ESSAYS IN ASSET ALLOCATION

A Dissertation

Presented to

The Faculty of the C.T. Bauer College of Business

University of Houston

In Partial Fulfillment

of the Requirements for the Degree

Doctor of Philosophy

by

Xin Gao

May, 2016

ACKNOWLEDGMENTS

First and foremost I want to thank my advisor Dr. Federico Nardari for his guidance, understanding, patience, and most importantly, his mentorship during my graduate studies at the University of Houston. It has been an honor to be his Ph.D. student. He has taught me how good finance research is done. I appreciate his continuous encouragement and support during tough times in the Ph.D. pursuit. For everything you have done for me, Dr. Nardari, I thank you.

I would like to thank the rest of my dissertation committee members: Dr. Kris Jacobs, Dr. Rauli Susmel, and Dr. Norman Johnson, for their encouragement, insightful comments, and hard questions. Their support also contributes to the success of this dissertation.

I would also like to thank the faculty at the Department of Finance at C. T. Bauer College of Business, especially Dr. Praveen Kumar, Dr. Stuart Turnbull, Dr. Thomas George, Dr. Nisan Langberg, Dr. Hitesh Doshi and Dr. Natalia Piqueira, for providing me with the foundation for becoming an academic researcher.

In my daily work, I have been blessed with a friendly and cheerful group of fellow Ph.D. students at the Department of Finance. I am grateful for their friendship, discussion, encouragement, and companion.

Last but not the least, I would like to thank my family: my parents, Pengfei Gao and Qingping Li, and my wife, Meina Cai, for their love, support, and sacrifices. Without them, this thesis would never have been written.

ESSAYS IN ASSET ALLOCATION

Abstract

Xin Gao

May, 2016

This dissertation consists of two essays in asset allocation. In the first essay, I explore the question of how investors should optimally incorporate commodities in their multi-asset portfolios, or even if they should at all. To tackle this problem, I conduct a comprehensive out-of-sample assessment on the economic value of commodities in multi-asset investment strategies for both mean-variance and non-mean-variance investors who exploit the predictability of time-varying asset return moments. With both monthly and quarterly rebalancing frequencies, I find that predictability makes the addition of commodities profitable even when short-selling and high leverage are not permitted. For instance, a mean-variance (non mean-variance) investor rebalancing quarterly, with moderate risk aversion and leverage, would be willing to pay up to 108 (155) basis points per year after transaction cost for adding commodities into her stock, bond and cash portfolio.

In the second essay, I study the economic value generated by active equity mutual funds from an investor's perspective. I employ an optimization-based portfolio approach to construct a composite investment strategy of U.S. active equity mutual funds. The strategy jointly exploits the conditioning information conveyed by multiple fund characteristics and macroeconomic variables about the cross-section of fund performance. Based on an extensive out-of-sample performance evaluation, I find that the proposed strategy consistently outperforms a large set of passive investments that rely on index funds as well as the strategies that exploit the fund characteristics on an individual basis. The outperformance is net of fees and expenses and after precluding short-sales and leverage. I further show that the proposed strategy's superior performance derives from effectively exploiting the predictive power of distinct fund characteristics to shift portfolio allocation toward (away from) funds with future outperformance (underperformance) as market conditions evolve over time. The findings indicate that investing in active equity mutual funds can add significant economic value for investors if the time-varying predictability in fund performance is properly taken into account and if an optimal portfolio approach, as opposed to simpler strategies based on sorting or on equal-weighted schemes, is adopted.

Contents

List of Tables

List of Figures

Chapter 1

Do Commodities Add Economic Value in Asset Allocation? New Evidence From Time-Varying Moments

1.1 Introduction

Commodities, as an alternative class of investable assets, have attracted substantial interest from both institutional and individual investors over the course of the past decade. According to a report by McKinsey, by the end of 2011 the amount of all forms of alternatives in global assets under management (AUM) had exceeded \$6.5 trillion representing 14 percent weight in the global market portfolio. Among all alternative strategies, commodities have grown rapidly at an annual rate of 21 percent during 2005-2011, and stood at a peak of roughly \$600 billion or approximately 6% in global AUM at the year-end of 2011.[1] More recent figures

[1]McKinsey's Global Alternative Investment Report is available at `http://www.mckinsey.com/clientservice/financial_services/knowledge_highlights/recent_reports/mainstreaming%20of%20alternatives.aspx?sc_lang=en`.

show increasingly larger inflows and outflows associated with commodity-linked funds.[2]

In the asset management industry the dramatic boom of commodity investing is linked to at least three perceived qualities of commodities: risk diversification, high historical returns and protection against inflation.[3] The increasing popularity of commodities recorded in investment practice and the alleged merits pursued by investors raise the critical question of how investors should optimally incorporate commodities in their multi-asset portfolios, or even if they should at all.[4]

Academic researchers have conducted numerous analyses of the economic value adding of commodity investment, but the results appear to be inconclusive. On one side, some studies show that investing in commodities indeed improves the risk-return profiles of mean-variance (MV) investors' multi-asset portfolios based on in-sample (IS) assessments. On the other hand, the ability of commodities to generate significant out-of-sample (OOS) economic gains has been questioned in recent studies. As a prominent example, Daskalaki and Skiadopoulos (2011) present the most recent and provocative OOS evidence that investing in commodities adds no value for either MV or non mean-variance (non-MV) investors. In the present paper we argue that most, if not all, existing studies that examine (IS and/or OOS) the value adding of commodities in multi-asset portfolios are based on rather over-simplifying approaches to the estimation of the return moments that become input to the asset allocation problem. Namely, future return moments are either assumed to be constant and equal to their full sample counterparts, or their variation is assumed to perfectly reproduce their own dynamics in the recent past through the reliance on rolling or expanding sample esti-

[2]Citi research reports for the US (Citigroup (2013)) show nearly \$30Bn in combined cumulative outflows from passive commodity index funds and commodity-linked exchange traded funds for 2013 compared to more than \$20Bn in net inflows for the sector during 2012 and almost \$6bn in net inflows for the first three months of 2014.

[3]According to a survey by Barclays Capital who interviewed over 100 institutional investors and advisors, almost half of respondents choose portfolio diversification as their main reason investing in commodities, a third choose absolute returns, and one tenth inflation protection. The report is available at `http://www.barcap.com/about-barclays-capital/press-office/research-reports.html`.

[4]This issue is also reflected in McKinsey' research report: the surveyed traditional asset managers fully agree with the potential of alternatives; on the other hand, many of them admit to be constrained by limited knowledge in risk management and product expertise for moving into alternatives.

mates.[5] We label these strategies as backward-looking (BWD). For instance, Daskalaki and Skiadopoulos (2011) rely on rolling sample moments at any given date t as estimates for the moments at time $t+1$ that, then, determine optimal portfolio weights. But there is by now compelling empirical evidence that asset return moments are time-varying and, to some extent, predictable by variables other than themselves. Erb and Harvey (2006) warn against naively using past average returns to infer expected returns and recommend developing a forward-looking framework for thinking about prospective returns. Specific to commodities, several papers find empirical links between variations in economic conditions and the performance of a broad-based commodity market indicator, both in absolute terms and relatively to equities and bonds.[6] These findings suggest that, in aggregate, commodity expected returns may respond systematically to shocks to state variables. Several studies show that exploiting the predictability of returns by economic variables leads, indeed, to tangible economic gains for portfolios that include either equities and cash or equities, bonds and cash. Similarly, several papers show the advantages for asset allocation purposes of carefully modeling the dynamics of volatilities and correlations rather than relying on historical second moments; but the empirical evidence is limited to equities or equity and bond portfolios. A few recent studies point to the importance of including the dynamics of return skewness and/or kurtosis in the asset allocation exercise with equities and/or bonds and cash. To separate them from the BWD approaches defined above, we label as forward-looking (FWD) all these approaches that aim to better capture the time-variation in return moments rather than relying on their

[5] Throughout the paper we denote by static (or, full sample) estimates those computed using the entire available sample; by rolling estimates we denote those computed at each date t using data up to t on a rolling window of a fixed length, by expanding estimates we denote those computed at each date t using data up to t on a window of expanding length.

[6] Jensen, Johnson, and Mercer (2000) and Jensen, Johnson, and Mercer (2002) show that the GSCI index, the one we describe and use in our empirical work, outperformed stocks and bonds during periods of expansionary monetary policy by the U.S. Federal Reserve. Strongin and Petsch (1996) report that the GSCI has above-average returns and performed well relative to stocks and bonds in periods of rising inflation. Nijman and Swinkels (2008) document that nominal and real portfolio efficient frontiers can be improved by timing allocation to the GSCI in response to variation in a number of macroeconomic variables such as bond yields, the rate of inflation, the term spread, and the default spread. Vrugt, Bauer, Molenaar, and Steenkamp (2004) find that GSCI return variation is affected by measures of the business cycle, the monetary environment, and market sentiment.

sample counterparts.[7] No study that we know of investigates the predictable dynamics of return moments in the context of asset allocation strategies that include commodities in addition to equities and bonds. Without careful examination of the return dynamics in a forward-looking framework while implementing portfolio strategies, we believe the above conclusion about the lack of value added by commodities to be somewhat in hasty.

In this paper, we provide a comprehensive analysis of the OOS performance of investment strategies incorporating commodities into traditional asset portfolios for both MV and non-MV investors. A major innovation differentiating our study from the existing literature is that we recursively construct optimal portfolios by exploiting the predictable variations of all the first four moments and co-moments of asset returns. We find that, by exploiting predictability, the inclusion of commodities into traditional asset portfolios does generate significant out-of-sample economic gains. Furthermore, for both traditional and commodity-augmented portfolios, FWD strategies outperform their BWD peers. Finally, adopting an FWD framework for both the assessment of expected returns and the forecast of higher moments appears to be especially relevant for commodity-augmented portfolios. Overall, our study presents a solid argument in favor of combining commodities with equities and fixed income exposures, whereas previous research had reached mixed or even opposite conclusions, especially in an out-of-sample context.

1.2 Literature

The potential benefits of investing in commodities have been suggested in several academic studies. In a seminal paper, Gorton and Rouwenhorst (2006) construct an equally weighted long-only commodity futures index that generates an average annualized geometric return of 9.98% with monthly rebalancing over the 1959-2004 period. They also document the pattern

[7] As we will detail in Sections 4 and 5, FWD strategies will involve the assessment of expected returns based on the predictive ability of economic variables and of technical analysis rules as well as the forecast of volatilities, correlations, co-skewness and co-kurtoses *not* based on sample moments.

that the monthly (quarterly and annual) returns of the index are insignificantly (negatively) correlated with stocks and bonds but positively correlated with inflation. Consequently, the authors suggest that commodity futures could be an ideal diversifier to traditional investment portfolios. However, Gorton and Rouwenhorst do not attempt to directly assess the empirical benefits of investing in commodities, so it is not clear whether and how the potential benefits could be realized practically. In a simple asset allocation exercise Erb and Harvey (2006) demonstrate that incorporating commodity futures into an equity-bond portfolio improves the risk-return profile significantly if the excess return of the commodity portfolio exceeds 3%.[8] Erb and Harvey, however, do not offer an OOS evaluation based on actual data of asset returns.

More generally, several researchers examine the economic value of commodities in multi-asset allocation exercises, but no consensus on whether a commodity exposure adds value to traditional equity-bond investors has been reached thus far. On one hand, a number of studies provide evidence that commodities can be effective alternatives to achieve portfolio diversification. For example, Bodie and Rosansky (1980) find that simply switching from a 100% stock portfolio to 60-40% stocks and commodities makes an investor better off by trimming off one third of the portfolio risk without sacrificing any return performance during the period 1950 to 1976. Similarly, Fortenbery and Hauser (1990) find that adding individual agricultural commodity futures into a well diversified stock portfolio does not enhance the return performance but does reduce risk. After adding commodities into an investment portfolio that consists of stocks, bonds, Treasury bills, and real estate, Jensen et al. (2000) report that the Markowitz optimization gives substantial weights towards commodities so that the portfolio's return is enhanced during restrictive monetary policy periods, but little or no weights during expansive monetary periods. Anson (1999) investigates the diversification contribution of commodities with respect to investors' risk tolerance, and finds that more risk averse investors gain higher utility from investing in commodity index funds than less risk

[8]Erb and Harvey also show that an 18-60-22% commodity-equity-bond portfolio yields much higher return than a traditional 60-40% equity-bond portfolio given the same level of volatility.

averse investors during 1974-1997. More recently, some researchers provide more supportive evidence at the levels of individual commodities and sub-sectors. For instance, Geman and Kharoubi (2008) document that WTI crude oil futures provide significant diversification opportunities to the S&P500 index from 1990 to 2006. You and Daigler (2012) confirm the diversification benefits of 39 commodity futures to traditional equity-bond portfolios in the period 1994-2010. Belousova and Dorfleitner (2012) document the heterogeneous diversification effects across five commodity sectors that energy and precious metals yield the highest value in both return enhancement and risk reduction, and agricultural, livestock and industrial metals only contribute to the risk reduction dimension. It is important to notice that the commodity-augmented portfolios in most of these studies are constructed using historical mean returns and sample variance/covariance structures and then evaluated within a MV or IS framework.[9]

On the other hand, other recent studies have challenged the alleged view by showing that including commodities in investors' portfolios adds little or no value, particularly, in an OOS assessment. The most recent and striking evidence is documented in Daskalaki and Skiadopoulos (2011), in which the authors conduct a comprehensive examination on the diversification value of the two most popular commodity indexes (S&P GSCI and DJ-UBSCI) and five individual commodity futures under four different specifications, namely the four cross-combinations of MV or non-MV investors and in- or OOS settings. They find that, after accounting for investors' preferences over higher-order moments, commodities only contribute to non-MV investors in the IS setting, but are not beneficial under any of the other specifications. Even though a large body of literature has suggested or directly confirmed the benefits of commodities in an IS setting, the reported results in Daskalaki and Skiadopoulos (2011) inevitably raise some concerns over the validity of such benefits in an OOS context. Some studies employ regression-based spanning tests to examine whether

[9]You and Daigler (2012) construct ex ante portfolios without infrequent rebalancing and evaluate their performance based on efficient frontiers and the Sharpe ratios within a MV framework; Belousova and Dorfleitner (2012) consider non-normal returns, but the performance evaluation is based on IS statistical spanning tests.

investing in commodities indexes or individual futures improves the MV efficient frontier of benchmark portfolios within a MV and IS framework, and fail to find any value.[10] [See Cao, Jayasuriya, and Shambora (2010), Galvani and Plourde (2010) and Nijman and Swinkels (2008).] Another concern on the diversification value of commodities comes from the recent debate on the pattern of increasing correlation between commodity and stock returns since the crash of financial markets in 2007.[11] Investigating the causes of such phenomena goes beyond the scope of this paper. Nevertheless, the observed rising commodity-equity correlation is certainly of investors' concern, as it could hurt the risk diversification value of commodities, and thus, in turn, would have influence on their optimal portfolio selection. Therefore, it is interesting to re-examine the diversification role using updated data during the post-crisis period.

To summarize, despite the fact that investing in commodities has become popular in recent years and that a large number of academic studies have looked into its potential benefits in improving portfolio performance, there have been thus far mixed answers to the question of whether commodities add value in multi-asset allocation exercises, particularly and more importantly, OOS. To explore the economic value of commodities in portfolio allocation, this paper sets out to better account for the dynamic nature of asset return moments than previously done in the literature.

1.3 Extensions of Existing Approaches

In this study, we extend the existing literature on the role of commodities in multi-asset allocation along several dimensions. Firstly, the predictability of commodity returns has been largely neglected by researchers. Instead, all prior studies rely on sample means of

[10] It is worth noting that these studies rely on the outcomes of statistical spanning tests. However, there has been a debate on "statistical" vs. "economical" significance for spanning tests. See Glabadanidis (2009) and Kan and Zhou (2012) for detailed discussion.

[11] See Domanski and Heath (2007), Hamilton (2008), Smith (2009), Tang and Xiong (2010), Chong and Miffre (2010), Büyükşahin and Robe (2010) and Kilian and Murphy (2010) for the debate.

historical returns as the estimates for future expected returns.[12] To the best of our knowledge, this is the first study that explicitly takes into account commodity return predictability in forming optimal portfolios that incorporate multiple asset classes.[13] Secondly, previous studies exclusively rely on static or rolling/expanding covariance estimators to derive optimal portfolio rules. Instead, we explicitly consider the dynamics of covariance structures of commodities and other asset classes in the portfolio optimization problem. The combined analysis of predictable first and second moments for portfolio allocation is typically absent from previous studies, whether or not considering commodities. Thirdly, the asset allocation exercises involving commodities have been almost always conducted within the classic Markowitz MV framework. As we will detail below, commodity returns exhibit negative skewness and substantial leptokurtosis, making problematic the reliance on first and second moments only when implementing and evaluating portfolio strategies. In addition to the MV case, we also conduct the analysis in a non-MV context by incorporating higher-order moments of asset returns whose significance and time variation are well documented in the literature.[14] Lastly, the results of existing studies that support the inclusion of commodities into a stock-bond portfolios are exclusively based on an IS assessment. However, there have been legitimate concerns about the OOS validity, which motivates our analysis in an OOS context.[15] In this paper we exclusively rely on an OOS performance evaluation.

[12]Bodie and Rosansky (1980), Fortenbery and Hauser (1990), Jensen et al. (2000), Anson (1999) and Belousova and Dorfleitner (2012) all employ constant historical estimators; Daskalaki and Skiadopoulos (2011) use rolling-sample based estimator.

[13]Erb and Harvey (2006) simply assume a set of forward-looking commodity futures index returns for demonstrating purposes only.

[14]The studies that document the impact of higher moments of asset returns in asset allocation context include Harvey and Siddique (1999), Ang and Bekaert (2002), Timmermann (2006) and Jondeau and Rockinger (2006, 2012).

[15]Daskalaki and Skiadopoulos (2011) perform both in- and out-of-sample tests, and, as noted above, they find commodities add no value to investors OOS. See also Welch and Goyal (2008) for related concerns on IS evaluations of return predictability.

1.3.1 Predictable Commodity Returns

In principle, expected returns, as one of the crucial inputs to the portfolio optimization problem, should be forward-looking. In practice, as demonstrated in Timmermann and Blake (2005), sophisticate investors indeed forecast time-varying future investment opportunities and invest accordingly. The theoretical work by Merton (1971, 1973) implies that return predictability could have significant impact on investors' optimal portfolio choices. Motivated by the theoretical implication and the overwhelming empirical findings on stock return predictability, a number of studies show that such predictability, even if statistically weak, could lead to significant economic gains, if exploited by investors who allocate wealth in equity markets. [See Solnik (1993), Pesaran and Timmermann (1995), Rapach, Strauss, and Zhou (2010), and Cenesizoglu and Timmermann (2012) among many others.]

In commodity space, several (mostly, recent) studies have also documented the IS and OOS return predictability by a collection of variables at both individual commodity and broad index levels. Bessembinder and Chan (1992), Bakshi, Panayotov, and Skoulakis (2011), Gargano and Timmermann (2014), Hong and Yogo (2012) and Chen, Rogoff, and Rossi (2010) are prominent examples.[16]. All previous studies investigating the value of commodities in asset allocation tend, however, to use sample or rolling/expanding averages as estimates for future expected returns without taking account their time-varying characteristics. Hence, it seems important to investigate the economic value of commodity return predictability in portfolio selection.

[16] The general rationale is that these variables contain information about the anticipation of future economic activity, which in turn drives the movements in commodity prices in future. We detail the exhaustive list of predictive variables in Section 6.1.

1.3.2 Predictable Volatility and Correlations

It is now widely agreed that the covariance structure of asset returns vary substantially across assets, asset classes, countries, time periods, market conditions and business cycles.[17] Particularly, Chong and Miffre (2010) and Büyükşahin et al. (2010) document the large variation in commodity-equity correlations at both index and individual futures levels over time, which, in turn, implies time-varying diversification benefits of commodities for traditional equity-bond investors. Some researchers have examined the impact of covariance dynamics on portfolio strategies without considering commodities, and find that it yields substantial economic gains (loss) for investors who account for (ignore) the dynamics of covariance structures. For example, Fleming, Kirby, and Ostdiek (2001, 2003) demonstrate that volatility predictability in stock markets would be worth 50-200 bps per year for an investor who allocates her wealth in the S&P500 index, Treasury bonds and gold futures. Della Corte, Sarno, and Tsiakas (2012) find substantial economic value in timing correlations in addition to the gains from volatility timing in FX markets. Engle and Colacito (2006) theoretically and empirically show that, keeping other conditions constant, the economic loss of stock-bond portfolio performance could be as high as 40% of return if a static correlation specification is assumed but the true structure is dynamic.

Given the empirical evidence on time-varying covariance highlighted in the data and the economic significance of dynamic covariance modeling, it is somewhat surprising that all previous studies evaluating the value of commodities in asset allocation fail to take into account the dynamic nature in the OOS portfolio analyses. Hence, another question this paper aims to address is whether capturing such covariance dynamics between commodities and other assets adds OOS economic value for investors.

[17] See Erb, Harvey, and Viskanta (1994), Longin and Solnik (1995), Ball and Torous (2000), Ang and Bekaert (2002), Moskowitz (2003), Goetzmann, Li, and Rouwenhorst (2005), and Cappiello, Engle, and Sheppard (2006) for international and U.S. equities and bonds; Büyükşahin, Haigh, and Robe (2010), Chong and Miffre (2010) for commodities and stocks; Huang and Zhong (2010) for commodities, real estate and TIPS.

1.3.3 Predictable Skewness and Kurtosis

One of the inadequacies of the classic Markowitz portfolio theory and its empirical implementations is its inability to handle higher-order moments of the return distribution. However, it seems reasonable to assume that risk averse investors favor positive skewness and low kurtosis in asset returns.[18] Moreover, there exists overwhelming empirical evidence suggesting that financial asset returns exhibit excess skewness and kurtosis rather than normality.[19] Gorton and Rouwenhorst (2006), Erb and Harvey (2006) and Gorton, Hayashi, and Rouwenhorst (2012) all report that monthly return distributions of commodity futures indexes and individual futures have pronounced skewness and excess kurtosis during the periods of 1959-2004, 1982-2004 and 1971-2010, respectively. At weekly frequency, the results are mixed. You and Daigler (2010) report 55% of 20 commodity futures have positive skewness during the 1992-2006 period. At daily frequency, Eastman and Lucey (2008) show that the returns of 14 futures are all negatively skewed except the 10-year notes. In summary, the skewness and kurtosis of commodity returns are well pronounced in the data although sensitive to data frequencies.

Several studies find that risk averse investors do adjust optimal portfolio weights accordingly to time-varying skewness and kurtosis in stock returns, and that portfolio strategies accounting for the dynamics of higher-order moments leads to economically significant gains.[20] However, the literature has been extremely skewed towards the impact of higher moments in optimal allocations within equity markets. There has been very limited exploration on whether these findings in equity markets are preserved in other asset classes, in particular, commodities.[21] Given the presence of excess skewness and kurtosis in commodity return data, another goal of this study is to analyze the economic value of predicting higher-order

[18] Scott and Horvath (1980) establish the fact that investors prefer odd moments and are averse to the even ones. Harvey and Siddique (2000) and Dittmar (2002) offer the empirical evidence.

[19] E.g., see Ang and Bekaert (2002) for the evidence in equity markets.

[20] See Bekaert, Erb, Harvey, and Viskanta (1998), Patton (2004), Jondeau and Rockinger (2006), Guidolin and Timmermann (2008) and Harvey, Liechty, Liechty, and Müller (2010), among others.

[21] Daskalaki and Skiadopoulos (2011) and You and Daigler (2010) are exceptions.

moments and co-moments of commodity and other assets returns in an OOS asset allocation context.[22]

1.4 The Asset Allocation Problem

We consider a risk-averse investor with a constant relative risk aversion (CRRA) utility function[23]:

$$U(W_{t+1}) = \frac{W_{t+1}^{1-\gamma}}{1-\gamma} \tag{1.1}$$

where W_{t+1} denotes the investor's wealth level at time $t+1$, and γ ($\gamma > 0$ and $\gamma \neq 1$) is the coefficient representing the investor's degree of risk aversion. At each time t, the investor chooses the portfolio weight vector $\omega_t \in \mathbb{R}^{N+1}$ to maximize her one-period-ahead expected utility $E_t[U(W_{t+1})]$ by trading N risky assets and a risk-free asset.[24] Following much of the asset allocation literature, we rule out short-selling (i.e., negative portfolio weights). We also impose constraints on total portfolio leverage in order to avoid implausible positions, similarly to, e.g., Campbell and Thompson (2008) and Marquering and Verbeek (2004). The

[22] Admittedly, any sophisticated asset allocation models that either account for time-varying and state-dependent properties or introduce higher moments raises the concerns of overfitting. In the present study, the issue appears to be of a less concern as we focus on out-of-sample evidence.

[23] Within the CRRA family, power utility implies that absolute risk aversion is declining in wealth, while relative risk aversion is a constant. Relying on introspection Campbell and Viceira (2003) point out that, in a plausible portfolio choice model, absolute risk aversion should decline or, at the very least, should not increase with wealth, while relative risk aversion should be independent of wealth: this rules out quadratic utility and favors power utility over exponential utility.

[24] As most academic studies in asset allocation focus on solving recursive myopic portfolio optimization problems [see, for example, DeMiguel, Garlappi, and Uppal (2009), Daskalaki and Skiadopoulos (2011) and Cenesizoglu and Timmermann (2012).], and given that industry practice is also, by and large about tackling one-period problems, as illustrated by Brandt (2009a), we leave the dynamic portfolio choice analysis for a future study.

initial wealth is normalized to one. Formally, the investor's problem is

$$\begin{aligned}
\max_{\omega_t} \; & E_t[U(W_{t+1})] = E_t[\frac{(1+r_{p,t+1})^{1-\gamma}}{1-\gamma}] \\
\text{s.t.} \quad & \sum_{i=1}^{N} \omega_{i,t} - 1 \leq h \\
& \omega_{0,t} = \sum_{i=1}^{N} \omega_{i,t} - 1 \\
& \omega_{i,t} \geq 0, i = 1, \ldots, N
\end{aligned} \tag{1.2}$$

where $r_{p,t+1}$ is portfolio return at time $t+1$, $\omega_t = [\omega_{0,t}, \omega_{1,t}, \cdots, \omega_{n,t}]'$ denotes the portfolio weight vector at time t. In particular, $\omega_{0,t}$ denotes the weight on the risk-free asset, $\omega_{i,t}$ ($i = 1, \cdots, N$) is the fraction of wealth in the i^{th} risky asset and h denotes the maximum leverage (e.g., $h = 0.5$ indicates that the investor cannot borrow more than 50% of her total wealth.).

Since with power utility there is no closed form solution to the constrained optimization problem, we follow, among others, Jondeau and Rockinger (2012) and Guidolin and Timmermann (2008), and write the expected utility in equation (1.2) as an infinite-order Taylor series expansion around the wealth at time $t+1$:

$$E_t[U(W_{t+1})] = \sum_{k=0}^{\infty} \frac{U^{(k)}(W_{t+1})}{k!} m_{p,t+1}^{(k)} \tag{1.3}$$

where $U^{(k)}$ denotes the kth derivative of the utility function, and $m_{p,t+1}^{(k)} = E_t[r_{p,t+1}^k]$ is the kth non-central moment of expected portfolio returns. This k-moment framework is economically appealing and mathematically tractable.[25] As detailed below in Sections 1.4.2 and 1.4.1, the Taylor expansion allows one to make (approximate) expected utility an explicit function of selected moments of asset returns. To relate our analysis to the extant literature we consider

[25]See Garlappi and Skoulakis (2011) for a thorough analysis and theoretical foundations for using the Taylor expansion of expected utility.

the Taylor series expansion up to the second order ($k = 2$) for MV investors in Section 1.4.1 and the fourth ($k = 4$) for non-MV investors in Section 1.4.2.

1.4.1 The MV Case

The MV investor's expected utility is approximated by the Taylor series expansion as in Eq.(1.3) with $k = 2$:

$$E_t[U(W_{t+1})] \approx \phi_0 + \phi_1 m^{(1)}_{p,t+1} + \phi_2 m^{(2)}_{p,t+1} \tag{1.4}$$

where $\phi_0 = \frac{1}{1-\gamma}$, $\phi_1 = 1$, $\phi_2 = -\frac{\gamma}{2}$ are constant for given γ, and $m^{(1)}_{p,t+1}$ and $m^{(2)}_{p,t+1}$ are, respectively, the first and second non-central moments of expected portfolio returns, which, in turn, can be expressed as the functions of the expected return and variance of portfolio returns as:

$$\begin{aligned} m^{(1)}_{p,t+1} &= \mu_{p,t+1} = \omega_t' \mu_{t+1} \\ m^{(2)}_{p,t+1} &= \sigma^2_{p,t+1} + \mu^2_{p,t+1} = \omega_t' \Sigma_{t+1} \omega_t + \mu^2_{p,t+1} \end{aligned} \tag{1.5}$$

where $\mu_{t+1} \equiv E_t[r_{t+1}] \in \mathbb{R}^N$ the expected return vector, $\Sigma_{t+1} \equiv E_t[(r_{t+1} - \mu_{t+1})(r_{t+1} - \mu_{t+1})'] \in \mathbb{R}^{N \times N}$ is the covariance matrix of N risky assets.

Thus, to obtain the optimal weights ω_t^*, the MV investor needs to numerically maximize her expected utility defined in Eq.(1.4) with the estimates of μ_{t+1} and Σ_{t+1} as inputs. As mentioned above, in our study we consider two types of strategies: (i) the BWD strategy, relying on the sample moment estimators up to time t, $\bar{\mu}_{t+1|t}$ and $\bar{\Sigma}_{t+1|t}$; (ii) the FWD Strategy, employing the estimators computed using richer conditioning information sets and models up to time t, $\hat{\mu}_{t+1|t}$ and $\hat{\Sigma}_{t+1|t}$. As it is straightforward to compute the estimators for the BWD strategy, we only detail the implementation of FWD strategies in the following sections.

1.4.1.1 Forecasting Returns

We follow, among others, Rapach et al. (2010) and employ the forecast combination method to produce one-period-ahead OOS excess return forecasts for each asset class.[26] The general rationale for using a forecast combination is that forecasts based on individual predictors could suffer from model mis-specification and instability, whereas combining the individual forecasts could exploit the valuable information carried by each predictor and, at the same time, achieve benefits from forecast diversification. For each risky asset, we use the following linear model to produce the one-period-ahead OOS forecasts for excess return r_{t+1} at time $t+1$:

$$r_t = \alpha_i + \beta_i x_{i,t-1} + \varepsilon_{i,t}; \qquad \text{where} \quad i = 1 \cdots K \tag{1.6}$$

$$\hat{r}_{i,t+1|t} = \hat{\alpha}_{i,t} + \hat{\beta}_{i,t} x_{i,t} \tag{1.7}$$

$$\hat{r}^{comb}_{t+1|t} = \frac{1}{K} \sum_{i=1}^{K} \hat{r}_{i,t+1|t} \tag{1.8}$$

where $x_{i,t-1}$ is the ith predictor at time $t-1$, and K is the total number of predictive variables.

We first run the univariate predictive regression defined in Eq.(1.6) to produce the IS estimates for parameters $\hat{\alpha}_{i,t}$ and $\hat{\beta}_{i,t}$ using the conditional information up to time t. Next, we follow Eq.(1.7) to produce the next period OOS forecasts $\hat{r}_{i,t+1|t}$ using $\hat{\alpha}_{i,t}$, $\hat{\beta}_{i,t}$ and $x_{i,t}$. Thus, we have K individual return forecasts at each time t. Next, we combine the individual forecasts $\hat{r}_{i,t+1|t}$ across the K predictors with equal weights to obtain the combination forecast $\hat{r}^{comb}_{t+1|t}$.[27] Finally, we set $\hat{\mu}_{t+1|t} = \hat{r}^{comb}_{t+1|t}$. The IS predictive regression in Eq.(1.7) is based on an

[26] The forecast combination is originally pointed out by Bates and Granger (1969). Timmermann (2006) offers a comprehensive theoretical and empirical study on this method.

[27] Timmermann (2006) and Rapach et al. (2010) demonstrate the benefits of using equally weighted forecast combinations. Intuitively, using equal weights avoids an additional layer of estimation, which could potentially induce estimation error and thus deteriorate the OOS performance.

expanding procedure and only uses the information up to time t. To implement the forecast combination method, we employ a large set of predictive variables for each asset and detail them in Section 1.6.1.

We first use macroeconomic and market indicators widely adopted in the predictability literature. For robustness, we also use technical indicators to forecast returns, following the work of, among others, Neely, Rapach, Tu, and Zhou (2014) and Goh, Jiang, Tu, and Zhou (2013) that show how these indicators may be a valid complement to the more commonly used macro and market predictors for the equity risk premium. To incorporate information from the set of technical indicators, we follow Neely et al. (2014) and estimate predictive regressions based on principal components which we, then, aggregate using the forecast combination above. Appendix D details the procedure.

1.4.1.2 Forecasting the Covariance Matrix

We next detail the estimation of the other key input required in Eq.(1.5), namely the expected conditional covariance matrix Σ_{t+1}. We employ the Dynamic Conditional Correlation (DCC) model proposed by Engle (2002) to obtain the OOS forecasts of volatility and correlations of asset returns.[28] The DCC model offers a tractable and flexible multivariate framework to model the dynamics of conditional volatility and correlations. Essentially, the one-period ahead covariance matrix estimator can be decomposed as:

$$\hat{\Sigma}_{t+1|t} = \hat{D}_{t+1|t}\hat{P}_{t+1|t}\hat{D}_{t+1|t} \tag{1.9}$$

where $\hat{D}_{t+1|t}$ is an $N \times N$ diagonal matrix with conditional standard deviation $\hat{\sigma}_{i,t+1|t}$ on the i^{th} diagonal, and $\hat{P}_{t+1|t} = \{\hat{\rho}_{ij,t+1|t}\}$ is an $N \times N$ matrix with ones on the diagonal and conditional correlations off the diagonal. Given the decomposition, we can employ a two-

[28]The DCC model and its variations have been used by several studies in asset allocation context. For example, Billio, Caporin, and Gobbo (2006), Huang and Zhong (2010), Case, Yang, and Yildirim (2012) and Della Corte et al. (2012).

stage estimation procedure applied to the residuals from the forecast combination to obtain $\hat{\Sigma}_{t+1|t}$. In the first stage, we forecast each diagonal element ($\hat{\sigma}_{i,t+1|t}$) of $\hat{D}_{t+1|t}$ with a univariate asymmetric GARCH model for the forecast combination residuals. In the second stage, we standardize the residuals from the first stage by their conditional standard deviations and fit the standardized residuals into a multivariate GARCH model to obtain the one-period-ahead conditional correlation matrix $\hat{P}_{t+1|t}$. The estimation is based on an expanding estimation window and uses up-to-time-t asset return data only (i.e. no additional predictive variables). We detail the two-stage procedure in Appendix B.

1.4.2 The Non-MV (4-Moment) Case: Forecasting Higher Moments

Departing from the classic Markowitz paradigm, we next investigate the multiple asset class allocation problem faced by a non-MV investor, who takes into account the moments of the return distribution up to the fourth order. To capture the non-MV investor's preferences for the first 4 moments, we follow the literature[29] and approximate her expected utility using the fourth order Taylor series expansion as in Eq.(1.3) with $k = 4$:

$$E_t[U(W_{t+1})] \approx \phi_0 + \phi_1 m^{(1)}_{p,t+1} + \phi_2 m^{(2)}_{p,t+1} + \phi_3 m^{(3)}_{p,t+1} + \phi_4 m^{(4)}_{p,t+1} \tag{1.10}$$

where $\phi_0 = \frac{1}{1-\gamma}$, $\phi_1 = 1$, $\phi_2 = -\frac{\gamma}{2}$, $\phi_3 = \frac{\gamma(\gamma+1)}{6}$, $\phi_4 = -\frac{\gamma(\gamma+1)(\gamma+2)}{24}$ are constants for given γ, $m^{(1)}_{p,t+1}$ and $m^{(2)}_{p,t+1}$ are defined in Eq.(1.5), and $m^{(3)}_{p,t+1}$ and $m^{(4)}_{p,t+1}$ denote the third and fourth non-central moments of portfolio returns, which, as shown by Jondeau and Rockinger (2012), can be analytically expressed as functions of portfolio weights, expected returns, covariance, co-skewness and co-kurtosis of asset returns. The investor always favors the odd moments but dislikes the even moments, in accordance with the economic rationales

[29] See, among others, Harvey and Siddique (2000), Dittmar (2002), and Jondeau and Rockinger (2006, 2012).

suggested by Scott and Horvath (1980) and Dittmar (2002). To solve the 4-Moment portfolio optimization problem, the non-MV investor needs to maximize her utility defined in Eq.(1.10) with the estimates of the first 4 (co-)moments of asset returns. Notation wise, one needs to obtain estimators for $\{\mu_{t+1}, \Sigma_{t+1}, S_{t+1}, K_{t+1}\}$, where μ_{t+1}, Σ_{t+1}, S_{t+1} and K_{t+1} are expected returns, covariance, co-skewness and co-kurtosis matrices, respectively. Consistent with the implementation of the MV strategies, we consider two types of strategies in the 4-Moment case, namely the BWD with the (co)moment estimators $\{\bar{\mu}_{t+1|t}, \bar{\Sigma}_{t+1|t}, \bar{S}_{t+1|t}, \bar{K}_{t+1|t}\}$ and the FWD with the (co)moment estimators denoted by $\{\hat{\mu}_{t+1|t}, \hat{\Sigma}_{t+1|t}, \hat{S}_{t+1|t}, \hat{K}_{t+1|t}\}$. The estimators used in BWD strategies can be easily computed from sample return moments using information available up to time t. We have already introduced estimating $\hat{\mu}_{t+1|t}$ in Section 1.4.1. In estimating $\{\hat{\Sigma}_{t+1|t}, \hat{S}_{t+1|t}, \hat{K}_{t+1|t}\}$ we follow the procedure proposed by Jondeau and Rockinger (2009, 2012). We outline the entire procedure in Appendix C.

Armed with estimators from the BWD and FWD strategies we can numerically solve the non-MV investor's 4-Moment portfolio optimization problem for the optimal portfolio weights ω_t^*. By repeating this optimizing procedure at each time $t = \tau, \cdots, T-1$, we can obtain the optimal portfolio weights $\{\omega_t^*\}_{t=\tau,\cdots,T-1}$.

1.5 Trading Strategies and Performance Measures

1.5.1 Competing Strategies

Based on the considerations above, we implement the following strategies:

1. Backward-looking traditional asset strategy (BWD S-B): the investor allocates her wealth in Equity, Bond and Cash, and employs sample moments of returns computed on an expanding window as input to the optimization problem defined in Eq.(1.2).

2. Backward-looking commodity-augmented strategy (BWD S-B-C): the investor allocates her wealth in Equity, Bond, Commodity and Cash, and employs sample moments

of returns computed on an expanding window.

3. Forward-looking traditional asset strategy (FWD S-B): the investor allocates her wealth in Equity, Bond and Cash, and employs the forecasts of asset return moments illustrated in Sections 4.1 and 4.2.

4. Forward-looking commodity-augmented asset strategy (FWD S-B-C): the investor allocates her wealth in Equity, Bond, Commodity and Cash, and employs the forecasts of asset return moments illustrated in Sections 4.1 and 4.2.

5. Fixed-weight traditional asset strategy (FIX S-B): the investor rebalances her portfolio weights in Equity, Bond and Cash to predetermined weights [50%;40%;10%] at the beginning of each period. Noteworthy, the FIX strategy does not require the estimates of any moments of the return distribution.

6. Fixed-weight commodity-augmented strategy (FIX S-B-C): the investor rebalances her portfolio weights in Equity, Bond, Commodity and Cash to predetermined weights [50%; 30%;10%; 10%] at the beginning of each period.[30]

Following much of the asset allocation literature, we rule out short-selling and impose constraints on total portfolio leverages (which is defined as the percentage of debt in total portfolio value). Specifically, we report the empirical results based on five levels of leverage ranging from 0 to 100%.[31] Also following the extant literature, we consider alternative levels of the relative risk aversion coefficient, $\gamma = 3, 5, 10$, which respectively represent low, moderately and highly risk averse investors.[32]

[30]We analyze these fixed-weight strategies as several studies have documented how they may outperform more sophisticated schemes. In addition, the simple rebalancing to fixed weights is rather common in industry practice. Similarly, our choice of the actual fixed weights reflect benchmarks commonly used in the literature, and/or average portfolio allocations reported by industry surveys, as referenced in our Introduction. See Chaves, Hsu, Li, and Shakernia (2011) for an additional summary reference,

[31]As a point of reference, Ben-David, Franzoni, and Moussawi (2012) find that the mean leverage for hedge funds is 79% during the period of 2004-2009.

[32]Even though the asset pricing literature and, in particular, the equity-premium "puzzle" literature has not yet agreed upon a commonly accepted estimate of the coefficient of relative risk aversion, many studies suggest that plausible values could be ranging from as low as 0.1 to about 10. See, among others, Mehra and Prescot (1985), Mankiw (1985), Friend and Blume (1975) and Gordon and St-Amour (2004).

1.5.2 Performance Measures

We employ the CRRA Utility-based Certainty Equivalent Excess Return (CEQ)[33] net of transactions costs and the Portfolio Turnover (TO) to evaluate the OOS economic performance of the competing strategies specified in Section 1.5.1. CEQ for a given strategy is defined as the riskless return an investor is willing to accept instead of facing the uncertain return generated by such strategy. We focus on CEQ rather than other metrics, such as the Sharpe Ratio (SR) for two main reasons. First, while well suited within a world of IID Gaussian returns, the SR may generate misleading conclusions when applied to predictability-based strategies that exploit time variation in investment opportunities (see Farinelli and Tibiletti (2008)). As noted by Bianchi and Guidolin (2013), with predictable returns and CRRA utility, one cannot generally approximate preferences as mean-variance objectives: hence, a higher SR yielded by any given strategy does not necessarily imply an increase in the investor's welfare, especially if this is achieved by altering the higher-order moments of portfolio returns away from what they should be under multivariate Gaussian returns. Second, the SR is independent of portfolio leverage [see Kan and Zhou (2007)]: as a result, a sub-optimal weight in the risk-free asset does not affect the SR.

Specifically, the CRRA utility-based CEQ during the OOS evaluation period $[\tau + 1 : T]$ is computed as:

$$\text{CEQ}_{\tau+1:T} = [(1-\gamma)\bar{U}_{\tau+1:T}(W_t)]^{\frac{1}{1-\gamma}} - 1 \tag{1.11}$$

where $\bar{U}_{\tau+1:T}(W_t)$ denotes the average realized CRRA utility.[34]

We follow DeMiguel et al. (2009) to compute the Portfolio Turnover (TO) as a measure of the amount of trading required to implement a particular strategy. For any strategy, TO is

[33] CEQ has been widely adopted as a reliable measure in the asset allocation literature. Examples are, among others, Kandel and Stambaugh (1996), Campbell and Viceira (1999), Ang and Bekaert (2002), Campbell and Thompson (2008) and Rapach et al. (2010) and Cenesizoglu and Timmermann (2012).

[34] The difference of two CEQ's can be interpreted as the Performance Fee, the premium that needs to be added to the benchmark portfolio excess return so that the investor becomes indifferent between the competing and the benchmark portfolio. [See, e.g., Fleming et al. (2001) and Patton (2004)]. Given the simple relationship between Performance Fee and CEQ, we only consider CEQ in our studies.

defined as the average absolute change in the weights across the N assets (N=2 for S-B; N=3 for S-B-C) over the $T-\tau-1$ rebalancing dates in time. Essentially, the TO is calculated as:

$$TO_{\tau+1:T} = \frac{1}{T-\tau-1}\sum_{t=\tau}^{T-1}\sum_{j=1}^{N}(|\omega_{j,t+1} - \omega_{j,t^+}|) \tag{1.12}$$

where $\omega_{j,t+1}$ is the desired portfolio weight in asset j at time $t+1$; ω_{j,t^+} is the portfolio weight in asset j before rebalancing at time $t+1$.

As the FWD strategies tend to generate higher portfolio turnover than the BWD ones, we follow, among others, DeMiguel et al. (2009) and include an estimate of transaction costs for all the strategies. We set the proportional transaction cost equal to 50 bps for trading each asset class index.[35]

When a portfolio of N assets is rebalanced at time $t+1$, the magnitude of trading asset j is $|\omega_{j,t+1} - \omega_{j,t+}|$. Given a proportional transaction cost c, the trading cost of the entire portfolio is $c \cdot \sum_{j=1}^{N}|\omega_{j,t+1} - \omega_{j,t+}|$. Therefore, we can write the portfolio return net of transaction cost as

$$r^{net}_{p,t+1} = (1 + r_{p,t+1})(1 - c \cdot \sum_{j=1}^{N}|\omega_{j,t+1} - \omega_{j,t+}|) - 1 \tag{1.13}$$

where $r_{p,t+1} = \sum_{j=1}^{N} r_{j,t+1}\omega_{j,t}$ is the portfolio return with zero transaction cost.

1.6 Data and Descriptive Statistics

1.6.1 Data

We use major monthly and quarterly total return indexes for the following three asset classes: U.S. Equity, U.S. Bond and Commodity. Specifically, the equity class is proxied by the S&P500 Total Return Index over the period 1946/01 - 2012/12. The bond class is measured

[35] DeMiguel et al. (2009) assume 50 bps per transaction based on the studies for individual stocks on the NYSE by Stoll and Whaley (1983), Bhardwaj and Brooks (1992) and Lesmond, Ogden, and Trzcinka (1999). Daskalaki and Skiadopoulos (2011) assume 50 bps transaction cost for stock and bond indexes and 35 bps for commodity index based on their discussion with practitioners in the commodity markets.

by the Barclays Capital U.S. Aggregate Bond Index (Bond) from 1976/01 to 2012/12. The Bond index (previously known as Lehman Brother Aggregate Bond Index) is a broad-based benchmark that measures the investment grade, U.S. dollar-denominated, fixed-rate taxable bond market, including most Treasury, agency, corporate, mortgage-backed, asset-backed, and international dollar-denominated issues, all with maturities of 1 year or more.[36] The commodity class is represented by the S&P Goldman Sachs Commodity Total Return Index (GSCI) from 1970/01 to 2012/12. GSCI is a world-production weighted total return index and consists of 24 commodity futures on physical commodities across five sectors: energy, agriculture, industrial metals and precious metals.[37] The reason we consider GSCI as our base case instead of alternative commodities indexes or individual futures is two-folds: first, GSCI is by far the leading fully collateralized investable commodity index followed by a number of exchange-traded products and also has the longest data history on Datastream; second, a majority of professional asset managers choose to gain their exposure to commodities through investment vehicles such as ETFs, ETNs and mutual funds, which are index-based passive investment strategies.[38] [39] We use the 30-day U.S. Treasury Bill as the proxy for cash.

We collect a comprehensive set of predictive variables that have been previously relied on by the literature when forecasting monthly and quarterly aggregate index returns.[40] In what follows, we detail the predictors for each asset class.

Commodity. In general, the variables we use to forecast the returns of GSCI can be

[36]For detailed description, please refer to the factsheet at `https://ecommerce.barcap.com/indices/show?url=Home/Guides_and_Factsheets`.

[37]GSCI's factsheet is available at `http://us.spindices.com/index-family/commodities/sp-gsci`.

[38]According to Morningstar & Barron's Alternative Investment Survey 2011, over 60% of institutional investors choose commodity ETFs, ETNs and mutual funds as their primary vehicles to access the commodity investment.

[39]Specifically, the GSCI Total Return index measures a fully collateralized commodity futures investment that is rolled forward from the fifth to the ninth business day of each month. Its characteristics make it fully investable without any trading in physical commodities. On the other hand, its return may differ significantly from what yielded by trading the physicals.

[40]We attempt to be as comprehensive as possible within the set of predictive variables, rather than arbitrarily selecting a few predictors from previous studies. Together with the forecast combination method for expected returns (see Section 1.4.1.1 above), this strategy aims to limit the impact of model mis-specification and the concerns of data mining.

categorized into two sets: macroeconomic and commodity-specific. The macroeconomic set includes the long-term bond return, the default spread, the growth of industrial production, the money supply growth, the unemployment rate, the growth rate of Baltic Dry Index (BDI) and the levels of real economic activity. [See Bessembinder and Chan (1992); Bakshi et al. (2011); Gargano and Timmermann (2014).] The general rationale is that these economic variables contain information on the anticipation of future economic activity, which in turn drives the movements in commodity prices. Another set of predictive variables is commodity-specific and include the growth in commodity market interest, the commodity futures-cash basis and the changes in "commodity currency" exchange rates. [See Hong and Yogo (2012); Fama and French (1987); Chen et al. (2010).] Hong and Yogo (2012) find that the growth in total open interest can predict aggregate commodity returns, as the growth signals higher hedging demand and, consequently, increasing commodity prices.[41] Motivated by the Theory of Storage, Fama and French (1987) show that the basis has predictive power for commodity returns. Chen et al. (2010) find that the currency exchange rates of five major commodity exporting countries ("commodity currencies") can forecast aggregate commodity price indexes in- and out-of-sample, because the exchange rates are strongly forward-looking and convey information about expected future commodity price shocks.

Bond. Motivated by Campbell and Shiller (1991), Cochrane and Piazzesi (2005) and Ludvigson and Ng (2009), we collect three sets of variables to forecast the Bond returns: financial factors, real factors and stock market factors. The financial set includes the forward spreads and the yield spreads of 1- to 5-year U.S. Government bonds. The real factors are the NAPM Employment Index levels, the growth rate of Non-farm payroll employment, the changes of Capacity Utilization - Manufacturing, the PMI Composite Index, the levels of Manufacturing New Orders Index, the growth in Producer Price Index. The stock market factors include the S&P500 return and the first difference in dividend/price ratio.

Stock. We collect the predictors for S&P500 directly from Welch and Goyal (2008), who

[41] We download the data from the author's web site at `https://sites.google.com/site/motohiroyogo/home`.

provide a detailed description of the data in their paper.[42] We also include one additional variable, the VIX from the Chicago Board Option Exchange, which is often relied on as a gauge of investors general sentiment within predictive regressions as in, e.g., Baker and Wurgler (2007).

As mentioned in section 1.4.1.1 we also rely on indicators from technical analysis to generate expected returns. The specific technical predictors and their construction is detailed in Appendix D.

Other than the data directly from original authors, we compile other data from various sources, including Datastream, CRSP, St. Louis Federal Reserve Economic Database and the data libraries on Ken French's website. The Data Appendix reports the time span and the source for each series.

1.6.2 Descriptive Statistics

Table 1 shows the summary statistics for monthly and quarterly excess returns of the three asset class indexes. All return series are aligned for the period 1976/01 - 2012/12, during which returns on all three assets are available.

Panel A reports the statistics for monthly returns. We can see that Bond has the lowest mean monthly excess return (0.24%) and also the smallest standard deviation of 1.61%, exhibits positive skewness (0.20) and the most extreme excess kurtosis (5.96). SP500 has a moderate mean return (0.27%) and standard deviation (4.38%), and exhibits the most negative skewness (-0.59) and the least excess kurtosis (1.99). Commodity has the highest mean monthly excess return of 0.30% and a high standard deviation (5.55%), and distributes with negative skewness (-0.21) and a moderate excess kurtosis (2.24). Turning to the unconditional correlations, we find that the monthly return of GSCI is weakly positively correlated with Equity (0.18), but uncorrelated with Bond (-0.02). This is in consistent with the findings in Gorton and Rouwenhorst (2006) and Erb and Harvey (2006), making commodities

[42] The description and data set are available at `http://www.hec.unil.ch/agoyal/`

potentially value adding to traditional asset portfolios.

Panel B presents the statistics of the three asset excess return at quarterly frequency. The findings are comparable to those in the monthly panel.

[Table 1]

1.7 Empirical Results

In this section, we report and compare the OOS performance of the portfolio strategies specified in Section 1.5.1 along several dimensions. First, we focus on the comparisons of S-B vs. S-B-C: these represent our baseline results. Second, for both S-B and S-B-C, we decompose the gains induced by switching from BWD to FWD strategies. As a special case of the comparison between BWD and FWD strategies we investigate the role of technical indicators in forecasting asset returns. Last, we conduct sub-period analyses and several additional robustness checks.

1.7.1 S-B vs. S-B-C

Tables 2 through 5 report the performance metrics, annualized CEQs net of 50 bps of proportional transactions costs and TO, for the monthly (Tables 2 and 4) and quarterly (Tables 3 and 5) rebalanced S-B and S-B-C strategies evaluated based on MV (Tables 2 and 3) as well as non-MV (Tables 4 and 5) preferences. Across the columns we report figures for different levels of the constraint on the highest allowed portfolio leverage: Lev $<$ 100% , Lev $<$ 75%, Lev $<$ 50%, Lev $<$ 25% and Lev = 0. Across panels we present the figures for three levels of investor's relative risk aversion: 3, 5 and 10. Within each panel we compare the S-B and S-B-C trading strategies under three portfolio formation approaches: FIX, BWD and FWD.

Table 2 shows two main results. First, across all levels of risk aversion and leverage, the MV investor would not favor adding Commodity to the traditional Stock-Bond portfolio *if* she followed a rebalancing to fixed-weights strategy or a BWD strategy: the S-B-C strategies consistently underperform the S-B and the FIX ones in CEQ terms. For instance, a moderately risk-averse MV investor (i.e. $\gamma = 5$), with a 50% leverage constraint and who does not account for the predictability of first and second asset return moments and, instead, forms allocations based on expanding sample moments of returns, would like to pay up to 37 bps per year to drop Commodity from her Stock-Bond portfolio. The same qualitative consideration applies across alternative levels of risk aversion and leverage. This important result is fully consistent with the findings and conclusions in Daskalaki and Skiadopoulos (2011) who also employ the BWD strategies for their OOS analysis. Second, and most importantly for our study, when relying on FWD forecasting the commodity-augmented strategies dominate the traditional asset ones across all leverage constraints and all levels of risk aversion. As an intermediate case, the MV investor with $\gamma = 5$ and a 50% maximum leverage would have paid up to 84 basis points a year after transactions costs to switch from the S-B to the S-B-C allocation, A less risk-averse investor ($\gamma = 3$ and leverage up to 75%) would have paid up to 119 basis points. More generally, the spread in favor of S-B-C tends to increase with leverage and to decrease with risk aversion. At one extreme, with $\gamma = 3$ and 100% leverage, the investor would have earned an additional 142 annual basis points from adding the exposure to GSCI. At the other end of the spectrum, a very risk-averse MV investor ($\gamma = 10$) with no ability to leverage at all her portfolio would have paid a more modest 39 basis points for switching to S-B-C. In facts, the performance of all BWD and FWD strategies, whether or not they include commodities, follows this pattern. A Stock-Bond portfolio would have earned a relatively low risk-averse investor 119 more basis points with a 50% leverage than with no leverage.

It is also worth noting that implementing FWD strategies does lead to a substantially higher portfolio turnover. On average, FWD strategies need to rebalance between about 10 and 31% of wealth each month, approximately 5-10 times as much as the BWD and FIX ones do. This is to be expected as the forecasts based on predicting time-varying moments is much more volatile than what yielded by the simpler moment estimators computed on an expanding window. Remember, however, that all CEQs are computed net of transactions costs: it, hence, appears that the increased turnover and associated transactions costs are more than compensated by an improved risk-return trade-off from the S-B-C allocation.

[Table 2]

Table 3 reports the results of portfolio strategies with quarterly rebalancing, still from the perspective of an MV investor. Across alternative risk aversions and leverages, the performance of FIX strategies is very comparable to what observed with monthly rebalancing in Table 2: as a result, an MV investor relying on those strategies would not have wanted to include commodities on top of her equity-fixed income allocation. A similar implication emerges from the performance of the BWD strategies: the third and fourth rows of each panel show that the investor with moderate to high risk aversion would have been essentially indifferent between S-B and S-B-C, while the relatively less risk-averse investor would have paid up to 63 basis points to avoid the S-B-C allocation. Turning to the FWD strategies, though, we confirm that key result that S-B-C outperforms S-B by economically large margins. For example, a moderately risk averse investor with a 50% leverage constraint would be willing to pay up to 108 bps per year in order to adopt the commodity-augmented strategies instead of the traditional Stock-Bond ones. Again, FWD strategies require substantially higher turnover than BWD ones: 2-5 times more on average, as the latter require a turnover of only 4-5% per quarter, while the former need 15-20% turnover even for the more conservative investors ($\gamma = 5$ and $\gamma = 10$) Still, the FWD forecasts generate sizable economic gains for S-B-C, overcoming the transactions costs.

[Table 3]

Next, we turn to the results for non-MV investors, who take into account co-skewness and co-kurtosis of asset returns while constructing their multi-asset portfolios. Table 4 (Table 5) reports the comparisons between monthly (quarterly) rebalanced allocations. As we can see from both tables, under FIX and BWD strategies S-B-C underperforms S-B across all leverages and levels of risk aversion, which is consistent with the results for MV investors and with results in the extant literature. Once more, though, S-B-C significantly outperform S-B when the predictability of time-varying return moments is accounted for in portfolio formation. In the intermediate case of $\gamma = 5$ and 50% leverage (see Tables 4 and 5, Panel B), an investor rebalancing quarterly (monthly) would have paid up to 155 (72) bps per year after transaction costs to add the Commodity exposure. Accounting for higher moments of returns coupled with the FWD strategies appear to amplify the relative benefits of including commodities into a stock-bond portfolio, especially with quarterly rebalancing. Even with high risk aversion and low leverage (Table 5, Panel C) the investor would have still added about 80 bps per year in CEQ terms. With low risk aversion (Table 5, Panel A), the spread for S-B-C over S-B would have reached a very meaningful range of 200 to 230 annualized basis points. While confirming the findings of Jondeau and Rockinger (2012) that an investor can benefit from timing the dynamics of higher return moments, our results show that this is especially valuable when a commodity exposure is part of the asset allocation decision.

[Table 4]

[Table 5]

In summary, based on the multi-dimensional comparisons of the performance of S-B-C vs. S-B and FIX for both MV and non-MV investors, we find solid evidence that adding Commodity into Stock-Bond portfolios leads to material economic gains. The improvement, though, crucially depends on estimating the future dynamics of returns, volatilities, correlations, co-skewness and co-kurtosis based on a FWD framework: if investors construct their portfolios using FIX or BWD strategies the utility gains stemming from the commodity exposure appear to be lost.

1.7.2 Decomposing the Economic Gains

Given the important differences that arise from comparing S-B and S-B-C under the BWD and FWD approaches, it is natural to investigate the sources of such differences. In particular, since existing empirical studies on asset allocation do not typically consider first and second moment jointly when relying on FWD forecasts, we ask whether the benefits stemming from such forecasts are due to both the expected returns and the covariance matrix predictions or whether one of the two is the main driver of the improvement relatively to the BWD approach.[43] A related question is what dimension of the investor's utility function the economic gains induced by the FWD approach originate from. For the MV investor we ask whether the utility gains come primarily from a higher average portfolio return or from a lower portfolio volatility. For the non-MV investor we also ask how the BWD and FWD approaches differ in terms of generating portfolio skewness and kurtosis.

Table 6 reports the results that compare BWD and FWD strategies for an MV investor (Panel A) and for a non-MV investor (Panel B). To conserve space we only present the quarterly rebalancing case for moderately risk averse investors ($\gamma = 5$) and under three levels of leverage constraints (Lev $< 100\%$, Lev $< 50\%$ and Lev $= 0$), but the results are qualitatively

[43]Related to the discussion in Section 1.3, we are not aware of published work that empirically analyzes the effects of both excess return predictability and variance/covariance predictability on asset allocation decisions.

very similar with monthly rebalancing and alternative risk aversion coefficients.[44]

Across the rows there are four sections per panel, each representing a combination of the approach used for forming expected returns and the one used for the variance/covariance matrix (in Panel A) and for all second, third and fourth moments (Panel B). For each section we report the CEQ and the realized portfolio return moments. In the first section (BWD & BWD) of Panel A we report the figures from the case where both the first and second moments are computed using sample moments recomputed at each time t on an expanding window.[45] We can see that the commodity-augmented strategies underperform the traditional asset strategies for all three levels of leverage. The second section of each panel (FWD & BWD) shows the performance generated by relying on expected return from the forecast combination method and on expanding sample variances and covariances (Panel A) as well as on sample skewness and kurtosis (Panel B) also computed on an expanding window. We find that, while the performance of S-B does not change significantly relatively to the benchmark BWD & BWD, the performance of S-B-C receives a significant boost. In particular, by adding only FWD-based expected returns to the benchmark strategy, a moderately risk averse investor could gain up to 90 bps per year more with an S-B-C portfolio than with an S-B portfolio. Therefore, we argue that exploiting the predictability of the mean asset return *by itself* improves portfolio performance, and also makes Commodity value adding compared to Stock-Bond allocations. Moving further down to the third section (BWD & FWD) across the two panels, we can see that relying on the DCC-based forecasts for second, third and fourth moments also increases portfolio performance across all levels of leverages relatively to the baseline BWD & BWD strategy but the improvement is still more tangible for the commodity-augmented strategies. Lastly, we apply the FWD strategy to expected returns as well as to the forecasts of higher moments, as shown in the fourth section (FWD & FWD) of the panels, and find that the performance of all portfolios is maximized and S-B-C consistently outperforms S-B. In other words, by combining FWD expected returns and FWD

[44] The complete results for this section are available from the authors upon request.

[45] The CEQs for BWD & BWD case come from Table 3, Panel B, BWD case.

variances, covariances, (co-)skewness and (co-)kurtosis, the investor gains the largest economic value. All in all, commodity-augmented strategies underperform traditional ones only if one employs the BWD & BWD strategy. If any FWD forecast is employed, incorporating commodities into Stock-Bond portfolios adds significant economic value.

Next, the analysis of realized portfolio return moments (columns Mean, Std, Skew, Kurt) delivers several additional insights. First, the addition of commodities to a stock-bond portfolio invariably leads to a higher average return as well as to a higher volatility. This is true regardless of whether the BWD or the FWD approach is used. However, the increase in average returns from S-B to S-B-C is fairly comparable from BWD to FWD whereas the increase in volatility is not as sharp when the FWD approach is relied upon. As a representative and, yet, intermediate example consider the Lev<50% case in Panel A. Here, when adding commodities to the Stock-Bond mix relying on the BWD method, the increase in portfolio average return is about 270 basis points per year (from 261 to 535 for the BWD & BWD case) while portfolio volatility rises by almost 740 annual basis points (from 380 to 1108). When relying on the FWD approach the average return for the S-B-C portfolio is about 270 basis points per year higher (from 398 to 667 for the FWD & FWD case) while volatility is up only about 500 basis points (from 570 to 1081). For an MV investor it, thus, appears that the value adding generated by commodities stems from their ability to increase the mean return without raising portfolio volatility excessively. It is the reliance on the forward looking approach, though, that allows to achieve a better risk-return tradeoff. Moving, next, to the non-MV case the general patterns in portfolio mean and volatility are broadly similar to the MV case. Two distinctive features emerge from the analysis of higher realized portfolio moments: first, the addition of commodities induces positive overall portfolio skewness whereas a pure equity-bond portfolio displays, by and large, negative skewness; second, the addition of commodities elevates the kurtosis of portfolio returns. Importantly, though, the increase in kurtosis is significantly higher when relying on the BWD method than on the FWD method. A plot of portfolio weights over time for S-B-C vs.

S-B illustrates further. Figure 1 reports the difference in portfolio weights between S-B-C and S-B when the FWD approach is used, while Figure 2 reports the weight differences for the BWD case. From the top panel of Figure 1 it is clear that the possibility of diversifying into commodities allows the investor to frequently avoid large negative returns in equities: the blue line indicates that the allocation to equities is lower for S-B-C than for S-B (i.e., the difference is negative) in correspondence to several sizable dips in the $S\&P500$. The flip side of this can be seen in the third panel, which plots the allocation to commodities: as the investor is not forced to stay in commodities at all times, the allocations to equities and bonds spare the portfolio from many of the biggest drops in commodity prices. As a result, by rotating across asset classes the investor is able to hedge against the negative skewness of the individual assets (in particular, equities and commodities). For a non-MV investor it, thus, appears that the value adding generated by commodities stems from their ability to switch portfolio skewness from negative to positive without altering significantly the fat-taildness of the return distribution. Similarly to the MV case for volatility, it is the FWD method that allows to generate returns for the S-B-C portfolio with more tolerable tail realizations.

[Table 6]

As established above, the predictability of mean asset returns, if exploited through the forward looking approach, makes commodities value adding with respect to stock-bond allocations. An additional dimension is assessing which asset predictability contributes the most to the improvement in portfolio performance. Restated, are all three predictabilities in the mean (of S, B and C) equally important? To address the question we repeat the asset allocation exercise using the FWD method only for one asset expected return at the time; i.e., each time we use the predictive regression and the forecast combination only for the expected return of one asset class, while using the sample moments (i.e., the BWD method) for the other two asset classes. Table 7 reports the results for an MV investor (Panel A with monthly rebalancing and Panel B with quarterly rebalancing) and for a non-MV investor (Panels C and D). Across the rows we report the results for five different ways of forming expected returns, ranging from the pure BWD approach applied to all asset classes (BWD S-B-C) to the full FWD approach applied to all asset classes (FWD S-B-C). With monthly rebalancing the main pattern is very similar across the MV and non-MV cases: it is the predictability of commodity returns through the FWD approach that appears to generate the advantage for the S-B-C portfolio vs. the S-B portfolio. When expected returns are estimated through the FWD approach only for stock or for bonds the performance of S-B-C relatively to S-B is: a) not value adding; b) similar to what the pure BWD approach produces. This can be seen in Panels A and C both in terms of moments of portfolio returns and, more importantly, in terms of certainty equivalents. When commodity returns only are predicted with the FWD method, S-B-C dominates S-B by about 70 bps per year (from 327 to 396 in the MV case, from 267 to 337 for the no-MV case). This pattern is confirmed with quarterly rebalancing: here S-B-C outperforms S-B even when all expected returns come from realized sample moments: the outperformance is between 60 and 90 annual basis points (346 bps vs. 283 bps for the MV investor, 392 vs. 283 for the non-MV investor).[46] However, the outperformance becomes much larger when the FWD approach is applied to commodity expected returns only: about 135 basis points for the MV case (from 283 to 419) and 160 bps for the non-MV case (from 283 to 443).

[Table 7]

[46]Recall that in all cases reported in Table 7 higher moments are predicted with the FWD method.

1.7.2.1 Forecasting Returns Using Technical Analysis

Next, we replace the expected returns computed according to the variables used above with forecasts from technical analysis rules. Following the comprehensive analysis of Neely et al. (2014) we extract the first three principal components from a set of twelve technical indicators (listed in Appendix D). We, then, forecast returns out-of-sample based on a) the first principal component of individual forecasts from the twelve technical rules; b) a linear combination of the first two principal components; b) a linear combination of the first three principal components; d) a linear combination of the individual forecasts from all the twelve technical rules. Table 8 report the results for monthly rebalanced portfolio strategies for an MV (panel A) and for a non-MV (Panel B) investor and for three levels of leverage constraints.[47] For each leverage/utility function combination we also report (from previous tables) the portfolio performance based on the FWD approach that relies on the macroeconomic and market predictors.

Looking at the strategies based on the first principal component of the technical forecasts (denoted by 1st PC), it is clear that both an MV and a non-MV investors could not have improved upon a stock-bond allocation by including commodities. In none of the six reported cases is the certainty equivalent return for S-B-C higher than for S-B. Similar results (unreported) obtain for strategies based on the first two PC of technical rule forecasts and for those based on a linear combination of all twelve individual forecasts.

A different picture emerges when looking at the strategies based on the first three principal components of the technical indicators. Except for the MV case with no leverage, the S-B-C portfolio consistently outperforms the S-B allocation in terms of CEQs. Moreover, the outperformance is, at times, even higher than when using the macro combination. For instance, a non-MV investor with a 50% leverage constraint would have earned an additional 72 basis points per year by adding commodities and relying on the macroeconomic and mar-

[47]To conserve space we only report results for cases a) and c) above. All other results based on technical indicators are available upon request.

ket variables but 110 basis annual points had she exploited the predictive power of technical analysis rules. Even larger gains would have occurred with a 100% leverage constraint: 96 basis points using the macro indicators, over 200 basis points using technical rules.

To summarize, we find that technical analysis rules may be a useful alternative to economic variables when forming expected returns for portfolio allocations across asset classes, although their contribution appears to be more valuable for investors facing lower leverage constraints.

[Table 8]

1.7.3 Additional Robustness

To further assess the robustness of the results presented in the previous section, we perform four more sets of tests.

First, it is well known that commodity prices have experienced unprecedented high growth during the 2002 - 2008 period, the so-called commodity super-cycle. We, hence, investigate whether the superior performance of S-B-C strategies during the full evaluation period is purely driven by the commodity boom. We divide our full OOS evaluation period (1986/12 - 2012/12) into two sub-periods: 1986/01 - 2001/12 and 2002/01 - 2012/12.[48] Table 9 reports the sub-period results for MV and non-MV strategies. As in the previous section, we only report the quarterly rebalancing case for moderately risk averse investors ($\gamma = 5$) and under three levels of leverage constraints (Lev $<$ 100% , Lev $<$ 50% and Lev $=$ 0). Results are qualitatively the same with monthly rebalancing and alternative risk aversion coefficients.[49] Panel A shows that S-B-C tends to outperform S-B for both MV and non-MV investors over

[48] We aggregate the boom and post-boom (2009-2012) periods as the latter is simply too short to draw any concrete conclusion if one were to subject it to separate analysis.

[49] These results are also available from the authors upon request.

the early sample period, 1986-2001, with the outperformance being more pronounced when using the FWD approach. For instance, a non-MV investor with a 50% leverage constraint would have earned an additional 54 bps per year adding a commodity exposure based on the BWD strategies, while she would have earned about 140 bps per year had she formed her S-B-C allocation using the FWD strategies. Over the second sub-period (Panel B) it is the S-B portfolio that dominates S-B-C if one relies on either a fixed-weight or BWD strategy. More importantly, though, when employing the FWD strategies the addition of commodities still pays off as it earns a, e.g., non-MV investor between 150 and 210 annual bps more than the stock-bond allocation. Therefore, the sub-period analysis indicates that including commodities into traditional asset portfolios following the FWD approach is value adding for both MV and non-MV investors not only during the commodity super-cycle but also during the earlier 1986-2001 period.

[Table 9]

As a third set of checks, we employ rolling estimation windows, namely 10yr- and 20 yr-rolling windows, for the estimators of all BWD and FWD strategies as opposed to the expanding window our results above are based on. In unreported results we find that our baseline conclusions remain valid: it is, thus, confirmed that the S-B-C strategy does outperform S-B when one relies on the FWD approach.

Fourth, we use an alternative forecasting method for volatility and correlations. Specifically, instead of the GARCH-type models, we employ a first-order autoregressive specifications for realized second moments computed from daily returns.[50] In unreported results we find that realized volatility and correlation models better fit the data in-sample, although they tend to slightly underperform their GARCH/DCC counterparts in the out-of-sample

[50] As a prominent example in an asset allocation framework, Fleming et al. (2003) show the gains induced by a realized covariance measure.

context. More importantly, though, the FWD S-B-C strategy still generates economic gains over the S-B strategy and such gains are of very comparable magnitudes to those reported in Tables 2 through 5.

1.8 Concluding Remarks

We empirically examine the economic value of adding a commodity exposure to a traditional (stock-bond-cash) portfolio in an out-of-sample framework. When forming optimal portfolios we exploit the predictability of mean, volatility, correlations, co-skewness and co-kurtosis of returns while previous studies do not account for these predictable variations when assessing the role of commodities in multi-asset portfolios. We perform the analysis for both MV and non-MV investors and find that, by exploiting the predictability of return moments, the addition of commodities generates substantial out-of-sample economic value after transactions costs, with monthly as well as with quarterly rebalancing. We also decompose the gains induced by predictable moments and find that both excess return predictions and variance/covariance predictions are value adding.

We subject our baseline findings to a battery of robustness checks and demonstrate that the key results are not significantly affected by reasonable variations in the amount of portfolio leverage and investor's risk aversion. We find some room for using technical analysis rules as an alternative to economic variables when forming portfolios of stocks, bonds and commodities. We also show that the improved risk-return trade-off induced by allocation to commodities is not driven by the commodity super-cycle that started in the early 2000's.

Overall, our empirical evidence presents a solid argument in favor of combining commodities with equities and fixed income exposures, whereas previous research had reached mixed or even opposite conclusions, especially in an out-of-sample context.

Appendices

A Data Appendix

Data Description

This table lists the series, the sample periods and the sources of all of all the variables we use in the paper. In particular, GW2012 denotes the dataset used in Welch and Goyal (2008), which is extended by the authors and available at `http://www.hec.unil.ch/agoyal/`; CBOE denotes the website of Chicago Board Options Exchange: `http://www.cboe.com/micro/VIX/historical.aspx`; FRED denotes the Federal Reserve Economic Data - St. Louis Fed; the link to Lutz Kilian's website is `http://www-personal.umich.edu/~lkilian/`.

Time Series	Sample Period	Source
S&P500 Total Return Index	1946/01 - 2012/12	GW2012
Barclays US Aggregate Index	1976/01 - 2012/12	Datastream
S&P GSCI Commodity Total Return Index	1970/01 - 2012/12	Datastream
Dow Jones-UBS Commodity Total Return Index	1991/01 - 2012/12	Datastream
Rogers International Commodity Index	1998/08 - 2012/12	Datastream
12-month moving sum of dividend on SP500	1946/01 - 2012/12	GW2012
12-month moving sum of earnings on SP500	1946/01 - 2012/12	GW2012
AAA-rated corp. bond yield	1946/01 - 2012/12	GW2012
BAA-rated corp. bond yield	1946/01 - 2012/12	GW2012
Long-term corp. bond return	1946/01 - 2012/12	GW2012
Stock market volatility	1946/01 - 2012/12	GW2012
Cross-sectional premium	1946/01 - 2002/12	GW2012
Book-to-Market ratio	1946/01 - 2012/12	GW2012
Total Net Issues of NYSE	1946/01 - 2012/12	GW2012
3-month T-bill	1946/01 - 2012/12	GW2012
Long-term govt. bond yield	1946/01 - 2012/12	GW2012
Long-term govt. bond return	1946/01 - 2012/12	GW2012
Govt. bond term spread	1946/01 - 2012/12	GW2012
Inflation rate	1946/01 - 2012/12	GW2012
CBOE Volatility Index (VIX)	1986/01 - 2012/12	CBOE
Napm Employment Index	1976/01 - 2012/12	FRED
Nonfarm Payroll Employment - Total	1976/01 - 2012/12	FRED
Capacity Utilization - Manufacturing	1976/01 - 2012/12	FRED
PMI Composite Index	1976/01 - 2012/12	FRED
ISM Manufacturing: New Orders Index	1976/01 - 2012/12	FRED
Producer Price Index: Finished Consumer Goods	1976/01 - 2012/12	FRED

(Continues)

Time Series	Sample Period	Source
6-month T-bill yield	1976/01 - 2012/12	FRED
1yr T-bond yield	1976/01 - 2012/12	FRED
5yr T-bond yield	1976/01 - 2012/12	FRED
Kilian's Real Economic Activity Index	1970/01 - 2012/12	Lutz Kilian's website
Industrial Production Index	1970/01 - 2012/12	FRED
log growth in money stock (M1, in percentage)	1975/02 - 2012/12	FRED
Unemployment Rate	1970/01 - 2012/12	FRED
Baltic Dry Index (BDI)	1985/05 - 2012/12	Datastream
Commodity Futures Market Total Open Interest	1970/01 - 2008/12	HY2012
Commodity Futures-Spot Price Spread (Basis)	1970/01 - 2008/12	HY2012
Exchange Rate, Australian Dollar to 1 USD	1971/01 - 2012/12	Datastream
Exchange Rate, Canadian Dollar to 1 USD	1971/01 - 2012/12	Datastream
Exchange Rate, New Zealand Dollar to 1 USD	1971/01 - 2012/12	Datastream
Exchange Rate, Indian Rupee to 1 USD	1973/01 - 2012/12	Datastream
Exchange Rate, Chilean Peso to 1 USD	1994/01 - 2012/12	Datastream
Exchange Rate, South African Rand to 1 USD	1971/01 - 2012/12	Datastream

B Forecasting the Covariance Matrix Using the DCC Model

We follow the two-stage DCC model proposed by Engle (2002) to estimate and forecast the one-period-ahead conditional covariance matrix at time $t+1$. We first decompose the covariance matrix as:

$$\hat{\Sigma}_{t+1|t} = \hat{D}_{t+1|t}\hat{P}_{t+1|t}\hat{D}_{t+1|t} \tag{B.1}$$

where $\hat{\Sigma}_{t+1|t}$ is the covariance matrix forecast at time $t+1$, $\hat{D}_{t+1|t}$ is a diagonal matrix with individual volatility forecasts ($\hat{\sigma}_{i,t+1|t}$, $i = 1 \cdots N$) on the diagonal, and $\hat{P}_{t+1|t}$ is the correlation forecast.

Step 1: Forecast conditional volatility $\hat{\sigma}_{i,t+1|t}$ for asset i

We first estimate the following GJR-GARCH type model in-sample using data up to time t:

$$r_{i,t} = \beta_{i,k}x_{k,t-1} + \varepsilon_{i,k,t} \tag{B.2}$$

$$\varepsilon_{i,t} = \frac{1}{K}\sum_{k=1}^{K}\varepsilon_{i,k,t} \tag{B.3}$$

$$\sigma^2_{i,t} = \omega_{i,t} + \alpha_i\varepsilon^2_{i,t-1} + \beta_i\sigma^2_{i,t-1} + \psi_i\varepsilon^2_{i,t-1}\cdot\mathbf{1}_{(\varepsilon_{i,t-1}<0)} \tag{B.4}$$

where $r_{i,t}$ is asset i's return at time t, $x_{k,t-1}$ ($k = 1 \cdots K$) is the kth predictor for asset i, and $\varepsilon_{i,k,t}$ is the residual for asset i based on the kth predictor. Specifically, Eq.(B.2) is the univariate regression that decomposes the return into two parts using each predictor: the expected return and the unexpected one. Eq.(B.3) combines the residuals from the regression equation. Eq.(B.4) specifies the dynamics of conditional variance of expected returns.

With the in-sample estimates for the parameters, we then produce the OOS variance forecast $\hat{\sigma}^2_{t+1|t}$ for asset i at time $t+1$:

$$\hat{\sigma}^2_{i,t+1|t} = \hat{\omega}_{i,t} + \hat{\alpha}_{i,t}\varepsilon^2_{i,t} + \hat{\beta}_{i,t}\hat{\sigma}^2_{i,t} + \hat{\psi}_{i,t}\varepsilon^2_{i,t-1} \cdot \mathbf{1}_{(\varepsilon_{i,t-1}<0)} \tag{B.5}$$

where $\hat{\omega}_{i,t}$, $\hat{\alpha}_{i,t}$, $\hat{\beta}_{i,t}$ and $\hat{\psi}_{i,t}$ are coefficients estimated using data up to time t from the model specified in Eq.(B.2-B.4).

Thus, the next period OOS diagonal volatility matrix forecast $\hat{D}_{t+1|t}$ is given by:

$$\hat{D}_{t+1|t} = \begin{pmatrix} \hat{\sigma}_{1,t+1|t} & 0 & \cdots & 0 \\ 0 & \hat{\sigma}_{2,t+1|t} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \hat{\sigma}_{N,t+1|t} \end{pmatrix}$$

Step 2: Forecast the conditional correlation matrix $P_{t+1|t}$ across N assets.

We first standardize the residuals obtained from Eq.(B.3) in *Step 1* using the conditional standard deviations:

$$s_t = D_t^{-\frac{1}{2}}\varepsilon_t \tag{B.6}$$

where s_t and ε_t are $N \times 1$ vectors.

Next, we fit s_t into the following multivariate GARCH model:

$$P_t = (\text{diag}(Q_t))^{-1/2} Q_t (\text{diag}(Q_t))^{-1/2} \tag{B.7}$$

$$Q_t = (1-a-b)\Omega + a s_{t-1}s'_{t-1} + bQ_{t-1} \tag{B.8}$$

where a and b are scalars, Ω is the unconditional covariance matrix of s_t up to time t, Q_t is the conditional covariance matrix, and P_t is the conditional correlation matrix.

Last, we produce the next period OOS correlation matrix forecasts:

$$\hat{Q}_{t+1|t} = \hat{\Omega}_t + \hat{a}_t s_t s_t' + \hat{b}_t \hat{Q}_t \tag{B.9}$$

$$\hat{P}_{t+1|t} = (\mathrm{diag}(\hat{Q}_{t+1|t}))^{-1/2} \hat{Q}_{t+1|t} (\mathrm{diag}(\hat{Q}_{t+1|t}))^{-1/2} \tag{B.10}$$

where $\hat{\Omega}_t$, $\hat{a}_t$ and $\hat{b}_t$ are the in-sample estimates from Eq.(B.8).

Finally, we plug in the volatility and correlation forecasts from Step 1 and 2 above into Eq.(B.1), and obtain the one-period-ahead conditional covariance matrix forecast $\hat{\Sigma}_{t+1|t}$.

C Forecasting Higher-order Moments Using Skew-t DCC Model

In what follows we detail the procedure proposed by Jondeau and Rockinger (2012) to forecast higher-order moments of portfolio returns that are necessary to solve the portfolio optimization problem for a non-MV investor.

A portfolio's first four non-central moments in Eq.(1.10) can be express as:

$$\begin{aligned}
m^{(1)}_{p,t+1} &= \mu_{p,t+1} \\
m^{(2)}_{p,t+1} &= \sigma^2_{p,t+1} + \mu^2_{p,t+1} \\
m^{(3)}_{p,t+1} &= u^{(3)}_{p,t+1} + 3\mu_{p,t+1}\sigma^2_{p,t+1} + \mu^3_{p,t+1} \\
m^{(4)}_{p,t+1} &= u^{(4)}_{p,t+1} + 4u^{(3)}_{p,t+1}\mu_{p,t+1} + 6\sigma^2_{p,t+1}\mu^2_{p,t+1} + \mu^4_{p,t+1}
\end{aligned} \tag{C.1}$$

where $\mu_{p,t+1}$, $\sigma^2_{p,t+1}$, $u^{(3)}_{p,t+1}$ and $u^{(4)}_{p,t+1}$ are the portfolio's return, variance, third and fourth central moments of N assets, respectively. Furthermore, the expected portfolio return, variance, third and fourth central moments, for a given portfolio weight vector ω_t, can be expressed as:

$$\begin{aligned}
\mu_{p,t+1} &= \omega_t' \mu_{t+1} \\
\sigma^2_{p,t+1} &= \omega_t' \Sigma_{t+1} \omega_t \\
u^{(3)}_{p,t+1} &= \omega_t' S_{t+1}(\omega_t \otimes \omega_t) \\
u^{(4)}_{p,t+1} &= \omega_t' K_{t+1}(\omega_t \otimes \omega_t \otimes \omega_t)
\end{aligned} \tag{C.2}$$

where μ_{t+1}, Σ_{t+1}, S_{t+1} and K_{t+1} are expected asset returns, covariance, co-skewness and co-kurtosis matrices, respectively.

Provided the expected third and fourth central moments (i.e. $u^{(3)}_{i,t+1}$ and $u^{(4)}_{i,t+1}$) exist for each asset return series $r_{i,t}$, we can obtain the $n \times n^2$ conditional co-skewness matrix:

$$S_{t+1} = E_t[(r_{t+1} - \mu_{t+1})(r_{t+1} - \mu_{t+1})' \otimes (r_{t+1} - \mu_{t+1})'] = \{s_{ijk,t+1}\} \tag{C.3}$$

$$\text{with component } (i,j,k): \quad s_{ijk,t+1} = \sum_{r=1}^{N} \sigma_{ir,t+1}\sigma_{jr,t+1}\sigma_{kr,t+1}u_{r,t+1}^{(3)}$$

where $\sigma_{ij,t+1}$ is the element of the "square root" of the covariance matrix, $\Sigma_{t+1}^{\frac{1}{2}}$, which can be obtained using Eigen decomposition. The conditional co-kurtosis matrix:

$$K_{t+1} = E_t[(r_{t+1} - \mu_{t+1})(r_{t+1} - \mu_{t+1})' \otimes (r_{t+1} - \mu_{t+1})' \otimes (r_{t+1} - \mu_{t+1})'] = \{k_{ijkl,t+1}\} \quad \text{(C.4)}$$

with component $(i,j,k,l):\ k_{ijkl,t+1} = \sum_{r=1}^{N} \sigma_{ir,t+1}\sigma_{jr,t+1}\sigma_{kr,t+1}\sigma_{lr,t+1}u_{r,t+1}^{(4)} + \sum_{r=1}^{N}\sum_{s\neq r}\psi_{rs,t+1}$ where $\psi_{rs,t+1} = \sigma_{ir,t+1}\sigma_{jr,t+1}\sigma_{ks,t+1}\sigma_{ls,t+1} + \sigma_{ir,t+1}\sigma_{js,t+1}\sigma_{kr,t+1}\sigma_{ls,t+1} + \sigma_{is,t+1}\sigma_{jr,t+1}\sigma_{kr,t+1}\sigma_{ls,t+1}$.

Therefore, to derive the first four moments described in Eq.(C.1) - Eq.(C.4), we need to obtain the FWD estimates for expected asset returns, covariance matrix, and the third and fourth central moments of each asset return distribution, notation-wise $\{\mu_{p,t+1}, \Sigma_{t+1}, sk_{i,t+1}, ku_{i,t+1}\}$. As we have already discussed the estimation of FWD asset returns in Section 1.4.1.1, we only detail the procedure to estimate $\{\Sigma_{t+1}, sk_{i,t+1}, ku_{i,t+1}\}$ with Skew-t distribution in the follows.

Step 1: Following Eq.(B.2) - Eq.(B.3), we obtain the combined residual $\varepsilon_{i,t}$ for asset i, and form the residual vector $\varepsilon_t = [\varepsilon_{1,t}, \cdots, \varepsilon_{n,t}]'$:

$$\varepsilon_t = \Sigma_t^{\frac{1}{2}} z_t \quad \text{(C.5)}$$

$$z_t \sim g(z_t|\lambda_t, \eta_t) \quad \text{(C.6)}$$

where z_t denotes the independent innovation vector with zero mean and unit variance, and $\Sigma_t = D_t P_t D_t^{'}$ denotes the conditional covariance matrix, where D_t is a diagonal matrix with standard deviations on the diagonal and P_t is the symmetric conditional correlation matrix. Eq.(C.6) specifies that the marginal distribution of innovations z_t follows Hansen's generalized Skew-t distribution $g(z_t|\lambda_t, \eta_t)$, where λ_t and η_t are shape parameters that respectively capture the time-varying asymmetries and fat-tailed ness of the multivariate Skew-t return distributions.

Moreover, an asymmetric GARCH specification is adopted to fit the conditional variance for each asset:

$$\sigma_{i,t}^2 = \omega_{i,t} + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2 + \psi_i \varepsilon_{i,t-1}^2 \cdot \mathbf{1}_{(\varepsilon_{i,t-1}<0)} \tag{C.7}$$

And, a standard DCC specification is used to model the time-varying correlation matrix of N assets:

$$P_t = (diag(Q_t))^{-1/2} Q_t (diag(Q_t))^{-1/2} \tag{C.8}$$

$$Q_t = (1-a-b)\bar{Q} + a(s_{t-1}s_{t-1}^{'}) + bQ_{t-1} \tag{C.9}$$

where a and b are scalars, and $s_t = D_t^{-1}\varepsilon_t$ is standardized residuals.

The dynamics of conditional variance and correlations are driven by the innovation vector, z_t, which is drawn from the multivariate Skew-t distribution with time-varying individual asymmetry parameter and the degree of freedom, $\lambda_{i,t}$ and $\eta_{i,t}$ respectively. The dynamic process of the two shape parameters are modeled as:

$$\lambda_{i,t} = -0.9 + \frac{1.8}{1+e^{-\tilde{\lambda}_{i,t}}} \tag{C.10}$$

$$\tilde{\lambda}_{i,t} = d_0 + d_1^- z_{i,t-1} \cdot \mathbf{1}_{(z_{i,t-1}\leq 0)} + d_1^+ z_{i,t-1} \cdot \mathbf{1}_{(z_{i,t-1}>0)} + d_2 \tilde{\lambda}_{i,t-1} \tag{C.11}$$

$$\eta_{i,t} = -4.1 + \frac{25.9}{1+e^{-\tilde{\eta}_{i,t}}} \tag{C.12}$$

$$\tilde{\eta}_{i,t} = c_0 + c_1^- |z_{i,t-1}| \cdot \mathbf{1}_{(z_{i,t-1}\leq 0)} + c_1^+ |z_{i,t-1}| \cdot \mathbf{1}_{(z_{i,t-1}>0)} + c_2 \tilde{\eta}_{i,t-1} \tag{C.13}$$

Eq.(C.11) and Eq.(C.13) respectively specify the temporal dynamic process of the asymmetry parameter $\lambda_{i,t}$ and the degree of freedom $\eta_{i,t}$. Eq.(C.10) and Eq.(C.12) respectively denote the logistic mappings from estimated parameters to true Skew-t shape parameters that satisfy the theoretical restrictions pointed out by Hansen (1994).[51]

The model Eq.(C.5) - Eq.(C.13) can be estimated using the Maximum Likelihood method. The estimation is based on asset return data available up to time t only (i.e. no additional predictive variables). The complete set of parameter estimates is:

$$\{\hat{\omega}_{i,t}, \hat{\alpha}_{i,t}, \hat{\beta}_{i,t}, \hat{a}_t, \hat{b}_t, \hat{c}_{0,t}, \hat{c}_{1,t}^{-}, \hat{c}_{1,t}^{+}, \hat{c}_{2,t}; \hat{d}_{0,t}, \hat{d}_{1,t}^{-}, \hat{d}_{1,t}^{+}, \hat{d}_{2,t}\} \tag{C.14}$$

Step 2: Plug in the in-sample parameter estimates and obtain the one-period-ahead shape parameter forecasts.

$$\hat{\tilde{\lambda}}_{t+1|t} = \hat{d}_{0,t} + \hat{d}_{1,t}^{-} z_t \cdot \mathbf{1}_{(z_t \leq 0)} + \hat{d}_{1,t}^{+} z_t \cdot \mathbf{1}_{(z_t > 0)} + \hat{d}_{2,t} \hat{\lambda}_t \tag{C.15}$$

$$\hat{\lambda}_{t+1|t} = -0.9 + \frac{1.8}{1 + e^{-\hat{\tilde{\lambda}}_{t+1|t}}} \tag{C.16}$$

$$\hat{\tilde{\eta}}_{t+1|t} = \hat{c}_{0,t} + \hat{c}_{1,t}^{-} |z_t| \cdot \mathbf{1}_{(z_t \leq 0)} + \hat{c}_{1}^{+} |z_t| \cdot \mathbf{1}_{(z_t > 0)} + \hat{c}_{2,t} \hat{\eta}_t \tag{C.17}$$

$$\hat{\eta}_{t+1|t} = -4.1 + \frac{25.9}{1 + e^{-\hat{\tilde{\eta}}_{t+1|t}}} \tag{C.18}$$

where $\hat{\eta}_{t+1|t}$ and $\hat{\lambda}_{t+1|t}$ are the next period shape parameter OOS forecasts.

[51] To ensure the first four moments exist, the two restrictions need to be maintained: $-1 < \lambda_{i,t} < 1$ and $\eta_{i,t} > 4$.

Step 3: Plug in the shape parameter forecasts and obtain next period central moment forecasts for each asset:

$$\hat{\mu}^{(3)}_{t+1|t} = \hat{M}_{3,i,t+1|t} - 3\hat{M}_{1,t+1|t}\hat{M}_{2,t} + 2\hat{M}^{3}_{1,t+1|t} \tag{C.19}$$

$$\hat{\mu}^{(4)}_{t+1|t} = \hat{M}_{3,t+1|t} - 4\hat{M}_{1,t+1|t}\hat{M}_{2,t+1|t} + 6\hat{M}^{2}_{1,t+1|t}M_{2,t+1|t} - 3\hat{M}^{4}_{1,t+1|t} \tag{C.20}$$

where

$$\hat{M}_{r,t+1|t} = \frac{\Gamma(\frac{\hat{\eta}_{t+1|t}-r}{2})\Gamma(\frac{r+1}{2})(\hat{\eta}_{t+1|t}-2)^{\frac{r+1}{2}}}{\sqrt{\pi(\hat{\eta}_{t+1|t}-2)}\Gamma(\frac{\hat{\eta}_{t+1|t}}{2})} \cdot \frac{\hat{\lambda}^{r+1}_{t+1|t} + \frac{(-1)^r}{\hat{\lambda}^{r+1}_{t+1|t}}}{\hat{\lambda}_{t+1|t} + \frac{1}{\hat{\eta}_{t+1|t}}}$$

is the r^{th} raw moment of z_t. Clearly, the third and fourth central moments of z_t are non-linear functions of the shape parameter estimates $\hat{\eta}_{i,t+1|t}$ and $\hat{\lambda}_{i,t+1|t}$.

D Technical Indicators and Return Forecasting

We follow Neely et al. (2014) and use a total of 12 technical indicators based on two popular trend-following rules to forecast asset excess returns.

The first is a moving-average (MA) rule that generates a buy or sell signal ($S_{i,t} = 1$ or $S_{i,t} = 0$, respectively) at the end of t by comparing two moving averages:

$$S_{i,t} = \begin{cases} 1 & MA_{s,t} \geq MA_{l,t} \\ 0 & MA_{s,t} < MA_{l,t} \end{cases}$$

where

$$MA_{j,t} = (1/j) \sum_{i=0}^{j-1} P_{t-i} \quad \text{for} \quad j = s, l;$$

P_t is the level of a stock price index, and $s(l)$ is the length of the short (long) MA ($s < l$). We denote the MA indicator with MA lengths s and l by MA(s, l). Intuitively, the MA rule detects changes in stock price trends because the short MA will be more sensitive to recent price movement than will the long MA. We analyze monthly MA rules with $s = 1, 2, 3$ and $l = 9, 12, 18$: a total of 9 MA signals.

The second rule is based on momentum. A simple momentum rule generates the following signal:

$$S_{i,t} = \begin{cases} 1 & P_t \geq P_{t-m} \\ 0 & P_t < P_{t-m} \end{cases}$$

Intuitively, a current stock price that is higher than its level m periods ago indicates "positive" momentum and relatively high expected excess returns, thereby generating a buy signal. We denote the momentum indicator that compares P_t to P_{tm} by MOM(m), and we compute monthly signals for $m = 9, 12, 18$: a total of 3 momentum signals. All in all, we construct a total of 12 technical indicators using the MA and momentum rules[52].

[52] Neely et al. (2014) use an additional tech. rule, on-balance volume, which requires trading volume data. The volume data on the indexes we use are not available, so we only use the MA and Momentum rules.

To incorporate information from the set of technical indicators, we follow Neely et al. (2014) and estimate a predictive regression based on principal components.[53].

Let $x_t = [x_{1,t}, .., x_{N,t}]'$ denote the N-vector (N=12) of the entire set of technical indicators and let $F_t = [F_{1,t}, ..., F_{K,t}]'$ denote the vector containing the first K principal components extracted from x_t (where $K << N$). We first estimate the univariate principal component predictive regression in-sample:

$$r_{k,t+1} = \alpha_k + \beta_k F_{k,t} + \epsilon_{t+1}$$

Then, the univariate OOS forecast for time $t+1$ is obtained by:

$$\hat{r}_{k,t+1|t} = \hat{\alpha}_{k,t} + \hat{\beta}_{k,t} F_{k,t}$$

At last, the forecast combination is computed:

$$\hat{r}_{t+1|t} = \frac{1}{K} \sum_{k=1}^{K} \hat{r}_{k,t+1|t}$$

[53]Ludvigson and Ng (2007, 2009) estimate predictive regressions for excess stock and bond returns, respectively, based on principal components extracted from a large set of macroeconomic variables.

Bibliography

Amihud, Y., and R. Goyenko. 2013. Mutual fund's R2 as predictor of performance. *Review of Financial Studies* p. hhs182.

Ang, A., and G. Bekaert. 2002. International asset allocation with regime shifts. *Review of Financial studies* 15:1137–1187.

Anson, M. 1999. Maximizing utility with commodity futures diversification. *The Journal of Portfolio Management* 25:86–94.

Arditti, F. D. 1967. Risk and the required return on equity. *Journal of Finance* pp. 19–36.

Asness, C. S., T. J. Moskowitz, and L. H. Pedersen. 2013. Value and momentum everywhere. *The Journal of Finance* 68:929–985.

Avramov, D., and R. Wermers. 2006. Investing in mutual funds when returns are predictable. *Journal of Financial Economics* 81:339–377.

Baker, M., and J. Wurgler. 2007. Investor Sentiment in the Stock Market. *The Journal of Economic Perspectives* 21:129–151.

Baks, K. P., A. Metrick, and J. Wachter. 2001. Should investors avoid all actively managed mutual funds? A study in Bayesian performance evaluation. *The Journal of Finance* 56:45–85.

Bakshi, G., G. Panayotov, and G. Skoulakis. 2011. The Baltic Dry Index as a predictor of global stock returns, commodity returns, and global economic activity. In *AFA 2012 Chicago Meetings Paper*.

Ball, C., and W. Torous. 2000. Stochastic correlation across international stock markets. *Journal of Empirical Finance* 7:373–388.

Banegas, A., B. Gillen, A. Timmermann, and R. Wermers. 2013. The cross section of conditional mutual fund performance in European stock markets. *Journal of Financial Economics* 108:699–726.

Barroso, P., and P. Santa-Clara. 2014. Beyond the carry trade: Optimal currency portfolios. *Journal of Financial and Quantitative Analysis, Forthcoming* .

Bates, J., and C. Granger. 1969. The Combination of Forecasts. *Journal of the Operational Research Society* 20:451–468.

Bekaert, G., C. Erb, C. Harvey, and T. Viskanta. 1998. Distributional characteristics of emerging market returns and asset allocation. *The Journal of Portfolio Management* 24:102–116.

Belousova, J., and G. Dorfleitner. 2012. On the diversification benefits of commodities from the perspective of euro investors. *Journal of Banking and Finance* 36:2455–2472.

Ben-David, I., F. Franzoni, and R. Moussawi. 2012. Hedge fund stock trading in the financial crisis of 2007–2009. *Review of Financial Studies* 25:1–54.

Berk, J. B., and R. C. Green. 2004. Mutual fund flows and performance in rational markets. *Journal of political economy* 112:1269–1295.

Berk, J. B., and J. H. Van Binsbergen. 2015. Measuring skill in the mutual fund industry. *Journal of Financial Economics* 118:1–20.

Bessembinder, H., and K. Chan. 1992. Time-varying risk premia and forecastable returns in futures markets. *Journal of Financial Economics* 32:169–193.

Bhardwaj, R. K., and L. D. Brooks. 1992. The January Anomaly: Effects of Low Share Price, Transaction Costs, and Bid-Ask Bias. *The Journal of Finance* 47:553–575.

Bianchi, D., and M. Guidolin. 2013. Can Long-Run Dynamic Optimal Strategies Outperform Fixed-Mix Portfolios? Evidence from Multiple Data Sets. In *Manuscript, Bocconi University.*

Billio, M., M. Caporin, and M. Gobbo. 2006. Flexible dynamic conditional correlation multivariate GARCH models for asset allocation. *Applied Financial Economics Letters* 2:123–130.

Bodie, Z., and V. Rosansky. 1980. Risk and return in commodity futures. *Financial Analysts Journal* pp. 27–39.

Bollen, N. P., and J. A. Busse. 2005. Short-term persistence in mutual fund performance. *Review of Financial Studies* 18:569–597.

Brands, S., and D. R. Gallagher. 2005. Portfolio selection, diversification and fund-of-funds: a note. *Accounting & Finance* 45:185–197.

Brandt, M. 2009a. Portfolio choice problems. *Handbook of financial econometrics* 1:269–336.

Brandt, M. 2009b. Portfolio choice problems. *Handbook of financial econometrics* 1:269–336.

Brown, S. J., and W. N. Goetzmann. 1997. Mutual fund styles. *Journal of financial Economics* 43:373–399.

Brown, S. J., I. Hwang, and F. In. 2013. Why optimal diversification cannot outperform naive diversification: Evidence from tail risk exposure. *Available at SSRN* 2242694.

Busse, J. A. 1999. Volatility timing in mutual funds: Evidence from daily returns. *Review of Financial Studies* 12:1009–1041.

Büyükşahin, B., M. Haigh, and M. Robe. 2010. Commodities and Equities: Ever a Market of One? *The Journal of Alternative Investments* 12:76–95.

Büyükşahin, B., and M. Robe. 2010. Speculators, commodities and cross-market linkages. *Available at SSRN 1707103* .

Campbell, J., and S. Thompson. 2008. Predicting excess stock returns out of sample: Can anything beat the historical average? *Review of Financial Studies* 21:1509–1531.

Campbell, J., and L. Viceira. 1999. Consumption and Portfolio Decisions When Expected Returns Are Time Varying. *The Quarterly Journal of Economics* 114:433–495.

Campbell, J. Y., and R. J. Shiller. 1991. Yield spreads and interest rate movements: A bird's eye view. *The Review of Economic Studies* 58:495–514.

Campbell, J. Y., and L. M. Viceira. 2003. *Strategic asset allocation: portfolio choice for long-term investors*. Oxford University Press.

Cao, B., S. Jayasuriya, and W. Shambora. 2010. Holding a commodity futures index fund in a globally diversified portfolio: A placebo effect? *Economics Bulletin* 30:1842–1851.

Cappiello, L., R. Engle, and K. Sheppard. 2006. Asymmetric dynamics in the correlations of global equity and bond returns. *Journal of Financial econometrics* 4:537–572.

Carhart, M. M. 1997. On persistence in mutual fund performance. *The Journal of finance* 52:57–82.

Case, B., Y. Yang, and Y. Yildirim. 2012. Dynamic correlations among asset classes: REIT and stock returns. *The Journal of Real Estate Finance and Economics* 44:298–318.

Cenesizoglu, T., and A. Timmermann. 2012. Do return prediction models add economic value? *Journal of Banking & Finance* .

Chan, L. K., H.-L. Chen, and J. Lakonishok. 2002. On mutual fund investment styles. *Review of financial studies* 15:1407–1437.

Chaves, D., J. Hsu, F. Li, and O. Shakernia. 2011. Risk parity portfolio vs. other asset allocation heuristic portfolios. *The Journal of Investing* 20:108–118.

Chen, J., H. Hong, M. Huang, and J. D. Kubik. 2004. Does fund size erode mutual fund performance? The role of liquidity and organization. *American Economic Review* pp. 1276–1302.

Chen, Y.-C., K. S. Rogoff, and B. Rossi. 2010. Can exchange rates forecast commodity prices? *The Quarterly Journal of Economics* 125:1145–1194.

Chong, J., and J. Miffre. 2010. Conditional Correlation and Volatility in CommodityFutures and Traditional Asset Markets. *The Journal of Alternative Investments* 12:061–075.

Citigroup. 2013. Commodities Inflection Point, Still Cyclical, But Not So Super 2014 Annual Market Outlook. *Research Report* .

Cochrane, J., and M. Piazzesi. 2005. Bond Risk Premia. *American Economic Review* pp. 138–160.

Cremers, K. M., and A. Petajisto. 2009. How active is your fund manager? A new measure that predicts performance. *Review of Financial Studies* 22:3329–3365.

Cremers, M., A. Petajisto, and E. Zitzewitz. 2012. Should benchmark indices have alpha? Revisiting performance evaluation. Tech. rep., National Bureau of Economic Research.

Daskalaki, C., and G. Skiadopoulos. 2011. Should investors include commodities in their portfolios after all? New evidence. *Journal of Banking & Finance* 35:2606–2626.

Del Guercio, D., and J. Reuter. 2014. Mutual fund performance and the incentive to generate alpha. *The Journal of Finance* 69:1673–1704.

Del Guercio, D., and P. A. Tkac. 2002. The determinants of the flow of funds of managed portfolios: Mutual funds vs. pension funds. *Journal of Financial and Quantitative Analysis* 37:523–557.

Della Corte, P., L. Sarno, and I. Tsiakas. 2012. Volatility and Correlation Timing in Active Currency Management. *Handbook of Exchange Rates* pp. 421–447.

DeMiguel, V., L. Garlappi, and R. Uppal. 2009. Optimal versus naive diversification: How inefficient is the 1/N portfolio strategy? *Review of Financial Studies* 22:1915–1953.

diBartolomeo, D., and E. Witkowski. 1997. Mutual fund misclassification: Evidence based on style analysis. *Financial Analysts Journal* pp. 32–43.

Dittmar, R. 2002. Nonlinear pricing kernels, kurtosis preference, and evidence from the cross section of equity returns. *The Journal of Finance* 57:369–403.

Domanski, D., and A. Heath. 2007. Financial investors and commodity markets. *BIS Quarterly Review, March* .

Eastman, A., and B. Lucey. 2008. Skewness and asymmetry in futures returns and volumes. *Applied Financial Economics* 18:777–800.

Elton, E. J., M. J. Gruber, and C. R. Blake. 2006. The adequacy of investment choices offered by 401 (k) plans. *Journal of Public Economics* 90:1299–1314.

Engle, R. 2002. Dynamic conditional correlation. *Journal of Business & Economic Statistics* 20:339–350.

Engle, R., and R. Colacito. 2006. Testing and valuing dynamic correlations for asset allocation. *Journal of Business & Economic Statistics* 24:238–253.

Erb, C., and C. Harvey. 2006. The strategic and tactical value of commodity futures. *Financial Analysts Journal* pp. 69–97.

Erb, C., C. Harvey, and T. Viskanta. 1994. Forecasting international equity correlations. *Financial Analysts Journal* pp. 32–45.

Fama, E., and K. French. 1987. Commodity futures prices: Some evidence on forecast power, premiums, and the theory of storage. *Journal of Business* pp. 55–73.

Farinelli, S., and L. Tibiletti. 2008. Sharpe thinking in asset ranking with one-sided measures. *European Journal of Operational Research* 185:1542–1547.

Fleming, J., C. Kirby, and B. Ostdiek. 2001. The economic value of volatility timing. *The Journal of Finance* 56:329–352.

Fleming, J., C. Kirby, and B. Ostdiek. 2003. The economic value of volatility timing using realized volatility. *Journal of Financial Economics* 67:473–509.

Fortenbery, T., and R. Hauser. 1990. Investment potential of agricultural futures contracts. *American journal of agricultural economics* 72:721–726.

Friend, I., and M. E. Blume. 1975. The demand for risky assets. *The American Economic Review* 65:900–922.

Galvani, V., and A. Plourde. 2010. Portfolio diversification in energy markets. *Energy Economics* 32:257–268.

Gargano, A., and A. Timmermann. 2014. Forecasting commodity price indexes using macroeconomic and financial predictors. *International Journal of Forecasting* .

Garlappi, L., and G. Skoulakis. 2011. Taylor Series Approximations to Expected Utility and Optimal Portfolio Choice. *Mathematical and Financial Economoics* 5:121–156.

Geman, H., and C. Kharoubi. 2008. WTI crude oil Futures in portfolio diversification: The time-to-maturity effect. *Journal of Banking & Finance* 32:2553–2559.

Glabadanidis, P. 2009. Measuring the economic significance of mean-variance spanning. *The Quarterly Review of Economics and Finance* 49:596–616.

Glode, V. 2011. Why mutual funds underperform. *Journal of Financial Economics* 99:546–559.

Glode, V., B. Hollifield, M. T. Kacperczyk, and S. Kogan. 2012. Time-Varying Predictability in Mutual Fund Returns. *Available at SSRN 1364351* .

Goetzmann, W., L. Li, and K. Rouwenhorst. 2005. Long-Term Global Market Correlations*. *The Journal of Business* 78:1–38.

Goetzmann, W. N., and R. G. Ibbotson. 1994. Do winners repeat? *The Journal of Portfolio Management* 20:9–18.

Goh, J., F. Jiang, J. Tu, and G. Zhou. 2013. Forecasting Government Bond Risk Premia Using Technical Indicators. *ssrn.com* .

Gordon, S., and P. St-Amour. 2004. Asset returns and state-dependent risk preferences. *Journal of Business & Economic Statistics* 22:241–252.

Gorton, G., F. Hayashi, and K. Rouwenhorst. 2012. The Fundamentals of Commodity Futures Returns. *Review of Finance* .

Gorton, G., and K. Rouwenhorst. 2006. Facts and Fantasies about Commodity Markets. *Financial Analysts Journal* 62.

Grinblatt, M., and S. Titman. 1989. Mutual fund performance: An analysis of quarterly portfolio holdings. *Journal of business* pp. 393–416.

Grinblatt, M., S. Titman, and R. Wermers. 1995. Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior. *The American economic review* pp. 1088–1105.

Gruber, M. J. 1996. Another puzzle: The growth in actively managed mutual funds. *The journal of finance* 51:783–810.

Guidolin, M., and A. Timmermann. 2008. International asset allocation under regime switching, skew, and kurtosis preferences. *Review of Financial Studies* 21:889–935.

Hamilton, J. 2008. Understanding Crude Oil Prices. *NBER Working Paper* .

Hansen, B. E. 1994. Autoregressive conditional density estimation. *International Economic Review* pp. 705–730.

Harvey, C., J. Liechty, M. Liechty, and P. Müller. 2010. Portfolio selection with higher moments. *Quantitative Finance* 10:469–485.

Harvey, C., and A. Siddique. 2000. Conditional skewness in asset pricing tests. *The Journal of Finance* 55:1263–1295.

Harvey, C. R., and A. Siddique. 1999. Autoregressive conditional skewness. *Journal of financial and quantitative analysis* 34.

Hendricks, D., J. Patel, and R. Zeckhauser. 1993. Hot hands in mutual funds: Short-run persistence of relative performance, 1974–1988. *The Journal of Finance* 48:93–130.

Hong, H., and M. Yogo. 2012. What does futures market interest tell us about the macroeconomy and asset prices? *Journal of financial economics* 105:473–490.

Huang, J., and Z. Zhong. 2010. Time Variation in Diversification Benefits of Commodity, REITs, and TIPS. *The Journal of Real Estate Finance and Economics* pp. 1–41.

Jensen, G., R. Johnson, and J. Mercer. 2000. Efficient use of commodity futures in diversified portfolios. *Journal of Futures Markets* 20:489–506.

Jensen, G., R. Johnson, and J. Mercer. 2002. Tactical asset allocation and commodity futures. *The Journal of Portfolio Management* 28:100–111.

Jensen, M. C. 1968. The performance of mutual funds in the period 1945–1964. *The Journal of finance* 23:389–416.

Jiang, G. J., T. Yao, and T. Yu. 2007. Do mutual funds time the market? Evidence from portfolio holdings. *Journal of Financial Economics* 86:724–758.

Jiang, H., M. Verbeek, and Y. Wang. 2014. Information content when mutual funds deviate from benchmarks. *Management Science* 60:2038–2053.

Jondeau, E., and M. Rockinger. 2006. Optimal portfolio allocation under higher moments. *European Financial Management* 12:29–55.

Jondeau, E., and M. Rockinger. 2009. The impact of shocks on higher moments. *Journal of Financial Econometrics* 7:77–105.

Jondeau, E., and M. Rockinger. 2012. On the Importance of Time Variability in Higher Moments for Asset Allocation. *Journal of Financial Econometrics* 10:84–123.

Kacperczyk, M., C. Sialm, and L. Zheng. 2005. On the industry concentration of actively managed equity mutual funds. *The Journal of Finance* 60:1983–2011.

Kacperczyk, M., C. Sialm, and L. Zheng. 2008. Unobserved actions of mutual funds. *Review of Financial Studies* 21:2379–2416.

Kacperczyk, M., S. Van Nieuwerburgh, and L. Veldkamp. 2013. Time-Varying Fund Manager Skill. *The Journal of Finance* .

Kan, R., and G. Zhou. 2007. Optimal portfolio choice with parameter uncertainty. *Journal of Financial and Quantitative Analysis* 42:621–656.

Kan, R., and G. Zhou. 2012. Tests of mean-variance spanning. *Annals of Economics and Finance* 13:277–325.

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

Keswani, A., and D. Stolin. 2008. Which money is smart? Mutual fund buys and sells of individual and institutional investors. *The Journal of Finance* 63:85–118.

Kilian, L., and D. Murphy. 2010. The role of inventories and speculative trading in the global market for crude oil .

Kosowski, R. 2011. Do mutual funds perform when it matters most to investors? US mutual fund performance and risk in recessions and expansions. *The Quarterly Journal of Finance* 1:607–664.

Kosowski, R., A. Timmermann, R. Wermers, and H. White. 2006. Can mutual fund stars really pick stocks? New evidence from a bootstrap analysis. *The Journal of finance* 61:2551–2595.

Kraus, A., and R. H. Litzenberger. 1976. Skewness preference and the valuation of risk assets*. *The Journal of Finance* 31:1085–1100.

Lesmond, D. A., J. P. Ogden, and C. A. Trzcinka. 1999. A new estimate of transaction costs. *Review of Financial Studies* 12:1113–1141.

Longin, F., and B. Solnik. 1995. Is the correlation in international equity returns constant: 1960–1990? *Journal of international money and finance* 14:3–26.

Ludvigson, S. C., and S. Ng. 2007. The empirical risk–return relation: a factor analysis approach. *Journal of Financial Economics* 83:171–222.

Ludvigson, S. C., and S. Ng. 2009. Macro factors in bond risk premia. *Review of Financial Studies* 22:5027–5067.

Malkiel, B. G. 1995. Returns from investing in equity mutual funds 1971 to 1991. *The Journal of Finance* 50:549–572.

Mankiw, N. G. 1985. Consumer Durables and the Real Interest Rate. *The Review of Economics and Statistics* pp. 353–362.

Marquering, W., and M. Verbeek. 2004. The economic value of predicting stock index returns and volatility. *Journal of Financial and Quantitative Analysis* 39:407–429.

McLemore, P. 2014. Do Mutual Funds Have Decreasing Returns to Scale? Evidence from Fund Mergers .

Mehra, R., and E. Prescot. 1985. The Equity Premium: A Puzzle. *Journal of Monetary Economics* 15:145–161.

Merton, R. 1971. Optimum consumption and portfolio rules in a continuous-time model. *Journal of Economic Theory* 3:373–413.

Merton, R. 1973. An Intertemporal Capital Asset Pricing Model. *Econometrica* 41:867–887.

Moskowitz, T. 2003. An analysis of covariance risk and pricing anomalies. *Review of Financial Studies* 16:417–457.

Moskowitz, T. J. 2000. Mutual Fund Performance: An Empirical Decomposition into Stock-Picking Talent, Style, Transactions Costs, and Expenses: Discussion. *The Journal of Finance* 55:1695–1703.

Neely, C. J., D. E. Rapach, J. Tu, and G. Zhou. 2014. Forecasting the equity risk premium: the role of technical indicators. *Management Science* 60:1772–1791.

Nijman, T., and L. Swinkels. 2008. Strategic and Tactical Allocation to Commodities for Retirement Savings Schemes. *The Handbook of Commodity Investing* pp. 522–546.

Pástor, L., and R. F. Stambaugh. 2002. Investing in equity mutual funds. *Journal of Financial Economics* 63:351–380.

Pástor, L., R. F. Stambaugh, and L. A. Taylor. 2015. Scale and skill in active management. *Journal of Financial Economics* 116:23–45.

Patton, A. 2004. On the out-of-sample importance of skewness and asymmetric dependence for asset allocation. *Journal of Financial Econometrics* 2:130–168.

Pesaran, M., and A. Timmermann. 1995. Predictability of Stock Returns: Robustness and Economic Significance. *The Journal of Finance* 50:1201–1228.

Plazzi, A., W. Torous, and R. Valkanov. 2010. Expected returns and expected growth in rents of commercial real estate. *Review of Financial Studies* p. hhq069.

Rapach, D. E., J. K. Strauss, and G. Zhou. 2010. Out-of-sample equity premium prediction: Combination forecasts and links to the real economy. *Review of Financial Studies* 23:821–862.

Scott, R., and P. Horvath. 1980. On the Direction of Preference for Moments of Higher Order than the Variance. *The Journal of Finance* 35:915–919.

Sirri, E. R., and P. Tufano. 1998. Costly search and mutual fund flows. *The journal of finance* 53:1589–1622.

Smith, J. 2009. World oil: market or mayhem? *The journal of economic perspectives* 23:145–164.

Solnik, B. 1993. The performance of international asset allocation strategies using conditioning information. *Journal of Empirical Finance* 1:33–55.

Stoll, H. R., and R. E. Whaley. 1983. Transaction costs and the small firm effect. *Journal of Financial Economics* 12:57–79.

Strongin, S., and M. Petsch. 1996. Asset Returns and the Economic Environment. *Goldman Sachs Research Report* .

Sun, Z., A. Wang, and L. Zheng. 2009. Do active funds perform better in down markets? New evidence from cross-sectional study. *New Evidence from Cross-Sectional Study (September 1, 2009)* .

Tang, K., and W. Xiong. 2010. Index Investment and Financialization of Commodities. *NBER Working Paper* .

Timmermann, A. 2006. Forecast combinations. *Handbook of economic forecasting* 1:135–196.

Timmermann, A., and D. Blake. 2005. International Asset Allocation with Time-Varying Investment Opportunities*. *The Journal of Business* 78:71–98.

Vrugt, E. B., R. Bauer, R. Molenaar, and T. Steenkamp. 2004. Dynamic Commodity Trading Strategies. *Manuscript* .

Welch, I., and A. Goyal. 2008. A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies* 21:1455–1508.

Wermers, R. 2000. Mutual fund performance: An empirical decomposition into stock-picking talent, style, transactions costs, and expenses. *The Journal of Finance* 55:1655–1703.

Yan, X. S. 2008. Liquidity, investment style, and the relation between fund size and fund performance. *Journal of Financial and Quantitative Analysis* 43:741–767.

You, L., and R. Daigler. 2010. Using Four-Moment Tail Risk to Examine Financial and Commodity Instrument Diversification. *Financial Review* 45:1101–1123.

You, L., and R. Daigler. 2012. A Markowitz Optimization of Commodity Futures Portfolios. *Journal of Futures Markets* 00:1–26.

Zheng, L. 1999. Is money smart? A study of mutual fund investors' fund selection ability. *The Journal of Finance* 54:901–933.

Table 1.1 Descriptive Statistics

Panel A reports the summary statistics for monthly excess returns of three asset class indexes: S&P500, Barclays Aggregate Bond Index and S&P GSCI and the sample correlation matrix of excess returns. Panel B reports the summary statistics for quarterly excess returns and their sample correlation matrix. The monthly (quarterly) return series span the periods 1976:01-2012:12 (1976:Q1-2012:Q4).

Panel A: Monthly								
	N	Mean	Median	Min	Max	Stdev	Skew	XKurt
SP500	443	.0027	.0064	-.2227	.1272	.0438	-.59	1.99
Bond	443	.0024	.0031	-.0705	.1023	.0161	.20	5.96
GSCI	443	.0030	.0043	-.2825	.2233	.0555	-.21	2.24
Correlation matrix								
SP500	1							
Bond	.23	1						
GSCI	.18	-.02	1					
Panel B: Quarterly								
	N	Mean	Median	Min	Max	Stdev	Skew	XKurt
SP500	147	.0084	.0121	-.2467	.1977	.0801	-.43	.54
Bond	147	.0074	.0036	-.1251	.1702	.0338	.47	5.30
GSCI	147	.0103	.0175	-.4701	.5333	.1100	.07	4.88
Correlation matrix								
SP500	1							
Bond	.16	1						
GSCI	.08	-.10	1					

Table 1.2 Monthly Rebalanced MV Strategies: Fixed-weights vs. Stock-Bond vs. Stock-Bond-Commodity (1986-2012)

This table reports the portfolio performance of Fixed-weights (FIX), Stock-Bond (S-B) and Stock-Bond-Commodity (S-B-C) MV strategies with monthly rebalancing. The in-sample period is 1976:01 - 1985:12, the out-of-sample period is 1986:01 - 2012:12. All reported performance measures refer to the out-of-sample period. The FIX strategy rebalances portfolio weights each month to [50%,30%,10%] for S-B and [50%,20%,10%,10%] for S-B-C; the BWD strategy relies on sample means and covariance matrices recomputed each month on an expanding estimation window; the FWD strategy exploits predictability of excess returns and covariances and recursively forecasts portfolio return moments each month using an expanding estimation window. We report the annualized CRRA utility-based Certainty Equivalent Excess Return (CEQ) and the monthly Turnover (TO). The CEQ is calculated from net portfolio returns after a proportional transaction cost of 50 bps. We report the portfolio performance for different levels of risk aversion ($\gamma = 3, 5, 10$) and portfolio total leverage constraints (Lev<100%, 75%, 50%, 25% and Lev=0).

	Lev<100%		Lev<75%		Lev<50%		Lev<25%		Lev=0	
	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO
Panel A: $\gamma = 3$										
FIX:										
S-B	.0253	.02	.0253	.02	.0253	.02	.0253	.02	.0253	.02
S-B-C	.0254	.02	.0254	.02	.0254	.02	.0254	.02	.0254	.02
BWD:										
S-B	.0458	.02	.0422	.02	.0376	.02	.0320	.02	.0257	.02
S-B-C	.0372	.02	.0325	.02	.0268	.02	.0205	.02	.0136	.03
FWD:										
S-B	.0467	.12	.0399	.13	.0325	.15	.0246	.17	.0158	.20
S-B-C	.0609	.19	.0518	.21	.0420	.25	.0320	.29	.0247	.31
Panel B: $\gamma = 5$										
FIX:										
S-B	.0182	.02	.0182	.02	.0182	.02	.0182	.02	.0182	.02
S-B-C	.0174	.02	.0174	.02	.0174	.02	.0174	.02	.0174	.02
BWD:										
S-B	.0310	.02	.0308	.02	.0297	.02	.0275	.02	.0238	.02
S-B-C	.0276	.02	.0273	.02	.0260	.02	.0227	.02	.0179	.02
FWD:										
S-B	.0449	.10	.0391	.10	.0330	.11	.0262	.12	.0190	.14
S-B-C	.0554	.14	.0487	.15	.0414	.16	.0332	.19	.0233	.22
Panel C: $\gamma = 10$										
FIX:										
S-B	-.0003	.02	-.0003	.02	-.0003	.02	-.0003	.02	-.0003	.02
S-B-C	-.0039	.02	-.0039	.02	-.0039	.02	-.0039	.02	-.0039	.02
BWD:										
S-B	.0148	.02	.0148	.02	.0148	.02	.0148	.02	.0148	.02
S-B-C	.0132	.02	.0132	.02	.0132	.02	.0132	.02	.0132	.02
FWD:										
S-B	.0297	.09	.0288	.09	.0269	.09	.0238	.09	.0192	.10
S-B-C	.0378	.12	.0361	.12	.0337	.12	.0293	.12	.0231	.14

Table 1.3 Quarterly Rebalanced MV Strategies: Fixed-weights vs. Stock-Bond vs. Stock-Bond-Commodity (1986-2012)

This table reports the portfolio performance of Fixed-weights (FIX), Stock-Bond (S-B) and Stock-Bond-Commodity (S-B-C) MV strategies with quarterly rebalancing. The in-sample period is 1976:Q1 - 1985:Q4, the out-of-sample period is 1986:Q1 - 2012:Q4. All reported performance measures refer to the out-of-sample period. The FIX strategy rebalances portfolio weights each quarter to [50%,30%,10%] for S-B and [50%,20%,10%,10%] for S-B-C; the BWD strategy relies on sample means and covariance matrices recomputed each quarter on an expanding estimation window; the FWD strategy exploits predictability of excess returns and covariances and recursively forecasts portfolio return moments each quarter using an expanding estimation window. We report the annualized CRRA utility-based Certainty Equivalent Excess Return (CEQ) and the quarterly Turnover (TO). The CEQ is calculated from net portfolio returns after a proportional transaction cost of 50 bps. We report the portfolio performance for different levels of risk aversion ($\gamma = 3, 5, 10$) and portfolio total leverage constraints (Lev<100%, 75%, 50%, 25% and Lev=0).

	Lev<100%		Lev<75%		Lev<50%		Lev<25%		Lev=0	
	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO
Panel A: $\gamma = 3$										
FIX:										
S-B	.0271	.04	.0271	.04	.0271	.04	.0271	.04	.0271	.04
S-B-C	.0280	.05	.0280	.05	.0280	.05	.0280	.05	.0280	.05
BWD:										
S-B	.0382	.05	.0365	.05	.0337	.05	.0298	.05	.0248	.06
S-B-C	.0386	.05	.0359	.05	.0316	.05	.0251	.06	.0185	.07
FWD:										
S-B	.0451	.17	.0391	.17	.0327	.18	.0265	.20	.0201	.22
S-B-C	.0636	.28	.0569	.31	.0496	.35	.0431	.39	.0361	.42
Panel B: $\gamma = 5$										
FIX:										
S-B	.0199	.04	.0199	.04	.0199	.04	.0199	.04	.0199	.04
S-B-C	.0197	.05	.0197	.05	.0197	.05	.0197	.05	.0197	.05
BWD:										
S-B	.0226	.05	.0226	.05	.0226	.05	.0225	.05	.0209	.05
S-B-C	.0240	.05	.0240	.05	.0241	.05	.0232	.05	.0204	.05
FWD:										
S-B	.0392	.16	.0356	.16	.0318	.16	.0267	.17	.0207	.18
S-B-C	.0536	.21	.0487	.23	.0426	.25	.0365	.28	.0296	.32
Panel C: $\gamma = 10$										
FIX:										
S-B	.0016	.04	.0016	.04	.0016	.04	.0016	.04	.0016	.04
S-B-C	-.0029	.05	-.0029	.05	-.0029	.05	-.0029	.05	-.0029	.05
BWD:										
S-B	.0107	.05	.0107	.05	.0107	.05	.0107	.05	.0107	.05
S-B-C	.0115	.05	.0115	.05	.0115	.05	.0115	.05	.0115	.05
FWD:										
S-B	.0264	.15	.0245	.15	.0225	.15	.0204	.15	.0179	.16
S-B-C	.0311	.18	.0300	.18	.0289	.18	.0275	.19	.0242	.21

Table 1.4 Monthly Rebalanced Non-MV Strategies: Fixed-weights vs. Stock-Bond vs. Stock-Bond-Commodity (1986-2012)

This table reports the portfolio performance of Fixed-weights (FIX), Stock-Bond (S-B) and Stock-Bond-Commodity (S-B-C) non-MV strategies with monthly rebalancing. The in-sample period is 1976:01 - 1985:12, the out-of-sample period is 1986:01 - 2012:12. All reported performance measures refer to the out-of-sample period. The FIX strategy rebalances portfolio weights each month to [50%,30%,10%] for S-B and [50%,20%,10%,10%] for S-B-C; the BWD strategy relies on sample means, covariances. co-skewness and co-kurtoses recomputed each month on an expanding estimation window; the FWD strategy exploits predictability of excess returns, covariances, co-skewness and co-kurtoses and recursively forecasts portfolio return moments each month using an expanding estimation window. We report the annualized CRRA utility-based Certainty Equivalent Excess Return (CEQ) and the monthly Turnover (TO). The CEQ is calculated from net portfolio returns after a proportional transaction cost of 50 bps. We report the portfolio performance for different levels of risk aversion ($\gamma = 3, 5, 10$) and portfolio total leverage constraints (Lev<100%, 75%, 50%, 25% and Lev=0).

	Lev<100%		Lev<75%		Lev<50%		Lev<25%		Lev=0	
	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO
Panel A: $\gamma = 3$										
FIX:										
S-B	.0253	.02	.0253	.02	.0253	.02	.0253	.02	.0253	.02
S-B-C	.0254	.02	.0254	.02	.0254	.02	.0254	.02	.0254	.02
BWD:										
S-B	.0460	.02	.0423	.02	.0377	.02	.0320	.02	.0257	.02
S-B-C	.0355	.02	.0309	.02	.0255	.02	.0194	.02	.0128	.03
FWD:										
S-B	.0435	.13	.0370	.14	.0301	.16	.0222	.18	.0134	.21
S-B-C	.0569	.23	.0485	.25	.0397	.28	.0301	.32	.0242	.33
Panel B: $\gamma = 5$										
FIX:										
S-B	.0182	.02	.0182	.02	.0182	.02	.0182	.02	.0182	.02
S-B-C	.0174	.02	.0174	.02	.0174	.02	.0174	.02	.0174	.02
BWD:										
S-B	.0312	.02	.0311	.02	.0298	.02	.0276	.02	.0239	.02
S-B-C	.0261	.02	.0260	.02	.0247	.02	.0216	.02	.0170	.02
FWD:										
S-B	.0416	.12	.0367	.12	.0306	.12	.0240	.13	.0171	.15
S-B-C	.0512	.18	.0452	.19	.0378	.20	.0297	.22	.0207	.26
Panel C: $\gamma = 10$										
FIX:										
S-B	-.0003	.02	-.0003	.02	-.0003	.02	-.0003	.02	-.0003	.02
S-B-C	-.0039	.02	-.0039	.02	-.0039	.02	-.0039	.02	-.0039	.02
BWD:										
S-B	.0150	.02	.0150	.02	.0150	.02	.0150	.02	.0150	.02
S-B-C	.0125	.02	.0125	.02	.0125	.02	.0126	.02	.0125	.02
FWD:										
S-B	.0240	.12	.0235	.12	.0221	.12	.0200	.12	.0170	.12
S-B-C	.0316	.18	.0304	.18	.0279	.18	.0245	.18	.0197	.18

Table 1.5 Quarterly Rebalanced Non-MV Strategies: Fixed-weights vs. Stock-Bond vs. Stock-Bond-Commodity (1986-2012)

This table reports the portfolio performance of Fixed-weights (FIX), Stock-Bond (S-B) and Stock-Bond-Commodity (S-B-C) non-MV strategies with quarterly rebalancing. The in-sample period is 1976:Q1 - 1985:Q4, the out-of-sample period is 1986:Q1 - 2012:Q4. All reported performance measures refer to the out-of-sample period. The FIX strategy rebalances portfolio weights each quarter to [50%,30%,10%] for S-B and [50%,20%,10%,10%] for S-B-C; the BWD strategy relies on sample means, covariances. co-skewness and co-kurtoses recomputed each quarter on an expanding estimation window; the FWD strategy exploits predictability of excess returns, covariances, co-skewness and co-kurtoses and recursively forecasts portfolio return moments each quarter using an expanding estimation window. We report the annualized CRRA utility-based Certainty Equivalent Excess Return (CEQ) and the quarterly Turnover (TO). The CEQ is calculated from net portfolio returns after a proportional transaction cost of 50 bps. We report the portfolio performance for different levels of risk aversion ($\gamma = 3, 5, 10$) and portfolio total leverage constraints (Lev<100%, 75%, 50%, 25% and Lev=0).

	Lev<100%		Lev<75%		Lev<50%		Lev<25%		Lev=0	
	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO
					Panel A: $\gamma = 3$					
FIX:										
S-B	.0271	.04	.0271	.04	.0271	.04	.0271	.04	.0271	.04
S-B-C	.0280	.05	.0280	.05	.0280	.05	.0280	.05	.0280	.05
BWD:										
S-B	.0392	.05	.0374	.05	.0342	.05	.0301	.05	.0248	.06
S-B-C	.0347	.05	.0318	.05	.0272	.05	.0208	.06	.0151	.07
FWD:										
S-B	.0465	.18	.0412	.18	.0348	.18	.0285	.18	.0219	.19
S-B-C	.0700	.34	.0633	.37	.0564	.41	.0492	.45	.0404	.48
					Panel B: $\gamma = 5$					
FIX:										
S-B	.0199	.04	.0199	.04	.0199	.04	.0199	.04	.0199	.04
S-B-C	.0197	.05	.0197	.05	.0197	.05	.0197	.05	.0197	.05
BWD:										
S-B	.0236	.05	.0236	.05	.0236	.05	.0233	.05	.0213	.05
S-B-C	.0215	.05	.0215	.05	.0217	.05	.0206	.05	.0176	.05
FWD:										
S-B	.0366	.18	.0342	.18	.0308	.18	.0272	.17	.0219	.17
S-B-C	.0548	.28	.0513	.29	.0463	.30	.0401	.33	.0329	.38
					Panel C: $\gamma = 10$					
FIX:										
S-B	.0016	.04	.0016	.04	.0016	.04	.0016	.04	.0016	.04
S-B-C	-.0029	.05	-.0029	.05	-.0029	.05	-.0029	.05	-.0029	.05
BWD:										
S-B	.0112	.05	.0112	.05	.0112	.05	.0112	.05	.0112	.05
S-B-C	.0102	.05	.0102	.05	.0102	.05	.0102	.05	.0102	.05
FWD:										
S-B	.0211	.18	.0207	.18	.0197	.18	.0184	.18	.0166	.17
S-B-C	.0300	.26	.0291	.27	.0274	.27	.0263	.27	.0244	.28

Table 1.6 Quarterly Rebalanced Strategies: BWD vs. FWD Strategies (1986-2012)

This table reports the portfolio performance of Stock-Bond (S-B) and Stock-Bond-Commodity (S-B-C) strategies with quarterly rebalancing. The in-sample period is 1976:Q1-1985:Q4, the out-of-sample period is 1986:Q1-2012:Q4. All reported performance measures refer to the out-of-sample period. Panel A reports results for MV strategies, Panel B for non-MV strategies. In each panel the S-B and S-B-C allocations are implemented using four combinations of the BWD and FWD approaches to forecasting return moments, For instance, in Panel A, FWD & BWD denotes a portfolio allocation where expected returns are computed with the FWD approach and the covariance matrix is computed with the BWD approach. The BWD approach relies on sample moments recomputed each quarter on an expanding estimation window; the FWD approach exploits predictability of return moments and recursively forecasts portfolio return moments each quarter using an expanding estimation window. We report the annualized mean, standard deviation, skewness and kurtosis of realized portfolio returns and the annualized CRRA utility-based Certainty Equivalent Excess Return (CEQ). The CEQ is calculated from net portfolio returns after a proportional transaction cost of 50 bps. We report the measures for moderate risk aversion ($\gamma = 5$) and three portfolio total leverage constraints (Lev<100%, 50% and Lev=0).

	Lev<100%					Lev<50%					Lev=0%				
	Mean	Std	Skew	Kurt	CEQ	Mean	Std	Skew	Kurt	CEQ	Mean	Std	Skew	Kurt	CEQ
						Panel A: MV									
BWD & BWD:															
S-B	.0261	.0380	-.32	4.02	.0226	.0261	.0380	-.32	4.03	.0226	.0241	.0367	-.39	4.23	.0209
S-B-C	.0538	.1113	.89	12.48	.0240	.0535	.1108	.93	12.60	.0241	.0443	.1021	1.46	15.54	.0203
FWD & BWD:															
S-B	.0272	.0406	-.04	5.17	.0234	.0274	.0404	-.02	5.24	.0235	.0241	.0378	-.29	5.23	.0207
S-B-C	.0596	.1125	1.91	16.25	.0324	.0584	.1114	2.00	16.78	.0319	.0482	.1030	2.42	19.18	.0261
BWD & FWD:															
S-B	.0459	.0697	-.49	3.84	.0340	.0369	.0587	-.63	4.92	.0283	.0249	.0462	-1.10	8.79	.0194
S-B-C	.0750	.1153	1.18	12.10	.0449	.0599	.1054	1.30	13.79	.0346	.0419	.0926	1.34	14.58	.0221
FWD & FWD:															
S-B	.0503	.0677	-.45	4.16	.0392	.0398	.0570	-.77	5.27	.0318	.0259	.0449	-1.40	9.45	.0207
S-B-C	.0826	.1184	1.80	15.33	.0530	.0667	.1081	1.94	16.12	.0420	.0486	.0957	2.19	17.16	.0292

Table 1.6 (Continues)

	Lev<100%					Lev<50%					Lev=0%				
	Mean	Std	Skew	Kurt	CEQ	Mean	Std	Skew	Kurt	CEQ	Mean	Std	Skew	Kurt	CEQ
						Panel B: Non-MV									
BWD & BWD:															
S-B	.0275	.0392	-.31	4.01	.0236	.0275	.0392	-.31	4.01	.0236	.0249	.0372	-.41	4.29	.0214
S-B-C	.0550	.1154	.74	11.33	.0213	.0545	.1147	.79	11.48	.0215	.0437	.1049	1.27	14.16	.0173
FWD & BWD:															
S-B	.0291	.0423	.00	5.17	.0245	.0292	.0419	.02	5.25	.0248	.0251	.0387	-.31	5.21	.0213
S-B-C	.0623	.1174	1.75	14.63	.0309	.0606	.1162	1.85	15.17	.0302	.0484	.1068	2.20	17.15	.0235
BWD & FWD:															
S-B	.0425	.0614	-.31	3.50	.0328	.0359	.0543	-.43	3.94	.0283	.0251	.0434	-.64	5.81	.0202
S-B-C	.0732	.1023	.18	5.53	.0462	.0612	.0937	.45	6.46	.0392	.0439	.0833	.72	7.62	.0270
FWD & FWD:															
S-B	.0462	.0607	-.38	3.94	.0366	.0382	.0534	-.58	4.42	.0308	.0268	.0430	-.96	6.84	.0219
S-B-C	.0822	.1049	.40	5.57	.0544	.0692	.0972	.72	6.69	.0461	.0511	.0880	1.02	7.69	.0326

Table 1.7 Performance of Portfolio Strategies (1986-2012): Which Asset Predictability Matters the Most?

This table presents the performance of Stock-Bond (S-B) and Stock-Bond-Commodity (S-B-C) portfolios formed using various combinations of BWD and FWD expected returns during the out-of-sample period of 1986:01-2012:12. For instance, FWD S + BWD B-C denotes a portfolio allocation where expected returns for stocks are computed with the FWD approach while expected returns for bonds and commodities are computed with the BWD approach. In all cases the relevant higher moments are predicted with the FWD approach. The BWD approach relies on sample moments recomputed each period on an expanding estimation window; the FWD approach exploits predictability of return moments and recursively forecasts portfolio return moments each period using an expanding estimation window. We report the first four moments of portfolio realized excess returns and the annualized CRRA utility-based Certainty Equivalent Excess Return (CEQ) . The CEQ is calculated from net portfolio returns after a proportional transaction cost of 50 bps. We report the portfolio performance for risk aversion of 5 (γ=5) and portfolio total leverage constraint of 50% (Lev<50%). Panels A and B report results for mean-variance (MV) strategies with, respectively, monthly and quarterly rebalancing. Panels C and D report results for non-MV strategies.

	Mean	Std	Skew	Kurt	CEQ	Mean	Std	Skew	Kurt	CEQ
	Panel A: MV / Monthly					Panel B: MV / Quarterly				
BWD S-B-C										
S-B	.0415	.0581	-.55	4.96	.0327	.0369	.0587	-.63	4.92	.0283
S-B-C	.0506	.0863	-.01	4.28	.0313	.0599	.1054	1.30	13.79	.0346
FWD S + BWD B-C										
S-B	.0386	.0555	-.29	3.79	.0307	.0359	.0588	-.61	4.82	.0272
S-B-C	.0489	.0867	.00	4.28	.0294	.0586	.1043	1.28	13.12	.0339
FWD B + BWD S-C										
S-B	.0413	.0593	-.68	5.94	.0322	.0393	.0565	-.76	5.50	.0314
S-B-C	.0521	.0835	-.03	4.21	.0340	.0622	.1077	1.03	13.03	.0350
FWD C + BWD S-B										
S-B	.0415	.0581	-.55	4.96	.0327	.0369	.0587	-.63	4.92	.0283
S-B-C	.0581	.0841	.18	4.19	.0396	.0658	.1069	2.18	18.23	.0419
FWD S-B-C										
S-B	.0412	.0563	-.27	3.76	.0330	.0398	.0570	-.77	5.27	.0318
S-B-C	.0592	.0830	.11	4.04	.0412	.0667	.1081	1.94	16.12	.0420

Table 1.7 (Continues)

	Mean	Std	Skew	Kurt	CEQ	Mean	Std	Skew	Kurt	CEQ
	Panel C: Non-MV / Monthly					Panel D: Non-MV / Quarterly				
BWD S-B-C										
S-B	.0353	.0575	-.67	4.96	.0267	.0359	.0543	-.43	3.94	.0283
S-B-C	.0463	.0911	.10	4.36	.0250	.0612	.0937	.45	6.46	.0392
FWD S + BWD B-C										
S-B	.0335	.0544	-.39	3.33	.0258	.0356	.0539	-.42	3.91	.0280
S-B-C	.0454	.0908	.16	4.54	.0243	.0596	.0933	.44	6.13	.0379
FWD B + BWD S-C										
S-B	.0387	.0592	-.60	5.53	.0295	.0368	.0528	-.63	4.54	.0296
S-B-C	.0494	.0892	.11	4.19	.0290	.0641	.0968	.35	6.20	.0405
FWD C + BWD S-B										
S-B	.0353	.0575	-.67	4.96	.0267	.0359	.0543	-.43	3.94	.0283
S-B-C	.0541	.0893	.34	4.56	.0337	.0666	.0955	.78	7.30	.0443
FWD S-B-C										
S-B	.0388	.0564	-.23	3.51	.0306	.0382	.0534	-.58	4.42	.0308
S-B-C	.0578	.0884	.30	4.49	.0378	.0692	.0972	.72	6.69	.0461

Table 1.8 Monthly Rebalanced Portfolio Strategies (1986-2012): the Role of Technical Indicators

This table reports the performance of Stock-Bond (S-B) and Stock-Bond-Commodity (S-B-C) monthly rebalanced portfolios using either macroeconomic predictors or technical indicators to form expected returns and using the FWD approach for higher return moments. All reported performance measures refer to the out-of-sample period 1986:01-2012:12. Tech 1st PC denotes strategies where the return forecast is based on the first principal component of twelve technical indicators (listed in Appendix D); Tech 1st +2nd + 3rd PC denotes strategies where the return forecast is based on the first three principal components of the same twelve technical indicators; FWD Macro Comb denotes strategies where the return forecast is based on the combination of individual forecasts from macroeconomic and financial market variables. We report the first four moments of portfolio realized excess returns, the annualized CRRA Certainty Equivalent Excess Return (CEQ) and the monthly Turnover (TO). The CEQ is calculated from net portfolio returns after a proportional transaction cost of 50 bps. We report portfolio performance for a risk aversion of 5 (γ=5) and three portfolio total leverage constraints (Lev<100%, 50% and Lev=0). Panels A reports results for mean-variance (MV) strategies, Panel B for non-MV strategies.

	Lev<100%						Lev<50%						Lev=0%					
	Mean	Std	Skew	Kurt	CEQ	TO	Mean	Std	Skew	Kurt	CEQ	TO	Mean	Std	Skew	Kurt	CEQ	TO
Panel A: MV																		
Tech: 1st PC																		
S-B	.0443	.0863	-1.61	12.61	.0251	.16	.0313	.0775	-2.14	17.76	.0160	.17	.0175	.0690	-2.88	26.50	.0055	.20
S-B-C	.0443	.1124	-.36	6.74	.0120	.25	.0295	.1006	-.63	7.60	.0038	.28	.0109	.0852	-1.14	10.10	-.0073	.33
Tech: 1st + 2nd + 3rd PC Comb																		
S-B	.0494	.0805	.03	4.20	.0326	.24	.0403	.0727	.13	4.99	.0267	.24	.0253	.0611	-.14	4.74	.0158	.25
S-B-C	.0796	.1201	.25	4.99	.0415	.36	.0597	.1082	.09	4.63	.0293	.38	.0364	.0927	-.07	4.25	.0144	.42
FWD Macro Comb																		
S-B	.0580	.0706	-.23	4.06	.0450	.10	.0412	.0563	-.27	3.76	.0330	.11	.0232	.0405	-.36	3.45	.0190	.14
S-B-C	.0798	.0962	.07	3.76	.0552	.14	.0592	.0830	.11	4.04	.0412	.16	.0361	.0707	.15	4.54	.0232	.22

Table 1.8 (Continues)

	Lev<100%						Lev<50%						Lev=0%					
	Mean	Std	Skew	Kurt	CEQ	TO	Mean	Std	Skew	Kurt	CEQ	TO	Mean	Std	Skew	Kurt	CEQ	TO
Panel B: Non-MV																		
Tech: 1st PC																		
S-B	.0413	.0860	-1.62	12.77	.0204	.19	.0313	.0783	-2.10	17.19	.0136	.19	.0173	.0700	-2.78	25.19	.0030	.21
S-B-C	.0507	.1190	-.31	6.31	.0131	.28	.0345	.1043	-.63	7.13	.0053	.29	.0147	.0870	-1.06	9.54	-.0056	.33
Tech: 1st + 2nd + 3rd PC Comb																		
S-B	.0411	.0804	-.10	4.67	.0244	.26	.0340	.0742	-.08	5.37	.0199	.26	.0220	.0628	-.33	5.27	.0119	.26
S-B-C	.0862	.1263	.34	4.70	.0448	.37	.0637	.1128	.18	4.53	.0309	.38	.0385	.0953	.06	4.24	.0153	.42
FWD Macro Comb																		
S-B	.0537	.0682	-.15	3.80	.0416	.12	.0388	.0564	-.23	3.51	.0306	.12	.0217	.0421	-.38	3.54	.0171	.15
S-B-C	.0777	.1008	.23	4.05	.0512	.18	.0578	.0884	.30	4.49	.0378	.20	.0352	.0757	.33	5.07	.0207	.26

Table 1.9 Quarterly Rebalanced Strategies: Sub-period Performance and Tradability

This table reports sub-period portfolio performance and tradability using financial instruments (futures and ETFs) of Fixed-weights (FIX), Stock-Bond (S-B) and Stock-Bond-Commodity (S-B-C) MV (left portion of the table) and non-MV (right portion) strategies with quarterly rebalancing. Specifically, Panel A reports the out-of-sample performance of portfolio strategies using asset class indexes over the period of 1986:Q1-2001:Q4. Panel B presents the out-of-sample performance of portfolio strategies using an ETF tracking S&P500 (Ticker: SPY) to represent the equity class, a combination of Aggregate Bond Index and ETF (Ticker:AGG) for the bond class, and a combination of Futures and ETF (Ticker:GSG) that track the GSCI for commodity class for the period 1993:Q3-2012:Q4. Panel C reports the out-of-sample performance of portfolio strategies using SPY, AGG and Futures/GSG for equities, bonds and commodities, respectively, over the period of 2003:Q4-2012:Q4. Panel D shows the out-of-sample performance of monthly rebalanced portfolio strategies using SPY, AGG and GSG for for equities, bonds and commodities, respectively, over the period 2006:08-2012:12. Panel E shows the out-of-sample performance of monthly rebalanced portfolio strategies using SPY, AGG and DBC (tracks the DBIQ Optimum Yield Diversified Commodity Index) for for equities, bonds and commodities, respectively, over the period 2006:03-2012:12. All reported performance measures refer to the out-of-sample period. The FIX strategy rebalances portfolio weights each quarter to [50%,30%,10%] for S-B and [50%,20%,10%,10%] for S-B-C; the BWD strategy relies on sample means, covariances. co-skewness and co-kurtosis recomputed each quarter on an expanding estimation window; the FWD strategy exploits predictability of excess returns, covariances, co-skewness and co-kurtosis and recursively forecasts portfolio return moments each quarter using an expanding estimation window. We report the annualized CRRA utility-based Certainty Equivalent Excess Return (CEQ) and the quarterly Turnover (TO). The CEQ is calculated from net portfolio returns after a proportional transaction cost of 50 bps for indexes and futures and 10bps for ETFs. We report the measures based on moderate risk aversion ($\gamma = 5$) and three portfolio total leverage constraints (Lev<100%, 50% and Lev=0).

	MV						Non-MV					
	Lev<100%		Lev<50%		Lev=0		Lev<100%		Lev<50%		Lev=0	
	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO
Panel A: 1986:Q1-2001:Q4												
FIX:												
S-B	.0292	.04	.0292	.04	.0292	.04	.0292	.04	.0292	.04	.0292	.04
S-B-C	.0319	.05	.0319	.05	.0319	.05	.0319	.05	.0319	.05	.0319	.05
BWD:												
S-B	.0154	.09	.0154	.09	.0154	.09	.0160	.09	.0160	.09	.0160	.09
S-B-C	.0253	.07	.0253	.07	.0245	.06	.0214	.07	.0214	.07	.0201	.06
FWD:												
S-B	.0270	.23	.0237	.23	.0156	.24	.0253	.25	.0225	.25	.0175	.25
S-B-C	.0446	.25	.0364	.28	.0266	.34	.0415	.36	.0367	.37	.0258	.43

	MV						Non-MV					
	Lev<100%		Lev<50%		Lev=0		Lev<100%		Lev<50%		Lev=0	
	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO
Panel B: 1993:Q3-2012:Q4												
FIX:												
S-B	.0169	.05	.0169	.05	.0169	.05	.0171	.05	.0171	.05	.0171	.05
S-B-C	.0153	.05	.0153	.05	.0153	.05	.0145	.05	.0145	.05	.0145	.05
BWD:												
S-B	.0263	.03	.0263	.03	.0243	.03	.0275	.03	.0275	.03	.0247	.02
S-B-C	.0233	.04	.0233	.04	.0162	.04	.0174	.04	.0178	.04	.0118	.04
FWD:												
S-B	.0396	.09	.0325	.09	.0228	.11	.0383	.10	.0319	.09	.0229	.09
S-B-C	.0499	.17	.0398	.21	.0271	.30	.0555	.23	.0463	.26	.0344	.36

Table 1.9 (Continues)

	MV						Non-MV						MV						Non-MV					
	Lev<100%		Lev<50%		Lev=0		Lev<100%		Lev<50%		Lev=0		Lev<100%		Lev<50%		Lev=0		Lev<100%		Lev<50%		Lev=0	
	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO
				Panel C: 2003:Q4-2012:Q4																				
FIX:																								
S-B	.0136	.06	.0136	.06	.0136	.06	.0138	.06	.0138	.06	.0138	.06												
S-B-C	.0083	.07	.0083	.07	.0083	.07	.0068	.07	.0068	.07	.0068	.07												
BWD:																								
S-B	.0316	.03	.0316	.03	.0273	.03	.0331	.03	.0331	.03	.0274	.03												
S-B-C	.0172	.06	.0173	.05	.0096	.06	.0077	.06	.0084	.05	.0035	.06												
FWD:																								
S-B	.0492	.08	.0382	.09	.0255	.12	.0445	.11	.0371	.10	.0252	.10												
S-B-C	.0610	.19	.0487	.24	.0345	.34	.0679	.21	.0590	.24	.0467	.36												

Table 1.10 Quarterly Rebalanced Strategies: Sub-period Performance and Tradability

This table reports sub-period portfolio performance and tradability using financial instruments (futures and ETFs) of Fixed-weights (FIX), Stock-Bond (S-B) and Stock-Bond-Commodity (S-B-C) MV (left portion of the table) and non-MV (right portion) strategies with quarterly rebalancing. Specifically, Panel A reports the out-of-sample performance of portfolio strategies using asset class indexes over the period of 1986:Q1-2001:Q4. Panel B presents the out-of-sample performance of portfolio strategies using an ETF tracking S&P500 (Ticker: SPY) to represent the equity class, a combination of Aggregate Bond Index and ETF (Ticker:AGG) for the bond class, and a combination of Futures and ETF (Ticker:GSG) that track the GSCI for commodity class for the period 1993:Q3-2012:Q4. Panel C reports the out-of-sample performance of portfolio strategies using SPY, AGG and Futures/GSG for equities, bonds and commodities, respectively, over the period of 2003:Q4-2012:Q4. Panel D shows the out-of-sample performance of portfolio strategies using SPY, AGG and GSG for for equities, bonds and commodities, respectively, over the period 2006:Q4-2012:Q4. Panel E shows the out-of-sample performance of portfolio strategies using SPY, AGG and DBC (tracks the DBIQ Optimum Yield Diversified Commodity Index) for for equities, bonds and commodities, respectively, over the period 2006:Q3-2012:Q4. All reported performance measures refer to the out-of-sample period. The FIX strategy rebalances portfolio weights each quarter to [50%,30%,10%] for S-B and [50%,20%,10%,10%] for S-B-C; the BWD strategy relies on sample means, covariances. co-skewness and co-kurtosis recomputed each quarter on an expanding estimation window; the FWD strategy exploits predictability of excess returns, covariances, co-skewness and co-kurtosis and recursively forecasts portfolio return moments each quarter using an expanding estimation window. We report the annualized CRRA utility-based Certainty Equivalent Excess Return (CEQ) and the quarterly Turnover (TO). The CEQ is calculated from net portfolio returns after a proportional transaction cost of 50 bps for indexes and futures and 10bps for ETFs. We report the measures based on moderate risk aversion ($\gamma = 5$) and three portfolio total leverage constraints (Lev<100%, 50% and Lev=0).

Panel A: 1986:Q1-2001:Q4

	MV						Non-MV					
	Lev<100%		Lev<50%		Lev=0		Lev<100%		Lev<50%		Lev=0	
	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO
FIX:												
S-B	.0292	.04	.0292	.04	.0292	.04	.0292	.04	.0292	.04	.0292	.04
S-B-C	.0319	.05	.0319	.05	.0319	.05	.0319	.05	.0319	.05	.0319	.05
BWD:												
S-B	.0154	.09	.0154	.09	.0154	.09	.0160	.09	.0160	.09	.0160	.09
S-B-C	.0253	.07	.0253	.07	.0245	.06	.0214	.07	.0214	.07	.0201	.06
FWD:												
S-B	.0270	.23	.0237	.23	.0156	.24	.0253	.25	.0225	.25	.0175	.25
S-B-C	.0446	.25	.0364	.28	.0266	.34	.0415	.36	.0367	.37	.0258	.43

Panel B: 1993:Q3-2012:Q4

	MV						Non-MV					
	Lev<100%		Lev<50%		Lev=0		Lev<100%		Lev<50%		Lev=0	
	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO
FIX:												
S-B	.0169	.05	.0169	.05	.0169	.05	.0171	.05	.0171	.05	.0171	.05
S-B-C	.0153	.05	.0153	.05	.0153	.05	.0145	.05	.0145	.05	.0145	.05
BWD:												
S-B	.0263	.03	.0263	.03	.0243	.03	.0275	.03	.0275	.03	.0247	.02
S-B-C	.0233	.04	.0233	.04	.0162	.04	.0174	.04	.0178	.04	.0118	.04
FWD:												
S-B	.0396	.09	.0325	.09	.0228	.11	.0383	.10	.0319	.09	.0229	.09
S-B-C	.0499	.17	.0398	.21	.0271	.30	.0555	.23	.0463	.26	.0344	.36

Table 1.10 (Continues)

	MV						Non-MV					
	Lev<100%		Lev<50%		Lev=0		Lev<100%		Lev<50%		Lev=0	
	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO
Panel C: 2003:Q4-2012:Q4												
FIX:												
S-B	.0136	.06	.0136	.06	.0136	.06	.0138	.06	.0138	.06	.0138	.06
S-B-C	.0083	.07	.0083	.07	.0083	.07	.0068	.07	.0068	.07	.0068	.07
BWD:												
S-B	.0316	.03	.0316	.03	.0273	.03	.0331	.03	.0331	.03	.0274	.03
S-B-C	.0172	.06	.0173	.05	.0096	.06	.0077	.06	.0084	.05	.0035	.06
FWD:												
S-B	.0492	.08	.0382	.09	.0255	.12	.0445	.11	.0371	.10	.0252	.10
S-B-C	.0610	.19	.0487	.24	.0345	.34	.0679	.21	.0590	.24	.0467	.36
Panel E: 2006:03-2012:12												
FIX:												
S-B	.0088	.03	.0088	.03	.0088	.03	.0082	.03	.0082	.03	.0082	.03
S-B-C	.0013	.03	.0013	.03	.0013	.03	.0000	.03	.0000	.03	.0000	.03
BWD:												
S-B	.0612	.02	.0557	.02	.0371	.02	.0613	.02	.0557	.02	.0371	.02
S-B-C	.0432	.02	.0327	.02	.0181	.03	.0383	.02	.0305	.02	.0171	.02
FWD:												
S-B	.0811	.07	.0613	.09	.0403	.13	.0724	.09	.0575	.09	.0384	.12
S-B-C	.0968	.13	.0757	.17	.0534	.24	.0939	.15	.0761	.18	.0545	.24

	MV						Non-MV					
	Lev<100%		Lev<50%		Lev=0		Lev<100%		Lev<50%		Lev=0	
	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO
Panel D: 2006:08-2012:12												
FIX:												
S-B	.0088	.03	.0088	.03	.0088	.03	.0082	.03	.0082	.03	.0082	.03
S-B-C	-.0081	.03	-.0081	.03	-.0081	.03	-.0095	.03	-.0095	.03	-.0095	.03
BWD:												
S-B	.0612	.02	.0557	.02	.0371	.02	.0613	.02	.0557	.02	.0371	.02
S-B-C	.0077	.02	.0013	.02	-.0092	.02	.0020	.02	-.0017	.02	-.0108	.02
FWD:												
S-B	.0811	.07	.0613	.09	.0403	.13	.0724	.09	.0575	.09	.0384	.12
S-B-C	.0727	.14	.0533	.18	.0327	.25	.0663	.16	.0514	.19	.0327	.26

Table 1.11 Quarterly and Monthly Rebalanced Strategies: Sub-period Performance and Tradability

This table reports sub-period portfolio performance and tradability using financial instruments (futures and ETFs) of Fixed-weights (FIX), Stock-Bond (S-B) and Stock-Bond-Commodity (S-B-C) MV (left portion of the table) and non-MV (right portion) strategies with quarterly rebalancing. Specifically, Panel A reports the out-of-sample performance of portfolio strategies using asset class indexes over the period of 1986:Q1-2001:Q4. Panel B presents the out-of-sample performance of portfolio strategies using an ETF tracking S&P500 (Ticker: SPY) to represent the equity class, a combination of Aggregate Bond Index and ETF (Ticker:AGG) for the bond class, and a combination of Futures and ETF (Ticker:GSG) that track the GSCI for commodity class for the period 1993:Q3-2012:Q4. Panel C reports the out-of-sample performance of portfolio strategies using SPY, AGG and Futures/GSG for equities, bonds and commodities, respectively, over the period of 2003:Q4-2012:Q4. Panel D shows the out-of-sample performance of portfolio strategies using SPY, AGG and GSG for for equities, bonds and commodities, respectively, over the period 2006:Q4-2012:Q4. Panel E shows the out-of-sample performance of portfolio strategies using SPY, AGG and DBC (tracks the DBIQ Optimum Yield Diversified Commodity Index) for for equities, bonds and commodities, respectively, over the period 2006:Q3-2012:Q4. All reported performance measures refer to the out-of-sample period. The FIX strategy rebalances portfolio weights each quarter to [50%,30%,10%] for S-B and [50%,20%,10%,10%] for S-B-C; the BWD strategy relies on sample means, covariances. co-skewness and co-kurtosis recomputed each quarter on an expanding estimation window; the FWD strategy exploits predictability of excess returns, covariances, co-skewness and co-kurtosis and recursively forecasts portfolio return moments each quarter using an expanding estimation window. We report the annualized CRRA utility-based Certainty Equivalent Excess Return (CEQ) and the quarterly Turnover (TO). The CEQ is calculated from net portfolio returns after a proportional transaction cost of 50 bps for indexes and futures and 10bps for ETFs. We report the measures based on moderate risk aversion ($\gamma = 5$) and three portfolio total leverage constraints (Lev<100%, 50% and Lev=0).

	MV						Non-MV					
	Lev<100%		Lev<50%		Lev=0		Lev<100%		Lev<50%		Lev=0	
	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO
Panel A: 1986:Q1-2001:Q4												
FIX:												
S-B	.0292	.04	.0292	.04	.0292	.04	.0292	.04	.0292	.04	.0292	.04
S-B-C	.0319	.05	.0319	.05	.0319	.05	.0319	.05	.0319	.05	.0319	.05
BWD:												
S-B	.0154	.09	.0154	.09	.0154	.09	.0160	.09	.0160	.09	.0160	.09
S-B-C	.0253	.07	.0253	.07	.0245	.06	.0214	.07	.0214	.07	.0201	.06
FWD:												
S-B	.0270	.23	.0237	.23	.0156	.24	.0253	.25	.0225	.25	.0175	.25
S-B-C	.0446	.25	.0364	.28	.0266	.34	.0415	.36	.0367	.37	.0258	.43

	MV						Non-MV					
	Lev<100%		Lev<50%		Lev=0		Lev<100%		Lev<50%		Lev=0	
	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO
Panel B: 1993:Q3-2012:Q4												
FIX:												
S-B	.0169	.05	.0169	.05	.0169	.05	.0171	.05	.0171	.05	.0171	.05
S-B-C	.0153	.05	.0153	.05	.0153	.05	.0145	.05	.0145	.05	.0145	.05
BWD:												
S-B	.0263	.03	.0263	.03	.0243	.03	.0275	.03	.0275	.03	.0247	.02
S-B-C	.0233	.04	.0233	.04	.0162	.04	.0174	.04	.0178	.04	.0118	.04
FWD:												
S-B	.0396	.09	.0325	.09	.0228	.11	.0383	.10	.0319	.09	.0229	.09
S-B-C	.0499	.17	.0398	.21	.0271	.30	.0555	.23	.0463	.26	.0344	.36

Table 1.11 (Continues)

	MV						Non-MV					
	Lev<100%		Lev<50%		Lev=0		Lev<100%		Lev<50%		Lev=0	
	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO
Panel C: 2003:Q4-2012:Q4												
FIX:												
S-B	.0136	.06	.0136	.06	.0136	.06	.0138	.06	.0138	.06	.0138	.06
S-B-C	.0083	.07	.0083	.07	.0083	.07	.0068	.07	.0068	.07	.0068	.07
BWD:												
S-B	.0316	.03	.0316	.03	.0273	.03	.0331	.03	.0331	.03	.0274	.03
S-B-C	.0172	.06	.0173	.05	.0096	.06	.0077	.06	.0084	.05	.0035	.06
FWD:												
S-B	.0492	.08	.0382	.09	.0255	.12	.0445	.11	.0371	.10	.0252	.10
S-B-C	.0610	.19	.0487	.24	.0345	.34	.0679	.21	.0590	.24	.0467	.36

	MV						Non-MV					
	Lev<100%		Lev<50%		Lev=0		Lev<100%		Lev<50%		Lev=0	
	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO
Panel D: 2006:Q4-2012:Q4												
FIX:												
S-B	.0164	.08	.0164	.08	.0164	.08	.0171	.08	.0171	.08	.0171	.08
S-B-C	.0005	.09	.0005	.09	.0005	.09	-.0007	.09	-.0007	.09	-.0007	.09
BWD:												
S-B	.0464	.05	.0464	.05	.0388	.04	.0485	.05	.0485	.05	.0389	.04
S-B-C	.0015	.07	.0013	.07	-.0060	.07	-.0106	.07	-.0101	.07	-.0138	.07
FWD:												
S-B	.0731	.10	.0550	.11	.0348	.14	.0736	.11	.0569	.11	.0360	.12
S-B-C	.0595	.22	.0425	.28	.0246	.38	.0605	.23	.0481	.29	.0324	.38

	MV						Non-MV					
	Lev<100%		Lev<50%		Lev=0		Lev<100%		Lev<50%		Lev=0	
	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO	CEQ	TO
Panel E: 2006:Q3-2012:Q4												
FIX:												
S-B	.0167	.08	.0167	.08	.0167	.08	.0174	.08	.0174	.08	.0174	.08
S-B-C	.0098	.08	.0098	.08	.0098	.08	.0090	.08	.0090	.08	.0090	.08
BWD:												
S-B	.0444	.04	.0444	.04	.0374	.04	.0465	.04	.0465	.04	.0375	.04
S-B-C	.0282	.06	.0265	.06	.0137	.06	.0198	.06	.0187	.06	.0083	.06
FWD:												
S-B	.0695	.09	.0529	.10	.0339	.13	.0702	.11	.0548	.11	.0348	.12
S-B-C	.0709	.21	.0529	.26	.0337	.38	.0704	.24	.0561	.30	.0396	.40

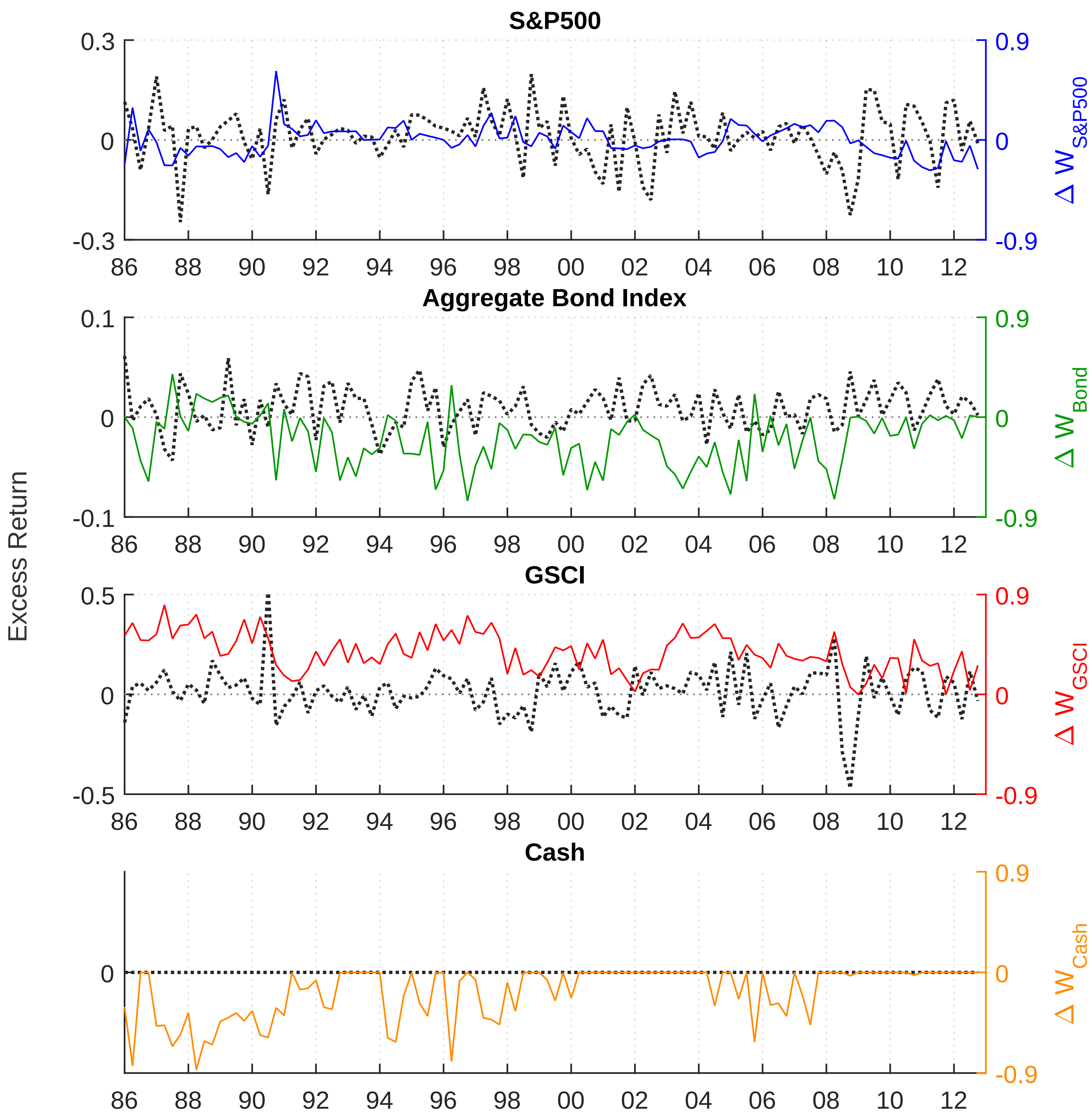

Figure 1.1 Non-MV Quarterly Rebalanced FWD S-B-C vs. FWD S-B Strategies: Weight Differences and Excess Returns for Each Asset Class
This figure shows the differences in portfolio weights assigned to each asset class index (colored solid line) between FWD S-B-C and FWD S-B portfolio strategies and the excess returns of asset class indexes (black dashed line). We report the portfolio weights generated for a moderately risk averse investor ($\gamma = 5$) and a medium portfolio total leverage constraint (Lev<50%). The out-of-sample period covers 1986:Q1-2012:Q4.

Chapter 2

Investing in Mutual Funds: Exploiting the Cross-sectional Predictability in Fund Performance

2.1 Introduction

With $15 trillion in assets under management, mutual funds serve as a significant component of U.S. households' investment holdings. Among all types of funds, about 3,195 actively managed domestic equity funds with approximately $6 trillion in total net assets constitute the largest portion of the average U.S. investor's investment portfolio at year-end of 2013.[1] Given such a large cross-section of funds, how should investors effectively invest in the universe of active equity mutual funds, or should they at all?

Despite numerous efforts, the literature has not been able to provide a definitive answer to this question. Early studies, e.g. Jensen (1968), Malkiel (1995), Gruber (1996) and Carhart (1997), find that active equity mutual funds, on average, persistently underperform the aggregate stock market and other passive benchmarks after fees and expenses, and suggest that these funds possess little skill and therefore investors would be better off investing in passively managed index funds. Instead of treating all active mutual funds as one group,

[1] See Investment Company Fact Book 2014 at `http://www.icifactbook.org`.

academics have examined subgroups of the active management industry. Some studies report that a small proportion of fund managers exhibit superior skill relative to their peers in stock picking, market timing, volatility timing or earning forecasting.[2] Implicitly, such empirical evidence indicates that investors may invest with those managers who were identified as skilled *ex-ante* and expect positive outcomes in return for their money. Nevertheless, Berk and Van Binsbergen (2015) argue that because of competition in capital markets, managerial skill does not necessarily translate into net gains to their investors. Moreover, Pástor, Stambaugh, and Taylor (2015) show that the active management industry has in fact become more skilled over time, whereas investors do not benefit from such improvement due to increasing competition as the industry size grows.

The above discussion suggests that neither buying the average mutual fund nor investing with skilled fund managers would be an effective solution for investors who seek to select a portfolio of mutual funds. In this paper, I reexamine this problem within an optimal portfolio choice framework. Specifically, using a large sample of U.S. domestic active equity mutual funds, I construct optimal investment strategies that jointly exploit the cross-sectional predictability in fund performance induced by a number of fund-level characteristics and macroeconomic variables, and evaluate their performance out-of-sample over the investment period 1996:01–2013:12.

A number of papers find that mutual fund characteristics, such as past performance, fund size, recent cash inflows and the degree of activeness in management, can help predict the future relative performance of funds.[3] These studies further show that the predictive power

[2]See, among others, Grinblatt and Titman (1989); Busse (1999); Bollen and Busse (2005); Kosowski, Timmermann, Wermers, and White (2006); Jiang, Yao, and Yu (2007); Kacperczyk, Van Nieuwerburgh, and Veldkamp (2013); Jiang, Verbeek, and Wang (2014).

[3]Related studies include Hendricks, Patel, and Zeckhauser (1993), Goetzmann and Ibbotson (1994), Chen,

of each individual characteristic could be exploited using a sorting rule to build a long-short portfolio and this portfolio produces a positive benchmark-adjusted return, suggesting that the information content conveyed by fund characteristics is economically valuable. However, the profitability of the hypothetical long-short portfolio may not truly reflect the economic gains that the characteristics could generate for a real-world investor, because short-selling a mutual fund is very hard, if not impossible, in practice. By eliminating short positions, one could still form a long-only strategy that recursively selects a small group of top-ranked funds based on a particular characteristic. Albeit simple and intuitive, such an approach may not be optimal due to at least three reasons: (i) it does not take full advantage of conditioning information available to investors, such as the potentially valuable information in other fund characteristics and the time-variability in the cross-sectional predictability of fund performance; (ii) it requires a subjective choice about the number of groups funds are sorted into; (iii) it does not align with the principles of portfolio theory that takes into account investors' preferences and attitude toward risk taking. I detail these issues in the following.

The advantages of integrating the predictive information from multiple cross-sectional predictors of asset returns in trading strategies are recently investigated outside the mutual fund literature.[4] This strand of research shows that the cross-sectional predictors, when used on an individual basis in trading strategies, could generate significant economic gains, but could produce even larger economic value if properly combined in a single composite strategy

Hong, Huang, and Kubik (2004), Gruber (1996), Zheng (1999), Cremers and Petajisto (2009), Kacperczyk, Sialm, and Zheng (2005), Kacperczyk, Sialm, and Zheng (2008) and Amihud and Goyenko (2013).

[4]For example, Asness, Moskowitz, and Pedersen (2013) average momentum and value portfolios within and across multiple asset classes. Brandt (2009a) optimally combine size, value and momentum in an equity-only portfolio. Barroso and Santa-Clara (2014) bundle the carry trade with other characteristics, such as momentum, reversal, real exchange rate and current account to build optimal currency portfolios.

that relies on all of them. The added value stems from the advantages of diversifying across multiple return predictors whose predictive ability can vary over time. I contend that similar advantages may be present when exploiting the cross-sectional performance predictability of mutual funds. Funds with distinct characteristics may differ in their trading strategies and therefore in their performance. For instance, previous studies find that hot-hand and high alpha funds are likely to be momentum followers in the equity market.[5] In addition, highly active funds tend to exhibit strong stock selection skill and perform relative well during recessions and poor business conditions.[6] Such distinct trading behavior and abilities could lead to wide spreads in the cross-section of fund performance during different periods of time. Recent studies provide empirical evidence that the characteristic-based predictability of fund performance does change over time and appears to be dependent on the macroeconomic environment and on market conditions.[7] From the mutual fund investor's perspective, a single characteristic portfolio approach that maintains a constant tilt toward funds with a particular characteristic could result in factor or sector biases, and, consequently, poor performance. For instance, persistently chasing hot-hand and/or high alpha funds would have loaded up on the technology sector prior to the Dot-com collapse in 2000. Similarly, constantly buying highly active funds that typically pick value stocks might miss profit opportunities offered by momentum stocks in bull markets. On the contrary, a composite portfolio strategy with tactical exposures to multiple fund characteristics is

[5] See, e.g., Grinblatt, Titman, and Wermers (1995); Carhart (1997).

[6] See, among others, Moskowitz (2000); Kosowski (2011); Glode (2011). Sun, Wang, and Zheng (2009) offer two plausible economic rationales for this performance counter-cyclicality: (i) the information opaqueness provides a better profit opportunity for informed managers in the down market; (ii) as noise traders withdraw from the market, professional money managers are more likely to succeed by trading on signals about the fundamentals of firms.

[7] E.g. Glode, Hollifield, Kacperczyk, and Kogan (2012), Kacperczyk et al. (2013) and Banegas, Gillen, Timmermann, and Wermers (2013)

poised to take advantage of more opportunities than the single characteristic strategies: when certain type of funds is underperforming, investors may benefit from another type that is outperforming. As a result, the composite strategy could achieve greater consistency in performance compared with a single characteristic strategy.

To summarize, the above discussion suggests that, in order to effectively capitalize on the cross-sectional performance predictability of mutual funds, one needs to be concerned with the problems of what fund characteristics to use as performance predictors, as well as how to optimally weigh predictive signals over time in order to align with the investor's investment objectives. In addition, the investor/econometrician also needs to deal with issues such as the restrictions on short-sales and leverage. To the best of my knowledge, the literature has been silent on these aspects.

Empirically, this paper brings these issues to an out-of-sample optimal portfolio choice framework and provides new evidence on the economic value generated by investing in active equity mutual funds through investment strategies that simultaneously incorporate the cross-sectional performance predictability based on multiple fund characteristics and on macroeconomic variables. First, I find that the proposed optimal composite strategies significantly outperform passive investments based on a large set of low-cost index funds that maintain constant exposures to different segments of the market, after fees and expenses and without relying on short-sales or leverage.[8] Quantitatively, a moderately risk-averse investor characterized by a relative risk aversion coefficient of 5 (RRA=5) is willing to pay up to 4.29% per annum in certainty equivalent return (CEQ) in order to switch from the best-performing

[8]As this paper is primarily interested in net investment outcomes experienced by investors in the funds, all performance measures are computed based on funds' net returns, i.e. after fees and expenses. However, as in Avramov and Wermers (2006) and Banegas et al. (2013), brokerage commissions and taxes are ignored in the results.

index fund to the optimal composite strategy that exploits the predictive power of multiple fund characteristics. The switching could earn the investor an extra 4-Factor alpha of 3.35% per year and increase the Sharpe ratio from 0.51 to 0.69. Second, given the identical conditioning information contained in each individual fund characteristic, the strategies based on maximization of expected utility generate extra economic gains compared to their counterparts relying on a sorting rule, suggesting that the sorting-based portfolio approach understates the economic value added by exploiting the predictive power of fund characteristics. Third, the optimal composite strategy that maintains tactical exposures to funds with different characteristics consistently delivers superior performance out-of-sample in comparison with their peers that are formed using the same optimized portfolio approach but only rely on a single characteristic. Fourth, motivated by recent asset allocation literature on the superiority of naïve diversification over more complex optimized approaches [See, e.g. DeMiguel et al. (2009)], I construct and evaluate a naïve composite strategy that simply takes equal-weighted long positions in five single characteristic sorted portfolios. Despite its simplicity and parsimony in incorporating the predictive information contained across all fund characteristics, the simple averaging rule fails to fully capitalize on the predictability out of sample, as the naïve composite strategy significantly underperforms its optimized counterparts.

Next, I show that the superior performance of the optimal composite strategy relative to the alternative strategies is driven by effectively utilizing predictive information in multiple fund characteristics to shift portfolio allocation toward (away from) funds with future outperformance (underperformance) as market conditions evolve over time. For instance, as the aggregate market shifts from good to poor states, funds with good past performance (i.e. hot-hand and high alpha funds) relative to those with other characteristics declines remarkably; at the same time, highly active funds turn to be the top-performer among all the characteristics, whereas they are the worst-performing one in good market states. As in turns out, the state dependence in the relative performance of strategies concentrating on a single characteristic is identified and captured by the optimal composite strategy, as evidenced by the shifts in its portfolio characteristics. A further investigation reveals that the state-dependent performance of strategies formed on the basis of single fund characteristic is, at least partially, linked to variation in their factor loadings across different market states. Specifically, high alpha and hot-hand funds significantly outperform highly active funds in bull markets, as they benefit from having higher market beta and larger loadings on size and momentum factors. However, in bear markets, highly active funds become the top-performer because of their lower exposures to market, size and momentum factors but higher loading on the value factor.

Lastly, I conduct several additional analyses to test the robustness of the baseline results. First, I find that accounting for macroeconomic information improves the optimal composite strategy's performance, but the improvement is marginal. Second, I let the investor select smaller numbers of funds in vestment strategies and find that the results are not sensitive to the sizes of investment universe and all the conclusions still hold. Third, the baseline results are robust across the separate investment sub-periods of 1996:01–2004:12 and 2005:01–2013:12.

This paper makes several contributions to the literature. First, this study is related to prior work that compares the value of active and passive investments from an investor's point of view. Early research argues that investors are no better off investing with active mutual funds rather than just indexing their money passively. Recent studies show that even if skilled active managers can be identified *ex-ante*, investors are still not able to benefit from them due to competition in capital markets. In contrast, I provide empirical evidence that investing in actively managed equity mutual funds is value adding relative to a set of index-based passive investments, if the cross-sectional predictability in fund performance is properly exploited.

Second, my work is similar in spirit to several papers that examine the predictability-based investment strategies of U.S. active equity mutual funds, such as Baks, Metrick, and Wachter (2001), Pástor and Stambaugh (2002) and Avramov and Wermers (2006). These papers focus exclusively on the time-series predictability of funds' alphas. I complement this area of research by building optimal portfolio strategies that exploit the cross-sectional predictability in fund performance induced by multiple fund characteristics and macroeconomic variables. More importantly, I show that integrating the predictive information in multiple fund characteristics into a single composite investment strategy leads to considerably larger economic gains than relying separately on each characteristic.

Third, this paper adds to the asset allocation literature on the efficacy of optimized versus simpler portfolio formation approach. The sorting-based rule has been extensively used to form portfolios capturing the cross-sectional predictability in asset returns. I show that, based on the same conditioning information, the portfolio approach based on maximization of expected utility is superior to the sorting method in terms of the ability to generate economic value for investors. Moreover, recent studies, e.g. DeMiguel et al. (2009), advocate that naïve diversification, such as the 1/N rule, tend to outperform more complex optimized methods out-of-sample. In contrast, I show that, at least within the universe of mutual funds, optimization-based portfolio strategies outperform out-of-sample those constructed using the 1/N rule.

This paper may also be relevant to large institutional investors, such as funds of mutual funds (FoMFs).[9] Fixed weighting schemes across mutual fund styles (e.g. aggressive, growth and income or large-, mid- and small-cap) are widely used as the basis for making portfolio allocation decisions by FoMFs.[Brands and Gallagher (2005); Elton, Gruber, and Blake (2006).] However, style-based approaches have been questioned by academic researchers who argue that mutual fund style classifications do a poor job on forecasting differences in future performance and consequently such misclassification has an adverse effect on investors' ability to build diversified portfolios.[Brown and Goetzmann (1997); diBartolomeo and Witkowski (1997); Chan, Chen, and Lakonishok (2002).] The characteristic-based portfolio approach proposed in this paper offers an alternative to aid FoMFs managers in making mutual fund investment decisions.

The rest of this paper proceeds as follows: Section 2.2 introduces mutual fund characteristics and their measures. Section 2.3 discusses methodologies for constructing optimal composite strategies. Section 2.4 introduces the data. Section 2.5 reports all empirical results. Section 2.6 concludes.

2.2 Fund characteristics and measures

In this section, I introduce the set of selected mutual fund characteristics that have been extensively studied in the literature and their measures. Specifically, five fund characteristics

[9] FoMFs have emerged as a popular investment vehicle in recent times. According to the 2014 Investment Company Fact Book, the FoMFs industry grew from as little as \$1.4 billion in early 1990s to nearly \$1.6 trillion in AUM at the year-end 2013.

are considered in this paper: historical alpha, hot-hand, new money inflows, fund size and the degree of activeness in management.[10]

Alpha. Starting with Carhart (1997), a fund's alpha, the intercept in a regression of the fund's excess return on the Fama-French-Carhart 4 factors, is widely interpreted as a measure of skill. Cremers, Petajisto, and Zitzewitz (2012) argue that the Fama-French factor model produces biased assessments of fund performance and recommend using index-based benchmarks, as such benchmarks better explain the cross-section of mutual fund returns. Therefore, I follow Pástor et al. (2015) and use the benchmark-adjusted alpha as the alpha characteristic, which is estimated regressing a fund's net return on the returns of the fund's benchmark index designated by Morningstar.[11]

$$r_{i,t} = \alpha_i + \beta_i \cdot r_{\mathrm{BMK},t} + e_{i,t} \tag{2.1}$$

where $r_{i,t}$ denote fund i's net return during period t; $r_{\mathrm{BMK},t}$ is the return of Morningstar designated benchmark index; α_i is the benchmark alpha. The estimation is performed recursively with a 12-month rolling sample at the end of each month t. Thus, the benchmark alpha measures a fund manager's ability to beat its benchmark index portfolio over a 12-month sample period.

[10] I acknowledge that other characteristics that are related to mutual funds' cross-sectional differences in performance have been proposed in the literature, e.g. the Return Gap of Kacperczyk et al. (2008), Active Shares of Cremers and Petajisto (2009) and industry- or sector-concentration of Kacperczyk et al. (2005). These findings are of course interesting from the performance evaluation point of view. However, constructing these predictors often entails creating portfolios from funds' quarterly stock positions, which are often difficult for many investors to obtain and calculate. Furthermore, relying on a mutual fund' self-reported quarterly positions may distort our view of the fund's actual performance due to potential reporting biases, such as missing cash and bond holdings in the database [Wermers (2000)] and/or window dressing and tax-motivated trading [Moskowitz (2000)]. Therefore, in this paper, I only focus on the five characteristics discussed earlier, as they can be relatively accurately measured using the information available to retail investors. Nevertheless, it is important to note that the analytical framework provided in this paper can be easily extended to include additional cross-sectional predictors of mutual fund performance.

[11] Pástor et al. (2015) note that Morningstar chooses benchmarks based on funds' holdings rather than their reported objective, so the Morningstar benchmark does not suffer from the cherry-picking bias.

Hot-hand. Hendricks et al. (1993) and Goetzmann and Ibbotson (1994) examine the short-term persistence phenomenon in mutual fund returns, and find that recently top-performing funds tend to continue to be good performers in the near term and a portfolio strategy purchasing the good performing funds and selling the underperforming ones could earn positive risk-adjusted returns. Following Hendricks et al. (1993), I compute 12-month compounded prior net returns as the hot-hand characteristic.

Money inflows. Gruber (1996) and Zheng (1999) document that funds that experience recent positive net money inflows tend to outperform their less popular peers subsequently. The authors term this phenomenon as "smart money" effect. Berk and Green (2004) provide an explanation for the flow-for-performance relationship that investors rationally update their beliefs about managers' skill based on past performance. Following the literature, I calculate the normalized new money net flow as the flow characteristic, which is calculated as the quarterly net cash flow divided by the TNA at the end of the previous quarter:

$$\mathrm{Flow}_{i,t} = \frac{\mathrm{netflow}_{i,t}}{\mathrm{TNA}_{i,t-1}} \tag{2.2}$$

where $\mathrm{netflow}_{i,t}$ is fund i's net cash inflows during time t; $\mathrm{TNA}_{i,t-1}$ is the fund's total net assets at the end of time $t-1$.

Fund size. In the spirit of Berk and Green (2004), fund performance is inversely related to fund size: a small fund can easily put all of its money in its best ideas, but a lack of liquidity forces a large fund to have to invest in its not-so-good ideas and take larger positions per stock than optimal, thereby eroding performance. Chen et al. (2004), Yan (2008) and McLemore (2014) provide supportive empirical evidence. Following the literature, I compute the size characteristic as:

$$\text{Size}_{i,t} = 1 - \frac{\text{TNA}_{i,t}}{\text{IndSize}_t} \tag{2.3}$$

where IndSize_t denotes the industry size, computed as the sum of TNAs across all funds at time t; $\text{TNA}_{i,t}$ is fund i's TNA at time t. To be consistent with other characteristics that better performing funds have higher measures, I use one minus the fund-to-industry size ratio.

Activeness. A fund manager can attempt to outperform her benchmark only by taking positions that are different from the benchmark portfolio. The deviations from the benchmark holdings can be attributed to the manager's ability in selecting stocks or timing the market. To measure the degree of activeness in management, Amihud and Goyenko (2013) propose an intuitive and easily calculable measure, which is defined as $1 - R^2$, where R^2 is estimated by regressing the fund's returns on benchmark returns (e.g. the Fama-French-Carhart 4-Factors). Thus, lower R^2 indicates greater degree of activeness, which in turn predicts better performance. In this paper, I use the $1 - R^2$ computed from Eq.(2.1) as the active characteristic.

2.3 Optimal portfolio strategies and performance measures

To optimally integrate the information content from individual fund characteristics in a single investment strategy, I employ the parametric portfolio policy proposed by Brandt (2009a) (hereafter, BSV). The BSV approach is especially suited here for several reasons. First, it directly models portfolio weights as a linear function of fund characteristics. In such a way, it effectively avoids the extremely sensitive (co)moments estimation of fund return distributions, which often involves substantial sampling errors and leads to extreme portfolio weights.[12] Second, it mitigates the dimensionality problem: the complexity of BSV approach depends only on the number of characteristics rather than the number of assets as in traditional portfolio methods.[13] Third, it captures implicitly the impacts of fund characteristics on expected returns, variances, covariances and even higher-order moments of the return distribution.[14] This is nontrivial in the portfolio choice problem. For example, a specific characteristic might be found to be positively associated with funds' expected returns. Naturally, portfolio methods focusing on mean returns, such as the sorting-based rule, would favor the funds possessing this characteristic. On the contrary, those funds may not look attractive to the BSV approach, if the characteristic is also associated to undesirable moments of the resulting portfolio's returns, such as volatility and negative skewness. In this paper, I provide the first application of the BSV parametric portfolio policy in the context of optimal mutual fund portfolio selection.

[12] Brandt (2009b) provides a comprehensive discussion on the issue of estimation errors in asset allocation context.

[13] For example, in a classic MV portfolio optimization with N assets, it requires modeling N first and $(N^2 + N)/2$ second moments of returns.

[14] Brandt (2009a): "To better understand this point, we can approximate the expected utility of the investor with a Taylor series expansion around the portfolio's expected return $E[r_{p,t+1}] \approxeq u(E[r_{p,t+1}]) + \frac{1}{2}u''(E[r_{p,t+1}])E[(r_{p,t+1} - E[r_{p,t+1}])^2] + \frac{1}{6}u'''(E[r_{p,t+1}])E[(r_{p,t+1} - E[r_{p,t+1}])^3] + \cdots$. This expansion shows that, in general, the investor cares about all the moments of the distribution of the portfolio return. Since the portfolio return is given by $r_{p,t+1} = \sum_{i=1}^{N_t} f(x_{i,t};\theta)r_{i,t+1}$, the moments of its distribution depend implicitly on the joint distribution of the returns and characteristics of all assets. The coefficients θ affect the distribution of the portfolios return by changing the weights given to the returns of the individual assets in the overall portfolio."

2.3.1 Estimating optimal portfolio weights: unconditional case

Following BSV, I optimize mutual fund portfolios from the perspective of a risk-averse investor characterized by a CRRA utility function:

$$U(r_p) = \frac{(1+r_p)^{1-\gamma}}{1-\gamma} \tag{2.4}$$

The investor's problem is to recursively choose the portfolio weights $\omega_{i,t}$ at time t to maximize her conditional expected utility of the portfolio's return $r_{p,t+1}$ at time $t+1$:

$$\max_{\{\omega_{i,t}\}_{i=1}^{N_t}} \quad E_t[U(r_{p,t+1})] = E_t\left[U\left(\sum_{i=1}^{N_t}\omega_{i,t}r_{i,t+1}\right)\right] \tag{2.5}$$

where $r_{p,t+1}$ and $r_{i,t+1}$ are the portfolio's and fund i's returns at time $t+1$, respectively; N_t is the number of mutual funds available to trade at time t. Fund i's weight, $\omega_{i,t}$, is parameterized as a linear function of the fund's standardized characteristics:

$$\omega_{i,t} = f(z_{i,t};\theta_t) = \frac{1}{N_t}\theta_t^\top z_{i,t} \tag{2.6}$$

where θ is a $K \times 1$ vector of parameters to be estimated and K is the number of fund characteristics; $z_{i,t}$ is a $K \times 1$ vector of fund i's standardized characteristic measures with zero mean and unit standard deviation across all funds at time t.

Rewrite the investor's problem by plugging Eq.(2.6) into Eq.(2.5) with a general CRRA utility function:

$$\max_{\theta_t} \quad \frac{1}{\tau(1-\gamma)}\sum_{t'=t-\tau}^{t}\left[1+\sum_{i=1}^{N_{t'}}\left(\frac{1}{N_{t'}}\theta_t^\top z_{i,t'}r_{i,t'+1}\right)\right]^{1-\gamma} \tag{2.7}$$

The optimal parameter vector θ_t^* is obtained by solving Eq.(2.7) numerically over the rolling sample period $[t-\tau,t]$. With the estimated parameter vector, the desired portfolio weight on fund i for time $t+1$ is calculated as $w^*_{i,t} = \frac{1}{N_t}\theta_t^{*\top} z_{i,t}$. Note that I only use the information available up to time t to derive the optimal weights for time $t+1$. By repeating this procedure at each time $t \in [T_0, T-1]$, I can obtain the out-of-sample unconditional optimal portfolio policy $\{\omega^*_t\}_{t=T_0,\cdots,T-1}$.

2.3.2 Estimating optimal portfolio weights: conditional case

While able to incorporate the information in fund characteristics, the unconditional BSV algorithm cannot account for the impact of macroeconomic information on the optimal portfolio policy. As a result, the investor's expected utility may not be fully optimized if the additional conditioning information is relevant. To accommodate the possible effects, I follow BSV and extend the coefficient vector, θ_t, to be a linear function of M macroeconomic variables $y_t = [y_{1,t}, \cdots, y_{M,t}]'$:

$$\theta_t = \begin{bmatrix} \theta_{1,t} \\ \vdots \\ \theta_{K,t} \end{bmatrix} = \Lambda_t y_t = \begin{bmatrix} \lambda_{1,1,t} & \cdots & \lambda_{1,M,t} \\ \vdots & & \vdots \\ \lambda_{K,1,t} & \cdots & \lambda_{K,M,t} \end{bmatrix} \begin{bmatrix} y_{1,t} \\ \vdots \\ y_{M,t} \end{bmatrix} \tag{2.8}$$

where Λ_t is a $K \times M$ coefficient matrix and its element $\lambda_{k,m,t}$ reflects the sensitivity of the coefficient $\theta_{k,t}$ to the corresponding conditioning macroeconomic variable $y_{m,t}$. Then, the extended portfolio weight function for fund i at time t becomes:

$$\omega_{i,t} = f(z_{i,t}; y_t; \Lambda_t) = \frac{1}{N_t} z'_{i,t} \Lambda_t y_t \tag{2.9}$$

In this conditional form, portfolio weights are determined jointly by standardized fund characteristics and macroeconomic variables.

Rewrite the investor's conditional optimal portfolio problem by plugging Eq.(2.9) into

Eq.(2.5) with a general CRRA utility function:

$$\max_{\Lambda_t} \quad \frac{1}{\tau(1-\gamma)} \sum_{t'=t-\tau}^{t} \left[1 + \sum_{i=1}^{N_{t'}} \left(\frac{1}{N_{t'}} (z'_{i,t'} \Lambda y_{t'}) r_{i,t'+1} \right) \right]^{1-\gamma} \tag{2.10}$$

At each time t, the optimal parameter matrix Λ_t^* is obtained by solving Eq.(2.10) numerically over a sample period $[t-\tau, t]$. With the estimated parameter matrix, the desired portfolio weight on fund i for time $t+1$ is calculated as $\omega_{i,t}^* = \frac{1}{N_t} z'_{i,t} \Lambda_t^* y_t$. Note that I only use the information available up to time t to derive the optimal weights for time $t+1$. By repeating this procedure at each time $t \in [T_0, T-1]$, I can obtain the out-of-sample conditional optimal portfolio policy $\{\omega_t^*\}_{t=T_0,\cdots,T-1}$.

2.3.3 Implementation issues

To implement the parametric portfolio approach, several issues are worth bearing in mind. First, BSV apply this approach to individual stocks, allowing for short positions. In contrast, I am interested in long-only investment strategies for mutual funds. To work around this problem, BSV recommend to simply truncate negative weights of the unconstrained optimal portfolio at zero and then re-scale the truncated weights so that they sum to one.[15] It is worth mentioning that the ex post adjusted weights are theoretically suboptimal.[16]

Second, to estimate the BSV coefficients in Eq.(2.7) and Eq.(2.10), I use a rolling sample window of 24 months.[17] For the sake of robustness, I also entertain other window lengths,

[15] In applications of the BSV algorithm, Plazzi, Torous, and Valkanov (2010) and Barroso and Santa-Clara (2014) follow BSV's suggestions to truncate and re-normalize the optimal portfolio weights in order to satisfy the constraints.

[16] I experimented by imposing short-sale and no-leverage constraints directly into the optimization, but it resulted in too conservative characteristic weight estimates. This is because the number of control parameters (=5 in this case) is significantly smaller than the number of funds, and satisfying all portfolio weight constraints at every instant t during the whole sample period might require artificially low parameter estimates due to lack of degrees of freedom.

[17] The 24-month rolling sample estimation has been commonly used for evaluating mutual fund performance in the literature. See, for example, Jiang et al. (2007), Amihud and Goyenko (2013), Del Guercio and Reuter

including 12, 36, 48, 60 months. I find that all the baseline results are qualitatively unchanged and that the performance of optimal composite strategies tend to decrease with the window length, consistent with the well documented short-lived superior performance of mutual funds in the literature.[18]

2.3.4 Performance measures

Through out this paper, I employ three conventional metrics to measure the out-of-sample performance of investment strategies, namely the 4-Factor alpha (*Alpha*), Sharpe ratio (*Sharpe*) and certainty equivalent excess returns (*CEQ*). In particular, *Alpha*, to date the most widely used performance measure in the mutual fund literature, measures a portfolio's mean returns adjusted for the Fama-French-Carhart benchmarks. In addition to focusing on the first moment, Moskowitz (2000) advocates looking at the second moment of fund returns in mutual fund performance evaluation, as active managers could add value by reducing the volatility of their managed portfolios, meanwhile, delivering similar mean returns to the market. Following Moskowitz's suggestion, I compute Sharpe ratios as the second performance measure to capture both mean and volatility of fund returns. Researchers, e.g. Arditti (1967), Kraus and Litzenberger (1976) and Scott and Horvath (1980), have shown that investors also care about the moments of return distributions beyond mean and variance. Hence, to accommodate an investor's preferences for portfolio's mean, variance, skewness, kurtosis as well as her level of risk aversion, I add the third measure — CEQ.[19]

(2014), Pástor et al. (2015).

[18] Berk and Green (2004) argue that superior performance in mutual funds cannot persist even if it is a result of skill because it induces an inflow of funds that makes the fund grow in size and causes its performance to worsen because of decreasing returns to scale in fund management. Bollen and Busse (2005) and Keswani and Stolin (2008) provide empirical supports.

[19] Under CRRA utility, the CEQ is computed as: $\text{CEQ}_{\tau+1:T} = [(1-\gamma)\bar{U}_{\tau+1:T}(W_t)]^{\frac{1}{1-\gamma}} - 1$, where $\bar{U}_{\tau+1:T}(W_t)$ is the average realized CRRA utility.

Given its inherent superiority relative to other two metrics, I will mainly focus on CEQs in the rest discussions of empirical results.[20]

2.4 Data

The mutual fund data used in this paper come from two main sources: the CRSP survivorship bias free mutual fund database and the mutual fund dataset from Morningstar. In particular, I use CRSP to collect the data on fund returns, share-level total net assets (TNA), fees and expense ratios, investment objectives and other fund characteristics. Morningstar assigns each fund into a category based on the fund's holdings and designates a benchmark portfolio to each fund category. In addition to the data offered by CRSP, I collect the benchmark return data for each fund from Morningstar.

Next, I follow the procedures specified in the Data Appendix of Pástor et al. (2015) to merge CRSP and Morningstar datasets.[21] Briefly, I first use funds' tickers, CUSIPs and names to match funds that are available in both datasets. I then double check the matching accuracy by comparing the matched funds' TNAs and returns across the two datasets. To minimize the impacts caused by data errors, I apply the algorithms proposed by Berk and Van Binsbergen (2015) to correct the discrepancies in the data. If some observations are not fixable, I set them to missing. For instance, I set fund returns to missing if they still differ across the two datasets by more than 10 bps after the correcting process.

To obtain a clean set of domestic active equity mutual funds, I use fund investment

[20] In the asset allocation literature, CEQ has been commonly employed as a reliable performance measure. See, among others, Brandt (2009a); DeMiguel et al. (2009); Cenesizoglu and Timmermann (2012); Barroso and Santa-Clara (2014).

[21] The Data Appendix can be downloaded at `http://faculty.chicagobooth.edu/lubos.pastor/research/Data_Appendix_Aug_2013_V3.pdf`

objective codes as well as the keywords in the Morningstar Fund Category variable and fund names to exclude bond funds, money market funds, international funds, index funds, funds of funds, industry funds, real estate funds, target retirement funds, and other non-equity funds. To eliminate the return bias of small-sized funds, I exclude fund/month observations with lagged TNA below $10 million from the sample.[22]

Finally, I use the filtered fund data to construct the five characteristic measures specified in Section 2.2. Due to the missing data problem, there are some fund/month observations with zero non-missing characteristic measures. I exclude them from the sample. For comparison purposes, I generate two data samples: the large sample which contains all the fund/month observations with at least one non-missing characteristic measure and the small sample which only includes the fund/month observations with five non-missing characteristic measures. The large and small samples respectively contain 3,438 and 3,423 unique actively managed domestic equity mutual funds during the period between January 1981 and December 2013. Figure 1 depicts the number of funds in the two sample sets over time.

[Figure 1]

In particular, the thick line represents the large sample, in which the number of funds increases from 110 in January 1981 to 1,932 in December 2013 and reaches the maximum of 2,198 in June 2008. The fine line represents the small sample, in which the number of funds

[22] I also considered other variations that have been used in the literature, such as $5 million and $15 million. My empirical results are not sensitive to the changes of the threshold value.

starts with 7 in January 1981, then peaks at 2,173 in June 2008 and finally ends with 1,930 in December 2013. Comparing the two sample paths, we see that there is a substantially lower number of funds during the first 10 years. The loss is due to two reasons: (i) a large number of mutual funds report TNA only quarterly or yearly before February 1991, so the characteristic measures, such as Size and Flow, could not be constructed. (ii) The recorded expense ratios across the two databases often disagree and exhibit large jumps during this period. Due to the limited number of funds, I further exclude this sample period and only use the data of 1991:02–2013:12 as my final sample for empirical analysis.

2.5 Empirical results

In this section, I present the empirical results. I begin by first assessing single characteristic sorted strategies that rely on the sorting-based rule to incorporate the predictions from individual fund characteristics. Next, I discuss the results of composite portfolio strategies that simultaneously exploit the predictive ability of multiple fund characteristics and macroeconomic variables, and compare their out-of-sample performance with that of various alternative investment strategies. Lastly, I identify the sources for the superior performance of optimal composite strategies.

2.5.1 Single characteristic sorted strategies

I first reexamine the predictive ability of each individual fund characteristic for the performance of single characteristic sorted portfolios. To do so, I sort funds at each re-balancing date into 10 decile portfolios based on rankings of lagged individual fund characteristics and then compare their performance out-of-sample. Five groups of single characteristic decile portfolios are formed and I, for the sake of brevity, label them as the Alpha, Hot, Flow, Size and Active decile portfolios. By construction, these single characteristic strategies overlook the information from other fund characteristics and also that they do not take into account any additional conditioning information, such as macroeconomic and market conditions.

Table 2.1 reports the out-of-sample performance of the 10 decile portfolios and a long-short portfolio for each fund characteristic. In particular, Decile 10 - 1 represent the top- to bottom-decile or best- to worst-performing portfolios; L-S denotes the long-short portfolio that longs the top-decile portfolio and shorts the bottom-decile one. Their performance is measured out-of-sample for the investment period of 1996:01–2013:12.

[Table 2.1]

Let us first examine the performance of 10 decile portfolios based on each fund characteristic. The general observation seems to be a clear-cut: all three performance measures show large dispersions and monotonically declining trends from the top to bottom decile. The results lend support to prior literature that these characteristics are related to the cross-sectional variations in funds' performance and therefore could be utilized by investors in selecting funds. Moving to the last row (L-S) of Table 2.1, we find that all long-short portfolios produce positive alphas. In particular, the Alpha portfolio yields the highest 4-Factor alpha of 4.89% per annum, which is statistically and economically significant. Hot also returns a high alpha of 3.18%, but not statistically significant at conventional levels. Flow and Active, respectively, generate 1.43% and 1.89%, both of which are statistically significant at the 10%

level. Size appears to be the worst-performer. Again, these results are broadly consistent with previous findings, suggesting that these fund characteristics contain valuable predictive information.

As discussed earlier, mutual fund investors face short-selling restrictions in practice. Consequently, the implied profitability of the long-short portfolios in Table 2.1 may not truly reflect the economic gains that could be earned by a real-world investor. Therefore, a more meaningful assessment for the investor should be based on the performance of long-only strategies, i.e. the top-decile portfolios. Following the literature, e.g. Pástor and Stambaugh (2002) and Avramov and Wermers (2006), a sorting-based single characteristic long-only strategy is constructed as the equally weighted portfolio of the top 10% funds ranked on the lagged characteristic measure at each re-balancing date. By restricting our attention to strategies with long-only positions in mutual funds, i.e. the first row of Table 2.1, we find the following: (i) the alphas generated from long-only portfolios are significantly lower than those from the long-short strategies and none is statistically significant at conventional levels; (ii) the short-only portfolios (Decile 1) based on all measures appear attractive relative to their long-only peers (Decile 10), suggesting that the characteristics seem to be better at locating losers rather than winners. In summary, we can conclude that fund characteristics appear to convey the predictive information for future fund performance. However, after eliminating the possibility of short-sales, their capability to generate economic value turns to be significantly lower than that implied with hypothetic short positions.

From now on, I will refer to the long-only top-decile portfolios as *single characteristic sorted strategies*. Table 2.2 presents summary statistics of their monthly net excess returns over the period from 1992:02 to 2013:12.[23]

[Table 2.2]

Panel A of Table 2.2 summarizes the sample moments. The return distributions exhibit large degrees of heterogeneity in both means and standard deviations across the five fund characteristics. In particular, the Hot and Alpha sorted strategies show high mean returns and high standard deviations. In contrast, Size and Active yield relatively low returns and low volatility. All return series, except Hot, are negatively skewed and have fat tails in returns as evident by the large kurtosis estimates.

Panel B of Table 2.2 shows pairwise unconditional correlations of single characteristic sorted portfolio returns. In general, the correlation coefficients are high: greater than 0.8 in all pairs. In particular, the correlations of Hot-Alpha and Flow-Alpha are very high (≥ 0.97). This may not be surprising, as a number of studies have shown that mutual fund flows tend to chase funds' past performance.[See, among others, Sirri and Tufano (1998); Del Guercio and Tkac (2002); Del Guercio and Reuter (2014).] Moreover, Size and Active are also highly correlated at 0.98, which again is consistent with the prior findings that smaller funds tend to be more active than larger peer.[See, among others, Cremers and Petajisto (2009); Amihud and Goyenko (2013).] On the other hand, Hot-Size, Hot-Active and Alpha-Active have relatively low correlations: all below 0.89.

Panel C of Table 2.2 provides the regression coefficients of 4-Factor model for each single

[23]The sample data span the period from 1991:02 to 2013:12. The first 12 month data are used to construct the first characteristic measures, so the return series of single characteristic portfolios start from 1992/02.

characteristic sorted portfolio. Not surprisingly, we see that all portfolios have statistically significant and close-to-one market betas (MKT). Moving to SMB, we observe that the five portfolios have significant, positive but different sensitivities to the size factor, indicating that funds with distinct characteristics tend to hold small-cap stocks to different extents. The estimated coefficients on the value factor (HML) reflect that, on average, hot-hand and high alpha funds are likely to hold growth stocks, whereas the small-sized and highly active funds tend to include value stocks in their portfolios. Finally, the loadings on the momentum factor (UMD) suggest that hot-hand, high alpha and large inflow funds like to hold momentum stocks, whereas small-sized and highly active funds do not exhibit such pattern.

To sum up, the above analyses indicate that (i) Portfolio strategies formed on the basis of a single fund characteristic exhibit heterogeneous risk-return profiles. (ii) The returns of Alpha, Hot and Flow portfolios are highly correlated, suggesting that they are likely to have a high degree of overlap in fund holdings and hence that combining these characteristics would be less likely to build a well-diversified portfolio. (iii) Strategies focusing on distinct fund characteristics have different exposures to equity factors, such as value and momentum. Such distinctions are of course interesting from a diversification perspective.

2.5.2 Optimal composite strategies

In this subsection, I assess the out-of-sample investment results of the unconditional and conditional optimal composite strategies derived using the methods specified in Section 2.3.1 and 2.3.2, respectively.[24] I first discuss the results of the BSV coefficient estimation. Next, I

[24]For the sake of simplicity, I, hereafter, refer to the unconditional (conditional) optimal composite strategy as the unconditional (conditional) strategy.

compare the out-of-sample performance of optimal composite strategies with that of various alternative strategies: these represent the baseline results of my empirical analyses. Lastly, I examine the attributes of optimal composite portfolios and determine the sources of their economic gains.

2.5.2.1 BSV coefficient estimates

As explained in Section 2.3.1, to derive the optimal composite strategy, we need to estimate the BSV coefficients that combine the information content conveyed by the selected fund characteristics. Table 2.3 provides the out-of-sample coefficient estimates (Coef) coupled with corresponding single characteristic sorted portfolio performance (CEQ with RRA=5) over the period from 1996:01 to 2013:12.

[Table 2.3]

Specifically, the first row (Full) of Table 2.3 gives the time-series averages of Coefs and CEQs over the full investment period. Overall, all the coefficients have positive signs, indicating that on average all five characteristic signals are relevant in determining the optimal portfolio weights. This is consistent with prior findings in the literature. Recall that before entering the portfolio weight function, each characteristic signal is cross-sectionally standardized to have zero mean and unit standard deviation. Hence, we can further assess these characteristics' relevance by comparing the magnitudes of the coefficients to each other. The results show that the Alpha and Active predictors receive larger coefficients (1.80 and 1.45) than do Size and Flow (0.98 and 1.17). Interestingly, we also find that the Alpha and Active strategies perform relative well (2.11% and 1.85% in CEQ), whereas Size and Flow are the two worst-performing ones (0.14% and 0.72% in CEQ). These results indicate that the BSV portfolio approach seems to be able to capture the relative predictive performance of fund characteristic signals on average.

To further assess the efficacy of BSV approach, I examine the coefficient estimates under different market conditions. Following the definition of Glode et al. (2012), I categorize the aggregate stock market into four states: *Up*, *Mid-Up*, *Mid-Down* and *Down*, which are respectively defined as when the three-month average of past market excess return is higher than the 75th, between 50th and 75th, between 25th and 50th and lower than 25th percentile of the historical three-month averages of past market excess return. Noteworthily, the average return percentiles are computed in an out-of-sample way: for time period t, the percentiles are computed based on the three-month averages of CRSP value-weighted market excess returns from July 1926 up to period t.

The second to fifth row of Table 2.3 depict the results. Focusing on the columns of Coef, we notice that the estimated coefficients for each characteristic fluctuate substantially across different market states. For example, the Hot coefficients decline from 1.36 in the *Up* market to 0.23 in the *Down* market, indicating that hot-hand funds are much more relevant under good market conditions than they are in poor ones in the optimal composite strategy. In contrast, the coefficients of Active exhibit an inverse pattern: the values increase monotonically from 0.81 to 1.75 while the overall market becomes worse. To see whether or not such changes are sensible, we need to compare them with the performance of portfolios that focus on corresponding characteristics. We can see that, across different market conditions, the shifts in Coefs tend to coincide with those in CEQs: as market conditions change from *Up* to *Down*, the Hot and Alpha sorted portfolios turn to be losers from winners, meanwhile, the magnitudes of their estimated coefficients decline substantially; on the other hand, the performance and coefficient of Active exhibit almost the opposite pattern. Again, the results support the robustness of BSV estimation procedures. It is also interesting to point out that no single characteristic dominates in either Coef or CEQ across all market states, suggesting that constantly picking funds with a particular characteristic is unlikely to be the most efficient way to form a portfolio of mutual funds.

2.5.2.2 Out-of-sample investment results

Next, I compare the performance of the proposed optimal composite strategies with that of various alternative investment strategies available to investors at the same time. Specifically, I consider four sets of competing strategies. The first set includes seven low-cost Vanguard index funds.[25] The idea here is to use actually traded investment vehicles rather than non-traded indexes to represent the passive investment opportunities available to real-world investors. The second set consists of the five single characteristic sorted strategies that I introduced and analyzed in Section 2.5.1. Each of these strategies relies on a particular fund characteristic to form a long-only and equal-weighted portfolio by recursively selecting the top 10% funds based on the lagged characteristic measure at each re-balancing date. The sorting-based rule has been extensively utilized to take advantage of the cross-section predictability in asset returns in the finance literature . The third set contains five single

[25] I choose the Vanguard index family because of its well-known cost efficiency and market-leading role in the index fund industry. To conduct accurate and concise comparisons, I exclude funds that (i) hold more than 10% international stocks; (ii) have missing net return data for the period of 1996-2013 in the Morningstar mutual fund database; (iii) are already spanned by existing funds for each category. The screening process results in seven Vanguard index funds, each of which measures a specific segment of the market. Table A1 in Appendix A gives detailed information about the seven index funds.

characteristic optimized strategies, each of which exploits the predictive power of an individual characteristic and is optimized using the BSV portfolio approach introduced in Section 2.3.1. Although both aim to capitalize on the cross-section performance predictability based on a particular fund characteristic, the optimization-based approach is different from the sorting-based method: the former parsimoniously takes into account an investor's preferences and risk appetite, whereas the latter excels in simplicity. The fourth alternative is a naïve composite strategy that simply allocates equally across the five single characteristic sorted portfolios in the second set.[26] Compared with the optimization-based strategies, the most appealing feature of this strategy is that it makes good use of the predictive information in all fund characteristic signals without involving portfolio weight estimation, as there is evidence, e.g. DeMiguel et al. (2009), showing that simple portfolio rules can outperform more complex optimized peers out-of-sample due to estimation error. For all the investment strategies except the passive ones, portfolio weights are derived and rebalanced recursively at the end of each month starting from December 1995 and through November 2013. The month-t realized net excess return on each portfolio is calculated by multiplying the desired weights of month $t-1$ by the month-t realized net excess returns (i.e. after fees and expenses, and above the risk-free rate) of funds included in the portfolio.

The out-of-sample investment results of all the strategies are presented in Table 2.4. On the columns, I report the first to fourth sample moments of portfolio net excess return distributions (Mean, Std, Skew, Kurt) and three risk-adjusted performance measures: 4-Factor alphas (Alpha), Sharpe ratios (Sharpe) and CEQs with three risk aversion levels (i.e.

[26] In the equity market, Asness et al. (2013) construct an equal-weighted 50/50 momentum and value combination strategy and find that the resulting portfolio outperforms each individual one.

RRA=3, 5, 10). Panel A, B, C and D of Table 2.4 provide the results for the passive, single characteristic sorted, single characteristic optimized and composite strategies, respectively. In particular, Panel D includes three types of composite strategies: the naïve, unconditional and conditional.

[Table 2.4]

The insights about these investment strategies can be inferred from comparisons along several dimensions. Let us first compare the results of passive investments using index funds and the unconditional optimal composite strategy (i.e. Panel A vs. Unc). Panel A shows that index funds that focus on different segments of the market exhibit large heterogeneity in their return distribution and across all performance measures. For the sake of brevity, I will center the following discussion on the comparisons between the unconditional composite strategy and the best-performing index fund measured by both Sharpe ratio and CEQ — the one that focuses on the Mid-Blend sector in this case. Needless to say, all the results also qualitatively apply to other index funds in Panel A. Starting with the sample moments, we see that the optimal composite strategy generates the mean return of 11.70% per year and annualized standard deviation of 16.85%, whereas the corresponding figures are 9.36% and 18.22% for the best-performing index fund during the same period. In addition, the composite portfolio's returns have a slightly positive skewness of 0.09, whereas the returns of the index fund is negatively skewed at -0.77. Despite exhibiting a higher kurtosis than the passive peer, the optimal composite portfolio's positively skewed returns suggest that the associated high kurtosis is more likely driven by large positive, rather than negative, realized portfolio returns, which is desirable. These return moments indicate that an investor would have achieved a preferable risk-return profile by investing with the optimal composite strategy rather than passively indexing with any of the low-cost index funds.

Moving to the risk-adjusted performance measures in next few columns, we find that the results from the return moment examination are further strengthened: the unconditional composite strategy, net of fees and expenses, consistently outperforms all the index funds and this result holds across all performance measures and for investors with all levels of risk aversion. For instance, a moderately risk-averse investor (RRA=5) who holds the Mid-Blend index fund would be willing to pay up to 4.29% per year in CEQ to switch to the composite strategy. By doing so, she earns an extra annual 4-Factor alpha of 3.35%, which is economically and statistically significant, and also increases the Sharpe ratio from 0.51 to 0.69. The above results suggest that when we allow for the predictability in fund performance, investing in active equity mutual funds can be value adding relative to passively holding index funds even when both short-selling and leveraging are precluded.

As introduced earlier, I consider two methods for forming portfolio strategies exploiting the predictability of single fund characteristics: the sorting rule and the optimization of the investor's expected utility. Let us compare the two approaches (i.e. Panel B vs. Panel C). In general, the optimization-based strategies appear to outperform their sorting-based counterparts in almost all cases. In particular, a moderately risk-averse investor who adopts the Size sorted strategy would be willing to pay up to 1.12% per annum in CEQ to switch to the Size optimized strategy. For other characteristics, such as Hot, Alpha and Active, the investor also enjoys moderate gains ranging from 49 to 12 bps per year in CEQ by switching from the sorted to optimized portfolios. The results show that the optimization method, given the same *ex-ante* information from a certain characteristic, tends to be more effective than the sorting rule. Hence, hereinafter and unless otherwise stated, I will continue strategy comparisons by benchmarking composite strategies on the single characteristic optimized ones. Of course, the results hold qualitatively for single characteristic sorted strategies.

To investigate the economic significance of incorporating predictions from multiple fund characteristics, I compare single characteristic optimized strategies with the unconditional optimal composite strategy (i.e. Panel C vs. Unc). It is worth repeating that these strategies are optimized using the same portfolio approach specified in Section 2.3.1, but differ in the number of fund characteristics utilized in deriving optimal portfolio weights. Therefore, the differences in their investment outcomes should reflect the distinctions of exploiting single vs. multiple characteristic predictability. Again, we first examine the sample moments. One initial observation is that the composite strategy is able to produce an average return that is comparable to that of the best single characteristic optimized strategy (i.e. Hot) but with lower volatility. It is also interesting that most single characteristic strategies, except Hot, have negative skewness, while the returns of the optimal composite portfolio are slightly positively skewed. These results suggest that combining fund characteristics in a single investment strategy could achieve more desirable risk-return profiles for risk-averse investors through risk reduction without sacrificing high mean returns. Moving to the portfolio performance measures, the results appear to be clearly outlined: the composite strategy consistently delivers superior performance over all single characteristic peers regardless of metrics or risk aversion levels. Quantitatively, the composite strategy, benchmarked on the best-performing single characteristic portfolio — Hot, still outperforms by 1.79% per year in CEQ (RRA=5) or 90 bps in 4-Factor alpha, and 11% in Sharpe ratio. These results highlight the advantages of diversifying across fund characteristics and, more importantly, that such qualities can translate into significant economic gains for investors when exploited in investment strategies.

Despite not being the main focus of this paper, it is still interesting to point out that all single characteristic strategies (both sorted and optimized), except the one based on size sorting, outperform the top-performing index fund in terms of both Sharpe ratio and CEQ. The results indicate that even though inferior to the optimal composite strategy, portfolio strategies that utilize the predictions from single fund characteristics can perform better than passive investment strategies using index funds, highlighting the promise of predictability-based active investment strategies in the U.S. equity mutual fund space.

Next, I continue the empirical analyses by focusing on comparisons within the composite strategy category. Motivated by recent findings in the asset allocation literature on the superiority of simple portfolio formation approaches, such as the 1/N rule of DeMiguel et al. (2009), over more complex optimized methods, I also compare the out-of-sample performance of the naïve with that of the optimal composite strategy (i.e. Naïve vs. Unc). The results appear to be clear-cut: the naïve composite portfolio that equally combines five single characteristic sorted portfolios produces a much lower mean return and similar volatility compared with the optimal composite strategy. In addition, the naïve strategy has a negative and lower skewness of -0.53, which mirrors the findings by Brown, Hwang, and In (2013) that naïve diversification relative to optimal diversification comes with increases in tail risk and reduced upside potential associated with the concave payoff. Moving to the performance measures, the naïve strategy substantially underperforms its optimized counterpart across all metrics, suggesting that when applied within the space of equity mutual funds, the BSV approach based on expected utility maximization is preferable to the 1/N rule advocated in other asset universes, such as stocks.

Finally, I examine the economic value of incorporating macroeconomic information into the investor's portfolio allocation decisions. In the spirit of Avramov and Wermers (2006) and Banegas et al. (2013), the variables used to characterize economic states include the dividend yield, short-term interest rate, term spread and default spread. The last row (Con) of Table 2.4 reports the investment outcomes. We can see that the conditional composite strategy delivers slightly higher mean return as well as volatility than its unconditional counterpart. However, the conditional strategy's returns are more positively skewed, making it more favorable for investors who care about higher-order moments and also indicating that conditioning on macroeconomic variables helps mitigating downside risk of the resulting portfolio. Looking through the performance measures, we see that the strategy conditioning on macroeconomic variables outperforms the unconditional peer, but the outperformance appears to be marginal. For example, incorporating the macroeconomic information, a moderately risk-averse investor is better off by earning only 13 bps in CEQ or comparably 14 bps in 4-Factor alpha. The results seems to imply that the information content conveyed by these variables can hardly translate into economic gains in asset allocation excises. One possible reason could be that the macroeconomic variables are slow-moving over time, whereas in order to capture the short persistence in fund characteristics' predictive power we need to employ a short look-back window (typically, 24 months). Another possible reason is that the set of state variables does not sufficiently characterize the economic conditions that are associated with mutual fund performance and thus introduce additional noise into the portfolio optimization process. As a result, it erodes part of the improvement in portfolio performance.[27]

To complete my empirical analyses, in Figure 2 I plot the differences in cumulative wealth of the unconditional and conditional optimal composite strategies and the three sets of alternative investment opportunities, namely the passive, single characteristic optimized and naïve composite strategies. In particular, each graph from A to M depicts the cumulative wealth paths (relative to corresponding benchmarks) of a $100 investment in the unconditional and conditional optimal composite strategies starting from 1996:01. The results support the previous findings that both unconditional and conditional composite strategies outperform all the alternative investment strategies in terms of long-term terminal wealth levels. An interesting observation is that the conditional composite strategy (dashed line) produces comparable performance to its unconditional counterpart (solid line) during the earlier part of the sample period (1996–2009), but starts to outperform significantly since 2010.

[Figure 2]

To summarize, the above analyses demonstrate that simultaneously incorporating the information conveyed by multiple fund characteristics into a single composite portfolio strategy generates significant economic value, which makes the resulting portfolio outperform several

[27]It is worth keeping in mind that I have considered only the set of macroeconomic variables that have been used in the mutual fund literature. Nevertheless, a broader range of macro variables have been found to be related to stock returns in the finance literature. Hence, it would be interesting to see whether other macro variables are able to produce superior performance for the conditional composite strategy. I leave this extension for future research.

passive investments using the Vanguard index funds, the single characteristic sorted and optimized strategies that rely on the predictions from a particular fund characteristic and the naïve composite portfolio that simply averages all single fund characteristic sorted portfolios without involving estimation. The superior performance is pronounced after subtracting funds' fees and expenses as well as precluding short-sales and leverage. Moreover, conditioning on a set of macroeconomic variables improves the investment outcomes, but the improvement appears to be marginal.

2.5.2.3 Portfolio attributes of investment strategies

In this section, I address the question of what explains the superior performance of optimal composite strategies relative to other benchmarks. To do so, I first examine the portfolio weight distribution of optimal composite strategies and then analyze their portfolio-level characteristics.

A. Portfolio weights

The superior performance of optimal composite strategies might be the results of unreasonably large bets on very few funds that perform well in short periods. To mitigate this concern, I show the statistics of optimal composite strategies' portfolio weight distributions in Table 2.5.

[Table 2.5]

In particular, the left (right) panel of Table 2.5 reports the statistics for the unconditional

(conditional) composite portfolio. As short positions and leverage are precluded, the minimum weight on a specific fund is zero and the cross-sectional weights always sum up to 1. Hence, these two statistics are omitted. In each panel, I compute two statistics on the columns: the cross-sectional *average* and *maximum* weights. For each statistic, I report its time-series average, minimum and maximum for the full out-of-sample investment period (1996:01–2013:12) on the rows. Let us first look at the time-series statistics of cross-sectional average weights, i.e. Avg$\{w_{i,t}\}$: the unconditional (conditional) strategy produces a time-series average, minimum and maximum of 0.29% (0.26%), 0.17% (0.17%) and 0.63% (0.52%), indicating that the optimal weights of both portfolios are stable over time. Moving to the distribution of cross-sectional maximum weights, i.e. Max$\{w_{i,t}\}$, we can see that the time-series mean of the maximum weights is low (1.45% for unconditional; 1.42% for conditional) and that the all-time maximum weight on a single fund is only 5.41% for the unconditional optimal portfolio and 3.76% for the conditional one. Overall, these time-series weight distributions show that the optimal portfolios do not involve extremely large weights on individual funds. Therefore, the outperformance of optimal composite strategies is unlikely driven by taking extreme bets on very few funds at certain times.

B. Portfolio characteristics

What could explain the superior performance of optimal composite strategies? To answer this question, I compute and compare the portfolio-level characteristics of all investment strategies. In particular, for each strategy, its time-t portfolio characteristics are computed as follows:

$$[c_1, \cdots, c_K]_{p,t} = \sum_{i=1}^{N_t} \omega_{i,t}[z_1, \cdots, z_K]_{i,t} \tag{2.11}$$

where $\omega_{i,t}$ is the desired portfolio weight assigned to fund i at time t; $[z_1, \cdots, z_K]_{i,t}$ are fund i's K *standardized* characteristics; N_t is the number of investable funds; $[c_1, \cdots, c_K]_{p,t}$ are the portfolio's desired characteristics at time t. As all the active investment strategies are constructed on the basis of fund characteristics, it is straightforward to compare the variation in portfolio characteristics across these strategies.

Table 2.6 reports the statistics of portfolio characteristics ($[c_1, \cdots, c_K]_{p,t}$) of all portfolio strategies and the performance (Sharpe and CEQ) of single characteristic sorted portfolios under different market conditions.

[Table 2.6]

Specifically, Panel A, B, C and D, respectively, provide the results for single characteristic sorted strategies, single characteristic optimized strategies, composite strategies and the performance of single characteristic sorted portfolios. For all sub-tables in each panel, the first row (Full) shows the average characteristics for the full sample; the second to fifth rows present the averages under four market conditions from good to poor: *Up*, *Mid-Up*, *Mid-Down* and *Down*. Let us first look at Panel A, the figures for single characteristic sorted strategies. Not surprisingly, we see that each strategy concentrates on its desired characteristic and that the loadings are evenly distributed across all market conditions, reflecting the nature of sorting-based portfolio approach. Further looking at the performance (CEQ) of single characteristic sorted strategies in Panel D, we find that concentrating on a single fund characteristic seems implausible, as no single characteristic dominates in performance all the time.

Moving to Panel B, we can see that single characteristic optimized strategies on average allocate even more aggressively on their desired characteristics than do their sorting-based counterparts. However, in contrast to their sorted peers, the optimized strategies produce substantial variation in desired characteristic loadings across different market states. Interestingly, the variation appears to capture the state-dependent relative performance of single characteristic sorted portfolios, as evidenced by CEQs in Panel D. For example, the Alpha sorted strategy turns from the second best performer to be the worst as the market shifts from the *Up* to *Down* state; meanwhile, the Alpha optimized strategy's loadings on the Alpha characteristic decline significantly from 4.8 to 2.56, suggesting that it allocates less capital toward high alpha funds. The results may explain the outperformance of single characteristic optimized strategies relative to their sorting-based peers. Recall that both the sorted and optimized strategies are constructed based on the same conditioning information, i.e. each individual fund characteristic, but using different portfolio methods. Therefore, the added value could be attributed to the superiority of optimization-based portfolio method over the sorting rule.

Next, let us examine the characteristics of composite strategies shown in Panel C. By its nature, the characteristics of naïve composite strategy ($\text{Naïve}_{[\text{comp}]}$) appear to have no bias toward any single characteristic and are evenly distributed across all market states. Turning to the unconditional composite strategy ($\text{Unc}_{[\text{comp}]}$), we can see that, over the full sample period, it allocates aggressively in high alpha and hot-hand funds, moderately in highly active and large inflow funds but not concentrated on very small-sized funds. Interestingly, such an allocation scheme closely reflects the rankings of overall performance of single characteristic strategies: Hot and Alpha are the two top performers, Active and Flow perform moderately and Size is the worst-performing one. The results indicate that the optimal composite strategy seems to be able to exploit fund characteristics according to their overall performance for the full sample. Next, I examine how the optimal composite strategy changes its allocation in response to different market conditions. The results are reported in the second to fifth rows of Table 2.6. A few interesting observations are worth mentioning here. First, all the characteristics, except Size, exhibit large dispersions across different market states. More specifically, the optimal composite strategy tends to overweight high alpha, hot-hand and large inflow funds in good market states. However, as the market worsens, the strategy starts loading off those funds, and meanwhile increases holdings on highly active funds. Second, and perhaps most interestingly, the direction of shifts in the optimal composite strategy's portfolio holdings across funds with different characteristics is consistent with that of changes in relative performance of single characteristic concentrated strategies. For example, in the *Up* market, high alpha and hot-hand funds are the top-performers and Alpha and Hot are the two most prominent characteristics of the optimal composite portfolio; at the same time, highly active funds perform poorly and also Active is much less pronounced in the portfolio characteristics. In the *Down* market, highly active funds become the top-performers among all five characteristics, meanwhile, the allocation toward them increases substantially as evidenced from the changes in portfolio characteristics. As the characteristics of conditional composite strategy are very comparable to those of the unconditional one, I skip the discussions here to conserve the space. These results imply that the optimal composite strategy is able to rotate its allocation to exploit the conditioning information contained in different fund characteristics, and more importantly, the shifts in portfolio allocation plausibly align with the changes in relative performance of funds with different characteristics as market conditions evolve over time.

In summary, the results demonstrate that the optimal composite strategy's superior performance relative to the alternative strategies can be attributed to its efficacy in exploiting the conditioning information contained in multiple fund characteristics about future fund performance to shift its portfolio allocation away from (toward) funds that are likely to underperform (outperform) as market conditions change over time.

2.5.2.4 State-dependent performance of single characteristic strategies: evidence from factor loadings

What could possibly explain the state-dependent performance of funds with distinct characteristics? I explore this question by examining their conditional factor loadings. In particular, I estimate the regression coefficients of the 4-factor model of Carhart (1997) for each single characteristic sorted strategy (i.e. the top-decile mutual fund portfolio based on a single fund characteristic) conditioning on the four market states defined in Section sec:BSVEstimates. I report summary statistics of loadings on the market (MKT), size (SMB), value (HML) and momentum (UMD) factors in Table 2.7. More specifically, Panel A, B, C and D of Table 2.7 respectively present the results for the *Up*, *Mid-UP*, *Mid-Down* and *Down* markets.

[Table 2.7]

Focusing on Panel A and B, we can see that, in good market states, the Alpha and Hot portfolios have higher market, size and momentum factor loadings than the Size and Active portfolios, suggesting that these funds invest aggressively in high beta, small and momentum stocks. Turning to Panel C and D, we find that the Alpha and Hot portfolios still maintain high loadings on the market, size and momentum factors; on the contrary, the Active portfolio loads weakly on the three factors but has relatively high exposure to the value factor, suggesting that highly active funds tend to hold value stocks.

The above results, combined with the findings from previous literature that small-cap and momentum (value) stocks perform relatively well in bull (bear) markets but not in bear (bull) markets, indicate that funds having the same characteristic tend to consistently pick certain styles of stocks, implying that strategies that select and invest in funds based on a single fund characteristic is unlikely to benefit from stock characteristic timing (i.e. holding high beta, small, value or momentum stocks when they perform relatively well). Interestingly, the optimal composite strategy that maintains tactical exposures to multiple fund characteristics appears to have the ability to time stock characteristics as evidenced by the changes in its portfolio characteristics documented in Section 2.5.2.3.

2.5.3 Robustness of the results

In this section, I undertake additional checks to see how sensitive the baseline results are to changes in the number of funds the investor can invest in as well as to different investment sub-periods.

2.5.3.1 Number of funds

In the baseline results, a single characteristic sorted strategy allows the investor recursively to take equal-weighted long positions in the top 10% funds, ranked by one of their characteristics, at each re-balancing date. By doing so, each portfolio on average contains about 160 funds over the entire out-of-sample period. For robustness, I now relax this assumption and let the investor pick the top 5% and 2.5% funds instead. As a result, each sorted portfolio becomes much smaller and respectively contains about 80 and 40 funds on average.[28] Table 2.8 provides the out-of-sample investment results of the reduced-size strategies.

[Table 2.8]

Essentially, the reported values show that the superior performance of optimal composite strategies still remains economically large relative to the alternative investment strategies, confirming that the baseline results are robust to different numbers of funds available for forming the investor's portfolios.

Specifically, comparing the results of Panel A with B, we can see that reducing the number of funds included in portfolios leads to a more favorable risk-return profile for all strategies: increases in mean and skewness of the return distribution, while the volatility remains little changed. The figures from performance measures show that reducing portfolio sizes boosts investment outcomes, as evidenced by higher and more significant 4-Factor alpha as well as higher Sharpe ratio and CEQ. Interestingly, we can also observe that the performance increases associated with reduced-size portfolios seem to be more pronounced in optimal composite strategies: the performance of unconditional composite strategy increases by 93bps in CEQ(RRA=5), whereas the best-performing single characteristic optimized strategy, i.e. Hot, gains 36 bps. Therefore, the results support to the conclusion that incorporating cross-

[28] I consider the alternative cases with smaller counts of funds, because they may more closely represent the typical situation faced by investors in practice.

sectional predictability in fund performance substantially improves investment profitability.

2.5.3.2 Portfolio performance in sub-periods

The mutual fund industry has grown rapidly in the sample period of 1996:01–2013:12. As a result, there are many more funds available for investment in the second part of the sample. It is of interest to see if the main results hold for different time periods. To do so, I split the entire out-of-sample investment period into two separate periods, 1996:01–2004:12 and 2005:01–2013:12, and report their results in Panel A and B of Table 2.9, respectively. Each sub-period covers very different market conditions, such as the bull market of 1990s, Asian financial crisis and Dot-Com bust in the first period; the subprime mortgage crisis and European debt crises in the second period. For the sake of brevity, I report only the Sharpe ratio and CEQ for each strategy.

[Table 2.9]

Looking at the first investment sub-period (Panel A), we find that optimal composite strategies produce remarkably large economic gains and substantially outperform all alternative strategies in both Sharpe ratios and CEQs. Compared to the full sample results, the Mid-Blend index fund still the best-performing index fund, but single characteristic strategies focusing on highly active funds dominate other single characteristic strategies and become the top-performer. Moreover, the conditional composite strategy underperforms its unconditional counterpart, implying that conditioning on the macroeconomic variables may have introduced noise to the portfolio allocation process and thus erodes its performance. Turning to the second sub-period (Panel B), we find that all mutual fund strategies deliver significantly lower performance than do they during the first sub-period. This observation tends to support the empirical evidence documented by Pástor et al. (2015) that a fund's ability to outperform passive benchmarks declines as the size of the active mutual fund industry increases. Despite suffered from the effect of diseconomies of scale, the unconditional (conditional) composite strategies still outperforms the best-performing passive benchmark (Large-Blend) by 1.81% (2.50%) per year in CEQ. In contrast to the full sample results, the Hot optimized strategy performs as well as the unconditional composite strategy, but still underperforms the conditional composite strategy by 64 bps in CEQ, suggesting that macroeconomic variables provide complementary and valuable information that is not captured in fund characteristics. Overall, the sub-period analysis indicates that the superior performance of optimal composite strategies that allow for predictability based on fund characteristics and macroeconomic variables still prevails under these separate investment periods. Therefore, the main results of this paper hold across sub-periods.

2.6 Conclusion

In this paper, I explore the question of whether investing in the universe of active equity mutual funds may be value enhancing for an investor. Relying on a large sample of U.S. domestic active equity mutual funds, I employ a parametric portfolio approach to construct optimal composite strategies that simultaneously exploits the cross-sectional predictability in fund performance based on multiple fund characteristics as well as on macroeconomic variables. I find that the resulting composite strategies significantly outperform (i) a set of passive investments using low-cost index funds that focus on different segments of the market, (ii) single characteristic strategies that rely on the sorting-based trading rule to utilize the predictive power of individual fund characteristics, (iii) single characteristic strategies formed using an optimized portfolio approach, (iv) the naïve composite strategy that simply averages all single characteristic sorted portfolios. The findings shed new light on the value of investing in active equity mutual funds. Specifically, strategies that use an optimization-based portfolio approach and allow for the cross-sectional predictability in fund performance make investing in active equity funds value adding relative to passive investments in index funds. In addition, the results provide new insights into the economic significance of jointly exploiting the predictive power of fund characteristics in a composite investment strategy relative to its single characteristic counterparts. Moreover, within the space of active equity mutual funds, the optimization-based approach that takes into account investors' preferences is more effective in capitalizing on the predictability in fund performance in comparison to simpler portfolio methods, such as the sorting-based rule and the 1/N policy. I further demonstrate that the outperformance of the optimal composite strategy can be attributed to its efficacy in smartly weighing different fund characteristic signals and in effectively rotating portfolio allocation among funds with future outperformance as market conditions evolve over time.

This paper suggests several avenues for future research. First, although U.S. domestic equity mutual funds are examined, the framework proposed in the present paper could be applied to other mutual fund classes (e.g., fixed income, non-U.S. equities, commodities) and other active investment vehicles (e.g., hedge funds, ETFs). Given the limited or even nonexistent research in these areas, these extensions could offer further insights into the value of active asset management. In addition, this study could also be extended to include a multiperiod investment objective, within which the time-varying variation in fund performance predictability might play an even larger role. Such extensions could be of interest to a target fund that typically pursues a long-term investment strategy.

Appendix

Vanguard index fund list

This table provides the list of selected Vanguard index funds used as alternative passive investments. The listed fund names, category and tickers are provided by Vanguard. All funds seek to track the performance of a benchmark index that measures the investment return of a specific U.S. stock category and are available for trading over the period of 1996:01–2013:12.

Fund name	Category	Ticker
Vanguard Value Index Fund	Large Value	VVIAX
Vanguard 500 Index Fund	Large Blend	VFIAX
Vanguard Morgan Growth Fund	Large Growth	VMRGX
Vanguard Strategic Equity Fund	Mid Blend	VSEQX
Vanguard Extended Market Index Fund	Mid Growth	VEXMX
Vanguard Small Cap Index Fund	Small Blend	NAESX
Vanguard Explorer Fund	Small Growth	VEXPX

Bibliography

Amihud, Y., and R. Goyenko. 2013. Mutual fund's R2 as predictor of performance. *Review of Financial Studies* p. hhs182.

Ang, A., and G. Bekaert. 2002. International asset allocation with regime shifts. *Review of Financial studies* 15:1137–1187.

Anson, M. 1999. Maximizing utility with commodity futures diversification. *The Journal of Portfolio Management* 25:86–94.

Arditti, F. D. 1967. Risk and the required return on equity. *Journal of Finance* pp. 19–36.

Asness, C. S., T. J. Moskowitz, and L. H. Pedersen. 2013. Value and momentum everywhere. *The Journal of Finance* 68:929–985.

Avramov, D., and R. Wermers. 2006. Investing in mutual funds when returns are predictable. *Journal of Financial Economics* 81:339–377.

Baker, M., and J. Wurgler. 2007. Investor Sentiment in the Stock Market. *The Journal of Economic Perspectives* 21:129–151.

Baks, K. P., A. Metrick, and J. Wachter. 2001. Should investors avoid all actively managed mutual funds? A study in Bayesian performance evaluation. *The Journal of Finance* 56:45–85.

Bakshi, G., G. Panayotov, and G. Skoulakis. 2011. The Baltic Dry Index as a predictor of global stock returns, commodity returns, and global economic activity. In *AFA 2012 Chicago Meetings Paper*.

Ball, C., and W. Torous. 2000. Stochastic correlation across international stock markets. *Journal of Empirical Finance* 7:373–388.

Banegas, A., B. Gillen, A. Timmermann, and R. Wermers. 2013. The cross section of conditional mutual fund performance in European stock markets. *Journal of Financial Economics* 108:699–726.

Barroso, P., and P. Santa-Clara. 2014. Beyond the carry trade: Optimal currency portfolios. *Journal of Financial and Quantitative Analysis, Forthcoming* .

Bates, J., and C. Granger. 1969. The Combination of Forecasts. *Journal of the Operational Research Society* 20:451–468.

Bekaert, G., C. Erb, C. Harvey, and T. Viskanta. 1998. Distributional characteristics of emerging market returns and asset allocation. *The Journal of Portfolio Management* 24:102–116.

Belousova, J., and G. Dorfleitner. 2012. On the diversification benefits of commodities from the perspective of euro investors. *Journal of Banking and Finance* 36:2455–2472.

Ben-David, I., F. Franzoni, and R. Moussawi. 2012. Hedge fund stock trading in the financial crisis of 2007–2009. *Review of Financial Studies* 25:1–54.

Berk, J. B., and R. C. Green. 2004. Mutual fund flows and performance in rational markets. *Journal of political economy* 112:1269–1295.

Berk, J. B., and J. H. Van Binsbergen. 2015. Measuring skill in the mutual fund industry. *Journal of Financial Economics* 118:1–20.

Bessembinder, H., and K. Chan. 1992. Time-varying risk premia and forecastable returns in futures markets. *Journal of Financial Economics* 32:169–193.

Bhardwaj, R. K., and L. D. Brooks. 1992. The January Anomaly: Effects of Low Share Price, Transaction Costs, and Bid-Ask Bias. *The Journal of Finance* 47:553–575.

Bianchi, D., and M. Guidolin. 2013. Can Long-Run Dynamic Optimal Strategies Outperform Fixed-Mix Portfolios? Evidence from Multiple Data Sets. In *Manuscript, Bocconi University*.

Billio, M., M. Caporin, and M. Gobbo. 2006. Flexible dynamic conditional correlation multivariate GARCH models for asset allocation. *Applied Financial Economics Letters* 2:123–130.

Bodie, Z., and V. Rosansky. 1980. Risk and return in commodity futures. *Financial Analysts Journal* pp. 27–39.

Bollen, N. P., and J. A. Busse. 2005. Short-term persistence in mutual fund performance. *Review of Financial Studies* 18:569–597.

Brands, S., and D. R. Gallagher. 2005. Portfolio selection, diversification and fund-of-funds: a note. *Accounting & Finance* 45:185–197.

Brandt, M. 2009a. Portfolio choice problems. *Handbook of financial econometrics* 1:269–336.

Brandt, M. 2009b. Portfolio choice problems. *Handbook of financial econometrics* 1:269–336.

Brown, S. J., and W. N. Goetzmann. 1997. Mutual fund styles. *Journal of financial Economics* 43:373–399.

Brown, S. J., I. Hwang, and F. In. 2013. Why optimal diversification cannot outperform naive diversification: Evidence from tail risk exposure. *Available at SSRN* 2242694.

Busse, J. A. 1999. Volatility timing in mutual funds: Evidence from daily returns. *Review of Financial Studies* 12:1009–1041.

Büyükşahin, B., M. Haigh, and M. Robe. 2010. Commodities and Equities: Ever a Market of One? *The Journal of Alternative Investments* 12:76–95.

Büyükşahin, B., and M. Robe. 2010. Speculators, commodities and cross-market linkages. *Available at SSRN 1707103* .

Campbell, J., and S. Thompson. 2008. Predicting excess stock returns out of sample: Can anything beat the historical average? *Review of Financial Studies* 21:1509–1531.

Campbell, J., and L. Viceira. 1999. Consumption and Portfolio Decisions When Expected Returns Are Time Varying. *The Quarterly Journal of Economics* 114:433–495.

Campbell, J. Y., and R. J. Shiller. 1991. Yield spreads and interest rate movements: A bird's eye view. *The Review of Economic Studies* 58:495–514.

Campbell, J. Y., and L. M. Viceira. 2003. *Strategic asset allocation: portfolio choice for long-term investors*. Oxford University Press.

Cao, B., S. Jayasuriya, and W. Shambora. 2010. Holding a commodity futures index fund in a globally diversified portfolio: A placebo effect? *Economics Bulletin* 30:1842–1851.

Cappiello, L., R. Engle, and K. Sheppard. 2006. Asymmetric dynamics in the correlations of global equity and bond returns. *Journal of Financial econometrics* 4:537–572.

Carhart, M. M. 1997. On persistence in mutual fund performance. *The Journal of finance* 52:57–82.

Case, B., Y. Yang, and Y. Yildirim. 2012. Dynamic correlations among asset classes: REIT and stock returns. *The Journal of Real Estate Finance and Economics* 44:298–318.

Cenesizoglu, T., and A. Timmermann. 2012. Do return prediction models add economic value? *Journal of Banking & Finance* .

Chan, L. K., H.-L. Chen, and J. Lakonishok. 2002. On mutual fund investment styles. *Review of financial studies* 15:1407–1437.

Chaves, D., J. Hsu, F. Li, and O. Shakernia. 2011. Risk parity portfolio vs. other asset allocation heuristic portfolios. *The Journal of Investing* 20:108–118.

Chen, J., H. Hong, M. Huang, and J. D. Kubik. 2004. Does fund size erode mutual fund performance? The role of liquidity and organization. *American Economic Review* pp. 1276–1302.

Chen, Y.-C., K. S. Rogoff, and B. Rossi. 2010. Can exchange rates forecast commodity prices? *The Quarterly Journal of Economics* 125:1145–1194.

Chong, J., and J. Miffre. 2010. Conditional Correlation and Volatility in CommodityFutures and Traditional Asset Markets. *The Journal of Alternative Investments* 12:061–075.

Citigroup. 2013. Commodities Inflection Point, Still Cyclical, But Not So Super 2014 Annual Market Outlook. *Research Report* .

Cochrane, J., and M. Piazzesi. 2005. Bond Risk Premia. *American Economic Review* pp. 138–160.

Cremers, K. M., and A. Petajisto. 2009. How active is your fund manager? A new measure that predicts performance. *Review of Financial Studies* 22:3329–3365.

Cremers, M., A. Petajisto, and E. Zitzewitz. 2012. Should benchmark indices have alpha? Revisiting performance evaluation. Tech. rep., National Bureau of Economic Research.

Daskalaki, C., and G. Skiadopoulos. 2011. Should investors include commodities in their portfolios after all? New evidence. *Journal of Banking & Finance* 35:2606–2626.

Del Guercio, D., and J. Reuter. 2014. Mutual fund performance and the incentive to generate alpha. *The Journal of Finance* 69:1673–1704.

Del Guercio, D., and P. A. Tkac. 2002. The determinants of the flow of funds of managed portfolios: Mutual funds vs. pension funds. *Journal of Financial and Quantitative Analysis* 37:523–557.

Della Corte, P., L. Sarno, and I. Tsiakas. 2012. Volatility and Correlation Timing in Active Currency Management. *Handbook of Exchange Rates* pp. 421–447.

DeMiguel, V., L. Garlappi, and R. Uppal. 2009. Optimal versus naive diversification: How inefficient is the 1/N portfolio strategy? *Review of Financial Studies* 22:1915–1953.

diBartolomeo, D., and E. Witkowski. 1997. Mutual fund misclassification: Evidence based on style analysis. *Financial Analysts Journal* pp. 32–43.

Dittmar, R. 2002. Nonlinear pricing kernels, kurtosis preference, and evidence from the cross section of equity returns. *The Journal of Finance* 57:369–403.

Domanski, D., and A. Heath. 2007. Financial investors and commodity markets. *BIS Quarterly Review, March* .

Eastman, A., and B. Lucey. 2008. Skewness and asymmetry in futures returns and volumes. *Applied Financial Economics* 18:777–800.

Elton, E. J., M. J. Gruber, and C. R. Blake. 2006. The adequacy of investment choices offered by 401 (k) plans. *Journal of Public Economics* 90:1299–1314.

Engle, R. 2002. Dynamic conditional correlation. *Journal of Business & Economic Statistics* 20:339–350.

Engle, R., and R. Colacito. 2006. Testing and valuing dynamic correlations for asset allocation. *Journal of Business & Economic Statistics* 24:238–253.

Erb, C., and C. Harvey. 2006. The strategic and tactical value of commodity futures. *Financial Analysts Journal* pp. 69–97.

Erb, C., C. Harvey, and T. Viskanta. 1994. Forecasting international equity correlations. *Financial Analysts Journal* pp. 32–45.

Fama, E., and K. French. 1987. Commodity futures prices: Some evidence on forecast power, premiums, and the theory of storage. *Journal of Business* pp. 55–73.

Farinelli, S., and L. Tibiletti. 2008. Sharpe thinking in asset ranking with one-sided measures. *European Journal of Operational Research* 185:1542–1547.

Fleming, J., C. Kirby, and B. Ostdiek. 2001. The economic value of volatility timing. *The Journal of Finance* 56:329–352.

Fleming, J., C. Kirby, and B. Ostdiek. 2003. The economic value of volatility timing using realized volatility. *Journal of Financial Economics* 67:473–509.

Fortenbery, T., and R. Hauser. 1990. Investment potential of agricultural futures contracts. *American journal of agricultural economics* 72:721–726.

Friend, I., and M. E. Blume. 1975. The demand for risky assets. *The American Economic Review* 65:900–922.

Galvani, V., and A. Plourde. 2010. Portfolio diversification in energy markets. *Energy Economics* 32:257–268.

Gargano, A., and A. Timmermann. 2014. Forecasting commodity price indexes using macroeconomic and financial predictors. *International Journal of Forecasting* .

Garlappi, L., and G. Skoulakis. 2011. Taylor Series Approximations to Expected Utility and Optimal Portfolio Choice. *Mathematical and Financial Economoics* 5:121–156.

Geman, H., and C. Kharoubi. 2008. WTI crude oil Futures in portfolio diversification: The time-to-maturity effect. *Journal of Banking & Finance* 32:2553–2559.

Glabadanidis, P. 2009. Measuring the economic significance of mean-variance spanning. *The Quarterly Review of Economics and Finance* 49:596–616.

Glode, V. 2011. Why mutual funds underperform. *Journal of Financial Economics* 99:546–559.

Glode, V., B. Hollifield, M. T. Kacperczyk, and S. Kogan. 2012. Time-Varying Predictability in Mutual Fund Returns. *Available at SSRN 1364351* .

Goetzmann, W., L. Li, and K. Rouwenhorst. 2005. Long-Term Global Market Correlations*. *The Journal of Business* 78:1–38.

Goetzmann, W. N., and R. G. Ibbotson. 1994. Do winners repeat? *The Journal of Portfolio Management* 20:9–18.

Goh, J., F. Jiang, J. Tu, and G. Zhou. 2013. Forecasting Government Bond Risk Premia Using Technical Indicators. *ssrn.com* .

Gordon, S., and P. St-Amour. 2004. Asset returns and state-dependent risk preferences. *Journal of Business & Economic Statistics* 22:241–252.

Gorton, G., F. Hayashi, and K. Rouwenhorst. 2012. The Fundamentals of Commodity Futures Returns. *Review of Finance* .

Gorton, G., and K. Rouwenhorst. 2006. Facts and Fantasies about Commodity Markets. *Financial Analysts Journal* 62.

Grinblatt, M., and S. Titman. 1989. Mutual fund performance: An analysis of quarterly portfolio holdings. *Journal of business* pp. 393–416.

Grinblatt, M., S. Titman, and R. Wermers. 1995. Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior. *The American economic review* pp. 1088–1105.

Gruber, M. J. 1996. Another puzzle: The growth in actively managed mutual funds. *The journal of finance* 51:783–810.

Guidolin, M., and A. Timmermann. 2008. International asset allocation under regime switching, skew, and kurtosis preferences. *Review of Financial Studies* 21:889–935.

Hamilton, J. 2008. Understanding Crude Oil Prices. *NBER Working Paper* .

Hansen, B. E. 1994. Autoregressive conditional density estimation. *International Economic Review* pp. 705–730.

Harvey, C., J. Liechty, M. Liechty, and P. Müller. 2010. Portfolio selection with higher moments. *Quantitative Finance* 10:469–485.

Harvey, C., and A. Siddique. 2000. Conditional skewness in asset pricing tests. *The Journal of Finance* 55:1263–1295.

Harvey, C. R., and A. Siddique. 1999. Autoregressive conditional skewness. *Journal of financial and quantitative analysis* 34.

Hendricks, D., J. Patel, and R. Zeckhauser. 1993. Hot hands in mutual funds: Short-run persistence of relative performance, 1974–1988. *The Journal of Finance* 48:93–130.

Hong, H., and M. Yogo. 2012. What does futures market interest tell us about the macroeconomy and asset prices? *Journal of financial economics* 105:473–490.

Huang, J., and Z. Zhong. 2010. Time Variation in Diversification Benefits of Commodity, REITs, and TIPS. *The Journal of Real Estate Finance and Economics* pp. 1–41.

Jensen, G., R. Johnson, and J. Mercer. 2000. Efficient use of commodity futures in diversified portfolios. *Journal of Futures Markets* 20:489–506.

Jensen, G., R. Johnson, and J. Mercer. 2002. Tactical asset allocation and commodity futures. *The Journal of Portfolio Management* 28:100–111.

Jensen, M. C. 1968. The performance of mutual funds in the period 1945–1964. *The Journal of finance* 23:389–416.

Jiang, G. J., T. Yao, and T. Yu. 2007. Do mutual funds time the market? Evidence from portfolio holdings. *Journal of Financial Economics* 86:724–758.

Jiang, H., M. Verbeek, and Y. Wang. 2014. Information content when mutual funds deviate from benchmarks. *Management Science* 60:2038–2053.

Jondeau, E., and M. Rockinger. 2006. Optimal portfolio allocation under higher moments. *European Financial Management* 12:29–55.

Jondeau, E., and M. Rockinger. 2009. The impact of shocks on higher moments. *Journal of Financial Econometrics* 7:77–105.

Jondeau, E., and M. Rockinger. 2012. On the Importance of Time Variability in Higher Moments for Asset Allocation. *Journal of Financial Econometrics* 10:84–123.

Kacperczyk, M., C. Sialm, and L. Zheng. 2005. On the industry concentration of actively managed equity mutual funds. *The Journal of Finance* 60:1983–2011.

Kacperczyk, M., C. Sialm, and L. Zheng. 2008. Unobserved actions of mutual funds. *Review of Financial Studies* 21:2379–2416.

Kacperczyk, M., S. Van Nieuwerburgh, and L. Veldkamp. 2013. Time-Varying Fund Manager Skill. *The Journal of Finance* .

Kan, R., and G. Zhou. 2007. Optimal portfolio choice with parameter uncertainty. *Journal of Financial and Quantitative Analysis* 42:621–656.

Kan, R., and G. Zhou. 2012. Tests of mean-variance spanning. *Annals of Economics and Finance* 13:277–325.

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

Keswani, A., and D. Stolin. 2008. Which money is smart? Mutual fund buys and sells of individual and institutional investors. *The Journal of Finance* 63:85–118.

Kilian, L., and D. Murphy. 2010. The role of inventories and speculative trading in the global market for crude oil .

Kosowski, R. 2011. Do mutual funds perform when it matters most to investors? US mutual fund performance and risk in recessions and expansions. *The Quarterly Journal of Finance* 1:607–664.

Kosowski, R., A. Timmermann, R. Wermers, and H. White. 2006. Can mutual fund stars really pick stocks? New evidence from a bootstrap analysis. *The Journal of finance* 61:2551–2595.

Kraus, A., and R. H. Litzenberger. 1976. Skewness preference and the valuation of risk assets*. *The Journal of Finance* 31:1085–1100.

Lesmond, D. A., J. P. Ogden, and C. A. Trzcinka. 1999. A new estimate of transaction costs. *Review of Financial Studies* 12:1113–1141.

Longin, F., and B. Solnik. 1995. Is the correlation in international equity returns constant: 1960–1990? *Journal of international money and finance* 14:3–26.

Ludvigson, S. C., and S. Ng. 2007. The empirical risk–return relation: a factor analysis approach. *Journal of Financial Economics* 83:171–222.

Ludvigson, S. C., and S. Ng. 2009. Macro factors in bond risk premia. *Review of Financial Studies* 22:5027–5067.

Malkiel, B. G. 1995. Returns from investing in equity mutual funds 1971 to 1991. *The Journal of Finance* 50:549–572.

Mankiw, N. G. 1985. Consumer Durables and the Real Interest Rate. *The Review of Economics and Statistics* pp. 353–362.

Marquering, W., and M. Verbeek. 2004. The economic value of predicting stock index returns and volatility. *Journal of Financial and Quantitative Analysis* 39:407–429.

McLemore, P. 2014. Do Mutual Funds Have Decreasing Returns to Scale? Evidence from Fund Mergers .

Mehra, R., and E. Prescot. 1985. The Equity Premium: A Puzzle. *Journal of Monetary Economics* 15:145–161.

Merton, R. 1971. Optimum consumption and portfolio rules in a continuous-time model. *Journal of Economic Theory* 3:373–413.

Merton, R. 1973. An Intertemporal Capital Asset Pricing Model. *Econometrica* 41:867–887.

Moskowitz, T. 2003. An analysis of covariance risk and pricing anomalies. *Review of Financial Studies* 16:417–457.

Moskowitz, T. J. 2000. Mutual Fund Performance: An Empirical Decomposition into Stock-Picking Talent, Style, Transactions Costs, and Expenses: Discussion. *The Journal of Finance* 55:1695–1703.

Neely, C. J., D. E. Rapach, J. Tu, and G. Zhou. 2014. Forecasting the equity risk premium: the role of technical indicators. *Management Science* 60:1772–1791.

Nijman, T., and L. Swinkels. 2008. Strategic and Tactical Allocation to Commodities for Retirement Savings Schemes. *The Handbook of Commodity Investing* pp. 522–546.

Pástor, L., and R. F. Stambaugh. 2002. Investing in equity mutual funds. *Journal of Financial Economics* 63:351–380.

Pástor, L., R. F. Stambaugh, and L. A. Taylor. 2015. Scale and skill in active management. *Journal of Financial Economics* 116:23–45.

Patton, A. 2004. On the out-of-sample importance of skewness and asymmetric dependence for asset allocation. *Journal of Financial Econometrics* 2:130–168.

Pesaran, M., and A. Timmermann. 1995. Predictability of Stock Returns: Robustness and Economic Significance. *The Journal of Finance* 50:1201–1228.

Plazzi, A., W. Torous, and R. Valkanov. 2010. Expected returns and expected growth in rents of commercial real estate. *Review of Financial Studies* p. hhq069.

Rapach, D. E., J. K. Strauss, and G. Zhou. 2010. Out-of-sample equity premium prediction: Combination forecasts and links to the real economy. *Review of Financial Studies* 23:821–862.

Scott, R., and P. Horvath. 1980. On the Direction of Preference for Moments of Higher Order than the Variance. *The Journal of Finance* 35:915–919.

Sirri, E. R., and P. Tufano. 1998. Costly search and mutual fund flows. *The journal of finance* 53:1589–1622.

Smith, J. 2009. World oil: market or mayhem? *The journal of economic perspectives* 23:145–164.

Solnik, B. 1993. The performance of international asset allocation strategies using conditioning information. *Journal of Empirical Finance* 1:33–55.

Stoll, H. R., and R. E. Whaley. 1983. Transaction costs and the small firm effect. *Journal of Financial Economics* 12:57–79.

Strongin, S., and M. Petsch. 1996. Asset Returns and the Economic Environment. *Goldman Sachs Research Report* .

Sun, Z., A. Wang, and L. Zheng. 2009. Do active funds perform better in down markets? New evidence from cross-sectional study. *New Evidence from Cross-Sectional Study (September 1, 2009)* .

Tang, K., and W. Xiong. 2010. Index Investment and Financialization of Commodities. *NBER Working Paper* .

Timmermann, A. 2006. Forecast combinations. *Handbook of economic forecasting* 1:135–196.

Timmermann, A., and D. Blake. 2005. International Asset Allocation with Time-Varying Investment Opportunities*. *The Journal of Business* 78:71–98.

Vrugt, E. B., R. Bauer, R. Molenaar, and T. Steenkamp. 2004. Dynamic Commodity Trading Strategies. *Manuscript* .

Welch, I., and A. Goyal. 2008. A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies* 21:1455–1508.

Wermers, R. 2000. Mutual fund performance: An empirical decomposition into stock-picking talent, style, transactions costs, and expenses. *The Journal of Finance* 55:1655–1703.

Yan, X. S. 2008. Liquidity, investment style, and the relation between fund size and fund performance. *Journal of Financial and Quantitative Analysis* 43:741–767.

You, L., and R. Daigler. 2010. Using Four-Moment Tail Risk to Examine Financial and Commodity Instrument Diversification. *Financial Review* 45:1101–1123.

You, L., and R. Daigler. 2012. A Markowitz Optimization of Commodity Futures Portfolios. *Journal of Futures Markets* 00:1–26.

Zheng, L. 1999. Is money smart? A study of mutual fund investors' fund selection ability. *The Journal of Finance* 54:901–933.

Table 2.1 The predictive power of fund characteristics for the cross-section of fund performance

This table reports the out-of-sample performance of five sets of mutual fund decile portfolios over the period of 1996:01–2013:12. The decile portfolios in each set are formed based on rankings of a single fund characteristic. Decile 10 represents the "top-decile" or "best-performing" portfolio, Decile 1 is the "bottom-decile" or "worst-performing" portfolio and L-S denotes the long-short portfolio that longs the top-decile portfolio and shorts the bottom-decile one. The performance of all portfolios is measured by three metrics: the annualized 4-Factor alpha (Alpha), Sharpe ratio (Sharpe) and certainty equivalent excess returns (CEQ) with a relative risk aversion coefficient of 5 (RRA=5). Funds included in each decile portfolio are equal-weighted and re-balanced monthly.

	Alpha			Hot			Flow			Size			Active		
Decile	Alpha	Sharpe	CEQ	Alpha	Sharpe	CEQ	Alpha	Sharpe	CEQ	Alpha	Sharpe	CEQ	Alpha	Sharpe	CEQ
10	.0187	.60	.0211	.0151	.60	.0219	.0007	.49	.0072	-.0019	.44	.0014	.0029	.52	.0185
	[1.48]			[1.11]			[0.10]			[-0.25]			[0.27]		
9	-.0001	.50	.0091	.0000	.54	.0155	-.0045	.46	.0016	-.0039	.45	.0045	.0052	.52	.0154
	[-0.01]			[0.00]			[-0.71]			[-0.59]			[0.59]		
8	-.0054	.47	.0075	-.0036	.52	.0136	-.0084	.42	-.0031	-.0004	.47	.0083	-.0050	.45	.0015
	[-0.81]			[-0.49]			[-1.42]			[-0.06]			[-0.70]		
7	-.0068	.44	.0038	-.0089	.47	.0065	-.0076	.41	-.0030	-.0073	.44	.0003	-.0046	.45	.0018
	[-1.23]			[-1.48]			[-1.39]			[-1.15]			[-0.70]		
6	-.0089	.42	.0002	-.0103	.42	.0000	-.0088	.40	-.0046	-.0064	.42	-.0034	-.0077	.42	-.0030
	[-1.67]			[-1.81]			[-1.63]			[-0.96]			[-1.39]		
5	-.0081	.40	-.0025	-.0106	.39	-.0057	-.0081	.40	-.0039	-.0097	.42	-.0031	-.0086	.40	-.0076
	[-1.48]			[-1.83]			[-1.36]			[-1.51]			[-1.41]		
4	-.0086	.40	-.0039	-.0123	.35	-.0133	-.0056	.43	.0011	-.0115	.39	-.0088	-.0124	.38	-.0095
	[-1.56]			[-1.92]			[-0.93]			[-1.81]			[-2.20]		
3	-.0102	.36	-.0102	-.0122	.31	-.0221	-.0072	.41	-.0030	-.0131	.38	-.0108	-.0132	.36	-.0142
	[-1.71]			[-1.56]			[-0.99]			[-2.18]			[-2.70]		
2	-.0153	.32	-.0199	-.0154	.24	-.0378	-.0119	.37	-.0124	-.0117	.38	-.0094	-.0157	.34	-.0177
	[-2.28]			[-1.57]			[-1.48]			[-2.13]			[-3.02]		
1	-.0303	.20	-.0542	-.0167	.15	-.0680	-.0136	.36	-.0159	-.0091	.38	-.0074	-.0160	.34	-.0193
	[-3.14]			[-1.18]			[-1.59]			[-2.01]			[-2.93]		
L-S	.0489	.75	.0528	.0318	.53	.0235	.0143	.38	.0144	.0072	.29	.0060	.0189	.31	.0098
	[3.29]			[1.38]			[1.73]			[1.27]			[1.70]		

Table 2.2 Statistical properties of single characteristic sorted strategy returns

This table reports sample moments, correlations and factor loadings of excess returns of five single characteristic sorted strategies over the period of 1992:02–2013:12. The p-values associated with the estimated factor loadings are reported in parentheses in Panel C. Each portfolio strategy is formed by taking equal-weighted long positions in the funds that are ranked in the top-decile portfolio on basis of one lagged fund characteristic. All portfolios are re-balanced monthly.

	Alpha	Hot	Flow	Size	Active
			Panel A: Sample Moments		
Mean	.1124	.1168	.0831	.0730	.0766
Std	.1759	.1832	.1567	.1474	.1338
Skew	-.11	.18	-.59	-.80	-.89
Kurt	5.58	6.36	4.68	4.80	5.55
			Panel B: Correlations		
Alpha	1				
Hot	.97	1			
Flow	.98	.94	1		
Size	.91	.83	.96	1	
Active	.89	.82	.94	.98	1
			Panel C: Factor Loadings		
MKT	.9687	.9671	.9406	.9281	.8363
	(.000)	*(.000)*	*(.000)*	*(.000)*	*(.000)*
SMB	.5181	.5337	.3358	.1859	.1832
	(.000)	*(.000)*	*(.000)*	*(.000)*	*(.000)*
HML	-.0403	-.1171	-.0194	.0985	.1882
	(.149)	*(.000)*	*(.232)*	*(.000)*	*(.000)*
UMD	.1562	.3213	.0896	-.0138	.0134
	(.000)	*(.000)*	*(.000)*	*(.017)*	*(.347)*

Table 2.3 BSV coefficient estimates and single characteristic sorted portfolio performance

This table reports the out-of-sample BSV coefficient estimates (Coef) and corresponding single characteristic portfolio performance (CEQ with RRA=5) over the period of 1996:01–2013:12. The first row (Average) provides the time-series averages over the full sample period. The second to the fifth row (Up - Down) present the time-series averages under different market conditions. The BSV coefficients are estimated using the methodology specified in Section 2.3.1.

	Alpha		Hot		Flow		Size		Active	
Market	Coef	CEQ	Coef	CEQ	Coef	CEQ	Coef	CEQ	Coef	CEQ
Full	1.80	.0211	1.17	.0219	1.17	.0072	.98	.0014	1.45	.0185
Up	2.09	.4629	1.36	.4883	1.04	.4288	1.58	.4006	.81	.3754
Mid-Up	2.14	.2449	2.14	.2304	1.70	.2043	1.39	.1955	1.61	.1805
Mid-Down	2.14	-.0710	.74	-.0953	1.63	-.0660	.76	-.0599	1.51	-.0529
Down	.67	-.4805	.23	-.4546	.03	-.4739	.14	-.4739	1.75	-.3844

Table 2.4 Out-of-sample investment results of portfolio strategies

This table reports out-of-sample results of mutal fund portfolio strategies over the period of 1996:01–2013:12. Reported metrics include the first four sample moments of portfolio realized excess returns (Mean, Std, Skew and Kurt), the annualized 4-Factor alpha (Alpha), Sharpe ratio (Sharpe) and certainty equivalent excess returns (CEQ) with three levels of risk aversion coefficients (RRA=3,5,10). Panel A reports the results for seven passive strategies using Vangard index funds; Panel B presents the results for five single characteristic sorted strategies, each of which takes equal-weighted long positions in the top 10% funds sorted on a specific lagged characteristic measure; Panel C shows the results for five single characteristic optimized strategies, each of which is formed based on a single characteristic predictive signal and using the methodology specified in Section 2.3.1; Panel D reports the results for composite strategies which combine predictive signals from five fund characteristics (and macroeconomic state variables). Figures in parentheses denote the block-bootstrap p-values under the null hypothesis that the performance of the competing strategy is equal or superior to that of the unconditional composite strategy (one-sided test). All strategies except the passive ones in Panel A are re-balanced monthly.

Strategy	Mean	Std	Skew	Kurt	Alpha	Sharpe	CEQ		
							RRA=3	RRA=5	RRA=10
				Panel A: Vanguard Index Funds					
Large-Value	.0659	.1601	-.72	4.32	-.0020	.41	.0257	-.0032	-.0843
					(.000)	*(.000)*	*(.000)*	*(.000)*	*(.000)*
Large-Blend	.0654	.1575	-.65	3.86	.0020	.42	.0268	-.0006	-.0762
					(.000)	*(.000)*	*(.000)*	*(.000)*	*(.000)*
Large-Growth	.0723	.1798	-.71	4.08	.0039	.40	.0213	-.0156	-.1208
					(.000)	*(.000)*	*(.000)*	*(.000)*	*(.000)*
Mid-Blend	.0936	.1822	-.77	4.99	-.0004	.51	.0408	.0018	-.1148
					(.000)	*(.000)*	*(.000)*	*(.000)*	*(.000)*
Mid-Growth	.0873	.2042	-.62	4.21	-.0072	.43	.0213	-.0269	-.1670
					(.000)	*(.000)*	*(.000)*	*(.000)*	*(.000)*
Small-Blend	.0895	.2041	-.51	4.14	-.0127	.44	.0242	-.0230	-.1582
					(.000)	*(.000)*	*(.000)*	*(.000)*	*(.000)*
Small-Growth	.0896	.2105	-.31	3.86	-.0073	.43	.0212	-.0272	-.1620
					(.000)	*(.000)*	*(.000)*	*(.000)*	*(.000)*
				Panel B: Single Characteristic Sorted Strategies					
$\text{Alpha}_{[\text{sort}]}$	.1126	.1883	-.10	5.14	.0187	.60	.0588	.0211	-.0823
					(.070)	*(.003)*	*(.005)*	*(.000)*	*(.000)*
$\text{Hot}_{[\text{sort}]}$	.1178	.1953	.18	5.93	.0151	.60	.0609	.0219	-.0824
					(.000)	*(.005)*	*(.033)*	*(.000)*	*(.000)*
$\text{Flow}_{[\text{sort}]}$	.0821	.1676	-.57	4.31	.0007	.49	.0384	.0072	-.0801
					(.000)	*(.000)*	*(.000)*	*(.000)*	*(.000)*
$\text{Size}_{[\text{sort}]}$	.0691	.1583	-.76	4.35	-.0019	.44	.0297	.0014	-.0789
					(.000)	*(.000)*	*(.000)*	*(.000)*	*(.000)*
$\text{Active}_{[\text{sort}]}$	.0738	.1427	-.87	5.16	.0029	.52	.0417	.0185	-.0480
					(.000)	*(.000)*	*(.000)*	*(.000)*	*(.044)*

Table 2.4 (Continues)

				Panel C: Single Characteristic Optimized Strategies					
$Alpha_{[optm]}$	.1130	.1856	-.08	5.12	.0229	.61	.0608	.0245	-.0747
					(.216)	*(.019)*	*(.008)*	*(.016)*	*(.000)*
$Hot_{[optm]}$	.1178	.1905	.19	5.84	.0241	.62	.0637	.0268	-.0714
					(.014)	*(.044)*	*(.041)*	*(.018)*	*(.000)*
$Flow_{[optm]}$	.0822	.1684	-.58	4.44	.0013	.49	.0380	.0063	-.0827
					(.000)	*(.000)*	*(.000)*	*(.000)*	*(.000)*
$Size_{[optm]}$	.0807	.1593	-.70	4.23	.0022	.51	.0410	.0126	-.0565
					(.000)	*(.000)*	*(.000)*	*(.000)*	*(.000)*
$Active_{[optm]}$	.0688	.1346	-.92	5.24	.0023	.51	.0403	.0197	-.0389
					(.000)	*(.000)*	*(.000)*	*(.000)*	*(.194)*
				Panel D: Composite Strategies					
$Nave_{[comp]}$	.0911	.1650	-.53	4.23	.0086	.55	.0489	.0190	-.0641
					(.000)	*(.000)*	*(.000)*	*(.000)*	*(.000)*
$Unc_{[comp]}$	.1170	.1685	.09	6.11	.0331	.69	.0745	.0447	-.0345
					(1.00)	*(1.00)*	*(1.00)*	*(1.00)*	*(1.00)*
$Con_{[comp]}$	.1205	.1731	.35	6.42	.0345	.70	.0764	.0460	-.0323
					...	...	...	...	...

Table 2.5 Statistics of optimal composite portfolio weights

This table reports the time-series statistics of cross-sectional portfolio weights of unconditional and conditional optimal composite strategies over the period of 1996:01–2013:12.

	$\text{Unc}_{[\text{comp}]}$		$\text{Con}_{[\text{comp}]}$	
	$\text{Avg}\{w_{i,t}\}$	$\text{Max}\{w_{i,t}\}$	$\text{Avg}\{w_{i,t}\}$	$\text{Max}\{w_{i,t}\}$
Average	0.29%	1.45%	0.26%	1.42%
Min	0.17%	0.37%	0.17%	0.65%
Max	0.63%	5.41%	0.52%	3.76%

Table 2.6 Portfolio-level characteristics of all investment strategies

This table reports the statistics of fund characteristic holdings in portfolio strategies over the investment period of 1996:01–2013:12. Panel A shows the results for single characteristic sorted strategies, Panel B present the results for single characteristic optimized strategies, Panel C dipicts the results for composite strategies, and Panel D reports the out-of-sample performance (Sharpe and CEQ with RRA=5) of single characteristic sorted strategies. In each panel, the first row (Full) provides the time-series averages over the full sample period. The second to the fifth row present the time-series averages under four market conditions from good to poor: Up, Mid-Up, Mid-Down and Down.

Panel A: Single Characteristic Sorted Strategies

Market	Alpha$_{[sort]}$				
	$\bar{C}_{\text{Alpha}}$	$\bar{C}_{\text{Hot}}$	$\bar{C}_{\text{Flow}}$	$\bar{C}_{\text{Size}}$	$\bar{C}_{\text{Active}}$
Full	1.83	1.25	.52	.07	.65
Up	1.81	1.18	.52	.09	.63
Mid-Up	1.83	1.23	.52	.03	.71
Mid-Down	1.85	1.31	.52	.07	.70
Down	1.81	1.26	.50	.08	.55

Market	Hot$_{[sort]}$				
	$\bar{C}_{\text{Alpha}}$	$\bar{C}_{\text{Hot}}$	$\bar{C}_{\text{Flow}}$	$\bar{C}_{\text{Size}}$	$\bar{C}_{\text{Active}}$
Full	1.24	1.84	.56	.06	.35
Up	1.20	1.81	.53	.07	.33
Mid-Up	1.22	1.85	.59	.05	.26
Mid-Down	1.28	1.83	.56	.07	.33
Down	1.27	1.86	.54	.06	.50

Market	Flow$_{[sort]}$				
	$\bar{C}_{\text{Alpha}}$	$\bar{C}_{\text{Hot}}$	$\bar{C}_{\text{Flow}}$	$\bar{C}_{\text{Size}}$	$\bar{C}_{\text{Active}}$
Full	.60	.62	1.88	.18	.21
Up	.61	.59	1.86	.18	.26
Mid-Up	.60	.65	1.89	.18	.20
Mid-Down	.61	.64	1.89	.19	.20
Down	.58	.60	1.87	.18	.18

Market	Size$_{[sort]}$				
	$\bar{C}_{\text{Alpha}}$	$\bar{C}_{\text{Hot}}$	$\bar{C}_{\text{Flow}}$	$\bar{C}_{\text{Size}}$	$\bar{C}_{\text{Active}}$
Full	-.05	-.10	.14	.27	.29
Up	-.04	-.10	.15	.28	.31
Mid-Up	-.05	-.11	.13	.27	.30
Mid-Down	-.04	-.11	.13	.27	.27
Down	-.05	-.05	.14	.27	.27

Market	Active$_{[sort]}$				
	$\bar{C}_{\text{Alpha}}$	$\bar{C}_{\text{Hot}}$	$\bar{C}_{\text{Flow}}$	$\bar{C}_{\text{Size}}$	$\bar{C}_{\text{Active}}$
Full	.26	.03	.09	.10	2.25
Up	.16	-.04	.13	.11	2.22
Mid-Up	.34	-.07	.08	.09	2.23
Mid-Down	.36	.04	.10	.11	2.29
Down	.15	.24	.06	.09	2.27

Panel B: Single Characteristic Optimized Strategies

Market	Alpha$_{[optm]}$				
	$\bar{C}_{\text{Alpha}}$	$\bar{C}_{\text{Hot}}$	$\bar{C}_{\text{Flow}}$	$\bar{C}_{\text{Size}}$	$\bar{C}_{\text{Active}}$
Full	4.80	3.41	1.30	.03	.76
Up	5.00	3.50	1.43	.09	.63
Mid-Up	5.70	3.90	1.56	.00	1.09
Mid-Down	5.50	4.01	1.45	.03	.98
Down	2.56	1.94	.65	.03	.18

Market	Hot$_{[optm]}$				
	$\bar{C}_{\text{Alpha}}$	$\bar{C}_{\text{Hot}}$	$\bar{C}_{\text{Flow}}$	$\bar{C}_{\text{Size}}$	$\bar{C}_{\text{Active}}$
Full	2.34	3.41	1.02	.00	-.27
Up	2.34	3.37	.96	.02	-.39
Mid-Up	2.95	4.56	1.47	-.01	-.45
Mid-Down	2.47	3.45	1.00	.01	-.14
Down	1.37	1.85	.51	.00	-.09

Market	Flow$_{[optm]}$				
	$\bar{C}_{\text{Alpha}}$	$\bar{C}_{\text{Hot}}$	$\bar{C}_{\text{Flow}}$	$\bar{C}_{\text{Size}}$	$\bar{C}_{\text{Active}}$
Full	1.23	1.45	5.76	.21	.04
Up	1.10	1.16	4.64	.18	.10
Mid-Up	1.55	1.95	7.49	.28	.03
Mid-Down	1.50	1.76	7.20	.25	.08
Down	.60	.70	2.77	.11	-.05

Market	Size$_{[optm]}$				
	$\bar{C}_{\text{Alpha}}$	$\bar{C}_{\text{Hot}}$	$\bar{C}_{\text{Flow}}$	$\bar{C}_{\text{Size}}$	$\bar{C}_{\text{Active}}$
Full	.07	.04	.41	2.32	.32
Up	.19	.10	.38	1.31	.39
Mid-Up	-.01	-.01	.46	3.26	.33
Mid-Down	.06	.02	.48	2.86	.39
Down	.08	.09	.29	1.40	.16

Market	Active$_{[optm]}$				
	$\bar{C}_{\text{Alpha}}$	$\bar{C}_{\text{Hot}}$	$\bar{C}_{\text{Flow}}$	$\bar{C}_{\text{Size}}$	$\bar{C}_{\text{Active}}$
Full	.98	-.15	.08	.18	6.22
Up	.59	-.55	.12	.19	5.21
Mid-Up	1.29	-.44	.07	.18	6.89
Mid-Down	1.24	-.09	.10	.21	7.38
Down	.64	.53	.01	.12	4.89

Table 2.6 (Continues)

Panel C: Composite Strategies

Market	Nave$_{[comp]}$					Unc$_{[comp]}$					Con$_{[comp]}$				
	$\bar{C}_{\text{Alpha}}$	$\bar{C}_{\text{Hot}}$	$\bar{C}_{\text{Flow}}$	$\bar{C}_{\text{Size}}$	$\bar{C}_{\text{Active}}$	$\bar{C}_{\text{Alpha}}$	$\bar{C}_{\text{Hot}}$	$\bar{C}_{\text{Flow}}$	$\bar{C}_{\text{Size}}$	$\bar{C}_{\text{Active}}$	$\bar{C}_{\text{Alpha}}$	$\bar{C}_{\text{Hot}}$	$\bar{C}_{\text{Flow}}$	$\bar{C}_{\text{Size}}$	$\bar{C}_{\text{Active}}$
Full	.78	.73	.64	.14	.75	1.26	1.18	.72	.11	.97	1.20	1.17	.79	.11	1.04
Up	.75	.69	.64	.15	.75	1.47	1.34	.70	.13	.70	1.43	1.36	.70	.12	.79
Mid-Up	.79	.71	.64	.13	.74	1.28	1.13	.74	.10	.89	1.22	1.17	.94	.10	.86
Mid-Down	.81	.74	.64	.14	.76	1.21	1.07	.87	.12	1.04	1.16	1.04	.90	.12	1.09
Down	.75	.78	.62	.13	.75	1.09	1.25	.55	.11	1.23	1.00	1.15	.53	.11	1.43

Panel D: Single Characteristic Sorted Strategy Performance

	Sharpe					CEQ				
	Alpha$_{[sort]}$	Hot$_{[sort]}$	Flow$_{[sort]}$	Size$_{[sort]}$	Active$_{[sort]}$	Alpha$_{[sort]}$	Hot$_{[sort]}$	Flow$_{[sort]}$	Size$_{[sort]}$	Active$_{[sort]}$
Full	.60	.60	.49	.44	.52	.0211	.0219	.0072	.0014	.0185
Up	3.64	3.82	4.04	4.10	4.21	.4629	.4883	.4288	.4006	.3754
Mid-Up	1.95	1.70	2.05	2.14	2.07	.2449	.2304	.2043	.1955	.1805
Mid-Down	-.15	-.22	-.18	-.17	-.19	-.0710	-.0953	-.0660	-.0599	-.0529
Down	-1.50	-1.46	-1.66	-1.83	-1.62	-.4805	-.4546	-.4739	-.4739	-.3844

Table 2.7 Conditional factor loadings of single characteristic sorted strategies

This table reports the conditional loadings on the 4 factors (MKT, SMB, HML and UMD) of single characteristic sorted strategies for the overall period of 1992:02–2013:12. Panel A, B, C and D report the results for Up, Mid-Up, Mid-Down and Down markets, respectively. Corresponding p-values are reported in parentheses.

Factor	$Alpha_{[sort]}$	$Hot_{[sort]}$	$Flow_{[sort]}$	$Size_{[sort]}$	$Active_{[sort]}$	$Alpha_{[sort]}$	$Hot_{[sort]}$	$Flow_{[sort]}$	$Size_{[sort]}$	$Active_{[sort]}$
	Panel A: Up					Panel B: Mid-Up				
MKT	1.123	1.112	1.024	.9991	.8327	.9212	.9654	.8973	.9432	.8765
	(.000)	*(.000)*	*(.000)*	*(.000)*	*(.000)*	*(.000)*	*(.000)*	*(.000)*	*(.000)*	*(.000)*
SMB	.5520	.4920	.3241	.2287	.1930	.5120	.5199	.3202	.1859	.1511
	(.000)	*(.000)*	*(.000)*	*(.000)*	*(.000)*	*(.000)*	*(.000)*	*(.000)*	*(.000)*	*(.000)*
HML	-.0669	-.1367	-.0590	.0722	.0125	-.2156	-.3325	-.1189	.0772	.1308
	(.558)	*(.257)*	*(.356)*	*(.044)*	*(.786)*	*(.000)*	*(.000)*	*(.000)*	*(.029)*	*(.012)*
UMD	.0776	.2460	.0624	.0165	-.0358	.1838	.3558	.0966	-.0392	-.0300
	(.133)	*(.000)*	*(.033)*	*(.297)*	*(.089)*	*(.000)*	*(.000)*	*(.000)*	*(.065)*	*(.333)*
	Panel C: Mid-Down					Panel D: Down				
MKT	.9390	.9924	.9146	.8914	.8126	1.013	.9066	.9635	.9346	.8452
	(.000)	*(.000)*	*(.000)*	*(.000)*	*(.000)*	*(.000)*	*(.000)*	*(.000)*	*(.000)*	*(.000)*
SMB	.4462	.4123	.3192	.2401	.2634	.3877	.4978	.2957	.1271	.1408
	(.000)	*(.000)*	*(.000)*	*(.000)*	*(.000)*	*(.000)*	*(.000)*	*(.000)*	*(.010)*	*(.059)*
HML	-.0017	-.0489	.0130	.1237	.2121	-.0095	-.0782	.0073	.1102	.2302
	(.967)	*(.309)*	*(.629)*	*(.000)*	*(.000)*	*(.838)*	*(.162)*	*(.826)*	*(.002)*	*(.000)*
UMD	.1948	.3538	.0983	-.0382	.0332	.2080	.3409	.1063	-.0148	.0407
	(.000)	*(.000)*	*(.000)*	*(.134)*	*(.313)*	*(.000)*	*(.000)*	*(.000)*	*(.535)*	*(.267)*

Table 2.8 Out-of-sample investment results of reduced-size portfolio strategies

This table reports out-of-sample results of reduced-size mutal fund portfolio strategies over the investment period of 1996:01–2013:12. Reported metrics include the first four sample moments of portfolio realized excess returns (Mean, Std, Skew and Kurt), the annualized 4-Factor alpha (Alpha), Sharpe ratio (Sharpe) and certainty equivalent excess returns (CEQ) with risk aversion coefficient of 5 (RRA=5). Panel A and B, respectively, report the results for taking equal-weighted long positions in the top 5% and 2.5% funds ranked on a specific lagged characteristic measure in single characteristic sorted strategies. All strategies are re-balanced monthly.

	Panel A: Top 5%									Panel B: Top 2.5%								
							CEQ									CEQ		
	Mean	Std	Skew	Kurt	Alpha	Sharpe	RRA=3	RRA=5	RRA=10	Mean	Std	Skew	Kurt	Alpha	Sharpe	RRA=3	RRA=5	RRA=10
	Single Characteristic Sorted Strategies																	
$\text{Alpha}_{[sort]}$	.1231	.2009	.07	5.58	.0270	.61	.0624	.0203	-.0954	.1298	.2119	.11	5.83	.0328	.61	.0623	.0153	-.1145
					[1.68]	…	…	…	…					[1.81]	…	…	…	…
$\text{Hot}_{[sort]}$	.1282	.2034	.27	6.37	.0252	.63	.0667	.0246	-.0890	.1404	.2079	.28	6.65	.0384	.68	.0762	.0320	-.0896
					[1.51]	…	…	…	…					[1.94]	…	…	…	…
$\text{Flow}_{[sort]}$	.0841	.1689	-.55	4.67	.0005	.50	.0397	.0079	-.0819	.0809	.1696	-.57	4.52	.0006	.48	.0361	.0040	-.0865
					[0.07]	…	…	…	…					[0.07]	…	…	…	…
$\text{Size}_{[sort]}$	.0698	.1588	-.77	4.44	-.0037	.44	.0301	.0015	-.0799	.0688	.1559	-.73	4.17	-.0047	.44	.0307	.0034	-.0730
					[-0.48]	…	…	…	…					[-0.61]	…	…	…	…
$\text{Active}_{[sort]}$	.0662	.1319	-.87	5.08	-.0037	.50	.0390	.0195	-.0357	.0558	.1189	-.94	5.70	-.0026	.47	.0337	.0178	-.0268
					[-0.48]	…	…	…	…					[-0.22]	…	…	…	…
	Single Characteristic Optimized Strategies																	
$\text{Alpha}_{[optm]}$	.1209	.1911	.03	5.45	.0292	.63	.0660	.0279	-.0757	.1272	.1960	.09	5.63	.0352	.65	.0696	.0298	-.0783
					[1.70]	…	…	…	…					[1.88]	…	…	…	…
$\text{Hot}_{[optm]}$	.1247	.1944	.25	6.16	.0310	.64	.0687	.0304	-.0717	.1320	.1982	.29	6.54	.0395	.67	.0738	.0340	-.0738
					[1.75]	…	…	…	…					[2.00]	…	…	…	…
$\text{Flow}_{[optm]}$	.0848	.1695	-.54	4.56	.0036	.50	.0402	.0083	-.0813	.0843	.1710	-.51	4.63	.0031	.49	.0388	.0064	-.0847
					[0.37]	…	…	…	…					[0.30]	…	…	…	…
$\text{Size}_{[optm]}$	.0848	.1578	-.66	4.15	.0069	.54	.0461	.0184	-.0589	.0864	.1556	-.59	4.01	.0094	.56	.0489	.0223	-.0509
					[0.73]	…	…	…	…					[0.91]	…	…	…	…
$\text{Active}_{[optm]}$	.0680	.1293	-.89	5.08	.0041	.53	.0418	.0231	-.0297	.0651	.1240	-.85	5.19	.0036	.53	.0411	.0241	-.0238
					[0.32]	…	…	…	…					[0.25]	…	…	…	…

Table 2.8 (Continues)

	Panel A: Top 5%									Panel B: Top 2.5%								
							CEQ									CEQ		
	Mean	Std	Skew	Kurt	Alpha	Sharpe	RRA=3	RRA=5	RRA=10	Mean	Std	Skew	Kurt	Alpha	Sharpe	RRA=3	RRA=5	RRA=10
Composite Strategies																		
Nave$_{[comp]}$	.0850	.1597	-.65	4.18	.0059	.53	.0452	.0168	-.0626	.0951	.1639	-.44	4.25	.0143	.58	.0538	.0247	-.0552
					[0.63]	…	…	…	…					[1.17]	…	…	…	…
Unc$_{[comp]}$	.1209	.1719	.27	6.72	.0374	.70	.0771	.0458	-.0351	.1297	.1757	.62	7.90	.0456	.74	.0849	.0551	-.0237
					[1.78]	…	…	…	…					[1.99]	…	…	…	…
Con$_{[comp]}$	.1258	.1768	.56	7.36	.0410	.71	.0803	.0503	-.0291	.1346	.1813	.70	7.69	.0489	.74	.0873	.0558	-.0220
					[1.98]	…	…	…	…					[2.04]	…	…	…	…

Table 2.9 Sub-period performance of portfolio strategies

This table reports the out-of-sample performance of portfolio strategies over two sub-periods: 1996:01–2004:12 (Panel A) and 2005:01–2013:12 (Panel B). Reported metrics include the Sharpe ratio (Sharpe) and certainty equivalent excess returns (CEQ) with risk aversion coefficient of 5 (RRA=5). All strategies are re-balanced monthly.

	Panel A: 1996/01 - 2004/12		Panel B: 2005/01 - 2013/12	
	Sharpe	CEQ (RRA=5)	Sharpe	CEQ (RRA=5)
	Vanguard Index Funds			
Large-Value	.43	-.0004	.39	-.0060
Large-Blend	.42	-.0017	.41	.0004
Large-Growth	.38	-.0271	.43	-.0040
Mid-Blend	.65	.0313	.40	-.0274
Mid-Growth	.38	-.0440	.48	-.0097
Small-Blend	.42	-.0280	.46	-.0179
Small-Growth	.41	-.0408	.45	-.0136
	Single Characteristic Sorted Strategies			
$\text{Alpha}_{[\text{sort}]}$	.71	.0375	.47	.0049
	…	…	…	…
$\text{Hot}_{[\text{sort}]}$	.69	.0298	.50	.0141
	…	…	…	…
$\text{Flow}_{[\text{sort}]}$	.58	.0190	.39	-.0045
	…	…	…	…
$\text{Size}_{[\text{sort}]}$	.50	.0118	.37	-.0089
	…	…	…	…
$\text{Active}_{[\text{sort}]}$	.68	.0428	.36	-.0054
	…	…	…	…

Table 2.9 (Continues)

	Panel A: 1996/01 - 2004/12		Panel B: 2005/01 - 2013/12	
	Sharpe	CEQ (RRA=5)	Sharpe	CEQ (RRA=5)
	Single Characteristic Optimized Strategies			
$\text{Alpha}_{[\text{optm}]}$	.72	.0428	.47	.0065
	…	…	…	…
$\text{Hot}_{[\text{optm}]}$	.70	.0346	.52	.0190
	…	…	…	…
$\text{Flow}_{[\text{optm}]}$	.58	.0192	.38	-.0065
	…	…	…	…
$\text{Size}_{[\text{optm}]}$	.60	.0267	.41	-.0015
	…	…	…	…
$\text{Active}_{[\text{optm}]}$	.67	.0421	.34	-.0024
	…	…	…	…
	Composite Strategies			
$\text{Nave}_{[\text{comp}]}$	.67	.0368	.42	.0013
	…	…	…	…
$\text{Unc}_{[\text{comp}]}$	.88	.0802	.51	.0185
	…	…	…	…
$\text{Con}_{[\text{comp}]}$	.82	.0668	.59	.0254
	…	…	…	…

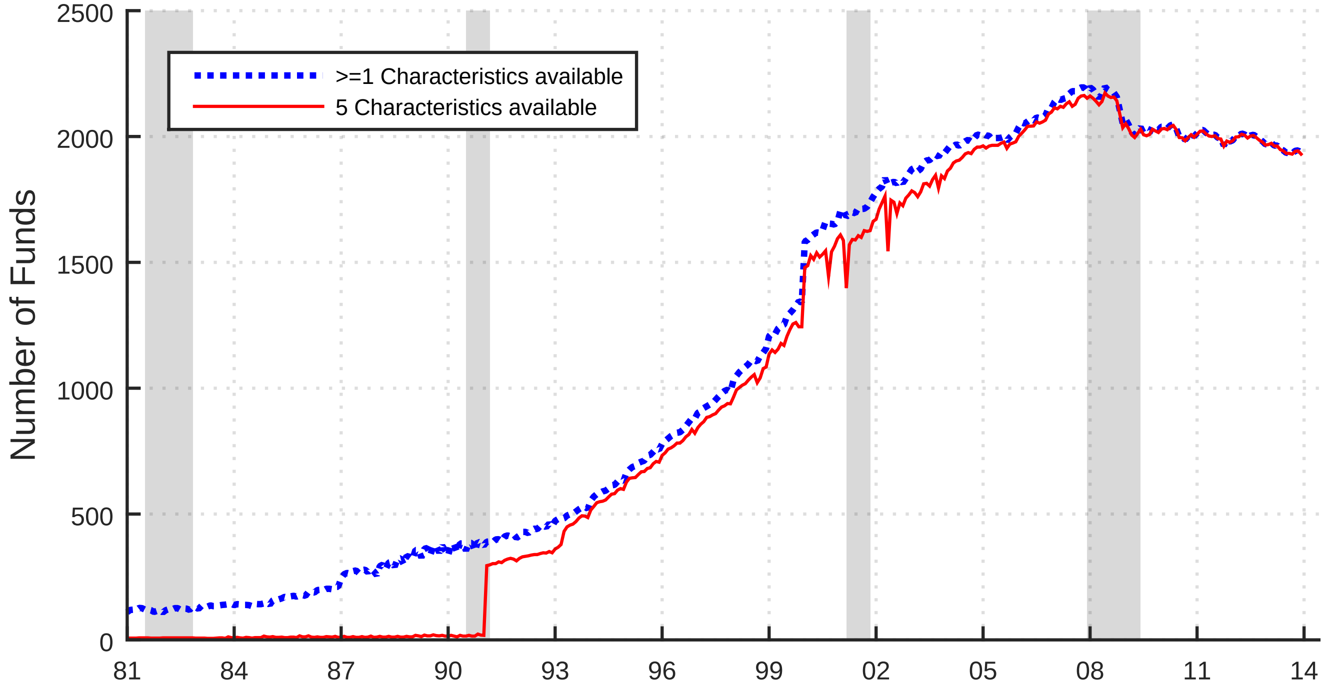

Figure 2.1 Sample property: number of funds

This figure shows how the number of funds included in the sample set changes over time. The dashed line on the top represents the number of funds with at least one non-missing characteristic measure. The solid line at the bottom shows the number of funds with all five non-missing characteristic measures.

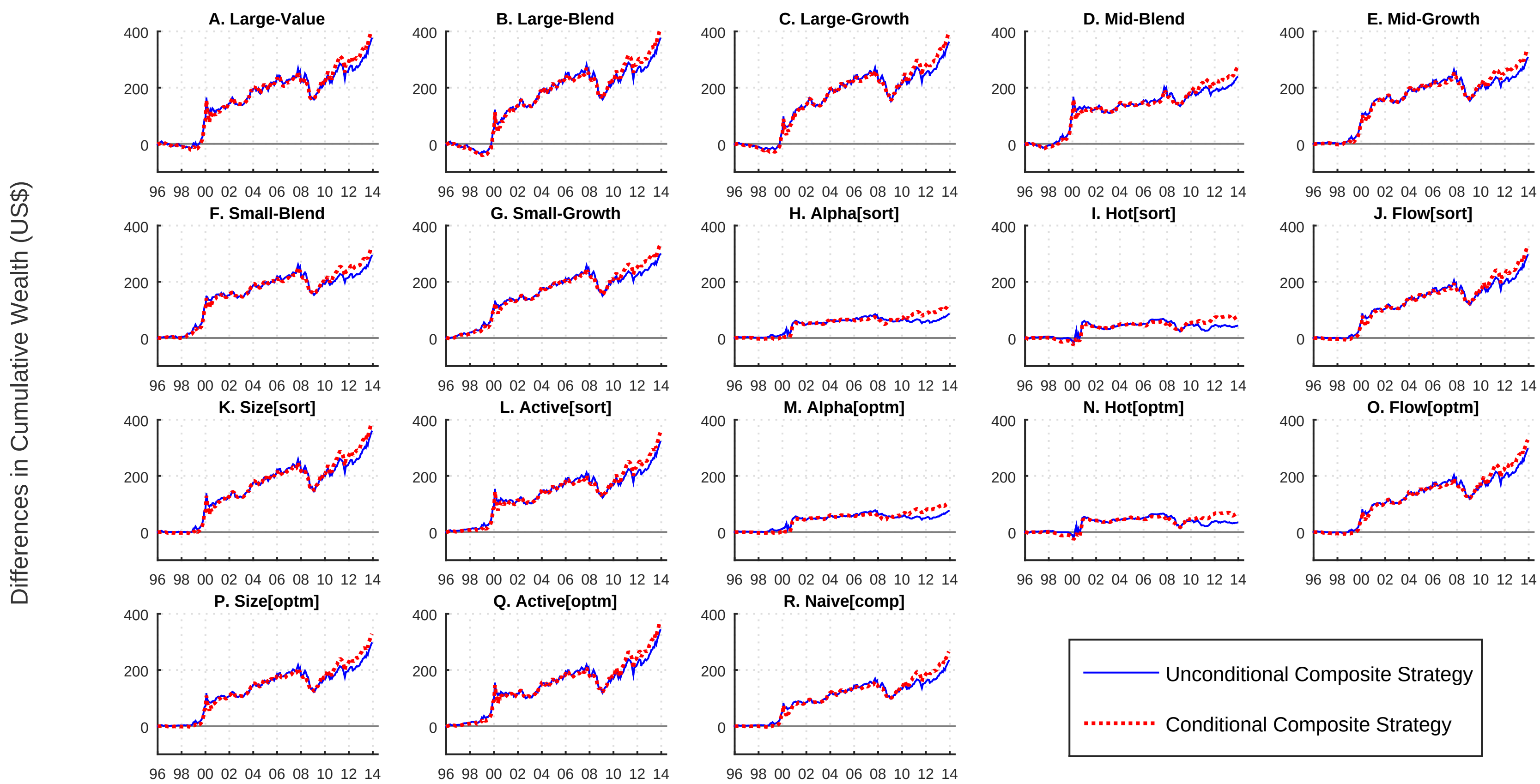

Figure 2.2 Differences in cumulative wealth: optimal composite strategies vs. alternative investment strategies
This figure depicts differences in cumulative wealth between optimal composite strategies and alternative investment strategies from 1996:01 to 2013:12. In January 1996, each strategy starts with $100 USD one-time investment. The solid (dashed) line represents the wealth difference between the unconditional (conditional) optimal composite strategy and the alternative investment strategy as titled in each subplot.