ECONOMIC RESEARCH
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WORKING PAPER SERIES

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Authors	Hui Guo
Working Paper Number	2002-008C
Citable Link	https://doi.org/10.20955/wp.2002.008
Suggested Citation	Guo, H.; On the Out-of-Sample Predictability of Stock Market Returns, Federal Reserve Bank of St. Louis Working Paper 2002-008. URL https://doi.org/10.20955/wp.2002.008

Published In	Journal of Business

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On the Out-of-Sample Predictability of Stock Market Returns

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First Version: June 2002

This Version: October 2003

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Abstract

In this paper, we provide new evidence of the out-of-sample predictability of stock returns. In particular, we find that the consumption-wealth ratio in conjunction with a measure of aggregate stock market volatility exhibits substantial out-of-sample forecasting power for excess stock market returns. Also, simple trading strategies based on the documented predictability generate returns of higher mean and lower volatility than the buy-and-hold strategy does, and this difference is economically important.

Keywords: Consumption-Wealth Ratio, Stock Market Volatility, Stock Return Predictability, Out-of-Sample Forecast, Stock Market Timing Strategy, and Portfolio Choices.

JEL number: G1.

There is an ongoing debate about stock return predictability in the time series data. Campbell (1987) and Fama and French (1989), among many others, find that macrovariables such as the dividend yield, the default premium, the term premium, and the short-term interest rate forecast excess stock market returns. However, Bossaerts and Hillion (1999), Ang and Bekaert (2001), and Goyal and Welch (2003) cast doubt on the in-sample evidence documented by the early authors by showing that these variables have negligible out-of-sample predictive power.

In this paper, we provide new evidence of the out-of-sample predictability of stock returns. In particular, we find that the consumption-wealth ratio (*cay*) by Lettau and Ludvigson (2001)—the error term from the cointegration relation among consumption, wealth, and labor income—exhibits substantial out-of-sample forecasting abilities for stock returns if augmented by a measure of aggregate stock market volatility (σ_m^2). More importantly, the improvement of the forecast model of *cay* augmented by σ_m^2 over the model of *cay* by itself is statistically significant. Our results reflect a classic omitted variable problem: While *cay* and σ_m^2 are negatively related to one another, they are both positively correlated with future stock returns.[1]

For robustness, we also investigate whether we can use simple trading strategies to exploit the predictability documented in this paper. As suggested by Leitch and Tanner (1991), this evaluation criteria is potentially more sensible than the statistical counterpart. We consider two widely used and relatively naïve portfolio strategies. First, following Breen, Glosten, and Jagannathan (1989), among others, we hold stocks if the predicted excess return is positive and hold bonds otherwise. In the second strategy, which has been used by Johannes, Polson, and Stroud (2002), among others, we allocate wealth between stocks and bonds according to the formula of the static capital asset pricing model

[1] Brennan and Xia (2002) argue that the forecasting power of *cay* is spurious because if calendar time is used in place of consumption, the resulting cointegration error, *tay*, performs as well as or better than *cay* in predicting stock returns. In Appendix A, we shows that *cay* always drives out *tay* if we add past stock market variance and the stochastically detrended risk-free rate to the forecasting equation. Therefore, although the results by Brennan and Xia are interesting because they

(CAPM). We find that the managed portfolio generates higher mean returns with lower volatility than the market portfolio, and this difference is economically important. For example, the certainty equivalence calculation suggests that an investor would agree to pay annual fees of 2 to 3 percent to hold the managed portfolio rather than the market portfolio over the period 1968:Q2 to 2002:Q4. Also, neither the CAPM nor the Fama and French (FF, 1993) three-factor model can explain returns on the managed portfolio, and we reject the null hypothesis of no market timing ability using Cumby and Modest's (1987) test. Moreover, our trading strategies require relatively infrequent rebalancing of portfolios, and, therefore, these results are robust to the adjustment of reasonable transaction costs. Interestingly, consistent with Pesaran and Timmermann (1995), we find substantial variations in the profitability of trading strategies through time.

Our results are in sharp contrast with those of Bossaerts and Hillion (1999), Ang and Bekaert (2001), and Goyal and Welch (2003), as mentioned above. This difference is explained by the fact that our forecasting variables drive out most variables used by the early authors, including the dividend yield, the default premium, and the term premium. There is one exception. The stochastically detrended risk-free rate (*rrel*) used by Campbell et al. (1997), among others, provides information beyond *cay* and σ_m^2 about future stock returns in the in-sample regression over the post-World War II period, although it becomes insignificant after 1980.[2] We also find mixed evidence of its out-of-sample forecast performance.

Our forecasting variables are motivated by Guo (2003), who shows that, in addition to the risk premium as stressed by standard models, investors also require a liquidity premium on stocks because of limited stock market participation. Therefore, σ_m^2 and *cay* forecast stock returns because they proxy

reflect an unstable relation between *cay* and excess stock market returns due to the omitted variable problem documented in this paper, they do not pose a challenge to the forecasting power of *cay*.

[2] The short-term interest rate and stock prices fell dramatically in 2001-02. This episode has a large impact on the forecasting power of *rrel*: It is significant if we exclude these two years from the post-1980 sample.

for the risk and liquidity premiums, respectively.[3] Moreover, Guo shows that, although the two variables both are positively related to future stock returns, they could be negatively correlated with one another, as observed in the data.

The paper is organized as follows. We discuss the data in Section I and report the out-of-sample forecasting exercises in Section II. Some simple trading strategies are analyzed in Section III and Section IV offers some concluding remarks.

I. Data

The consumption, net worth, labor income data and the generated variable *cay* over the period 1952:Q2 to 2002:Q3 are obtained from Martin Lettau at New York University. We use the value-weighted stock market return obtained from the Center for Research in Security Prices (CRSP) as a measure of market returns. The risk-free rate obtained from CRSP is used to construct excess stock returns. As in Merton (1980) and many others, we construct realized stock market variance, σ_m^2, using the daily stock market return data, which is obtained from Schwert (1990) before July 1962 and from CRSP thereafter. Following Campbell et al. (2001), we adjust downward realized stock market variance for 1987:Q4, on which the 1987 stock market crash has confounding effects. The stochastically detrended risk-free rate, *rrel*, is the difference between the nominal risk-free rate and its last four-quarter average.

[Insert Table 1 Here]

Table 1, which includes the full sample and two subsample periods, presents summary statistics of excess stock market return, $r_m - r_r$, and its forecasting variables used in this paper. It should be noted that the autocorrelation coefficients of the forecasting variables are less than 0.90 in both the full sample and the subsamples. There are some differences between the two subsamples. First, *cay* is more

[3] Patelis (1997) suggests that variables such as *rrel* reflect the stance of monetary policies, which have state-dependent

negatively related with σ_m^2 in the second half (panel C) than the first half (panel B) of the sample. Second, while *cay* is negatively related to *rrel* in panel B, the two are slightly positively related in panel C. Third, excess stock market return, $r_m - r_r$, is more negatively related with *rrel* in panel B than in panel C.

[Insert Figures 1-3 Here]

Figures 1-3 plot the forecasting variables through time. While *cay* (Figure 1) fell sharply, σ_m^2 (Figure 2) rose dramatically during the second half of the 1990s. This pattern explains the strong negative relation between the two variables as reported in Table 1. Also, *rrel* (Figure 3) fell steeply during the stock market "bubble" burst in 2001-02. As we show below, this episode weakens the forecasting ability of σ_m^2 and *rrel* for stock market returns. However, the stock market correction in 2001-02 reinforces the forecasting ability of *cay*, which has been below its historical average since 1997. Nevertheless, our main results are not sensitive to whether we include these two years in our sample.

We first discuss the in-sample regression results. As argued by Inoue and Kilian (2002), while out-of-sample tests are not necessarily more reliable than in-sample tests, in-sample tests are more powerful than out-of-sample tests, even asymptotically. Table 2 presents the ordinary least-squares (OLS) estimation results with heteroskedasticity- and autocorrelation-corrected t-statistics in parentheses. It should be noted that we construct *cay* using the full sample, even in the subsample analysis.

[Insert Table 2 Here]

Panel A is the full sample spanning from 1952:Q3 to 2002:Q4. Row 1 confirms the results by Lettau and Ludvigson (2001) that *cay* is a strong predictor of stock returns with the adjusted R-squared

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effects on real economic activities through a credit channel (e.g., Bernanke and Gertler [1989]).

of 8.2 percent. Row 2 shows that σ_m^2 has negligible forecasting power for stock returns (row 2).[4] However, σ_m^2 becomes highly significant if *cay* is also included in the forecasting equation with the adjusted R-squared of 14.7 percent, as shown in row 3. It should also be noted that, in the augmented model (row 3), the adjusted R-squared and the point estimates of *cay* and σ_m^2 are much higher than their counterparts in rows 1 and 2. These results reflect a classic omitted variable problem in rows 1 and 2: Although both *cay* and σ_m^2 are positively related to future stock returns, they are negatively correlated with one another, as shown in Table 1. Finally, row 4 shows that *rrel* provides additional information beyond *cay* and σ_m^2 about future stock returns, and we find very similar results using two-period-lagged *cay* in row 5.[5]

We report the estimation results using two subsample periods (1952:Q3 to 1977:Q4 and 1978:Q1 to 2002:Q4) in panels B and C, respectively. In general, the results are very similar to those reported in panel A. For example, the forecasting ability improves substantially if we include both *cay* and σ_m^2 in the forecasting equation, as shown in rows 8 and 13. It should also be noted that their point estimates are strikingly similar to their full-sample counterparts in row 3, indicating a stable forecasting relation over time. This pattern explains their strong out-of-sample forecasting power presented in the next section. There are, however, some noticeable differences between the two subsamples. First, the predictability is substantially weaker in the second than the first subsample. Second, while σ_m^2 by itself is statistically significant in the first subsample (row 7), it is insignificant in the second subsample (row 12). Third, although *rrel* is statistically significant in the first subsample, it is insignificant in the second subsample. However, the two latter results are sensitive to the inclusion of observations from 2001-02 for the reasons mentioned above.

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[4] This result is sensitive to the observations of the last a few years in our sample, during which σ_m^2 rose steeply, as shown in Figure 2: It becomes statistically significant if we use only the data up to 2000.

II. Out-of-Sample Forecasts

This section presents the analysis of the out-of-sample performance of various forecast models. We consider two cases. First, investors are assumed to know the cointegration parameters of *cay*, which we estimate using the full sample. They also observe consumption, labor income, and net worth without delay. This scenario is consistent with rational expectations models, in which agents have full information about the economy.[6] Second, we estimate recursively the cointegration parameters using only information available at the time of forecast. Moreover, we lag *cay* twice, given that consumption and labor income data are available with a one-quarter delay. This scenario has appeal to practitioners, who must rely on the real-time data.[7]

[Insert Figure 4 Here]

Figure 4 plots the recursively estimated coefficients on labor income (solid line) and net worth (dashed line). As in Lettau and Ludvigson (2001), we estimate the cointegration parameters using dynamic least squares with eight leads and lags. The point estimates show large variations until the 1990s because it requires a relatively large number of observations to consistently estimate the cointegration parameters. Therefore, it should not be a surprise that the forecasting ability of *cay* deteriorates significantly if the cointegration parameters are estimated recursively relative to the fixed parameters using the full sample, especially during the early period. It should also be noted that the test in the second scenario is likely to be more stringent than investors would encounter in real time, given

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[5] Adding other commonly used forecasting variables, e.g., the dividend yield, the default premium, and the term premium, does not improve the forecasting power. These results are available upon request.

[6] The Bureau of Economic Analysis (BEA) releases consumption and labor income data with about a one-month delay. Given that BEA only processes but does not create data, it is possible although unlikely that practitioners in financial markets may obtain these data without delay. More importantly, *cay* is a proxy for conditional stock market return and practitioners may obtain similar information from alternative sources. That said, we find similar results using two-period-lagged *cay*.

[7] Because consumption, net worth, and labor income data are subject to revisions, our results, which utilize the current vintage data, are potentially different from those obtained using the real-time data. While it is not clear whether the current vintage data are biased toward finding predictability, the real-time issue is beyond the scope of this paper and we leave it for future research.

that investors may have fairly accurate estimates of the cointegration parameters. With these caveats in mind, we report the out-of-sample forecast exercises below.

A. Fixed Cointegration Parameters

Table 3 reports the out-of-sample regression results using the fixed cointegration parameters obtained from the full sample. We analyze four forecast models, including (1) a benchmark model of constant excess returns, (2) the model using only *cay*, (3) the model of *cay* augmented by σ_m^2, and (4) the model of *cay* augmented by σ_m^2 and *rrel*. Throughout the paper, we denote the model of *cay* augmented by σ_m^2, which is the main focus of our analysis, as *augmented cay*. We report five commonly used forecast evaluation statistics: (1) RMSE, the root-mean-squared error; (2) MAE, the mean of absolute error; (3) CORR, the correlation between the forecast and the actual value; (4) *Sign*, the percentage of times when the forecast and the actual value have the same signs; and (5) Pseudo R-squared, 1 minus the ratio of MSE from a forecast model to the benchmark model of constant excess returns. We highlight the best forecast model by * for each criteria.

[Insert Table 3 Here]

Panel A is the sample from 1968:Q2 to 2002:Q4, which is similar to the sample analyzed by Lettau and Ludvigson (2001). In the out-of-sample forecast, we first run an in-sample regression using data from 1952:Q2 to 1968:Q1 and make a forecast for 1968:Q2. Then we update the sample to 1968:Q2 and make a forecast for 1968:Q3 and so forth. Consistent with Lettau and Ludvigson, *cay* (column 2) exhibits some out-of-sample forecasting power; for example, it has a smaller RMSE than the benchmark model of constant returns (column 1). Consistent with the in-sample regression results in Table 2, its forecasting power improves dramatically by all the criteria if we add σ_m^2 to the forecasting equation (column 3). Adding *rrel* to augmented *cay* (column 4), however, does not provide discernable improvement for the forecast performance: Overall, *cay* augmented by σ_m^2 has the best out-of-sample performance.

Panel B is the subsample from 1976:Q1 to 2002:Q4. Consistent with Brennan and Xia (2002), *cay* (column 2) has a larger RMSE than the benchmark model of constant returns (column 1) over this period. However, this result is completely reversed if we augment *cay* with σ_m^2 (column 3): Again, augmented *cay* beats the other models by all criteria.

[Insert Figure 5 Here]

To check the robustness of our results, Figure 5 plots the recursive RMSE ratio of augmented *cay* (column 3 of Table 3) to the benchmark model of constant returns (column 1, solid line) and to the model of *cay* by itself (column 2, dashed line) through time. The horizontal axis denotes the starting forecast date. For example, the value corresponding to June 1968 is the RMSE ratio over the forecast period from 1968:Q2 to 2002:Q4. We choose the range 1968:Q2 to 1996:Q4 for the starting forecast date; therefore, the out-of-sample test utilizes at least 25 observations. The two ratios are always smaller than one in Figure 5, indicating that (1) adding σ_m^2 to the forecasting equation substantially improves the forecasting ability of *cay* and (2) augmented *cay* has substantial out-of-sample predictive power. In contrast, the model of *cay* by itself does not always outperform the benchmark model of constant returns since the solid line is above the dashed line over various periods.

B. Recursively Estimated Cointegration Parameters

Table 4 reports the out-of-sample performance using recursively estimated *cay*. The exercise is the same as the case of the fixed parameters except that the cointegration parameters are estimated recursively using only information available at the time of forecast. It should be noted that consumption, labor income, and net worth are available with a one-quarter delay. For example, we first estimate the cointegration relation among consumption, net worth, and labor income and obtain the fitted *cay* using data from 1952:Q2 to 1967:Q4. Then we run an in-sample forecasting regression using data from 1952:Q2 to 1968:Q1 (*cay* is two-period lagged) and make a forecast for 1968:Q2. Then we update the sample to 1968:Q2 and make a forecast for 1968:Q3 and so forth. In general, the results are consistent with those in Table 3. However, the forecasting ability of all models is substantially weaker in Table 4 than in Table 3, as expected.

[Insert Table 4 Here]

In particular, for the period from 1968:Q2 to 2002:Q4, the augmented model of *cay* (column 3) performs better than the benchmark model (column 1) and the model of *cay* by itself (column 2). Interestingly, inclusion of *rrel* (column 4) improves the forecasting performance of augmented *cay*: Overall, it has the best forecasting performance among all four models.[8] For the period 976:Q1 to 2002:Q4, the benchmark model of constant returns has the smallest RMSE. Figure 6 plots the recursive RMSE ratio of augmented *cay* (column 3 of Table 4) to the benchmark model of constant returns (column 1, solid line) and to the model of *cay* by itself (column 2, dashed line) through time. The solid line remains below one after 1990, when the recursively estimated cointegration parameters become relatively stable, as shown in Figure 4. Therefore, the poor out-of-sample performance of augmented *cay* is mainly attributed to the large estimation errors in the cointegration parameters. Moreover, the dashed line is always below one, indicating that adding σ_m^2 to the forecasting equation substantially improves the forecasting ability of *cay.* It should also be noted that the solid line is always above the dashed line, indicating that the model of *cay* by itself has negligible out-of-sample predictive power if the cointegration parameters are estimated recursively.

[Insert Figure 6 Here]

[8] This result is in contrast with that in Table 3, in which *rrel* provides negligible information beyond augmented *cay.* One possible explanation is that, given that recursively estimated *cay* is likely to have large measurement errors in the early

C. Testing Nested Forecast Models

In this subsection, we provide two formal out-of-sample tests for nested forecast models. The first is the encompassing test ENC-NEW proposed by Clark and McCracken (1999). It tests the null hypothesis that the benchmark model incorporates all the information about the next quarter's excess stock market return against the alternative hypothesis that past variance provides additional information. The second is the equal forecast accuracy test MSE-F developed by McCracken (1999). Its null hypothesis is that the benchmark model has a mean-squared forecasting error less than or equal to that of the model augmented by past return; the alternative is that the augmented model has a smaller mean-squared forecasting error. These two tests have also been used in Lettau and Ludvigson (2001), and Clark and McCracken (1999) find that they have the best overall power and size properties among a variety of tests proposed in the literature.

[Insert Table 5 Here]

Table 5 presents the results of the out-of-sample tests. In panel A, we estimate the cointegration parameters for *cay* using the full sample, and the macrovariables are available without delay. We focus on two pairs of nested forecast models: the benchmark model of constant stock returns versus augmented *cay* (row 1) and the model of *cay* by itself versus augmented *cay* (row 2). Again, we use observations from the period 1952:Q4 to 1968:Q1 for the initial in-sample estimation and form the out-of-sample forecast recursively. The column Asy. CV reports the asymptotic 95 percent critical value provided by Clark and McCraken (1999). We find that, in both tests, augmented *cay* outperforms the model of constant returns and the model of *cay* by itself at any conventional significant levels. In panel B, the cointegration parameters are estimated recursively and the macrovariables are available with a one-quarter lag. Again, we find evidence that augmented *cay* outperforms the two competing models at

period, *rrel* provides additional information in Table 4 because it is closely related to "true" *cay* estimated using the full sample (as shown in Table 1).

the conventional significance level with only one exception: the MSE-F test shows that the difference between augmented *cay* and the benchmark model of constant returns is not statistically significant.

III. Economic Values of Market Timing

Leitch and Tanner (1991) argue that the forecast models chosen according to statistical criteria are not necessarily the models that are profitable in timing the market. To address this issue, we investigate whether the documented predictability can be exploited to generate returns of higher mean and lower volatility than a buy-and-hold strategy offers. To conserve space, we report only the case of recursively estimated cointegration parameters, which is relevant to practitioners. Nevertheless, we find very similar results using the fixed cointegration parameters, which are available upon request.

A. Switching Strategies

We adopt two widely used and relatively naïve market timing strategies. The first strategy, which has been utilized by Breen, Glosten, and Jagannathan (1989) and Pesaran and Timmermann (1995), among many others, requires holding stocks if the predicted excess return is positive and holding bonds otherwise. Table 6 reports the results of four trading strategies: a benchmark of buy-and-hold and three strategies based on the forecast models analyzed in Tables 3 and 4. We present the mean, the standard deviation (SD), the ratio of the mean to the standard deviation (Mean/SD), and the adjusted Sharpe ratio (SR) for the annualized returns on these portfolios.[9]

[Insert Table 6 and Table 7 Here]

Over the period 1968:Q2 to 2002:Q4, all managed portfolios have returns of higher mean and lower standard deviation than those of the buy-and-hold strategy. For example, the managed portfolio

[9] As in Graham and Harvey (1997) and Johannes, Polson, and Stroud (2002), we scale the return on the managed portfolio, for example, through leverage, so that it has the same standard deviation as stock market return. The scaled return is then used to calculate the Sharpe ratio in the usual way.

based on the forecast model of *cay* (column 2) generates an average annual return of 13.7 percent with a standard deviation of 14.2 percent, compared with 11.3 percent and 18.0 percent, respectively, for the buy-and-hold strategy (column 1). And the adjusted Sharpe ratio of the managed portfolio is about 120 percent higher than the market portfolio. Therefore, even though the out-of-sample forecasting ability of *cay* is statistically negligible as shown in Table 4, it is economically important. Our results thus confirm Leitch and Tanner's (1991) skepticism of using statistical criteria such as RMSE for forecast evaluation. Also, in contrast with the results of Table 4, the model augmented with σ_m^2 and *rrel* (column 4) has an adjusted Sharpe ratio lower than the model that uses *cay* only. This is also true for the model augmented with σ_m^2 (column 3). As we show below, these results reflect the fact that we do not use information efficiently in the switching strategy.

We find very similar patterns in the three subsample periods, which are reported in panels B through D of Table 6. However, the performance of the managed portfolio relative to the benchmark fluctuates widely over time, which is consistent with the finding of Pesaran and Timmermann (1995). For example, for the market timing strategy based on *cay* only, we observe the biggest improvement in the 1970s: The managed portfolio has an adjusted Sharpe ratio of 0.48, compared with 0.08 for the market portfolio. In contrast, the managed portfolio has an adjusted Sharpe ratio of 0.67 (0.76) for the period 1980:Q1 to 1989:Q4 (1990:Q1 to 2002:Q4), compared with 0.48 (0.34) for the market portfolio. We find a similar pattern for the other forecast models.

[Insert Figure 7 Here]

Figure 7 provides some details of the strategy based on augmented *cay* (column 3 of Table 6). The upper panel plots the weight of stocks in the managed portfolio, which assumes two values of zero (100 percent of bonds) and one (100 percent of stocks). Interestingly, investors did not have to rebalance the portfolio very often, especially during the stock market run-up in the 1980s and 1990s. The lower panel shows that, by using our forecasting variables to time the market, investors avoid some large downward movements in the stock market, e.g., around the 1973 oil shock. Finally, the middle panel plots the value of a \$100 investment in a market index (dashed line) and in the managed portfolio (solid line), respectively, starting from 1968:Q2. We find that the latter is always higher than the former. By the end of 2002:Q4, the managed portfolio is worth \$5,338, compared with \$2,793 for the buy-and-hold strategy.

Table 7 investigates the effect of a proportional transaction cost of 25 basis points. For example, when investors switch from stocks to bonds or vice versa, they have to pay a fee of 0.25 percent of the value of their portfolios. It should be noted that a 25-basis-point fee is in the upper range of transaction costs for the market index (e.g., Balduzzi and Lynch [1999]). Compared with the results in Table 6, we find that transaction costs have a small impact on the performance of the managed portfolio. This result should not be a surprise because investors did not rebalance the managed portfolio very often, as shown in Figure 7.

B. Choosing Optimal Portfolio Weights

In the second strategy, which has been adopted by Johannes, Polson, and Stroud (2002), among others, we allocate wealth among stocks and bonds using the static CAPM. Specifically, we invest a fraction of total wealth, $\omega_t = \frac{1}{\gamma}\frac{E_t[R_{t+1} - R_f]}{E_t\sigma^2_{m,t+1}}$, in stocks and a fraction, $1-\omega_t$, in bonds, where γ is a measure of the investor's relative risk aversion, $E_t[R_{t+1} - R_f]$ is the predicted value from the excess return forecasting regression, and $E_t\sigma^2_{m,t+1}$ is the conditional variance measured by the fitted value from a regression of realized variance, $\sigma^2_{m,t+1}$, on a constant and its two lags. Compared with the first strategy, this strategy is plausible because it incorporates the information of not only signs, but also the magnitude of the predicted excess return normalized by its variance. For simplicity, we ignore the estimation uncertainty, on which Johannes, Polson, and Stroud (2002) offer some detailed discussion.

We also assume that ω_t is in the range [0,1] or that investors are not allowed to short-sell stocks or borrow from bond markets because those transactions might be infeasible in practice due to high costs. It should be noted that the profitability of timing strategies should in principle be lower under these assumptions than otherwise because they reduce the set of investment opportunities and lead to a lower mean-variance frontier.

[Insert Table 8 and Table 9 Here]

Table 8 reports the statistics for returns on the managed portfolio based on various forecast models. In the calculation of the optimal weight for stocks, we assume that γ is equal to 5.[10] As expected, the portfolio based on augmented *cay* (column 3) has substantially higher Sharpe ratios than those reported in Table 6 for the switching strategy. For example, over the period 1968:Q2 to 2002:Q4, the Sharpe ratio is 0.59 if investors choose portfolio weight optimally, compared with 0.45 for the switching strategy. Nevertheless, the other results are very similar to those reported in Table 6. For example, market timing strategies based on models using *cay* as a forecasting variable generate returns of higher mean and lower volatility than the buy-and-hold strategy. Also, the relative performance of market timing strategies fluctuates widely over time and is the most effective in the 1970s.

[Insert Figure 8 Here]

Figure 8 provides some details of the market timing strategy based on augmented *cay* (column 3 of Table 7). Again, the upper panel plots the weight of stocks in the managed portfolio, which is very similar to that of Figure 7 except that the weight occasionally takes a value between zero and one. The lower panel plots the return on the managed portfolio (solid line) as well as the market return (dashed line). Compared with the first strategy plotted in Figure 7, the second strategy successfully avoids additional major downward movements in the stock market. The middle panel shows that a $100 initial investment in the managed portfolio grows to $7,227 by the end of year 2002, which is over 2.5 times as much as the market portfolio. Again, Table 9 shows that transaction costs have small effects on the performance of the managed portfolio.

C. Some Further Tests

Cumby and Modest (1987) propose a formal test of market timing ability by regressing the realized excess return, $r_{m,t+1} - r_{f,t+1}$, on a constant and an indicator variable, I_t, which is equal to one if $r_{m,t+1} - r_{f,t+1}$ is expected to be positive and is equal to zero otherwise, as in equation (1) below

(1) $$r_{m,t+1} - r_{f,t+1} = a + b * I_t + \varepsilon_{t+1}.$$

Under the null hypothesis of no market timing ability, the coefficient of the indictor variable, *b*, should not be statistically different from zero. Table 10 reports the regression results. Over the period 1968:Q2 to 2002:Q4, we reject the null hypothesis of no market timing ability for all the forecast models.

[Insert Table 10 Here]

We also investigate whether the CAPM and the FF model can explain returns on the managed portfolio. For the CAPM, we run regressions of excess returns on the managed portfolio, $r_{mp,t+1} - r_{f,t+1}$, on a constant and a single factor of excess stock market returns, as in equation (2). We include two additional factors: the return on a portfolio that is long in small stocks and is short in large stocks (SMB) and the return on a portfolio that is long in high book-to-market stocks and is short in low book-to-market stocks (HML) for the FF model[11]:

(2) $$r_{mp,t+1} - r_{f,t+1} = \alpha + \sum \beta_i f_i + \varepsilon_{t+1}.$$

Under the joint null hypothesis that (1) the CAPM or the FF model is the correct model and (2) the managed portfolio is rationally priced, the constant term, α, should not be statistically different from

[10] The results are not sensitive to reasonable variations in γ.

zero. We report the regression results in Table 11. Panels A and B are the cases of no transaction costs. For both strategies, the CAPM cannot explain returns on the managed portfolio over the period 1968:Q2 to 2002:Q4. The FF model explains the returns somewhat better; however, α is still significant for *cay* augmented by σ_m^2 and *rrel* (column 3), is marginally significant for *cay* augmented by σ_m^2 (column 2) in panel B, and is marginally significant for *cay* by itself (column 1) in panel A. Again, we find essentially the same results if we incorporate a proportional transaction cost of 25 basis points in panels C and D.

[Inset Table 11 Here]

Lastly, we calculate the certainty equivalence gain of holding the managed portfolio, as in Fleming, Kirby, and Ostdiek (2001). We assume that the utility function has the form

$$U = W_0\Big(\sum_{t=0}^{T-1} R_{p,t+1} - \frac{\gamma}{2(1+\gamma)} R_{p,t+1}^2\Big), \tag{3}$$

where W_0 is initial wealth and $R_{p,t+1}$ is the return on the agent's portfolio. The certainty equivalence gain, Δ, is defined in equation (4) as the fee that an investor would pay in exchange for holding the managed portfolio that pays a rate of return $R_{mp,t+1}$; otherwise, he holds the market portfolio that pays $R_{m,t+1}$:

$$\sum_{t=0}^{T-1} (R_{mp,t+1} - \Delta) - \frac{\gamma}{2(1+\gamma)} (R_{mp,t+1} - \Delta)^2 = \sum_{t=0}^{T-1} R_{m,t+1} - \frac{\gamma}{2(1+\gamma)} R_{m,t+1}^2 . \tag{4}$$

Table 12 shows that the certainty equivalent gain of holding the managed portfolio is quite substantial, usually ranging from 2 to 3 percent. Moreover, transaction costs have a small effect on our results.

[Insert Table 12 Here]

[11] SMB and HML are obtained from Kenneth French at Dartmouth College.

IV. Conclusion

In this paper, we show that the out-of-sample predictability of stock market returns is both statistically and economically significant. More importantly, in sharp contrast with early empirical work, we find that, in conjunction with the consumption-wealth ratio, stock market volatility has strong forecasting power for stock market returns—a key implication of the CAPM. Our results thus suggest that stock return predictability is not inconsistent with rational pricing, a point that has been emphasized by Campbell and Cochrane (1999) and Guo (2003), among others.

We also want to stress that the forecasting ability of the consumption-wealth ratio is well-motivated: It reflects a liquidity premium due to limited stock market participation, as in Guo (2003). In particular, it helps explain why the early authors failed to find significant forecasting power of volatility for stock returns: The risk and liquidity premiums are negatively related in the post-World War II sample. It also sheds light on the puzzling negative risk-return relation documented in the early literature: Guo (2002a) shows that market risk is indeed positively priced if controlling for the liquidity premium.

It is important to notice that evidence that the CAPM and the FF model cannot explain the return on the managed portfolio does not necessarily pose a challenge to rational asset pricing theories. This is because, as shown by Merton (1973) and Campbell (1993), among others, a hedge for investment opportunity changes is also an important determinant of expected asset return, in addition to market risk. Using the same forecasting variables as in this paper, Guo (2002b) shows that Campbell's (1993) intertemporal CAPM is quite successful in explaining the cross section of stock returns, including the momentum profit, which also challenges the CAPM and the FF model.[12]

Overall, stock return predictability documented in this paper has important implications on asset pricing and portfolio management and warrants attention in future research.

[12] Although the FF model is intended to capture the hedge for investment opportunity changes, its choice of additional risk factors is admittedly ad hoc.

Appendix A. CAY versus TAY

Brennan and Xia (2002) suggest that the predictive power of *cay* is spurious because, if calendar time is used in place of consumption, the resulting cointegration error, *tay*—an inanimate variable—performs as well as or better than *cay*. In the reply, Lettau and Ludvigson (2002) argue that, given that 99 percent of variations of consumption are explained by a time trend, *tay*, a seemingly inanimate variable, has more economic content than it appears. However, we still need to show that c*ay* performs at least as well as *tay*, which we discuss in this appendix.

Table A1 presents the in-sample regression results using the full sample from 1952:Q3 to 2002:Q4. Consistent with Brennan and Xia, row 1 shows that *cay* becomes statistically insignificant at the 5 percent level if *tay* is also included in the forecasting equation. However, this result is dramatically reversed if we add σ_m^2 to the forecasting equation: *cay* drives out *tay* in row 2. We find the same results if we also add *rrel* to the forecasting equation (row 3) or use two-period-lagged *cay* and *tay* (row 4).

We also repeat the exercises of Sections II and III using *tay* in place of *cay*. Consistent with the in-sample regression results, we find that *cay* always outperforms *tay* in the out-of-sample tests if augmented with σ_m^2. To conserve space, these results are not reported here but are available upon request. Therefore, although the results by Brennan and Xia are interesting because they reflect an unstable relation between *cay* and excess stock market returns due to the omitted variable problem documented in this paper, they do not pose a challenge to the forecasting power of *cay*.

Table A1. Forecasting One-Quarter-Ahead Excess Stock Market Returns: *cay* versus *tay*

	$\hat{tay}_{t-1}$	$\hat{tay}_{t-2}$	$\hat{cay}_{t-1}$	$\hat{cay}_{t-2}$	σ^2_{t-1}	$rrel_{t-1}$	$\overline{R}^2$
1	0.002		1.190				0.089
	(1.749)		(1.801)				
2	0.001		**2.152**		**5.607**		0.147
	(0.999)		**(2.969)**		**(3.439)**		
3	0.001		**2.238**		**5.262**	**-4.116**	0.160
	(0.457)		**(3.045)**		**(3.312)**	**(-2.418)**	
4		0.001		**1.735**	**5.033**	**-4.258**	0.123
		(0.797)		**(2.367)**	**(2.990)**	**(-2.402)**	

NOTE: We report the heteroskedasticity- and autocorrelation-adjusted t-statistics in parentheses. Regressors significant at the 5 percent level are in bold.

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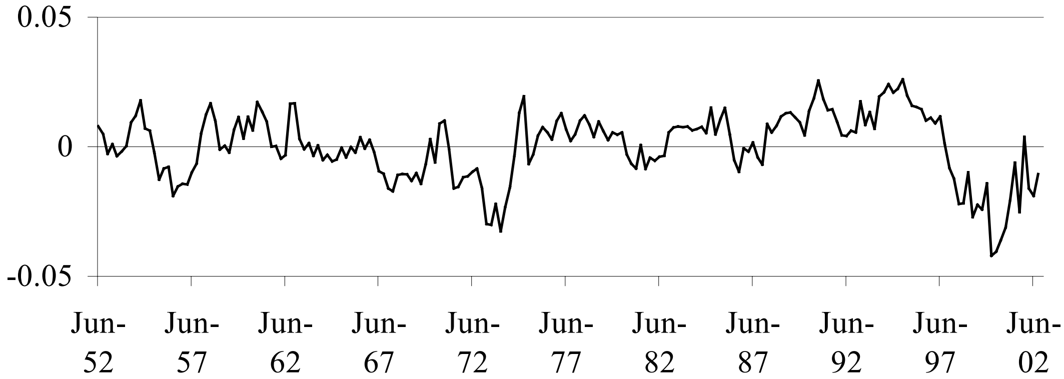


Figure 1. Consumption-Wealth Ratio

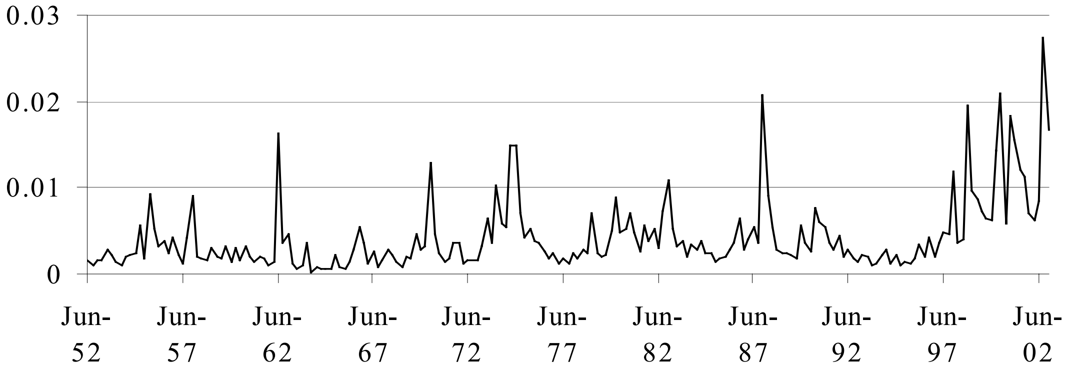


Figure 2. Realized Stock Market Variance

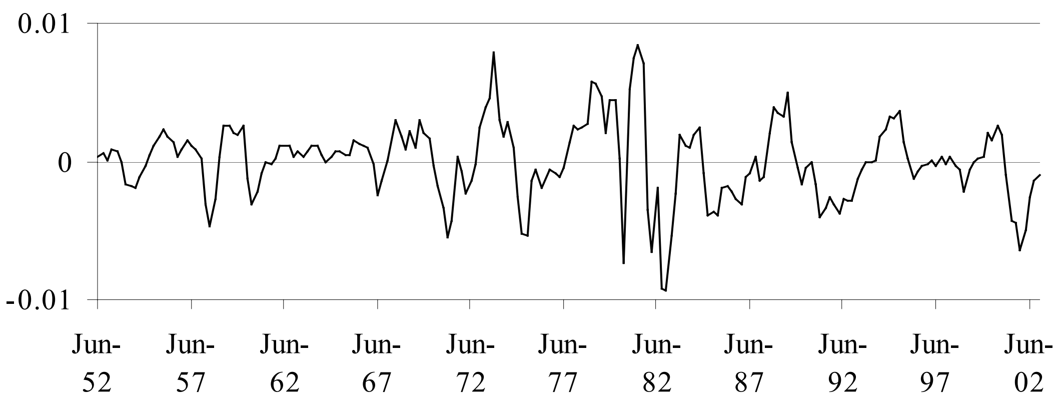


Figure 3. Stochastically Detrended Risk-Free Rate

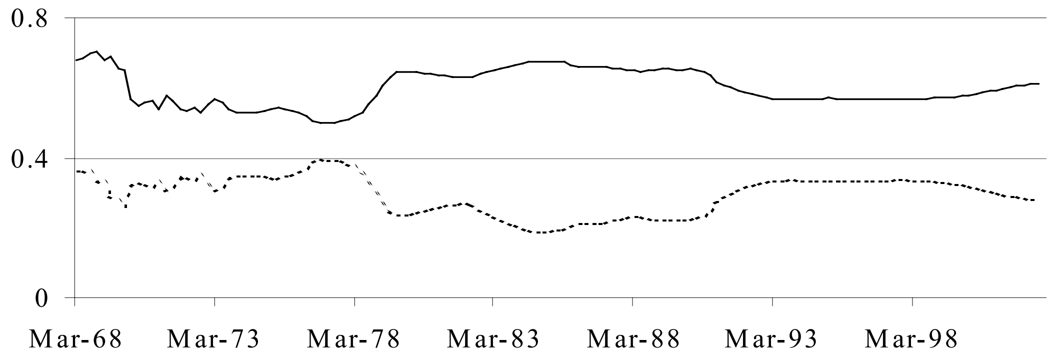


Figure 4. Parameters of Labor Income (Solid Line) and Net Worth (Dashed Line)

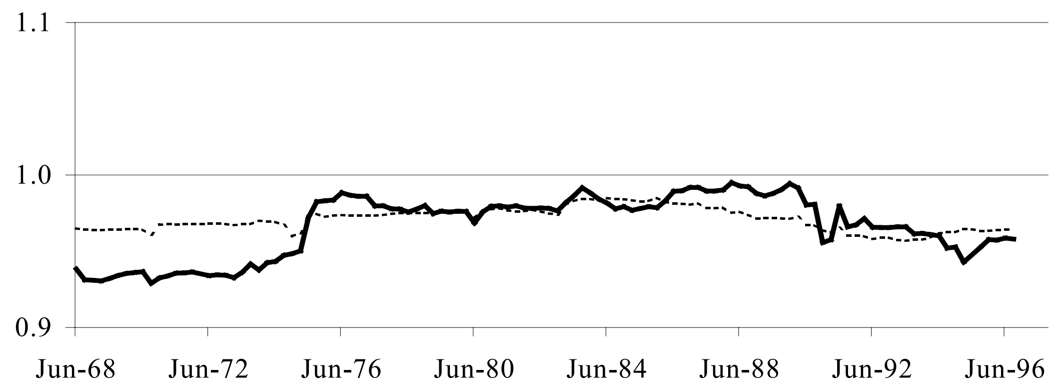


Figure 5. RMSE Ratio of Augmented *cay* to Benchmark Model (Solid Line) and to Model of *cay* (Dashed Line): Fixed Parameters

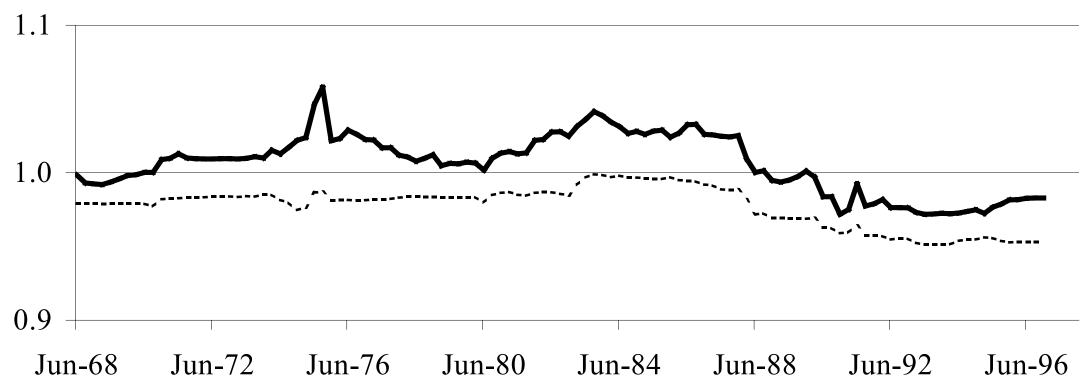
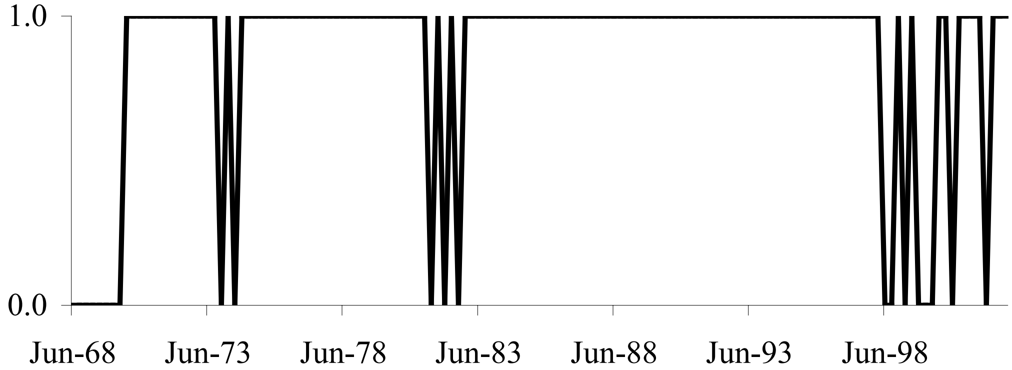
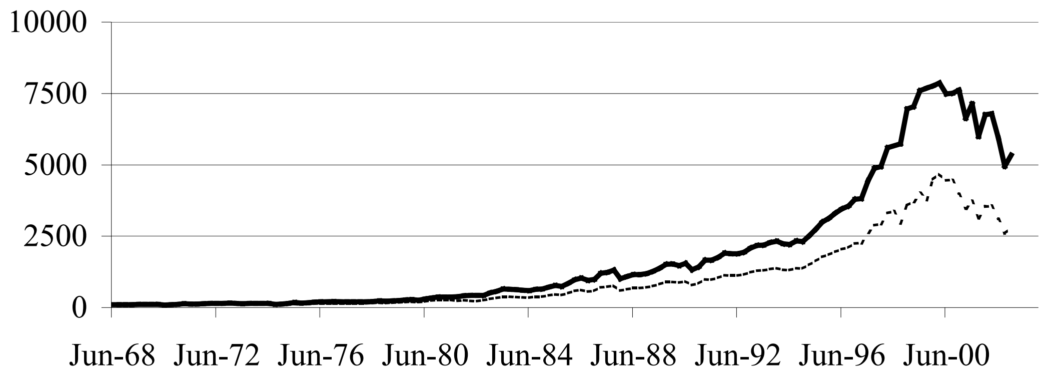


Figure 6. RMSE Ratio of Augmented *cay* to Benchmark Model (Solid Line) and to Model of *cay* (Dashed Line): Recursive Parameters

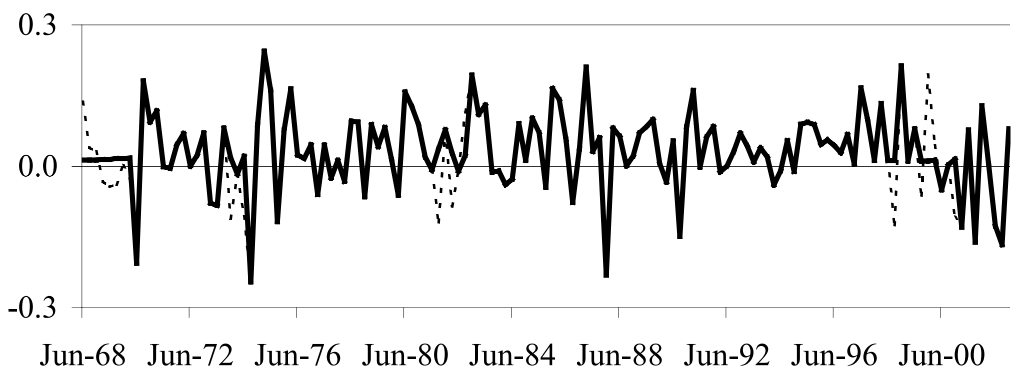
Figure 7. Switching Strategies



Weight of Stocks in Managed Portfolio

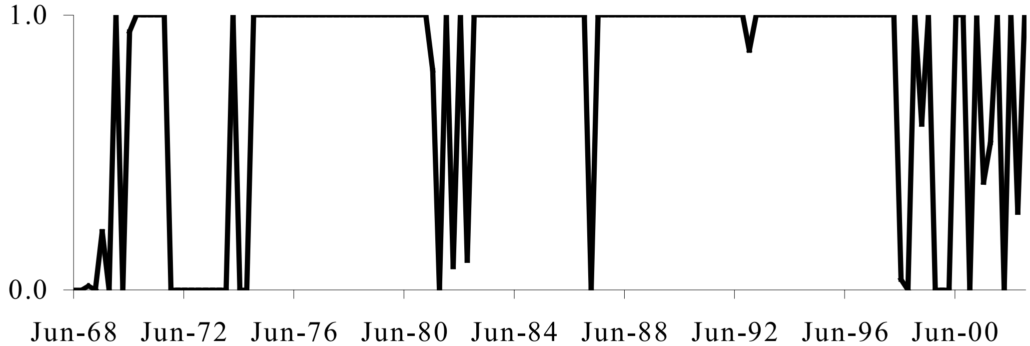


Values of Managed Portfolio (Solid Line) vs. Market Portfolio (Dashed Line)

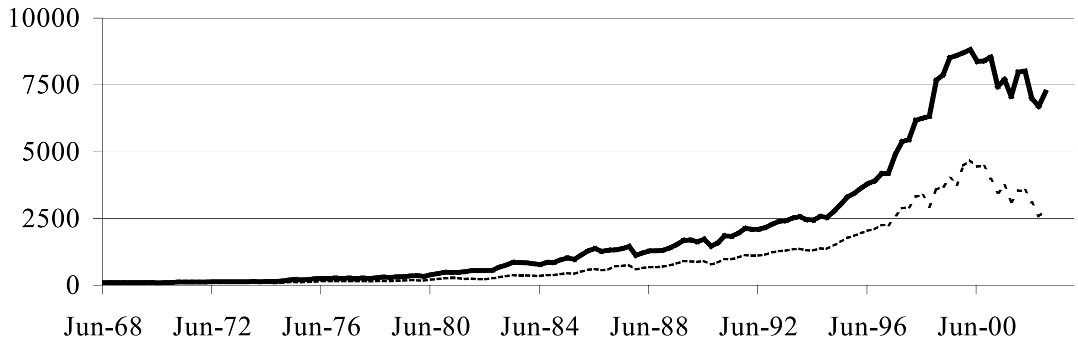


Returns on Managed Portfolio (Solid Line) vs. Market Portfolio (Dashed Line)

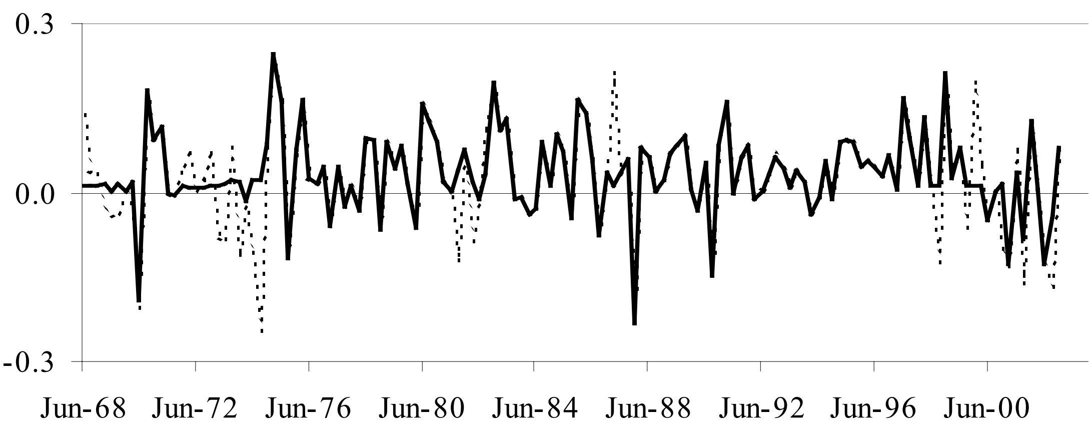
Figure 8. Choosing Optimal Portfolio Weights



Weight of Stocks in Managed Portfolio



Values of Managed Portfolio (Solid Line) vs. Market Portfolio (Dashed Line)



Returns on Managed Portfolio (Solid Line) vs. Market Portfolio (Dashed Line)

Table 1. Summary Statistics

	$r_m - r_r$	$\hat{cay}$	σ_m^2	$rrel$
Panel A: 1952:Q2—2002:Q4				
Correlation Matrix				
$r_m - r_r$	1.000			
$\hat{cay}$	0.334	1.000		
σ_m^2	-0.415	-0.392	1.000	
$rrel$	-0.260	-0.138	-0.087	1.000
Univariate Statistics				
Mean	0.017	0.000	0.004	0.000
Standard Deviation	0.084	0.013	0.004	0.003
Autocorrelation	0.070	0.831	0.488	0.720
Panel B: 1952:Q2—1977:Q4				
Correlation Matrix				
$r_m - r_r$	1.000			
$\hat{cay}$	0.403	1.000		
σ_m^2	-0.466	-0.104	1.000	
$rrel$	-0.397	-0.507	0.075	1.000
Univariate Statistics				
Mean	0.016	0.000	0.003	0.000
Standard Deviation	0.083	0.010	0.003	0.002
Autocorrelation	0.154	0.779	0.391	0.743
Panel C: 1978:Q1—2002:Q4				
Correlation Matrix				
$r_m - r_r$	1.000			
$\hat{cay}$	0.293	1.000		
σ_m^2	-0.424	-0.633	1.000	
$rrel$	-0.185	0.059	-0.127	1.000
Univariate Statistics				
Mean	0.017	0.000	0.005	0.000
Standard Deviation	0.086	0.015	0.005	0.003
Autocorrelation	-0.012	0.854	0.481	0.709

NOTE: $r_m - r_r$ is excess stock market return. The consumption-wealth ratio, *cay*, is the error term from the cointegration relation among consumption, labor income, and net worth. Realized stock market variance, σ_m^2, is constructed using daily data as in Merton (1980). The stochastically detrended risk free rate, *rrel*, is the difference between a nominal risk-free rate and its last four-quarter average.

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Table 2. Forecasting One-Quarter-Ahead Excess Stock Market Returns

	$\hat{cay}_{t-1}$	$\hat{cay}_{t-2}$	σ^2_{t-1}	$rrel_{t-1}$	$\overline{R}^2$
Panel A. 1952:Q3 to 2002:Q4					
1	**1.911**				0.082
	(4.062)				
2			2.559		0.011
			(1.315)		
3	**2.639**		**5.832**		0.147
	(5.278)		**(3.585)**		
4	**2.448**		**5.336**	**-4.365**	0.163
	(5.137)		**(3.372)**	**(-2.571)**	
5		**2.065**	**5.099**	**-4.643**	0.125
		(4.027)	**(3.058)**	**(-2.579)**	
Panel B. 1952:Q3 to 1977:Q4					
6	**3.105**				0.163
	(4.027)				
7			**6.385**		0.045
			(2.491)		
8	**3.329**		**7.687**		0.234
	(4.538)		**(4.245)**		
9	**2.472**		**7.823**	**-8.759**	0.264
	(3.080)		**(4.702)**	**(-2.100)**	
10		**1.619**	**8.172**	**-10.660**	0.212
		(2.019)	**(4.897)**	**(-3.262)**	
Panel C. 1978:Q1 to 2002:Q4					
11	**1.273**				0.036
	(2.352)				
12			1.207		-0.006
			(0.539)		
13	**2.543**		**6.066**		0.096
	(3.892)		**(2.984)**		
14	**2.517**		**5.737**	-3.036	0.100
	(3.812)		**(2.849)**	(-1.496)	
15		**2.324**	**5.456**	-3.309	0.080
		(3.067)	**(2.369)**	(-1.546)	

NOTE: We report the heteroskedasticity- and autocorrelation-adjusted t-statistics in parentheses. Regressors significant at the 5 percent level are in bold.

Table 3. Out-of-Sample Forecast: Fixed Parameters

	Constant	$c\hat{a}y_{t-1}$	$c\hat{a}y_{t-1}+\sigma^2_{t-1}$	$c\hat{a}y_{t-1}+rrel_{t-1}+\sigma^2_{t-1}$
Panel A. 1968:Q2 to 2002:Q4				
RMSE	0.0909	0.0884	0.0853*	0.0858
MAE	0.0701	0.0668	0.0637*	0.0647
CORR	-0.1838	0.2332	0.3135	0.3379*
Sign	0.5971	0.6115	0.6403*	0.6259
Pseudo R^2		0.0542	0.1194*	0.1091
Panel B. 1976:Q1 to 2002:Q4				
RMSE	0.0843	0.0852	0.0829*	0.0832
MAE	0.0653	0.0645	0.0624*	0.0639
CORR	-0.2102	0.1790	0.2510*	0.2336
Sign	0.6296	0.5926	0.6389*	0.6204
Pseudo R^2		-0.0215	0.0329*	0.0259

NOTE: This table reports five statistics for the out-of-sample test: (1) RMSE, the root-mean-squared error; (2) MAE, the mean of the absolute error; (3) CORR, the correlation between the forecast and the actual value; (4) *Sign*, the percentage of times when the forecast and the actual value have the same sign; and (5) Pseudo R^2, which is equal to one minus the ratio of MSE from a forecasting model to that of the benchmark model of constant excess returns. The cointegration parameters used to calculate c*ay* are estimated using the full sample. Macrovariables are assumed to be available with no delay. We highlight the best forecast model by *.

Table 4. Out-of-Sample Forecast: Recursive Parameters

	Constant	$c\hat{a}y_{t-2}$	$c\hat{a}y_{t-2}+\sigma^2_{t-1}$	$c\hat{a}y_{t-2}+rrel_{t-1}+\sigma^2_{t-1}$
		Panel A. 1968:Q2 to 2002:Q4		
RMSE	0.0909	0.0927	0.0907	0.0899*
MAE	0.0701	0.0704	0.0678	0.0674*
CORR	-0.1838	0.1214	0.2586	0.3035*
Sign	0.5971	0.6259*	0.6187	0.6187
Pseudo R^2		-0.0400	0.0004	0.0219*
		Panel B. 1976:Q1 to 2002:Q4		
RMSE	0.0843*	0.0879	0.0862	0.0853
MAE	0.0653*	0.0675	0.0658	0.0657
CORR	-0.2102	0.0839	0.1935	0.1955*
Sign	0.6296*	0.6204	0.6204	0.6111
Pseudo R^2		-0.0872	-0.0456	-0.0239*

NOTE: The cointegration parameters used to calculate c*ay* are estimated recursively using only information available at the time of forecast. Macrovariables are assumed to be available with a one-quarter delay. We highlight the best forecast model by *. Also see note of Table 3.

Table 5: One-Quarter-Ahead Forecasts of Excess Stock Market Returns: Nested Comparisons

	Nested Models	ENC-NEW Statistic	ENC-NEW Asy. CV	MSE-F Statistic	MSE-F Asy. CV
	Panel A. Fixed Cointegration Parameters				
1	C+$\sigma^2_{M,t-1}$ + cay_{t-1} vs. C	24.47	2.96	18.85	1.52
2	C+$\sigma^2_{M,t-1}$ + cay_{t-1} vs. C+cay_{t-1}	14.02	2.13	10.25	1.70
	Panel B. Recursively estimated Parameters				
3	C+$\sigma^2_{M,t-1}$ + cay_{t-2} vs. C	14.81	2.96	0.40	1.52
4	C+$\sigma^2_{M,t-1}$ + cay_{t-2} vs. C+cay_{t-2}	10.22	2.13	5.97	1.70

NOTE: This table reports two out-of-sample tests for nested forecast models: (1) the encompassing test ENC-NEW developed by Clark and McCracken (1999) and (2) the equal forecast accuracy test MSE-F developed by McCracken (1999). ENC-NEW tests the null hypothesis that the benchmark model encompasses all the relevant information for the next quarter's excess stock market return, against the alternative hypothesis that past stock market variance contains additional information. MSE-F tests the null hypothesis that the benchmark model has a mean-squared forecasting error that is less than or equal to the model augmented by past stock market variance, against the alternative hypothesis that the augmented model has smaller mean-squared forecasting error. Observations from the period 1952:Q3 to 1968:Q1 are used to obtain the initial in-sample estimation, and the forecasting error is calculated for the remaining period 1968:Q2 to 2002:Q4, recursively. For example, the forecast for the 1968:Q2 is based on the estimation using the sample 1952:Q3 to 1968:Q1 and so forth. The Asy. CV column reports the asymptotic 95 percent critical values provided by Clark and McCracken (1999). We estimate the cointegration parameters using the full sample in panel A and recursively in panel B. We compare the benchmark model of constant returns with augmented *cay* in rows 1 and 3 and compare the model of *cay* by itself with augmented *cay* in rows 2 and 4.

Table 6. Switching Strategies with No Transaction Costs

	Buy and Hold	$\hat{cay}_{t-2}$	$\hat{cay}_{t-2}+\sigma^2_{t-1}$	$\hat{cay}_{t-2}+rrel_{t-1}+\sigma^2_{t-1}$
		Panel A. 1968:Q2 to 2002:Q4		
Mean	0.1132	0.1373	0.1297	0.1327
SD	0.1801	0.1421	0.1645	0.1560
Mean/SD	0.6287	0.9660	0.7885	0.8508
SR	0.2873	0.6247	0.4471	0.5094
		Panel B. 1968:Q2 to 1979:Q4		
Mean	0.0764	0.1230	0.1025	0.1114
SD	0.1895	0.1538	0.1749	0.1450
Mean/SD	0.4033	0.7995	0.5861	0.7683
SR	0.0840	0.4802	0.2669	0.4490
		Panel C. 1980:Q1 to 1989:Q4		
Mean	0.1700	0.1879	0.1879	0.1850
SD	0.1781	0.1634	0.1634	0.1692
Mean/SD	0.9543	1.1468	1.1468	1.0929
SR	0.4795	0.6718	0.6719	0.6181
		Panel D. 1990:Q1 to 2002:Q4		
Mean	0.1029	0.1114	0.1096	0.1117
SD	0.1737	0.1099	0.1556	0.1556
Mean/SD	0.5924	1.0134	0.7046	0.7181
SR	0.3354	0.7564	0.4477	0.4611

NOTE: The table reports returns on switching strategies, which require holding stocks if the predicted excess return is positive and holding bonds otherwise. We present four statistics for the annualized return on the managed portfolio, including the mean (Mean), the standard deviation (SD), the ratio of the mean to the standard deviation (Mean/SD), and the adjusted Sharpe ratio (SR). As in Graham and Harvey (1997), we scale the return on the managed portfolio, for example, through leverage, so that it has the same standard deviation as the market return. The scaled return is then used to calculate the Sharpe ratio in the usual way. The cointegration parameters used to calculate c*ay* are estimated recursively using only information available at the time of forecast. Macrovariables are assumed to be available with a one-quarter delay.

Table 7. Switching Strategies with Transaction Costs

	Buy and Hold	$c\hat{a}y_{t-2}$	$c\hat{a}y_{t-2}+\sigma^2_{t-1}$	$c\hat{a}y_{t-2}+rrel_{t-1}+\sigma^2_{t-1}$
Panel A. 1968:Q2 to 2002:Q4				
Mean	0.1132	0.1363	0.1282	0.1315
SD	0.1801	0.1422	0.1647	0.1562
Mean/SD	0.6287	0.9585	0.6917	0.7031
SR	0.2873	0.6171	0.4369	0.5005
Panel B. 1968:Q2 to 1979:Q4				
Mean	0.0764	0.1224	0.1015	0.1100
SD	0.1895	0.1540	0.1754	0.1454
Mean/SD	0.4033	0.7944	0.5787	0.7564
SR	0.0840	0.4752	0.2595	0.4372
Panel C. 1980:Q1 to 1989:Q4				
Mean	0.1700	0.1862	0.1862	0.1840
SD	0.1781	0.1636	0.1636	0.1694
Mean/SD	0.9543	1.1380	1.1380	1.0856
SR	0.4795	0.6632	0.6632	0.6108
Panel D. 1990:Q1 to 2002:Q4				
Mean	0.1029	0.1104	0.1077	0.1105
SD	0.1737	0.1101	0.1558	0.1556
Mean/SD	0.5924	1.0031	0.6913	0.7104
SR	0.3354	0.7462	0.4344	0.4534

NOTE: We assume that investors have to pay a proportional transaction cost of 25 basis points when they switch from stocks to bonds or vice versa. The other specifications are the same as in Table 6.

Table 8. Choosing Optimal Portfolio Weights with No Transaction Costs

	Buy and Hold	$c\hat{a}y_{t-2}$	$c\hat{a}y_{t-2}+\sigma^2_{t-1}$	$c\hat{a}y_{t-2}+rrel_{t-1}+\sigma^2_{t-1}$
Panel A. 1968:Q2 to 2002:Q4				
Mean	0.1132	0.1156	0.1355	0.1381
SD	0.1801	0.1235	0.1454	0.1459
Mean/SD	0.6287	0.9367	0.9316	0.9467
SR	0.2873	0.5953	0.5902	0.6053
Panel B. 1968:Q2 to 1979:Q4				
Mean	0.0764	0.0941	0.1211	0.1353
SD	0.1895	0.1243	0.1454	0.1242
Mean/SD	0.4033	0.7570	0.8332	1.0887
SR	0.0840	0.4378	0.5140	0.7695
Panel C. 1980:Q1 to 1989:Q4				
Mean	0.1700	0.1476	0.1690	0.1741
SD	0.1781	0.1446	0.1550	0.1653
Mean/SD	0.9543	1.0207	1.0906	1.0532
SR	0.4795	0.5459	0.6158	0.5784
Panel D. 1990:Q1 to 2002:Q4				
Mean	0.1029	0.1106	0.1227	0.1129
SD	0.1737	0.1049	0.1396	0.1494
Mean/SD	0.5924	1.0535	0.8786	0.7558
SR	0.3354	0.7965	0.6217	0.4988

NOTE: The table reports returns on strategies for choosing optimal portfolio weights. In particular, investors allocate a fraction of total wealth, $\omega_t = \frac{1}{\gamma}\frac{E_t[R_{t+1} - R_f]}{E_t\sigma^2_{m,t+1}}$, in stocks and a fraction, $1-\omega_t$, in bonds, where γ is a measure of the investor's relative risk aversion. $E_t[R_{t+1} - R_f]$ is the predicted value from the excess return forecasting regression and $E_t\sigma^2_{m,t+1}$ is the conditional variance measured by the fitted value from a regression of $\sigma^2_{m,t+1}$ on a constant and its two lags. For simplicity, we ignore the estimation uncertainty and assume that ω_t is in the range [0,1]. The cointegration parameters used to calculate c*ay* are estimated recursively using only information available at the time of forecast. Macrovariables are assumed to be available with a one-quarter delay. Also see note of Table 6.

Table 9. Choosing Optimal Portfolio Weights with Transaction Costs

	Buy and Hold	$\hat{cay}_{t-2}$	$\hat{cay}_{t-2}+\sigma^2_{t-1}$	$\hat{cay}_{t-2}+rrel_{t-1}+\sigma^2_{t-1}$
		Panel A. 1968:Q2 to 2002:Q4		
Mean	0.1132	0.1141	0.1335	0.1363
SD	0.1801	0.1234	0.1456	0.1459
Mean/SD	0.6287	0.9245	0.9171	0.9343
SR	0.2873	0.5831	0.5757	0.5929
		Panel B. 1968:Q2 to 1979:Q4		
Mean	0.0764	0.0921	0.1195	0.1330
SD	0.1895	0.1240	0.1457	0.1239
Mean/SD	0.4033	0.7430	0.8204	1.0729
SR	0.0840	0.4237	0.5012	0.7537
		Panel C. 1980:Q1 to 1989:Q4		
Mean	0.1700	0.1455	0.1670	0.1726
SD	0.1781	0.1447	0.1549	0.1656
Mean/SD	0.9543	1.0056	1.0784	1.0424
SR	0.4795	0.5308	0.6036	0.5676
		Panel D. 1990:Q1 to 2002:Q4		
Mean	0.1029	0.1099	0.1204	0.1115
SD	0.1737	0.1052	0.1399	0.1496
Mean/SD	0.5924	1.0452	0.8609	0.7451
SR	0.3354	0.7882	0.6040	0.4881

NOTE: We assume that investors have to pay a proportional transaction cost, which is equal to 0.25 percent times the absolute value of the change in weight of stocks in the managed portfolio. The other specifications are the same as in Table 8. Also see note in Table 6.

Table 10. Cumby and Modest (1987) Market Timing Ability Test: 1968:Q2 to 2002:Q4

	$\hat{cay}_{t-2}$	$\hat{cay}_{t-2}+\sigma^2_{t-1}$	$\hat{cay}_{t-2}+rrel_{t-1}+\sigma^2_{t-1}$
a	-0.025	-0.027	-0.022
	(-1.352)	(-1.433)	(-1.364)
b	**0.050**	**0.047**	**0.448**
	(2.490)	**(2.271)**	**(2.453)**

NOTE: The table reports the Cumby and Modest (1987) market timing ability test:

(1) $r_{m,t+1} - r_{f,t+1} = a + b * I_t + \varepsilon_{t+1}$,

where $r_{m,t+1} - r_{f,t+1}$ is the realized excess stock market return, I_t is an indicator variable, which is equal to one if $r_{m,t+1} - r_{f,t+1}$ is expected to be positive and is equal to zero otherwise. Regressors significant at the 5 percent level are in bold. The cointegration parameters used to calculate c*ay* are estimated recursively using only information available at the time of forecast. Macrovariables are assumed to be available with a one-quarter delay.

Table 11. Jensen's α Tests: 1968:Q2 to 2002:Q4

	$\hat{cay}_{t-2}$	$\hat{cay}_{t-2}+\sigma^2_{t-1}$	$\hat{cay}_{t-2}+rrel_{t-1}+\sigma^2_{t-1}$
Panel A. Switching Strategies with No Transaction Costs			
CAPM	**0.011**	**0.006**	**0.008**
	(2.791)	**(2.154)**	**(2.245)**
FF	0.008	0.005	0.006
	(1.955)	(1.434)	(1.606)
Panel B. Optimal Weight Strategies with No Transaction Costs			
CAPM	0.007	**0.010**	**0.010**
	(1.895)	**(2.678)**	**(2.768)**
FF	0.004	0.008	**0.008**
	(1.081)	(1.926)	**(2.094)**
Panel C. Switching Strategies with Transaction Costs			
CAPM	**0.011**	**0.006**	**0.008**
	(2.725)	**(2.033)**	**(2.162)**
FF	0.008	0.004	0.006
	(1.894)	(1.328)	(1.530)
Panel D. Optimal Weight Strategies with Transaction Costs			
CAPM	0.007	**0.009**	**0.010**
	(1.792)	**(2.542)**	**(2.648)**
FF	0.004	0.007	**0.008**
	(0.994)	(1.801)	**(1.984)**

NOTE: The table reports Jensen's α test for returns on the managed portfolio. As in equation (2), we run a regression of excess return on the managed portfolio, $r_{mp,t+1} - r_{f,t+1}$, on a constant and risk factors.

(2) $$r_{mp,t+1} - r_{f,t+1} = \alpha + \sum \beta_i f_i + \varepsilon_{t+1}$$

The risk factor includes only the excess stock market return in the CAPM. For the FF model, we include two additional factors: The return on a portfolio that is long in small stocks and short in large stocks and the return on a portfolio that is long in high book-to-market stocks and short in low book-to-market stocks. Regressors significant at the 5 percent level are in bold. The cointegration parameters used to calculate c*ay* are estimated recursively using only information available at the time of forecast. Macrovariables are assumed to be available with a one-quarter delay.

Table 12. Certainty Equivalence Gains from Holding Managed Portfolio: 1968:Q2 to 2002:Q4

$\widehat{cay}_{t-2}$	$\widehat{cay}_{t-2}+\sigma^2_{t-1}$	$\widehat{cay}_{t-2}+rrel_{t-1}+\sigma^2_{t-1}$
Panel A. Switching Strategies with No Transaction Costs		
0.0292	0.0188	0.0229
Panel B. Optimal Weight Strategies with No Transaction Costs		
0.0097	0.0270	0.0296
Panel C. Switching Strategies with Transaction Costs		
0.0282	0.0172	0.0216
Panel D. Optimal Weight Strategies with Transaction Costs		
0.0082	0.0251	0.0278

NOTE: We assume that the utility function has the form

$$U = W_0\left(\sum_{t=0}^{T-1} R_{p,t+1} - \frac{\gamma}{2(1+\gamma)} R^2_{p,t+1}\right), \tag{3}$$

where W_0 is initial wealth and $R_{p,t+1}$ is the return on the agent's portfolio. The certainty equivalence gain, Δ, is defined in equation (4), which is the fee that an investor would pay in exchange for holding the managed portfolio that pays a rate of return $R_{mp,t+1}$; otherwise, he holds the market portfolio that pays $R_{m,t+1}$:

$$\sum_{t=0}^{T-1}(R_{mp,t+1} - \Delta) - \frac{\gamma}{2(1+\gamma)}(R_{mp,t+1} - \Delta)^2 = \sum_{t=0}^{T-1} R_{m,t+1} - \frac{\gamma}{2(1+\gamma)} R^2_{m,t+1}. \tag{4}$$

The cointegration parameters used to calculate c*ay* are estimated recursively using only information available at the time of forecast. Macrovariables are assumed to be available with a one-quarter delay.