size-weighted portfolios.[45]

The improvements in the performance results by moving from unconditional to conditional alphas are presented in panel H of table A9. More funds (9) now have positive and significant performance, and 57 funds have a better alpha. The Bonferroni p-values are all significant, which rejects the joint null hypothesis of zero conditional alphas.

Overall, the conditional alphas estimated for this four-factor model indicate that fund performance is weakly positive but not significant. This indicates that fund managers are marginally able to realize abnormal returns equivalent to their management fees once we control for conditional information effects. This confirms the conclusions of Kryzanowski et al. (1997) that performance improves using a conditional multifactor model. However, the results suggest

[45] The same test cannot reject (at the 10% significance level) the hypothesis of time-varying betas for almost 60% of the funds.

that this proposed conditional model does not provide a good description of mutual fund returns in Canada.

3.4.5.2 Conditional Four-Index Model with Time-Varying Alphas and Betas

This extended model assumes that conditional performance is related to some predetermined information variables as in Ferson and Harvey (1999) and Lynch et al. (2002).[46] The conditional four-index model with time-varying alphas and betas has the following form:

$$(3.13)\quad r_{p,t+1} = \alpha^{c}_{p,t} + \beta_{p,m}(z_t) r_{m,t+1} + \beta_{p,SL}(z_t) r_{SL,t+1} + \beta_{p,GV}(z_t) r_{GV,t+1} + \beta_{p,B}(z_t) r_{B,t+1} + \nu_{p,t+1},$$

$$t = 0, \ldots, T-1,\ p = 1, \ldots, N$$

The conditional alpha is linearly related to the set of instruments known at time t:

$$(3.14)\qquad \alpha^{c}_{p,t} = \alpha_{p0} + \alpha'_p z_t$$

where all the time-varying factor loading coefficients are linear in the vector of instruments as in the partial conditional model and α_{p0} measures the conditional risk-adjusted performance. The estimation is subject to the regularity conditions given by:

$$E(z^{l}_{t} \nu_{p,t+1}) = E(r_{k,t+1} \nu_{p,t+1}) = E(z^{l}_{t} r_{k,t+1} \nu_{p,t+1}) = E(\nu_{p,t+1}) = 0$$

$$k = \{m, SL, GV, B\} \text{ and } l = 1, \ldots, L$$

The time-varying structures of the conditional factor loadings and alphas are tested using Wald tests.

The performance and risk statistics for the equal- and size-weighted portfolios of funds are presented in panels E and F of table A10. There is a notable increase in the alphas of all portfolios compared to the partial and unconditional models. However, none of the alphas are significant and only the growth/income portfolios have negative alphas. The beta estimates are similar to those for the two previous models with positive weightings on the size index for all portfolios, and negative weightings on the growth-value index with the exception of the aggressive growth and growth/income portfolios. The Wald test results show that time-variation in the conditional alphas cannot be rejected except for the equal-weighted portfolio of growth funds and the joint time-variation in the all coefficients is highly significant.

The changes in the performance results by moving from unconditional to conditional alphas are presented in panel I of table A9. More funds (11) now have positive and significant performance, and 56 funds have a better alpha than from the unconditional and partial conditional models. The Bonferroni p-values are all significant, which rejects the joint null hypothesis of zero conditional alphas.

Overall, the results from the full conditional model tend to confirm the positive impact of conditioning information on performance inferences.

3.5 Market Timing Models and Tests

Most studies on mutual funds find little evidence of timing ability (Chang and Lewellen, 1984; Henriksson, 1984; and Cumby and Glen, 1990). Conditional tests on the market-timing ability of Canadian fund managers by Kryzanowski et al. (1994, 1997) confirm this conclusion. Bollen and Busse (2001) identify positive market-timing ability using daily data, and report that market-timing inferences depend on the frequency used in measuring mutual fund returns.

3.5.1 The Unconditional Treynor-Mazuy Timing Model

Treynor and Mazuy (1966) demonstrate that the relation between the excess returns of the portfolio and the market becomes nonlinear when the portfolio manager is timing the market. The

---

[46] Ferson and Harvey (1999) develop conditional models for stock and bond return predictability.

unconditional specification of their model requires that stock returns not be co-skewed with the benchmark return, and is based on the following quadratic nonlinear equation:

$$(3.15) \qquad r_{p,t+1} = \alpha_p + \beta_p r_{m,t+1} + \gamma_p r_{m,t+1}^2 + u_{p,t+1}, \quad t = 0,\dots,T-1, \; p = 1,\dots,N$$

$$E(r_{m,t+1} u_{p,t+1}) = E(r_{m,t+1}^2 u_{p,t+1}) = E(u_{p,t+1}) = 0$$

where α_p is a measure of timing-adjusted selectivity, β_p is the unconditional beta, and γ_p is the market timing coefficient. Positive alpha and gamma values indicate that the manager has superior selection and timing skills, respectively.[47]

The results of estimating the quadratic regression model (15) on the twelve portfolios of funds are presented in table A11. The gamma coefficients are negative and significant using the two market benchmarks. This clearly suggests that this model is misspecified. The estimated alphas are insignificant positive and negative using the TSE 300 index and the value-weighted TSE index, respectively, as the benchmark. These timing adjusted performances are clearly superior to those obtained by the unconditional CAPM.[48] This result differs from the finding by Dahlquist et al. (2000) that the selectivity measure is not sensitive to this non-linear adjustment in the benchmark model. Moreover, the size-weighted performance statistics consistently dominate the equal-weighted ones for the three largest groups of funds. The explanatory power of the regressions of above 79% is quite high for all of the models.

[Please insert table A11 about here.]

Information on the distribution of the p-values associated with the estimated selectivity and timing measures is provided in table A12. Few funds have positive and significant alphas for the two market benchmarks. While ten funds have negative and significant alphas, only four funds

[47] Admati et al. (1986) analyze the asymptotic properties of alpha and gamma in the quadratic regression assuming that the investment strategy involves linear risk adjustment to timing information.

have positive and significant alphas for the value-weighted TSE index as the benchmark. Based on the conservative p-value estimates using the Bonferroni inequality, the joint null hypothesis of zero alphas is rejected. The only exception is for the maximum t-statistic calculated using the value-weighted TSE index as the benchmark (p-value of 0.660). At least 82 funds have negative (often significant) timing coefficients for each of the two market benchmarks. These results are corroborated by the Bonferroni p-values computed using the extreme values of the t-statistics. These p-values are only significant per fund group and for all funds using the minimum t-statistics, and are rarely significant for the maximum t-statistics. This evidence is not only similar to that reported for U.S. funds by Ferson and Schadt (1996) and for Japanese funds by Cai et al. (1997) but it supports the view that the unconditional timing model is inappropriate to measure the timing abilities of fund managers.

[Please insert table A12 about here.]

3.5.2 The Conditional Treynor-Mazuy Timing Model

The conditional format of this model builds upon the work of Admati et al. (1986) that assumes exponential utility and multivariate normality. This implies that the portfolio beta is a linear function of the timing signal (the future market return plus the noise κ) and the conditioning information, or:

$$\beta_{p,t+1} = a_0 + a_1' z_t + a_2 (r_{m,t+1} + \kappa) \tag{3.16}$$

This model was first derived and tested by Ferson and Schadt (1996) on U.S. mutual fund managers. The conditional equation is written as:

$$r_{p,t+1} = \alpha_p^c + \beta_p^c r_{m,t+1} + A_p'(z_t r_{m,t+1}) + \gamma_p^c r_{m,t+1}^2 + u_{p,t+1}, \quad t = 0,\ldots,T-1, \quad p = 1,\ldots,N \tag{3.17}$$

[48] This evidence is further confirmed with individual fund performances where 57 and 88 of the 95 funds have an increase in the alpha point estimates using the TSE 300 index and value-weighted TSE index, respectively, as the benchmark in the timing adjusted regressions.

$$E(r_{m,t+1}u_{p,t+1}) = E(z_t^l r_{m,t+1}u_{p,t+1}) = E(r_{m,t+1}^2 u_{p,t+1}) = E(u_{p,t+1}) = 0,\ l = 1,\ldots,L$$

The adjustment for conditioning information is captured by the new A_p coefficients. α_p^c and γ_p^c measure conditional selectivity and market-timing performances, respectively.

The estimation results for the three major equal- and size-weighted portfolios of funds are summarized in table A11. While all of the timing coefficients are negative for all portfolios for the two market benchmarks, not all coefficients are significant for the TSE 300 index benchmark where only the growth and aggregate portfolios have negative and significant gammas. Compared to their unconditional counterparts, there is a small deterioration and amelioration in the point estimates and their significance levels for the value-weighted TSE and TSE 300 index benchmarks, respectively.[49] This is inconsistent with the conclusions of Ferson and Schadt (1996) that conditioning information has a positive impact on the timing statistics. Moreover, the little positive impact on the selectivity measures across the two types of portfolios with the inclusion of conditioning information using the value-weighted TSE index as the benchmark is reversed using the other benchmark variable.

Information on the distribution of the p-values of both parameters is summarized in table A12. Few funds have significant positive or negative alphas for the two market benchmarks, as was the case for the unconditional statistics. The Bonferroni p-values are all significant except for the one associated with the maximum t-statistic using the value-weighted TSE index as benchmark. Therefore, the joint null hypothesis of zero alphas is rejected, with the exception of the aggressive growth group for the value-weighted TSE index as benchmark. With the introduction of conditioning information, the number of funds with negative and significant gammas decreases from 52 to 39 and 35 to 11 using the value-weighted TSE and TSE 300 indexes as benchmarks, respectively. Similarly, only a few funds have positive and significant

[49] This result is further corroborated using individual funds with decreasing conditional timing measures for 58 of 95 funds based on the value-weighted TSE index as the benchmark.

gammas. Moreover, the conservative p-values are only significant for the minimum extreme t-statistics. This rejects the joint null hypothesis of zero gammas.

These additional results on individual funds suggest that Canadian mutual fund managers have weak negative market timing ability once we control for conditioning information. One alternate explanation for these results is that the assumptions underlying the conditional Treynor and Mazuy timing model are violated. This is consistent with the conclusions of Kryzanowski et al. (1994), and confirms the results of Cai et al. (1997) where the conditional gamma coefficient is negative and statistically significant for Japanese mutual funds. However, it only partially agrees with the evidence obtained by Ferson and Schadt (1996) for two particular U.S. fund groups, the maximum gain and specialty, which exhibit negative conditional market timing coefficients.

3.5.3 The Unconditional Henriksson-Merton Timing Model

Henriksson and Merton (1981) argue that the portfolio manager may time the market by changing the exposure of her portfolio through switching the asset allocation between risky assets and risk-free securities based on the manager's prediction of whether the market portfolio return will be higher or lower than the risk-free rate.[50] A successful market timer increases the portfolio weight on the risky asset prior to a market rise and decreases this weight prior to a market decline. The Henriksson and Merton unconditional model is given by:[51]

(3.18) $$r_{p,t+1} = \alpha_p + \beta_p r_{m,t+1} + \gamma_p Y_{t+1} + e_{p,t+1}, \; t = 0,\ldots,T-1, \; p = 1,\ldots,N$$

where $Y_{t+1} \equiv \max(0, -r_{m,t+1})$. The equation is subject to the following conditions:

$$E(r_{m,t+1} e_{p,t+1}) = E(Y_{t+1} e_{p,t+1}) = E(e_{p,t+1}) = 0$$

[50] This approach does not consider the magnitude of the relative returns.

[51] Jagannathan and Korajczyk (1986) show that this model might lead to incorrect inferences for managers with no abilities using simple portfolio strategies such as buying call options in the market.

The additional term in equation (3.18) represents the terminal payoff of a put option on the benchmark portfolio with a strike price equal to the risk-free return.

The results for the various portfolios of funds reported in panels E and F of table A11 are basically identical to those with the unconditional Treynor and Mazuy model. Most of the gammas are negative and significant for the two market benchmarks, which indicates perverse timing ability. The alphas are positive but not significant for reported portfolios except for the size-weighted portfolio of growth funds. The point estimates for both of these two parameters are higher compared to those reported earlier for the unconditional timing model. There is no evidence of a large fund effect associated with stock selection and/or timing performance.

Table A12 reports information on the distributions of p-values of the selectivity and timing estimates. They indicate that there are more funds with positive and significant alphas (13) than with negative and significant alphas (2). In addition, the Bonferroni p-values are significant rejecting the joint null hypothesis of zero alphas using the two benchmark variables for all but the growth/income group based on the maximum t-statistics. Furthermore, the majority of funds (77 and 89) exhibit negative timing coefficients using the two market benchmarks. Their respective p-values are less than 5% for 19 and 41 cases. The constructed Bonferroni p-values are only significant for those tests corresponding to the minimum t-statistics for most of the fund groups and for all funds. This rejects the null hypothesis of zero gammas. Such a negative market timing result is consistent with that reported by Chang and Lewellen (1984), Henriksson (1984), and Ferson and Schadt (1996).

3.5.4 The Conditional Henriksson-Merton Timing Model

Ferson and Schadt (1996) proposed a conditional version of this model where the timing ability of the manager is related to the forecast of the non-expected market excess return, and the expected excess return is measured with respect to predetermined information variables. The equations for the conditional test are given by:

(3.19) $$r_{p,t+1} = \alpha_p^c + \beta_p^c r_{m,t+1} + A_p'(z_t r_{m,t+1}) + \gamma_p^c r_{m,t+1}^* + C_p'(z_t r_{m,t+1}^*) + e_{p,t+1},$$

$$t = 0,\dots,T-1,\; p = 1,\dots,N$$

$$E(r_{m,t+1}e_{p,t+1}) = E(z_t^l r_{m,t+1}e_{p,t+1}) = E(r_{m,t+1}^* e_{p,t+1}) = E(z_t^l r_{m,t+1}^* e_{p,t+1}) = E(e_{p,t+1}) = 0,\; l = 1,\dots,L$$

where $r_{m,t+1}^* = D\{r_{m,t+1} - E_t(r_{m,t+1}) > 0\}$ and $D\{r_{m,t+1} - E_t(r_{m,t+1}) > 0\}$ is an indicator function that equals one if the difference between the excess return on the benchmark and the conditional mean of that excess return or the unexpected component is positive, and is zero otherwise. The conditional mean is estimated by a linear projection of the excess return for the benchmark on the lagged values of a set of instrumental variables. The interpretations of the signs of α_p^c and γ_p^c are as in the unconditional version of the model discussed above.

The results for the various portfolios of funds reported in panels G and H of table A11 are somewhat different from the unconditional statistics. All portfolios have insignificant gammas except the equal- and size-weighted growth and aggregate portfolios that have significant (and negative) gammas using the value-weighted benchmark. These estimates are a notable improvement over the unconditional estimates. The alphas of the equal- and size-weighted portfolios of all funds are still positive at 0.1222% and 0.1491% per month but are not significant. Most of the portfolios have positive but not significant alphas with the exception of the growth/income fund group. These timing-adjusted performances are consistently weaker than the unconditional counterparts across the two portfolio types and market benchmarks.

The distributions of the p-values for the alphas and gammas are summarized in table A12. The number of funds with positive and significant alphas decreases from 12 to 3 and from 13 to 7 using the TSE 300 and value-weighted TSE indexes as benchmarks, respectively. This is essentially due to the weak performance of certain growth funds. In addition, more funds have negative and significant alphas (7 compared to 4), especially using the TSE 300 index as the benchmark. Only the Bonferroni p-values related to the positive extreme t-statistic are significant for all funds (p-value of 0.067) and for the aggressive growth group for the value-weighted TSE index as the benchmark. Only the conservative p-values associated with the minimum t-statistic are significant for all funds, growth, and growth/income funds for the TSE 300 index as the benchmark. Both observations lead to the rejection of the joint null hypothesis of zero alphas. Fewer funds exhibit negative and significant gammas using the two market benchmarks when conditioning information effects are controlled for. Most of these funds belong to the aggressive growth and growth groups. The number of funds with positive and significant gammas is unchanged. The Bonferroni p-values are only significant when constructed using the minimum t-statistics for all funds, and for the aggressive growth group for the value-weighted TSE index as the benchmark. Such results suggest the existence of weak inferior market timing ability for Canadian fund managers. The overall evidence for this conditional model partially corroborates the conclusions of Ferson and Schadt (1996) and Kryzanowski et al. (1994, 1997).[52]

3.5.5 Similarity of the Performance Rankings Across the Various Performance Metrics

The similarity of the performance rankings across the various metrics used for measuring performance is tested in this section. As is evident from an examination of the Spearman rank correlations between the seventeen alpha estimates that are reported in panel A of table A13, the performances of individual funds vary across the various performance measurement models. Not only are 99 of the 136 correlations below 0.9 but also the correlation coefficients decrease with the introduction of conditioning information, and with the introduction of a multifactor structure into the measurement model.

This is supported further by an examination of the sign and ranking of performance results for the individual funds across the seventeen performance models that are reported in panels B and C of table A13. Only 32 of the 95 funds have the same sign for alpha (26 negative and 6 positive)

[52] The validity of the timing models is further assessed by examining the timing performance of ten size-based passive portfolios. The unreported results indicate that only the conditional Henriksson and Merton

across the selection-only performance measurement models. This decreases to 24 funds (18 negative and 6 positive) when all performance measures are considered. Only two funds have a significant positive or negative alpha across all models when the selection-only performance measures are examined.[53]

To test the hypothesis that the rankings under the different benchmark models are not significantly related, the non-parametric Kendall coefficient of Concordance (W) for several sets of rankings is calculated, as in Peterson and Rice (1980).[54] The concordance values are significant for all of the comparisons reported in panel C of table A13. Thus, the null hypothesis that the various sets of performance rankings are unrelated cannot be rejected at the 0.01% level of significance. Nevertheless, the values of the concordance measure are only 0.665 and 0.716 for a comparison of the rankings across all the linear performance measurement models without and with a market-timing adjustment, respectively. These values of the concordance measure increase to 0.979 and 0.857, respectively, when only the rankings from the unconditional performance measurement models are examined, and decrease to 0.615 and 0.663, respectively, when only the rankings from the conditional performance measurement models are considered. Thus, conditioning accentuates differences in performance rankings across the various performance measurement models examined herein. Furthermore, partial but not full conditioning of CAPM-based performance measures of selection changes the rankings materially. To illustrate, the value of the concordance measure for the selection performance rankings for the unconditional CAPM

---

model and to a lesser extent the conditional Treynor and Mazuy model produce timing statistics that are not significantly different from zero.

[53] Additional but unreported tests find that only a small number of funds maintain their rankings across all of the portfolio performance models for all fund groups. Almost an equal number of funds improve or lower their rankings for most pairs of performance measures. The same conclusions follow when the performance rankings are examined from the perspective of an investor interested in examining which managers provide the most value added to the fund where the rankings are established only for funds with positive alphas.

[54] The concordance coefficient measures the association between different sets of rankings and is defined as the ratio of the sum of squares of ranking deviations from the mean of the sums of the ranks (variability of the rankings) to the maximum possible sum of the squared deviations. W takes values between 0 and 1, where 0 and 1 indicate no agreement and perfect agreement in the rankings, respectively. This statistic is

for the TSE 300 and value-weighted TSE indices versus their conditional counterparts with both time-varying alphas and betas of 0.975 and 0.972, respectively, are much higher than the corresponding values of 0.619 and 0.616, respectively, when their conditional counterparts only have time-varying betas. The concordance values for these comparisons are nearly identical across the market index benchmarks. The value of the concordance measure for the selection performance rankings for the unconditional versus partial and full conditional four-factor models is fairly high at 0.884 and 0.869, respectively. Furthermore, the impact on the selection performance rankings is minor when a CAPM-based performance measure with a market-timing adjustment is conditioned.

The choice of market index from among a set of reasonably representative market index benchmarks also has a minor impact on the selection performance rankings. Specifically, the values for the concordance of the selection performance rankings for the unconditional versus conditional Treynor and Mazuy (1966) timing model for the TSE 300 and value-weighted TSE indices of 0.987 and 0.988, respectively, are high. Their counterparts for the Henriksson and Merton (1981) timing model are only marginally lower at 0.936 and 0.960, respectively. The concordance values for these comparisons are nearly identical across market index benchmarks. Together with the results reported in previous sections of this paper, this suggests that full conditioning is likely to have a greater impact on absolute than on relative performance inferences. Thus, the choice of the performance measurement benchmark and its implementation are important for assessing the performance of Canadian equity mutual funds.

[Please insert table A13 about here.]

3.6 Relationship between Performance and Fund Characteristics

---

distributed as Chi-square in large samples (more than seven items ranked). See Siegel and Castellan (1988) for more details.

Numerous studies examine the relationship between risk-adjusted performance and fund characteristics such as age, size, expenses, turnover, and flows. If the mutual fund market is perfectly competitive, fund expenses will reflect the costs of generating the risk-adjusted returns. Ippolito (1989) examines this hypothesis and finds that the Jensen alphas are unrelated to fund expenses. This evidence supports the costly information market efficiency argument of Grossman (1976) and Grossman and Stiglitz (1980).[55] Elton et al. (1993) reformulate Ippolito's approach and use a three-factor model that incorporates the effects of holding non S&P stocks and bonds and document a negative relationship between alphas and management expense ratios. Various authors, such as Grinblatt and Titman (1994), Carhart (1997), and Chevalier and Ellison (1999), report corroborating evidence. Otten and Bams (2002) find evidence of economies of scale for European mutual funds as reflected in a positive relationship between risk-adjusted performance and fund size as measured by the log of the total net assets of the fund. Otten and Bams also obtain a negative correlation between the expense ratio and their conditional multifactor alpha. Dahlquist et al. (2000) find a strong negative relation between risk-adjusted performance and fund size for a subgroup of Swedish equity mutual funds, and that funds with high fees under-perform those with low fees. Similarly, Chen et al. (2003) find evidence for diseconomies of scale based on a large sample of U.S. equity funds using both gross and net fund returns. They argue that fund size erodes performance because of liquidity and organizational diseconomies. Some of these empirical stylized facts or regularities are reproduced using the rational equilibrium model of Berk and Green (2002). This model assumes competitive provision of capital by investors to mutual funds, differential ability to generate excess returns, and learning about managerial ability from past returns.

---

[55] The noisy rational expectations model of competitive equilibrium in Grossman and Stiglitz (1980) asserts that when the information is costly to collect and implement, the market is efficient if the prices of trades made by informed investors are sufficiently different from those obtained in full information in order to compensate these investors for the cost of becoming informed.

As in Grinblatt and Titman (1994) and Chen et al. (2003), this issue is addressed herein in a cross-sectional setting using the (un)conditional risk-adjusted performance measures and several fund attributes (defined below). The following equation is used to conduct the GMM estimation:

$$\alpha_p^j = c_0 + C'X_p + \xi_p, \;\; j = \{u,c\}, \;\; p = 1,\dots,N, \;\; i = 1,\dots,I \tag{3.20}$$

$$E(X_p^i \xi_p) = E(\xi_p) = 0$$

where $X_p = (\text{Expense Ratio Management Fees Ln(TNA) Ln(Age) D(Load)})'$ is a vector of fund characteristics with a dimension equal to I. The vector of coefficients C measures the marginal effect of each attribute variable on the risk-adjusted performance of the fund. ξ_p is a vector of random errors.

3.6.1 Mutual Fund Characteristics

Net asset values per share or NAVPS and total number of shares are used to compute the total net asset value or TNA to reflect the size of the fund. The average fund size is $288.7 million, and ranges between $67.4 million for the Templeton Canadian Stock fund and $2876.6 million for the PH&N Equity PI Fund. These statistics illustrate the relatively smaller size of Canadian mutual funds compared to those in the U.S. where the average size is $1.1 billion in 1999.

The management expense ratio or MER represents the total of all management and other fees charged to the fund, as a percentage of the fund's total assets.[56] For our sample, it varies from 0.09% to 4.60%. Management fees or MGF are charged by the fund's investment advisor(s) for managing the fund and selecting the different securities. They range from 0.13% of a fund's total assets to 2.50% annually, and average 1.73%.

Six fund types are considered herein; namely, aggressive growth, growth, growth/income, income, balanced, and specialty. Fund age or AGE averages 21 years, and ranges from 67 years for the Spectrum United Canadian Investment Fund to 10 years for the Strategic Value Canadian O'Donnell Fund.

The dummy variable or LOAD is used to indicate if the fund is a load fund with sales charges or front-end loads upon purchase of shares and/or deferred sales charges or back-end loads if shares are sold within a set time. Another dummy variable or OPTLO captures if the fund has optional load charges. For our sample, 15 funds have front-load charges, 5 have deferred sales charges, 34 have optional load charges, and 41 are no-load funds. By fund type, there are 5 aggressive growth funds and 9 growth funds with front and/or back-end load charges. All the variables are estimated at the end of the sampling period. Some descriptive statistics of fund attributes are presented in panel C of table A1.

3.6.2 Risk-Adjusted Performance and Mutual Fund Characteristics

Based on the results reported in table A14, a strong relationship exists between performance and fund age, management fees, and size, and to a lesser extent with the management expense ratio. The coefficients of the two dummy variables are not significant for all regressions. Since fund age is negatively related to performance, this suggests that younger funds perform better than older funds. This result is robust to the introduction of conditioning information and to the market timing adjustment. It confirms prior evidence for U.S. funds by Chevalier and Ellison (1999) and for European funds by Otten and Bams (2002).

[Please insert table A14 about here.]

Fund size, as measured by the log of the total net assets of the fund, has a significantly positive relation with the risk-adjusted performance for most of the tests, and especially for the conditional and market timing adjusted performance measures. This indicates the presence of economies of scale in the Canadian mutual fund market. Such a result is consistent with the

[56] The other expenses include the shareholder servicing costs, custodian and transfer-agent fees, shareholder reporting costs, legal fees, auditing fees, interest expense, and directors' fees. These expense

European results reported by Otten and Bams (2002) but contrasts with those of Grinblatt and Titman (1994) and Chen et al. (2003) for the U.S. and with Dahlquist et al. (2000) for Sweden.

The results for the impact of the fee structure, as reflected by the management expense ratio, management fees, and the load dummy variables, on the risk-adjusted performance are mixed. Management fees are consistently positively related to the alphas across the performance measurement models. This suggests signaling through higher fees by fund managers. Moreover, the relationship between the management expense ratio and performance is weakly negative, which suggests that funds with high expenses do not perform as well as funds with low expenses. This evidence is consistent with that reported by Elton et al. (1993) and Carhart (1997), and differs from that reported by Ippolito (1989) and Otten and Bams (2002). It suggests a weak level of competition in the Canadian mutual fund industry. Finally, no evidence exists that load funds or funds with optional loads earn sufficiently high returns compared to no-load funds to pay for their extra sales charges.

3.7 Conclusion

This paper provides extensive new evidence on the sensitivity of performance inferences to the choice of performance measurement model and its implementation on a sample of 95 Canadian equity mutual funds using the flexible and robust GMM framework. Several linear models with and without conditioning information and/or a market-timing adjustment are used to examine the selection ability of this sample of fund managers. Significant differences in the selection performance measures and inferences using alternative performance measurement models are identified. The market-timing tests suggest perverse and weak market-timing abilities of fund managers using unconditional and conditional timing models, respectively. Tests of the

items are detailed in the statement of operations.

performance rankings across all the performance measurement models find that all of the rankings are significantly related, and that partial conditioning of betas (and not also alphas) accentuates the differences in performance rankings across performance measurement models. The findings also suggest that full model conditioning is likely to have a greater impact on absolute than on relative performance inferences.

This paper uncovers the determinants of performance by studying the relationship between performance and fund-specific attributes across performance measurement models. Measured performance is negatively related to fund age across the various performance measures, and is negatively related to the management expense ratio across the majority of performance measures. The finding that large funds seem to perform better than small funds implies the existence of economies of scale in the Canadian fund industry. Canadian fund managers also appear to signal their selection abilities via increased fund management fees.

CHAPTER 4

PORTFOLIO PERFORMANCE MEASUREMENT USING HIGHER-ORDER MOMENT AND NONLINEAR ASSET PRICING KERNEL MODELS

4.1 Introduction

The search for an adequate performance measure for actively managed portfolios has received wide interest in the portfolio performance literature during the last twenty years. This interest is closely related to theoretical and empirical developments in the asset pricing literature. One major development is the use of nonlinear asset pricing models free of any implicit or explicit restrictions on the joint distribution of factor realizations and asset returns. The nonlinear arbitrage pricing framework implies a nonlinear pricing equation and extends the classical linear factor models. Bansal and Viswanathan (1993) and Bansal, Hsieh, and Viswanathan (BHV, 1993) argue that nonlinear pricing models can price primitive securities whose payoffs are nonlinear functions of the underlying factors. Nonlinearities may also arise when derivative securities are traded even when the linear factor pricing restrictions are satisfied. Thus, the nonlinear asset pricing kernel is an unknown nonlinear function of factor realizations and is relevant for pricing any asset or portfolio irrespective of its payoff structure.[57] Recent studies have a similar focus where they develop higher-order moment models for testing asset pricing relationships. Harvey and Siddique (2000) make a strong argument for including skewness and develop an asset pricing kernel that is quadratic in the benchmark return. Dittmar (2002) derives a pricing kernel that is

[57] The unknown pricing kernel can be approximated using the semi-nonparametric (SNP) approach based on truncated series expansions. In effect, Gallant and Tauchen (1989), Bansal and Viswanathan (1993), and BHV (1993) approximate the pricing kernel using a truncated polynomial series expansion in asset returns. Another variant of the SNP proposed by Chapman (1997) rests on an orthonormal polynomial expansion in a small number of state variables implied from a stochastic version of the neoclassical growth model.

nonlinear in the return on aggregate wealth and is consistent with a set of restrictions on investors' preferences.[58]

A second major development is the integration of the role of conditioning information in tests of asset pricing theories. When expected returns and risks are time-varying, the unconditional performance metrics fail to produce a reliable measure of abnormal performance by confusing the inherent time-variation with the possibility of superior abilities of portfolio managers. Most tests on portfolio performance fail to exploit both developments since they use linear factor or kernel pricing models or develop unconditional performance statistics.[59]

Other studies attempt to unravel the determinants of fund performance based on linear benchmark models. They produce mixed results for non-U.S. and U.S. funds.[60] Fund attributes or properties examined as potential determinants of fund performance in this rapidly evolving literature include fund size, age, fees, trading activity, flows, and past returns. However, these studies do not account for potential nonlinearities in the fund payoffs and/or examine the robustness of their results to the choice of performance evaluation model, market index benchmark, and conditioning information.

Thus, given these limitations in the literature, the major objective of this paper is two-fold. The first objective is to complement previous research by providing new evidence on the impact of nonlinear dynamics in the benchmark model and conditioning information on the risk-adjusted performance of funds by using various higher-order moment and polynomial asset pricing kernel models. These models jointly accommodate the conditional pricing of portfolios with linear and nonlinear payoffs and have not yet been tested in the context of (un)conditional performance evaluation. As in previous research by Chen and Knez (1996), Ferson and Schadt (1996),

[58] His asset pricing equation accounts for the fourth moment of asset returns and outperforms the traditional CAPM and multifactor models in explaining the cross-section of expected returns.
[59] See, for example, Ang and Chua (1979), Leland (1999), Ferson and Schadt (1996), and Kryzanowski et al. (1997).

Kryzanowski et al. (1994, 1997), Christopherson et al. (1998), and Farnsworth et al. (2002), our frameworks are suitable to perform evaluations of fixed-weight and dynamic strategies. The importance of the restriction on the mean of the asset pricing kernel or equivalently the pricing of the risk-free asset in performance evaluation also is tested. The second objective is to relate nonlinear performance statistics to several fund characteristics or attributes such as fund type, age, size, and management fees and expenses, and to examine the robustness of these relations for Canadian equity mutual funds.

We develop the appropriate framework for the estimation of the SDF-based performance measures and the relationship between fund performance and fund characteristics. The flexible (un)conditional Generalized Method of Moments (GMM) of Hansen (1982) is used to estimate the various models. GMM permits adjustment of the standard errors for serial correlation and heteroskedasticity and can handle non *iid* distributions for the pricing errors. All of the tests are conducted on a sample of 95 Canadian equity mutual funds over the period, November 1989 through December 1999.

The first major finding is that the measured unconditional performance of fund managers is negative or neutral but improves as the pricing kernel-based benchmark model becomes nonlinear and conditional. However, the performance statistics and inferences are highly sensitive to the inclusion of the restriction on the pricing of the risk-free asset. The effects are mixed due to the interdependence of the pricing restriction with the set of conditioning information. This restriction has a pronounced impact on the some of the large fund effects observed with the conditional models.

The second major finding is that the determinants of Canadian equity mutual funds are somewhat concordant with those identified for U.S. and European funds, and reflect the different market structure that exists in the Canadian mutual fund industry. Three of these significant

[60] The evidence for U.S. funds includes Ippolito (1989), Elton et al. (1993), Gruber (1996), Carhart (1997), Sirri and Tufano (1998), Zheng (1999), Berk and Green (2002), and Chen et al. (2003). The evidence for

determinants of the performance of Canadian equity mutual funds are robust across the various nonlinear performance models evaluated herein. These determinants are age and size, and to a lesser extent the fund load structure. Performance as measured herein is unrelated to fund management fees.

The remainder of the paper is organized as follows: In section two, we discuss the sample of funds and data used in the empirical tests reported herein. In section three, we develop and explain the econometric methodology and the construction of the tests. In section four, the various asset-pricing kernel models are presented and the estimates of risk-adjusted portfolio performance for our sample of mutual funds are presented and analyzed. In section five, the relationship between risk-adjusted performance and several fund characteristics is examined. Finally, section six concludes the paper.

4.2 Data and Sample

The sample consists of 95 Canadian equity funds from the Financial Post mutual fund database with no more than 5% of their values missing over the period from November 1989 through December 1999. This selection screen imparts a survivorship bias in the results presented herein in favor of better performance. The 122 monthly returns for each fund are calculated using the monthly changes in the net asset value per share or NAVPS, and are adjusted for capital gains and dividend payments. To facilitate comparison with previous studies, only equity funds are examined.

Some summary statistics on these funds are presented in table A1. Panel A reports statistics on the cross-sectional distribution of the 95 mutual funds. The average annual fund returns vary from -3.08% for Cambridge Growth of Sagit Investment Management to 18.03% for AIC Advantage of AIC Limited, and the grand mean is 9.86%. The annual standard deviations range

---

non-U.S. (European) funds includes Dahlquist et al. (2000) and Otten and Bams (2002).

from 6.00% for Canadian Protected of Guardian Timing Services to 31.05% for Cambridge Special Equity of Sagit Investment Management. The corresponding average annual TSE 300 index return and volatility are 11.17% and 14.53%, respectively.

Summary statistics are provided in panel B of table A1 for equal-weighted portfolios of funds grouped by the six major investment objectives. If the one balanced fund is ignored, the highest and lowest mean returns occur for the aggressive growth grouping of 27 funds and the growth and income grouping of 12 funds. The aggressive growth and specialty funds exhibit the highest and lowest unconditional volatilities of 13.39% and 11.02%, respectively. The first-order autocorrelations of the fund returns are greater than 0.1 for 30 of the 95 funds.

4.3 Econometric Methodology

4.3.1 The Estimation Methods and Construction of the Tests

We use Hansen's (1982) generalized method of moments (GMM) to estimate the risk-adjusted performance and to examine the relationship between fund performance and fund attributes. This method is very convenient to estimate higher-order moment and nonlinear SDF models, allows easy integration of conditioning information, and produces p-values robust to errors due to serial correlation and conditional heteroskedasticity. This is true even with arbitrary forms, and when using different kernel functions such as the modified Bartlett kernel in Newey and West (1987a), the Parzen kernel in Gallant (1987), or the quadratic spectral kernel in Andrews (1991).

The conditional stochastic discount factor models involve the computation of conditional expectations. The empirical estimation of these conditional expectations is performed by creating general managed portfolios, and then examining the implications for the unconditional expectations as in Cochrane (1996).[61]

The conditional SDF assigns zero performance to passively managed portfolios or any portfolio based on public information:

$$\alpha_t^c \equiv E_t[M_{t+1}^c(1_N + R_{s,t+1})] \otimes z_t - 1_N \otimes z_t \tag{4.1}$$

$$\alpha_t^c \equiv E_t[M_{t+1}^c(1_N + R_{s,t+1}) \otimes z_t] - 1_N \otimes z_t = 0 \tag{4.2}$$

$$M_{t+1}^c \equiv M(R_{m,t+1}, z_t, \varphi) \tag{4.3}$$

where $\otimes$ is the Kronecker product obtained by multiplying every asset return by every instrument, M_{t+1}^c is the conditional SDF, $R_{s,t+1}$ is a N-vector of equity net returns, $R_{m,t+1}$ is a N-vector of benchmark portfolio returns, z_t is a L-vector of conditioning variables (including a constant), φ' is the vector of SDF unknown fixed parameters with a dimension equal to K, and 1_N is a N-vector of ones.

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

$$E[M_{t+1}^c((1_N + R_{s,t+1}) \otimes z_t)] = E(1_N \otimes z_t) \tag{4.4}$$

This last pricing equation is used to estimate the several proposed SDF models. The corresponding conditional performance measures are those for returns on actively managed portfolios. The construction of the unconditional SDFs and performance measures is trivial by assuming that the conditioning information includes only a constant.

[61] This approach consists in scaling the original returns by the instruments and avoids the specification of conditional moments and the increasing parameterization of the system. Moreover, it allows one to uncover an additional implication of the conditional SDF model that is not captured by the simple application of the

4.3.2 The Estimation Procedures

Our model implies the following conditional moment restriction:

$$E_t[M(R_{m,t+1}, z_t, \varphi_0)(1+R_{s,t+1})] = 1_N \tag{4.5}$$

Now define as a N-vector of residuals or pricing errors:

$$\varepsilon_{1,t+1} = [M(R_{m,t+1}, z_t, \varphi)(1+R_{s,t+1})] - 1_N \equiv \varepsilon_1(R_{m,t+1}, R_{s,t+1}, z_t, \varphi) \tag{4.6}$$

This relationship depends on the set of unknown parameters, the net returns on the benchmark portfolio, the conditioning variables, and the net returns on passive trading strategy-based portfolios (eventually net returns on individual assets). Given the model structure, the dimension of the vector of unknown parameters is KL. We then have:

$$E_t[\varepsilon_1(R_{m,t+1}, R_{s,t+1}, z_t, \varphi_0)] = 0_N \tag{4.7}$$

Using the law of iterated expectations, the moment conditions can be written as:

$$E[\varepsilon_1(R_{m,t+1}, R_{s,t+1}, z_t, \varphi_0) \otimes z_t] = 0_{NL} \tag{4.8}$$

The SDF parameters and the performance measures are jointly estimated in a system that includes moment conditions related to the returns of a set of passive strategies and additional moment restrictions related to the returns of a subset of funds or portfolios of funds that are supposedly managed actively.[62] These additional moment conditions are given by:

$$E[\varepsilon_2(R_{m,t+1}, R_{1p,t+1}, z_t, \theta_0) \otimes z_t] = 0_{n_2 L} \tag{4.9}$$

---

law of iterated expectations. These scaled returns can be interpreted as payoffs to managed portfolios or conditional assets.

[62] Farnsworth et al. (2002) show that the performance estimates and associated standard errors are invariant to the number of actively managed individual funds or portfolio of funds in the GMM system. Thus, estimating the system for each fund or portfolio of funds separately is equivalent to an extended system with several funds or portfolios of funds. Such a system setup limits the number of moment conditions and controls the saturation ratios in the estimation.

where $\varepsilon_2(R_{m,t+1}, R_{1p,t+1}, z_t, \theta_0) = \alpha_p - [M(R_{m,t+1}, z_t, \varphi_0)(1 + R_{1p,t+1}) - 1_{n_2}]$, $R_{1p,t+1}$ is the vector of net mutual fund returns with a dimension equal to n_2, and $\theta = (\varphi\ \alpha)'$ is the vector of unknown parameters with a dimension equal to $(KL+n_2)$. The GMM estimation exploits these moment restrictions by setting their sample analogues equal to zero. The sample moment conditions are constructed as:

(4.10) $$g_T(\theta) = T^{-1} \sum_{t=1}^{T} (\varepsilon_{1t}', \varepsilon_{2t}')'$$

Following Hansen (1982), the GMM estimator is obtained by selecting $\hat{\theta}_T$ to minimize the sample quadratic form $g_T(\theta)' W_T g_T(\theta)$. When W_T is the optimal weighting matrix, $TJ_T(\hat{\theta}_T)$ has an asymptotic standard central chi-square distribution with $(N\text{-}K)L+n_2(L\text{-}1)$ degrees of freedom. This is the well-known Hansen J_T-statistic.[63] This estimation can handle the assumption that the vector of disturbances exhibits non-normality, conditional heteroskedasticity, and/or serial correlation even with unknown form. This GMM efficient estimation of the portfolio performance measures is used in Chen and Knez (1996), Kryzanowski et al. (1997), and Farnsworth et al. (2002).

Although a unified estimation framework is used for all of the SDF models, the saturation ratios differ due to differences in the parameterization of each SDF specification. The saturation ratios are decreasing functions of the number of parameters and moment conditions, and they deteriorate with conditioning for each benchmark model. In this paper, the saturation ratios are managed so that they always exceed 14.

Several restrictions on the parameter estimates are tested under the GMM framework based on the Wald test developed by Newey and West (1987b). Let $s(.)$ be a known vector of functions

[63] 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. The choice of the weighting matrix only affects the efficiency of the GMM estimator.

with dimension of v, less or equal to the dimension of the vector of parameters, and $S_0 \equiv \partial s(.)/\partial\theta$ be the Jacobian of $s(.)$ evaluated at θ_0 and assumed to have a rank of v. Then, the restriction $s(\theta_0) = 0$ is tested using the Wald statistic, based on the unrestricted GMM estimator θ_T^u. It has the following construction:

$$\Delta_T \equiv T \times s(\theta_T^u)'(S_T V_T^{-1} S_T')^{-1} s(\theta_T^u) \tag{4.11}$$

where V_T^{-1} is a consistent estimator of the asymptotic variance-covariance matrix of the unconstrained estimator constructed using the optimal weighting matrix.

4.3.3 Information Variables and Predictability of Mutual Fund Excess Returns

For the conditional models, two instrumental variables are used based on their predictive power uncovered in studies of stock return predictability.[64] The variables, which are drawn from Statistics Canada's CANSIM database, are the lagged values of DY or the dividend yield of the TSE 300 index (Fama and French, 1988; Ferson and Schadt, 1996; Kryzanowski et al., 1997; and Farnsworth et al., 2002) and TB1 or the one-month Treasury bill rate (Ferson and Schadt, 1996; 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 A2, respectively. The correlations range from -0.825 to 0.841.

In order to motivate the implementation of the conditional methodology, we conduct a predictability analysis of mutual fund excess returns for six equal-weighted portfolios based on investment objectives, and six size- or NAV-weighted portfolios of funds. The predictability analysis consists of time-series regressions of portfolio excess returns on the five instruments

[64] Three additional instrumental variables are selected initially. They are RISK or 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, TERM or 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, and DUMJ or a dummy variable for the month of January.

described earlier. The predictive power of the instruments is assessed using the Wald test discussed earlier.

The reported results in panel D of table A1 indicate significant levels of predictability for both types of portfolios of funds. The null hypothesis, that all of the slope coefficients associated with the selected instruments are zeros, is largely rejected. The coefficient estimates for the dividend yield on the TSE 300 index and the one-month T-bill yield are significant for most of the portfolios. These findings provide strong support for conducting a conditional performance analysis.

4.3.4 Passive Strategies and Benchmark Assets

Passive or basis or 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 stock market strategies considering all of the stocks on the TSE/Western monthly database. 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, as in Kryzanowski et al. (1997).

Panels A and C in table A2 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% for the sixth portfolio to 58.58% for the first portfolio. All of the series indicate a low degree of persistence where all of the first-order autocorrelations are less than 0.236.

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

4.4 Higher-Order Moment and Nonlinear Asset Pricing Kernel Models

(Un)conditional higher-order moment and nonlinear pricing kernel models are used to estimate 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 variability in total and per group of funds, and its sensitivity to the procedure for forming portfolios of funds and to the selected benchmark portfolio. For the four retained groups of funds, we construct four equal-weighted portfolios and four size-weighted portfolios based on the individual fund returns and total net asset values. We also examine the role of conditioning information and the restriction on the mean of the asset pricing kernel by analyzing their impact on the SDF specification and on the risk-adjusted performance.

4.4.1 The Unconditional Skewness Pricing Kernel Model

Several studies have provided considerable evidence against the symmetry of asset and portfolio returns or the normality assumption.[65] Harvey and Siddique (2000, 2002) extend the model of Kraus and Litzenberger to account for conditioning information. They define a stochastic discount factor that is quadratic in the market return in order to account for conditional co-skewness.[66] Such a framework may be useful for portfolio performance evaluation given the growing evidence provided by Merton (1981) and Glosten and Jagannathan (1994) that portfolio

[65] He and Leland (1993) show that asset return distributions cannot be characterized by only the first two moments (mean and variance). They argue that it is important to account for higher order moments such as skewness and kurtosis. Kraus and Litzenberger (1976) derive an unconditional asset-pricing model, which explicitly accounts for skewness in the assumed preferences, and is based on a second-order approximation of the marginal utility. They find that skewness is priced.

managers may follow option-like trading or dynamic strategies, and given that managers prefer positively skewed portfolios that generate large positive returns with high probability.

We use the unconditional version of the model of Harvey and Siddique (2000) where the asset-pricing kernel is quadratic in the aggregate wealth return and all the coefficients are time-invariant, which is written as:[67,68]

$$M^{u}_{t+1} = \varphi_1 + \varphi_2 R_{m,t+1} + \varphi_3 R^2_{m,t+1} \tag{4.12}$$

The abnormal unconditional performance measure is obtained by taking the difference between the unconditional expectations of the product of the SDF and the fund gross return, and one. Specifically, it is given by:

$$\alpha_{p,t} \equiv E[M^{u}_{t+1}(1 + R_{p,t+1})] - 1 \tag{4.13}$$

A significantly positive alpha indicates superior use of private information by the fund manager or the non-control in the evaluation process of the use of public information.

The results for portfolios of funds are reported in table A15 and reveal two important results. First, all of the portfolios produce negative alphas except for size-weighted portfolios of aggressive growth and growth funds but none of the alphas is significant. Overall, the alphas of the equal- and size-weighted portfolios of all funds are -0.0816% (p-value of 0.58) and 0.0138% (p-value of 0.92), respectively, using the value-weighted TSE index as the benchmark. These results suggest neutral performance since the average management fees is 1.73% per year. Second, the size-weighted performance statistics are higher compared to their equal-weighted counterparts across all portfolios with the exception of the growth/income portfolios.

---

[66] Their model is useful in explaining the cross-sectional variation of expected returns and the time-series variation of ex-ante market risk premiums.

[67] It has an equivalent representation in terms of expected return where the unconditional expected excess return for the asset is linearly related to the unconditional covariance with the excess return for the market, and to the unconditional covariance with the square of the excess return for the market. The last term measures the unconditional co-skewness.

[Please insert table A15 about here.]

A detailed analysis of individual fund performance is presented in tables A15 and A16. These results tend to corroborate the results obtained with the portfolios of funds. The average alpha is negative and the size-weighted portfolios of individual performances perform better than the equal-weighted portfolios. The distribution of the alphas is negatively skewed with close to normal tails.

[Please insert table A16 about here.]

This weak performance is examined further by examining the distribution of p-values reported in table A17. This examination indicates that there are more funds with negative alphas than with positive alphas. Only a limited number of funds have positive and significant alphas, specifically, 9 and 11 funds using the TSE 300 and value-weighted TSE indices as the benchmarks, respectively. Moreover, the null joint hypothesis of zero alphas is rejected using the conservative Bonferroni p-values except for the one-tailed test associated with the minimum t-statistics when the value-weighted TSE index is used as the benchmark.

[Please insert table A17 about here.]

Despite the nonlinear dynamics inherent in the model structure, the overall results indicate either the absence of any selection abilities by the Canadian fund managers or the limitation of the model as the appropriate benchmark to measure normal performance. These performance figures and inferences are weaker than those reported by Ferson and Schadt (1996) using the unconditional CAPM and by Kryzanowski et al. (1997) using an unconditional APT.

---

[68] This unconditional specification is implicit in the model of Kraus and Litzenberger (1976) and does account for the skewness in the asset return distribution.

4.4.2 The Conditional Skewness Pricing Kernel Model

The original model of Harvey and Siddique (2000) is based on the conditional asset-pricing kernel quadratic in the aggregate wealth return with time-varying coefficients and is given by:

$$M_{t+1}^{c} = \varphi_1(z_t) + \varphi_2(z_t)R_{m,t+1} + \varphi_3(z_t)R_{m,t+1}^{2} \tag{4.14}$$

where all the φ coefficients are functions of the information set available to the uniformed investor.[69] This model is equivalent to a fully conditional skewness model with time varying alphas, betas, and co-skewness. It extends the conditional CAPM with time-varying alphas and betas of Christopherson et al. (1998). Given the complexity of the estimation system, we limit our choice of predetermined information variables to the dividend yield on the TSE 300 index and the yield on a one month T-bill. Extending the conditioning set to more than two variables increases the parameterization of the system and affects the power of the tests. Thus, as in most previous tests of asset pricing and portfolio performance (Cochrane, 1996; Chen and Knez, 1996; Ferson and Schadt, 1996; Kryzanowski et al., 1997; and Christopherson et al., 1998),[70] linear response functions are assumed for the time-varying coefficients such that:

$$\varphi_1(z_t) = \varphi_{10} + \varphi_{11}' z_t$$
$$\varphi_2(z_t) = \varphi_{20} + \varphi_{21}' z_t$$
$$\varphi_3(z_t) = \varphi_{30} + \varphi_{31}' z_t$$

The validity of each linear response function and that of the complete conditioning structure is tested using the Wald tests under the GMM system framework.

The conditional abnormal performance measure is given by:

---

[69] The pricing equation implied by this conditional specification has the equivalent representation in terms of expected returns where the conditional expected excess return for the asset is linearly related to the conditional covariance with the excess return for the market, and to the conditional covariance with the square of the excess return for the market.

[70] Harvey (2001) provides sufficient conditions on the data distribution to form expectations linear in the conditioning information.

(4.15) $$\alpha_{p,t}^{c} \equiv E_t[M_{t+1}^{c}(1+R_{p,t+1})]-1$$

The conditional alpha is estimated via the conditional expectations of the product of the conditional SDF and the gross return on the fund minus one. A positive value of this measure indicates the efficient use of private information by the fund manager.

The conditional performances of four portfolios of funds are reported in table A15. There is a notable increase in all of the alphas and significance levels using the two benchmark variables. In addition, all of the portfolios of funds display positive and significant performance where the alphas of the equal- and size-weighted portfolios of all funds are 0.4449% and 0.4904%, respectively, using the value-weighted TSE index as the benchmark. In all cases, there is a large fund effect associated with the aggressive growth, growth, and aggregate portfolios manifested by the better performance of the size-weighted statistics compared to the equal-weighted ones. In contrast to the unconditional estimation, the performance figures under the TSE 300 index are now higher than those obtained with the value-weighted TSE index due to the differential effect of the nonlinear risk adjustment with the scaled factors.

Overall, conditioning information seems to positively impact performance, preserves the superior performance of large funds, and reverses the performance relationship between the two benchmark variables. Furthermore, the conditional performance evaluation seems to be justified. The Wald tests associated with the hypotheses on the time variability of the individual and joint coefficients deliver significant p-values.

The evidence on the individual fund performances for both portfolio formation approaches as reported in tables A15 and A16 supports these conclusions. It indicates a positive average alpha for all portfolios of performance. The performance figures are higher than those obtained with the unconditional model producing an average alpha of 0.4060% per month for the equal-weighted portfolios and 0.4192% per month for the size-weighted portfolios using the value-weighted TSE index as the benchmark. In addition, the shape of the alpha distribution has changed with positive asymmetry and fewer extreme observations. A comparison of the performance of the equal-weighted portfolios with the size-weighted portfolios reveals the existence of a large fund effect that is robust across the fund portfolios and the benchmark variables. Based on the Wald tests on the marginal contribution of the conditioning variables, all of the joint tests are highly significant, while some of the individual tests are only significant at the 13% level.

The sources of this positive average performance are examined next by analyzing the distribution of the p-values for all of the funds and per fund group using heteroskedasticity and autocorrelation consistent t-statistics for the two benchmarks. Based on the results reported in table A17 almost 60% of the funds have p-values less than 5%, and only four funds exhibit significant negative alphas using the value-weighted TSE index as the benchmark. There is a predominance of funds with good performance across all fund groups. Moreover, the p-values based on the Bonferroni inequality indicate that positive extreme t-statistics are significant for all funds and across all fund groups. This rejects the joint hypothesis of zero alphas. However, the conservative p-values corresponding to the minimum t-statistics for all fund groups are rarely significant using the two benchmark variables.

Overall, this positive and significant conditional risk-adjusted performance shows that the fund managers have the ability to efficiently exploit their private information and generate excess returns. This shift in the performance statistics compared to the unconditional estimates corroborates the findings of Ferson and Schadt (1996) and Kryzanowski et al. (1997).

4.4.3 The Unconditional Kurtosis Pricing Kernel Model

Dittmar (2002) extends the conditional skewness model of Harvey and Siddique (2000) and proposes to account for the fourth moment in the asset pricing equation. A nonlinear asset-pricing kernel cubic in the return on aggregate wealth is endogenously derived and is consistent with intuitive preference restrictions.[71] The pricing equation is equivalent to a fourth-moment CAPM, as derived by Fang and Lai (1997).[72] The unconditional kurtosis pricing kernel model is based on the following specification:

$$(4.16) \qquad M_{t+1}^{u} = \varphi_1 + \varphi_2 R_{m,t+1} + \varphi_3 R_{m,t+1}^{2} + \varphi_4 R_{m,t+1}^{3}$$

where all the φ are time-invariant. The corresponding performance measure is estimated using equation (4.13). A positive unconditional alpha is associated with superior use of private information or the lack of adequate controls for public information effects.

The summary estimation results for the performance of four equal- and size-weighted portfolios of funds are reported in table A15. The performance for all portfolios is consistently positive and significant for most of them, across the two benchmark variables. Specifically, the alphas of the equal-weighted portfolios of all funds are equal to 0.3602% and 0.4544% using the TSE 300 and value-weighted TSE indices, respectively. These figures are higher when the fund returns are weighted by their total net asset values in the portfolios suggesting superior performance of large funds. These results show significant improvements compared to those estimated using the unconditional skewness pricing kernel model. They suggest that accounting for the fourth moment in asset return distributions has a positive impact on measured performance.

The analysis of the individual mutual fund performances, which is presented in tables A15 and A16, confirms the previous conclusions with respect to positive average performance and the large fund effect. The mean and median alphas are positive at 0.5450% and 0.5476%, respectively, using the value-weighted TSE index. However, the averages of the p-values do not

[71] This approach considers a general utility function where the form is restricted by standard assumptions such as positive marginal utility and risk aversion, decreasing absolute risk aversion, augmented by decreasing absolute prudence. These restrictions are then used to sign the coefficients of the first polynomial terms in the Taylor expansion of the approximated utility function.

[72] In the same vein, Chung et al. (2001) show that a high-order moment framework is appropriate when the asset return distribution diverges from normality. They find that once high-order co-moments are accounted for, the standard Fama and French (1995, 1996) three-factor model loses its significance.

give reliable inferences on the significance of the performance statistics. The positive alphas for the 27 aggressive growth funds, the 50 growth funds, and the 12 growth/income fund portfolios of performances could explain this good performance. These results are confirmed using the TSE 300 index as the benchmark. Moreover, the size-weighted portfolios of performances dominate the equal-weighted portfolios of performances using the two benchmark variables. The distribution of the alphas is negatively skewed but less asymmetric with fewer observations in the tails than that for the unconditional skewness pricing kernel model.

To better understand the sources of this good performance, we examine the distribution of the p-values reported in table A17. A large number of funds have positive and significant alphas. Specifically, 47 and 53 funds have significantly positive alphas using the TSE 300 and value-weighted TSE indexes as the benchmarks, respectively. This represents almost five times the number obtained with the unconditional skewness model (9 and 11, respectively). Most of these funds belong to the aggressive growth and growth groups (16 and 28 funds, respectively). Moreover, all of the Bonferroni p-values are significant except for the ones associated with the minimum t-statistics when the TSE 300 index is used as the benchmark. This rejects the null hypothesis of joint zero alphas.

Overall, this unconditional kurtosis model produces different results than those for the unconditional skewness model in that this model finds more instances of superior abilities among the studied fund managers. This switch in the performance statistics towards better results appears to be due to the increasing complexity in the nonlinear structure of this benchmark model.

4.4.4 The Conditional Kurtosis Pricing Kernel Model

The conditional kurtosis stochastic discount factor is cubic in the benchmark return with time-varying coefficients and is given by:

$$(4.17) \qquad M_{t+1}^{c} = \varphi_1(z_t) + \varphi_2(z_t)R_{m,t+1} + \varphi_3(z_t)R_{m,t+1}^{2} + \varphi_4(z_t)R_{m,t+1}^{3}$$

where all the φ are functions of the set of conditioning variables. This specification implies a fully conditional four-moment asset-pricing model with time-varying alphas. As in most conditional performance tests, we assume a linear conditioning structure on the time-varying coefficients with respect to the two selected information variables, or:

$$\varphi_1(z_t) = \varphi_{10} + \varphi_{11}' z_t$$

$$\varphi_2(z_t) = \varphi_{20} + \varphi_{21}' z_t$$

$$\varphi_3(z_t) = \varphi_{30} + \varphi_{31}' z_t$$

$$\varphi_4(z_t) = \varphi_{40} + \varphi_{41}' z_t$$

Wald statistics are constructed to test the separate and joint validity of the response functions.

The conditional risk-adjusted performance is measured by calculating equation (4.15). Table A15 summarizes the performance results for four portfolios of funds. All portfolios have positive and significant alphas across the two benchmark variables. However, there is no conclusive evidence that conditioning information produces superior performance statistics and inferences since few portfolios are better off without conditioning. The better performance of the size-weighted statistics is less pronounced since it is only observed with the value-weighted TSE index as the benchmark. Finally, the performance figures are higher using the TSE 300 index as the benchmark compared to the other benchmark.

The individual and joint tests on the validity of the conditional model are all significant. Time-variation can only be rejected in the first (constant) and the fourth coefficient associated with the cubic benchmark return in the SDF specification when the value-weighted TSE index is used as the benchmark (p-values of 0.21 and 0.56, respectively).

Based on tables A15 and A16, the conditional performances of the individual mutual funds tend to confirm the previous results. All portfolios of performances display positive alphas. The average conditional alpha is positive and exceeds the alpha for the unconditional model, except when the value-weighted TSE index is used as the benchmark (0.4895% compared to 0.5450%

per month). These differences in performance become smaller when weighted by the size of the funds. However, the performance of the size-weighted portfolios of performances remains superior to that of the equal-weighted portfolios.

With the conditional model, the distribution of the alphas becomes positively skewed with fewer observations in the tails. The inferences from the Wald tests are similar to those obtained with the portfolios of funds, which supports our conditional performance evaluation approach.

An examination of the sources of these good conditional performance statistics in table A17 reveals that more funds have positive alphas and fewer funds have negative alphas. However, the number of those funds with p-values less than 5% is comparable to that for the unconditional model across the two benchmark variables. In addition, the conservative p-values constructed using the Bonferroni inequality are all significant for the maximum t-statistics, which rejects the joint null hypothesis of zero conditional alphas. Those p-values corresponding to the minimum t-statistics are not significant for all funds and per fund group. This result is consistent with the results on the alpha distribution.

The performance figures and tests with the conditional kurtosis stochastic discount factor model confirm that conditioning information and the nonlinear dynamics in the benchmark model have a positive impact on risk-adjusted performance.

4.4.5 The Unconditional BHV Nonlinear Pricing Kernel Model

BHV (1993) propose a nonlinear approximation of the true stochastic discount factor using a polynomial series expansion.[73] They argue that their framework is convenient for pricing any asset or portfolio return with potential nonlinearities in the underlying payoff structure such as derivative securities or actively managed portfolios with option-like features.[74] The expression for their unconditional nonlinear pricing kernel is given by:

[73] Bansal and Viswanathan (1993) use neural networks to approximate the unknown pricing kernel.
[74] In the same spirit, Glosten and Jagannathan (1994) approximate the nonlinear payoff of managed portfolios by a function of payoffs of options on well chosen index portfolios.

(4.18) $$M_{t+1}^{u} = \varphi_0 + \varphi_{1f} R_{f,t+1} + \varphi_1 R_{m,t+1} + \varphi_2 R_{m,t+1}^{2} + \varphi_5 R_{m,t+1}^{5}$$

BHV (1993) motivate the use of the fifth order instead of the third order in order to reduce the collinearity between the variables. It is easily shown that both the unconditional CAPM and the unconditional skewness model are nested under this nonlinear specification. The unconditional performance measure is given by equation (4.13). This unconditional alpha provides a reliable measure of performance in the absence of any public information.

The results for the four portfolios of funds, which are reported in table A15, show an improvement in the performance point estimates compared to those delivered by the unconditional kurtosis pricing kernel model. However, there is a decrease in significance levels. The alphas of the equal-weighted portfolio of all funds are now 1.2110% with a p-value = 0.12, and 1.3244% with a p-value = 0.06, respectively, using the value-weighted TSE index as the benchmark. This is due to the good performance of all funds with positive alphas. Those with negative alphas display poor but not significant performance. With the increasing nonlinearity, the large fund effect is maintained for all portfolios and is robust across the two benchmark variables. The only exception is the growth/income group using the value-weighted TSE index as the benchmark.

When the same tests are conducted on individual mutual funds, as reported in tables A15 and A16, we observe an improvement in the alphas but a deterioration in their significance levels. The distribution of the alphas becomes more concentrated around its mean and weakly asymmetric with small tails. In addition, the superior performance of the size-weighted statistics remains for the two benchmark variables.

The obtained results are well explained by examining the distribution of p-values reported in table A17. The number of funds with positive alphas has increased from 78 to 83. However, the number of funds with positive and significant alphas has decreased from 53 to 43, and the number of funds with negative and significant alphas remains at zero. Only the one-tailed test for strictly positive alphas based on the Bonferroni inequality is significant. This rejects the null hypothesis that all alphas are jointly zero.

Overall, there is evidence of weak positive unconditional abnormal performance. This may reflect true performance or it could be biased since it does not account for public information effects.

4.4.6 The Conditional BHV Nonlinear Pricing Kernel Model

The conditional BHV pricing kernel is a polynomial function in the non-central moments of the benchmark return with time-varying coefficients. This kernel has the following expression:

$$M_{t+1}^{c} = \varphi_0(z_t) + \varphi_{1f} R_{f,t+1} + \varphi_1(z_t) R_{m,t+1} + \varphi_2(z_t) R_{m,t+1}^2 + \varphi_5(z_t) R_{m,t+1}^5 \tag{4.19}$$

where φ_0, φ_1, φ_2, and φ_5, are assumed to be linearly related to the two selected conditioning variables. This gives a fully conditional pricing model with time-varying alphas. The conditioning structure on the time-varying coefficients is assumed to be linear with respect to the two selected information variables, or:

$$\varphi_0(z_t) = \varphi_{00} + \varphi_{01}' z_t$$

$$\varphi_1(z_t) = \varphi_{10} + \varphi_{11}' z_t$$

$$\varphi_2(z_t) = \varphi_{20} + \varphi_{21}' z_t$$

$$\varphi_5(z_t) = \varphi_{50} + \varphi_{51}' z_t$$

The above linear specifications are individually and jointly tested using the Wald statistics. The conditional abnormal performance measure is calculated using equation (4.15). The alpha in this pricing equation is obtained by calculating the conditional expectations and is suitable for actively managed portfolios with potential nonlinear payoffs.

The estimates of the conditional performance of the four portfolios of funds exhibit comparable results to those obtained with the conditional kurtosis model, and they exhibit divergent results from the unconditional estimates (see table A15). The alphas of the equal- and size-weighted portfolios of all funds are 0.6968% and 0.7742% per month using the TSE 300 index as the benchmark, respectively. Similar figures are obtained using the other benchmark with a notable difference related to the equal-weighted portfolio of aggressive growth funds. With conditioning information, the performance statistics are consistently below the unconditional estimates for all portfolios and across the two benchmark variables. This result could be explained by the negative impact of the interaction between the fifth moment of benchmark return and the two information variables. This interaction also has weakened the previously established unconditional returns-based large fund effect.

Furthermore, the Wald tests on the marginal significance of the conditioning variables provide significant results about the joint time-variation of all coefficients. These test results reject the individual time-variation in $\varphi_0(z_t)$ and $\varphi_5(z_t)$ coefficients of the SDF equation using both benchmarks.

The same tests are conducted next using individual fund data. These results are reported in tables A15 and A16. They suggest similar performance inferences as with the portfolios of funds. The average conditional alpha is positive for all portfolios but lower than the corresponding unconditional average alpha. The inclusion of conditioning information does not seem to positively affect the point estimates of performance. In addition, the distribution of the conditional alphas becomes positively skewed with less extreme observations in the tails using the value-weighted TSE index as the benchmark. The shape of the distribution of conditional alphas changes for the other two benchmarks. The equal-weighted portfolios underperform portfolios formed based on fund size, which supports the superior performance of large funds. Tests on the validity of the conditional methodology support the joint time-variation in all coefficients but reject this hypothesis for the first, third and fourth coefficients of the SDF equation.

Based on the p-value distributions reported in table A17, there are more funds with positive and significant alphas when the two benchmark variables are used compared to the unconditional results. All the funds with negative alphas have p-values greater than 5%. Since all of the Bonferroni p-values associated with the maximum t-statistics are significant, this rejects the joint null hypothesis of zero alphas. These new results based on the conditional polynomial BHV model are similar to those obtained with the other two conditional nonlinear SDF models.

The overall evidence suggests that the performance inferences are sensitive to the selected benchmark model, and that nonlinear dynamics and conditioning information have a positive effect on risk-adjusted performance for our sample of funds. Such results are consistent with previous studies by Lehmann and Modest (1987), Grinblatt and Titman (1994), Kryzanowski et al. (1997, 1998), and Farnsworth et al. (2002) for information conditioning. They extend previous findings to both information conditioning and pricing nonlinearities.

4.4.7 Risk-Adjusted Performance and the Risk-Free Asset Pricing Restriction

The robustness of the performance statistics and inferences is tested by imposing the restriction that the mean of the asset pricing kernel should be equal to the inverse of the gross return of the risk-free asset.[75] The estimation is then conducted by including an additional moment condition for the one-month T-bill for all of the models. The results, which are reported in table A18, reveal that the restriction on the pricing of the risk-free asset has a pronounced impact on the risk-adjusted performance inferences compared to those for the restriction-free case. The estimation with the additional restriction produces mixed evidence with performance improvement and deterioration using unconditional and conditional returns, respectively. This result is consistent across the three pricing kernel models and the two benchmark variables. It suggests the presence of interdependence between the additional moment condition and the conditioning information. The unconditional performance statistics now exceed the conditional ones for all of the models except for the skewness pricing kernel using the value-weighted TSE index as the benchmark. Finally, the restriction-based estimation has no impact on the superior performance of large funds inherent in the unconditional tests but reverses or mitigates some of the large fund effects observed with conditioning information.

[Please insert table A18 about here.]

4.5 Relationship between Performance and Fund Characteristics

Numerous studies examine the relationship between linear risk-adjusted performance and fund characteristics such as age, size, expenses, turnover, and flows. If the mutual fund market is perfectly competitive, fund expenses will reflect the costs of generating the risk-adjusted returns. Ippolito (1989) examines this hypothesis and finds that the Jensen alphas are unrelated to fund expenses. This evidence supports the costly information market efficiency argument of Grossman (1976) and Grossman and Stiglitz (1980).[76] Elton et al. (1993) reformulate Ippolito's approach and use a three-factor model that incorporates the effects of holding non S&P stocks and bonds and document a negative relationship between alphas and management expense ratios. Grinblatt and Titman (1994), Carhart (1997), and Chevalier and Ellison (1999) report corroborating findings. Otten and Bams (2002) find evidence of economies of scale for European mutual funds as reflected in a positive relationship between risk-adjusted performance and fund size as measured by the log of the total net assets of the fund. Otten and Bams also obtain a negative correlation between the expense ratio and their conditional multifactor alpha. Dahlquist et al. (2000) find a strong negative relation between risk-adjusted performance and fund size for a

[75] Dahlquist and Soderlind (1999) and Farnsworth et al. (2002) stress the importance of the risk-free asset pricing restriction in conducting performance evaluation.
[76] The noisy rational expectations model of competitive equilibrium in Grossman and Stiglitz (1980) asserts that when the information is costly to collect and implement, the market is efficient if the prices of trades made by informed investors are sufficiently different from those obtained in full information in order to compensate these investors for the cost of becoming informed.

subgroup of Swedish equity mutual funds, and that funds with high fees underperform those with low fees. Similarly, Chen et al. (2003) find evidence for diseconomies of scale based on a large sample of U.S. equity funds using both gross and net fund returns. They argue that fund size erodes performance because of liquidity and organizational diseconomies. Some of these empirical stylized facts or regularities are reproduced using the rational equilibrium model of Berk and Green (2002). This model assumes competitive provision of capital by investors to mutual funds, differential ability to generate excess returns, and learning about managerial ability from past returns.

As in Grinblatt and Titman (1994) and Chen et al. (2003), this issue is addressed herein in a cross-sectional setting using the (un)conditional risk-adjusted performance measures and several fund attributes that are defined below. The following equation is used to conduct the estimation:

$$\alpha_p^j = a_0 + A'X_p + \xi_p,\ j = \{u,c\},\ p = 1,\ldots,N,\ i = 1,\ldots,I \tag{4.20}$$

$$E(X_p^i \xi_p) = E(\xi_p) = 0$$

where $X_p = (\text{Expense Ratio Management Fees Ln(TNA) Ln(Age) D(Load)})'$ is a vector of fund characteristics with a dimension equal to I. The vector of coefficients A measures the marginal effect of each attribute variable on the risk-adjusted performance of the fund. ξ_p is a vector of random errors.

4.5.1 Mutual Fund Characteristics

Net asset values per share or NAVPS and total number of shares are used to compute the total net asset value or TNA to reflect the size of the fund. The average fund size is \$288.7 million, and ranges between \$67.4 million for the Templeton Canadian Stock fund and \$2876.6 million for the PH&N Equity PI Fund. These statistics illustrate the relatively smaller size of Canadian mutual funds compared to those in the U.S. where the average size is \$1.1 billion in 1999.

The management expense ratio or MER represents the total of all management and other fees charged to the fund, as a percentage of the fund's total assets.[77] For our sample, it varies from 0.09% to 4.60%. Management fees or MGF are charged by the fund's investment advisor(s) for managing the fund and selecting the different securities. They range from 0.13% of a fund's total assets to 2.50% annually, and average 1.73%.

Six fund types are considered; namely, aggressive growth, growth, growth/income, income, balanced, and specialty. Fund age or AGE averages 21 years, and ranges from 67 years for the Spectrum United Canadian Investment Fund to 10 years for the Strategic Value Canadian O'Donnell Fund.

The dummy variable or LOAD is used to indicate if the fund is a load fund with sales charges or front-end loads upon purchase of shares and/or deferred sales charges or back-end loads if shares are sold within a set time. Another dummy variable or OPTLO captures if the fund has optional load charges. For our sample, 15 funds have front-load charges, 5 have deferred sales charges, 34 have optional load charges, and 41 are no-load funds. By fund type, there are 5 aggressive growth funds and 9 growth funds with front and/or back-end load charges. All of the variables are estimated at the end of the sampling period. Some descriptive statistics for all of the fund attributes are presented in panel C of table A1.

4.5.2 Risk-Adjusted Performance and Mutual Fund Characteristics

Based on the results reported in table A19, a strong relationship exists between performance and fund age and size. Since fund age is negatively related to performance, this suggests that younger funds perform better than older funds. This result is robust to the nonlinear specifications and to the introduction of conditioning information. This result confirms prior evidence in the U.S. by Chevalier and Ellison (1999) and in several European markets by Otten and Bams (2002).

[77] The other expenses include shareholder servicing costs, custodian and transfer-agent fees, shareholder reporting costs, legal fees, auditing fees, interest expense, and directors' fees. These expense items are detailed in the statement of operations.

[Please insert table A19 about here.]

Fund size, as measured by the log of the total net assets of the fund, has a significantly positive relation with the risk-adjusted performance in most of the tests, and especially in tests using the conditional performance measures. This indicates the presence of economies of scale in the Canadian mutual funds market. Such a result is consistent with the European results reported by Otten and Bams (2002) but contrasts with the conclusions of Grinblatt and Titman (1994) for the U.S. and with Dahlquist et al. (2000) for Sweden.

The results for the impact of the fee structure, as reflected by the management expense ratio, management fees, and the load dummy variables, on the risk-adjusted performance are not significant for most of the regressions. At best, the relationship between the load structure reflected by the two dummy variables and performance is negative and highly significant using the unconditional measures. This suggests that load funds or funds with optional loads earn low returns compared to no-load funds to pay for their extra sales charges. This relationship becomes insignificant when we integrate conditioning information. This result contrasts with the evidence produced by Ippolito (1989) where the load coefficient is positive and significant. Finally, there is no evidence that performance of the funds with high expenses is different from that of the funds with low expenses. This conclusion is parallel to that reported by Ippolito (1989) and differs from that reported by Elton et al. (1993), Carhart (1997), and Otten and Bams (2002). These last two results on the influence of the load structure and management fees are inconsistent with the implications of the costly information equilibrium model of Grossman (1976) and Grossman and Stiglitz (1980).

4.6 Conclusion

In this paper, various higher-order moment and polynomial kernel models are used to assess the risk-adjusted performance of a sample of 95 Canadian equity mutual funds. These frameworks are convenient to price portfolios with nonlinear payoffs and non-symmetrical distributions. The impact of conditioning information on the estimated performance is assessed using the flexible GMM of Hansen (1982). The results indicate that the measure of performance is sensitive to the return-generating process and that nonlinear dynamics, conditioning information, and the restriction on the mean of the asset pricing kernel impact the performance statistics and inferences. Furthermore, the tests on the relationship between fund characteristics and fund performance reveal that risk-adjusted performance is related to the age and size of the fund and to a lesser extent to the fund load structure but is unrelated to management fees.

The approach used herein may be extended in at least two ways. First, it can be extended to test the performance of other fund types such as fixed income and global funds with highly nonlinear payoffs. Second, it can be extended by adopting alternative structures of nonlinear dynamics and conditioning information.

CHAPTER 5

PERFORMANCE OF CANADIAN FIXED-INCOME MUTUAL FUNDS

5.1 Introduction

Performance measurement and evaluation of actively managed funds have received wide interest in the academic literature and among practitioners. However, most of the attention focuses on equity mutual funds,[78] and much less research examines the performance of bond/fixed-income funds. This alternative category of funds is as important as equity funds considering the increasing number of fixed-income funds and the notable growth in total assets under management over the last fifteen years.

The majority of the papers in the bond fund stream of research rely on traditional asset pricing models adapted to bond pricing. These models range from single- to multi-factor specifications.[79] For example, Cornell and Green (1991) study the performance of U.S. high-yield bond funds to obtain information on the time-series behavior of low-grade bond returns using a two-factor model reflecting movements in interest rates and stock prices.[80] Blake et al. (1993) conduct the first rigorous test of the performance of U.S. bond funds using linear and nonlinear single- and multi-factor models. Their results suggest that bond funds underperform the selected indices post-expenses and that this performance is robust across several bond return generating processes. In a similar vein, Lee (1994) uses several benchmark model specifications, which are

[78] For example, see Jensen (1968, 1969), Lehmann and Modest (1987), Grinblatt and Titman (1989, 1993, 1994), Chen and Knez (1996), Kryzanowski et al. (1994, 1997, 1998), Ferson and Schadt (1996), Carhart (1997), Christopherson et al. (1998), and Farnsworth et al. (2002).

[79] Another approach relies on the stochastic discount factor (SDF) methodology. He et al. (1999) test the performance of a small sample of corporate bond mutual funds using the non-parametric (un)conditional models of Hansen and Jagannathan (1991) and Chen and Knez (1996). Kang (1997) adapts the numeraire portfolio approach of Long (1990) to evaluate the performance of U.S. government and corporate bond funds and concludes that the numeraire-denominated abnormal returns after expenses are negative and similar to the Jensen alpha estimates. Ferson et al. (2003) use extended SDF representations of continuous-time term structure models to assess the conditional performance of U.S. fixed-income funds. They find

selected based on their mean-variance efficiency, to assess the performance of a large sample of U.S. bond funds. Lee finds that a multi-factor structure with medium- and short-term bond indices and a stock market index is the most appropriate for performance evaluation and that bond fund managers do not exhibit any superior abilities after expenses. Elton et al. (1995) evaluate the performance of bond funds using a relative pricing APT model based on a few bond indices and unanticipated changes in macroeconomic variables. The reported risk-adjusted performance is negative and comparable to the level of transaction costs. Detzler (1999) extends the analysis to global bond funds and reports evidence of underperformance.[81] Kryzanowski and Lalancette (1996) develop a conditional version of the positive period weighting measure of Grinblatt and Titman (1989) to measure the performance of a small sample of bond funds over the period 1981-1988. Their Canadian results seem to be consistent with the U.S. evidence. All of these papers fail to develop conditional performance statistics based on linear benchmark models, and fail to conduct their tests on a large sample of fixed-income funds. Moreover, most of these studies suffer from a potential survivorship bias since they do not conduct a comprehensive analysis of the survivorship bias inherent in their samples of fixed-income mutual funds.

Other studies attempt to unravel the determinants of fixed-income fund performance based on linear benchmark models. They produce mixed results for U.S. and non-U.S. funds.[82] Fund attributes or properties examined as potential determinants of fund performance in this rapidly evolving literature include fund size, age, fees, trading activity, flows, and past returns. However, most of these studies do not account for fund dynamic strategies and/or examine the robustness of their results to the choice of performance evaluation model, market index benchmark, and conditioning information.

---

that a two-factor affine model outperforms a single factor model and report evidence of conditional underperformance during 1985-1999.

[80] They conclude that the risk-adjusted bond fund returns are well explained by this two-factor model.

[81] Her framework stems from unconditional single and multi-index benchmark models and fails to account for the time-variation in the expected international bond returns, which are documented by Harvey et al. (2002).

Thus, given these limitations in the literature, this paper has three major objectives. The first major objective is to provide extensive and robust evidence on the performance and the sensitivity of performance inferences based on (un)conditional linear single- and multi-factor benchmark models for Canadian fixed-income mutual funds. These models must accommodate the unique features of fixed-income funds such as non-stationarity in returns, their frequent use of derivatives in their hedging and speculative activities, and the time-variation in their expected returns and risks. As in previous research by Chen and Knez (1996), Ferson and Schadt (1996), Kryzanowski et al. (1994, 1997), Christopherson et al. (1998), He et al. (1999), and Farnsworth et al. (2002), the frameworks applied herein are suitable to perform evaluations of fixed-weight and dynamic strategies.[83] All of the models are estimated using the flexible and robust Generalized Method of Moments or GMM of Hansen (1982) on two samples of Canadian surviving and non-surviving fixed-income mutual funds over the period 1985-2000. GMM permits adjustment of the standard errors for serial correlation and heteroskedasticity and can handle non *iid* distributions for the pricing errors. This paper is the first to examine partial and full conditional single- and multi-factor models using a comprehensive sample of funds. To deal with inference problems caused by returns of individual funds being contemporaneously correlated that have plagued most previous tests, the performance inferences drawn herein are based on equal- and size-weighted portfolios of funds grouped by common investment objectives.

The second major objective is to estimate the survivorship bias inherent in the fixed-income mutual funds database and to examine its impact and properties with respect to risk-adjusted performance, benchmark model, and fund investment objective. The third major objective is to examine the robustness of the relation between performance differentials across fund groups and the differences in fund characteristics or attributes for Canadian fixed-income mutual funds, and

[82] The evidence for U.S. funds includes Blake et al. (1993) and Elton et al. (1995). The evidence for non-U.S. (European) funds includes Dahlquist et al. (2000).

to draw inferences about what the estimated relations imply about economies of scale and the level of competition in this segment of the Canadian mutual fund industry. This paper is the first to address these issues using partial and full conditional benchmark models.

The first major finding is that the measured performance of fixed-income fund managers is negative and weakly sensitive to the return generating process. The performance statistics and inferences improve with partial conditioning. Tests that do not incorporate the contemporaneous cross-correlations in the returns among individual funds consistently alter and reverse the conditioning information-based inferences and the superior performance of large funds across all benchmark models. The stock market factor is useful in describing the return generating process of Canadian fixed-income funds. Inclusion of a stock market factor not only improves the performance statistics but also preserves the single factor-based superior performance of large funds.

The second major finding is that survivorship bias due to the elimination of funds with shorter lives is not overly material for the performance of Canadian fixed-income mutual funds. This limited effect is similar to that estimated for European funds but is lower than that estimated for U.S. funds. While survivorship bias is reasonably stable across performance models, it differs materially across funds grouped by their investment objectives.

The third major finding is that the determinants of Canadian fixed-income mutual funds is a mix of that identified for U.S. and European funds, and reflects the different market structure that exists in that segment of the Canadian mutual fund industry. Five of these significant determinants of the performance of Canadian fixed-income mutual funds are somewhat robust across the various (un)conditional linear performance models evaluated herein. These determinants are the age, management expense ratio, load structure, and to a lesser extent the size and management fees of each fund. Two of the identified relationships provide information about

[83] Conditioning is performed using information publicly available to uninformed investors. Such information includes interest rates, term structures, and bond yields, which previous studies identify as

the economics of the fixed-income mutual fund industry in Canada. First, the weak positive relation between performance and fund size suggests very limited scale economies in that segment of the Canadian mutual fund industry. This is partially consistent with the evidence found for funds in the U.S. (Ferson et al., 2003) and Europe (Dahlquist et al., 2000). Second, the negative relation between performance and the management expense ratio suggests a pronounced level of competition in that segment of the Canadian mutual fund industry. This finding is consistent with that reported by Blake et al. (1993) and Elton et al. (1995) for U.S. funds.

The remainder of the paper is organized as follows: In section two, we discuss the samples of funds and data used in the empirical tests reported herein. In section three, we develop and explain the econometric methodology and the construction of the tests employed in this paper. In section four, the various benchmark models are presented and the estimates of risk-adjusted portfolio performance for our samples of mutual funds are presented and analyzed. In section five, we estimate the survivorship bias for our sample of fixed-income funds and assess its impact on the performance statistics. In section six, the relations between risk-adjusted performance and several fund characteristics are examined. Finally, section seven concludes the paper.

5.2 Samples and Data

5.2.1 Samples

Two different samples of Canadian fixed-income funds are carefully constructed based on information from the Financial Post mutual fund database over the period from March 1985 through February 2000. The first sample consists of 162 fixed-income funds that existed at the end of that period with a varying number of observations per fund. This sample includes 108 government funds, 28 corporate funds, 21 mortgage funds, and 5 high-yield funds. The non-surviving funds sample is smaller with 72 funds. All of these funds have been terminated before

---

being useful in predicting bond return movements.

February 2000. Potential mergers and name changes are accounted for in constructing the two samples. Several sources of information, such as the Financial Post quarterly reports, individual fund reports, and specific fund news in the financial press, are used to supplement the original information. Most of the terminated funds invest in government securities (46), followed by corporate (11), mortgage (13), and high-yield (2) as investment objectives. For the two samples, the monthly returns for each fund are given by the monthly changes in the net asset values per share, and are adjusted for all distributions. The size of each fund is taken as its total net asset value. By using the second sample of terminated funds, the impact of survivorship bias can be assessed across performance models and metrics, and across groupings of funds by investment category.

Some summary statistics on the surviving funds are presented in table A20. Panel A of table A20 gives statistics on the cross-sectional distribution by investment objective and for all of the 162 funds. The average annual fund returns vary from 1.07% for Industrial Alliance bond 2 fund to 10.92% for SSQ bond fund, and have a cross-sectional mean of 7.13%. The fund annual volatilities or standard deviations range from 0.53% for Synergy Canadian ST income fund to 7.96% for Spectrum United LT bond fund. Over the same sample, the annual average mean and volatility of the return on the Scotia Universe bond index are 10.54% and 2.26%, respectively.

[Please insert table A20 about here.]

In panel B of table A20, equal-weighted and size-weighted portfolios of funds grouped by investment objective and for all of the funds are obtained using the 162 surviving funds in the sample. The number of funds in each of four investment objective categories depends on the timing of the entry of each fund in the sample resulting in different portfolio compositions across time. The size-weighted portfolio of government funds and the equal-weighted portfolio of mortgage funds exhibit the highest and the lowest unconditional mean returns of 9.19% and 8.20% per annum, respectively. In contrast, the size-weighted portfolio of corporate bond funds has the highest unconditional volatility of 5.65% per annum, and the equal-weighted portfolio of mortgage funds has the lowest unconditional volatility of 2.49% per annum. The average annual returns on portfolios of all funds are 8.82% and 8.98% using equal- and size-weighted structures, respectively. For all groups but the high-yield portfolios, the unconditional mean returns and volatilities of the size-weighted portfolios are higher than those of the equal-weighted portfolios. On average, the estimation of the performance statistics is conducted using 111 observations.

Panel C of table A20 provides similar information for portfolios of terminated funds. For the major fund groups (government, corporate, and mortgage), the mean return and volatility statistics are higher and lower than those obtained with the surviving funds, respectively, with the exception of the equal-weighted portfolio of corporate bond funds. The average annual returns on portfolios of all funds are 8.05% and 8.30% using the equal- and size-weighted structures, respectively. Given the nature of these funds, the minimum, maximum, and average number of observations for the 72 individual funds across the four fund groups are smaller, which leads to an average sample length of approximately seven years.

5.2.2 Fund Survival and Mortality

The two constructed samples include virtually all of the fixed-income funds that existed between 1985 and 2000. They mirror the evolution of the Canadian bond fund market over this period of time. In table A21, we report the entry and exit of funds on a yearly basis and estimate the corresponding attrition and mortality rates. The attrition rate reflects the percentage of funds that are left in the sample at each point in time, and ranges between 0% and 10.44% with an average of 1.60%. These figures are somewhat similar (with more variability) that those obtained for the U.S. equity mutual fund market. Elton et al. (1996) find an attrition rate of 2.3% that varies across the fund groups. Carhart et al. (2002) use a comprehensive sample of funds over a long time period of 1962-1995 and estimate an attrition rate between 0.5% and 8.6% with an average of 3.6%. However, our average rate is lower than the 9.37% reported by Dahlquist et al.

(2000) for Swedish bond funds. Our sample exhibits a mortality rate that is decreasing over the sample period. Nevertheless, more than 20% of the funds that existed at the beginning of the sample period did not survive by the end of the studied period. Over the sample period, the number of funds more than triples.

[Please insert table A21 about here.]

5.3 Econometric Methodology

5.3.1 The Estimation Method and Construction of the Tests

The GMM method is used to estimate the risk-adjusted performance and to examine the relationship between fund performance and fund attributes.[84] To estimate the performance measures for each benchmark model, a separate time-series regression is run for each fixed-income fund and for each size and equal-weighted portfolio of fixed-income funds. Not only does the GMM allow for an easy integration of conditioning information but it uses a robust estimator for the variance-covariance matrix to construct p-values that are robust to serial correlation and conditional heteroskedasticity. This is true even with arbitrary forms, using different kernel functions such as the modified Bartlett kernel in Newey and West (1987a), the Parzen kernel in Gallant (1987), or the quadratic spectral kernel in Andrews (1991).

For the (un)conditional linear models used to measure performance, we define the vector of residuals of fund i or portfolio of funds i as:

(5.1) $$u_{i,t+1} = r_{i,t+1} - \alpha_i - \delta' X$$

[84] 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. GMM is an alternative to the maximum likelihood approach with no requirement to specify the law of motion of the underlying variables.

where $r_{i,t+1}$ denote the excess returns on fund or portfolio of funds i, α_i is the risk-adjusted performance, δ is a vector of the coefficients with dimension equal to J, and X is a vector of independent variables whose dimension is model specific. The total number of parameters to be estimated is (J+1) for each fund. The models imply that:

(5.2) $$E(u_{i,t+1} \mid \Omega_t) = 0 \text{ for all } i \text{ and } t$$

For the unconditional tests, $\Omega_t = \{1, X_1\}$, where X_1 corresponds to the vector of the original regressors in the model. When conditioning information is introduced, $\Omega_t = \{1, X_2\}$, where X_2 includes the original regressors augmented by their cross-products with the instrumental variables. For the case of the conditional factor models with time-varying alphas and factor loadings, four instrumental variables (described below) are added to $\Omega_t = \{1, X_2, z\}$. Assuming a dimension n_1 for Ω_t, the orthogonality conditions are constructed using:

(5.3) $$E(u_{i,t+1} \otimes \Omega_t) = 0_{n_1} \text{ for all } i \text{ and } t$$

5.3.2 The Estimation Procedures

The estimates of the portfolio performance measures are obtained from minimizing the GMM criterion function constructed from the set of moment conditions based on the normal equations in the time-series regression. This requires a consistent estimate of the weighting matrix. 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.[85] This GMM efficient estimation of portfolio performance is used in Chen and Knez (1996), Kryzanowski et al. (1997), and Farnsworth et al. (2002) for equity funds.

[85] 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.

Several restrictions on the parameters estimates are tested under the GMM framework based on the Wald test developed by Newey and West (1987b). Let $g(.)$ be a known vector of functions with dimension of v, less or equal to the dimension of the vector of parameters, and $G_0 \equiv \partial g(.)/\partial\theta$ be the Jacobian of $g(.)$ evaluated at θ_0 and assumed to have a rank of v. Then, the restriction $g(\theta_0)=0$ is tested using the Wald statistic, based on the unrestricted GMM estimator θ_T^u. It has the following construction:

$$\Delta_T \equiv T \times g(\theta_T^u)'(G_T V_T^{-1} G_T')^{-1} g(\theta_T^u) \tag{5.4}$$

where θ is the vector of unknown parameters and V_T^{-1} is a consistent estimator of the asymptotic variance-covariance matrix of the unconstrained estimator constructed using the optimal weighting matrix.

5.3.3 Information Variables

For the conditional models, four instrumental variables are used based on their predictive power uncovered in studies of bond return predictability.[86] They are drawn from Statistics Canada's CANSIM database and are the lagged values of TB1 or the one-month Treasury bill rate (Fama and French, 1989; Ilmanen, 1995; and Balduzzi and Robotti, 2001), DEF or the default premium as measured by the yield spread between the long-term corporate McLeod, Young, Weir bond index and long-term government of Canada bonds (Chang and Huang, 1990; Fama and French, 1989, 1993; Kirby, 1997; and Aït-Sahalia and Brandt, 2001), TERM or the slope of the term structure as measured by the yield spread between long-term government of Canada bonds and the one period lagged three-month Treasury bill rate (Chang and Huang, 1990; Fama and French, 1989, 1993; Ilmanen, 1995; Kirby, 1997; and Aït-Sahalia and Brandt, 2001),

[86] Several other conditioning variables have been tested such as inflation rate, yield spread between the three-month T-bill and the one-month T-bill, yield spread between the six-month T-bill and the one-month T-bill, real yield on one-month T-bill, an equal-weighted stock index, and a dummy variable for the month of January. They lead to similar inferences.

and REALG or the real return on long-term government bonds measured by the difference between the yield on the long-term government bond (5 to 10 years) and the inflation rate lagged by one month (Ilmanen, 1995). To allow for a simple interpretation of the estimated coefficients, the variables are demeaned in the conditional tests, as in Ferson and Schadt (1996).

Descriptive statistics and autocorrelations, and a correlation analysis of these variables are provided in panels A and B of table A22, respectively. The correlations between all of the instruments range from -0.81 to 0.39.

[Please insert table A22 about here.]

5.3.4 Bond Indices and Factors

Several bond and stock indices are used as factors as in Cornell and Green (1991), Blake et al. (1993), Lee (1994), and Elton et al. (1995) to construct and assess the performance of the proposed benchmark models. There are eight Scotia Capital (henceforth SC) bond indices reflecting the Canadian domestic bond and mortgage markets and one aggregate stock market index. We use a broad Canadian bond index that is the SC Universe bond index. It contains 900 marketable Canadian bonds with terms to maturity longer than 1 year. The average term is 9 years and the average duration is 5.5 years. Similarly, there are six bond indices related to government and corporate bond issues with different maturity structures (long-term and medium-term). The only included mortgage-backed securities overall bond index accounts for the performance of closed and open pools with an average term of 2.75 years and an average duration of 2.25 years. It is used to span the movements in the returns of mortgage funds. Finally, the TSE 300 index is used as a stock factor that could be useful in describing the return generating process of bond fund returns. All of these indices and factors are obtained from Datastream, CANSIM, and the CFMRC databases.

Descriptive statistics and autocorrelations, and a correlation analysis of these variables are provided in panels A and C of table A22, respectively. All of the bond fund index categories have correlations of 0.83 or higher, and the majority are above 0.90. The correlations between the bond indexes and the TSE 300 index range from 0.35 to 0.44.

5.3.5 Predictability of Bond and Bond Fund Excess Returns

In order to motivate the implementation of the conditional methodology, a predictability analysis is conducted of bond excess returns using nine bond portfolios and six equal- and size-weighted portfolios of bond funds based on investment objectives. The predictability analysis consists of time-series regressions of the excess return on each portfolio on the four instruments described earlier. The predictive power of the instruments is assessed using the GMM-based Wald tests discussed earlier.

The results reported in table A23 indicate significant levels of predictability for both types of portfolios of bonds and of bond funds. The null hypothesis, that all of the slope coefficients associated with the selected instruments are zeros, is rejected with p-values below 8%. The reported coefficient estimates for the one-month Treasury bill rate and the term premium are positive and significant for most of the bond indices and portfolios of funds. These findings provide strong support for conducting a conditional performance analysis.

[Please insert table A23 about here.]

5.4 Performance Evaluation

5.4.1 Unconditional Benchmark Models

The evidence reported in this section should be interpreted with care given the theoretical and empirical limitations of the underlying unconditioned benchmark models. However, measures of their performance are required in order to assess the performances of their conditional counterparts, which are reported in the next section of this paper.

5.4.1.1 Unconditional Single Factor Models

The most commonly used measure of mutual fund performance is the Jensen alpha or α_i based on the following single factor unconditional specification:

$$r_{i,t+1} = \alpha_i + \beta_i r_{b,t+1} + u_{i,t+1},\ t = 0,\ldots,T-1,\ i = 1,\ldots,N \tag{5.5}$$

where $r_{i,t+1}$ and $r_{b,t+1}$ denote the excess returns on fund or portfolio of funds i and on the benchmark between t and $t+1$, respectively. The slope β_i is the systematic risk of the fund or portfolio of funds i, and $u_{i,t+1}$ is the error term specific to the fund or portfolio of funds in month $t+1$. The validity of this model relies on the assumption that the returns of the underlying bond portfolios are stationary, and that the systematic risk measures capture the two risk dimensions of a bond; namely, interest rate risk and default risk.

Two versions of this model are implemented herein depending on the specification of the benchmark factor. The *single market factor* (SMF) model uses the SC Universe bond index, which includes a large number of government and corporate marketable securities. The *single specific factor* (SSF) model uses a benchmark portfolio that is consistent with the investment objective of each fund (as in Blake et al., 1993). Thus, the SC government bond index, the SC corporate bond index, and the SC mortgage backed securities overall index are used as benchmark variables for government, corporate, and mortgage bond funds or portfolios thereof, respectively.

The results for ten portfolios of funds (five equal-weighted and five size-weighted) using the unconditional SMF model are reported in panels A and B of table A24. While the mortgage and high-yield portfolios exhibit insignificant and positive alphas, the other portfolios exhibit negative and significant alphas. The portfolios of corporate funds exhibit the poorest alphas. The alphas of the equal- and size-weighted portfolios of all funds are -0.0671% and -0.0513% per month, respectively. Performance superiority of large (small) funds is only observed for portfolios with negative (positive) alphas. All of the portfolios with significant alphas also have relatively high weightings or estimated unconditional betas compared to the two other portfolios with insignificant alphas. As expected, this result implies that the SC Universe bond index is not a reliable market index for the funds concentrating in mortgage or high yield securities. The betas of the equal-weighted portfolios of government and corporate funds of 0.844 and 0.820 are lower than the 0.880 and 0.900 estimates, respectively, for their size-weighted counterparts. With the exception of the portfolios of mortgage and high-yield funds, the adjusted R^2 are relatively high at close to 95%.

[Please insert table A24 about here.]

The results for the ten portfolios of funds using the unconditional SSF model are reported in panels C and D of table A24. The estimated alphas now imply lower performance for the various portfolios of government, corporate, and mortgage funds. As expected, the risk sensitivities of the equal- and size-weighted portfolios of mortgage funds increases from 0.242 and 0.283 to 0.501 and 0.568, respectively, using the SC Universe mortgage backed securities overall index instead of the SC Universe bond index.

Equal- and size-weighted averages of the alphas of individual funds for various fund samples using the SMF model are reported in panel A of table A25. The results are consistent with those reported for the portfolios of funds. The equal- and size-weighted average alphas are -0.0852% and -0.0912% per month.[87] They are essentially due to the negative performance of the government and corporate fund groups. Only the average alphas of the high-yield funds are

[87] Unreported results on the SSF models show that the average alphas are weaker that their counterparts based on the SFM.

positive. Unlike the evidence for the portfolios of funds, small funds consistently outperform large funds.

[Please insert table A25 about here.]

An examination of the distribution of the p-values for all individual funds and across individual fund groupings, which are reported in panel A of table A26, shows that less than 2% of the funds have positive and significant alphas, and half of the funds have negative and significant performance. This result is confirmed with the unreported evidence from the SSF model, where the numbers of funds with positive and negative alphas decrease and increase, respectively. The Bonferroni p-values tend to support these inferences for both models. The negative extreme t-statistics are all significant with the exception of the high-yield group, and none of the Bonferroni p-values associated with the maximum t-statistics are significant.

[Please insert table A26 about here.]

The overall performance inferences for the unconditional single factor models are similar to those reported by Blake et al. (1993), Lee (1994), Elton et al. (1995), and Kang (1997) for U.S. mutual funds, by Dahlquist et al. (2000) for Swedish bond mutual funds, and to some extent with those reported by Kryzanowski and Lalancette (1996) for Canadian bond funds for the period 1981-1988.

5.4.1.2 Unconditional Multi-factor Models

Numerous papers argue that multi-factor return generating processes are superior to their single factor counterparts for capturing bond risks. Blume et al. (1987) and Cornell and Green (1991) propose a two-factor model consisting of a bond and a stock index to examine the risk-return relationship of high- and low-grade bonds. Gultekin and Rogalski (1985) and Elton et al. (1988) use an APT approach to model bond returns, and conclude that the average returns on default-free bonds are linearly related to at least two factors. Elton et al. (1995) develop a relative

APT model for the expected returns of bonds consisting of multi-factor structures with four or six fundamental economic variables. The bond pricing and term structure of interest rate literature also suggests a multi-factor model for bond returns.[88] Brennan and Schwartz (1982) advocate an equilibrium bond-pricing model with two risk factors measured by the instantaneous yields on a maturity and on a consol bond, which represent the short and long ends of the yield curve, respectively. Other two-factor models specifications include one real and one nominal factor as in Pennacchi (1991), or one short-term factor and a stochastic volatility of interest rates factor as in Longstaff and Schwartz (1992).[89]

Three unconditional multi-factor models are used herein to estimate the risk-adjusted performance of bond funds; namely, two different two-factor models and one five-factor model. The *two-factor risk model* has a similar construction to the model in Blake et al. (1993). It uses the SC Universe bond index and the SC mortgage backed securities overall index to capture the risk characteristics of these types of securities. The *two-factor stock model* uses the returns on both the TSE 300 index and the SC Universe bond index. The two-factor stock model aims to assess the different sensitivities of various bonds or portfolios thereof to movements in the bond and stock markets, as in Blume et al. (1987) and Cornell and Green (1991). This model also captures equity-like characteristics embedded in some corporate bond issues.

The unconditional *five-factor model* reflects differences in maturity structure and default risk. The latter risk is captured by the differences in risk premiums between different securities. The SC intermediate and long-term government bond indices are used herein to capture maturity differences. The SC intermediate and long-term corporate bond indices and the SC mortgage

[88] Factors proposed to determine nominal bond prices include the uncertainty about good prices, differences among investors in investment horizons and wealth, uncertainty about future production opportunities, illiquidity, and changes in regulations and taxes. These models are based on the premise that the prices of default-free bonds with different maturities and coupons are deterministic functions of a small number of underlying state variables that follow a continuous diffusion process. These state variables are often proxied by changes in one or more spot rates in the empirical tests.

[89] Extended specifications are proposed by Garbade (1986) and Litterman and Scheikman (1991). The latter authors uncover a linear three-factor model in which the three factors implicitly account for the level, steepness, and curvature of the yield curve.

backed securities overall index are used to capture default risk differences. This five-factor model is very close to the Reg-6 model of Blake et al. (1993), except for the exclusion of a high-yield bond index in our model.

For all of these multi-factor models, fund performance is obtained by comparing the return of a fund or portfolio of funds to the return on a tracking portfolio with similar factor loadings that combines a set of passive bond indices and the risk-free asset. The multi-factor Jensen alphas α_i are estimated by the following time-series regressions:

$$r_{i,t+1} = \alpha_i + \sum_{k=1}^{K} \beta_{ik} I_{k,t+1} + u_{i,t+1},\ t = 0,\dots,T-1,\ i = 1,\dots,N \tag{5.6}$$

where $r_{i,t+1}$ and $I_{k,t+1}$ denote the excess returns on fund or portfolio of funds i and on the kth factor between t and $t+1$, respectively. β_{ik} is the sensitivity of the excess return on the fund or portfolio of funds to the excess return on the kth factor, and $u_{i,t+1}$ is the error term specific to fund or portfolio of funds i in month $t+1$.

The alpha and beta estimates for the various portfolios of individual funds are presented in tables A27 and A28 for the three multi-factor models. The alphas for the equal- and size-weighted portfolios of all of the funds are consistently negative and significant. The deterioration in performance is more pronounced when the risk factor related to the mortgage backed securities overall index is in the specification of the return-generating dynamics. The lowest average alpha of about -0.0975% per month is obtained using the five-factor model and the equal-weighted portfolio of all funds. The overall negative performance is caused by the underperformance of the government and corporate bond fund groups. Performance superiority of large funds also exists across the three multi-factor models and for most fund groupings, and it is stronger in the presence of the stock factor. The average risk sensitivities are high for all of the portfolios of funds for the market index that best describes the investment objective for the fund grouping, and the sensitivities to the stock factor are low for all of the portfolios of funds. For the five-factor model, high factor loadings occur for the portfolio of government bond funds on the medium-term government bond factor, and for the portfolio of corporate bond funds on the long- and medium-term government and medium-term corporate bond factors. Such results reveal information on the investment styles of these bond fund managers.

[Please insert tables A27 and A28 about here.]

Equal- and size-weighted averages of the alphas of individual funds for various fund samples using the three multi-factor models are reported in table A25. The equal-weighted average alphas for all of the funds are -0.0910%, -0.0973%, and -0.1041% per month using the two-factor risk model, two-factor stock model, and the five-factor model, respectively. Performance superiority of small funds exists across these three benchmark models.

The distribution of the p-values for the alpha estimates for the multi-factor benchmarks are reported in table A26. Only two government funds have positive and significant alphas for the two-factor stock model. This number of funds decreases to one when the TSE 300 index is replaced by the mortgage backed securities index and to zero with the use of the five-factor benchmark model. In contrast, the number of funds with negative and significant alphas is substantial across the three benchmark models, and it is 95 with the five-factor benchmark model. Since the computed Bonferroni p-values are highly significant only for the minimum t-statistics, with the exception of the high-yield fund category, the null joint hypothesis of zero for the multi-index-based alphas is not supported by the data. The evidence for this model seems to indicate that fund mangers weakly outperform the benchmark when management fees are considered.

This evidence is consistent with that obtained in the U.S. for the six-factor model of Blake et al. (1993), the three-factor model of Lee (1994), and the fundamental-six model of Elton et al. (1995). Multi-factor models appear to provide a better description of the returns on Canadian bond funds by capturing the various risk characteristics of fixed-income securities. The validity of the unconditional approach requires that the returns of bond portfolios are stationary over time. This condition is likely to be violated for three reasons. First, the various bond issues in the portfolio have different fixed payoffs at specific maturity dates, which lead to changes in the probability distribution of the returns of the portfolio over time. Second, the betas of bonds change as their durations change due to movements in interest rates. Third, most bond fund managers invest in derivative securities with time-varying betas.[90]

5.4.2 Conditional Benchmark Models

5.4.2.1 Conditional Single Factor Models

The unconditional single market factor is extended to a conditional setting where conditional expectations are linearly constructed using the vector of predetermined information variables.[91] The approach of Ferson and Schadt (1996) is used by assuming that the beta of each fund varies over time according to the following linear reaction function:

$$\beta_{i,t} = b_{i0} + b_i' z_t \qquad (5.7)$$

The intercept coefficient b_{i0} is the unconditional mean of the conditional beta. The vector of slope coefficients b_i' measures the response of the conditional beta to movements in the innovations in the conditioning variables, $z_t = Z_t - E(Z_t)$. The augmented *conditional beta single factor* model can then be written as:

$$r_{i,t+1} = \alpha_i^c + b_{i0} r_{b,t+1} + b_i'(z_t r_{b,t+1}) + u_{i,t+1},\ t = 0,\ldots,T-1,\ i = 1,\ldots,N \qquad (5.8)$$

[90] Dybvig and Ingersoll (1982) demonstrate that the CAPM fails to price derivative assets.
[91] Such a structure is implicitly or explicitly assumed in most previous tests of asset pricing and portfolio performance (Cochrane, 1996; Chen and Knez, 1996; Ferson and Schadt, 1996; Kryzanowski et al., 1997; Christopherson et al., 1998; and Aït-Sahalia and Brandt, 2001).

where α_i^c is the conditional risk-adjusted alpha.[92] The validity of this conditional model is tested using the Wald test on the time-variation in the systematic risk of the funds.

A *conditional alpha single factor model* also is used. This fully conditioned model has both time-varying alphas and betas as in Christopherson et al. (1998). The conditional alpha is approximated by the following linear function:

$$\alpha_{i,t}^c = \alpha_{i0} + \alpha_i' z_t \tag{5.9}$$

This conditional equation can be modified as follows:

$$r_{i,t+1} = \alpha_{i0} + \alpha_i' z_t + b_{i0} r_{b,t+1} + b_i'(z_t r_{b,t+1}) + u_{i,t+1},\ t = 0,\dots,T-1,\ i = 1,\dots,N \tag{5.10}$$

The validity of this extended specification is tested through Wald tests on the alpha, beta, and on their joint time-varying structures.

The performance and risk results for the equal- and size-weighted portfolios of individual funds are presented in panels E, F, G, and H of table A24 for the two conditional single-factor benchmark models. Most alphas improve but remain negative and significant. To illustrate, the alpha of the equal-weighted portfolio of all funds is -0.0537% and -0.0538% per month using the conditional beta and alpha models, respectively. Since this is smaller than the average monthly management fees of 0.1205%, this implies weak positive performance pre-expenses. The portfolios of government and of corporate bond funds have negative and significant performance, respectively, unlike the portfolios of other fund categories. These results are somewhat consistent with those obtained for U.S. and Canadian equity funds by Ferson and Schadt (1996) and Kryzanowski et al. (1997), respectively. Both of these studies find that the inclusion of

[92] This model can be viewed as an unconditional multi-factor model where the additional factors are the products of the SC Universe bond index and the lagged information variables, which are the yield on one-month T-bills, the slope of the term structure, the default premium, and the real yield on long-maturity government bonds. These factors are interpreted as returns to self-financing dynamic strategies by purchasing z_t units of the market portfolio by borrowing at the risk-free rate.

conditioning information moves their performance statistics towards better performance.[93] Partial and full conditioning seems to preserve the unconditional performance superiority of large funds for most of the portfolios. The beta coefficients are higher for most of the portfolios of funds under the conditional methodology. This suggests that unconditional betas may be biased and that bond fund managers could be revising their portfolios to changing economic conditions.

The Wald tests conducted on the marginal contribution of the predetermined information variables in the conditional beta specification are highly significant for all of the portfolios, with the exception of the portfolios of high-yield funds. The Wald statistics largely reject time-variation in the alphas, and cannot reject joint time-variation of the alphas with the betas.[94]

An analysis of the average performances of the individual funds reported in tables A25 reverses the inferences about the effect of conditioning. The simple average conditional alpha is still negative at -0.0893% but now is marginally inferior to the unconditional estimate of -0.0852%. The magnitude of the difference is higher for the conditional alpha model. This result could be caused by the extremely weak performance of some government and corporate bond funds. Moreover, performance superiority shifts from large to small firms with partial but not with full conditioning.

The distributions of the p-values for the alpha estimates that are adjusted for serial correlation and heteroskedasticity are reported in table A26. The number of funds with positive and significant alphas is higher at 7 for the conditional alpha model. This is due essentially to the government and mortgage funds. The number of funds with negative and significant alphas decreases to 50 for the fully conditional model.[95] This last observation tends to support our previous argument that a few extreme funds are driving the weak average conditional

---

[93] This argument holds if the covariance between the conditional beta and the excess return on the benchmark portfolio is negative. In this case, the unconditional Jensen alpha is negatively biased.

[94] Unreported results show similar conclusions based on the individual fund regressions. The time-variation in the beta coefficient hypothesis is significant at the 10% level for over 70% of the funds for the conditional beta model. The null hypotheses of fixed betas and of fixed alphas and betas with a full conditional model are rejected for 114 and 125 funds, respectively.

performance. All of the Bonferroni p-values are significant, except for the minimum t-statistics associated with the mortgage and high-yield funds and the corporate bond funds. This rejects the joint hypothesis of zero conditional alphas.

Overall, the conditional alphas estimated for the two conditional single-factor models indicate that fund performance improves, although fund managers marginally underperform the market, once we control for conditional information effects. This confirms the conclusions of He et al. (1999) and Dahlquist et al. (2000) for U.S. and Swedish bond funds, respectively.

5.4.2.2 Conditional Multi-factor Models

We use two versions of the conditional multi-factor models to estimate the risk-adjusted performance of fixed-income funds. The first specification called the *partial conditional model* is based on time-varying factor sensitivity coefficients and is written as:

$$r_{i,t+1} = \alpha_i + \sum_{k=1}^{K} \beta_{ik}(z_t) I_{k,t+1} + u_{i,t+1},\ t = 0,\dots,T-1,\ i = 1,\dots,N \tag{5.11}$$

where α_i is the conditional multifactor abnormal performance, and all of the conditional betas are linearly related to the vector of the four lagged instruments as in (5.7). The *full conditional model* relies on time-varying structures for all of the coefficients including the alphas and betas, and has the following expression:

$$r_{i,t+1} = \alpha_{io} + \alpha_i' z_t + \sum_{k=1}^{K} \beta_{ik}(z_t) I_{k,t+1} + u_{i,t+1},\ t = 0,\dots,T-1,\ i = 1,\dots,N \tag{5.12}$$

where all of the coefficients have a linear reaction function in the four conditioning variables as in (5.7) and (5.9).

Under partial and full conditioning, we have two two-factor risk models, two two-factor stock models, and two-five factor models. The validity of all conditional specifications is assessed

[95] Unreported results indicate similar statistics using the conditional beta model.

using the Wald tests on the time-varying structure of each coefficient and on the joint structure of all of the coefficients.

The performance and risk estimates for the ten equal- and size-weighted portfolios of funds using the two-factor models and the five-factor models are reported in tables A27 and A28, respectively. The conditional alphas are consistently negative across all portfolios with the exception of the mortgage and high-yield groups. The latter portfolios have non significant positive and/or negative alphas. With partial conditioning, these performance estimates are better than their unconditional counterparts across all of the models. For example, the alphas of the equal-weighted portfolio of all funds are -0.0691%, -0.0557%, and -0.0782% per month using the two-factor risk model, the two-factor stock model, and the five-factor model, respectively. Surprisingly, when all of the coefficients are time-varying, there is a deterioration in the alphas point estimates in all specifications that include the Scotia MBS index. For the two-factor stock model, the performance figures improve with full conditioning except for the portfolios of high-yield funds but with marginal differences compared to the partial information-based estimates. Moreover, the performance statistics are consistently higher using the two-factor stock benchmark compared to the two other models with partial and full conditionings. These last two observations suggest that the stock market factor has a positive impact on the performance statistics and inferences. The superior performance of large funds uncovered with the unconditional models is mitigated with the conditional two-factor risk models and becomes superior small fund performance with the full conditional five-factor model.

The average conditional risk sensitivities on the Scotia market factor are lower (higher) than the unconditional estimates for the two-factor risk (stock) models. For the five-factor model, the estimation of the risk sensitivities yields similar conclusion to the case without conditioning. The only exception is related to the factor loadings of the portfolios of five high yield funds with extreme values on the Scotia LT government and corporate bond factors. The small relative size of these portfolios could partially explain these unusual patterns.

The Wald test results indicate strong support for all of the conditional models where the joint null hypothesis of fixed coefficients is strongly rejected by the data. However, the individual time-variation in the alphas is not significant for all of the portfolios for the three benchmark models. These tests also suggest that conditional two-factor stock models better describe the dynamics of the returns of fixed-income funds compared to the two other competing models.[96]

An examination of the equal- and size-weighted averages of individual fund performances, which are reported in table A25, reveal three important results.[97] First, there is evidence of significant underperformance. Second, the performance-based tests of individual funds reverse the effect of conditioning obtained for the portfolios of funds. Third, unlike the tests that incorporate the contemporaneous cross-correlation across individual funds, the performance statistics for individual funds suggest superior performance of small funds for most fund groupings.

The examination of the p-value distributions in panels B, C, and D of table A26 indicates that more (less) funds have positive (negative) and significant performance compared to the unconditional tests for the three multi-factor models. These improvements are more pronounced for the two-factor stock model and the five-factor model with 46 (8) and 38 (9) funds have positive (positive and significant) alphas, respectively.[98] In addition, the Bonferroni conservative p-values are significant for the minimum extreme t-statistics for most groupings, rejecting the joint hypothesis of zero conditional alphas against the alternative that at least one alpha is negative.

Overall, the results from the partial and full conditional multifactor benchmark models confirm the weak performance of Canadian fixed-income fund managers and the positive impact

[96] Unreported results the tests on individual funds indicate similar evidence where the test on the joint time-variation of all coefficients is significant for more than 84% of all of the funds across the six conditional benchmark models.
[97] For the partial and full conditional five-factor models, the estimation cannot be undertaken for four government funds and two corporate funds due to reduced degrees of freedom.

of conditioning information on performance inferences. They also uncover the central role of the stock market factor in the return generating process, and depiction the need for its inclusion in the evaluation of fixed-income fund performance. This evidence is partially consistent with the conclusions of Cornell and Green (1991) using an unconditional stock factor-based framework.

5.5 Survivorship Bias and Performance

The estimation of the risk-adjusted performance is not affected by survivorship biases since the global sample of mutual funds includes all funds that existed over the full studied period. This sampling procedure permits us to uncover the performance of the surviving funds and to produce an estimate of survivorship bias. Relatively little research has estimated this bias and examined its properties based upon the performance of fixed-income funds.[99] Blake et al. (1993) argue that survivorship bias has a lesser impact on bond funds compared to equity funds due to the stability of their performance. Blake et al. find the annualized average alpha for a small sample of terminated funds. Their estimate based on a six-index model is 1.02% below that of all of the funds in the sample over the period 1979-1988. Dahlquist et al. (2000) estimate a survivorship bias of 0.10% per year using average excess returns of equal-weighted portfolios of surviving and non-surviving Swedish bond funds over the period 1993-1997. Their estimate becomes negative using a conditional risk-adjusted performance measure.

Thus, in this section, the survivorship bias for Canadian bond mutual funds is estimated across fund investment objectives and chosen benchmark models. Survivorship bias is estimated using raw returns and on a risk-adjusted basis for equal-and size-weighted portfolios of funds. It

[98] Unreported results on the partial conditional models indicate comparable and weaker figures. There are 1, 5, and 8 funds with positive and significant alphas using the two-factor risk model, the two-factor stock model, and the five-factor model, respectively.
[99] In contrast, the literature for equity mutual funds is more extensive and uses different methodologies. See, for example, Grinblatt and Titman (1989), Malkiel (1995), Wermers (1997), Carhart (1997), and Carhart et al. (2002).

is measured by the difference between the performances of portfolios of all surviving and non-surviving funds, and of surviving funds only.

For this purpose, the monthly returns and total net asset values of funds with at least one monthly return from the period between March 1985 through February 2000 are tracked. Five size- and five equal-weighted portfolios of government, corporate, mortgage, high-yield, and all funds are constructed using all of the funds, where portfolio composition changes as funds commence and terminate their operations.

Based on the results reported in table A29, our first estimate of the survivorship bias is positive for most fund groups indicating that the non-surviving funds exhibit lower performance than the surviving funds. The bias is fairly high at about 20 basis points per year for the equal-weighted portfolios of funds. The bias diminishes for the size-weighted portfolios to about 8 basis points per year. The bias also fluctuates considerably on an annual basis.

[Please insert table A29 about here.]

When risk-adjusted performance measures are used, the estimates of the survivorship bias are comparable to those based on the raw returns (see table A30). The bias estimates are relatively stable across the twelve benchmark models. The survivorship bias ranges from almost zero basis points per year using the conditional factor models to 3 basis points per year with the partial conditional five-factor model. The size of the survivorship bias decreases with full conditioning of the benchmark models. Moreover, the survivorship bias differs across fund objective categories in that the bias is more pronounced for the mortgage category at 15 basis points per year than for the government and corporate categories where the bias averages 6 and 8 basis points per year, respectively. These bias estimates and their properties differ from those reported by Blake et al. (1993) for U.S. bond mutual funds and parallel the findings of Dahlquist et al. (2000) for Swedish bond funds. Overall, we conclude that the survivorship bias in the Canadian bond fund market has little impact on risk-adjusted performance.

[Please insert table A30 about here.]

5.6 Portfolio Performance and Bond Fund Characteristics

The relationship between risk-adjusted performance and fund characteristics such as age, size, expenses, turnover, and flows has been marginally examined in the context of bond mutual funds.[100] Most of this research emphasizes the role of the management expense ratio and its impact on several risk-adjusted performance measures. Blake et al. (1993) and Elton et al. (1995) find that the performance of U.S. bond funds is negatively associated with the level of their expense ratios. These results are robust to different specifications of the return generating process for the funds. Detzler (1999) obtains corroborating evidence for global bond funds. For Swedish mutual funds, Dahlquist et al. (2000) report that the performance of bond funds is related to net flows of money into funds, past performance, expense measures, administrative fees, and fund size but unrelated to fund turnover. Ferson et al. (2003) report weak cross-sectional differences in performance for portfolios of U.S. funds grouped according to fund size, expense ratio, turnover, income yield, and lagged return or lagged new money flows.

As in Grinblatt and Titman (1994), this issue is addressed herein in a cross-sectional setting using the (un)conditional risk-adjusted performance measures and several fund attributes that are defined below. The following equation is used to conduct the estimation:

$$\alpha_i^j = c_0 + C'X_i + e_i,\ j = \{u, c\},\ p = 1, \ldots, N,\ s = 1, \ldots, S \tag{5.13}$$

where $X_i = (\text{Expense Ratio} \quad \text{Management Fees} \quad \text{Ln(TNA)} \quad \text{Ln(Age)} \quad \text{D(Load)})'$ is a vector of fund characteristics with a dimension equal to S. The vector of coefficients C measures

[100] This differs from the extensive research on equity mutual funds by Ippolito (1989), Elton et al. (1996), Grinblatt and Titman (1994), Carhart (1997), Chevalier and Ellison (1999), Dahlquist et al. (2000), and Otten and Bams (2002).

the marginal effect of each attribute variable on the risk-adjusted performance of the fund. e_i is a vector of random errors.

5.6.1 Mutual Fund Characteristics

Net asset values or NAV and total number of shares are used to compute the total net asset value or TNA to reflect the size of the fund. The average fund size is $367.7 million, and ranges between $23.3 million for the Ivy mortgage fund of Mackenzie Financial Corporation and $2431.9 million for the Income fund (B) of the Great West Life Insurance Company.

The management expense ratio or MER represents the total of all management and other fees charged to the fund, as a percentage of the fund's total assets.[101] For our sample, it varies from 0.10% to 4.16%. Management fees or MGF are charged by the fund's investment advisor(s) for managing the fund and selecting the different securities. They range from 0.00% of the total assets of a fund to 2.40% annually, and average 1.45%. The MER is higher than that estimated for 209 U.S. bond funds of 1.027% reported by Blake et al. (1993).

Four fund types are considered; namely, government, corporate, mortgage, and high-yield. Fund age or AGE averages 13 years, and ranges from 42 years for the Scotia Canadian Income fund to two years for the Synergy Canadian ST Income fund.

The dummy variable LOAD is used to indicate if the fund is a load fund with sales charges or front-end load upon purchase of shares and/or deferred sales charges or back-end loads if shares are sold within a set time. Another dummy variable or OPTLO captures if the fund has optional load charges. For our sample, seven funds have front-load charges, 37 have deferred sales charges, 39 have optional load charges, and 80 are no-load funds. By fund type, there are 32 government funds, 7 corporate funds, and 5 mortgage funds with front and/or back-end load

[101] The other expenses include shareholder servicing costs, custodian and transfer-agent fees, shareholder reporting costs, legal fees, auditing fees, interest expense, and directors' fees. These expense items are detailed in the statement of operations.

charges. All of the variables are estimated at the end of the sampling period. Some descriptive statistics for all of the fund attributes are presented in panel D of table A20.

5.6.2 Risk-Adjusted Performance and Mutual Fund Characteristics

Based on the results reported in table A31, a strong relationship exists between performance and fund age, load structure, and management expense ratio, and to a lesser extent with the size and management fees. Since fund age is positively related to performance, this suggests that older funds perform better than younger funds. This result weakens with the full conditional models. It contrasts with prior evidence on equity funds obtained for the U.S. by Chevalier and Ellison (1999) and in several European markets by Otten and Bams (2002).

[Please insert table A31 about here.]

Fund size, as measured by the log of the total net assets of the fund, has a weak positive relation with the risk-adjusted performance for most of the tests, and especially for the unconditional performance measures. This indicates limited evidence for the existence of economies of scale in the Canadian fixed-income mutual fund market. Such a result is somewhat inconsistent with the evidence of Ferson et al. (2003) of insignificant differences in the conditional performances of large and small U.S. funds. This finding partially confirms the Swedish evidence reported by Dahlquist et al. (2000) of positive and significant risk-adjusted performance of a trading strategy of buying equal-weighted portfolios of large size funds and short-selling the small size funds or using cross-sectional regressions.

The relationship between the management expense ratio and performance is negative for all of the regressions but essentially significant with the unconditional measures.[102] This result suggests that funds with high expenses do not perform as well as funds with low expenses. When the unconditional five-factor model is used, a percentage point increase in expenses reduces

[102] Similar and highly significant results are obtained using only the management expense ratio as the independent variable in the cross-sectional regression, as in Blake et al. (1993) and Elton et al. (1995).

performance by 0.06%. This sensitivity coefficient decreases with the presence of conditioning information. This evidence confirms the results reported by Blake et al. (1993) and Elton et al. (1995) but not by Ferson et al. (2003) for U.S. bond funds, and by Detzler (1999) for global bond funds but with a smaller magnitude. Finally, the relation between performance and fund load structure is negative and significant, which suggests that funds with higher exit/load fees perform worse than other funds. This result becomes non significant using the full conditional performance measures. This finding is consistent with the results for Swedish bond funds reported by Dahlquist et al. (2000).

5.7 Conclusion

The performance of Canadian fixed-income funds is examined in this paper by testing several linear benchmark models with and without conditioning information. All of the estimations are conducted on a comprehensive sample of surviving and non-surviving Canadian fixed-income mutual funds using the GMM framework. The results indicate that performance inferences are negative and weakly sensitive to the choice of the benchmark. Conditioning information and the stock market factor positively impact the performance statistics and inferences. Tests on the relation between fund performance and fund characteristics reveal that the former is related to fund age, management expense ratio, and load structure, and to a lesser extent to fund size and management fees. Survivorship bias is less material as it ranges from 0 to 15 basis points per year for the total sample. While survivorship bias is reasonably stable across performance models, it differs materially across fund objective categories.

Our approach may be extended in various directions, such as using a stochastic discount factor methodology adapted to the pricing of fixed-income securities, assessing the market timing behavior of bond fund mangers, and identifying the determinants of fund flows based on several fund characteristics. These alternative directions are left for future work.

CHAPTER 6

CONCLUSION

The main objective of this dissertation is to provide new evidence on several issues related to the performance of Canadian equity and fixed-income mutual funds. In particular, the thesis develops and proposes various frameworks to better assess the risk-adjusted performance of these actively managed portfolios. The thesis also attempts to uncover the determinants of fund performance using several fund characteristics or attributes such as fund type, age, size, and management fees and expenses, and to examine the robustness of these relations across several benchmark models and to assess their implications for the economics of the Canadian mutual funds industry. Finally, the thesis aims to estimate the survivorship bias for the two types of funds and examine the properties of this survivorship bias with respect to the performance measurement model, fund objective, and conditioning information. Although the theoretical developments and empirical examinations are presented in four chapters, the contribution of this dissertation to the portfolio performance literature can be summarized from three perspectives.

First, in the second chapter, we extend the traditional approaches to measure the performance by using the SDF representation of asset prices to derive an asset pricing kernel that is adapted for performance evaluation. Our approach reflects the predictability of asset returns and permits an easy integration of conditioning information with different structures. We construct empirical frameworks that are suitable for unconditional evaluation of fixed-weight strategies, and (un)conditional evaluations of dynamic strategies using the GMM method. In the third chapter, we examine a full conditional multi-index model, and the assessed performance inferences are based on tests that do incorporate the contemporaneous cross-correlations across individual fund returns. In the fourth chapter, we provide the first tests of (un)conditional higher-order and polynomial asset pricing kernel models in the context of performance evaluation. These models jointly accommodate the conditional pricing of portfolios with linear and nonlinear payoffs. In the fifth chapter, partial and full linear conditional models are developed and tested on a large sample of fixed-income funds. These frameworks permit us to uncover the appropriate return generating process for this type of funds.

Secondly, the dissertation addresses important empirical questions and issues. In the second chapter, we examine the effect of conditioning with a limited and an extended information set on the performance statistics and inferences. We also test the sensitivity of performance to changes in the level of relative risk aversion of the uninformed investor. Finally, we assess the survivorship bias inherent in our database of surviving and non-surviving Canadian equity mutual funds. The third chapter studies the sensitivity of the performance inferences based on the family of (un)conditional linear benchmark models for stock selection and market timing. Additional non-parametric tests based on performance rankings across all models are conducted. The robustness of the relation between performance differentials across fund groups and the differences in fund characteristics or attributes also are examined. In the fourth chapter, we examine the joint effect of nonlinear dynamics and conditioning information on risk-adjusted performance and inferences. Moreover, the importance of the restriction on the mean of the asset pricing kernel or equivalently the pricing of the risk-free asset in performance evaluation is assessed. In the fifth chapter, we shed light on the sensitivity of the performance inferences to several single- and multi-factor benchmark models and on the role of partial and full information conditioning. We also estimate survivorship bias and uncover its properties based on samples of surviving and non-surviving Canadian fixed-income mutual funds, and examine the robustness of the relationship between the risk-adjusted performance and bond fund characteristics.

Thirdly, the empirical results of this dissertation convey important and valuable implications for the literature. In the second chapter, we obtain a surprising result contrasting with prior evidence on the positive effect of conditional information. Such a result could be explained by the greater impact of the time-variation in the conditional risky asset allocation compared to the common linear information scaling applied in most SDF-based performance tests. We also show that the reversal in the size-based performance results with limited information conditioning is alleviated somewhat with an expansion of the conditioning set. Performance inferences are weakly related to changes in the relative risk aversion of the uninformed investor. Finally, our estimate of survivorship bias is important and is similar to that estimated for U.S. and European funds. It ranges from 36 to 58 basis points per year for equity funds, and is stable across performance models but differs across groupings by fund objective. In the third chapter, we find that using a conditional multifactor benchmark model improves measured performance. Canadian mutual funds managers display pervasive negative market-timing ability, and controlling for conditioning information somewhat mitigates the pervasiveness of the negative market-timing inferences. The performance ranking tests indicate that full model conditioning appears to have a much greater impact on absolute rather than on relative portfolio performance inferences. Finally, the test on the relation between fund performance and fund characteristics finds that the determinants of Canadian equity mutual funds is a mix of that identified for U.S. and European funds, and suggest the presence of scale economies and a weak level of competition in the Canadian mutual fund industry. In the fourth chapter, we report evidence that nonlinear dynamics and conditioning information positively impact measured performance. The inclusion of the additional restriction on the mean of the asset pricing kernel produces mixed effects on the performance statistics and inferences, and it alters the conditioning information-based large fund effect. Finally, there are three significant determinants of the Canadian equity fund performance that are robust across the various nonlinear performance models. These determinants are age and size, and to a lesser extent the fund load structure. In the fifth chapter, the risk-adjusted performance is negative and performance inferences are weakly sensitive to the return generating process and improve with partial conditioning. Performance tests that do not incorporate the contemporaneous cross-correlations in the returns among individual funds consistently alter and reverse the conditioning information-based inferences and the superior performance of large funds across all benchmark models. The stock market factor is useful in describing the return generating process of Canadian fixed-income funds. Inclusion of a stock market factor not only improves the performance statistics but also preserves the single factor-based superior performance of large funds. The estimation of the survivorship bias indicates that it is less material for Canadian fixed-income mutual funds than for their equity counterparts, that it is reasonably stable across performance models, but differs across funds grouped by their investment objectives. Finally, five of the significant determinants of the performance of Canadian fixed-income mutual funds are robust across the various linear performance models. These determinants are the age, management expense ratio, load structure, and to a lesser extent the size and management fees of each fund. This result suggests very limited scale economies and a pronounced level of competition in that segment of the Canadian mutual fund industry.

This thesis addresses various questions and issues in portfolio performance and could be extended in at least four ways. The first extension is by developing a dynamic framework that integrates business cycle indicator variables and SDF-based performance measures. The second extension is to conduct the unfeasible fully efficient conditional GMM estimation, which is based on general interactions between functions of conditioning variables and pricing errors, using nonparametric estimates for the optimal set of instruments as suggested in Newey (1993). The third extension is to test for alternative specifications of the nonlinear dynamics and optimal structures of conditioning information. The fourth extension is to examine the determinants of fund flows based on several fund characteristics. We leave these alternative directions for future work.

REFERENCES

Admati, A. R., and S. A. Ross, 1985, "Measuring Investment Performance in a Rational Expectations Equilibrium Model", *Journal of Business*, 58, 1-26.

Admati, A. R., S. Bhattacharaya, P. C. Pfleiderer, and S. A. Ross, 1986, "On Timing and Selectivity", *Journal of Finance*, 41, 715-730.

Aït-Sahalia, Y., and M. W. Brandt, 2001, "Variable Selection and Portfolio Choice", *Journal of Finance*, 56, 1297-1351.

Andrews, D. W. K., 1991, "Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation", *Econometrica*, 59, 817-858.

Ang, J. S., and J. H. Chua, 1979, "Composite Measures for the Evaluation of Investment Performance", *Journal of Financial and Quantitative Analysis*, 14, 361-384.

Balduzzi, P., and C. Robotti, 2001, "Minimum-Variance Kernels, Economic Risk Premia, and Tests of Multi-Beta Models", *Working Paper*, Boston College.

Bansal, R., and C. R. Harvey 1996, "Performance Evaluation in the Presence of Dynamic Trading Strategies", *Working Paper*, Duke University.

Bansal, R., and S. Viswanathan, 1993, "No Arbitrage and Arbitrage Pricing: A New Approach", *Journal of Finance*, 48, 1231-1262.

Bansal, R., D. Hsieh, and S. Viswanathan, 1993, "A New Approach to International Arbitrage Pricing Theory", *Journal of Finance*, 48, 1719-1748.

Barberis, N. C., 2000, "Investing for the Long Run when Returns are Predictable", *Journal of Finance*, 55, 225-264.

Bekaert, G., and R. J. Hodrick, 1992, "Characterizing Predictable Components in Excess Returns on Equity and Foreign Exchange Markets", *Journal of Finance*, 47, 467-509.

Bekaert, G., and J. Lui, 1999, "Conditioning Information and Variance Bounds on Pricing Kernels", *Working Paper* (6880), NBER.

Berk, J. B., and R. C. Green, 2002, "Mutual Fund Flow and Performance in Rational Markets", *Working Paper*, University of California, Berkley.

Blake, C. R., E. J. Elton, and M. J. Gruber, 1993, "The Performance of Bond Mutual Funds", *Journal of Business*, 66, 371-403.

Blume, M., D. Keim, and S. Patel, 1987, "Returns and Volatility of Low-Grade Bonds", *Journal of Finance*, 46, 49-74.

Bollen, N. P. B., and J. A. Busse, 2001, "On the Timing Ability of Mutual Fund Managers", *Journal of Finance*, 56, 1075-1094.

Brandt, M. W., 1999, "Estimating Portfolio and Consumption Choice: A Conditional Euler Equations Approach", *Journal of Finance,* 54, 1609-1645.

Breeden, D., 1979, "An Intertemporal Asset Pricing Model with Stochastic Consumption and Investment Opportunities", *Journal of Financial Economics*, 7, 265-296.

Brennan, M. J., and E. S. Schwartz, 1982, "An Equilibrium Model of Bond Pricing and a Test of Market Efficiency", *Journal of Financial and Quantitative Analysis*, 62, 301-329.

Brennan, M. J., E. S. Schwartz, and R. Lagnado, 1997, "Strategic Asset Allocation", *Journal of Economic Dynamics and Control*, 21, 1377-1403.

Brown, S. J., and W. N. Goetzman, 1995, "Performance Persistence", *Journal of Finance*, 50, 679-698.

Cai, J., K. C. Chan, and T. Yamada, 1997, "The Performance of Japanese Mutual Funds", *Review of Financial, Studies*, 10, 237-273.

Campbell, J. Y., and J. H. Cochrane, 2000, "Explaining the Poor Performance of Consumption-based Asset Pricing Models", *Journal of Finance*, 55, 2863-2878.

Campbell, J. Y., and L. M. Viceira, 1999, "Consumption and Portfolio Decisions when Expected Returns are Time-Varying", *Quarterly Journal of Economics*, 114, 433-495.

Carhart, M., 1997, "On Persistence in Mutual Fund Performance", *Journal of Finance*, 52, 57-82.

Carhart, M., J. Carpenter, A. W. Lynch, and D. K. Musto, 2002, "Mutual Fund Survivorship", *Review of Financial Studies*, 15, 1439-1463.

Chang, E., and R. Huang, 1990, "Time-Varying Return and Risk in the Corporate Bond Market", *Journal of Financial and Quantitative Analysis*, 25, 323-340.

Chang, E., and W. Lewellen, 1984, "Market Timing and Mutual Fund Investment Performance", *Journal of Business*, 57, 57-72.

Chapman, D. A., 1997, "Approximating the Asset Pricing Kernel", *Journal of Finance*, 51, 1383-1410.

Chen, J., H. Hong, M. Huang, and J. D. Kubik, 2003, "Does Fund Size Erode Performance? Liquidity, Organizational Diseconomies, and Active Money Management", *Working Paper*, University of Southern California.

Chen, N. F., R. Roll, and S. A. Ross, 1986, "Economic Forces and the Stock Market", *Journal of Business*, 59, 383-403.

Chen, Z., and P. J. Knez, 1996, "Portfolio Performance Measurement: Theory and Applications", *Review of Financial Studies*, 9, 511-555.

Chevalier, J., and G. Ellison, 1999, "Are Some Mutual Fund Managers Better than Others? Cross-Sectional Patterns and Performance", *Journal of Finance*, 54, 875-899.

Christopherson, J. A., W. E. Ferson, and D. A. Glassman, 1998, "Conditioning Manager Alphas on Economic Information: Another Look at the Persistence of Performance", *Review of Financial Studies*, 11, 111-142.

Chung, Y. P., H. Johnson, and M. J. Schill, 2001, "Asset Pricing when Returns are Nonnormal: Fama-French Factors vs. Higher-Order Systematic Co-Moments", *Working Paper*, University of Virginia.

Cochrane, J. H., 1996, "A Cross-Sectional Test of an Investment-Based Asset Pricing Model", *Journal of Political Economy*, 104, 572-621.

Cochrane, J. H., 2000, "A Resurrection of the Stochastic Discount Factor/GMM Methodology", *Working Paper*, University of Chicago.

Coggin, T. D., F. J. Fabozzi, and S. Rahman, 1993, "The Investment Performance of U.S. Equity Pension Fund Managers: An Empirical Investigation", *Journal of Finance*, 48, 1039-1055.

Cornell, B., and K. Green, 1991, "The Investment Performance of Low-Grade Bond Funds", *Journal of Finance*, 46, 29-48.

Cumby, R. E., and J. D. Glen, 1990, "Evaluating the Performance of International Mutual Funds", *Journal of Finance*, 45, 497-521.

Dahlquist, M., and P. Soderlind, 1999, "Evaluating Portfolio Performance with Stochastic Discount Factors", *Journal of Business*, 72, 347-384.

Dahlquist, M., S. Engtsrom, and P. Soderlind, 2000, "Performance and Characteristics of Swedish Mutual Funds", *Journal of Financial and Quantitative Analysis*, 35, 409-423.

Daniel, K., M. Grinblatt, S. Titman, and R. Wermers, 1997, "Measuring Mutual Fund Performance with Characteristic Based Benchmarks", *Journal of Finance*, 52, 1035-1058.

Detzler, M. E., 1999, "The Performance of Global Bond Mutual Funds", *Journal of Banking and Finance*, 23, 1195-1217.

Dittmar, R., 2002, "Nonlinear Pricing Kernels, Kurtosis Preference, and Evidence from the Cross-Section of Equity Returns", *Journal of Finance*, 57, 369-403.

Dybvig, P. H., and J. E. Ingersoll Jr., 1982, "Mean-Variance Theory in Complete Markets", *Journal of Business*, 55, 233-251.

Dybvig, P. H., and S. A. Ross, 1985, "Performance Measurement using Differential Information and a Security Market Line", *Journal of Finance*, 40, 483-496.

Elton, E. J., M. J. Gruber, and C. R. Blake, 1995, "Fundamental Economic Variables, Expected Returns, and Bond Fund Performance", *Journal of Finance*, 50, 1229-1256.

Elton, E. J., M. J. Gruber, and C. R. Blake, 1996, "Survivorship Bias and Mutual Fund Performance", *Review of Financial Studies*, 9, 1097-1120.

Elton, E. J., M. J. Gruber, and C. R. Blake, 1996, "The Persistence of Risk-Adjusted Mutual Fund Performance", *Journal of Business*, 69, 133-157.

Elton, E. J., M. J. Gruber, and C. R. Blake, 1999, "Common Factors in Active and Passive Portfolios", *European Finance Review*, 3, 53-78.

Elton, E. J., M. J. Gruber, and P. Nabar, 1988, "Bond Returns, Immunization, and the Return Generating Process", *Studies in Banking and Finance*, 5, 125-154.

Elton, E. J., M. J. Gruber, S. Das, and M. Hlavka, 1993, "Efficiency with Costly Information: A Reinterpretation of Evidence from Managed Portfolios", *Review of Financial Studies*, 6, 1-22.

Fama, E. F., and K. R. French, 1988, "Dividend Yields and Expected Stock Returns", *Journal of Financial Economics*, 22, 3-25.

Fama, E. F., and K. R. French, 1989, "Business Conditions and Expected Stock Returns", *Journal of Financial Economics*, 25, 23-50.

Fama, E. F., and K. French, 1993, "Common Risk Factors in the Returns on Stocks and Bonds", *Journal of Financial Economics*, 33, 3-56.

Fama, E. F., and K. R. French, 1995, "Size, and Book-to-Market Factors in Earnings and Returns", *Journal of Finance*, 50, 131-156.

Fama, E. F., and K. R. French, 1996, "Multifactor Explanations of Asset Pricing Anomalies", *Journal of Finance*, 51, 55-84.

Fang, H., and T-Y. Lai, 1997, "Co-Kurtosis and Capital Asset Pricing", *Financial Review*, 32, 293-307.

Farnsworth, H., W. E. Ferson, D. Jackson, and S. Todd, 2002, "Performance Evaluation with Stochastic Discount Factors", *Journal of Business*, 75, 473-503.

Ferson, W. E., and A. F. Siegel, 2001, "The Efficient Use of Conditioning Information in Portfolios", *Journal of Finance*, 56, 967-982.

Ferson, W. E., and C. R. Harvey, 1991, "The Variation of Economic Risk Premia", *Journal of Political Economy*, 99, 385-415.

Ferson, W. E., and C. R. Harvey, 1999, "Conditioning Variables and Cross-Section of Stock Returns", *Journal of Finance*, 54, 1325-1360.

Ferson, W. E., and R. A. Korajczyk, 1995, "Do Arbitrage Pricing Models Explain the Predictability of Stock Returns", *Journal of Business*, 68, 309-350.

Ferson, W. E., and R. Schadt, 1996, "Measuring Fund Strategy and Performance in Changing Economic Conditions", *Journal of Finance*, 51, 425-461.

Ferson, W. E., and S. R. Foerster, 1994, "Small Sample Properties of the GMM in Tests of Conditional Asset Pricing Models", *Journal of Financial Economics*, 36, 29-55.

Ferson, W. E., D. Kisgen, and T. Henry, 2003, "Evaluating Fixed Income Fund Performance with Stochastic Discount Factors", *Working Paper*, Boston College.

Gallant, A. R., 1987, *Nonlinear Statistical Models*, Wiley, NY.

Gallant, A. R., and G. F., Tauchen, 1989, "Seminonparametric Estimation of Conditionally Constrained Heterogeneous Processes", *Econometrica*, 57, 1091-1120.

Gallant, A. R., and H. White, 1988, *A Unified Theory of Estimation and Inference for Nonlinear Dynamic Models*, Basil Blackwell, NY.

Garbade, K. D., 1986, "Modes of Fluctuations in Bond Yields – An Analysis of Principal Components", *Bankers Trust Company*, Topics in Money and Security Markets, 20, June.

Glosten, L., and R. Jagannathan, 1994, "A Contingent Claims Approach to Performance Evaluation", *Journal of Empirical Finance*, 1, 133-166.

Goldbaum, D., 1999, "A Nonparametric Examination of Market Information: Application to Technical Trading Rules", *Journal of Empirical Finance*, 6, 59-85.

Grinblatt, M., and S. Titman, 1989, "Portfolio Performance Evaluation: Old Issues and New Insights", *Review of Financial Studies*, 2, 393-422.

Grinblatt, M., and S. Titman, 1993, "Performance Measurement without Benchmarks: An Examination of Mutual Fund Returns", *Journal of Business*, 66, 47-68.

Grinblatt, M., and S. Titman, 1994, "A Study of Monthly Mutual Funds Returns and Performance Evaluation Techniques", *Journal of Financial and Quantitative Analysis*, 29, 419-444.

Grossman, S., 1976, "On the Efficiency of Competitive Stock Markets when Trades Have Diverse Information", *Journal of Finance*, 31, 573-585.

Grossman, S., and J. Stiglitz, 1980, "On the Impossibility of Informationally Efficient Markets", *American Economic Review*, 70, 393-408.

Gruber, M. J., 1996, "Another Puzzle: The Growth in Actively Managed Mutual Funds", *Journal of Finance*, 51, 783-416.

Gruber, M. J., 2001, "Identifying the Risk Structure of Mutual Fund Returns", *European Financial Management*, 7, 147-159.

Gultekin, B., and R. Golaski, 1985, "Government Bond Returns, Measurement of Interest Rate Risk, and the Arbitrage Pricing Theory", *Journal of Finance*, 40, 43-61.

Hansen, L. P., 1982, "Large Sample Properties of Generalized Method of Moments Estimators", *Econometrica*, 50, 1029-1054.

Hansen, L. P. and R. Jagannathan, 1991, "Implications of Security Market Data for Models of Dynamic Economies", Journal of Political Economy, 99, 225-262.

Hansen, L. P., and S. F. Richard, 1987, "The Role of Conditioning Information in Deducing Testable Restrictions Implied by Dynamic Asset Pricing Models", *Econometrica*, 55, 587-613.

Hansen, L. P., and K. J. Singleton, 1982, "Generalized Instrumental Variable Estimation of Nonlinear Rational Expectations Models", *Econometrica*, 50, 1269-1286.

Harrison, M., and D. Kreps, 1979, "Martingales and Arbitrage in Multiperiod Security Markets", *Journal of Economic Theory*, 20, 381-408.

Harvey, C. R., 1989, "Time-Varying Conditional Covariances in Tests of Asset Pricing Models", *Journal of Financial Economics*, 24, 289-318.

Harvey, C. R., 2001, "The Specification of Conditional Expectations", *Journal of Empirical Finance*, 8, 573-637.

Harvey, C. R., and A. Siddique, 2000, "Conditional Skewness in Asset Pricing Tests", *Journal of Finance*, 55, 1263-1295.

Harvey, C. R., and A. Siddique, 2002, "Time-Varying Skewness and the Market Risk Premiums", *Working Paper*, Duke University.

Harvey, C. R., B. Solnik, and G. Zhou, 2002, "What Determine Expected International Returns?", *Annals of Economics and Finance*, 3, 249-298.

He, H., and H. E. Leland, 1993, "On Equilibrium Asset Price Processes", *Review of Financial Studies*, 6, 593-617.

He, J., L. Ng, and C. Zhang, 1999, "Asset Pricing Specification Errors and Performance Evaluation", *European Finance Review*, 3, 205-232.

Henriksson, R. D., 1984, "Market Timing and Mutual Fund Performance: An Empirical Investigation", *Journal of Business*, 57, 73-96.

Henriksson, R. D., and R. C. Merton, 1981, "On Market Timing and Investment Performance II. Statistical Procedures for Evaluating Forecasting Skills", *Journal of Business*, 54, 513-533.

Ilmanen, A, 1995, "Time-Varying Expected Returns in International Bond Markets", *Journal of Finance*, 50, 481-506.

Ippolito, R., 1989, "Efficiency with Costly Information: A Study of Mutual Fund Performance", *Quarterly Journal of Economics*, 104, 1-23.

Jagannathan, R., and R. A. Korajczyk, 1986, "Assessing the Market Timing Performance of Managed Portfolios", *Journal of Business*, 59, 217-235.

Jagannathan, R., and Z. Wang, 1996, "The Conditional CAPM and the Cross-Section of Expected Returns", *Journal of Finance*, 51, 3-35.

Jagannathan, R., and Z. Wang, 2000, "Efficiency of the Stochastic Discount Factor Method for Estimating Risk Premiums", *Working Paper*, Columbia University.

Jensen, M. C., 1968, "The Performance of Mutual Funds in the Period 1945-1964", *Journal of Finance*, 23, 389-346.

Jensen, M. C., 1969, "Risk, the Pricing of Assets and the Evaluation of Investment Portfolios", *Journal of Business*, 50, 549-572.

Kan, R., and C. Zhang, 1999, "GMM Tests of Stochastic Discount Factor Models with Useless Factors", *Journal of Financial Economic*, 54, 103-127.

Kan, R., and G. Zhou, 1999, "A Critique of the Stochastic Discount Factor Methodology", *Journal of Finance*, 54, 1221-1248.

Kandel, S., and R. F. Stambaugh, 1996, "On the Predictability of Stock Returns: An Asset Allocation Perspective", *Journal of Finance*, 51, 385-424.

Kang, J., 1997, "The Numeraire Portfolio Approach to Bond Mutual Fund Performance Evaluation", *Working Paper*, University of Rochester.

Kirby, C., 1997, "Measuring the Predictable Variation in Stock and Bond Returns", *Review of Financial Studies*, 3, 579-630.

Koenker, R., and J. A. F. Machado, 1999, "GMM Inference when the Number of Moment Conditions is Large", *Journal of Econometrics*, 43, 327-344.

Koutoulas G., and L. Kryzanowski, 1996, "Macrofactor Conditional Volatilities, Time-Varying Risk Premia and Stock Return Behavior", *Financial Review*, 31, 169-195.

Kraus, A., and R. Litzenberger, 1976, "Skewness Preference and the Valuation of Risk Assets", *Journal of Finance*, 31, 1085-1100.

Kryzanowski, L. and S. Lalancette, 1996, "Conditional Performance Evaluation of Portfolios with Linear and Nonlinear Payoffs", *Working Paper*, Concordia University.

Kryzanowski, L., and H. Zhang, 1992, "Economic Forces and Seasonality in Security Returns", *Review of Quantitative Finance and Accounting*, 1, 227-244.

Kryzanowski, L., S. Lalancette, and M. C. To, 1994, "Performance Attribution using a Multivariate Intertemporal Asset Pricing Model with One State Variable", *Canadian Journal of Administrative Sciences*, 11, 75-85.

Kryzanowski, L., S. Lalancette, and M. C. To, 1997, "Performance Attribution using an APT with Prespecified Macrofactors and Time-Varying Risk Premia and Betas", *Journal of Financial and Quantitative Analysis*, 32, 205-224.

Kryzanowski, L., S. Lalancette, and M. C. To, 1998, "Benchmark Invariancy, Seasonality, and APM-free Portfolio Performance Measures", *Review of Quantitative Finance and Accounting*, 10, 75-94.

Lee, S., 1994, "The Evaluation of Bond Mutual Fund Performance", *Working Paper*, University of New York at Buffalo.

Lehmann, B. N., and D. M. Modest, 1987, "Mutual Funds Performance Evaluation: A Comparison of Benchmarks and Benchmarks Comparisons", *Journal of Finance*, 42, 233-265.

Leland, H. E., 1999, "Beyond Mean-Variance: Performance Measurement in a Nonsymmetrical World", *Financial Analyst Journal*, January-February, 27-36.

Litterman, R. and J. Scheinkman, 1991, "Common Factors Affecting Bond Returns", *Journal of Fixed Income*, 1, 131-170.

Long, J. B. Jr., 1990, "The Numeraire Portfolio", *Journal of Financial Economics*, 26, 29-69.

Longstaff, F. and E. S. Schwartz, 1992, "Interest Rate Volatility and the Term Structure: A Two Factor General Equilibrium Model", *Journal of Finance*, 47, 1259-1282.

Lucas, R., 1978, "Asset Prices in Exchange Economy", *Econometrica*, 46, 1429-1445.

Luttmer, E. G. L., 1996, "Asset Pricing in Economies with Frictions", *Econometrica*, 64, 1439-1467.

Lynch, A. W., J. Watcher, and W. Boudry, 2002, "Does Mutual Fund Performance Vary over the Business Cycle?", *Working Paper*, New York University.

Malkiel, B. G., 1995, "Returns from Investing in Equity Mutual Funds 1971-1991", *Journal of Finance*, 50, 549-572.

Merton, R. C., 1973, "An Intertemporal Capital Asset Pricing Model", *Econometrica*, 41, 867-887.

Merton, R. C., 1981, "On Market Timing and Investment Performance I: An Equilibrium Theory of Market Forecasts", *Journal of Business*, 54, 363-406.

Newey, W. K., 1993, "Efficient Estimation of Models with Conditional Moment Restriction", *Handbook of Statistics*, 11, 519-445.

Newey, W. K, and K. D. West, 1987a, "A Simple Positive Semi-Definite Heteroskedasticity and Autocorrelation Consistent Covariance Matrix", *Econometrica*, 55, 703-708.

Newey, W. K., and K. D. West, 1987b, "Hypothesis Testing with Efficient Method of Moments Estimation", *International Economic Review*, 28, 777-787.

Otten, R., and D. Bams, 2002, "European Mutual Fund Performance", *European Financial Management*, 8, 75-101.

Pennacchi, G., 1991, "Identifying the Dynamics of Real Interest Rates and Inflation: Evidence using Survey Data", *Review of Financial Studies*, 4, 53-86.

Peterson, D., and M. L. Rice, 1980, "A Note on Ambiguity in Portfolio Performance Measures", *Journal of Finance*, 35, 1251-1256.

Priestley, M. B., 1981, *Spectral Analysis and Time Series*, Academic Press, NY.

Roll, R., 1977, "A Critique of the Asset Pricing Theory's Tests; Part I: On Past and Potential Testability of the Theory", *Journal of Financial Economics*, 4, 129-176.

Roll, R., 1978, "Ambiguity when Performance is Measured by the Security Market Line", *Journal of Finance*, 38, 1051-1069.

Ross, S. A., 1976, "Arbitrage Theory of Capital Asset Pricing", *Journal of Economic Theory*, 13, 341-360.

Schwert, G. W., 1989, "Why Does Stock Market Volatility Change over Time", *Journal of Finance*, 44, 1115-1153.

Sharpe, W. F., 1964, "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risks", *Journal of Finance*, 19, 425-442.

Sharpe, W. F., 1992, "Asset Allocation: Management Style and Performance Measurement", *Journal of Portfolio Management*, Winter, 7-19.

Sharpe, W. F., 1995, "The Styles and Performance of Large Seasoned U.S. Mutual Funds", *Working Paper*, Stanford University.

Siegel, S., and N. J. Castellan, Jr., 1988, *Nonparametric Statistics for the Behavioral Sciences*, McGraw-Hill, New York.

Sirri, E. R., and P. Tufano, 1998, "Costly Search and Mutual Fund Flows", *Journal of Finance*, 53, 1589-1622.

Treynor, J., and K. Mazuy, 1966, "Can Mutual Funds Outguess the Market", *Harvard Business Review*, 44, 131-136.

Wermers, R., 1997, "Momentum Investment Strategies of Mutual Funds, Performance Persistence, and Survivorship Bias", *Working Paper*, University of Colorado at Boulder.

Zheng, L., 1999, "Is Money Smart? A Study of Mutual Fund Investor' Fund Selection Ability", *Journal of Finance*, 54, 901-933.

APPENDICES

Appendix A

The conditional asset allocation problem is based on the following maximization:

$$\underset{\alpha_t}{Max}\, E_t[U(R_{w,t+1})]$$

where $R_{w,t+1} = \alpha_t r_{b,t+1} + R_{f,t+1}$ and the conditional expectation is based upon the information set Ω_t. The following first-order condition or FOC is obtained by differentiating $E_t[U(R_{w,t+1})]$ with respect to α_t and setting the result equal to zero:

$$\begin{aligned}
\frac{\partial}{\partial \alpha_t} E_t[U(R_{w,t+1})] &= E_t[U'(R_{w,t+1})]E_t(r_{b,t+1}) + \mathrm{Cov}_t[U'(R_{w,t+1}), r_{b,t+1}] \\
&= E_t[U'(R_{w,t+1})]E_t(r_{b,t+1}) + E_t[U''(R_{w,t+1})]\mathrm{Cov}_t(R_{w,t+1}, r_{b,t+1}) \\
&= E_t[U'(R_{w,t+1})]E_t(r_{b,t+1}) + \alpha_t E_t[U''(R_{w,t+1})]\mathrm{Var}_t(r_{b,t+1}) \\
&= 0
\end{aligned}$$

The last expression follows by applying Stein's lemma. The optimal risky asset allocation is obtained by solving the last expression:

$$\alpha_t = \frac{1}{\Phi}\frac{E_t(r_{b,t+1})}{\mathrm{Var}_t(r_{b,t+1})}$$

where $\Phi = \dfrac{-E_t[U''(R_{w,t+1})]}{E_t[U'(R_{w,t+1})]}$ is the uninformed investor's global absolute risk aversion, which is assumed to be a fixed parameter.

The optimal risky asset allocation or portfolio policy is no longer a constant parameter but a nonlinear function of the first and second conditional moments of the benchmark returns. It is measurable with respect to the set of state or conditioning information, or:

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

Table A1. Summary statistics for the mutual funds and attributes, and mutual fund excess return predictability

This table reports the summary statistics for the mutual fund returns (in %) and for 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 using monthly data from November 1989 through December 1999, for a total of 122 observations. The instruments are dividend yield, risk premium, slope of the term structure, one-month Treasury bill rate, and dummy variable for January. The abbreviations AG, G, and GI refer to aggressive growth, growth, and growth & income, respectively, and the prefixes EW and SW refer to equal- and size-weighted portfolios of funds with these investment objectives, respectively. Panel A provides the statistics on the distribution of various parameter estimates for the sample of 95 equity mutual funds. Panel B reports some statistics on the equal-weighted portfolios of funds for the major groupings by investment objectives and for all funds. Panel C reports the summary statistics for the fund attributes (measured at period end). MER and MGF are the % management expense ratio and management fees of the fund, respectively. AGE is the age of the fund measured in years since fund inception. SIZE is the total net asset value of the fund in millions. LOAD is a dummy variable equal to one if the fund charges front- or back-end sales charges. Panel D reports the mutual fund excess return predictability results where the estimations are conducted using the GMM method. The χ^2-row presents the Newey and West (1987b) tests of the hypothesis that all the slope coefficients are zeros. The next row includes the corresponding p-values.

Panel A: Individual mutual funds

Statistics	Mean Return	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis
Mean	0.8215	4.1030	-17.9935	12.2822	-0.695	4.105
Std. Dev.	0.2920	0.9536	3.3824	5.8822	0.603	1.884
Minimum	-0.2563	1.7320	-23.7762	5.9845	-1.562	0.305
1%	-0.1198	2.6242	-23.2102	6.2039	-1.514	0.356
2.5%	0.1464	2.8489	-22.6766	6.5448	-1.476	0.967
5%	0.3798	3.1518	-21.7504	7.2469	-1.401	1.298
10%	0.5600	3.2865	-20.7581	7.7613	-1.231	1.714
25%	0.7014	3.6534	-20.0053	9.1103	-1.048	2.900
Median	0.8040	3.9964	-18.8240	10.9419	-0.870	4.192
75%	0.9302	4.2270	-16.7178	12.9623	-0.518	5.089
90%	1.1170	4.8647	-14.6339	15.8471	0.097	6.014
95%	1.4009	5.7417	-11.5281	26.6862	0.462	7.225
97.5%	1.4491	6.6748	-8.4121	31.3842	0.732	8.308
99%	1.4720	7.7122	-5.0960	36.9568	1.349	9.675
Maximum	1.5024	8.9621	-4.5660	39.2593	2.054	10.437

Panel B: Investment objective portfolios

Objective	N	Mean Return	Std. Dev.
Ag. Growth	27	0.8409	3.8646
Growth	50	0.8143	3.5717
Growth & Income	12	0.8156	3.3359
All	95	0.8215	3.5226

Panel C: Descriptive statistics for the fund attributes

Fund Attribute	Mean	Median	Std. Dev.	Min.	Max.	Skew.	Kurt.
MER	2.055	2.130	0.741	0.090	4.600	0.363	3.287
MGF	1.732	2.000	0.498	0.130	2.500	-1.918	3.747
AGE	21.361	14.053	12.906	10.185	67.157	1.410	1.474
SIZE	288.712	191.179	333.448	67.416	2876.553	5.447	39.042
LOAD	0.170	0.000	0.376	0.000	1.000	1.801	1.268

Panel D: Mutual fund excess return predictability

Fund Portfolio	EWAG	EWG	EWGI	SWAG	SWG	SWGI
N	27	50	12	27	50	12
χ^2	15.343	16.467	17.531	15.268	16.250	16.978
p-value	0.009	0.006	0.004	0.009	0.006	0.005

Table A2. Summary statistics for the instrumental variables and passive portfolios

This table reports the summary statistics for the monthly returns of the instrumental variables and ten size-sorted passive portfolios using all TSE stocks. TSEVWX and TSE300X are the value-weighted and 300 TSE index returns less the 1-month Treasury bill rate in % or TB1, respectively. DY is the dividend yield on the TSE 300 index. TERM is the yield spread between long Canadas and the one period lagged 3-month Treasury bill rate or TB3 in % per month. RISK is the yield spread between the long-term corporate bond (McLeod, Young, Weir bond index) and long Canadas in % per month. 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 reports various statistics for these instruments and passive portfolios, including autocorrelation coefficients of order 1, 3, 6, and 12. Panel B presents the correlation matrix of the instruments. Panel C presents the correlation matrix of the passive portfolios. 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}
TSEVWX	0.545	0.569	4.194	-19.552	11.436	-0.787	6.686	0.063	0.026	0.043	-0.037
TSE300X	0.417	0.710	4.243	-20.490	11.559	-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	0.073	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
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 of instruments

Instruments	TSEVWX	TSE300X	DY	TERM	RISK	TB1	TB3
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

Panel C: Correlation matrix of passive portfolios

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 A3. Portfolios of funds performance measures using the unconditional and conditional pricing kernels

This table reports the performance measures (λ in %) per investment objective using the unconditional 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 system estimation, including the ten size-based passive strategies, is conducted using the GMM method. All represents the statistics of the portfolios of all funds. Size is defined as the total net asset value of the fund. TSE 300 and TSEVW are the TSE 300 and value-weighted TSE indexes, respectively. The J-Statistic is the minimized value of the sample quadratic form constructed using the moment conditions and the optimal weighting matrix. Wald corresponds to the p-value based on the Newey and West (1987b) Wald test of the marginal significance of the two conditioning variables. Monthly data are used from November 1989 through December 1999, for a total of 122 observations per portfolio of funds.

Fund Group	TSE 300			TSEVW		
	λ	p-value	Wald	λ	p-value	Wald
Panel A: Equal-weighted portfolio of funds and unconditional pricing kernel						
Ag. Growth	0.1884	0.012		0.1789	0.016	
Growth	0.2144	0.001		0.2098	0.001	
Growth/Inc.	0.2681	0.000		0.2591	0.000	
All	0.1994	0.000		0.1933	0.000	
J-Stat	0.1506			0.1505		
Panel B: Size-weighted portfolio of funds and unconditional pricing kernel						
Ag. Growth	0.2565	0.001		0.2463	0.002	
Growth	0.2697	0.000		0.2626	0.000	
Growth/Inc.	0.1923	0.006		0.1830	0.008	
All	0.2514	0.000		0.2438	0.000	
J-Stat	0.1506			0.1505		
Panel C: Equal-weighted portfolio of funds and conditional pricing kernel with DY as instrumental variable						
Ag. Growth	0.3077	0.000		0.2785	0.000	
Growth	0.1012	0.024		0.0919	0.040	
Growth/Inc.	0.1479	0.002		0.1290	0.008	
All	0.1599	0.000		0.1371	0.000	
J-Stat	0.1792			0.1792		
Panel D: Size-weighted portfolio of funds and conditional pricing kernel with DY as instrumental variable						
Ag. Growth	0.2885	0.000		0.2510	0.000	
Growth	0.1289	0.004		0.1129	0.011	
Growth/Inc.	0.0033	0.947		-0.0130	0.794	
All	0.1414	0.001		0.1209	0.007	
J-Stat	0.1794			0.1793		
Panel E: Equal-weighted portfolio of funds and conditional pricing kernel with DY and TB1 as instrumental variables						
Ag. Growth	0.0299	0.445	0.000	0.0056	0.890	0.000
Growth	-0.0899	0.099	0.000	-0.0746	0.134	0.000
Growth/Inc.	-0.0818	0.152	0.000	-0.0522	0.338	0.000
All	-0.0605	0.182	0.000	-0.0573	0.183	0.000
J-Stat	0.1843			0.1828		
Panel F: Size-weighted portfolio of funds and conditional pricing kernel with DY and TB1 as instrumental variables						
Ag. Growth	0.1097	0.008	0.000	0.0824	0.046	0.000
Growth	-0.0529	0.324	0.000	-0.0236	0.621	0.000
Growth/Inc.	-0.0961	0.114	0.000	-0.0803	0.156	0.000
All	-0.0197	0.676	0.000	-0.0129	0.763	0.000
J-Stat	0.1840			0.1825		

Table A4. Individual fund performance measures using the unconditional and conditional pricing kernels

This table reports summary statistics of performance (λ in %) per investment objective based on individual fund performances using the unconditional and conditional pricing kernels for the two benchmark variables. 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 in addition to the ten size-based passive strategies. All represents the equal- or the size-weighted portfolio of the performances of all individual funds. The J-Statistic using the Bartlett kernel is the minimized value of the sample quadratic form constructed using the moment conditions and the optimal weighting matrix. Wald corresponds to the p-value based on the Newey and West (1987b) Wald test of the marginal significance of the two conditioning variables. Size is defined as the total net asset value of the fund. TSE 300 and TSEVW are the 300 and value-weighted TSE indices, respectively. Monthly data are used from November 1989 through December 1999, for a total of 122 observations per fund.

Fund Group	TSE 300							TSEVW						
	Mean λ	Med. λ	Std.Dev.	Mean p-val	Skew.	Kurt.	Mean Wald	Mean λ	Med. λ	Std.Dev.	Mean p-val	Skew.	Kurt.	Mean Wald
Panel A: Equal-weighted portfolios of individual fund performances using the unconditional pricing kernel														
Ag. Growth	0.1884	0.1743	0.004	0.263	-0.99	2.66		0.1796	0.1778	0.004	0.258	-1.17	3.34	
Growth	0.2145	0.1941	0.003	0.288	0.30	4.39		0.2106	0.1858	0.003	0.285	0.33	4.14	
Growth/Inc.	0.2684	0.1991	0.005	0.204	1.31	4.38		0.2597	0.1944	0.005	0.190	1.30	4.37	
All	0.1996	0.1743	0.004	0.281	0.14	4.25		0.1931	0.1778	0.004	0.275	0.00	4.62	
Mean J-Stat	0.1506							0.1505						
Panel B: Equal-weighted portfolios of individual fund performances using the conditional pricing kernel with DY as the instrument														
Ag. Growth	0.2988	0.2215	0.003	0.152	0.81	0.91		0.2715	0.2212	0.003	0.158	0.70	0.74	
Growth	0.1034	0.0934	0.003	0.224	-0.05	0.49		0.0844	0.0857	0.003	0.210	-0.20	0.36	
Growth/Inc.	0.1669	0.0725	0.006	0.114	1.83	4.68		0.1522	0.0681	0.006	0.118	1.75	4.48	
All	0.1614	0.1538	0.003	0.198	1.06	3.54		0.1412	0.1452	0.003	0.198	0.95	3.30	
Mean J-Stat	0.1799							0.1805						
Panel C: Equal-weighted portfolios of individual fund performances using the conditional pricing kernel with DY and TB1 as the instruments														
Ag. Growth	0.1137	0.0854	0.004	0.165	-0.04	0.42	0.000	0.0902	0.0521	0.004	0.179	-0.17	0.77	0.000
Growth	-0.0971	-0.1178	0.002	0.170	0.90	1.80	0.000	-0.0911	-0.1140	0.002	0.171	0.80	1.75	0.000
Growth/Inc.	-0.0984	-0.1590	0.004	0.201	2.40	7.50	0.000	-0.0890	-0.1585	0.004	0.168	2.61	8.29	0.000
All	-0.0461	-0.0742	0.003	0.168	1.02	2.08	0.000	-0.0474	-0.0897	0.003	0.181	0.99	2.65	0.000
Mean J-Stat	0.1848							0.1833						
	Mean λ	Mean t(λ)	Mean p-val	Mean Wald				Mean λ	Mean t(λ)	Mean p-val	Mean Wald			
Panel D: Size-weighted portfolios of individual fund performances using the unconditional pricing kernel														
Ag. Growth	0.2391	1.950	0.204					0.2308	1.934	0.198				
Growth	0.2474	2.284	0.218					0.2417	2.279	0.213				
Growth/Inc.	0.1918	1.273	0.292					0.1835	1.230	0.268				
All	0.2293	1.993	0.231					0.2224	1.978	0.225				
Mean J-Stat	0.1506							0.1505						
Panel E: Size-weighted portfolios of individual fund performances using the conditional pricing kernel with DY as the instrument														
Ag. Growth	0.2590	2.392	0.185					0.2309	2.214	0.179				
Growth	0.1311	1.623	0.205					0.1169	1.541	0.182				
Growth/Inc.	0.0207	-0.302	0.169					0.0063	-0.444	0.175				
All	0.1469	1.526	0.204					0.1289	1.405	0.195				
Mean J-Stat	0.1797							0.1799						
Panel F: Size-weighted portfolios of individual fund performances using the conditional pricing kernel with DY and TB1 as the instruments														
Ag. Growth	0.1384	1.392	0.154	0.000				0.1157	1.170	0.148	0.000			
Growth	-0.0557	-0.147	0.149	0.000				-0.0511	-0.222	0.143	0.000			
Growth/Inc.	-0.1245	-1.529	0.258	0.000				-0.1154	-1.520	0.210	0.000			
All	-0.0218	-0.042	0.159	0.000				-0.0239	-0.153	0.158	0.000			
Mean J-Stat	0.1849							0.1833						

Table A5. Summary statistics for the unconditional and conditional pricing kernels

This table presents summary statistics for the unconditional and conditional performance measures (λ in %) 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. All of the p-values are based on a GMM system estimation using the Bartlett kernel. Information related to the funds with significant performance and with positive significant performance at the 5% level 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. N is the number of funds in each group.

Fund Group	N	Max. p	Min. p	Percent of funds with $p < 5\%$	Number of funds with $\lambda > 0$ & $p < 5\%$	Bonferroni p-value Min. t	Max. t
Panel A: TSE 300 index and unconditional pricing kernel							
Ag. 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/Inc.	12	0.984	0.000	41.67	4	0.073	0.000
All	95	0.984	0.000	42.11	37	0.577	0.000
Panel B: Value-weighted TSE index and unconditional pricing kernel							
Ag. 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/Inc.	12	0.866	0.000	50.00	5	0.058	0.000
All	95	0.948	0.000	43.16	38	0.458	0.000
Panel C: TSE 300 index and conditional pricing kernel with DY as the instrumental variable							
Ag. 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/Inc.	12	0.715	0.000	75.00	6	0.000	0.000
All	95	0.959	0.000	60.00	44	0.000	0.000
Panel D: Value-weighted TSE index and conditional pricing kernel with DY as the instrumental variable							
Ag. 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/Inc.	12	0.655	0.000	83.33	6	0.000	0.000
All	95	0.912	0.000	60.00	42	0.000	0.000
Panel E: TSE 300 index and conditional pricing kernel with DY and TB1 as the instrumental variables							
Ag. 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/Inc.	12	0.978	0.000	66.67	1	0.000	0.000
All	95	0.978	0.000	58.95	21	0.000	0.000
Panel F: Value-weighted TSE index and conditional pricing kernel with DY and TB1 as the instrumental variables							
Ag. 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/Inc.	12	0.787	0.000	58.33	1	0.000	0.000
All	95	0.944	0.000	54.74	16	0.000	0.000

Table A6. Summary statistics for performance for the unconditional and conditional pricing kernels for various relative risk aversion levels

This table reports the performance measures or lambda (λ in %) per investment objective for various levels of the relative risk aversion or RRA coefficient Gamma or γ using the unconditional and conditional pricing kernels for two selected benchmarks. The dividend yield (DY) and the yield on the one-month T-bill (TB1) are used as instrumental variables. Simultaneous system estimation that includes the ten size-based passive strategies is conducted using the GMM method. All represents the statistics of the portfolios of all funds. Information related to the estimated performance, the p-values, and the J-statistic using the Bartlett kernel is provided in the table. TSE 300 and TSEVW are the 300 and value-weighed TSE indexes, respectively. The J-statistic is the minimized value of the sample quadratic form constructed using the moment conditions and the optimal weighting matrix. Monthly data are used from November 1989 to December 1999, for a total of 122 observations per portfolio of funds.

Benchmark	TSE 300								TSEVW							
Gamma	3		4		5		6		3		4		5		6	
Fund Group	λ	p-val.	λ	p-val.	λ	p-val.	λ	p-val.	λ	p-val.	λ	p-val.	λ	p-val.	λ	p-val.
Panel A: Unconditional pricing kernel for equal-weighted portfolios of funds																
Ag. Growth	0.1899	0.01	0.1884	0.01	0.1865	0.01	0.1855	0.01	0.1822	0.01	0.1789	0.02	0.1766	0.02	0.1757	0.02
Growth	0.2157	0.00	0.2144	0.00	0.2124	0.00	0.2113	0.00	0.2131	0.00	0.2098	0.00	0.2076	0.00	0.2068	0.00
Growth/Inc.	0.2704	0.00	0.2681	0.00	0.2652	0.00	0.2635	0.00	0.2638	0.00	0.2591	0.00	0.2559	0.00	0.2544	0.00
All	0.2017	0.00	0.1994	0.00	0.1975	0.00	0.1964	0.00	0.1959	0.00	0.1933	0.00	0.1902	0.00	0.1892	0.00
J-Stat	0.1506		0.1506		0.1505		0.1505		0.1504		0.1505		0.1505		0.1505	
Panel B: Unconditional pricing kernel for size-weighted portfolios of funds																
Ag. Growth	0.2592	0.00	0.2565	0.00	0.2540	0.00	0.2524	0.00	0.2505	0.00	0.2463	0.00	0.2435	0.00	0.2422	0.00
Growth	0.2725	0.00	0.2697	0.00	0.2671	0.00	0.2655	0.00	0.2668	0.00	0.2626	0.00	0.2598	0.00	0.2585	0.00
Growth/Inc.	0.1951	0.01	0.1923	0.01	0.1898	0.01	0.1883	0.01	0.1873	0.01	0.1830	0.01	0.1802	0.01	0.1790	0.01
All	0.2545	0.00	0.2514	0.00	0.2489	0.00	0.2474	0.00	0.2460	0.00	0.2438	0.00	0.2410	0.00	0.2388	0.00
J-Stat	0.1506		0.1506		0.1505		0.1505		0.1504		0.1505		0.1505		0.1505	
Panel C: Conditional pricing kernel with DY as instrumental variable for equal-weighted portfolios of funds																
Ag. Growth	0.3264	0.00	0.3077	0.00	0.3049	0.00	0.3076	0.00	0.2729	0.00	0.2785	0.00	0.2700	0.00	0.2710	0.00
Growth	0.1110	0.01	0.1012	0.02	0.1064	0.02	0.1097	0.01	0.0939	0.04	0.0919	0.04	0.0910	0.04	0.0935	0.03
Growth/Inc.	0.1458	0.00	0.1479	0.00	0.1487	0.00	0.1488	0.00	0.1279	0.01	0.1290	0.01	0.1294	0.01	0.1289	0.01
All	0.1588	0.00	0.1599	0.00	0.1598	0.00	0.1592	0.00	0.1376	0.00	0.1371	0.00	0.1364	0.00	0.1361	0.00
J-Stat	0.1794		0.1792		0.1791		0.1791		0.1794		0.1792		0.1790		0.1789	
Panel D: Conditional pricing kernel with DY as instrumental variable for size-weighted portfolios of funds																
Ag. Growth	0.2941	0.00	0.2885	0.00	0.2831	0.00	0.2701	0.00	0.2613	0.00	0.2510	0.00	0.2444	0.00	0.2336	0.00
Growth	0.1222	0.01	0.1289	0.00	0.1312	0.00	0.1320	0.00	0.1082	0.02	0.1129	0.01	0.1144	0.01	0.1153	0.01
Growth/Inc.	-0.0003	0.99	0.0033	0.95	0.0055	0.91	0.0070	0.89	-0.0167	0.74	-0.0130	0.79	-0.0105	0.83	-0.0079	0.87
All	0.1493	0.00	0.1414	0.00	0.1438	0.00	0.1450	0.00	0.1270	0.00	0.1209	0.01	0.1258	0.00	0.1224	0.01
J-Stat	0.1795		0.1794		0.1793		0.1792		0.1795		0.1793		0.1791		0.1789	
Panel E: Conditional pricing kernel with DY and TB1 as the instrumental variables for equal-weighted portfolios of funds																
Ag. Growth	0.0400	0.31	0.0299	0.44	0.0224	0.56	0.0226	0.56	0.0122	0.76	0.0056	0.89	0.0023	0.95	0.0012	0.98
Growth	-0.0886	0.11	-0.0899	0.10	-0.0887	0.10	-0.0869	0.10	-0.0726	0.15	-0.0746	0.13	-0.0751	0.13	-0.0749	0.12
Growth/Inc.	-0.0791	0.17	-0.0818	0.15	-0.0817	0.15	-0.0807	0.15	-0.0489	0.37	-0.0522	0.34	-0.0534	0.32	-0.0538	0.32
All	-0.0573	0.21	-0.0605	0.18	-0.0618	0.17	-0.0603	0.17	-0.0537	0.22	-0.0573	0.18	-0.0592	0.16	-0.0597	0.15
J-Stat	0.1865		0.1843		0.1830		0.1821		0.1847		0.1828		0.1816		0.1808	
Panel F: Conditional pricing kernel with DY and TB1 as the instrumental variables for size-weighted portfolios of funds																
Ag. Growth	0.1190	0.00	0.1097	0.01	0.1048	0.01	0.1018	0.01	0.0904	0.03	0.0824	0.05	0.0782	0.06	0.0756	0.06
Growth	-0.0541	0.32	-0.0529	0.32	-0.0505	0.34	-0.0482	0.36	-0.0225	0.64	-0.0236	0.62	-0.0237	0.61	-0.0235	0.61
Growth/Inc.	-0.0966	0.11	-0.0961	0.11	-0.0953	0.12	-0.0945	0.12	-0.0800	0.16	-0.0803	0.16	-0.0802	0.15	-0.0799	0.15
All	-0.0175	0.71	-0.0197	0.68	-0.0196	0.67	-0.0190	0.68	-0.0092	0.83	-0.0129	0.76	-0.0148	0.73	-0.0157	0.71
J-Stat	0.1861		0.1840		0.1828		0.1819		0.1843		0.1825		0.1813		0.1805	

Table A7. Survivorship bias and risk-adjusted performance

This table reports the performance measures (λ in %) per investment objective group for size-weighted portfolios of surviving and non-surviving funds and estimates of the survivorship bias using three asset pricing kernel models and two selected benchmarks. The survivorship bias is the difference between the risk-adjusted performance of the size-weighted portfolios of all funds and of surviving funds only. Simultaneous system estimation, including the ten size-based passive strategies, is conducted using the GMM method. Panel A provides information on the performance estimates of four size-weighted portfolios of all funds using the unconditional asset pricing kernel and an estimate of the survivorship bias. Panel B provides information on the performance estimates of four size-weighted portfolios of all funds using the conditional asset pricing kernel with one instrumental variable (DY) and an estimate of the survivorship bias. Panel C provides similar information to panel B using the conditional asset pricing kernel with two instrumental variables (DY and TB1) and an estimate of the survivorship bias. All represents the statistics of the size-weighted portfolio of all funds. The standard errors of the estimates are adjusted for serial correlation and heteroskedasticity (Newey and West, 1987a). Size is defined as the total net asset value of the fund. TSE 300 and TSEVW are the TSE 300 index and the value-weighted TSE index, respectively. Monthly data are from November 1989 through December 1999, for a total of 122 observations per portfolio of funds.

Fund Group	TSE 300			TSEVW		
	λ	p-val	Surv. Bias	λ	p-val	Surv. Bias
Panel A: Size-weighted portfolios of all funds using the unconditional asset pricing kernel						
Aggressive Growth	0.2364	0.00	0.2412	0.2265	0.01	0.2376
Growth	0.2071	0.00	0.7512	0.2017	0.00	0.7308
Growth/Income	0.1336	0.05	0.7044	0.1259	0.06	0.6852
Income	0.1911	0.05	-0.0180	0.1826	0.05	-0.0312
All	0.2030	0.00	0.5808	0.1956	0.00	0.5784
Panel B: Size-weighted portfolios of all funds using the conditional asset pricing kernel with one instrumental variable DY						
Aggressive Growth	0.2736	0.00	0.1788	0.2334	0.00	0.2112
Growth	0.0967	0.03	0.3864	0.0854	0.06	0.3300
Growth/Income	-0.0582	0.17	0.7385	-0.0687	0.11	0.6684
Income	-0.0363	0.60	-0.0072	-0.0523	0.45	-0.0084
All	0.1086	0.01	0.3936	0.0912	0.03	0.3564
Panel C: Size-weighted portfolios of all funds using the conditional asset pricing kernel with two instrumental variables DY and TB1						
Aggressive Growth	0.0977	0.02	0.1440	0.0699	0.10	0.1500
Growth	-0.0874	0.06	0.4140	-0.0645	0.13	0.4908
Growth/Income	-0.1879	0.00	1.1016	-0.1794	0.00	1.1892
Income	-0.2810	0.00	-0.0048	-0.2545	0.00	-0.0012
All	-0.0584	0.16	0.4644	-0.0499	0.19	0.4440

Table A8. Performance and risk measures for portfolios of funds using the unconditional and conditional CAPM

This table reports the performance (α in %) and risk measures for each investment objective group using the unconditional CAPM and the conditional CAPM with time-varying betas and/or alphas for two benchmark variables. The conditional CAPMs are based on four instrumental variables; namely, the lagged values of the dividend yield (DY), the yield on one-month T-bill (TB1), the risk premium (RISK), and the slope of the term structure (TERM). GMM estimation is conducted by regressing each portfolio of funds excess return on a constant, the benchmark excess return, and variables representing the lagged instruments and the product of the four lagged instrumental variables and the benchmark excess return. The alpha and beta are the estimates of the intercept and the slope of the regression, respectively. The standard errors of these estimates are adjusted for serial correlation and heteroskedasticity (Newey and West, 1987a). The number of funds in portfolio is given in panel B of table 2.1. All represents the statistics for the portfolios of all funds. Information related to the estimated performance or alpha, the beta, the p-values, and the adjusted R^2 is provided in the table. TSE 300 is the TSE 300 index and TSEVW is the value-weighted TSE index. W1, W2, and W3 correspond to the p-values based on the Newey and West (1987b) Wald test on the validity of the time-varying alphas, time-varying betas, and time-varying alphas and betas, respectively. Size is defined as the total net asset value of the fund. Monthly data are from November 1989 to December 1999, for a total of 122 observations per portfolio of funds.

	TSE 300								TSEVW							
Fund Group	α	p-val	β	p-val	W1	W2	W3	Adj. R^2	α	p-val	β	p-val	W1	W2	W3	Adj. R^2
Panel A: Equal-weighted portfolios of mutual funds and unconditional CAPM																
Ag. Growth	-0.0122	0.95	0.81	0.00				0.78	-0.1262	0.55	0.83	0.00				0.80
Growth	-0.0489	0.46	0.84	0.00				0.97	-0.1594	0.05	0.84	0.00				0.96
Growth/Inc.	-0.0240	0.73	0.78	0.00				0.96	-0.1290	0.11	0.79	0.00				0.96
All	-0.0315	0.75	0.81	0.00				0.94	-0.1411	0.19	0.82	0.00				0.94
Panel B: Size-weighted portfolios of mutual funds and unconditional CAPM																
Ag. Growth	0.0116	0.95	0.82	0.00				0.82	-0.1026	0.58	0.84	0.00				0.84
Growth	0.0034	0.95	0.86	0.00				0.97	-0.1095	0.13	0.86	0.00				0.96
Growth/Inc.	-0.0817	0.20	0.76	0.00				0.96	-0.1827	0.01	0.77	0.00				0.95
All	-0.0020	0.98	0.83	0.00				0.95	-0.1128	0.22	0.84	0.00				0.95
Panel C: Equal-weighted portfolios of mutual funds and conditional CAPM with time-varying betas																
Ag. Growth	0.0080	0.97	0.80	0.00		0.26		0.79	-0.1060	0.59	0.83	0.00		0.60		0.80
Growth	-0.0399	0.53	0.84	0.00		0.00		0.97	-0.1467	0.03	0.84	0.00		0.41		0.96
Growth/Inc.	-0.0232	0.71	0.78	0.00		0.00		0.97	-0.1253	0.06	0.79	0.00		0.00		0.96
All	-0.0195	0.84	0.81	0.00		0.00		0.94	-0.1261	0.19	0.82	0.00		0.30		0.94
Panel D: Size-weighted portfolios of mutual funds and conditional CAPM with time-varying betas																
Ag. Growth	0.0293	0.87	0.81	0.00		0.06		0.83	-0.0839	0.63	0.82	0.00		0.38		0.84
Growth	0.0167	0.77	0.85	0.00		0.00		0.97	-0.0920	0.15	0.86	0.00		0.17		0.96
Growth/Inc.	-0.0850	0.12	0.77	0.00		0.00		0.97	-0.1812	0.00	0.78	0.00		0.00		0.96
All	0.0091	0.91	0.82	0.00		0.00		0.95	-0.0983	0.24	0.83	0.00		0.14		0.95
Panel E: Equal-weighted portfolios of mutual funds and conditional CAPM with time-varying alphas and betas																
Ag. Growth	0.0221	0.90	0.79	0.00	0.04	0.10	0.00	0.80	-0.0928	0.60	0.82	0.00	0.02	0.39	0.02	0.82
Growth	-0.0376	0.48	0.83	0.00	0.00	0.00	0.00	0.97	-0.1504	0.01	0.84	0.00	0.00	0.27	0.00	0.96
Growth/Inc.	-0.0242	0.64	0.77	0.00	0.00	0.00	0.00	0.97	-0.1317	0.01	0.78	0.00	0.00	0.10	0.00	0.97
All	-0.0150	0.85	0.80	0.00	0.00	0.00	0.00	0.95	-0.1260	0.11	0.82	0.00	0.00	0.27	0.00	0.95
Panel F: Size-weighted portfolios of mutual funds and conditional CAPM with time-varying alphas and betas																
Ag. Growth	0.0382	0.81	0.79	0.00	0.01	0.01	0.00	0.84	-0.0773	0.61	0.81	0.00	0.00	0.13	0.00	0.85
Growth	0.0187	0.71	0.84	0.00	0.01	0.00	0.00	0.97	-0.0962	0.07	0.85	0.00	0.00	0.12	0.00	0.96
Growth/Inc.	-0.0892	0.06	0.76	0.00	0.00	0.00	0.00	0.97	-0.1913	0.00	0.77	0.00	0.00	0.04	0.00	0.96
All	0.0116	0.87	1.06	0.87	0.00	0.00	0.00	0.96	-0.1008	0.15	0.83	0.00	0.00	0.05	0.00	0.95

Table A9. Summary statistics for the performance estimates based on the unconditional and conditional CAPM and four-index models for the fund groups based on individual fund performances

This table presents summary statistics for the performance measures based on the unconditional and the conditional CAPM and four-index model with time-varying betas and/or alphas for each fund group and for all funds. The instrumental variables are the lagged values of the dividend yield (DY), the yield on one-month T-bill (TB1), the risk premium (RISK), and the slope of the term structure (TERM). N is the number of funds in each group. Panels A, C, and E present these results for the CAPM using the TSE 300 index as the benchmark. Panels B, D, and F present these results for the CAPM using the value-weighted TSE index as the benchmark. N is the number of funds in each group. All the p-values are based on GMM estimation and are adjusted for serial correlation and heteroskedasticity (Newey and West, 1987a). Information related to the funds with significant performance at the 5% level 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.

Fund Group	N	Max. p	Min. p	Percent of funds with $p < 5\%$	Number of funds with $\alpha > 0$ and $p < 5\%$	Bonferroni p-value (Min. t)	Bonferroni p-value (Max. t)
Panel A: TSE 300 index as benchmark variable and unconditional CAPM							
Ag. Growth	27	0.974	0.021	7.41	1	0.323	0.276
Growth	50	0.993	0.000	16.00	1	0.000	0.161
Growth/Inc.	12	0.844	0.000	16.67	0	0.000	0.616
All	95	0.993	0.000	12.63	2	0.000	0.305
Panel B: Value-weighted TSE index as benchmark variable and unconditional CAPM							
Ag. Growth	27	0.999	0.007	11.11	0	0.092	1.000
Growth	50	0.995	0.000	30.00	0	0.000	1.000
Growth/Inc.	12	0.752	0.000	33.33	0	0.000	1.000
All	95	0.999	0.000	24.21	0	0.000	1.000
Panel C: TSE 300 index as benchmark variable and conditional CAPM with time-varying betas							
Ag. Growth	27	0.962	0.003	11.11	1	0.042	0.073
Growth	50	0.988	0.000	24.00	1	0.000	0.004
Growth/Inc.	12	0.579	0.000	25.00	0	0.000	0.319
All	95	0.988	0.000	18.95	2	0.000	0.008
Panel D: Value-weighted TSE index as benchmark variable and conditional CAPM with time-varying betas							
Ag. Growth	27	0.927	0.001	14.81	1	0.007	0.314
Growth	50	0.850	0.000	34.00	1	0.000	0.227
Growth/Inc.	12	0.675	0.000	25.00	0	0.000	1.000
All	95	0.927	0.000	26.32	2	0.000	0.431
Panel E: TSE 300 index as benchmark variable and conditional CAPM with time-varying alphas and betas							
Ag. Growth	27	0.984	0.001	22.22	3	0.009	0.009
Growth	50	0.948	0.000	26.00	2	0.000	0.001
Growth/Inc.	12	0.622	0.000	33.33	1	0.000	0.226
All	95	0.984	0.000	26.32	7	0.000	0.001
Panel F: Value-weighted TSE index as benchmark variable and conditional CAPM with time-varying alphas and betas							
Ag. Growth	27	0.838	0.000	22.22	1	0.000	0.050
Growth	50	0.834	0.000	42.00	1	0.000	0.023
Growth/Inc.	12	0.589	0.000	58.33	0	0.000	0.956
All	95	0.838	0.000	38.95	2	0.000	0.043
Panel G: Unconditional four-index model							
Ag. Growth	27	0.973	0.000	22.22	3	0.011	0.026
Growth	50	0.986	0.000	20.00	2	0.000	0.297
Growth/Inc.	12	0.953	0.000	33.33	1	0.000	0.218
All	95	0.986	0.000	22.11	7	0.000	0.092
Panel H: Conditional four-index model with time-varying betas							
Ag. Growth	27	0.905	0.006	18.52	3	0.007	0.029
Growth	50	0.988	0.000	22.00	4	0.000	0.108
Growth/Inc.	12	0.958	0.000	50.00	1	0.000	0.018
All	95	0.988	0.000	24.21	9	0.000	0.100
Panel I: Conditional four-index model with time-varying alphas and betas							
Ag. Growth	27	0.958	0.000	18.52	4	0.098	0.004
Growth	50	0.996	0.000	28.00	6	0.000	0.054
Growth/Inc.	12	0.905	0.000	50.00	1	0.000	0.002
All	95	0.996	0.000	27.37	11	0.000	0.012

Table A10. Performance and risk measures for portfolios of funds using the unconditional and conditional four-index models

This table reports the performance (α in %) and risk measures by investment objective using the unconditional and conditional four-index model. GMM estimation is conducted for each portfolio of funds by regressing its excess return on the market index excess return, the return differential between small and large-cap stock portfolios, the return differential between growth and value stock portfolios, and the excess return on an aggregate bond index representing corporate and government bonds. Beta of M, SL, GV, and B are the estimates of the coefficients associated with the market index excess return, the size factor, the growth-value factor, and the bond factor, respectively. The instrumental variables are the lagged values of the dividend yield (DY), the yield on one-month T-bill (TB1), the risk premium (RISK), and the slope of the term structure (TERM). The standard errors of these estimates are adjusted for serial correlation and heteroskedasticity (Newey and West, 1987a). All represents the statistics for the portfolios of all funds. Information related to the estimated performance (alpha), the factor betas (estimated value and p-values), and the adjusted R^2 is provided in the table. W1, W2, W3, W4, W5, and W6 correspond to the p-values based on the Newey and West (1987b) Wald test on the validity of the time-varying alphas, time-varying betas of the market factor, the size factor, the growth-value factor, and the bond factor, and the joint time-variation in all coefficients, respectively. Size is defined as the total net asset value of the fund. Monthly data used are from November 1989 to December 1999, for a total of 122 observations per portfolio of funds.

Fund Group	α	p-val	β(M)	p-val	β(SL)	p-val	β(GV)	p-val	β(B)	p-val	W1	W2	W3	W4	W5	W6	Adj. R^2
Panel A: Equal-weighted portfolios of mutual funds and unconditional four-index model																	
Ag. Growth	0.0275	0.79	0.91	0.00	0.51	0.00	0.02	0.69	-0.04	0.36							0.95
Growth	-0.0459	0.26	0.88	0.00	0.15	0.00	-0.05	0.05	-0.01	0.75							0.98
Growth/Inc.	-0.0267	0.55	0.82	0.00	0.15	0.00	-0.05	0.01	0.01	0.79							0.98
All	-0.0164	0.73	0.87	0.00	0.25	0.00	-0.03	0.22	-0.01	0.64							0.98
Panel B: Size-weighted portfolios of mutual funds and unconditional four-index model																	
Ag. Growth	0.0362	0.70	0.91	0.00	0.43	0.00	0.01	0.79	-0.04	0.36							0.95
Growth	0.0042	0.92	0.89	0.00	0.13	0.00	-0.03	0.11	-0.01	0.81							0.98
Growth/Inc.	-0.0878	0.05	0.79	0.00	0.13	0.00	-0.05	0.01	0.03	0.32							0.97
All	0.0053	0.91	0.87	0.00	0.21	0.00	-0.02	0.34	-0.01	0.74							0.98
Panel C: Equal-weighted portfolios of mutual funds and conditional four-index model with time-varying betas																	
Ag. Growth	0.1379	0.26	0.92	0.00	0.47	0.00	0.07	0.03	-0.03	0.65		0.73	0.18	0.00	0.42	0.00	0.95
Growth	-0.0126	0.77	0.88	0.00	0.13	0.00	-0.01	0.59	0.02	0.62		0.22	0.00	0.00	0.18	0.00	0.98
Growth/Inc.	-0.0487	0.38	0.82	0.00	0.13	0.00	-0.01	0.73	0.02	0.55		0.18	0.01	0.18	0.08	0.00	0.98
All	0.0285	0.58	0.87	0.00	0.22	0.00	0.00	0.87	0.00	0.92		0.60	0.00	0.00	0.35	0.00	0.98
Panel D: Size-weighted portfolios of mutual funds and conditional four-index model with time-varying betas																	
Ag. Growth	0.1485	0.18	0.91	0.00	0.41	0.00	0.06	0.08	-0.00	0.93		0.01	0.00	0.00	0.54	0.00	0.96
Growth	0.0289	0.56	0.89	0.00	0.11	0.00	0.00	0.96	0.03	0.45		0.03	0.02	0.24	0.08	0.00	0.98
Growth/Inc.	-0.0955	0.09	0.81	0.00	0.10	0.00	-0.00	0.85	0.03	0.50		0.11	0.00	0.08	0.04	0.00	0.98
All	0.0469	0.38	0.87	0.00	0.18	0.00	0.01	0.74	0.01	0.68		0.02	0.00	0.01	0.30	0.00	0.98
Panel E: Equal-weighted portfolios of mutual funds and conditional four-index model with time-varying alphas and betas																	
Ag. Growth	0.1525	0.21	0.92	0.00	0.47	0.00	0.07	0.05	-0.01	0.86	0.89	0.95	0.17	0.00	0.40	0.00	0.95
Growth	0.0077	0.86	0.88	0.00	0.12	0.00	-0.01	0.49	0.03	0.53	0.06	0.17	0.00	0.00	0.07	0.00	0.98
Growth/Inc.	-0.0462	0.40	0.82	0.00	0.12	0.00	0.00	0.87	0.00	0.91	0.51	0.18	0.00	0.27	0.22	0.00	0.98
All	0.0422	0.43	0.87	0.00	0.22	0.00	0.01	0.74	0.01	0.80	0.29	0.49	0.00	0.00	0.21	0.00	0.98
Panel F: Size-weighted portfolios of mutual funds and conditional four-index model with time-varying alphas and betas																	
Ag. Growth	0.1551	0.16	0.91	0.00	0.41	0.00	0.06	0.09	0.00	1.00	0.77	0.08	0.00	0.00	0.73	0.00	0.96
Growth	0.0442	0.38	0.88	0.00	0.10	0.00	0.00	0.98	0.04	0.35	0.33	0.02	0.01	0.24	0.08	0.00	0.98
Growth/Inc.	-0.0945	0.08	0.80	0.00	0.10	0.00	0.00	0.99	0.01	0.83	0.54	0.12	0.00	0.25	0.07	0.00	0.98
All	0.0550	0.32	0.87	0.00	0.18	0.00	0.01	0.56	0.02	0.59	0.45	0.02	0.00	0.00	0.26	0.00	0.98

Table A11. Performance and timing measures for portfolios of funds using the unconditional and conditional models of Treynor and Mazuy and of Henriksson and Merton

This table reports the performance (α in %) and timing measures for various investment objectives grouping using the unconditional and conditional Treynor and Mazuy (1966) and Henriksson and Merton (1981) models for two benchmark variables. GMM estimation is conducted for each portfolio of funds by regressing the individual fund or fund grouping excess return on the benchmark excess return, the squares of the benchmark excess return, and the product of the instrumental variables and the benchmark excess return for the conditional Treynor and Mazuy (1966) model. For the conditional Henriksson and Merton model, the excess return on each portfolio of funds is regressed on the benchmark excess return, an indicator function that depends on the benchmark conditional expected return, the product of the instrumental variables and the benchmark excess return, and the product of the indicator function with the instrumental variables. The instrumental variables are the lagged values of the dividend yield (DY), the yield on one-month T-bill (TB1), the risk premium (RISK), and the slope of the term structure (TERM). The standard errors of the performance and timing estimates are adjusted for serial correlation and heteroskedasticity (Newey and West, 1987a). TSE 300 and TSEVW are the TSE 300 index and the value-weighted TSE index, respectively. All represents the statistics for the portfolios of all funds. Size is defined as the total net asset value. The number of funds in portfolio is given in panel B of table 2.1. Monthly data are used from November 1989 through December 1999, for a total of 122 observations per portfolio of funds.

	TSE 300					TSEVW				
Fund Group	α	p-val	γ	p-val	Adj. R^2	α	p-val	γ	p-val	Adj. R^2
Panel A: Equal-weighted portfolios of mutual funds grouped by investment objectives for unconditional Treynor and Mazuy model										
Ag. Growth	0.1741	0.42	-0.97	0.00	0.79	0.0879	0.68	-1.03	0.00	0.81
Growth	0.0342	0.60	-0.43	0.00	0.97	-0.0267	0.71	-0.64	0.00	0.96
Growth/Inc.	0.0474	0.47	-0.37	0.01	0.96	-0.0236	0.75	-0.51	0.00	0.96
All	0.0747	0.46	-0.55	0.00	0.94	0.0017	0.99	-0.76	0.00	0.94
Panel B: Size-weighted portfolios of mutual funds grouped by investment objectives for unconditional Treynor and Mazuy model										
Ag. Growth	0.1798	0.33	-0.87	0.00	0.83	0.0936	0.61	-0.94	0.00	0.85
Growth	0.0742	0.22	-0.37	0.00	0.97	0.0117	0.86	-0.58	0.00	0.96
Growth/Inc.	-0.0233	0.68	-0.30	0.04	0.96	-0.0868	0.20	-0.46	0.00	0.96
All	0.0882	0.30	-0.47	0.00	0.95	0.0162	0.86	-0.68	0.00	0.95
Panel C: Equal-weighted portfolios of mutual funds grouped by investment objectives for conditional Treynor and Mazuy model										
Ag. Growth	0.1534	0.52	-0.95	0.07	0.79	0.0890	0.70	-1.33	0.01	0.81
Growth	0.0113	0.87	-0.34	0.01	0.97	-0.0226	0.77	-0.85	0.00	0.96
Growth/Inc.	0.0067	0.92	-0.20	0.25	0.97	-0.0361	0.64	-0.61	0.00	0.97
All	0.0518	0.65	-0.47	0.05	0.94	0.0080	0.94	-0.92	0.00	0.95
Panel D: Size-weighted portfolios of mutual funds grouped by investment objectives for conditional Treynor and Mazuy model										
Ag. Growth	0.1365	0.51	-0.70	0.12	0.83	0.0730	0.72	-1.07	0.01	0.85
Growth	0.0529	0.40	-0.24	0.04	0.97	0.0178	0.80	-0.75	0.00	0.97
Growth/Inc.	-0.0559	0.36	-0.19	0.26	0.97	-0.0912	0.21	-0.62	0.00	0.96
All	0.0599	0.52	-0.33	0.09	0.96	0.0171	0.86	-0.79	0.00	0.95
Panel E: Equal-weighted portfolios of mutual funds grouped by investment objectives for unconditional Henriksson and Merton model										
Ag. Growth	0.4065	0.13	-0.26	0.02	0.79	0.3759	0.14	-0.32	0.00	0.81
Growth	0.1188	0.21	-0.10	0.03	0.97	0.1432	0.11	-0.19	0.00	0.96
Growth/Inc.	0.0891	0.39	-0.07	0.29	0.96	0.0893	0.33	-0.14	0.00	0.96
All	0.1913	0.16	-0.14	0.03	0.94	0.1959	0.11	-0.21	0.00	0.94
Panel F: Size-weighted portfolios of mutual funds grouped by investment objectives for unconditional Henriksson and Merton model										
Ag. Growth	0.3765	0.12	-0.22	0.03	0.83	0.3517	0.12	-0.29	0.00	0.85
Growth	0.1488	0.09	-0.09	0.03	0.97	0.1741	0.05	-0.18	0.00	0.96
Growth/Inc.	0.0175	0.85	-0.06	0.32	0.96	0.0284	0.74	-0.13	0.00	0.96
All	0.1852	0.13	-0.11	0.04	0.95	0.1950	0.08	-0.19	0.00	0.95
Panel G: Equal-weighted portfolios of mutual funds grouped by investment objectives for conditional Henriksson and Merton model										
Ag. Growth	0.1737	0.51	-0.06	0.63	0.80	0.2426	0.37	-0.19	0.14	0.82
Growth	0.0122	0.88	-0.02	0.67	0.97	0.0917	0.37	-0.15	0.01	0.97
Growth/Inc.	-0.0482	0.56	0.03	0.49	0.97	0.0180	0.87	-0.09	0.12	0.97
All	0.0488	0.69	-0.02	0.72	0.95	0.1222	0.37	-0.15	0.02	0.95
Panel H: Size-weighted portfolios of mutual funds grouped by investment objectives for conditional Henriksson and Merton model										
Ag. Growth	0.1657	0.49	-0.05	0.64	0.84	0.2414	0.35	-0.19	0.12	0.85
Growth	0.0752	0.36	-0.03	0.48	0.97	0.1505	0.15	-0.16	0.01	0.97
Growth/Inc.	-0.1136	0.17	0.03	0.46	0.97	-0.0336	0.75	-0.09	0.12	0.96
All	0.0727	0.52	-0.03	0.63	0.96	0.1491	0.26	-0.16	0.02	0.96

Table A12. Summary statistics for the performance and timing measures for portfolios of funds using the unconditional and conditional models of Treynor and Mazuy and of Henriksson and Merton

This table presents summary statistics for the performance and timing measures α and γ, respectively, based on the unconditional and the conditional Treynor and Mazuy (1966) and the Henriksson and Merton (1981) models for each fund group and for all funds. N is the number of funds in each group. All the p-values are based on GMM estimation and are adjusted for serial correlation and heteroskedasticity (Newey and West, 1987a). Information related to the funds with significant performance (timing) at the 5% level and with positive significant performance (timing) 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.

Fund Group	N	Performance measure						Timing measure					
		p		% of funds, p<5%	# of funds, α>0 & p<5%	Bonferroni p-value		p		% of funds, p<5%	# of funds, γ>0 & p<5%	Bonferroni p-value	
		Max	Min			Min. t	Max. t	Max	Min			Min. t	Max. t
Panel A: TSE 300 index as benchmark variable and unconditional Treynor and Mazuy model													
Ag. Growth	27	0.973	0.000	11.11	3	1.000	0.120	0.840	0.000	55.56	1	0.000	0.326
Growth	50	0.978	0.000	10.00	2	0.000	0.052	0.972	0.000	30.00	0	0.000	1.000
Growth/Inc.	12	0.875	0.000	16.67	1	0.000	0.164	0.718	0.000	41.67	0	0.001	1.000
All	95	0.978	0.000	11.58	6	0.000	0.100	0.972	0.000	36.84	3	0.000	0.727
Panel B: Value-weighted TSE index as benchmark variable and unconditional Treynor and Mazuy model													
Ag. Growth	27	0.948	0.024	7.41	2	1.000	0.315	0.900	0.000	66.67	0	0.000	1.000
Growth	50	0.988	0.000	14.00	1	0.011	0.347	0.907	0.000	50.00	0	0.000	1.000
Growth/Inc.	12	0.910	0.000	25.00	1	0.000	0.285	0.517	0.000	66.67	0	0.000	1.000
All	95	0.988	0.000	14.74	4	0.000	0.660	0.907	0.000	55.79	1	0.000	0.369
Panel C: TSE 300 index as benchmark variable and conditional Treynor and Mazuy model													
Ag. Growth	27	0.964	0.007	7.41	2	0.795	0.095	0.988	0.002	11.11	0	0.026	1.000
Growth	50	0.998	0.007	12.00	1	0.000	0.019	0.964	0.000	18.00	2	0.002	0.300
Growth/Inc.	12	0.932	0.000	8.33	0	0.000	0.395	0.839	0.008	16.67	1	0.299	0.045
All	95	0.998	0.000	11.58	3	0.000	0.036	0.988	0.000	15.79	4	0.005	0.125
Panel D: Value-weighted TSE index as benchmark variable and conditional Treynor and Mazuy model													
Ag. Growth	27	0.998	0.015	7.41	2	1.000	0.199	0.950	0.000	48.15	0	0.001	1.000
Growth	50	0.977	0.000	16.00	1	0.001	0.154	0.933	0.000	40.00	0	0.000	1.000
Growth/Inc.	12	0.996	0.000	16.67	0	0.002	0.415	0.797	0.001	50.00	1	0.003	0.035
All	95	0.998	0.000	14.74	3	0.001	0.292	0.950	0.000	42.11	1	0.000	0.279
Panel E: TSE 300 index as benchmark variable and unconditional Henriksson and Merton model													
Ag. Growth	27	0.896	0.002	14.81	4	1.000	0.028	0.917	0.000	33.33	0	0.005	1.000
Growth	50	0.999	0.000	18.00	7	0.000	0.088	0.994	0.000	18.00	0	0.004	1.000
Growth/Inc.	12	0.969	0.000	16.67	1	0.000	0.286	0.920	0.000	8.33	0	0.001	1.000
All	95	0.999	0.000	16.84	12	0.000	0.098	0.994	0.000	21.05	1	0.008	1.000
Panel F: Value-weighted TSE index as benchmark variable and unconditional Henriksson and Merton model													
Ag. Growth	27	0.839	0.002	14.81	4	1.000	0.024	0.985	0.000	51.85	0	0.000	1.000
Growth	50	0.978	0.001	16.00	7	0.058	0.015	0.996	0.000	42.00	0	0.000	1.000
Growth/Inc.	12	0.947	0.044	16.67	2	1.000	0.261	0.436	0.000	50.00	0	0.000	1.000
All	95	0.978	0.001	15.79	13	0.110	0.028	0.996	0.000	44.21	1	0.000	1.000
Panel G: TSE 300 index as benchmark variable and conditional Henriksson and Merton model													
Ag. Growth	27	0.886	0.004	7.41	2	1.000	0.048	0.998	0.104	0.00	0	1.000	1.000
Growth	50	0.987	0.000	8.00	1	0.000	0.294	0.993	0.001	6.00	1	0.021	0.785
Growth/Inc.	12	0.934	0.000	16.67	0	0.000	0.322	0.839	0.218	0.00	0	1.000	1.000
All	95	0.987	0.000	10.53	3	0.000	0.167	0.998	0.001	4.21	2	0.040	1.000
Panel H: Value-weighted TSE index as benchmark variable and conditional Henriksson and Merton model													
Ag. Growth	27	0.869	0.002	11.11	3	1.000	0.019	0.961	0.010	14.81	0	0.119	1.000
Growth	50	0.967	0.008	14.00	4	0.250	0.180	0.975	0.000	26.00	0	0.003	1.000
Growth/Inc.	12	0.956	0.085	0.00	0	0.871	0.496	0.895	0.016	25.00	0	0.089	0.522
All	95	0.967	0.002	10.53	7	0.475	0.067	0.975	0.000	21.05	0	0.005	1.000

Table A13. Rank correlations, performance sign maintenance, and ranking concordance for the various performance measures

This table reports the rank correlation between seventeen performance measures and some statistics related to the sign and ranking of these performance measures for all funds and per fund group. The risk-adjusted measures are constructed using several performance models. All models with the exception of the four-index models are tested with two market index benchmarks: TSE 300 and value-weighted TSE indices. M1 and M2 are related to the unconditional CAPM; M3 and M4 are related to the conditional CAPM with time-varying betas; M5 and M6 are related to the conditional CAPM with time-varying alphas and betas; M7, M8, and M9 are related to the unconditional and conditional four factor models with time-varying betas and with time-varying alphas and betas, respectively; M10 and M11 are related to the unconditional Treynor and Mazuy (1966) timing model; M12 and M13 are related to the unconditional Henriksson and Merton (1981) timing model; M14 and M15 are related to the conditional Treynor and Mazuy (1966) timing model; and M16 and M17 are related to the conditional Henriksson and Merton (1981) timing model. Panel A presents the Spearman rank correlations between all pairs of performance measures. Panel B provides information on the number with consistent positive and negative alphas across all performance models per fund group and for all funds. The number of significant alphas for each sign is reported in parentheses. These statistics are estimated for the stock selection performance measures and for all measures. Panel C reports the Kendall coefficient of concordance (W) for sixteen sets of performance rankings.

Panel A: Spearman rank correlations between the various performance estimates

Performance Measure																	
	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14	M15	M16	M17
M1	1.000																
M2	0.994**	1.000															
M3	0.238*	0.221*	1.000														
M4	0.242*	0.232*	0.992**	1.000													
M5	0.949**	0.941**	0.236*	0.231*	1.000												
M6	0.940**	0.944**	0.225*	0.228*	0.989**	1.000											
M7	0.960**	0.952**	0.248*	0.245*	0.962**	0.950**	1.000										
M8	0.712**	0.720**	0.293**	0.291**	0.764**	0.774**	0.767**	1.000									
M9	0.686**	0.695**	0.288**	0.285**	0.745**	0.756**	0.738**	0.980**	1.000								
M10	0.900**	0.894**	0.211*	0.211*	0.921**	0.922**	0.885**	0.733**	0.746**	1.000							
M11	0.890**	0.888**	0.199	0.200	0.912**	0.919**	0.865**	0.728**	0.747**	0.992**	1.000						
M12	0.642**	0.640**	0.173	0.178	0.724**	0.738**	0.649**	0.608**	0.659**	0.861**	0.867**	1.000					
M13	0.638**	0.635**	0.145	0.150	0.727**	0.740**	0.646**	0.598**	0.651**	0.849**	0.865**	0.989**	1.000				
M14	0.879**	0.870**	0.232*	0.226*	0.929**	0.927**	0.892**	0.729**	0.747**	0.975**	0.971**	0.855**	0.855**	1.000			
M15	0.863**	0.859**	0.213*	0.208*	0.919**	0.926**	0.866**	0.728**	0.750**	0.966**	0.976**	0.863**	0.872**	0.989**	1.000		
M16	0.780**	0.769**	0.250*	0.245*	0.833**	0.839**	0.775**	0.683**	0.711**	0.899**	0.905**	0.872**	0.883**	0.925**	0.922**	1.000	
M17	0.749**	0.739**	0.197	0.196	0.810**	0.817**	0.751**	0.643**	0.679**	0.893**	0.904**	0.900**	0.919**	0.919**	0.923**	0.978**	1.000

** Significant at the 1% level (2-tailed).
* Significant at the 5% level (2-tailed).

Panel B: Performance sign maintenance

Fund Group	N	Stock Selection Measures		All Measures	
		Positive	Negative	Positive	Negative
Ag. Growth	27	4 (0)	4 (1)	4 (0)	2 (0)
Growth	50	0 (0)	13 (1)	0 (0)	9 (0)
Growth/Inc.	12	1 (0)	5 (0)	1 (0)	3 (0)
All	95	6 (0)	26 (2)	6 (0)	18 (0)

Panel C: Performance ranking concordance between the various performance estimates

Ranking Set	Kendall's W	Ranking Set	Kendall's W
(M1,M3)	0.6188*	(M12,M16)	0.9362*
(M1,M5)	0.9747*	(M13,M17)	0.9595*
(M2,M4)	0.6158*	Unconditional measures without timing	0.9792*
(M2,M6)	0.9722*	Unconditional measures with timing	0.8572*
(M7,M8)	0.8835*	Conditional measures without timing	0.6154*
(M7,M9)	0.8688*	Conditional measures with timing	0.6634*
(M10,M14)	0.9873*	All selection measures	0.6645*
(M11,M15)	0.9881*	All measures	0.7159*

* Significant at the 0.01% level (1-tailed).

Table A14. The relationship between risk-adjusted performance and mutual fund attributes

This table reports the cross-sectional regression statistics of the relationship between risk-adjusted performance and mutual fund attributes. 22 performance measures and 6 fund characteristics are selected for the tests using the GMM method. The risk-adjusted measures are constructed using several performance models tested with two benchmark variables: TSE 300 and value-weighted TSE indices. M1 and M2 are related to the unconditional CAPM; M3 and M4 are related to the conditional CAPM with time-varying betas; M5 and M6 are related to the conditional CAPM with time-varying alphas and betas; M7, M8, and M9 are related to the unconditional and conditional four factor models with time-varying betas and with time-varying alphas and betas, respectively; M10 and M11 are related to the unconditional Treynor and Mazuy (1966) timing model; M12 and M13 are related to the unconditional Henriksson and Merton (1981) timing model; M14 and M15 are related to the conditional Treynor and Mazuy (1966) timing model; and M16 and M17 are related to the conditional Henriksson and Merton (1981) timing model. The fund attributes are: the MER (management expense ratio), MGF (management fees), the log of the age of the fund in years, the log of the size of the fund in millions, and two dummy variables indicating if the fund is a load fund or LOAD and if the fund has optional sales charges or OPTLO. The risk-adjusted performance measures are estimated using monthly observations over the period November 1989 to December 1999. The fund characteristic variables are measured at the end of the sampling period. Information related to the estimated coefficients, p-values, and the adjusted R2 is provided in the table. 95 observations are used representing the total number of funds. The last two rows provide information on the number of regressions where each coefficient is significant at the levels of 5% and 10%, and where the adjusted R2 is greater than 5% and 10%.

Performance Measure	Constant	p-val	MER	p-val	MGF	p-val	Ln (AGE)	p-val	Ln (SIZE)	p-val	LOAD	p-val	OPTLO	p-val	Adj. R^2
M1	-0.0066	0.32	-0.0025	0.02	0.0028	0.03	-0.0018	0.01	0.0010	0.11	-0.0004	0.61	-0.0002	0.77	0.214
M2	-0.0075	0.26	-0.0026	0.02	0.0027	0.04	-0.0018	0.01	0.0010	0.12	-0.0002	0.82	-0.0001	0.85	0.217
M3	-0.0074	0.28	-0.0031	0.01	0.0030	0.03	-0.0019	0.01	0.0011	0.07	0.0000	0.99	0.0002	0.82	0.250
M4	-0.0083	0.22	-0.0032	0.01	0.0029	0.03	-0.0018	0.01	0.0011	0.07	0.0003	0.72	0.0003	0.70	0.260
M5	0.0078	0.27	-0.0003	0.81	-0.0003	0.73	0.0007	0.40	-0.0008	0.22	0.0005	0.50	0.0003	0.72	-0.049
M6	-0.0079	0.26	-0.0029	0.02	0.0028	0.05	-0.0018	0.01	0.0011	0.09	0.0003	0.72	0.0002	0.72	0.225
M7	-0.0044	0.54	-0.0031	0.01	0.0033	0.02	-0.0018	0.02	0.0008	0.20	-0.0001	0.91	0.0003	0.73	0.213
M8	-0.0040	0.59	-0.0030	0.00	0.0026	0.03	-0.0018	0.01	0.0009	0.20	0.0013	0.16	0.0008	0.22	0.197
M9	-0.0043	0.56	-0.0030	0.02	0.0027	0.04	-0.0017	0.02	0.0009	0.20	0.0011	0.22	0.0008	0.22	0.171
M10	-0.0118	0.09	-0.0017	0.18	0.0027	0.06	-0.0020	0.00	0.0014	0.02	-0.0004	0.59	-0.0007	0.29	0.145
M11	-0.0120	0.09	-0.0019	0.15	0.0028	0.07	-0.0019	0.00	0.0014	0.03	-0.0003	0.74	-0.0006	0.33	0.153
M12	-0.0179	0.04	-0.0009	0.53	0.0027	0.12	-0.0022	0.01	0.0019	0.01	-0.0004	0.77	-0.0007	0.52	0.055
M13	-0.0159	0.04	-0.0016	0.27	0.0031	0.06	-0.0019	0.01	0.0018	0.01	-0.0005	0.66	-0.0006	0.55	0.070
M14	-0.0100	0.17	-0.0017	0.09	0.0026	0.04	-0.0018	0.01	0.0012	0.06	-0.0002	0.84	-0.0001	0.88	0.095
M15	-0.0102	0.15	-0.0019	0.08	0.0026	0.05	-0.0017	0.01	0.0012	0.06	0.0001	0.94	0.0000	0.96	0.108
M16	-0.0122	0.11	-0.0014	0.27	0.0020	0.16	-0.0020	0.00	0.0015	0.03	-0.0006	0.60	-0.0004	0.69	0.058
M17	-0.0131	0.06	-0.0012	0.30	0.0021	0.12	-0.0020	0.00	0.0016	0.01	-0.0010	0.34	-0.0004	0.66	0.062
Significance (5%)		2		8		10		16		6		0		0	16
Significance (10%)		5		10		13		16		11		0		0	12

Table A15. Performance measures for portfolios of funds using the unconditional and conditional skewness, kurtosis, and BHV pricing kernel models

This table reports the performance measures (α in %) for the groups by investment objective using the unconditional and conditional skewness, kurtosis, and BHV pricing kernel models 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 for each portfolio of funds using that portfolio of funds and the ten size-based passive strategies. All represents the statistics for the portfolios of all funds. Information related to the estimated performance, the p-values, and the J-statistic using the Bartlett kernel is provided in the table. W1, W2, W3, W4, and W5 correspond to the p-values based on the Newey and West (1987b) Wald test on the validity of the time-variation in various coefficients. Thus, W1 through W4 correspond to such tests for the $\varphi_1(z_t)$ coefficient, the $\varphi_2(z_t)$ coefficient, the $\varphi_3(z_t)$ coefficient, and all three coefficients, respectively, for the conditional skewness model. W1 through W5 correspond to such tests for the $\varphi_1(z_t)$ coefficient, the $\varphi_2(z_t)$ coefficient, the $\varphi_3(z_t)$ coefficient, the $\varphi_4(z_t)$ and all four coefficients for the conditional skewness model. W1 through W5 correspond to such test for the $\varphi_0(z_t)$ coefficient, the $\varphi_1(z_t)$ coefficient, the $\varphi_2(z_t)$ coefficient, the $\varphi_5(z_t)$ and all four coefficients, respectively, for the conditional kurtosis model. 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 and TSEVW are the TSE 300 and the value-weighted TSE indexes, respectively. Monthly data are used from November 1989 to December 1999, for a total of 122 observations per portfolio of funds.

Fund Group	TSE 300									TSEVW								
	Unconditional		Conditional							Unconditional		Conditional						
	α	p-val	α	p-val	W1	W2	W3	W4	W5	α	p-val	α	p-val	W1	W2	W3	W4	W5
Panel A: Equal-weighted portfolios of funds using the skewness pricing kernel models																		
Ag. Growth	-0.0561	0.70	1.0749	0.00	0.08	0.00	0.00	0.00		-0.0483	0.73	0.6932	0.00	0.19	0.00	0.00	0.00	
Growth	-0.0767	0.54	0.3939	0.00	0.00	0.43	0.00	0.00		-0.0400	0.76	0.3813	0.00	0.37	0.00	0.00	0.00	
Growth/Inc.	-0.1082	0.58	0.5369	0.00	0.47	0.00	0.00	0.00		-0.0636	0.74	0.3850	0.00	0.05	0.00	0.00	0.00	
All	-0.1133	0.44	0.6198	0.00	0.27	0.00	0.00	0.00		-0.0816	0.58	0.4449	0.00	0.15	0.00	0.00	0.00	
Mean J-Stat	0.142		0.141							0.145		0.156						
Panel B: Size-weighted portfolios of funds using the skewness pricing kernel models																		
Ag. Growth	0.0295	0.83	1.2723	0.00	0.10	0.00	0.00	0.00		0.0444	0.74	0.7577	0.00	0.16	0.00	0.00	0.00	
Growth	0.0241	0.83	0.4547	0.00	0.24	0.00	0.00	0.00		0.0706	0.54	0.4593	0.00	0.35	0.00	0.00	0.00	
Growth/Inc.	-0.2056	0.33	0.4249	0.00	0.65	0.00	0.00	0.00		-0.1618	0.45	0.1661	0.18	0.05	0.00	0.00	0.00	
All	-0.0259	0.84	0.6915	0.00	0.27	0.00	0.00	0.00		0.0138	0.92	0.4904	0.00	0.15	0.00	0.00	0.00	
Mean J-Stat	0.142		0.143							0.145		0.157						
Panel C: Size-weighted portfolios of individual fund performances using the skewness pricing kernel models																		
Ag. Growth	0.0055	0.35	0.9393	0.05	0.05	0.00	0.24	0.00		0.0118	0.31	0.7588	0.03	0.10	0.00	0.01	0.00	
Growth	-0.0030	0.36	0.4541	0.12	0.05	0.00	0.20	0.00		0.0409	0.33	0.3300	0.17	0.07	0.00	0.01	0.00	
Growth/Inc.	-0.1986	0.45	0.3941	0.23	0.05	0.00	0.07	0.00		-0.1593	0.45	0.1787	0.42	0.16	0.00	0.00	0.00	
All	-0.0513	0.36	0.5655	0.11	0.05	0.00	0.19	0.00		-0.0170	0.34	0.4192	0.16	0.09	0.00	0.01	0.00	
Mean J-Stat	0.142		0.155							0.145		0.155						
Panel D: Equal-weighted portfolios of funds using the kurtosis pricing kernel models																		
Ag. Growth	0.3473	0.12	1.1329	0.00	0.28	0.00	0.11	0.14	0.00	0.5401	0.03	0.7064	0.00	0.53	0.00	0.00	0.79	0.00
Growth	0.4249	0.03	0.4477	0.00	0.20	0.00	0.19	0.05	0.00	0.5886	0.00	0.4091	0.00	0.14	0.00	0.00	0.12	0.00
Growth/Inc.	0.3759	0.16	0.3691	0.02	0.13	0.00	0.23	0.04	0.00	0.5735	0.05	0.3618	0.03	0.40	0.00	0.04	0.97	0.00
All	0.3602	0.10	0.6667	0.00	0.23	0.00	0.16	0.09	0.00	0.5450	0.02	0.4544	0.00	0.18	0.00	0.05	0.73	0.00
Mean J-Stat	0.128		0.133							0.112		0.154						
Panel E: Size-weighted portfolios of funds using the kurtosis pricing kernel models																		
Ag. Growth	0.4874	0.03	0.7191	0.00	0.20	0.00	0.18	0.02	0.00	0.6777	0.01	0.7653	0.00	0.07	0.00	0.07	0.58	0.00
Growth	0.4972	0.00	0.4661	0.00	0.23	0.00	0.21	0.06	0.00	0.6165	0.00	0.4677	0.00	0.16	0.00	0.00	0.10	0.00
Growth/Inc.	0.2738	0.34	0.2464	0.12	0.24	0.00	0.22	0.02	0.00	0.4944	0.12	0.1613	0.35	0.53	0.00	0.00	0.63	0.00
All	0.4510	0.03	0.6447	0.00	0.19	0.00	0.21	0.06	0.00	0.6142	0.00	0.6108	0.00	0.08	0.00	0.00	0.19	0.00
Mean J-Stat	0.128		0.138							0.111		0.147						
Panel F: Size-weighted portfolios of individual fund performances using the kurtosis pricing kernel models																		
Ag. Growth	0.4188	0.20	0.8621	0.04	0.22	0.00	0.08	0.22	0.00	0.5974	0.17	0.8259	0.06	0.13	0.00	0.02	0.38	0.00
Growth	0.4484	0.19	0.3083	0.13	0.22	0.01	0.05	0.19	0.00	0.5657	0.17	0.4262	0.17	0.15	0.00	0.09	0.35	0.00
Growth/Inc.	0.2710	0.13	0.3251	0.34	0.34	0.02	0.04	0.21	0.00	0.4965	0.26	0.4430	0.25	0.34	0.00	0.12	0.25	0.00
All	0.3990	0.19	0.4534	0.14	0.24	0.01	0.05	0.20	0.00	0.5546	0.19	0.5394	0.15	0.17	0.00	0.07	0.34	0.00
Mean J-Stat	0.128		0.151							0.112		0.146						
Panel G: Equal-weighted portfolios of funds using the BHV pricing kernel models																		
Ag. Growth	1.1284	0.17	0.9649	0.00	0.21	0.00	0.00	0.06	0.00	1.3565	0.09	0.7567	0.00	0.85	0.00	0.00	0.42	0.00
Growth	1.0986	0.11	0.4735	0.00	0.57	0.00	0.03	0.31	0.00	1.2170	0.07	0.3988	0.00	0.36	0.00	0.00	0.33	0.00
Growth/Inc.	0.9928	0.29	0.3643	0.02	0.08	0.00	0.40	0.03	0.00	1.3186	0.17	0.5215	0.00	0.69	0.00	0.02	0.73	0.00
All	0.9972	0.21	0.6968	0.00	0.51	0.00	0.02	0.30	0.00	1.2110	0.12	0.5366	0.00	0.23	0.00	0.00	0.51	0.00
Mean J-Stat	0.024		0.126							0.024		0.146						
Panel H: Size-weighted portfolios of funds using the BHV pricing kernel models																		
Ag. Growth	1.3847	0.08	1.2802	0.00	0.23	0.00	0.02	0.24	0.00	1.5719	0.04	0.7289	0.00	0.64	0.00	0.00	0.91	0.00
Growth	1.1624	0.06	0.5512	0.00	0.57	0.00	0.06	0.40	0.00	1.2396	0.03	0.4553	0.00	0.37	0.00	0.00	0.33	0.00
Growth/Inc.	0.9513	0.33	0.1956	0.22	0.16	0.00	0.15	0.00	0.00	1.2912	0.20	0.4495	0.03	0.10	0.00	0.00	0.55	0.00
All	1.1630	0.11	0.7742	0.00	0.47	0.00	0.04	0.34	0.00	1.3244	0.06	0.6026	0.00	0.26	0.00	0.00	0.42	0.00
Mean J-Stat	0.024		0.125							0.024		0.144						
Panel I: Size-weighted portfolios of individual fund performances using the BHV pricing kernel models																		
Ag. Growth	1.2303	0.26	0.9326	0.07	0.09	0.00	0.40	0.40	0.00	1.4280	0.26	0.9353	0.06	0.07	0.00	0.28	0.12	0.00
Growth	1.0867	0.18	0.4256	0.16	0.10	0.00	0.36	0.34	0.00	1.1730	0.18	0.4614	0.21	0.12	0.00	0.27	0.22	0.00
Growth/Inc.	0.9288	0.31	0.5402	0.32	0.08	0.01	0.27	0.37	0.00	1.2712	0.31	0.5409	0.24	0.14	0.02	0.22	0.25	0.00
All	1.0644	0.23	0.5882	0.16	0.10	0.00	0.36	0.35	0.00	1.2344	0.22	0.5943	0.18	0.10	0.00	0.26	0.20	0.00
Mean J-Stat	0.024		0.152							0.024		0.143						

Table A16. Performance measures for individual funds using the unconditional and conditional skewness, kurtosis, and BHV pricing kernel models

This table reports the performance measures (α in %) for the groups by investment objective based on individual fund performances using the unconditional and conditional skewness, kurtosis, and BHV pricing kernel models 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 for each individual fund using that fund and the ten size-based passive strategies. All represents the equal- or the size-weighted portfolio of the performances of all individual funds. Information related to the estimated performance (mean, median, standard deviation, skewness, and kurtosis), the p-values, and the J-statistic using the Bartlett kernel is provided in the table. W1, W2, W3, W4, and W5 correspond to the p-values based on the Newey and West (1987b) Wald test on the validity of the time-variation in various coefficients. Thus, W1 through W4 correspond to such tests for the $\varphi_1(z_t)$ coefficient, the $\varphi_2(z_t)$ coefficient, the $\varphi_3(z_t)$ coefficient, and all three coefficients, respectively, for the conditional skewness model. W1 through W5 correspond to such tests for the $\varphi_1(z_t)$ coefficient, the $\varphi_2(z_t)$ coefficient, the $\varphi_3(z_t)$ coefficient, the $\varphi_4(z_t)$ and all four coefficients for the conditional skewness model. W1 through W5 correspond to such test for the $\varphi_0(z_t)$ coefficient, the $\varphi_1(z_t)$ coefficient, the $\varphi_2(z_t)$ coefficient, the $\varphi_5(z_t)$ and all four coefficients, respectively, for the conditional kurtosis model. The J-Statistic is the minimized value of the sample quadratic form constructed using the moment conditions and the optimal weighting matrix. TSE 300 and TSEVW are the TSE 300 and the value-weighted TSE indexes, respectively. Monthly data are used from November 1989 to December 1999, for a total of 122 observations per fund.

Fund Group	TSE 300						TSEVW					
	Mean α	Med. α	Stdev.	Mean p-val	Skew.	Kurt.	Mean α	Med. α	Stdev.	Mean p-val	Skew.	Kurt.
Panel A: Equal-weighted portfolios of individual fund performances for the unconditional skewness pricing kernel model												
Ag. Growth	-0.0561	0.0922	0.00	0.34	-0.30	-0.74	-0.0483	0.0691	0.00	0.31	-0.10	-0.90
Growth	-0.0767	-0.1081	0.00	0.34	0.16	0.15	-0.0400	-0.0931	0.00	0.35	0.37	0.33
Growth/Inc.	-0.1082	-0.0559	0.01	0.42	0.46	3.14	-0.0636	0.0114	0.01	0.40	0.15	2.64
All	-0.1133	-0.0750	0.00	0.34	-0.52	3.68	-0.0816	-0.0685	0.01	0.34	-0.43	2.85
Mean J-Stat	0.142						0.145					
Panel B: Equal-weighted portfolios of individual fund performances for the unconditional kurtosis pricing kernel model												
Ag. Growth	0.3473	0.4811	0.01	0.21	0.17	1.72	0.5401	0.6450	0.01	0.20	-0.22	2.37
Growth	0.4249	0.3965	0.01	0.23	-0.26	0.17	0.5886	0.5274	0.01	0.19	-0.07	0.59
Growth/Inc.	0.3760	0.5879	0.01	0.10	-1.17	1.33	0.5735	0.6647	0.01	0.19	-0.60	0.74
All	0.3602	0.4215	0.01	0.22	-0.24	1.21	0.5450	0.5476	0.01	0.21	-0.23	2.52
Mean J-Stat	0.128						0.112					
Panel C: Equal-weighted portfolios of individual fund performances for the unconditional BHV pricing kernel model												
Ag. Growth	1.1284	1.1581	0.02	0.30	0.68	1.69	1.3565	1.3092	0.01	0.32	1.15	1.84
Growth	1.0986	1.1641	0.01	0.22	-0.67	0.59	1.2170	1.2247	0.01	0.23	-0.56	0.75
Growth/Inc.	0.9928	1.3503	0.02	0.28	-0.62	1.42	1.3186	1.3265	0.01	0.27	0.52	1.51
All	0.9972	1.1370	0.02	0.26	-0.20	1.27	1.2110	1.2665	0.01	0.27	0.10	1.70
Mean J-Stat	0.024						0.024					
	Mean α	Med. α	Stdev.	Mean p-val	Skew.	Kurt.	W1	W2	W3	W4	W5	J-Stat
Panel D: TSE 300 index as benchmark and conditional skewness pricing kernel												
Ag. Growth	0.6955	0.5948	0.01	0.07	0.41	2.61	0.083	0.000	0.108	0.000		0.155
Growth	0.4321	0.3929	0.00	0.15	-0.10	0.32	0.087	0.000	0.145	0.000		0.154
Growth/Inc.	0.4818	0.3592	0.01	0.20	1.47	3.00	0.067	0.000	0.125	0.000		0.159
All	0.5024	0.4418	0.01	0.13	0.69	3.49	0.081	0.000	0.129	0.000		0.155
Panel E: Value-weighted TSE index as benchmark and conditional skewness pricing kernel												
Ag. Growth	0.6150	0.5732	0.01	0.06	-0.54	2.76	0.125	0.000	0.009	0.000		0.156
Growth	0.3342	0.3009	0.00	0.17	0.05	0.57	0.113	0.000	0.006	0.000		0.153
Growth/Inc.	0.3258	0.1809	0.01	0.31	1.87	4.19	0.149	0.000	0.002	0.000		0.156
All	0.4060	0.3932	0.00	0.16	0.29	1.53	0.119	0.000	0.007	0.000		0.155
Panel F: TSE 300 index as benchmark and conditional kurtosis pricing kernel												
Ag. Growth	0.7113	0.7184	0.00	0.08	0.53	0.55	0.255	0.000	0.041	0.244	0.000	0.148
Growth	0.3329	0.3559	0.00	0.16	-0.64	1.73	0.212	0.004	0.075	0.212	0.000	0.147
Growth/Inc.	0.4043	0.2064	0.01	0.28	2.21	5.78	0.323	0.011	0.045	0.210	0.000	0.165
All	0.4367	0.4039	0.00	0.17	0.99	2.60	0.244	0.004	0.059	0.216	0.000	0.150
Panel G: Value-weighted TSE index as benchmark and conditional kurtosis pricing kernel												
Ag. Growth	0.6343	0.6037	0.01	0.11	-0.53	0.90	0.144	0.000	0.029	0.295	0.000	0.151
Growth	0.4069	0.3103	0.00	0.20	0.86	1.07	0.198	0.000	0.070	0.353	0.000	0.143
Growth/Inc.	0.4796	0.2965	0.01	0.21	0.92	-0.09	0.353	0.000	0.072	0.320	0.000	0.145
All	0.4895	0.4024	0.01	0.18	0.55	1.25	0.205	0.000	0.056	0.319	0.000	0.146
Panel H: TSE 300 index as benchmark and conditional BHV pricing kernel												
Ag. Growth	0.7299	0.6663	0.01	0.11	0.66	2.12	0.149	0.001	0.238	0.406	0.001	0.165
Growth	0.4193	0.3677	0.00	0.17	0.76	1.53	0.110	0.002	0.241	0.292	0.000	0.146
Growth/Inc.	0.5648	0.4635	0.01	0.24	1.18	0.64	0.109	0.009	0.278	0.332	0.001	0.143
All	0.5414	0.4574	0.01	0.17	1.23	3.03	0.119	0.003	0.251	0.318	0.001	0.152
Panel I: Value-weighted TSE index as benchmark and conditional BHV pricing kernel												
Ag. Growth	0.7291	0.8386	0.01	0.13	-0.65	1.28	0.112	0.000	0.156	0.148	0.000	0.136
Growth	0.4559	0.3657	0.00	0.21	1.48	3.07	0.155	0.003	0.204	0.252	0.009	0.140
Growth/Inc.	0.5977	0.6179	0.01	0.16	0.65	0.37	0.156	0.012	0.246	0.293	0.002	0.149
All	0.5479	0.4702	0.01	0.19	0.34	0.98	0.135	0.003	0.194	0.231	0.005	0.144

Table A17. Summary statistics for the performance estimates using the unconditional and conditional skewness, kurtosis, and BHV pricing kernel models based on individual fund performances

This table presents summary statistics for the performance measures based on the unconditional and conditional skewness, kurtosis, and BHV pricing kernel models for each fund group and for all funds. Panels A, C, and E present the unconditional results using the TSE 300 index as the benchmark. Panels B, D, and F present the unconditional results using the value-weighted TSE index as the benchmark. Panels G, K, and I present the conditional results using the TSE 300 index as the benchmark. Panels H, J, and L present the conditional results using the value-weighted TSE index as the benchmark. N is the number of funds in each group. All of the p-values are based on GMM estimation and are adjusted for serial correlation and heteroskedasticity (Newey and West, 1987a). Information related to the funds with significant performance at the 5% level 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.

Fund Group	N	Max. p	Min. p	Percent of funds with $p < 5\%$	Number of funds with $\alpha > 0$ and $p < 5\%$	Bonferroni p-value (Min. t)	Bonferroni p-value (Max. t)
Panel A: TSE 300 index as benchmark and the unconditional skewness pricing kernel model							
Ag. Growth	27	0.979	0.000	25.93	4	0.044	0.003
Growth	50	1.000	0.001	18.00	4	0.016	0.021
Growth/Inc.	12	0.939	0.000	16.67	1	0.250	0.001
All	95	1.000	0.000	20.00	9	0.030	0.004
Panel B: Value-weighted TSE index is as benchmark and the unconditional skewness pricing kernel model							
Ag. Growth	27	0.777	0.000	29.63	4	0.068	0.001
Growth	50	0.992	0.000	20.00	6	0.099	0.004
Growth/Inc.	12	0.884	0.000	16.67	1	0.215	0.001
All	95	0.992	0.000	22.11	11	0.187	0.003
Panel C: TSE 300 index as benchmark and the unconditional kurtosis pricing kernel model							
Ag. Growth	27	0.997	0.000	55.56	14	0.227	0.000
Growth	50	0.976	0.000	50.00	24	0.235	0.000
Growth/Inc.	12	0.447	0.000	66.67	8	0.631	0.000
All	95	0.997	0.000	52.63	47	0.447	0.000
Panel D: Value-weighted TSE index as benchmark and the unconditional kurtosis pricing kernel model							
Ag. Growth	27	0.998	0.000	62.96	16	0.021	0.000
Growth	50	0.975	0.000	56.00	28	1.000	0.000
Growth/Inc.	12	0.977	0.000	66.67	8	1.000	0.000
All	95	0.998	0.000	57.89	53	0.075	0.000
Panel E: TSE 300 index as benchmark and the unconditional BHV pricing kernel model							
Ag. Growth	27	0.818	0.000	33.33	9	1.000	0.000
Growth	50	0.921	0.000	40.00	20	1.000	0.002
Growth/Inc.	12	0.889	0.000	50.00	6	1.000	0.001
All	95	0.930	0.000	38.95	36	0.498	0.001
Panel F: Value-weighted TSE index as benchmark and the unconditional BHV pricing kernel model							
Ag. Growth	27	0.969	0.000	44.44	12	1.000	0.000
Growth	50	0.991	0.000	48.00	24	1.000	0.001
Growth/Inc.	12	0.930	0.002	50.00	6	1.000	0.010
All	95	0.991	0.000	45.26	43	1.000	0.000
Panel G: TSE 300 index as benchmark and the conditional skewness pricing kernel model							
Ag. Growth	27	0.585	0.000	77.78	20	0.135	0.000
Growth	50	0.907	0.000	60.00	29	0.195	0.000
Growth/Inc.	12	0.844	0.000	41.67	5	1.000	0.000
All	95	0.907	0.000	62.11	55	0.371	0.000
Panel H: Value-weighted TSE index is as benchmark and the conditional skewness pricing kernel model							
Ag. Growth	27	0.852	0.000	74.07	19	0.137	0.000
Growth	50	0.891	0.000	56.00	27	0.188	0.000
Growth/Inc.	12	0.986	0.000	41.67	5	0.553	0.000
All	95	0.986	0.000	60.00	53	0.014	0.000
Panel I: TSE 300 index as benchmark and the conditional kurtosis pricing kernel model							
Ag. Growth	27	0.627	0.000	74.07	20	1.000	0.000
Growth	50	0.945	0.000	46.00	21	0.263	0.000
Growth/Inc.	12	0.989	0.000	25.00	3	1.000	0.000
All	95	0.989	0.000	49.47	45	0.500	0.000
Panel J: Value-weighted TSE index as benchmark and the conditional kurtosis pricing kernel model							
Ag. Growth	27	0.754	0.000	66.67	17	0.581	0.000
Growth	50	0.961	0.000	54.00	27	1.000	0.000
Growth/Inc.	12	0.751	0.000	41.67	5	1.000	0.000
All	95	0.961	0.000	56.84	52	0.317	0.000
Panel K: TSE 300 index as benchmark and the conditional BHV pricing kernel model							
Ag. Growth	27	0.752	0.000	66.67	18	1.000	0.000
Growth	50	0.980	0.000	52.00	26	1.000	0.000
Growth/Inc.	12	0.926	0.000	41.67	5	1.000	0.000
All	95	0.980	0.000	53.68	51	1.000	0.000
Panel L: Value-weighted TSE index as benchmark and the conditional BHV pricing kernel model							
Ag. Growth	27	0.812	0.000	70.37	19	1.000	0.000
Growth	50	0.977	0.000	40.00	20	1.000	0.000
Growth/Inc.	12	0.658	0.000	41.67	5	1.000	0.000
All	95	0.977	0.000	47.37	45	1.000	0.000

Table A18. Performance measures for portfolios of funds using the unconditional and conditional skewness, kurtosis, and BHV pricing kernel models with the restriction on the pricing of the risk-free asset

This table reports the performance measures (α in %) for the groups by investment objective using the unconditional and conditional skewness, kurtosis, and BHV pricing kernel models for the two selected benchmarks with the restriction on the pricing of the risk-free asset. 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 for each portfolio of funds using that portfolio of funds and the ten size-based passive strategies and additional moment conditioned on the one-month T-bill. All represents the statistics for the portfolios of all funds. 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. Size is defined as the total net asset value of the fund. TSE 300, and TSEVW are the TSE 300 and the value-weighted TSE indexes, respectively. Monthly data are used from November 1989 to December 1999, for a total of 122 observations per portfolio of funds.

	TSE 300				TSEVW			
	Unconditional		Conditional		Unconditional		Conditional	
Fund Group	α	p-val	α	p-val	α	p-val	α	p-val
Panel A: Equal-weighted portfolios of funds using the skewness pricing kernel models								
Ag. Growth	0.0977	0.21	-0.0091	0.92	0.0487	0.50	0.3289	0.00
Growth	0.0562	0.30	0.1109	0.09	0.0533	0.34	0.1652	0.00
Growth/Inc.	0.0886	0.17	0.0254	0.70	0.0841	0.22	0.0416	0.47
All	0.0500	0.33	0.0245	0.69	0.0332	0.53	0.1421	0.00
Mean J-Stat	0.142		0.158		0.146		0.158	
Panel B: Size-weighted portfolios of funds using the skewness pricing kernel models								
Ag. Growth	0.1650	0.04	0.1656	0.02	0.1190	0.11	0.3377	0.00
Growth	0.1019	0.08	0.1400	0.03	0.1066	0.08	0.1332	0.03
Growth/Inc.	0.0376	0.56	0.0215	0.76	0.0354	0.59	-0.0100	0.87
All	0.1004	0.07	0.1173	0.04	0.0910	0.12	0.1365	0.01
Mean J-Stat	0.142		0.160		0.146		0.154	
Panel C: Equal-weighted portfolios of funds using the kurtosis pricing kernel models								
Ag. Growth	0.3840	0.00	0.4088	0.00	0.4395	0.00	0.3578	0.00
Growth	0.4540	0.00	0.1203	0.13	0.5209	0.00	0.0965	0.26
Growth/Inc.	0.4156	0.00	0.0442	0.54	0.4799	0.00	-0.0159	0.85
All	0.3961	0.00	0.1950	0.01	0.4576	0.00	0.0978	0.26
Mean J-Stat	0.127		0.134		0.122		0.141	
Panel D: Size-weighted portfolios of funds using the kurtosis pricing kernel models								
Ag. Growth	0.5184	0.00	0.3951	0.00	0.5907	0.00	0.3724	0.00
Growth	0.5148	0.00	0.0887	0.30	0.5756	0.00	0.0604	0.46
Growth/Inc.	0.3217	0.00	0.0996	0.20	0.3837	0.00	-0.0112	0.90
All	0.4785	0.00	0.1667	0.03	0.5409	0.00	0.1430	0.04
Mean J-Stat	0.127		0.138		0.122		0.145	
Panel E: Equal-weighted portfolios of funds using the BHV pricing kernel models								
Ag. Growth	1.0556	0.00	0.4267	0.00	1.0161	0.00	0.0376	0.77
Growth	1.0326	0.00	0.1096	0.25	0.9185	0.00	-0.0727	0.46
Growth/Inc.	0.8983	0.00	-0.2024	0.06	0.8631	0.00	-0.1865	0.03
All	0.9201	0.00	0.1586	0.06	0.8564	0.00	-0.1075	0.24
Mean J-Stat	0.025		0.140		0.037		0.146	
Panel F: Size-weighted portfolios of funds using the BHV pricing kernel models								
Ag. Growth	1.3150	0.00	0.5266	0.00	1.2513	0.00	0.3407	0.00
Growth	1.1070	0.00	0.0732	0.48	0.9990	0.00	-0.0135	0.89
Growth/Inc.	0.8532	0.00	-0.0753	0.51	0.8099	0.00	-0.2820	0.00
All	1.0947	0.00	0.1671	0.06	1.0151	0.00	0.0134	0.88
Mean J-Stat	0.025		0.138		0.037		0.146	

Table A19. The relationship between risk-adjusted performance and mutual fund attributes

This table reports the cross-sectional regression statistics of the relationship between risk-adjusted performance and mutual fund attributes. 12 performance measures and 6 fund characteristics are selected for the tests using the GMM method. The risk-adjusted measures are constructed using several benchmark models tested with two benchmark variables: TSE 300 and value-weighted TSE indices. M1 and M2 are related to the unconditional skewness pricing kernel model. M3 and M4 are related to the unconditional kurtosis pricing kernel model. M5 and M6 are related to the unconditional BHV pricing kernel model. M7 and M8 are related to the conditional skewness pricing kernel model. M9 and M10 are related to the conditional kurtosis pricing kernel model. M11 and M12 are related to the conditional BHV pricing kernel model. The fund attributes are: the MER (management expense ratio), MGF (management fees), the log of the age of the fund in years, the log of the size of the fund in millions, and two dummy variables indicating if the fund is a load fund or LOAD and if the fund has optional sales charges or OPTLO. The risk-adjusted performance measures are estimated using monthly observations over the period November 1989 to December 1999. The fund characteristic variables are measured at the end of the sampling period. Information related to the estimated coefficients, p-values, and the adjusted R2 is provided in the table. 95 observations are used representing the total number of funds. The last two rows provide information on the number of regressions where each coefficient is significant at the levels of 5% and 10%, and where the adjusted R2 is greater than 5% and 10%.

Performance Measure	Constant	p-val	MER	p-val	MGF	p-val	Ln (AGE)	p-val	Ln (SIZE)	p-val	LOAD	p-val	OPTLO	p-val	Adj. R2
M1	-0.0204	0.01	-0.0005	0.56	0.0020	0.11	-0.0021	0.06	0.0020	0.01	-0.0029	0.04	-0.0019	0.13	0.050
M2	-0.0190	0.01	-0.0008	0.27	0.0022	0.08	-0.0020	0.06	0.0019	0.01	-0.0032	0.03	-0.0017	0.16	0.057
M3	-0.0132	0.30	-0.0033	0.05	0.0058	0.01	-0.0029	0.03	0.0020	0.08	-0.0062	0.01	-0.0035	0.03	0.147
M4	-0.0114	0.40	-0.0045	0.03	0.0074	0.01	-0.0031	0.02	0.0020	0.10	-0.0059	0.01	-0.0037	0.02	0.186
M5	-0.0230	0.41	0.0007	0.89	0.0068	0.11	-0.0053	0.14	0.0034	0.19	-0.0146	0.00	-0.0100	0.02	0.083
M6	-0.0140	0.53	-0.0004	0.93	0.0060	0.07	-0.0049	0.11	0.0029	0.17	-0.0103	0.00	-0.0081	0.02	0.077
M7	-0.0206	0.15	0.0011	0.72	0.0008	0.81	-0.0024	0.08	0.0024	0.05	-0.0009	0.52	-0.0025	0.15	0.014
M8	-0.0089	0.45	-0.0007	0.68	0.0022	0.29	-0.0034	0.00	0.0018	0.07	-0.0021	0.11	-0.0028	0.07	0.106
M9	-0.0136	0.29	0.0008	0.58	0.0008	0.64	-0.0033	0.00	0.0021	0.07	0.0004	0.73	-0.0020	0.22	0.077
M10	-0.0164	0.18	-0.0009	0.65	0.0012	0.61	-0.0025	0.05	0.0024	0.02	-0.0009	0.48	-0.0021	0.19	0.056
M11	-0.0182	0.19	0.0008	0.75	0.0004	0.89	-0.0024	0.06	0.0023	0.05	0.0007	0.52	-0.0013	0.42	0.009
M12	-0.0205	0.13	-0.0007	0.78	0.0017	0.53	-0.0027	0.05	0.0027	0.02	0.0013	0.36	-0.0023	0.14	0.092
Significance (5%)		2		2		2		6		6		6		4	10
Significance (10%)		2		2		4		10		10		6		5	3

Table A20. Summary statistics and characteristics for the surviving and non-surviving fixed-income funds

This table reports the summary statistics for the mutual fund returns (in %) and fund attributes for surviving and non-surviving fixed-income funds using monthly data from March 1985 through February 2000. The number of observations per fund varies. The prefixes EW and SW refer to equal- and size-weighted portfolios of funds with these investment objectives, respectively. Panel A provides the statistics on the distribution (mean, standard deviation, and quartiles) of various parameter estimates for the sample of 162 surviving bond mutual funds for three investment objective groups (government, corporate, and mortgage) and for all funds (including the five high-yield funds). Panel B reports some statistics on the equal- and size-weighted portfolios of funds for the major groupings by investment objectives. Panel C reports some statistics on the equal- and size-weighted portfolios of terminated funds for the major groupings by investment objectives and for all funds. Both panels B and C provide information on the minimum, maximum, and average number of observations per fund in the two samples. Panel D reports the summary statistics for the fund attributes (measured at period end). MER and MGF are the % management expense ratio and management fees of the fund, respectively. AGE is the age of the fund measured in years since fund inception. SIZE is the total net asset value of the fund in millions. LOAD is a dummy variable equal to one if the fund charges front- or back-end sales charges.

Panel A: Individual surviving mutual funds

Fund Group	Statistics	N	Mean	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis
Government		108						
	Mean		0.6029	1.5335	-4.0229	4.8587	0.0404	1.1322
	Std. Dev.		0.1756	0.3656	1.9483	1.3748	0.5390	2.0927
	Minimum		0.0889	0.5614	-15.8482	2.0416	-2.7884	-0.5629
	Q1		0.4965	1.3380	-4.9100	4.0167	-0.2324	0.3676
	Median		0.6414	1.5945	-4.3135	4.8047	-0.0621	0.6633
	Q3		0.7312	1.7937	-2.5906	5.7593	0.3082	1.2173
	Maximum		0.9104	2.2980	-0.6689	9.1036	1.5032	19.8652
Corporate		28						
	Mean		0.5624	1.4000	-3.3443	4.3628	0.0306	1.1229
	Std. Dev.		0.1834	0.4421	1.6483	1.5351	0.5607	1.7597
	Minimum		0.1659	0.1521	-5.7803	0.5780	-1.5818	-0.0686
	Q1		0.4162	1.2119	-5.0036	3.5605	-0.1747	0.2904
	Median		0.5691	1.4862	-2.6052	4.4672	0.2060	0.5663
	Q3		0.7330	1.7341	-1.9949	5.4582	0.4234	0.9476
	Maximum		0.7868	2.0311	-0.1931	7.4068	0.7121	7.6597
Mortgage		21						
	Mean		0.5759	0.8499	-2.5107	3.0989	-0.4280	2.6615
	Std. Dev.		0.1390	0.1936	0.9507	0.8103	0.6270	1.9414
	Minimum		0.2815	0.4306	-4.1706	1.2507	-1.4958	-0.6361
	Q1		0.5070	0.7851	-3.2092	2.6409	-0.7562	1.6662
	Median		0.6443	0.8041	-2.5474	3.2118	-0.3136	2.4802
	Q3		0.6764	0.9988	-1.7357	3.5714	0.0769	3.5712
	Maximum		0.7389	1.2276	-0.5774	4.3893	0.5591	7.4843
All		162						
	Mean		0.5941	1.4244	-3.7461	4.5262	-0.0304	1.3770
	Std. Dev.		0.1719	0.4236	1.8643	1.4532	0.5720	2.0922
	Minimum		0.0889	0.1521	-15.8482	0.5780	-2.7884	-0.6361
	Q1		0.4779	1.1150	-4.8937	3.5015	-0.2577	0.3722
	Median		0.6356	1.4832	-3.8908	4.4594	-0.0673	0.7561
	Q3		0.7232	1.7433	-2.2010	5.4237	0.3021	1.6410
	Maximum		0.9104	2.2980	-0.1931	9.1036	1.5032	19.8652

Panel B: Portfolios for surviving funds based on fund investment objectives

Objective	N	Observations Min.	Max.	Avg.	Mean Return	Std. Dev.	Min.	Max.
Government	108	29	180	112				
EW					0.7500	1.5280	-4.4224	4.5072
SW					0.7660	1.5926	-4.6236	4.9678
Corporate	28	26	180	100				
EW					0.7348	1.4915	-3.8431	4.3442
SW					0.7590	1.6296	-4.4199	4.9724
Mortgage	21	38	180	131				
EW					0.6835	0.7176	-2.5916	2.2557
SW					0.6923	0.7500	-2.5025	2.3061
High-Yield	5	40	64	53				
EW					0.7391	1.3540	-3.9683	3.4148
SW					0.7125	1.3071	-3.8651	3.2676
All	162	26	180	111				
EW					0.7353	1.3391	-4.0295	4.1192
SW					0.7480	1.3266	-4.0633	3.8652

Panel C: Portfolios for non-surviving funds based on fund investment objectives

Objective	N	Observations Min.	Max.	Avg.	Mean Return	Std. Dev.	Min.	Max.
Government	46	2	152	71				
EW					0.6794	1.5369	-4.3564	4.6760
SW					0.7449	1.6546	-4.4057	5.3036
Corporate	11	3	158	86				
EW					0.7502	1.5573	-4.4624	5.8676
SW					0.7637	1.6514	-4.5432	6.0950
Mortgage	13	62	180	131				
EW					0.6321	0.7689	-2.8212	2.4455
SW					0.6405	0.7332	-2.8697	2.0962
High-Yield	2	13	13	13				
EW					0.1335	1.1885	-3.3962	2.0629
SW					0.1335	1.1885	-3.3962	2.0629
All	72	2	180	83				
EW					0.6712	1.2045	-3.9501	3.8492
SW					0.6916	1.0872	-3.7586	3.5944

Panel D: Descriptive statistics for the fund attributes

Fund Attribute	Mean	Median	Std. Dev.	Min.	Max.	Skewness	Kurtosis
MER	1.615	1.690	0.578	0.100	4.160	-0.095	1.762
MGF	1.446	1.500	0.506	0.000	2.400	-0.343	-0.143
AGE	12.640	8.649	10.120	2.162	42.353	1.137	0.166
SIZE	367.744	158.290	539.514	23.344	2431.859	2.555	5.741
LOAD	0.272	0.000	0.446	0.000	1.000	1.037	-0.937

Table A21. Entries and exits of funds

This table reports the number of funds at the end of each year for the period of March 1985 to February 2000. It reports the number of funds which enter and exit during each year. The attrition rate (%) is given by the number of exiting funds divided by the number of funds at the end of the year. Survived funds are funds still in existence in March 2000. The mortality rate (%) is computed as one minus the number of survived funds divided by the number of funds at the end of the year.

Year/Statistic	Entry	Exit	Year End	Attrition Rate	Survived	Mortality Rate
1985	-	-	59	-	46	22.03
1986	7	0	66	0.00	52	21.21
1987	14	0	80	0.00	63	21.25
1988	12	0	92	0.00	73	20.65
1989	15	0	107	0.00	85	20.56
1990	6	1	112	0.89	91	18.75
1991	6	2	116	1.72	96	17.24
1992	10	0	126	0.00	106	15.87
1993	13	0	139	0.00	117	15.83
1994	30	0	169	0.00	142	15.98
1995	18	3	184	1.63	153	16.85
1996	17	19	182	10.44	170	6.59
1997	18	3	197	1.52	186	5.58
1998	3	7	193	3.63	189	2.07
1999	5	5	193	2.59	193	0.00

Table A22. Summary statistics for the instrumental variables, bond indices, and factors

This table reports the summary statistics for the monthly returns of the instrumental variables, bond indices, and factors. TB1 is the yield on one-month Treasury bills in % per month. TERM is the yield spread between long Canadas and the one period lagged 3-month Treasury bill rate in % per month. DEF is the default premium measured by the yield spread between the long-term corporate bond (McLeod, Young, Weir bond index) and long Canadas in % per month. REALG is the difference between the long-maturity (5-10 years) government bond yield and the inflation rate lagged by one month in % per month. The bond indices and factors are the Scotia Capital universe bond index (SC), the Scotia Capital government bond index (SCG), the Scotia Capital government long term bond index (SCGLT), the Scotia Capital government medium term bond index (SCGMT), the Scotia Capital corporate bond index (SCC), the Scotia Capital corporate long term bond index (SCCLT), the Scotia Capital corporate medium term bond index (SCCMT), the Scotia Capital mortgage backed-securities overall bond index (SCMBS), and the return on the TSE 300 index (TSE 300). Panel A reports various statistics for all variables, including autocorrelation coefficients of order 1, 3, 6, and 12. Panel B presents the correlation matrix of instruments. Panel C presents the correlation matrix of bond indices and factors. The data cover the period from March 1985 to February 2000, for a total of 180 observations.

Panel A: Descriptive statistics and autocorrelations

Statistic	Mean	Median	Std. Dev.	Min.	Max.	Skew.	Kurt.	ρ_1	ρ_3	ρ_6	ρ_{12}
TB1	0.5924	0.5912	0.244	0.2117	1.1433	0.425	2.211	0.978	0.929	0.863	0.694
DEF	0.0698	0.0683	0.017	0.0383	0.1033	0.098	1.978	0.913	0.790	0.629	0.505
TERM	0.1047	0.1196	0.144	-0.2450	0.3675	-0.624	2.904	0.935	0.837	0.712	0.435
REALG	0.2291	0.1997	0.310	-0.6863	2.5913	2.448	20.515	0.038	0.170	0.074	0.397
SC	0.8787	0.9031	6.576	-4.8235	1.7852	0.012	3.461	0.066	0.016	-0.047	0.051
SCG	0.8948	0.9463	6.571	-4.9653	1.8197	-0.023	3.403	0.059	0.006	-0.042	0.047
SCGLT	1.0530	1.1166	8.785	-6.4339	2.6209	0.095	3.008	0.044	0.005	-0.035	0.039
SCGMT	0.8958	0.9092	6.838	-5.3207	1.9513	-0.019	3.285	0.065	0.011	-0.033	0.037
SCC	0.9208	1.0500	5.415	-4.9476	1.7423	-0.099	3.174	0.104	-0.010	0.004	-0.058
SCCLT	1.0392	1.1787	7.727	-5.8679	2.3838	0.053	2.920	0.090	-0.033	0.000	0.021
SCCMT	0.9191	0.9694	5.882	-4.9702	1.7854	-0.101	3.145	0.104	-0.007	0.020	-0.068
SCMBS	0.6781	0.6920	3.172	-3.6992	1.0509	-0.586	5.391	0.171	0.038	0.074	-0.016
TSE300	1.0285	1.1814	11.944	-22.5231	4.3249	-1.399	9.603	0.051	-0.017	0.020	-0.084

Panel B: Correlation matrix of instruments

Variable	TB1	DEF	TERM	REALG
TB1	1.00			
DEF	0.29	1.00		
TERM	-0.81	-0.34	1.00	
REALG	0.39	0.04	-0.31	1.00

Panel C: Correlation matrix of bond indices and factors

Portfolio	SC	SCG	SCGLT	SCGMT	SCC	SCCLT	SCCMT	SCMBS	TSE300
SC	1.00								
SCG	1.00	1.00							
SCGLT	0.97	0.97	1.00						
SCGMT	1.00	1.00	0.96	1.00					
SCC	0.99	0.99	0.97	0.98	1.00				
SCCLT	0.95	0.95	0.98	0.94	0.98	1.00			
SCCMT	0.99	0.99	0.96	0.99	1.00	0.96	1.00		
SCMBS	0.94	0.93	0.84	0.94	0.92	0.83	0.93	1.00	
TSE300	0.39	0.40	0.40	0.39	0.44	0.44	0.44	0.35	1.00

Table A23. Bond and bond mutual fund excess return predictability

This table reports the summary statistics on the bond portfolios and mutual fund return predictability based on time series multivariate predictive regressions using four lagged instrumental variables and monthly data from the period March 1985 through February 2000, for a total of 180 monthly observations. The abbreviations GOVT, CORP, and ALL refer to government, corporate, and all funds, respectively, and the prefixes EW and SW refer to equal- and size-weighted portfolios of funds with these investment objectives, respectively. The instruments are the yield on one-month Treasury bills, the default premium, the slope of the term structure or term premium, and the real yield on long-maturity (5 to 10 years) government bonds minus the inflation rate lagged one month. The nine bond portfolios (indices) are the Scotia Capital universe bond index (SC), the Scotia Capital universe long term bond index (SCLT), the Scotia Capital universe medium term bond index (SCMT), the Scotia Capital government bond index (SCG), the Scotia Capital government long term bond index (SCGLT), the Scotia Capital government medium term bond index (SCGMT), the Scotia Capital corporate bond index (SCC), the Scotia Capital corporate long term bond index (SCCLT), and the Scotia Capital corporate medium term bond index (SCCMT). The statistics reported are the slope coefficients associated with each instrumental variable, the χ^2-values, and the probability of observing a larger χ^2 statistic under the null hypothesis of no time-variation from the GMM-based Wald tests proposed by Newey and West (1987b).

Portfolio	TB1	DEF	TERM	REALG	χ^2	p-value
SC	1.990***	-9.680	3.640***	-0.311	9.680	0.046
SCLT	2.799**	-19.948*	5.192***	-0.549	10.067	0.039
SCMT	2.186***	-10.669	3.941***	-0.368	9.794	0.044
SCG	2.031***	-9.444	3.811***	-0.304	9.896	0.042
SCGLT	2.799**	-18.279	5.376***	-0.515	10.274	0.036
SCGMT	2.189***	-10.012	4.016***	-0.339	9.890	0.042
SCC	1.818***	-6.043	3.858***	-0.225	10.229	0.037
SCCLT	2.551**	-10.832	5.477***	-0.426	10.137	0.038
SCCMT	1.931***	-7.041	3.863***	-0.262	10.421	0.034
EWGOVT	1.654***	-7.371	3.184***	-0.209	10.237	0.037
SWGOVT	1.747***	-8.152	3.276***	-0.244	10.280	0.036
EWCORP	1.458**	-7.469	3.004***	-0.198	9.261	0.055
SWCORP	1.678**	-9.508	3.308***	-0.237	9.852	0.043
EWALL	1.299**	-6.014	2.626**	-0.155	9.012	0.061
SWALL	1.272**	-6.623	2.484**	-0.164	8.515	0.074

*** Significant at the 1% level (2-tailed).
** Significant at the 5% level (2-tailed).
* Significant at the 10% level (2-tailed).

Table A24. Performance and risk measures for portfolios of funds using unconditional and conditional single factor models

This table reports summary statistics on the performance (α in %) and risk measures for equal- and size weighted portfolios of individual funds using unconditional and conditional single factor models. The unconditional models are the single market factor model and the single specific factor model. The conditional models are single factor models with time-varying betas and/or alphas based on four instrumental variables. The instrumental variables are the lagged values of the yield on one-month T-bills (TB1), the slope of the term structure (TERM), the default premium (DEF), and the real yield on long-maturity government bonds (REALG). GMM estimation is conducted for each portfolio of funds by regressing the excess return on the portfolio of funds on a constant, the excess return on the factor, and variables representing the lagged instruments and the product of the four lagged instrumental variables and the excess return on the factor in the case of the conditional models. The alpha is the estimate of the intercept of the regression and the beta or $\beta(.)$ is the estimate of the slope of the regression. $\beta(.)$ is for the respective specific factors in panels C and D, and for the market factor in the other panels. The standard errors of these estimates are adjusted for serial correlation and heteroskedasticity (Newey and West, 1987a). The five portfolios of funds are described in table 5.1. All represents the performances and risks of portfolios of all individual funds. Information related to the estimated performance and betas is provided in the table. W1, W2, and W3 correspond to the p-values based on the Newey and West (1987b) Wald test on the validity of the time-varying alphas, time-varying betas, and time-varying alphas and betas, respectively. Monthly data are used from March 1985 to February 2000, for a maximum of 180 observations per portfolio of funds.

Fund Group	N	α	p-val	$\beta(.)$	p-val	W1	W2	W3	Adj. R2
Panel A: Equal-weighted portfolios and unconditional single market factor model									
Government	108	-0.0840	0.00	0.844	0.00				0.97
Corporate	28	-0.0922	0.00	0.820	0.00				0.96
Mortgage	21	0.0219	0.59	0.242	0.00				0.38
High-Yield	5	0.0817	0.51	0.707	0.00				0.51
All	162	-0.0671	0.00	0.734	0.00				0.96
Panel B: Size-weighted portfolios and unconditional single market factor model									
Government	108	-0.0781	0.00	0.880	0.00				0.97
Corporate	28	-0.0911	0.00	0.900	0.00				0.97
Mortgage	21	0.0188	0.64	0.283	0.00				0.47
High-Yield	5	0.0666	0.59	0.677	0.00				0.50
All	162	-0.0513	0.02	0.723	0.00				0.95
Panel C: Equal-weighted portfolios and unconditional single specific factor model									
Government	108	-0.0932	0.00	0.829	0.00				0.98
Corporate	28	-0.1317	0.00	0.834	0.00				0.95
Mortgage	21	0.0104	0.84	0.501	0.00				0.50
Panel D: Size-weighted portfolios and unconditional single specific factor model									
Government	108	-0.0875	0.00	0.864	0.00				0.98
Corporate	28	-0.1337	0.00	0.914	0.00				0.96
Mortgage.	21	0.0102	0.84	0.568	0.00				0.59
Panel E: Equal-weighted portfolios and conditional beta single factor model									
Government	108	-0.0736	0.00	0.863	0.00		0.00		0.98
Corporate	28	-0.0829	0.00	0.839	0.00		0.00		0.97
Mortgage	21	0.0310	0.46	0.266	0.00		0.00		0.40
High-Yield	5	0.0128	0.93	0.720	0.00		0.31		0.51
All	162	-0.0537	0.00	0.756	0.00		0.00		0.97
Panel F: Size-weighted portfolios and conditional beta single factor model									
Government	108	-0.0703	0.00	0.899	0.00		0.00		0.98
Corporate	28	-0.0855	0.00	0.922	0.00		0.00		0.98
Mortgage	21	0.0304	0.46	0.309	0.00		0.00		0.50
High-Yield	5	0.0038	0.98	0.657	0.00		0.13		0.50
All	162	-0.0401	0.04	0.749	0.00		0.00		0.96
Panel G: Equal-weighted portfolios and conditional alpha single factor model									
Government	108	-0.0728	0.00	0.863	0.00	0.80	0.00	0.00	0.98
Corporate	28	-0.0822	0.00	0.837	0.00	0.42	0.00	0.00	0.97
Mortgage	21	0.0275	0.51	0.273	0.00	0.46	0.02	0.01	0.40
High-Yield	5	-0.0310	0.87	0.750	0.00	0.91	0.38	0.03	0.48
All	162	-0.0538	0.00	0.757	0.00	0.83	0.00	0.00	0.97
Panel H: Size-weighted portfolios and conditional alpha single factor model									
Government	108	-0.0694	0.00	0.899	0.00	0.86	0.00	0.00	0.98
Corporate	28	-0.0840	0.00	0.920	0.00	0.23	0.00	0.00	0.98
Mortgage	21	0.0273	0.50	0.316	0.00	0.65	0.00	0.00	0.50
High-Yield	5	-0.0272	0.89	0.681	0.00	0.94	0.20	0.07	0.47
All	162	-0.0401	0.04	0.750	0.00	0.90	0.00	0.00	0.96

Table A25. Averages of individual fund performance using the unconditional and conditional single- and multi-factor models

This table reports equal-weighted (EW) and size-weighted (SW) averages of individual fund performances (α in %) using unconditional and conditional single- and multi-factor models. The models are the single market factor model, the two-factor risk model, the two-factor stock model, and the five-factor model. Partial conditioning refers to models with time-varying betas only and full conditioning refers to models with both time-varying alphas and betas. All of the time-varying coefficients are linear functions in the four instrumental variables. The instrumental variables are the lagged values of the yield on one-month T-bills (TB1), the slope of the term structure (TERM), the default premium (DEF), and the real yield on long-maturity government bonds (REALG). GMM estimation is conducted for each fund. The alpha is the estimate of the intercept of the time-series regression. The number of funds in each of the five groups is described in table 5.1. All represents the portfolios of performances of all individual funds. Monthly data are used from March 1985 to February 2000, for a maximum of 180 observations per fund.

Fund Group	Unconditional		Partial Conditional		Full Conditional	
	EW $\bar{\alpha}$	SW $\bar{\alpha}$	EW $\bar{\alpha}$	SW $\bar{\alpha}$	EW $\bar{\alpha}$	SW $\bar{\alpha}$
Panel A: Single market factor model						
Government	-0.1007	-0.1070	-0.1045	-0.1191	-0.1607	-0.1555
Corporate	-0.1115	-0.1213	-0.1156	-0.1323	-0.1735	-0.1618
Mortgage	-0.0094	-0.0091	-0.0096	-0.0036	-0.0006	-0.0068
High-Yield	0.0782	0.0591	0.0502	0.0394	-0.5009	-0.5277
All	-0.0852	-0.0912	-0.0893	-0.1003	-0.1526	-0.1347
Panel B: Two-factor risk model						
Government	-0.1065	-0.1109	-0.1068	-0.1276	-0.1899	-0.1659
Corporate	-0.1123	-0.1238	-0.1179	-0.1309	-0.2389	-0.0632
Mortgage	-0.0167	-0.0161	-0.0241	-0.0210	-0.0374	-0.0040
High-Yield	0.0514	0.0261	0.0311	0.0129	-0.8623	-0.9257
All	-0.0910	-0.0957	-0.0937	-0.1090	-0.1993	-0.1312
Panel C: Two-factor stock model						
Government	-0.1115	-0.1252	-0.0941	-0.1160	-0.0928	-0.1731
Corporate	-0.1220	-0.1275	-0.0894	-0.1087	-0.0940	-0.1011
Mortgage	-0.0184	-0.0165	-0.0149	-0.0105	-0.0308	-0.0299
High-Yield	0.0142	-0.0021	0.2329	0.2301	0.3644	0.4564
All	-0.0973	-0.1063	-0.0730	-0.0944	-0.0709	-0.1338
Panel D: Five-factor model						
Government	-0.1166	-0.1194	-0.0926	-0.0820	-0.0289	-0.1432
Corporate	-0.1342	-0.1345	-0.1246	-0.1529	-0.1727	-0.1711
Mortgage	-0.0211	-0.0216	-0.0327	-0.0275	-0.2425	-0.1855
High-Yield	-0.0140	-0.0323	0.1246	0.1252	-0.7549	-0.7818
All	-0.1041	-0.1043	-0.0834	-0.0808	-0.1049	-0.1597

Table A26. Summary statistics for the performance estimates based on the unconditional and conditional factor models for the fund categories based on individual fund performances

This table presents summary statistics for the performance measures based on the unconditional and the full conditional factor models for each fund category and for all funds. The models are the single market factor model, the two-factor risk model, the two-factor stock model, and the five-factor model. Full conditional models are models with time-varying alphas and betas based on four instrumental variables. The instrumental variables are the lagged values of the yield on one-month T-bills (TB1), the slope of the term structure (TERM), the default premium (DEF), and the real yield on long-maturity government bonds (REALG). The number of funds in each of the five groups is described in table 5.1. All of the p-values are based on GMM estimation and are adjusted for serial correlation and heteroskedasticity (Newey and West, 1987a). Information related to the funds with significant performance at the 5% level 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.

Fund Group	Unconditional						Full Conditional					
	p		% funds	# funds	Bonferroni p		p		% funds	# funds	Bonferroni p	
	Max.	Min.	p < 5%	α>0 & p<5%	Max.	Min.	Max.	Min.	p < 5%	α>0 & p<5%	Max.	Min.
Panel A: Single market factor model												
Government	0.961	0.000	58.33	2	0.000	0.880	0.981	0.000	43.52	5	0.000	0.034
Corporate	0.887	0.000	57.14	0	0.000	1.000	0.979	0.000	28.57	0	0.000	1.000
Mortgage	0.954	0.000	23.81	1	0.000	0.465	0.797	0.014	9.52	2	0.694	0.138
High-Yield	0.887	0.219	0.00	0	1.000	0.535	0.956	0.200	0.00	0	0.480	1.000
All	0.961	0.000	51.85	3	0.000	1.000	0.981	0.000	35.19	7	0.000	0.051
Panel B: Two-factor risk model												
Government	0.984	0.000	62.96	1	0.000	1.000	0.998	0.000	28.70	0	1.000	0.000
Corporate	0.890	0.000	64.29	0	0.000	1.000	0.917	0.004	21.43	0	1.000	0.031
Mortgage	0.993	0.000	19.05	0	0.000	0.677	0.990	0.003	9.52	1	0.023	0.119
High-Yield	0.964	0.223	0.00	0	1.000	0.542	0.933	0.084	0.00	0	1.000	0.186
All	0.993	0.000	55.56	1	0.000	1.000	0.998	0.000	24.07	1	0.177	0.000
Panel C: Two-factor stock model												
Government	0.988	0.000	64.81	2	0.000	1.000	0.975	0.000	47.22	7	0.051	0.000
Corporate	0.920	0.000	60.71	0	0.000	1.000	0.977	0.000	25.00	0	1.000	0.000
Mortgage	0.954	0.000	19.05	0	0.000	0.617	1.000	0.012	14.29	1	0.120	0.105
High-Yield	0.923	0.385	0.00	0	1.000	0.951	0.828	0.233	0.00	0	0.633	0.568
All	0.988	0.000	56.17	2	0.000	1.000	1.000	0.000	37.65	8	0.076	0.000
Panel D: Five-factor model												
Government	0.985	0.000	62.96	0	0.000	1.000	0.953	0.000	41.35	8	0.000	0.000
Corporate	0.449	0.000	78.57	0	0.000	1.000	1.000	0.001	30.77	1	0.001	0.000
Mortgage	0.989	0.000	23.81	0	0.000	0.853	0.882	0.000	38.10	0	1.000	0.000
High-Yield	0.950	0.213	0.00	0	0.519	0.781	0.930	0.102	0.00	0	1.000	0.207
All	0.989	0.000	58.64	0	0.000	1.000	1.000	0.000	37.82	9	0.000	0.000

Table A27. Performance and risk measures for portfolios of funds using unconditional and conditional two-factor models

This table reports summary statistics on the performance (α in %) and risk measures for equal- and size weighted portfolios of individual funds using unconditional and conditional versions of the two two-factor models. The two-factor risk model has the Scotia Universe bond index and the Scotia overall MBS index as factors. The two factor stock model has the Scotia universe bond index and the TSE 300 index (S) as factors. Partial and full conditionings refer to models with time varying betas and time-varying betas and alphas, respectively. GMM estimation is conducted for each portfolio of funds in a time-series regression. The standard errors of these estimates are adjusted for serial correlation and heteroskedasticity (Newey and West, 1987a). The five portfolios of funds are described in table 5.1. All represents the performances and risks of portfolios of all individual funds. Information related to the estimated performance, betas, p-values, and the adjusted R^2 is provided in the table. $\beta(.)$ refers to $\beta(MBS)$ for the two-factor risk models, and $\beta(S)$ for the two-factor stock models. W1, W2, W4, and W5 correspond to the p-values based on the Newey and West (1987b) Wald test on the validity of the time-varying alphas, time-varying $\beta(M)$, time-variation of all betas, and time-varying alphas and betas, respectively. Monthly data are used from March 1985 to February 2000, for a maximum of 180 observations per portfolio of funds.

Fund Group	N	α	p-val	$\beta(M)$	p-val	$\beta(.)$	p-val	W1	W2	W4	W5	Adj. R^2
Panel A: Equal-weighted portfolios and unconditional two-factor risk model												
Government	108	-0.0986	0.00	1.000	0.00	-0.125	0.01					0.99
Corporate	28	-0.0942	0.00	1.019	0.00	-0.198	0.00					0.98
Mortgage	21	0.0095	0.84	0.159	0.11	0.265	0.19					0.51
High-Yield	5	0.0806	0.52	0.806	0.00	-0.203	0.58					0.50
All	162	-0.0780	0.00	0.876	0.00	-0.081	0.15					0.98
Panel B: Size-weighted portfolios and unconditional two-factor risk model												
Government	108	-0.0933	0.00	1.029	0.00	-0.132	0.01					0.99
Corporate	28	-0.1004	0.00	1.166	0.00	-0.318	0.00					0.98
Mortgage	21	0.0086	0.85	0.269	0.00	0.170	0.32					0.63
High-Yield	5	0.0657	0.60	0.762	0.00	-0.173	0.63					0.49
All	162	-0.0663	0.00	0.890	0.00	-0.120	0.13					0.97
Panel C: Equal-weighted portfolios and unconditional two-factor stock model												
Government	108	-0.0905	0.00	0.828	0.00	0.025	0.00					0.98
Corporate	28	-0.0989	0.00	0.803	0.00	0.026	0.00					0.96
Mortgage	21	0.0150	0.71	0.225	0.00	0.027	0.00					0.40
High-Yield	5	0.0328	0.77	0.615	0.00	0.079	0.02					0.57
All	162	-0.0743	0.00	0.716	0.00	0.028	0.00					0.97
Panel D: Size-weighted portfolios and unconditional two-factor stock model												
Government	108	-0.0859	0.00	0.861	0.00	0.030	0.00					0.98
Corporate	28	-0.0964	0.00	0.887	0.00	0.021	0.00					0.97
Mortgage	21	0.0113	0.78	0.265	0.00	0.029	0.00					0.50
High-Yield	5	0.0184	0.87	0.586	0.00	0.077	0.02					0.57
All	162	-0.0594	0.01	0.703	0.00	0.032	0.00					0.96
Panel E: Equal-weighted portfolios and partial conditional two-factor risk model												
Government	108	-0.0856	0.00	1.012	0.00	-0.165	0.08		0.51	0.23		0.99
Corporate	28	-0.0897	0.00	0.994	0.00	-0.160	0.16		0.01	0.02		0.98
Mortgage	21	0.0199	0.72	0.165	0.14	0.342	0.09		0.38	0.01		0.57
High-Yield	5	-0.0163	0.92	0.469	0.24	0.482	0.50		0.59	0.41		0.52
All	162	-0.0691	0.00	0.872	0.00	-0.074	0.41		0.35	0.02		0.98
Panel F: Size-weighted portfolios and partial conditional two-factor risk model												
Government	108	-0.0862	0.00	1.014	0.00	-0.117	0.20		0.23	0.04		0.99
Corporate	28	-0.0946	0.00	1.100	0.00	-0.246	0.01		0.00	0.00		0.99
Mortgage	21	0.0101	0.85	0.235	0.02	0.317	0.08		0.47	0.01		0.67
High-Yield	5	-0.0346	0.82	0.222	0.55	0.820	0.22		0.30	0.19		0.51
All	162	-0.0631	0.01	0.834	0.00	-0.019	0.84		0.02	0.00		0.98
Panel G: Equal-weighted portfolios and partial conditional two-factor stock model												
Government	108	-0.0736	0.00	0.847	0.00	0.017	0.00		0.00	0.00		0.99
Corporate	28	-0.0864	0.00	0.821	0.00	0.018	0.00		0.00	0.00		0.97
Mortgage	21	0.0208	0.64	0.243	0.00	0.023	0.04		0.00	0.01		0.41
High-Yield	5	0.1001	0.29	0.672	0.00	0.057	0.11		0.37	0.00		0.63
All	162	-0.0557	0.00	0.738	0.00	0.018	0.00		0.00	0.00		0.98
Panel H: Size-weighted portfolios and partial conditional two-factor stock model												
Government	108	-0.0727	0.00	0.878	0.00	0.022	0.00		0.00	0.00		0.99
Corporate	28	-0.0873	0.00	0.910	0.00	0.013	0.00		0.00	0.00		0.98
Mortgage	21	0.0207	0.62	0.286	0.00	0.025	0.02		0.00	0.00		0.52
High-Yield	5	0.0908	0.33	0.597	0.00	0.074	0.03		0.37	0.00		0.64
All	162	-0.0441	0.01	0.727	0.00	0.022	0.00		0.00	0.00		0.97

Table A27. Continued.

Fund Group	N	α	p-val	β(M)	p-val	β(.)	p-val	W1	W2	W4	W5	Adj. R^2
Panel I: Equal-weighted portfolios and full conditional two-factor risk model												
Government	108	-0.1005	0.01	1.017	0.00	-0.162	0.11	0.06	0.38		0.01	0.99
Corporate	28	-0.1230	0.01	0.988	0.00	-0.130	0.26	0.16	0.00		0.00	0.98
Mortgage	21	0.0410	0.64	0.183	0.13	0.311	0.21	0.49	0.39		0.02	0.56
High-Yield	5	-0.0836	0.68	0.493	0.19	0.519	0.48	0.79	0.69		0.14	0.49
All	162	-0.0870	0.05	0.876	0.00	-0.066	0.52	0.12	0.15		0.00	0.98
Panel J: Size-weighted portfolios and full conditional two-factor risk model												
Government	108	-0.1119	0.01	1.017	0.00	-0.106	0.29	0.23	0.16		0.03	0.99
Corporate	28	-0.1010	0.02	1.103	0.00	-0.245	0.02	0.70	0.00		0.00	0.99
Mortgage	21	0.0401	0.62	0.255	0.02	0.278	0.22	0.55	0.44		0.02	0.67
High-Yield	5	-0.1141	0.58	0.274	0.43	0.819	0.24	0.78	0.45		0.14	0.48
All	162	-0.0755	0.09	0.842	0.00	-0.021	0.84	0.15	0.00		0.00	0.98
Panel K: Equal-weighted portfolios and full conditional two-factor stock model												
Government	108	-0.0735	0.00	0.847	0.00	0.017	0.00	0.74	0.00		0.00	0.99
Corporate	28	-0.0862	0.00	0.820	0.00	0.018	0.00	0.58	0.00		0.00	0.97
Mortgage	21	0.0210	0.63	0.252	0.00	0.021	0.07	0.66	0.00		0.04	0.41
High-Yield	5	-0.1550	0.28	0.746	0.00	0.069	0.07	0.36	0.45		0.00	0.61
All	162	-0.0555	0.00	0.740	0.00	0.018	0.00	0.93	0.00		0.00	0.98
Panel L: Size-weighted portfolios and full conditional two-factor stock model												
Government	108	-0.0728	0.00	0.878	0.00	0.023	0.00	0.53	0.00		0.00	0.99
Corporate	28	-0.0871	0.00	0.907	0.00	0.014	0.00	0.51	0.00		0.00	0.98
Mortgage	21	0.0207	0.62	0.294	0.00	0.023	0.02	0.79	0.00		0.00	0.51
High-Yield	5	-0.1723	0.22	0.672	0.00	0.086	0.01	0.25	0.45		0.00	0.62
All	162	-0.0441	0.01	0.729	0.00	0.022	0.00	0.87	0.00		0.00	0.97

Table A28. Performance and risk measures for portfolios of funds using unconditional and conditional five-factor models

This table reports summary statistics on the performance (α in %) and risk measures for equal- and size weighted portfolios of individual funds using unconditional and conditional versions of the five-factor model. The five factors are the Scotia LT and MT government bond indices, the Scotia LT and MT corporate bond indices, and the Scotia overall MBS index as factors. Partial and full conditioning refer to models with time varying betas and time-varying betas and alphas, respectively. GMM estimation is conducted for each portfolio of funds in a time-series regression. The standard errors of these estimates are adjusted for serial correlation and heteroskedasticity (Newey and West, 1987a). The five portfolios of funds are described in table 5.1. All represents the performances and risks of portfolios of all individual funds. Information related to the estimated performance, betas, p-values, and the adjusted R^2, is provided in the table. W1, W2, W6, and W7 correspond to the p-values based on the Newey and West (1987b) Wald test on the validity of the time-varying alphas, time-varying $\beta(M)$, time-varying set of all betas, and time-varying alphas and betas, respectively. Monthly data are used from March 1985 to February 2000, for a maximum of 180 observations per portfolio of funds.

Fund Group	N	α	p-val	β(LG)	p-val	β(MG)	p-val	β(LC)	p-val	β(MC)	p-val	β(MBS)	p-val	W1	W2	W6	W7	Adj. R^2
Panel A: Equal-weighted portfolios and unconditional model																		
Government	108	-0.1150	0.00	0.146	0.06	0.429	0.01	0.054	0.49	0.084	0.64	0.101	0.09					0.99
Corporate	28	-0.1190	0.00	0.183	0.08	0.304	0.11	0.053	0.60	0.163	0.37	0.068	0.34					0.99
Mortgage	21	-0.0033	0.95	0.032	0.85	-0.068	0.81	0.048	0.77	0.065	0.81	0.360	0.12					0.50
High-Yield	5	-0.0145	0.87	-0.355	0.16	-1.116	0.09	0.662	0.03	1.415	0.04	0.174	0.58					0.79
All	162	-0.0975	0.00	0.113	0.17	0.328	0.06	0.080	0.33	0.097	0.59	0.129	0.06					0.98
Panel B: Size-weighted portfolios and unconditional model																		
Government	108	-0.1131	0.00	0.129	0.06	0.415	0.00	0.056	0.36	0.164	0.28	0.071	0.29					0.99
Corporate	28	-0.1278	0.00	0.354	0.00	0.205	0.24	-0.084	0.44	0.297	0.04	0.027	0.74					0.99
Mortgage	21	-0.0064	0.90	0.080	0.59	-0.066	0.79	0.012	0.93	0.128	0.59	0.290	0.13					0.62
High-Yield	5	-0.0271	0.77	-0.353	0.16	-1.081	0.11	0.671	0.02	1.307	0.06	0.232	0.46					0.79
All	162	-0.0892	0.00	0.176	0.03	0.217	0.14	0.005	0.95	0.238	0.11	0.092	0.31					0.98
Panel C: Equal-weighted portfolios and partial conditional model																		
Government	108	-0.0900	0.00	0.171	0.16	0.393	0.03	0.100	0.47	0.104	0.60	-0.088	0.24		0.66	0.00		0.99
Corporate	28	-0.1099	0.00	0.171	0.25	0.366	0.06	0.143	0.38	0.032	0.88	-0.008	0.94		0.00	0.00		0.99
Mortgage	21	0.0056	0.93	0.149	0.61	-0.154	0.79	-0.159	0.65	0.297	0.65	0.375	0.18		0.25	0.00		0.56
High-Yield	5	0.0336	0.69	-1.941	0.24	0.803	0.65	2.524	0.15	-1.362	0.37	1.074	0.18		0.21	0.00		0.79
All	162	-0.0782	0.00	0.137	0.26	0.332	0.09	0.088	0.54	0.104	0.64	0.002	0.98		0.20	0.00		0.98
Panel D: Size-weighted portfolios and partial conditional model																		
Government	108	-0.0895	0.00	0.097	0.43	0.491	0.01	0.152	0.26	0.061	0.74	-0.085	0.24		0.07	0.00		0.99
Corporate	28	-0.1070	0.00	0.401	0.00	0.145	0.37	-0.066	0.62	0.300	0.11	-0.067	0.49		0.00	0.00		0.99
Mortgage	21	-0.0066	0.91	0.184	0.49	-0.133	0.81	-0.162	0.62	0.286	0.64	0.378	0.16		0.15	0.00		0.67
High-Yield	5	0.0086	0.91	-2.330	0.13	0.714	0.67	2.954	0.07	-1.494	0.30	1.380	0.07		0.20	0.00		0.80
All	162	-0.0718	0.00	0.152	0.20	0.300	0.14	0.046	0.74	0.150	0.49	0.033	0.75		0.12	0.00		0.98
Panel E: Equal-weighted portfolios and full conditional model																		
Government	108	-0.1420	0.00	0.143	0.24	0.287	0.18	0.129	0.36	0.207	0.36	-0.046	0.61	0.22	0.36		0.00	0.99
Corporate	28	-0.1171	0.00	0.169	0.25	0.362	0.08	0.144	0.38	0.035	0.87	0.001	1.00	0.84	0.01		0.00	0.99
Mortgage	21	-0.1060	0.29	0.096	0.76	-0.535	0.40	-0.070	0.85	0.629	0.36	0.474	0.16	0.01	0.22		0.00	0.56
High-Yield	5	-0.4601	0.19	-1.447	0.43	-1.030	0.73	2.055	0.28	0.460	0.86	1.329	0.19	0.11	0.07		0.00	0.80
All	162	-0.1305	0.00	0.111	0.39	0.214	0.34	0.119	0.44	0.214	0.38	0.047	0.66	0.30	0.45		0.00	0.98
Panel F: Size-weighted portfolios and full conditional model																		
Government	108	-0.1652	0.00	0.056	0.62	0.320	0.14	0.200	0.13	0.217	0.31	-0.020	0.82	0.00	0.00		0.00	0.99
Corporate	28	-0.1074	0.00	0.404	0.00	0.110	0.53	-0.058	0.67	0.318	0.09	-0.059	0.56	0.86	0.00		0.00	0.99
Mortgage	21	-0.1066	0.24	0.136	0.63	-0.483	0.41	-0.074	0.83	0.579	0.38	0.473	0.13	0.67	0.14		0.00	0.67
High-Yield	5	-0.5784	0.08	-1.659	0.33	-1.575	0.57	2.318	0.18	0.759	0.75	1.706	0.07	0.03	0.04		0.00	0.82
All	162	-0.1357	0.00	0.117	0.35	0.132	0.57	0.092	0.55	0.301	0.23	0.088	0.49	0.01	0.15		0.00	0.98

Table A29. Survivorship biases and average excess returns

This table reports the average excess returns (in %) for equal- and size-weighted portfolios of surviving and non-surviving funds grouped by investment objectives and estimates of the survivorship bias. The survivorship bias is the difference between the portfolio returns of all funds and of only surviving funds. All represents the equal- or size-weighted portfolios of all funds. Size is defined as the total net asset value of the fund. Monthly data are from March 1985 through February 2000.

Fund Group	Averages of Excess Returns for the Year/Period:										
	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	1985-2000
Panel A: Equal-weighted portfolios of all funds											
Government	0.7168	0.1229	0.8132	-0.8607	0.7888	0.4336	0.3444	0.1964	-0.5552	0.3946	0.1417
Corporate	0.6848	0.1014	0.7933	-0.7895	0.7597	0.4321	0.3532	0.1668	-0.5423	0.3810	0.1465
Mortgage	0.3929	0.1218	0.4584	-0.4251	0.3231	0.3012	0.0340	0.0401	-0.2725	-0.0184	0.0726
High-Yield	-	-	-	-0.5205	0.8776	0.6793	0.6476	-0.3015	-0.0035	0.0802	0.3424
All	0.6502	0.1186	0.7373	-0.7631	0.7044	0.4177	0.3072	0.1550	-0.4979	0.3272	0.1264
Panel B: Equal-weighted portfolios of surviving funds											
Government	0.7049	0.1904	0.8173	-0.8609	0.8284	0.4407	0.3680	0.1985	-0.5606	0.4206	0.1576
Corporate	0.6890	0.0858	0.7937	-0.7759	0.7737	0.4506	0.4085	0.1700	-0.5336	0.4113	0.1424
Mortgage	0.4063	0.1405	0.4743	-0.3839	0.3751	0.3435	0.0671	0.0973	-0.2907	-0.0003	0.0911
High-Yield	-	-	-	-0.5205	0.8776	0.6793	0.6487	-0.3059	0.0178	0.3575	0.3544
All	0.6583	0.1666	0.7559	-0.7673	0.7498	0.4364	0.3436	0.1649	-0.5031	0.3625	0.1429
Panel C: Equal-weighted portfolios and survivorship bias											
Government	-0.0118	0.0675	0.0041	-0.0002	0.0396	0.0071	0.0236	0.0021	-0.0055	0.0260	0.0159
Corporate	0.0042	-0.0156	0.0004	0.0135	0.0140	0.0186	0.0553	0.0032	0.0087	0.0303	-0.0041
Mortgage	0.0134	0.0187	0.0158	0.0411	0.0520	0.0423	0.0331	0.0572	-0.0183	0.0180	0.0185
High-Yield	-	-	-	0.0000	0.0000	0.0000	0.0011	-0.0044	0.0212	0.2773	0.0120
All	0.0081	0.0481	0.0186	-0.0042	0.0455	0.0187	0.0364	0.0099	-0.0052	0.0353	0.0165
Panel D: Size-weighted portfolios of all funds											
Government	0.7367	0.1714	0.8568	-0.8825	0.8347	0.4956	0.3909	0.1891	-0.5538	0.4143	0.1712
Corporate	0.7126	0.0704	0.8393	-0.8572	0.8898	0.4412	0.4336	0.2714	-0.6434	0.4939	0.1641
Mortgage	0.4476	0.1209	0.4567	-0.4376	0.3907	0.3345	0.1124	0.1088	-0.3319	0.0801	0.0889
High-Yield	-	-	-	-0.5755	0.7997	0.6890	0.6262	-0.3165	-0.0078	0.3150	0.3276
All	0.6497	0.1494	0.7408	-0.7450	0.7324	0.4586	0.3451	0.1831	-0.5214	0.3635	0.1491
Panel E: Size-weighted portfolios of surviving funds											
Government	0.7307	0.1801	0.8641	-0.8781	0.8387	0.4986	0.3954	0.1878	-0.5569	0.4195	0.1736
Corporate	0.7087	0.0624	0.8575	-0.8437	0.8829	0.4511	0.4569	0.2754	-0.6350	0.4910	0.1666
Mortgage	0.4670	0.1339	0.4813	-0.4217	0.4288	0.3571	0.1381	0.1173	-0.3428	0.0887	0.0999
High-Yield	-	-	-	-0.5755	0.7997	0.6890	0.6264	-0.3158	-0.0077	0.3156	0.3278
All	0.6584	0.1595	0.7674	-0.7535	0.7520	0.4691	0.3588	0.1836	-0.5247	0.3690	0.1556
Panel F: Size-weighted portfolios and survivorship bias											
Government	-0.0060	0.0087	0.0073	0.0045	0.0040	0.0030	0.0045	-0.0013	-0.0031	0.0052	0.0024
Corporate	-0.0039	-0.0080	0.0182	0.0134	-0.0069	0.0099	0.0233	0.0040	0.0083	-0.0029	0.0025
Mortgage	0.0195	0.0130	0.0246	0.0159	0.0381	0.0226	0.0257	0.0084	-0.0109	0.0086	0.0110
High-Yield	-	-	-	0.0000	0.0000	0.0000	0.0002	0.0007	0.0000	0.0006	0.0002
All	0.0087	0.0101	0.0266	-0.0086	0.0196	0.0105	0.0138	0.0005	-0.0032	0.0055	0.0065

Table A30. Survivorship biases and risk-adjusted performance

This table reports the performance measures (α in %) per investment objective category for size-weighted portfolios of surviving and non-surviving funds and estimates of the survivorship bias using twelve unconditional and conditional benchmark models. The survivorship bias in % per year is the difference between the risk-adjusted performance of the size-weighted portfolios of all funds and of surviving funds only. The estimation is conducted using the GMM method. All represents the equal-or size-weighted average of all funds. The standard errors of the estimates are adjusted for serial correlation and heteroskedasticity (Newey and West, 1987a). Size is defined as the total net asset value of the fund. Monthly data are from March 1985 through February 2000.

Fund Group	Size-weighted portfolios of surviving and non-surviving funds								
	Unconditional			Partial Conditional			Full Conditional		
	α	p-val	Surv. Bias	α	p-val	Surv. Bias	α	p-val	Surv. Bias
Panel A: Single market factor model									
Government	-0.0815	0.00	0.0408	-0.0740	0.00	0.0444	-0.0732	0.00	0.0456
Corporate	-0.0931	0.00	0.0240	-0.0875	0.00	0.0240	-0.0860	0.00	0.0240
Mortgage	0.0111	0.79	0.0924	0.0213	0.61	0.1092	0.0178	0.67	0.1140
High Yield	0.0664	0.59	0.0024	0.0036	0.98	0.0028	-0.0271	0.89	-0.0012
All	-0.0514	0.02	0.0012	-0.0395	0.05	-0.0072	-0.0397	0.05	-0.0048
Panel B: Two-factor risk model									
Government	-0.0964	0.00	0.0372	-0.0890	0.00	0.0336	-0.1141	0.01	0.0264
Corporate	-0.1064	0.00	0.0720	-0.1010	0.00	0.0768	-0.0966	0.03	-0.0528
Mortgage	-0.0037	0.94	0.1465	0.0016	0.98	0.1016	0.0327	0.69	0.0888
High Yield	0.0655	0.60	0.0024	-0.0347	0.82	0.0012	-0.1151	0.58	0.0120
All	-0.0682	0.00	0.0228	-0.0650	0.01	0.0228	-0.0748	0.10	-0.0084
Panel C: Two-factor stock model									
Government	-0.0890	0.00	0.0372	-0.0773	0.00	0.0552	-0.0774	0.00	0.0552
Corporate	-0.0980	0.00	0.0192	-0.0879	0.00	0.0072	-0.0877	0.00	0.0072
Mortgage	0.0040	0.92	0.0881	0.0107	0.80	0.1200	0.0108	0.80	0.1188
High Yield	0.0183	0.87	0.0012	0.0903	0.33	0.0060	-0.1726	0.22	0.0036
All	-0.0594	0.01	0.0000	-0.0443	0.02	0.0024	-0.0443	0.02	0.0024
Panel D: Five-factor model									
Government	-0.1148	0.00	0.0204	-0.0935	0.00	0.0480	-0.1654	0.00	0.0024
Corporate	-0.133	0.00	0.0624	-0.1115	0.00	0.0540	-0.1006	0.00	-0.0816
Mortgage	-0.0174	0.73	0.1324	-0.0126	0.84	0.0721	-0.1059	0.26	-0.0084
High Yield	-0.0271	0.77	0.0000	0.0087	0.91	-0.0012	-0.5771	0.08	-0.0156
All	-0.0906	0.00	0.0168	-0.0743	0.00	0.0300	-0.1307	0.00	-0.0600

Table A31. The relationship between risk-adjusted performance and mutual fund attributes

This table reports the cross-sectional regression statistics of the relationship between risk-adjusted performance and mutual fund attributes. Thirteen risk-adjusted performance measures and six fund characteristics are selected for the tests using the GMM method. M1, M2, M3, M4, and M5 are unconditional measures based on the single market factor model, the single specific factor model, the two-factor risk model, the two-factor stock model, and the five-factor model, respectively. M6, M7, M8, and M9 are partial conditional measures based on the same models, respectively. M10, M11, M12, and M13 are the full conditional measures based on the same models, respectively. The fund attributes are: the MER (management expense ratio), MGF (management fees), the log of the age of the fund in years, the log of the size of the fund in millions, and two dummy variables indicating if the fund is a load fund (LOAD), and if the fund has optional sales charges (OPTLO). The risk-adjusted performance measures are estimated using monthly observations over the period March 1985 to February 2000. The fund characteristic variables are measured at the end of the sampling period. Information related to the estimated coefficients, p-values, and the adjusted R^2 values is provided in the table. 162 observations are used, which represents the total number of surviving funds. The last two rows provide information on the number of regressions where each coefficient is significant at the levels of 5% and 10%, and where the adjusted R^2 is greater than 5% and 10%.

Performance Measure	Constant	p-val	MER	p-val	MGF	p-val	Ln (AGE)	p-val	Ln (SIZE)	p-val	LOAD	p-val	OPTLO	p-val	Adj. R^2
M1	-0.0009	0.23	-0.0319	0.05	-0.0316	0.12	0.0002	0.06	0.0001	0.36	-0.0004	0.04	-0.0001	0.46	0.212
M2	-0.0016	0.00	-0.0431	0.00	-0.0233	0.22	0.0002	0.01	0.0001	0.05	-0.0003	0.10	-0.0002	0.27	0.277
M3	-0.0008	0.25	-0.0480	0.00	-0.0269	0.08	0.0002	0.05	0.0001	0.28	-0.0003	0.04	-0.0001	0.41	0.238
M4	-0.0008	0.25	-0.0293	0.11	-0.0343	0.14	0.0002	0.01	0.0000	0.61	-0.0004	0.04	-0.0002	0.25	0.242
M5	-0.0012	0.05	-0.0629	0.00	-0.0149	0.30	0.0001	0.57	0.0001	0.05	-0.0003	0.06	-0.0001	0.68	0.196
M6	-0.0008	0.22	-0.0068	0.78	-0.0574	0.04	0.0003	0.01	0.0000	0.65	-0.0004	0.06	-0.0003	0.16	0.224
M7	-0.0004	0.64	-0.0005	0.01	-0.0002	0.18	0.0003	0.00	-0.0000	0.86	-0.0003	0.07	-0.0003	0.12	0.245
M8	0.0002	0.84	0.0002	0.57	-0.0008	0.03	0.0001	0.76	-0.0000	0.92	-0.0005	0.06	-0.0003	0.24	0.114
M9	-0.0011	0.34	-0.0007	0.01	0.0001	0.74	-0.0001	0.68	0.0001	0.33	-0.0002	0.32	0.0000	0.98	0.026
M10	-0.0003	0.94	0.2202	0.41	-0.2998	0.34	0.0003	0.69	0.0000	0.99	-0.0006	0.44	-0.0024	0.06	0.028
M11	-0.0037	0.34	-0.0007	0.73	0.0001	0.97	0.0010	0.19	0.0001	0.70	0.0002	0.85	-0.0016	0.20	0.017
M12	0.0068	0.08	-0.0001	0.86	0.0004	0.74	-0.0004	0.47	-0.0005	0.15	-0.0008	0.26	-0.0013	0.13	-0.004
M13	0.0058	0.51	-0.0006	0.75	0.0018	0.53	-0.0004	0.69	-0.0006	0.47	-0.0012	0.68	-0.0024	0.37	-0.025
Significance (5%)		1		6		1		5		0		3		0	8
Significance (10%)		3		6		2		6		2		7		1	8