Investing in size and book-to-market portfolios: Some New Trading Rules[A]

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Abstract

We propose new trading strategies that invest in size and book-to-market (B/M) decile portfolios. These trading strategies are based on a forecast model that uses mainly business cycle-related variables as predictors. Extensive out-of-sample experiments show profitable predictability in the returns of the decile portfolios. In particular, the proposed strategies outperform passive investments in the same deciles, as well as SMB- and HML-type of strategies. A key characteristic of the proposed strategies is that the long and short positions can be invested in different decile portfolios across time. This is in contrast to the traditional SMB- and HML-type of strategies that always go long and short on the same portfolios. Active strategies that involve the market portfolio, SMB and HML are also examined. A significant level of predictability is identified for SMB. Our results suggest that time variation in SMB and HML is linked to variations in aggregate, macroeconomic, nondiversifiable risk. Thus, our results most closely support a risk-based explanation for SMB and HML.

The sources of SMB and HML profits are the subject of considerable debate.[1] While some have argued that the profits to these two series arise from market inefficiency (see Lakonishok, Shleifer, and Vishny, (1994), Haugen and Baker (1996), and Daniel and Titman (1997)), others have argued that the profits from these and similar strategies arise from data snooping or data biases (see Lo and MacKinlay (1990b), Black (1993), MacKinlay (1995), Breen and Korajczyk (1995), Kothari, Shanken and Sloan (1995), Chan Jegadeesh, and Lakonishok (1995), Foster, Smith, and Whaley (1997), and Knez and Ready (1997)). A third possible explanation is that they are related to risk (see Fama and French (1993, 1995, 1996), Liew and Vassalou (2000), Lettau and Ludvigson (2002), Vassalou (2002), and Li, Vassalou, and Xing (2002)).

In this paper, we propose and implement alternative zero-investment trading strategies that reveal the extent to which the monthly performance of size- and value-sorted portfolios is related to fundamental risk in the economy. Specifically, the investment decisions of these strategies are made based on a forecast model that relies to a large extent on information about the state of the macroeconomy. The question we ask in this paper is whether variables that are related to fundamental risk in the economy can help predict the returns on SMB, HML, and other size-based and B/M-based portfolios. We use the link between information about the macroeconomy and these portfolios to propose new trading strategies.

We examine the performance of the strategies out-of-sample. Our findings clearly show that size portfolios are predictable using information about the macroeconomy, during the out-of-sample period of 1963 to 1998. This predictability translates into highly profitable size-based trading strategies. Our results are less strong for the B/M decile portfolios. We still find some evidence of predictability for B/M, albeit weak. There are trading strategies that can successfully exploit the level of predictability found in B/M portfolios, but their returns are lower than those of the size-based trading strategies. We also find predictability in the returns of SMB, which is also exploited through a dynamic trading strategy.

[1] SMB is a zero-investment portfolio that is long on small capitalization (cap) stocks and short on big cap stocks. Similarly, HML is a zero-investment portfolio that is long on high book-to-market (B/M) stocks and short on low B/M stocks.

It is notable that our forecast model can correctly identify periods of high returns for both small and big cap firms. For instance, the model correctly predicts higher expected returns for big rather than small cap stocks in part of the 1970's, as well as in the late 1980's and through the 1990's. Compared to a passive SMB-type of strategy, which is always long on small cap stocks and short on big caps, our proposed zero-investment strategies perform significantly better. A key characteristic of our strategies is that they are not always long and short on the same decile portfolios. In fact, all deciles have a chance to be held long or short at some periods during the life of the trading strategies. The result is that our strategies are profitable, even when SMB-type of strategies perform poorly.

Our initial analysis focuses on a trading rule that prescribes investing in the top and bottom expected return decile portfolios, using information about the relative magnitude of the expected return forecasts, but ignoring their absolute magnitude. This rule does not preclude the possibility that the highest expected return portfolio for a given month has a negative expected return estimate. To remedy this, we look at other simple trading strategies that take into account the absolute magnitude of expected returns. These strategies use expected return filters, and therefore boost the "signal-to-noise" ratio in the portfolio selection process (see Cooper (1999)).

The enhanced filter trading strategies provide evidence that both high and low return periods are linked to the most risky and least risky periods in the economy, as defined by filters on the expected returns from our forecasts. For example, using filters to screen on periods of high (low) expected returns results in much larger (smaller) realized returns to both B/M and size-based strategies. Thus, the proposed active trading strategies on B/M deciles are now also profitable, compared to passive investments in the same deciles. Moreover, the returns provided by the size trading strategies increase further. In addition, we are able to reliably forecast *negative* return periods for both B/M and size-based portfolios. Thus, conditioning on periods of extreme risk results in the ability of the forecasts to accurately predict extreme returns in the value-growth and small cap-large cap styles, and implies that SMB and HML factors are related to macroeconomic risk.

From the set of predictive variables included in our forecast model, variables related to interest rates and default premium are the most important for forecasting the returns of the decile portfolios. Lagged values of SMB, HML, and a momentum strategy have little ability to predict the returns on size and B/M portfolios. Finally, a January dummy appears to have predictive power for future returns on both the size and B/M decile portfolios.

We find that the ability of the macro variables to predict returns on size and B/M portfolios is strongly influenced by the state of the economy. In particular, the strategies act as hedges for a slowdown of the economy by providing higher returns during contractions than during expansions. For the traditional SMB- and HML-type of strategies, this is the case only for HML, while SMB provides higher returns in expansions and lower returns in recessions.

Overall, our results provide important insights into the sources of time-variation in value-growth and small cap-large cap styles of investing. In particular, our analysis suggests that SMB and HML related premiums are linked to aggregate macroeconomic risk. This view was initially advocated in Fama and French (1993, 1995, and 1996). Liew and Vassalou (2000) present evidence that SMB and HML are related to future Gross Domestic Product (GDP) growth, whereas Vassalou (2000) shows that much of the ability of HML and SMB to price equities is due to news related to future GDP growth contained in these factors. In addition, Li, Vassalou, and Xing (2002) link the information in SMB and HML to the investment component of GDP growth. The findings of this study support a risk-based explanation for the performance of SMB and HML.

The paper is organized as follows. Section I details the data and out-of-sample methodology. Section II reports in-sample regressions of size and B/M decile portfolios, as well regressions of the market factor (MKT), SMB, and HML on lagged predictive variables. Section III contains the out-of-sample performance of simple strategies using size and B/M decile portfolios, as well as the Fama-French (1996) three factors. We also examine in Section III the returns to strategies that use filters on expected returns to form portfolios. Section IV provides robustness tests that focus on the effects of simple variations in the formation of portfolios, the predictive power of subsets of variables in the forecast model, potential data-snooping problems, and the effects of transaction costs. In Section V, we examine the profitability of the strategies in expansionary and contractionary periods of the business cycles. We conclude in Section VI with a summary of our results.

I. Data and Methodology

A. Data

Dependent variables in our tests are the ten size decile portfolios and the ten B/M decile portfolios. In addition, we examine the predictability of HML and SMB as well as the excess return on the market portfolio (EMKT). All the dependent variables in our tests are obtained from the website of Kenneth French.[2] They are formed using all NYSE, AMEX, and NASDAQ stocks, for which the ranking information is available. The size deciles are constructed at the end of each June and use June market equity. Similarly, the B/M decile portfolios are formed at the end of each June. The B/M information used in June of a given year is the B/M at the end of the previous fiscal year.

The set of independent variables includes the following lagged macroeconomic variables; the difference between the three month and one month T-bill returns (HB3), the S&P 500 monthly dividend yield (DIV), the spread between Moody's Baa and Aaa yields (DEF), the spread between the 10-year and three month Treasury yields (TERM), and the nominal 1 month T-bill yield (TBILL). The DIV, DEF, and TERM variables are obtained from the Federal Reserve Bulletin, whereas HB3 and TBILL are from CRSP. The independent variables also include lagged values on EMKT, SMB, HML, and a momentum variable UMD (obtained form Kenneth French's web page). The variable UMD is formed from the intersection of two size portfolios and three portfolios formed on prior year's return. UMD is a zero-investment portfolio which is long on the two high prior return portfolios and short on the two low prior return portfolios. Finally, our set of independent variables includes a January dummy (see Loughran (1997)).

The macro variables HB3, DIV, DEF, TERM, and TBILL are considered business cycle variables in the sense that they can predict variations in future economic growth. Liew and Vassalou (2000) show that HML and SMB can also predict future economic growth and their ability to do so is largely independent of that of the market factor.

[2] We thank Kenneth French for making the data available. Details about the construction of the variables can be obtained from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/

Therefore, SMB and HML can also be considered business cycle variables. Furthermore, MKT is known to be a leading indicator of economic growth (see Fama 1981). Recently, some evidence has emerged that momentum may also be linked to economic risk (see Grundy and Martin (2000) and Chordia and Shivakumar (2000)). In other words, almost all the variables in our forecast model, except the January dummy, have a direct or indirect relation to fundamental economic risk. The question we ask in this paper is whether these variables can help predict the returns on SMB, HML, as well as the size and B/M portfolios. Our results show that they generally can. We use this link between information about the macroeconomy and size and B/M stock characteristics to propose profitable trading strategies.

Our data cover the period from May 1953 through November 1998. We use 1953 as the starting point because of the difficulties associated with obtaining accurate macroeconomic data prior to that date (see Ferson and Harvey (1991), (1999)).

Table 1 presents summary statistics for the variables used in the study. We observe some degree of dispersion across the means and standard deviations of the size and B/M portfolios. Small size portfolios tend to have higher means but also higher standard deviations, whereas the opposite is true for the big size portfolios. The small size portfolios also exhibit first order autocorrelation, which decreases to zero as the size decile increases. In the case of B/M portfolios, we observe again that the means of high B/M portfolios are higher than those of the low B/M portfolios, but there is no analogous pattern for the standard deviations. The autocorrelations are small, including the first-order autocorrelation, except in the case of the highest B/M portfolio (BM10). Panel C provides summary statistics for the remaining variables. As previously discussed, both SMB and HML exhibit substantial variability, with a monthly standard deviation of 2.63% and 2.44%, respectively. They also exhibit positive first-order autocorrelation on the order of 0.163 for SMB and 0.148 for HML.

The significant autocorrelations for the small size and large B/M portfolios have important implications for studies on predictability, such as ours. The large autocorrelations may emanate at least in part from a microstructure-induced positive autocorrelation due to stale prices of the individual stocks in these portfolios (see Lo and MacKinlay (1990a)). This is a consideration from the standpoint that it may result in false conclusions of out-of-sample predictability in forecasts of dependent variables that condition on their own lags. Fortunately, in most cases this does not directly affect our results. When we use the size and B/M decile portfolios as dependent variables, we do not use the assets' own lags as independent variables. However, when we predict SMB and HML, lagged values of these variables appear in the forecast model. In these cases, we also examine alternative forecast specifications in which we omit SMB and HML from the set of independent variables. In addition, our forecasts that use size and B/M decile portfolios as dependent variables may be indirectly affected by a spurious lead-lag effect from using SMB and HML as lagged independent variables. Again, in these cases we also examine alternative specifications that exclude SMB and HML from the independent variable group. In general, the evidence on predictability presented here is not driven by the dependent variables' own lags or the lags of SMB and HML when we forecast the size and B/M-based decile portfolios.

B. Forecasting Methodology

The main body of our tests focuses on the performance of recursive out-of-sample forecasts rather than in-sample predictive regressions.[3] There are two reasons for this choice. First, by focusing on out-of-sample forecasts, we minimize the type I error rate, i.e., the probability of falsely rejecting the null of no predictability - see Sullivan, Timmermann, and White (1999) and Foster, Smith, and Whaley (1997). Second, our results refer to realistic trading strategies that can be easily implemented in practice. This is because all the information used to predict the dependent variable at time *t* is available to the investor at time *t-1*.

The models we examine are linear and of the general form

$$R_{i,t} = \alpha + B_{i,1} X_{1,t} + B_{i,2} X_{2,t} + ... + B_{i,k} X_{k,t} + \varepsilon_{i,t} \quad (1)$$

[3] For examples of other papers that employ out-of-sample forecasting see Allen and Karjalainen (1999), Bossaerts and Hillion (1999), Breen, Glosten, and Jagannathan (1989), Chen, Roll, and Ross (1986), Chung and Zhou (1996), Cooper (1999), Fama and MacBeth (1973), Fama and Schwert (1977), Fama and French (1988), Ferson and Harvey (1991, 1999), Haugen and Baker (1996), Jegadeesh (1990), Kandel and

where $R_{i,t}$ is the return on portfolio *i* at time *t*, α is the intercept, $B_{i,k}$ is the OLS slope coefficient from a regression of the return on the ith portfolio on the returns of the predictive variables, $X_{k,t}$ is the kth predictive variable at time *t*, and $\varepsilon_{i,t}$ is an error term for portfolio *i* at time *t*. Note that equation (1) assumes that $Cov(\varepsilon_{i,t}\varepsilon_{i,t-j}) = 0 \;\; \forall_j$, and $Var(\varepsilon_{i,t}) = \sigma^2$.

The initial in-sample period is from 1953:5 to 1963:4 and it is used to estimate equation (1). Subsequently, the slope coefficients from equation (1) are used to compute the first monthly step-ahead expected return forecast which refers to 1963:5, using the formula:

$$\hat{R}_{i,t} = \hat{\alpha} + \hat{B}_{i,1}X_{1,t} + \hat{B}_{i,2}X_{2,t} + ... + \hat{B}_{i,k}X_{k,t} \qquad (2)$$

We then expand our in-sample period by one month to 1963:5, reestimate regression (1) and use relation (2) to compute the out-of-sample forecast for 1963:6. We repeat the procedure, increasing every time our in-sample window by one month, until we obtain 427 out-of-sample forecasts that cover the period from 1963:5 to 1998:11.

In Section II we present the general forecasting model and report results from in-sample regressions that cover the entire period from 1953:5 to 1998:11. We evaluate the out-of-sample performance of trading strategies based on the proposed model in Section III, as well as reduced forms of it in Section IV.

II. In-Sample Regressions

Table 2 presents the results from in-sample regressions. The first row lists the lagged independent variables. The dependent variables are listed in the first column.

Panel A reports the results from the regressions of the ten size portfolios on the ten independent variables. S1 denotes the smallest size portfolio whereas S10 denotes the portfolio with the biggest market capitalization. Note that the predictability of the portfolio returns decreases monotonically as the size decile increases. The adjusted R-square for S1 is 18%, while that of S10 is only 4%. In other words, there appears to be

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Stambaugh (1996), Keim and Stambaugh (1986), Lettau and Ludvigson (2001), Pesaran and Timmermann much more predictability in the small caps than there is in the big caps. In addition, the macro variables, with the exception of TERM seem to be the most important ones for explaining the future returns in the size portfolios. Lagged values of EMKT and SMB have some ability to explain future returns mainly in the two smallest size portfolios. In contrast, lagged values of HML and UMD appear to contain no information about the future returns of the size portfolios. Finally, the January dummy is of some importance, particularly for portfolios S1 to S5. In fact, its ability to explain future returns diminishes monotonically, as the size decile increases. This can be seen from the slope coefficients of the ten size portfolios.

In Panel B of Table 2 we present the results from regressions of the ten B/M portfolios. The panel is structured in the same way as Panel A. BM1 is the portfolio with the lowest B/M, whereas BM10 is the highest B/M portfolio. Similarly to what we observed in Panel A, the macro variables are more important for predicting future returns in the B/M portfolios than the other variables considered. The variables TBILL, HB3, and DEF have slope coefficients that are generally statistically significant. Lagged values of EMKT, SMB, HML and UMD do not seem to be important for predicting future returns in the B/M portfolios. The only exception is found in the case of BM10 where the lagged value of HML appears to have some ability to predict the return on that portfolio. In addition, the January dummy has predictive power over returns of portfolios BM7 to BM10, i.e., the portfolios with the highest B/M. Finally, the adjusted R-squares range from 4% to 10%, with the R-squares of the high B/M portfolios being higher than those of the low B/M portfolios. The results of Panel B indicate that there is somewhat less predictability in the returns of B/M portfolios than there is in the returns of size-sorted portfolios. This will be confirmed through our out-of-sample experiments.

In Panel C we provide results for the predictability of EMKT, SMB and HML, using the same set of predictors as in Panels A and B. We include EMKT in our tests in order for it to serve as a benchmark for comparing the remaining results in Table 2. The level of predictability of the excess return on the market portfolio has been documented in various previous studies and it is consistent with what we report here.[4]

(1995, 1999), Sullivan, Timmermann, and White (1999), and Swanson and White (1997).

[4] For a recent appraisal of the predictability of the market, see Lettau and Ludvingson (2000).

In predicting the future return on EMKT, the most important variables are the macro variables TBILL, HB3 and DEF. Lagged values of EMKT and the premiums HML, SMB, and UMD have no importance in predicting EMKT, as no importance has the January dummy. The adjusted R-square is 7%. In contrast, the predictability of SMB and HML is higher with adjusted R-squares of 14% and 10% respectively. Furthermore, contrary to what we found for the ten size portfolios, the macro variables have limited ability, if any, to predict SMB. The only macro variable that appears to have predictive power is DIV. In addition, lagged values of EMKT and SMB seem to be able to predict SMB. The January dummy also seems to be very important. The results for HML are similar in nature to those of SMB. The only macro variable with some ability to predict HML is the T-bill rate. The lagged value on HML is also important, as it is the January dummy. Our documented levels of in-sample predictability for SMB, HML, and EMKT are similar to those found in Ferson and Harvey (1999).[5]

The results of Table 2 suggest that macro variables are much more important for predicting the returns of decile portfolios sorted on size and B/M than they are for predicting time variation in the returns of SMB and HML. This finding will be confirmed by our out-of-sample results in Section III.

III. Out-of-Sample Trading Strategies

The previous in-sample regressions examine the existence of predictability in size and B/M portfolios as well as EMKT, SMB, and HML. However, Bossaerts and Hillion (1999) illustrate the pitfalls of relying on in-sample evidence of predictability. They document large degrees of in-sample predictability on international stock returns, but find that the evidence of predictability vanishes out-of-sample. Thus, in the remaining sections of the paper, we examine if an investor, equipped only with information from prior periods to form expectations on future returns is capable of finding predictability. We adopt a recursive forecasting methodology similar in spirit to approaches used

[5] Ferson and Harvey (1999) perform similar in-sample regressions, albeit, over a slightly different time period, for EMKT, SMB, and HML and in general find levels of predictability close to what we find. However, they do not include a January dummy in their regressions. This results in a noticeable difference in HML's R-square between their study and ours. We find an adjusted R-square of 10 percent for HML whereas they report an adjusted R-square of 2 percent.

previously in Fama and Schwert (1977), Breen, Glosten, and Jagannathan (1989), Pesaran and Timmerman (1995), and Bossaerts and Hillion (1999), among others.

Using equations (1) and (2), we compute out-of-sample forecasts of expected returns for the ten size portfolios and the ten B/M portfolios. We then create trading strategies based on these predictions. Our simplest trading strategies take into account only the relative magnitude of the expected returns rather than their absolute magnitude.

The simplest trading strategies use the following rule: Go long on the portfolios that have the highest expected returns next period and short on the portfolios that have the lowest expected returns next period. Initially, we limit ourselves to long and short positions that include only one decile portfolio each. We then generalize the strategies to long and short positions that include three decile portfolios each.

The main difference between the trading strategies we construct here and the traditional HML and SMB strategies, is the following. In our strategies, there is no constraint that the long position should always include small cap or high B/M portfolios. Similarly, there is no constraint that the short position should include only big size and low B/M portfolios. Our strategies choose the portfolios to go long and short according to the expected returns of the decile portfolios produced by our model. Therefore, the long (short) position can include at times small, medium or large size portfolios for the size strategy. By the same token, the long (short) position of the B/M strategy can include at times low, medium or high B/M portfolios. As we will see, our strategies prove to be profitable, even at times when the traditional strategies are not. This is particularly true for the size strategies.

A. Out-of-sample performance of simple strategies using size decile portfolios

Table 3 presents the results of trading strategies built based on return forecasts of the size decile portfolios.

In Panel A we compare the performance of two strategies. The first strategy (labeled as "active") goes long each period on the decile with the highest expected return, and short on the decile with the lowest expected return. The second strategy always goes long on the smallest size decile and short on the largest size decile. We call this SMB-type of strategy the "benchmark strategy" because it is in the spirit of SMB. It is not identical to SMB because the component portfolios of SMB are six portfolios sorted on both size and B/M rather than the ten size portfolios. This benchmark is useful for comparing the performance of the first strategy, which we call the "active strategy", because it highlights the importance of relaxing the constraint that the long position has to be invested in small caps and the short position in big caps.

As can be seen from Panel A, the mean return of the long position in the active strategy is 73 basis points (bps) per month higher than the mean return of the long position in the benchmark strategy. Furthermore, its standard deviation is lower whereas the terminal wealth is about $1589 higher than that of the long position in the benchmark strategy. The terminal wealth is calculated as the total wealth at the end of the out-of-sample period, from investing one dollar at the beginning of the out-of-sample period. The mean returns of long positions in both the active and benchmark strategies are highly statistically significant. Furthermore, the difference in their mean returns is statistically significant at the 10% level.

The short position of the active strategy has a much lower monthly average mean than the short position of the benchmark strategy.[6] In other words, the active short strategy, while not independently profitable as a short position per se, results in a portfolio that creates a large spread from the active long portfolio. In contrast, the short portfolio benchmark, S10 has a much lower relative spread from the long benchmark, S1. The difference in means between the short active portfolio and the short benchmark portfolio is 68 bps per month. This difference is statistically significant, with a t-statistic of –2.16. Thus, the dynamic active short portfolio is better able to predict which size-based portfolio will experience low returns than is a fixed investment in the benchmark of large capitalized stocks.

When we combine the long and short positions in the two strategies, the active strategy clearly dominates the benchmark. The mean return for the combined active position is 156bps per month, compared to only 15bps for the combined benchmark position. Furthermore, the standard deviation of the active long-short strategy is lower than that of the benchmark. The terminal wealth of the active long-short strategy is

[6] The returns of the short (long) portfolio are constructed from a positive investment in the appropriate portfolios. Therefore, profitable short (long) portfolio returns will be negative (positive).

$540.60 whereas that of the benchmark is only $1.23. The mean return on the combined active position is highly statistically significant and the difference in its mean return from the benchmark position is also highly statistically significant. The results of Panel A reveal that relaxing the constraint of always going long on small caps and short on big caps greatly enhances the performance of a trading strategy that exploits the size characteristics of portfolios.

In Panel B, we repeat the same trading strategy, allowing, however, the long and short positions to include now three decile portfolios, instead of just one. The component portfolios in the long and short positions are equally weighted. The results are similar to those of Panel A although the difference in the performance of the two strategies is less dramatic. The combined active position has a mean return which is 88bps per month higher than that of the benchmark combined position. This difference in the mean return is again statistically significant. The standard deviation of the combined active strategy is again lower than that of the combined benchmark strategy. The terminal wealth of the combined active strategy is $56.10 compared to only $1.26 for the combined benchmark strategy. Note that whether we go long and short on one or three portfolios makes little difference in the performance of the benchmark strategies, but it appears to have a bigger effect on the performance of the active strategies. This is at least partly the result of significant differences in the expected returns of the decile portfolios.

B. Out-of-sample performance of simple strategies using B/M decile portfolios

In Table 4, we report the results of the active and benchmark strategies performed using B/M portfolios instead.

When B/M portfolios are used to run the strategies, the active strategies do not outperform the passive ones. In fact, the differences in their mean returns are not statistically significant. This is the case regardless of whether we examine the difference in the mean returns of the long, short or combined positions, or whether the long and short positions include one or three decile portfolios. The standard deviations of the active positions are somewhat lower than those of the benchmark positions. The terminal wealth of the combined active position is $2.92 compared to $0.06 for the benchmark, when only one portfolio is included in the long and short positions. It becomes $2.82

versus \$0.17 for the benchmark when three portfolios are included in the long and short positions.

Overall, the conclusion emerging from Table 4, given our set of independent variables, is that simply relaxing the constraint of always going long on high B/M portfolios and short on low B/M portfolios is not sufficient to improve the performance of a strategy in the lines of the traditional HML strategy. In Section IV, however, we demonstrate that slightly more sophisticated strategies that require the expected returns of the portfolios in the long and short positions to also exceed some given threshold returns, greatly improve our ability to forecast B/M-based portfolios.

C. *Asset Inclusion Frequencies for Size and B/M Deciles in the Simple Active Trading Strategies.*

As mentioned above, in the active size and B/M strategies the long and short positions do not always include the same decile portfolios. It is therefore useful for our understanding of the strategies to examine how frequently each decile is actually held. Table 5 tabulates the percentage of periods that each of the ten portfolios is included in the long or short position, as well as the average turnover of a given decile portfolio in the long or short position.

In Panel A we report the inclusion frequencies for the size strategy when the long and short position contains only one decile. It is interesting that S1 and S10 are almost equally often held in the long position. Recall that in a traditional SMB-type of strategy, the long position would only include S1. In our active strategy, S1 is held only 36.8% of the time, while S10 is held as much as 39.3% of the time. The frequent inclusion of big caps in the long position, helps the strategy perform well, even when small caps perform poorly and the traditional SMB-type of strategy produces negative returns. Furthermore, all other deciles get a chance to appear in the long position. Note that the mid-caps, i.e., the deciles S4 to S7 appear collectively 16.4% of the time. These portfolios would have no role to play either in the long or short positions of an SMB-type of strategy.

The short position in Panel A exhibits a similar pattern. While we would always hold S10 under an SMB-type of strategy, our trading rule results in S10 being held only 29% of the time, while S1 is held about 32% of the time. Similar to the long portfolio, all deciles are included in the short portfolio at some point in time. The mid-caps S4 to S7 are collectively shorted 31 out of 427 months, or 7.26% of the time. The average turnover of the short position, which is calculated as the average change in the portfolio components in consecutive periods, is 61.74% versus 56.57% for the long position. In other words, both the long and short positions involve frequent turnover of the decile portfolios.

The results in Panel B for the size strategy that includes three deciles in the long and short positions are consistent with those in Panel A. Again, S10 appears in the long position 49.2% of the time, which is slightly more often than S1 (46.4% of the time). All deciles are actively held, including the mid-caps. The same picture emerges from examining the inclusion frequencies of the short position. The average turnover for both positions is somewhat lower than that in Panel A, exactly because three deciles rather than a single decile are included in each of the two positions. The average turnover is 51.25% for the long position, versus 47.10% for the short.

Panels C and D report the inclusion frequencies of the decile portfolios in the B/M strategies. The comments made for Panels A and B apply here as well but with one difference. In the long positions, the high B/M deciles appear more often than the low B/M deciles. Similarly, in the short positions, the low B/M deciles appear more often the high B/M deciles. For instance, in the long position of Panel C, the three highest B/M deciles, BM8 to BM10, are collectively held 48% of the time, while the three lowest B/M deciles BM1 to BM3 are held 29.5% of the time. In the short position, the three lowest B/M deciles are held 44.73%, whereas the highest B/M deciles are held only 31% of the time. This means that even after relaxing the constraint about which deciles should comprise the long and short positions, the active B/M trading rule continues to favor the deciles held in the long and short positions of a traditional HML-type of strategy. This may explain why the difference in the mean returns of the active and benchmark strategies of Table 4 is not statistically significant and the performance of the two strategies is almost the same. Our forecast model makes predictions which are in general consistent with the trading rule of the traditional HML strategy.

To make the mechanics of the active strategies even more transparent, we plot in Figure 1A the deciles in which the active long and short size strategy of Table 3 Panel A invests in. The long (short) portfolio's deciles are plotted in Figure 1A as the "Highest E(r)" ("Lowest E(r)") series. In Figure 1B, we plot the 12-month moving average of the returns on the benchmark SMB-type of strategy ("SMB") and the combined long-short active size strategy ("Combinedsize"). As can be seen from the graphs, the combined active strategy performs well even when SMB does not. This is more noticeable during the two recession periods of the 1970s and the one in the early 1990s. Figure 1A shows that when the passive and active strategies have similar performance, it is because our forecast model predicts that small cap portfolios will outperform big caps. In contrast, in periods when the active strategy outperforms the passive one, it is generally the case that our forecast model predicts that small caps will do poorly compared to bigger caps. In particular, our forecast model was able to predict the poor performance of the small caps in part of the 1970s as well as in the late 1980s and during the 1990s. In all these periods, the active size strategy outperforms the passive SMB-type of strategy.

Figures 2A and 2B provide analogous graphs for the B/M active strategy of Table 4, Panel A. However, it is clear from the graphs that the active B/M strategy does not always dominate the benchmark. Whereas in certain periods the model is able to forecast the poor performance of high B/M stocks and recommend that one should invest in lower B/M stocks instead, there are also periods during which the benchmark strategy outperforms the active one. The reason once again can be found in Figure 2A. More often than not, the recommendations of the model are consistent with the holdings of the HML-type of strategy. Therefore, our model cannot help us outperform the benchmark in a significant manner.

D. Out-of-Sample-Trading Strategies Using the Fama-French (1993) Three Factors

In this section, we examine the out-of-sample predictability of the Fama and French (1993) three factors, EMKT, SMB, and HML. The results are reported in Table 6. The strategies we examine here are slightly different from those in the previous sections. We use a trading rule according to which we go long on EMKT, SMB or HML if the expected return of these portfolios is greater than zero, and short on them otherwise. If we short SMB, for instance, then we effectively short small stocks and use the proceeds to invest in big stocks.

Panel A reports the results for EMKT. The performance of the actively managed investment in EMKT is given in the first row. The second row reports the performance of a buy-and-hold strategy in EMKT.

Note that the standard deviation of the active strategy is very similar to that of the buy-and-hold strategy, but its mean is much lower. Furthermore, despite the underperformance of the active strategy, the Henriksson and Merton (HM) p_1+p_2 suggests a small degree of market timing. This may be because the level of losses we incur in bad-timing periods are larger than the level of profits we have in good-timing periods. The HM measure ignores the forecast's level, and accounts only for directional accuracy. The associated p-value is 0.06.[7] We also report a forecast beta (see Bossaerts and Hillion (1999)), which is the estimate of the slope coefficient from a regression of monthly realized return on the return forecasts.[8] The forecast beta for EMKT indicates that expected returns can forecast the realized returns in a statistically significant manner. However, the magnitude of the beta is very small (0.07). Therefore, both the HM measure and the forecast beta indicate a small degree of predictability, which is not economically significant.

In Panel B we report the results for active and passive investments in SMB. Not only does the active strategy deliver a return which is more than five times larger than that of the buy-and-hold strategy, but its standard deviation is slightly lower as well. The superiority of the active strategy can also be seen from the terminal wealth it generates ($26.15) relative to the benchmark ($1.56). The HM measure suggests market timing ability which is statistically significant at the 1% level. The forecast beta is highly significant, and economically important (0.14). As expected, the difference in the mean returns of the active and benchmark strategies is also statistically significant. These

[7] Henriksson and Merton's (1981) market timing measure of forecast performance focuses on measuring the ability of the forecast model to predict correctly the direction of change of the predicted variable, rather than its absolute magnitude. It is a test of statistical significance of the correlation between the forecasts and the realized values of the forecasted variable. The investor trades only when the forecasted value is greater than zero. p_1 denotes the probability that the model correctly predicts a positive change in the forecasted variable. Similarly, p_2 is the probability that the model correctly predicts a negative change in the forecasted variable. According to the HM measure, market timing exists when $p_1+p_2>1$.

[8] We only report the Henriksson and Merton's (1981) market timing measure and the forecast beta for Table 6. This is because these two measures are directly interpretable for single asset forecasts, which is what we do in Table 6, whereas the measures do not have a straightforward interpretation for the multiple asset decile-based strategies reported in the other tables.

results further confirm the ability of our forecast model to correctly predict the periods during which small caps outperform big caps and vice versa.[9]

Finally, Panel C reports the results for the active and passive strategies invested in HML. The performance of the active strategy is worse than that of the benchmark. The mean return of the active strategy is slightly lower, whereas its standard deviation is practically identical to that of the benchmark. As expected, the terminal wealth generated by the active strategy is lower ($4.01) than that of the benchmark ($5.46). The HM measure indicates absence of market timing ability. Similarly to EMKT, the forecast beta indicates some forecast ability, but the point estimate of the beta is again very small (0.09).

The conclusion that emerges from Table 6 is that, given the forecast model we use, the return on SMB is highly predictable while those of EMKT and HML are not. The results for SMB and HML are consistent with those of the size and B/M decile portfolios.

E. Out-of-sample performance of active strategies that condition on the level of the expected return forecast by using filter rules.

In this section, we aim to enhance the active strategies presented above by imposing thresholds for the expected returns. The goal is to boost the signal-to-noise ratio of the portfolio screening process (see Cooper (1999)).[10] Since the strategies in Tables 3 and 4 do not take into account the magnitude of the expected returns forecasted by the model, there is always the risk that the long (short) position includes decile portfolios with negative (positive) expected returns. To eliminate this possibility, we impose filter rules on our expected return forecasts. Another advantage of the filter rules is that it allows us

[9] To control for possible spurious predictability due to stale prices in the component portfolios used to construct SMB and HML, we rerun Table 6, Panel B dropping SMB and HML as independent variables, but retaining all the other lagged variables. The mean return to the SMB active portfolio is now 0.71 percent per month with a t-statistic, which compares the mean of the benchmark to the active portfolio, of 3.97. Thus, this new profit is only 9 basis points lower per month than the results in Panel B which include SMB and HML as lagged variables, suggesting that microstructure effects are unlikely to be driving the profits of the SMB active portfolio.

[10] Pesaran and Timmermann (1995) also employ an expected return filter in forming portfolios on the S&P500. They define trade periods in the S&P500 by screening out periods of expected return less than the risk free rate. Other filter papers include Fama and Blume (1966), Sweeney (1986), Sweeney (1988), Brown and Harlow (1988), Lakonishok and Vermaelen (1990), and Brown and Sauer (1993), among others.

to further examine the link among macro economic risk and size and B/M predictability. Our assumption is that high (low) periods of risk, as defined by applying the filters to the forecasts' expected returns, should yield higher (lower) realized returns during these periods, if the forecasts have predictive ability.

The results on the enhanced strategies for size decile portfolios are presented in Table 7. The mechanics of these strategies are simple. For instance, we ask the question of what would be the performance of the long position, if the expected returns of the participating decile portfolios were constrained to be always *greater* than 0%. We do the same for all levels of threshold expected returns in increments of 0.5%, up to greater than 5%. Note that the imposed filter rule may result in *no* decile portfolio passing the constraint at a given month, or it may result in all deciles passing the constraint, although the latter case is unlikely at the higher filter levels. In these trading strategies, we do not limit the number of deciles in the long and short positions. In case no decile passes the filter rule, the portfolio is invested in the 30-day T-bill.

The investment strategy for the short position is in the same vein. We now require that the decile portfolios of the short position have expected returns *lower* than a given threshold return. These imposed thresholds are either zero or negative. The reason we impose the zero-or-negativity constraint is because we desire to eliminate short positions with positive expected returns, since that would potentially result in losses to the short portfolio. If no decile portfolio passes the threshold return constraint, the position is invested in the 30-day T-bill.

We report two means in Table 7. First, we report the mean return to the above switching strategy of investing in the deciles or the T-bills, (the row labeled as "Mean Return"). Second, we report the return for only the active trading periods, that is, the periods when deciles exceed the filter (the row labeled "Active Mean"). Thus, "Active Mean" only includes the trade months, and does not include the T-bill return.

Note that the long and short positions of these strategies should be viewed independently since they cannot always be directly combined into a zero-investment strategy. The reason is that for a given filter level, there may be many months in the sample when both an active long and short portfolio do not exist. The long and short strategies presented here are interesting because they can be implemented in practice more easily than the zero-investment strategies of Sections A and B.

Table 7 shows that imposing a filter rule on the expected returns of the decile portfolios improves the performance of the trading strategy. We compare the performance of the long positions with that of a benchmark portfolio which is always invested in all size deciles every month. The deciles in both the active long position and the benchmark portfolio are equally weighted. As can been seen in Table 7, the long filter-switching strategy outperforms the benchmark, as judged by mean return, up to the threshold return of greater than 2%. This means, that in the absence of the expected return constraint, the long positions in Table 3 may at times include deciles with even negative expected returns, as it becomes obvious from the results for the 0% filter rule. The standard deviations of the long positions are always smaller than that of the benchmark. The main reason for this reduction in risk is the fact that the portfolio is often invested in the 30-day T-bill rate. For example, in the case of the 0% threshold return, the long position is invested in size deciles only 322 months out of the 427. Nevertheless, it provides a higher expected return, and higher Sharpe ratio than the benchmark portfolio. In fact, the Sharpe ratio of the long position is always greater than that of the benchmark portfolio, regardless of the level of return filter. Therefore, if we are prepared to lever the long position up to the point of equating its standard deviation with that of the benchmark, the long strategy beats the benchmark at all levels of threshold return.

The results for the short position show that the mean return is now always negative. This means that our model is able to successfully forecast periods of negative returns. Notice also that the standard deviations of the short positions at different levels of threshold returns is quite low, especially when the level of terminal wealth is relatively high.

Table 8 presents results from the same type of trading strategies using the B/M decile portfolios. The results are similar to those of Table 7. The breakeven point for the active long position in terms of mean return is the 1.5% filter. After that, the benchmark return is higher than that of the active strategy because of the large number of months during which the portfolio is invested in T-bills. Exactly for the same reason, the standard deviation of the long active strategy is always lower than that of the benchmark. Again, this implies that if we lever the long position up to the point of equating its standard deviation with that of the benchmark, the active long position outperforms the benchmark at all levels of threshold return. This can also be seen from the reported Sharpe ratios.

The results for the short position show that the mean return is almost always negative, except in the cases of the 0% and –0.5% filters. The terminal wealth in those cases, however, is close to zero. In the remaining cases, we can successfully forecast negative returns. Notice that the standard deviations are also small, especially for the cases of threshold returns lower than –1%. In those cases, the terminal wealth is also higher, ranging from $1.44 at the –1% case to $9.16 for the –5% case.

Recall that the results of Table 4 reveal that a simple active strategy on B/M decile portfolios cannot outperform a passive HML-type of investment in those portfolios. The evidence in Table 8, however, shows that slight enhancements of the trading strategy, via the use of filter rules, can turn it into a strategy with better risk-return characteristics than the benchmark. Thus, the filters appear to boost the signal-to-noise ratio in the portfolio screening process. This point is made emphatically when we examine the "active mean" rows of Tables 7 and 8. Those rows report the mean return only during the months when a given filter is triggered. The average monthly returns for both size and B/M portfolios increase monotonically as we sweep over the filter levels. For example, in Table 7, the size portfolio has an average monthly return of 1.53 percent for 322 months at the greater than zero filter, 2.25 percent for 206 months at the greater than one percent filter, 3.02 percent for 124 months at the greater than two percent filter, up to 5.15 percent *monthly* average return (with a monthly standard deviation for the active months of 5.53 percent – not reported in the tables) for 46 months at the greater than five percent filter. Likewise, when we sweep over the negative return filters, we see evidence that the expected return filters can reliably forecast negative return periods for the size portfolios. We see similar results for the B/M portfolios in Table 8. Thus, the macro-based filter strategies are able to successfully predict periods of dramatically high and low returns for both size and B/M portfolios. If the investment periods triggered by the high and low filters define, defacto, high and low economic risk, then these results reinforce the idea that size and B/M based factors are related to fundamental economic risk.

How might a portfolio manager actually use the filter rules? One method would be to combine filter rules across size and B/M portfolios. For example, the greater than one percent filters in Tables 7 and 8 result in 206 and 209 trading months for the size and B/M portfolios, respectively, out of 427 total months. Combining together these portfolio months results in 236 months when either one or both of the portfolios trade. Similarly, one could combine the short forecasts across size and B/M. For example, the less than negative one percent filters in Tables 7 and 8 result in 135 and 115 trading months for the size and B/M portfolios, respectively, out of 427 total months. Combining the portfolio months results in 159 months when either one or both of the short portfolios trade. Therefore, a portfolio manager could join together the size-and B/M-based long and short strategies to find a new dual strategy that trades relatively more often than either strategy in isolation. For example, when we merge together the long and short portfolios across both size and B/M strategies at the one percent filter level, the 236 long trading months and the 159 short trading months result in 364 total active months. This grouping of active long and short active trades could then be used in a T-bill switching strategy in which the investor is either invested in active long and/or short positions in the size and B/M deciles or in the T-bill rate.

IV. Robustness Tests

A. *Variations in portfolio weights: Lehmann (1990) weights*

In this section, we examine the returns to a strategy that uses Lehmann (1990) weights on the forecasts' expected returns to form portfolio weights.[11] This approach weights the deciles in the long and short positions according to their expected returns. This weighting scheme takes advantage of information contained in the level of the forecast and provides a robustness test to our earlier practice of equally weighting deciles.

The Lehmann weights are constructed as follows. Consider the long portfolio. The weight placed in decile portfolio p in month t is equal to:

$$w_{pt} = \frac{\hat{R}_{pt}}{\sum_{p=1}^{Np} \hat{R}_{pt}} \qquad (3)$$

where N_p is the number of deciles with greater than zero expected returns, and $\hat{R}_{pt}$ is the expected return on decile p. The sum of weights in each month is equal to one. The short portfolio is constructed similarly.

The results are reported in Table 9 for the size decile portfolios and in Table 10 for the B/M portfolios under the "ALL" column. To conserve space, Tables 9 and 10 report only the results for the case of a 0% filter for long and short positions.

The use of Lehmann weights improves the performance of the long size and B/M trading strategies. This can be seen by comparing the results of the column "All" in Table 9 with the results of the 0% column in Table 7. The Sharpe ratio is higher, as is the terminal wealth. We observe similar results for the short portfolio. In Table 7 the 0% short portfolio has a return of –0.05. In Table 9, the short portfolio return is better, at –0.11%. This implies that our forecast model predicts relatively accurately the magnitude of the expected returns, in addition to their direction. The results of the active B/M strategies in Table 10 in the "ALL" column are similar in nature to those of Table 9. The Lehmann weights improve the performance of the strategy as compared with the results of the 0% column in Table 8.

B. *Which subsets of independent variables are the most important for predicting returns?*

In this section we use Lehmann weight-based portfolios to examine the ability of various subgroups of our predictive variables to forecast the size and B/M decile portfolios. We do this in order to gain insight into which variables, if any, are more important in predicting the size and B/M portfolios. Tables 9 and 10 report these reduced-form forecast models for size and B/M portfolios, respectively. Both tables are structured in the same fashion.

The column labeled "All" reports the performance of the strategy when all predictive variables are used in the forecasting model. The column "All-Jan" gives the results for the case where the January dummy is excluded from the set of predictive

[11] See for example Daniel and Titman (1997) who use Lehmann weights to form portfolios based on sorts of individual security B/M, size, and lagged returns.

variables. Loughran (1997) provides evidence which suggests that the January effect may be important for the B/M portfolios. The third column labeled "FF+UMD+Jan" corresponds to trading strategies that use a forecast model which includes the three Fama-French factors, the momentum factor UMD, and the January dummy. The fourth column results, labeled "FF+UMD", refer to a strategy that uses a forecast model which includes only the three Fama-French factors and UMD. We next examine the performance of strategies based on forecast models that include macro variables. Macro variables are the predictive variables HB3, DIV, DEF, TERM, and TBILL. In the column "Macro+Jan", the set of predictive variables includes also the January dummy, whereas in the column "Macro" the predictive variables are only the macro variables.

When we examine the results in Tables 9 and 10, we see that although the performance of the strategies is affected to some extent by which subset of the predictive variables is used, this effect is generally not dramatic. Any of the subsets of predictive variables we consider would result in a profitable trading strategy in the following sense: the Sharpe ratio of the strategy will be greater than the Sharpe ratio of the benchmark portfolio.

Out of the subsets of predictive variables examined, the macro variables together with the January dummy seem to be the most important for forecasting expected returns of both the long size and B/M portfolios. In both Tables 9 and 10, the "Macro+Jan" variable group results in the highest Sharpe ratio portfolios across all variable subgroups. Also, for both size and B/M portfolios, the Jan dummy appears to be important, as the "Macro" variable subgroup drops in performance relative to the "Macro+Jan" group. This drop is more severe for the B/M results in Table 10, confirming Loughran's (1997) results that the January effect is important in determining the profits for B/M portfolios. When we examine the lagged variable group of SMB, HML, UMD, and a January dummy (FF+UMD+Jan), we see in both Tables 9 and 10 that this subset of variables is slightly less important than the Macro+Jan group, as judged by portfolio means and Sharpe ratios.[12]

[12] Tables 9 and 10 also serve as a test to control for possible spurious predictability emanating from a stale-price induced lead-lag relationship between the size deciles and SMB and the B/M deciles and HML, respectively. The fact that we still find predictability using subsets of variables that do not include HML

C. *Reducing potential data snooping problems: endogenizing independent variable selection*

All of the out-of-sample forecasts from the various variable subgroups in Tables 9 and 10, and indeed throughout the previous sections of the paper, are based solely on ex ante information. However, the knowledge of the "best" out-of-sample forecasts is obtained ex post. Therefore, in this section we provide evidence on how an investor, operating without the benefit of hindsight as to which variables are the most important, would have performed across the sample period. We follow Pesaran and Timmermann (1995) and Bossaerts and Hillion (1999) who note that allowing for alternative, competing variables is the crucial element of proper ex ante out-of-sample testing. Realistically, for every investment period, an investor must choose which predictive variables to employ in forming expected return forecasts. Investors do not know which variables will or will not be useful in capturing future profits. To that end, the column labeled "R^2Model" in Tables 9 and 10 uses the R^2 objective function in the in-sample period to choose the predictive variable set for equation (1). The best model is then used to generate expected return forecasts using equation (2). In this manner, the R^2 model minimizes look-ahead bias in the predictive variable set, and provides evidence of how a real-time investor, who is unsure about the correct variable set, might perform.

For both size and B/M forecasts, the R^2 model results in almost as good a performance as the best variable subgroup. For example, for the long size forecasts of Table 9, the R^2 model yields a Sharpe ratio of 0.20, slightly under the "Macro+Jan" specification and equal to the Sharpe ratio of the "All" specification. Similarly, in Table 10, the R^2 model yields for the long B/M forecasts a Sharpe ratio of 0.21. This is the same Sharpe ratio as the one for the "Macro+Jan" specification, and only slightly higher than that generated by the "All" specification (0.20). For the short portfolios, the R^2 model does not perform quite as well as the best ex post variable group, but is still close in performance to the "ALL" models.

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and SMB suggests that microstructure effects are not likely to be driving the profits to the "ALL" portfolios in Tables 9 and 10.

The R^2 model also provides insight into which independent variables are the most important. For the size forecasts in Table 9, the R^2 model selects TBILL (92% of the best models), DEF (83%) and the Jan dummy (80%) as the three most often chosen variables, and selects SMB (27%), HML (19%), and TERM (13%) as the three least often chosen variables. For the B/M forecasts in Table 10, the R^2 model selects TBILL (93%), DEF (78%) and UMD (74%) as the three most often chosen variables, and selects MKT (24%), SMB (13%), and TERM (9%) as the three least often chosen variables. This suggests again that the macro variables, especially TBILL and DEF are important in the success of the out-of-sample forecasts.

D. *Transaction costs.*

So far, we examined the performance of trading strategies in the absence of transaction costs. Transaction costs in these strategies arise in two ways. First, one needs to update the membership of stocks in the size and B/M portfolios every year in order to maintain the firm characteristics of the portfolios. Second, one needs to rebalance the long and short positions of the active trading strategies according to the predictions of the forecast model.

The strategies we examined here were not designed to minimize transaction costs. Our aim in this paper is rather to present evidence of predictability in size and B/M portfolios as well as on EMKT, SMB, and HML, using a set of mainly business cycle variables as predictors. Nevertheless, it is useful to acquire an understanding of the size of transaction costs required to eliminate the superior performance of these strategies relative to their benchmarks.

Given that transaction costs may vary considerably across investors, it is difficult to reach a consensus on the size of realistic transaction costs for these strategies. We therefore simply calculate the breakeven transaction costs for the strategies in Tables 9 and 10.

Breakeven transaction costs are defined as the fixed transaction costs that equate the mean return of the active trading strategy with that of the benchmark. For simplicity, we assume that the same transaction costs apply to all decile portfolios. Obviously, this assumption is likely to be violated in practice. In our calculations, the transaction costs are not endogenized. In other words, the investor's decision is not affected by the existence of transaction costs. In our calculations, an investor incurs transaction costs only if the weight of the decile in the long or short position changes. We examine only the case where all predictive variables ("ALL") are used in the forecast model. We ignore any transaction costs arising from updating membership of stocks in the decile portfolios. Furthermore, we calculate the breakeven transaction costs only for the long positions.

Based on the above assumptions, we find that the one-way transaction cost that will equate the mean return of the long active size position with the mean return of the long buy-and-hold (benchmark) position in Table 9 is 42bps. Similarly, the breakeven one-way transaction cost for the strategy under the column "ALL" in Table 10 is 23bps.

Notice that the standard deviations of the active strategies are lower than those of the benchmarks. Therefore, it may be more fair to calculate the transaction costs that equate the mean of the active long position with that of the benchmark *after* taking into account the differences in the standard deviations. To equate the standard deviations, we ex post lever the active size strategy by a factor of 1.1226, and the active B/M strategy by a factor of 1.0721. When we do that, the breakeven one-way transaction costs for the active size position increase to 62bps, whereas those of the active B/M position become 35bps.

The above numbers suggest that the strategies should remain profitable in the presence of reasonable transaction costs. Depending on the size of transaction costs that a particular investor faces, one can modify the active strategies so as to minimize the effect of these costs. For example, one could restrict investments to the months in which the higher expected return filters are triggered – since those months are much more profitable and thus the profits during these months would presumably survive greater transaction costs.

V. Business Cycles and the Out-of-Sample Performance of the Trading Strategies

In the previous section we discussed the effect that the use of subsets of predictive variables has on the performance of the trading strategies. It is important to recall at this point, that all of the predictive variables, except the January dummy, can be considered variables related explicitly or implicitly to the business cycles. Since these variables can predict expected returns of size and, to some extent, B/M portfolios, it is useful to examine whether and how the performance of the proposed trading strategies differs during expansionary and contractionary periods of the business cycle.

The results are reported in Table 11. We use the NBER dates to define periods of expansion and contraction. Panel A contrasts the performance of the active size strategies of Table 3 with those of the benchmark, during different parts of the business cycles. The active combined position provides a much higher return during contractions than it does during expansions relative to the benchmark. In other words, it performs best when its performance is most needed: during the down periods of the economy. This is not the case for the benchmark, which performs best during expansions. Note, however, that the return of the active strategy is always better than that of the benchmark. Therefore, not only is the active strategy superior to the benchmark in terms of performance, it can also act as a hedge during periods of economic slowdown. The results in Panel A also suggest that the returns to the Long size portfolio are not simply due to a high-market-beta effect. That is, since the Long portfolio outperforms the small-size benchmark (S1) in both expansion and contraction periods, it is not simply the case that the Long portfolio earns high returns from primarily investing in a high beta asset (i.e., S1) during expansion periods.

We mention two items of note about the reward-per unit of risk of the active size-based portfolios in Panel A of Table 11. First, the Sharpe ratios of the active size-based portfolios are greater than the benchmark portfolios across both expansion and contraction states. Second, the active Long portfolio has a greater Sharpe ratio (not reported in the table) in expansion periods, at 0.30, than in contraction periods, at 0.08, suggesting that the better performance of the Long portfolio is in fact consistent with a hedging-demand risk story (i.e., the Long portfolio experiences greater (lower) payoffs in good (bad) states of the world).[13]

Panel B provides the results for the active B/M trading strategy of Table 4. Once again, the active strategy performs best during contractionary periods, but so does the

[13] Perez-Quiros and Timmerman, 2000, also explore issues of size based portfolio predictability over economic cycles. They find, contrary to our results, greater Sharpe ratios in recessions and lower Sharpe ratios in expansion periods. However, their macroeconomic forecasting model uses a different set of forecast variables, and their definition of expansion and contraction periods is different than ours.

benchmark. In fact, the benchmark provides higher returns than the active strategy, both during expansions and contractions. Therefore, the benchmark is preferable to the long B/M strategy of Table 4.

Finally, Panel C provides a similar analysis for the active trading strategies on EMKT, SMB and HML. Notice that, although the active strategy on EMKT underperforms its benchmark, it acts as a good hedge against slowdowns of the economy, providing a much higher return during contractions than it does during expansions. The active SMB, and HML strategies also emerge as good hedges against down times of the economy. Note, however, that, the benchmark HML strategy also provides a good hedge against economic contractions, in addition to superior returns. Therefore, it will always be preferred to the active HML strategy. This is not the case for the active EMKT and SMB strategies, both of which may be preferred to their respective benchmarks because of their ability to act as hedges against economic slowdowns. In addition, the active SMB strategy always outperforms its benchmark.

VI. Conclusions

This paper presents some new trading strategies on size and B/M decile portfolios as well as on EMKT, SMB, and HML. These trading strategies are constructed using the predictions of a forecast model that includes mainly business cycle related variables. Extensive out-of-sample experiments reveal that the proposed size and B/M strategies outperform passive strategies invested in the same portfolios, as well as SMB- and HML-type of strategies.

A key element of the proposed strategies is that the long and short positions may be invested in different decile portfolios across time. This is in contrast to the traditional SMB- and HML-type of strategies which go always long and short on the same portfolios.

Our results suggest that macroeconomic factors related to interest rates and default risk are particularly important for predicting the returns of the size and B/M decile portfolios. Furthermore, we show that the performance of strategies that exploit this predictability is greatly influenced by the state of the economy. The strategies provide higher returns during recessions than during expansions. As a result, they can also serve as hedges against a downturn of the economy.

The performance of the proposed strategies is generated using only publicly available information. One may therefore argue that one should conduct performance evaluation exercises for mutual funds using the active size and B/M strategies instead of the passive SMB and HML strategies of Fama and French (1993). The argument is that active strategies take into account variations in business conditions. Fund managers should account for such variations when they construct their investment strategies, without necessarily expecting to be rewarded with a high performance evaluation when they do so.

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Table 1. Summary Statistics

Panel A reports summary statistics for the size decile portfolios. We denote by S1 the portfolio with the smallest market capitalization and by S10 the portfolio with the biggest market capitalization. Panel B contains the summary statistics for the book-to-market (B/M) decile portfolios. BM1 is the portfolio with the lowest B/M whereas BM10 is the portfolio with the highest B/M. In Panel C we report summary statistics for the remaining variables used in our tests. The variable EMKT stands for the excess return of the market portfolio over the risk-free rate. SMB and HML are the Fama-French zero investment portfolios. SMB is a portfolio which is long on small capitalization stocks and short on big capitalization stocks. Similarly, HML is a zero-investment portfolio which is long on high B/M stocks and short on low B/M stocks. UMD, constructed from prior months' 2-12 returns, is a momentum zero-investment portfolio which controls for size. It is constructed by Fama and French. The variable HB3 is the difference between the three-month and the one-month Treasury Bill returns. We denote by DIV the S&P500 monthly dividend yield and by DEF the spread between the Moody's Baa and Aaa yields. The spread between the 10-year and the three-month Treasury yields is denoted by TERM. Finally, TBILL is the one-month Treasury Bill yield. The data cover the period from May 1953 to November 1998.

Portfolio	Mean	StdDev	ρ_1	ρ_3	ρ_6	ρ_{12}
Panel A: Size deciles						
S1	1.19	5.82	0.246	-0.016	-0002	0.115
S2	1.17	5.64	0.189	-0.029	-0.011	0.076
S3	1.23	5.52	0.160	-0.033	-0.024	0.048
S4	1.24	5.35	0.171	-0.020	-0.021	0.030
S5	1.21	5.11	0.152	-0.020	-0.021	0.019
S6	1.19	4.93	0.143	-0.011	-0.015	0.022
S7	1.16	4.81	0.117	-0.009	-0.036	0.011
S8	1.13	4.67	0.084	-0.015	-0.055	0.005
S9	1.12	4.36	0.072	-0.022	-0.045	0.009
S10	1.04	4.05	-0.002	0.011	-0.071	0.060
Panel B: B/M deciles						
BM1	1.02	4.96	0.078	-0.007	-0.060	0.054
BM2	1.09	4.57	0.052	-0.233	-0.056	0.025
BM3	1.09	4.55	0.052	0.009	-0.053	0.006
BM4	1.04	4.51	0.079	-0.015	-0.074	-0.002
BM5	1.13	4.13	0.037	-0.015	-0.034	0.008
BM6	1.19	4.21	0.004	0.004	-0.017	0.006
BM7	1.19	4.27	0.027	0.037	-0.055	0.008
BM8	1.32	4.33	0.032	0.031	-0.016	0.082
BM9	1.40	4.52	0.069	-0.009	-0.027	0.061
BM10	1.43	5.32	0.124	-0.018	-0.034	0.069
Panel C: Other variables						
EMKT	0.62	4.23	0.062	0.013	-0.062	0.029
SMB	0.09	2.63	0.163	-0.012	0.069	0.186
HML	0.39	2.44	0.148	0.003	0.046	0.099
UMD	0.87	3.12	-0.007	-0.047	0.008	0.042
HB3	0.06	0.10	0.296	0.049	-0.016	0.003
DIV	0.31	0.08	0.982	0.934	0.854	0.703
DEF	0.08	0.04	0.972	0.907	0.830	0.685
TERM	0.11	0.10	0.948	0.810	0.654	0.438
TBILL	0.43	0.23	0.966	0.914	0.867	0.773

Table 2. In-Sample Regressions

Monthly returns are regressed on a set of lagged predictive variables over the entire period 1953(5)-1998(11). The lagged predictive variables are the following. The excess return on the market portfolio (EMKT), the Fama-French size factor SMB, the Fama-French book-to-market (B/M) factor HML, a momentum factor constructed by Fama and French which controls for size, UMD, the difference between the three month and one month T-bill returns (HB3), the S&P500 monthly dividend yield (DIV), the spread between Moody's Baa and Aaa yields (DEF), the spread between the 10-year and three month Treasury yields (TERM), the nominal 1 month T-bill yield (TBILL), and a January dummy (JAN). Panel A reports the in-sample regression results for the 10 size portfolios, whereas Panel B reports the results for the ten B/M portfolios. In Panel C we report the in-sample regression results for the three Fama-French factors, i.e., EMKT, SMB and HML. The t-statistics, corrected for heteroskedasticity and serial correlation up to three lags using the Newey-West (1987) estimator appear in parentheses below the coefficient estimates. The R-squares are corrected for degrees of freedom.

Panel A: Size Deciles

	Lagged Predictive Variables											
Portfolio	Constant	EMKT	SMB	HML	UMD	JAN	TBILL	HB3	DIV	DEF	TERM	Adjusted-R^2
S1(Small)	-0.0114	0.2254	0.2895	0.0481	0.0595	0.0580	-4.964	0.0394	0.0640	0.2088	-0.0096	0.18
	(-1.14)	(3.76)	(2.86)	(0.48)	(0.68)	(5.96)	(-3.66)	(1.72)	(1.87)	(2.08)	(-0.38)	
S2	-0.0111	0.1300	0.1616	-0.0085	0.0290	0.0391	-4.9988	0.0594	0.0635	0.2242	-0.0086	0.11
	(-1.11)	(2.14)	(1.63)	(-0.08)	(0.34)	(3.96)	(-3.59)	(2.50)	(1.80)	(2.19)	(-0.33)	
S3	-0.0102	0.0962	0.1278	-0.0169	0.0102	0.0322	-4.7422	0.0606	0.0635	0.2185	-0.0082	0.09
	(-1.05)	(1.63)	(1.38)	(-0.18)	(0.13)	(3.30)	(-3.47)	(2.52)	(1.90)	(2.21)	(-0.32)	
S4	-0.0084	0.0814	0.1171	-0.0195	0.0120	0.0225	-4.7684	0.0647	0.0565	0.2335	-0.0081	0.08
	(-0.86)	(1.40)	(1.29)	(-0.21)	(0.15)	(2.34)	(-3.54)	(2.78)	(1.74)	(2.40)	(-0.32)	
S5	-0.0106	0.0743	0.0642	-0.0224	0.0093	0.0196	-4.3789	0.0614	0.0627	0.2149	-0.0049	0.07
	(-1.11)	(1.32)	(0.75)	(-0.25)	(0.13)	(2.15)	(-3.25)	(2.76)	(1.96)	(2.30)	(-0.20)	
S6	-0.0064	0.04779	0.04172	0.0134	-0.0046	0.0156	-4.9451	0.0651	0.0543	0.2312	-0.0083	0.07
	(-0.70)	(0.84)	(0.50)	(0.16)	(-0.06)	(1.76)	(-3.83)	(2.85)	(1.77)	(2.52)	(-0.35)	
S7	-0.0050	0.0221	0.0618	-0.0337	0.0309	0.0108	-4.7695	0.0755	0.0462	0.2352	-0.0132	0.07
	(-0.55)	(0.40)	(0.77)	(-0.42)	(0.46)	(1.26)	(-3.74)	(3.12)	(1.58)	(2.58)	(-0.57)	
S8	-0.0045	-0.0169	0.0443	-0.0292	0.0214	0.0094	-4.6138	0.0759	0.0477	0.2139	-0.0109	0.07
	(-0.53)	(-0.29)	(0.59)	(-0.38)	(0.33)	(1.16)	(-3.70)	(3.21)	(1.69)	(2.47)	(-0.47)	
S9	-0.0008	-0.0297	0.0604	-0.0376	0.0505	0.0069	-4.0590	0.0702	0.0356	0.1793	-0.0058	0.06
	(-0.10)	(-0.52)	(0.84)	(-0.53)	(0.83)	(0.93)	(-3.54)	(2.82)	(1.38)	(2.26)	(-0.27)	
S10 (Big)	0.0055	-0.0589	0.0842	-0.0429	0.0496	0.0005	-3.3951	0.0629	0.0094	0.1581	0.0028	0.04
	(0.74)	(-0.98)	(1.25)	(-0.61)	(0.85)	(0.07)	(-3.13)	(2.33)	(0.38)	(2.09)	(0.14)	

Table 2. In-Sample Regressions (Continued)

Panel B: Book-to-Market Deciles

Portfolio	Constant	EMKT	SMB	HML	UMD	JAN	Tbill	HB3	DIV	JUNK	TERM	Adjusted-R^2
BM1(Low)	0.0092	-0.0321	0.0831	-0.1238	0.0090	-0.0066	-4.7493	0.0746	0.0170	0.1815	-0.0140	0.04
	(1.02)	(-0.46)	(0.97)	(-1.33)	(0.13)	(-0.75)	(-3.48)	(2.16)	(0.61)	(1.83)	(-0.53)	
BM2	0.0023	-0.0379	0.0857	-0.1003	0.0323	-0.0004	-4.1349	0.0625	0.0232	0.2126	-0.087	0.04
	(0.29)	(-0.64)	(1.17)	(-1.23)	(0.52)	(-0.06)	(-3.47)	(2.26)	(0.90)	(2.46)	(-0.38)	
BM3	-0.0013	-0.0188	0.0597	-0.0349	0.0501	0.0038	-4.4722	0.0634	0.0365	0.2083	-0.0060	0.05
	(-0.16)	(-0.32)	(0.82)	(-0.46)	(0.81)	(0.50)	(-3.67)	(2.40)	(1.35)	(2.57)	(-0.26)	
BM4	-0.0045	-0.0015	0.0698	-0.0225	0.0451	0.0063	-3.7660	0.0608	0.0321	0.2082	0.0014	0.05
	(-0.50)	(-0.03)	(0.91)	(-0.31)	(0.73)	(0.76)	(-3.34)	(2.72)	(1.16)	(2.49)	(0.06)	
BM5	0.0002	-0.0351	0.0841	0.0082	0.0862	0.0046	-4.4289	0.0624	0.0436	0.1544	-0.0026	0.06
	(0.03)	(-0.63)	(1.21)	(0.12)	(1.41)	(0.62)	(-4.04)	(2.88)	(1.67)	(1.99)	(-0.12)	
BM6	-0.0015	-0.030	0.0116	0.0207	0.0645	0.0109	-3.6746	0.0530	0.0374	0.1585	0.0057	0.05
	(-0.18)	(-0.58)	(0.16)	(0.30)	(1.09)	(1.38)	(-3.50)	(2.49)	(1.44)	(2.16)	(0.28)	
BM7	0.0008	-0.0340	0.0463	0.0286	0.0729	0.0200	-3.2500	0.0530	0.0145	0.1937	-0.0008	0.06
	(0.10)	(-0.60)	(0.65)	(0.42)	(1.14)	(2.37)	(-2.69)	(2.72)	(0.53)	(2.32)	(-0.04)	
BM8	0.0001	-0.0246	0.0158	0.0376	0.0487	0.0229	-3.8857	0.0392	0.0386	0.1648	0.0021	0.06
	(0.02)	(-0.45)	(0.22)	(0.53)	(0.78)	(2.84)	(-3.03)	(2.08)	(1.36)	(1.97)	(0.10)	
BM9	-0.0038	0.0169	0.0850	0.0484	0.0442	0.0314	-3.4225	0.0510	0.0376	0.1740	0.0076	0.08
	(-0.52)	(0.29)	(1.14)	(0.67)	(0.71)	(3.63)	(-2.77)	(2.52)	(1.48)	(2.11)	(0.37)	
BM10(High)	-0.0035	0.0690	0.0966	0.1761	0.0465	0.0434	-3.8361	0.0496	0.0242	0.2349	0.0012	0.10
	(-0.42)	(1.18)	(1.09)	(1.99)	(0.68)	(4.31)	(-2.55)	(2.11)	(0.80)	(2.26)	(0.05)	

Panel C: Fama-French Factors

	Lagged Predictive Variables											
Portfolio	Constant	EMKT	SMB	HML	UMD	JAN	Tbill	HB3	DIV	JUNK	TERM	Adjusted-R^2
EMKT	0.0009 (0.12)	-0.0213 (-0.38)	0.0785 (1.15)	-0.0387 (-0.55)	0.0372 (0.63)	0.0053 (0.72)	-5.0610 (-4.48)	0.0666 (2.63)	0.0300 (1.20)	0.1763 (2.25)	-0.0047 (-0.23)	0.07
SMB	-0.0132 (-2.80)	0.1469 (4.42)	0.0802 (1.71)	0.0141 (0.28)	-0.0248 (-0.59)	0.0212 (4.35)	-0.5107 (-0.88)	0.0066 (0.58)	0.0378 (2.22)	0.0288 (0.65)	-0.0056 (-0.48)	0.14
HML	-0.0003 (-0.08)	0.0353 (1.29)	-0.0556 (-1.20)	0.1800 (3.26)	0.0060 (0.17)	0.0251 (5.62)	1.4213 (2.18)	-0.0184 (-1.12)	-0.0092 (-0.72)	-0.0402 (-0.79)	0.0192 (1.38)	0.10

Table 3. Out-of-Sample Performance of Simple Size-Decile Zero-Investment Strategies

The active long (short) portfolio in Panel A is formed by investing in the size decile for which the step-ahead return forecast is the highest (lowest) across 10 size decile forecasts. The combined, zero-investment portfolio is the difference between the active long and short portfolios. The long (short) benchmark invests in the smallest (biggest) size decile at all periods. The combined benchmark is the difference between the two. Similarly, the active long (short) portfolio in Panel B is formed by investing in the 3 size deciles with the highest (lowest) return forecasts. The combined, zero-investment portfolio is the difference between the active long and short portfolios. The benchmark strategies are always long in the three smallest size deciles and short in the three biggest size deciles. The expected return forecasts for each decile are obtained recursively in an OLS framework by using the forecast model of equation 2. The initial coefficient estimates are obtained over the ten-year period from 1953:5 to 1963:4. The first out-of-sample month is 1963:5. Subsequently, the monthly observation of 1963:5 is added to the initial period, the model is reestimated, and an out-of-sample forecast for 1963:6 is obtained. This process is repeated until the end of the sample, 1998:11. The total number of out-of-sample forecasts for each decile is N=427. Terminal wealth is defined as the total wealth at the end of the out-of-sample period from investing one dollar at the beginning of the period. For the column entitled "t-statistic," we compare the means of the long, short, and combined active portfolios to either zero or the respective benchmark means.

Panel A: Out-of-Sample Performance of Size Decile Strategies: Top 1 – Bottom 1

Active	Mean Return	t-statistic (mean vs 0)	t-statistic (active mean vs benchmark mean)	Standard Deviation	Terminal Wealth
$Long_{size}$	1.90	7.12	1.82	5.52	1654.33
$Short_{size}$	0.34	1.44	-2.16	4.94	0.14
$Combined_{size}$	1.56	8.27	4.79	3.89	540.60
Benchmark					
S = S1	1.17	3.92		6.17	64.45
B = S10	1.02	1.53		4.16	0.009
S - B	0.15	0.69		4.64	1.23

Panel B: Out-of-Sample Performance of Size Decile Strategies: Top 3 – Bottom 3

Active	Mean Return	t-statistic (mean vs 0)	t-statistic (active mean vs benchmark mean)	Standard Deviation	Terminal Wealth
$Long_{size}$	1.62	6.23	1.16	5.37	518.46
$Short_{size}$	0.64	2.63	-1.31	5.02	0.04
$Combined_{size}$	0.98	7.94	4.43	2.55	56.10
Benchmark					
S = (S1+S2+S3)/3	1.17	4.07		5.96	67.14
B = (S8+S9+S10)/3	1.06	4.95		4.45	0.007
S – B	0.10	0.67		3.18	1.26

Table 4. Out-of-Sample Performance of Simple Book-to-Market (B/M) Decile Zero-Investment Strategies

The active long (short) portfolio in Panel A is formed by investing in the B/M decile for which the step-ahead return forecast is the highest (lowest) across 10 B/M decile forecasts. The combined, zero-investment portfolio is the difference between the active long and short portfolios. The long (short) benchmark invests in the highest (lowest) B/M decile at all periods. The combined benchmark is the difference between the two. Similarly, the active long (short) portfolio in Panel B is formed by investing in the 3 B/M deciles with the highest (lowest) return forecasts. The combined, zero-investment portfolio is the difference between the active long and short portfolios. The benchmark strategies are always long in the three highest B/M deciles and short in the three lowest B/M deciles. The expected return forecasts for each decile are obtained recursively in an OLS framework by using the forecast model of equation 2. The initial coefficient estimates are obtained over the ten-year period from 1953:5 to 1963:4. The first out-of-sample month is 1963:5. Subsequently, the monthly observation of 1963:5 is added to the initial period, the model is reestimated, and an out-of-sample forecast for 1963:6 is obtained. This process is repeated until the end of the sample, 1998:11. The total number of out-of-sample forecasts for each decile is N=427. Terminal wealth is defined as the total wealth at the end of the out-of-sample period from investing one dollar at the beginning of the period. For the column entitled "t-statistic," we compare the means of the long, short, and combined active portfolios to either zero or the respective benchmark means.

Panel A: Out-of-Sample Performance of B/M Decile Strategies: Top 1 – Bottom 1

Active	Mean Return	t-statistic (mean vs 0)	t-statistic (active mean vs benchmark mean)	Standard Deviation	Terminal Wealth
$Long_{BM}$	1.42	5.87	-0.24	4.98	242.42
$Short_{BM}$	1.10	4.73	0.43	4.82	0.005
$Combined_{BM}$	0.31	1.82	-0.84	3.54	2.92
Benchmark					
H=BM10 (Long)	1.50	5.72		5.42	313.26
L=BM1 (Short)	0.96	3.87		5.11	0.009
H - L	0.54	6.75		4.44	0.063

Panel B: Out-of-Sample Performance of B/M Decile Strategies: Top 3 – Bottom 3

Active	Mean Return	t-statistic (mean vs 0)	t-statistic (active mean vs benchmark mean)	Standard Deviation	Terminal Wealth
$Long_{BM}$	1.33	6.11	-0.18	4.51	187.62
$Short_{BM}$	1.07	4.81	0.15	4.58	0.007
$Combined_{BM}$	0.27	2.52	-0.61	2.19	2.82
Benchmark					
H=(BM8+BM9+BM10)/3	1.39	6.24		4.60	233.11
L=(BM1+BM2+BM3)/3	1.02	4.45		4.73	0.008
H - L	0.37	4.15		2.77	0.17

Table 5. Size and B/M Decile Inclusion Frequencies in Trading Strategies

This table reports the inclusion frequency for which each size and B/M decile portfolio is included in the long and short positions of the trading strategies in Tables 3 and 4. Panel A reports the frequencies of inclusion of the size deciles in the trading strategy that invests only in the top and bottom deciles in terms of their expected returns, as determined by our forecast model. Panel B reports the frequencies of inclusion of the size deciles in the trading strategies that invest in the three top and three bottom deciles in terms of their expected returns. Similarly, Panels C and D report the frequencies for the B/M deciles of the strategies that invest in the one and three top and bottom deciles in terms of expected returns, respectively. Average turnover is the average percentage change in the portfolio components in consecutive periods. The number of out-of-sample periods is denoted by N.

Panel A: Inclusion Frequencies of Size Decile Portfolios in Long and Short Strategy Portfolios (Top 1 – Bottom 1)

		S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	Average Turnover	N
$Long_{size}$	Number	157	1	9	18	29	12	11	7	15	168	56.57%	427
	Freq.	36.77%	0.23%	2.11%	4.22%	6.79%	2.81%	2.58%	1.64%	3.51%	39.34%		
$Short_{size}$	Number	136	68	0	3	15	7	6	32	36	124	61.74%	427
	Freq.	31.85%	15.93%	0.00%	0.70%	3.51%	1.64%	1.41%	7.49%	8.43%	29.04%		

Panel B: Inclusion Frequencies of Size Decile Portfolios in Long and Short Strategy Portfolios (Top 3 – Bottom 3)

		S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	Average Turnover	N
$Long_{size}$	Number	198	105	153	116	100	52	61	124	162	210	51.25%	427
	Freq.	46.37%	24.59%	35.83%	27.17%	23.42%	12.18%	14.29%	29.04%	37.94%	49.18%		
$Short_{size}$	Number	190	212	111	40	64	55	64	186	195	164	47.10%	427
	Freq.	44.50%	49.65%	26.00%	9.37%	14.99%	12.88%	14.99%	43.56%	45.67%	38.41%		

Panel C: Inclusion Frequencies of B/M Decile Portfolios in Long and Short Strategy Portfolios (Top 1 – Bottom 1)

		BM1	BM2	BM3	BM4	BM5	BM6	BM7	BM8	BM9	BM10	Average Turnover	N
$Long_{BM}$	Number	72	44	10	14	7	23	52	41	61	103	67.14%	427
	Freq.	16.86%	10.30%	2.34%	3.28%	1.64%	5.39%	12.18%	9.60%	14.29%	24.12%		
$Short_{BM}$	Number	131	19	41	31	45	15	12	37	18	78	67.37%	427
	Freq.	30.68%	4.45%	9.60%	7.26%	10.54%	3.51%	2.81%	8.67%	4.22%	18.27%		

Panel D: Inclusion Frequencies of B/M Decile Portfolios in Long and Short Strategy Portfolios (Top 3 – Bottom 3)

		BM1	BM2	BM3	BM4	BM5	BM6	BM7	BM8	BM9	BM10	Average Turnover	N
$Long_{BM}$	Number	131	126	55	67	41	116	152	178	243	172	47.18%	427
	Freq.	30.68%	29.51%	12.88%	15.69%	9.60%	27.17%	35.60%	41.69%	56.91%	40.28%		
$Short_{BM}$	Number	183	154	187	159	145	83	73	101	52	144	46.56%	427
	Freq.	42.86%	36.07%	43.79%	37.24%	33.96%	19.44%	17.10%	23.65%	12.18%	33.72%		

Table 6. Out-of-Sample Performance of Active Strategies that Involve Investments in the Fama-French Factors

This table reports the out-of-sample performance of trading strategies that involve forecasting EMKT, SMB and HML, using the forecast model of equation 2. The strategies work as follows. When the forecast model indicates that EMKT will have a positive expected return, then the portfolio is invested in EMKT. Otherwise, the portfolio shorts EMKT, i.e., buys the T-bill and sells the market portfolio MKT. Analogous strategies are built for SMB and HML. The initial estimation of the forecast model is done over the period from 1953:5 to 1963:4. Using those coefficient estimates, we calculate the first out-of-sample forecast, which refers to 1963:5. Subsequently, the month of 1963:5 is added to the initial period and the model is reestimated. The second out-of-sample forecast refers to 1963:6. This procedure is repeated until 1998:11, producing a total of 427 out-of-sample forecasts. Terminal wealth is defined as the total wealth at the end of the out-of-sample period from investing one dollar at the beginning of the period. The Henriksson and Merton (1981) market timing statistics HM p_1+p_2 indicates market timing when $p_1+p_2 > 1$. The forecast beta is the estimate of the slope coefficient from a regression of monthly realized return on the return forecasts. The number of out-of-sample periods is denoted by N. For the column entitled "t-statistic," we compare the means of each panel's active trading strategy to that of the corresponding benchmark portfolio of always holding the underlying portfolio.

Panel A: Out-of-Sample Performance of MKT strategies

	Mean Return	Standard Deviation	Terminal Wealth	HM p_1+p_2	Forecast Beta	t-statistic (mean vs 0)	t-statistic (active mean vs benchmark mean)	N
$EMKT_{active}$	0.35	4.40	2.97	1.03*	0.07***	1.64	-0.56	427
$EMKT_{benchmark}$	0.52	4.38	6.03					427

Panel B: Out of Sample Performance Results for SMB

	Mean Return	Standard Deviation	Terminal Wealth	HM p_1+p_2	Forecast Beta	t-statistic (mean vs 0)	t-statistic (active mean vs benchmark mean)	N
SMB_{active}	0.80	2.72	26.15	1.22***	0.14***	6.10	3.47	427
$SMB_{benchmark}$	0.14	2.83	1.56					427

Panel C: Out of Sample Performance Results for HML

	Mean Return	Standard Deviation	Terminal Wealth	HM p_1+p_2	Forecast Beta	t-statistic (mean vs 0)	t-statistic (active mean vs benchmark mean)	N
HML_{active}	0.36	2.59	4.01	0.99*	0.09***	2.87	-0.41	427
$HML_{benchmark}$	0.43	2.58	5.46					427

*Denotes significance at 10% level, **denotes significance at 5% level,*** denotes significance at 1% level.

Table 7. Filter Results for Size Decile Trading Strategies

This table reports results of strategies that impose filter rules on the decile portfolios' return forecasts. In particular, the strategies go long on all decile portfolios whose expected returns exceed that of a given filter rule. They also go short on those deciles whose expected returns are lower than a given filter rule. The filter rules examined range from 0% to 5% for the long positions, and –5% to 0% for the short positions. The deciles in the long and short positions are equally weighted. The expected returns of the deciles are determined using the forecast model of equation 2. When no decile satisfies the given filter rule, then the portfolio is invested in the T-bill for that month. We report the terminal wealth (TW), mean return, t-statistic of the mean, standard deviation and Sharpe ratio of the trading strategies. Terminal wealth is defined as the wealth accumulated over the life of the strategy from investing one dollar at the beginning of the life of the trading strategy. The row labeled "Active Trades" reports the number of months during which the portfolio is invested in deciles as opposed to the T-bill. The row labeled "Active Mean" reports the monthly average return during which the portfolio is invested in deciles as opposed to the T-bill. The "Benchmark Portfolio" is an equally weighted portfolio invested in all the size deciles at all times. All trading strategies are performed over a period of 427 months from 1963:5 to 1998:11.

		Expected Return Filter											
		>0%	>0.5%	>1%	>1.5%	>2%	>2.5%	>3%	>3.5%	>4%	>4.5%	>5%	Benchmark Portfolio
	TW	160.10	130.02	223.75	200.17	126.01	100.57	125.36	107.22	82.00	71.87	65.94	74.71
Long	Mean Return	1.29	1.23	1.35	1.31	1.24	1.13	1.18	1.14	.107	1.03	1.01	1.15
	t-statistic	6.10	6.17	7.27	7.69	7.75	7.82	8.24	8.43	8.35	9.13	9.03	4.65
	Standard. Dev.	4.37	4.12	3.82	3.52	3.31	2.98	2.96	2.79	2.65	2.34	2.31	5.09
	Sharpe Ratio	0.18	0.17	0.22	0.23	0.22	0.21	0.22	0.22	0.21	0.22	0.21	0.12
	Active Trades	322	259	206	159	124	94	81	68	58	49	46	427
	Active Mean	1.53	1.69	2.25	2.65	3.02	3.32	4.03	4.44	4.62	5.05	5.15	
		<0%	<-0.5%	<-1%	<-1.5%	<-2%	<-2.5%	<-3%	<-3.5%	<-4%	<-4.5%	<-5%	
	TW	0.90	1.52	4.93	8.09	11.50	13.11	12.48	9.03	8.61	8.82	8.51	
Short	Mean Return	-0.05	-0.16	-0.43	-0.53	-0.6	-0.62	-0.6	-0.52	-0.51	-0.52	-0.51	
	t-statistic	-0.25	-0.91	-2.66	-4.06	-5.18	-7.46	-9.40	-11.14	-11.60	-11.98	-12.57	
	Standard. Dev.	3.87	3.73	3.31	2.67	2.10	1.71	1.32	0.97	0.91	0.89	0.83	
	Sharpe Ratio	-0.15	-0.18	-0.28	-0.39	-0.46	-0.66	-0.84	-1.07	-1.13	-1.16	-1.23	
	Active trades	246	201	135	79	52	31	22	13	12	10	8	
	Active Mean	0.29	0.21	-0.26	-0.64	-1.29	-2.04	-2.35	-0.85	-0.45	-0.69	-0.23	

Table 8. Filter Results for the Book-to-Market (BM) Decile Trading Strategies

This table reports results of strategies that impose filter rules (threshold returns) on the deciles, in addition to ranking them according to their expected returns. In particular, the strategies go long on all decile portfolios whose expected return exceeds that of a given filter rule. They also go short on those deciles whose expected return is lower than a given filter rule. The filter rules examined range from 0% to 5% for the long positions, and –5% to 0% for the short positions. The deciles in the long and short positions are equally weighted. The expected returns of the deciles are determined using the forecast model of Table 2. When no decile satisfies the given filter rule, then the portfolio is invested in the T-bill for that month. We report the terminal wealth (TW), mean return, t-statistic of the mean, standard deviation and Sharpe ratio of the trading strategies. Terminal wealth is defined as the wealth accumulated over the life of the strategy from investing one dollar at the beginning of the life of the trading strategy. The row labeled "Active Trades" reports the number of months during which the portfolio is invested in deciles as opposed to the T-bill. The row labeled "Active Mean" reports the monthly average return during which the portfolio is invested in deciles as opposed to the T-bill. The "Benchmark Portfolio" is an equally weighted portfolio invested in all the B/M deciles at all times. All trading strategies are performed over a period of 427 months from 1963:5 to 1998:11.

		Expected Return Filter											
		>0%	>.0.5%	>1%	>1.5%	>2%	>2.5%	>3%	>3.5%	>4%	>4.5%	>5%	Benchmark Portfolio
	TW	157.43	122.72	102.80	117.47	54.21	49.12	48.35	51.19	41.16	36.12	37.78	95.01
Long	Mean Return	1.27	1.20	1.14	1.16	0.97	0.94	0.94	0.95	0.89	0.86	0.87	1.17
	t-statistic	6.62	6.88	7.09	8.07	8.14	7.99	8.29	8.52	9.25	9.35	9.18	5.56
	Standard. Dev.	3.96	3.59	3.33	2.98	2.46	2.44	2.34	2.30	2.00	1.90	1.96	4.33
	Sharpe Ratio	0.19	0.19	0.19	0.22	0.18	0.18	0.18	0.19	0.19	0.18	0.18	0.15
	Active Trades	351	269	209	150	102	83	67	57	49	39	32	
	Active Mean	1.42	1.59	1.80	2.38	2.43	2.76	3.25	3.82	3.83	4.32	5.31	
		<0%	<-0.5%	<-1%	<-1.5%	<-2%	<-2.5%	<-3%	<-3.5%	<-4%	<-4.5%	<-5%	
	TW	0.20	0.30	1.44	5.10	7.82	8.26	8.53	8.22	7.58	8.85	9.16	
Short	Mean Return	0.31	0.23	-0.12	-0.40	-0.50	-0.5	-0.51	-0.50	-0.48	-0.51	-0.52	
	t-statistic	1.71	1.55	-0.97	-4.29	-6.47	-9.82	-11.55	-10.54	-13.10	-35.46	-43.20	
	St. Dev.	3.69	3.10	2.51	1.93	1.58	1.05	0.91	0.98	0.75	0.30	0.25	
	Sharpe Ratio	-0.06	-0.09	-0.25	-0.47	-0.64	-0.96	-1.13	-1.04	-1.32	-3.44	-4.16	
	Active Trades	261	186	115	65	45	23	17	10	7	2	1	
	Active Mean	0.82	1.18	0.91	0.15	-0.41	-0.36	-0.50	-0.14	1.29	-0.19	-3.16	

Table 9. Out-of-Sample Performance of Size Decile Trading Strategies using Lehmann Weights

This table reports the performance of trading strategies in which we form portfolios by weighting assets by their relative expected returns. When the expected return of a size decile portfolio exceeds 0% for the long strategy or is lower than 0% for the short strategy, the remaining assets are formed into a long or short portfolio based on their relative expected return forecasts from equation 2. If no portfolio has an expected return greater than 0% for the long strategy or less than 0% for the short strategy, then the long or short strategy invests in the T-bill for that month. Furthermore, the table provides the performance of the trading strategies when alternative forecast models are used. The column labeled "All" reports the performance of the trading strategies when all the predictive variables of the forecast model in Table 2 are used. "All-Jan" is the performance of the strategies when the January dummy is excluded from the list of predictive variables. "FF+UMD+Jan" is the performance of the strategies when the forecast model includes the Fama-French factors MKT, SMB, HML, the momentum variable UMD and the January dummy. In the column "FF+UMD" the forecast model includes only the three Fama-French factors and the momentum variable UMD. Furthermore, the column "Macro+Jan" considers the performance of the strategies when the forecast model includes only the macro variables and the January dummy. The macro variables are HB3, DIV, DEF, TERM, and TBILL. The column "Macro" reports the results from strategies based on a forecast model that includes only the macro variables. Finally, the column "R^2 Model" reports the result of a strategy where the best model is selected every month based on the in-sample model with the highest adjusted R^2. We report the terminal wealth (TW), mean return, t-statistic of the mean, standard deviation and Sharpe ratio of the trading strategies. Terminal wealth is defined as the wealth accumulated over the life of the strategy from investing one dollar at the beginning of the life of the trading strategy. The row labeled "Active Trades" reports the number of months during which the portfolio is invested in deciles as opposed to the T-bill. The "Benchmark Portfolio" is an equally weighted portfolio invested in all the size deciles at all times. All trading strategies are performed over a period of 427 months from 1963:5 to 1998:11.

Predictive variables in forecast model

		All	All-Jan	FF+UMD+Jan	FF+UMD	Macro+Jan	Macro	R^2Model	Benchmark Portfolio
	TW	254.23	193.62	239.62	163.92	273.09	167.46	303.03	74.74
Long	Mean Return	1.41	1.34	1.42	1.32	1.41	1.29	1.45	1.15
	t-statistic	6.41	6.19	5.88	5.60	6.91	6.36	6.49	4.65
	Standard. Dev.	4.54	4.47	4.97	4.88	4.22	4.20	4.62	5.09
	Sharpe Ratio	0.20	0.18	0.18	0.17	0.21	0.19	0.20	0.12
	Active trades	322	329	421	421	296	305	333	427

		All	All-Jan	FF+UMD+Jan	FF+UMD	Macro+Jan	Macro	R^2Model	Benchmark Portfolio
	TW	1.16	0.60	6.67	3.84	1.03	0.88	0.73	74.74
Short	Mean Return	-0.11	0.04	-0.50	-0.37	-0.09	-0.05	-0.01	1.15
	t-statistic	-0.57	0.19	-2.97	-2.35	-0.45	-0.25	-0.03	4.65
	Standard. Dev.	3.90	4.04	3.51	3.25	4.07	4.06	4.04	5.09
	Sharpe Ratio	-0.16	-0.12	-0.29	-0.27	-0.15	-0.14	-0.13	0.12
	Active trades	246	242	127	99	241	231	258	427

Table 10. Out-of-Sample Performance of BM Decile Trading Strategies using Lehmann Weights

This table reports the performance of trading strategies in which we form portfolios by weighting assets by their relative expected returns. When the expected return of a B/M decile portfolio exceeds 0% for the long strategy or is lower than 0% for the short strategy, the remaining assets are formed into a long or short portfolio based on their relative expected return forecasts from equation 2. If no portfolio has an expected return greater than 0% for the long strategy or less than 0% for the short strategy, then the long or short strategy invests in T-bill for that month. Furthermore, the table provides the performance of the trading strategies when alternative forecast models are used. The column labeled "All" reports the performance of the trading strategies when all the predictive variables of the forecast model in Table 2 are used. "All-Jan" is the performance of the strategies when the January dummy is excluded from the list of predictive variables. "FF+UMD+Jan" is the performance of the strategies when the forecast model includes the Fama-French factors MKT, SMB, HML, the momentum variable UMD and the January dummy. In the column "FF+UMD" the forecast model includes only the three Fama-French factors and the momentum variable UMD. Furthermore, the column "Macro+Jan" considers the performance of the strategies when the forecast model includes only the macro variables and the January dummy. The macro variables are HB3, DIV, DEF, TERM, and TBILL. The column "Macro" reports the results from strategies based on a forecast model that includes only the macro variables. Finally, the column "R^2 Model" reports the result of a strategy where the best model is selected every month based on the in-sample model with the highest adjusted R^2. The forecast model in this case is determined each month by the model with the maximal in-sample R-square We report the terminal wealth (TW), mean return, t-statistic of the mean, standard deviation and Sharpe ratio of the trading strategies. Terminal wealth is defined as the wealth accumulated over the life of the strategy from investing one dollar at the beginning of the life of the trading strategy. The row labeled "Active Trades" reports the number of months during which the portfolio is invested in deciles as opposed to the T-bill. The "Benchmark Portfolio" is an equally weighted portfolio invested in all the B/M deciles at all times. All trading strategies are performed over a period of 427 months from 1963:5 to 1998:11.

Predictive variables in forecast model

		All	All-Jan	FF+UMD+Jan	FF+UMD	Macro+Jan	Macro	R^2Model	Benchmark Portfolio
	TW	198.13	119.66	163.94	113.75	214.76	83.81	243.33	95.01
Long	Mean Return	1.33	1.21	1.30	1.21	1.34	1.12	1.38	1.17
	t-statistic	6.79	6.25	6.14	5.85	7.19	5.98	6.92	4.65
	Standard Dev.	4.04	3.99	4.36	4.25	3.85	3.86	4.11	4.33
	Sharpe Ratio	0.20	0.17	0.18	0.16	0.21	0.16	0.21	0.15
	Active trades	351	365	422	421	340	352	363	427

		All	All-Jan	FF+UMD+Jan	FF+UMD	Macro+Jan	Macro	R^2Model	Benchmark Portfolio
	TW	0.18	0.24	1.19	3.21	0.38	0.45	0.39	95.01
Short	Mean Return	0.33	0.27	-0.08	-0.29	0.16	0.12	0.16	1.17
	t-statistic	1.87	1.58	-0.60	-3.13	0.93	0.73	0.92	4.65
	Standard Dev.	3.70	3.59	2.64	1.94	3.58	3.54	3.56	4.33
	Sharpe Ratio	-0.05	-0.07	-0.22	-0.42	-0.10	-0.11	-0.10	0.15
	Active trades	261	247	96	59	243	239	245	427

Table 11. Out-of-Sample Performance of Simple Zero-Investment Trading Strategies Over Business Cycles

This table presents the performance of the simple zero-investment trading strategies of Table 3 over expansions and contractions of the business cycles, as they are defined by NBER. During the out-of-sample period (1963:5-1998:11), there are 6 expansionary periods: 1963:05-1969:12, 1970:12-1973:11, 1975:04-1980:01, 1980:08-1981:07, 1982:12-1990:07, and 1991:04-1998:11) that lasted in total 370 months, and 5 contractionary periods (1970:01-1970:11, 1973:12-1975:03, 1980:02-1980:07, 1981:08-1982:11, 1990:08-1991:03) that lasted in total 57 months. Panel A reports the average out-of-sample returns of the active and passive (benchmark) size decile portfolios for the long, short, and combined strategies for the (Top 1-Bottom 1) case as explained in Table 3. Panel B reports the average out-of-sample returns of the active and passive (benchmark) BM decile portfolios for the long, short, and combined strategies for the (Top1-Bottom 1) case as explained in Table 4. Reported under each return or profit number in parenthesis is the t-statistic of the portfolio. Finally, Panel C reports the average out-of-sample returns of the active and passive (benchmark) MKT, SMB, and HML portfolios. Number of months under expansionary and contactionary periods are denoted by N.

Panel A: Average Out-of-Sample Return of the Active/Benchmark Size Zero-Investment Strategies During Different Parts of the Business Cycles (Top 1 – Bottom 1)

	Active Trades			Benchmark			
	$Long_{size}$	$Short_{size}$	$Combined_{size}$	S1	S10	(S1-S10)	N
Expansionary	1.99	0.51	1.49	1.35	1.11	0.24	370
Periods	(7.53)	(2.11)	(7.63)	(4.54)	(5.61)	(1.04)	
Contractionary	1.31	-0.72	2.03	0.02	0.42	-0.39	57
Periods	(1.28)	(-0.81)	(3.22)	(0.02)	(0.53)	(-0.51)	

Panel B: Average Out-of-Sample Return of the Active/Benchmark B/M Zero-Investment Strategies During Different Parts of the Business Cycles (Top 1 – Bottom 1)

	Active Trades			Benchmark			
	$Long_{BM}$	$Short_{BM}$	$Combined_{BM}$	BM10	BM1	(BM10-BM1)	N
Expansionary	1.49	1.24	0.25	1.60	1.10	0.50	370
Periods	(6.17)	(5.32)	(1.42)	(6.10)	(4.62)	(2.22)	
Contractionary	0.93	0.23	0.70	0.88	0.02	0.86	57
Periods	(1.03)	(0.26)	(1.25)	(0.88)	(0.02)	(1.22)	

Panel C: Average Out of Sample Return of the Active/Benchmark Strategies on the Fama-French Factors During Different Parts of the Business Cycles

	Active			Benchmark			
	$EMKT_{active}$	SMB_{active}	HML_{active}	$EMKT_{benchmark}$	$SMB_{benchmark}$	$HML_{benchmark}$	N
Expansionary	-0.03	0.77	0.30	0.64	0.16	0.37	370
Periods	(-0.15)	(5.78)	(2.40)	(3.11)	(1.17)	(2.91)	
Contractionary	2.81	0.99	0.72	-0.28	0.02	0.85	57
Periods	(3.68)	(2.12)	(1.58)	(-0.33)	(0.05)	(1.89)	

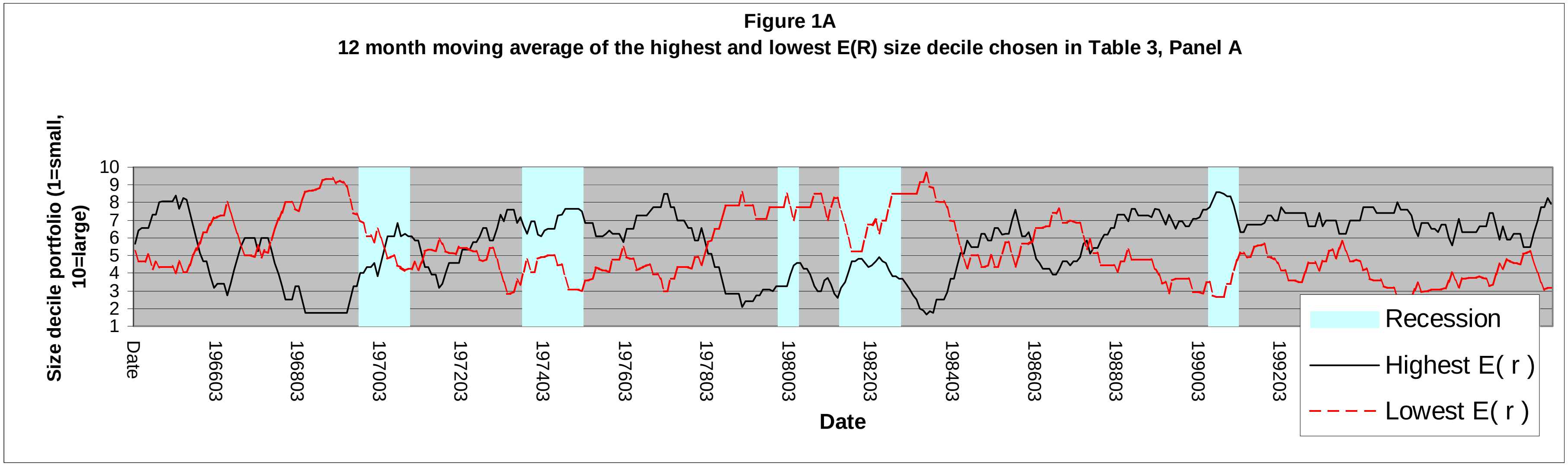

Figure 1A
12 month moving average of the highest and lowest E(R) size decile chosen in Table 3, Panel A
Size decile portfolio (1=small, 10=large)
10
9
8
7
6
5
4
3
2
1
Date
196603
196803
197003
197203
197403
197603
197803
198003
198203
198403
198603
198803
199003
199203
Date
Recession
Highest E(r)
Lowest E(r)

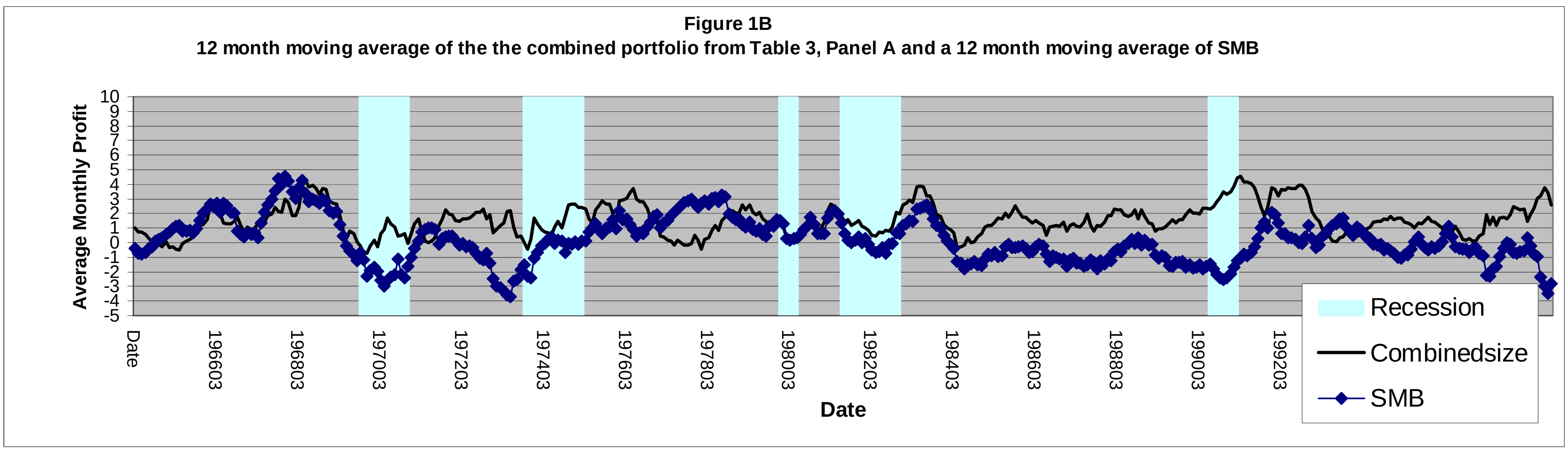

Figure 1B
12 month moving average of the the combined portfolio from Table 3, Panel A and a 12 month moving average of SMB
Average Monthly Profit
10
9
8
7
6
5
4
3
2
1
0
-1
-2
-3
-4
-5
Date
196603
196803
197003
197203
197403
197603
197803
198003
198203
198403
198603
198803
199003
199203
Date
Recession
Combinedsize
SMB

Figure 2A

12 month moving average of the highest and lowest E(R) B/M decile chosen in Table 4, Panel A

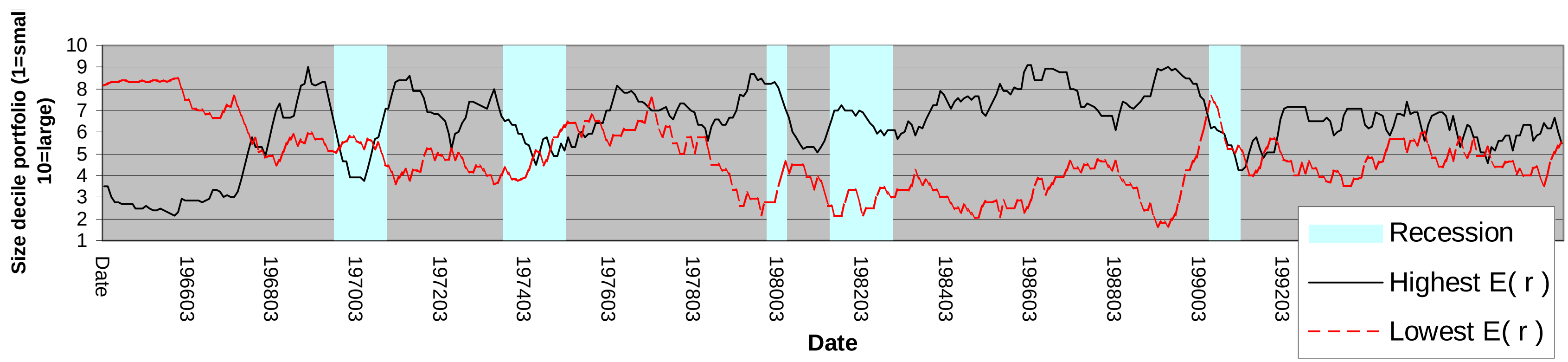

Figure 2B

12 month moving average of the the combined portfolio from Table 4, Panel A and a 12 month moving average of HML