Margin Credit and Stock Return Predictability

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Abstract

Margin credit, defined as the excess debt capacity of investors buying securities on the margin, is a *very strong* predictor of aggregate stock returns. It outperforms other forecasting variables proposed in the literature, in-sample as well as out-of-sample. Its out-of-sample R^2, 7.45% at the monthly horizon and 35.68% at the annual horizon, is more than twice as large as that of the next best predictor. It produces a Sharpe Ratio of 1.42 over recessions and 0.96 over expansions and overall annualized Certainty Equivalent Return gain of 9.5%, all considerably larger than those for the other predictors. Further, margin credit predicts market crashes and avoids substantial parts of the stock market downturns around 2001 and 2008. Margin credit predicts future returns because it contains information about future discount rates as well as future cash flows.

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1 Introduction

Formal equity premium prediction is at least as old as sliced bread.[1] Thousand of investors move millions of shares worth billions of dollars daily on formal or informal predictions of future returns. However, making a successful return prediction is not as easy as eating a sandwich. Only a subset of these investors are sophisticated enough to make a good prediction.

Academic literature has proposed a host of signals for future returns over time. Unfortunately, a comprehensive investigation of most popular of these variables by Welch and Goyal (2008) reveals that none of them outperform simple historical average of equity premium or can be used to make money. These variables – dividend price ratio, book to market ratio, volatility, various interest rate spreads among others – try to extract information from the prices, returns and valuation ratios of different financial assets. However, Huang, Jiang, Tu, and Zhou (2015) and Rapach, Ringgenberg, and Zhou (2016) have taken a different track recently. They develop much stronger and more actionable predictors by extracting information about beliefs of subsets of investors. Motivated by this, we extract information from investors who establish leveraged long positions using margin debt. These margin investors are likely to have strong beliefs since they are willing to lever up.

We construct a measure from the *excess debt capacity* of investors that use margin debt to establish long positions. This excess debt capacity – we call it margin credit – results from these investors *choosing not to reinvest* their gains from the levered long positions (details in Section 2). Over our sample period of 31 years from 1984 to 2014, we find that a higher margin credit predicts lower future market returns. We compare margin credit with other popular predictors and find that margin credit is the strongest predictor to date of future market returns.

A rule by the Financial Industry Regulatory Agency (FINRA) requires the brokers to

[1]"The Magazine of Wall Street" published Dow's "Scientific Stock Speculation" in 1920 while Otto Fredrick Rowedder completed the first machine capable of slicing and packaging a loaf of bread in July of 1927.

report monthly aggregate margin debt used by investors to take long positions and aggregate credit in such margin accounts. A credit in the margin account is typically posted when a levered long position appreciates in value and the investor decides not to reinvest the gain. Reinvesting the gains made from levered long positions requires further borrowing from the broker. Hence, a decision *not to reinvest* the gain results in excess debt capacity. This is a "hold" signal coming from winning investors. That is, the investors who are ex-post correct about their past beliefs now have pessimistic view about future returns. We thus expect an inverse relationship between margin credit and future returns.

We test this hypothesis using the monthly series of the aggregate margin debt and margin credit published by the New York Stock Exchange (NYSE) and the FINRA. We construct two new predictors: one based on margin debt and the other based on margin credit. The monthly values of margin debt and margin credit are scaled by the GDP to make them comparable across time. Each measure displays a strong and statistically significant upward trend over the period 1984 to 2014 most likely due to the expansion of the equity market, deregulation of margin purchasing and easing of access to credit.[2] We remove this uninformative increase by detrending the monthly ratios of margin debt to GDP and margin credit to GDP. Our two new predictors MD, based on margin debt, and MC, based on margin credit, are formed by standardizing the detrended series.

MD, quite popular among the practitioners and the financial press, is a strong negative predictor of the aggregate market return in-sample. But its performance out-of-sample is weak. However MC, largely ignored until now, is a significant predictor of market returns. Consistent with our hypothesis of an inverse relationship between margin credit and future returns, we find that a one standard-deviation increase in MC predicts that the next month's market return would be lower by 1.1 percentage point. MC generates an in-sample R^2 value of 6.25% for next month's returns which increases to 27.29% at the annual horizon, numbers typically at least twice as large as the next best predictor. MC performs strongly out-of-sample as well, generating an R^2 of 7.45% at monthly frequency, which rises to more

[2]Until January of 1974 the US Government through the Federal Reserve Board actively managed the margin requirement, amount of equity needed to take a margin position.

than 35% at annual frequency, again producing substantially better performance than other predictors. At most horizons, not only is MC the best performer, it also encompasses all the information contained in the other predictors.

We also examine how asset allocation strategies based on MC perform. We provide the key results here. The details are in Section 5. A market timing strategy based on MC, for a mean-variance investor, has substantially larger Sharpe Ratio at 1.0 than that of strategies based on previous predictors. Over the out-of-sample period, it produces an annualized Certainty Equivalent Return (CER) gain of 9.5% compared to strategy based on the historical average return. Over NBER recessions and expansions, it generates a Sharpe Ratio of 1.42 and 0.96, respectively. Figure 3 shows the cumulative log returns of this strategy and a simple S&P 500 buy-and-hold strategy from 1994 to 2014.

The high performance of an MC-based asset allocation strategy in our sample comes from avoidance of substantial parts of two large downturns, the dotcom bust of early 2000s and the 2008-9 financial crisis. In particular, a MC-based strategy predicts crashes in the near future. Figure 4 shows the returns of MC-based strategy during the 12 worst and best months of S&P 500. While the strategy misses only 4 of the best 12 S&P 500 months, it avoids 7 out of 12 worst monthly crashes. In fact, during those 7 months, the strategy allocates negative weight to the S&P 500 and positive weight on T-bills, generating high returns when market crashes.

While the MC-based strategy that takes a short position in the S&P 500 can be easily implemented using index futures, we also consider a long-only asset allocation strategy that invests 100% in the S&P 500 or 100% in the risk free asset. This strategy can be implemented even by small investors who do not trade in the S&P 500 futures market. We find that this long-only strategy also out-performs the simple buy-and-hold strategy by a large margin. It generates a Sharpe Ratio of 0.96 over recessions, compared to -0.81 for the buy-and-hold strategy. Over expansions as well the Sharpe of 0.95 of this strategy is larger than 0.79 of the buy-and-hold strategy. Figure 5 plots the cumulative log returns of long-only strategy based on margin credit.

Two questions arise. First, who are these margin long investors? And second, why does MC predicts future returns? Not much is known about composition of margin long investors. However, we can look at behavior of hedge funds, the market participants well-known for their use of leverage, for some clues as to why margin credit may information about the future returns. Chen and Liang (2007) find evidence that market timing hedge funds do time the market particularly during bear and volatile markets.[3] Ang, Gorovyy, and van Inwegen (2011) find that hedge funds reduced their leverage in mid-2007 just prior to the financial crisis. They also find that hedge funds reduce their leverage when the risk of the assets goes up. Agarwal, Ruenzi, and Weigert (2016) find that before the 2008 crisis, hedge funds reduced their exposure to tail risk by changing composition of their stock and option portfolio. Liu and Mello (2011) build a theoretical model to understand why hedge funds might increase their allocation to cash substantially before a crisis. They point to risk of runs by investors of hedge funds as a reason. Indeed, Ben-David, Franzoni, and Moussawi (2012) find that hedge funds substantially reduced their holdings of stocks during the 2007-8 crisis due to redemptions and pressure from their lenders. Such conservative behavior by hedge funds in response to greater risk would push up risk premium i.e. the discount rate. On the other hand, hedge funds, being sophisticated investors could posses superior information about the future cash flows. For example, Brunnermeier and Nagel (2004) find that hedge funds successfully anticipated price movements of technology stocks during the Nasdaq bubble and sold their positions prior to the crash. Indeed, Dai and Sundaresan (2010) theoretically model optimal leverage choice by hedge funds and show that, the optimal leverage, among other things, depends upon the Sharpe Ratio of the assets. Hedge funds optimally cut back the leverage if their estimate of the Sharpe Ratio declines – either due to increase in estimate of risk i.e. discount rate or decrease in estimate of return i.e. cash flows. To the extent that margin investors have similar beliefs and trading strategies as hedge funds, ability of MC to predict future returns could come from the discount rate channel or the cash flow channel.

[3]The evidence on timing ability of hedge funds is mixed. While Chen and Liang (2007) find support for the timing ability, Griffin and Xu (2009) do not.

We next investigate the channel through which MC predicts future returns. Using the log-linearized return identity in Campbell and Shiller (1988) and following the approach in Huang, Jiang, Tu, and Zhou (2015), we examine if MC predicts discount rate and cash flow proxies. Our evidence shows that MC's predictive power flows from both the cash flow and discount rate channels.

Our paper contributes to the long literature on return predictability. In a seminal paper, Fama (1970) reviews early work and casts the evidence in the framework of market efficiency. The work in 1970s and 1980s saw many predictors being examined, with the dividend-price ratio (examined by Campbell and Shiller (1988) among many others) being one of the most popular variables. A sequel by Fama (1991) reviews the later work. The literature has continued to explore newer macroeconomic and financial market variables (see Welch and Goyal (2008) and Rapach and Zhou (2013)). In this strand of literature, we extend recent work that focuses on a subset of investors to successfully predict returns. Huang, Jiang, Tu, and Zhou (2015) show that an index based on Baker and Wurgler (2006) investor sentiment proxies predicts lower future returns. Investor sentiment is likely to reflect the beliefs of unsophisticated investors and accordingly acts as a contrarian predictor. Kruttli, Patton, and Ramadorai (2015) show that aggregate illiquidity of hedge fund portfolios is a significant predictor of a large number of international equity indices including the U.S. index. Rapach, Ringgenberg, and Zhou (2016) show that an index based on aggregate positions of the short investors is a strong, negative predictor of S&P 500 returns through forecasts of lower future cash flows. The results suggest that short sellers are sophisticated investors whose actions contain useful information. Above studies suggest that for predicting equity premium it is more fruitful to extract information about beliefs of the right subset of investors. Similar to the above studies, we find that conservative behavior by levered investors indicates lower future market returns, thus linking the literature on hedge fund behavior (cited above) to the return predictability literature.

Our paper also contributes to the literature that examines impact of margin conditions and leverage ratios of financial market participants to asset prices. Rappoport and White

(1994) find that prior to the 1929 crash, interest rate on margin loans as well as margin requirements increased, indicating an increased expectation of the crash. Garleanu and Pedersen (2011) study, theoretically and empirically, the implications for differential margin requirements across assets. He and Krishnamurthy (2013) theoretically model asset pricing dynamics when the financial intermediaries are capital-constrained. Rytchkov (2014) presents an analysis of risk-free rate, risk-premium and volatilities in a general equilibrium model with endogenously changing margin constraints. He, Kelly, and Manela (2016) find that capital ratio of primary dealers is a cross-sectionally priced factor for many assets. While this literature focuses on the impact of margin requirements or capital constraints, we empirically show that *voluntary* reduction in leverage by margin investors has information about future returns.

Understanding the nature of our new predictors requires understanding the formalities of margin trading and levered accounting. So we turn to it next.

2 Understanding margin credit

In this section, we illustrate how actions of investors lead to changes in margin debt and how margin credit is generated.

2.1. Purchasing on margin

An investor wishing to take a long position in a stock can use 100% of her own funds to take the position or borrow part of the funds from her broker. When she chooses the latter, she must open a "margin" account with the broker. The purchased securities act as a collateral for the loan. As per Federal Reserve Board Regulation T (Reg T), in general, an investor can borrow up to 50% of the value of the stock, subject to the rules of her brokerage house which can be more stringent. The amount of investor's own funds is called margin. The fraction required to be financed by investor's equity at the time of establishing the position – which is

1 minus the maximum borrowing limit – is called the "initial margin". In addition, Financial Industry Regulatory Authority (FINRA) and the exchanges have rules about "maintenance margin", a fraction of the value of the securities, generally 25%, below which the investor's equity must not fall. If the equity falls below the maintenance margin due to a drop in price, the investor will receive a margin call to deposit additional funds into the margin account. On the other hand, if due to favorable price movements the investors' equity becomes higher than the initial margin required, the investor will get a credit in her margin account which she can withdraw without closing the position. We call this credit "margin credit". To clarify the accounting and the statutory rules regarding margin debt and credit, we work through an extended example below.

2.2. Margin accounting

Consider, investor P who wants to buy 10 shares of Apple at USD 100 each. She opens a margin account with broker B, who has a margin requirement of 60% and maintenance margin of 25%. P will need to invest 60% of the value of the position using her own money and can borrow remaining 40% from B. When the position is established the numbers look as follows:

Situation	Shares	Price	Position Value	Margin Debt	Equity	Margin Credit
0	10	100	1000	400	600	0

Now suppose the price falls to USD 50 per share. The 25% maintenance margin is now binding.

Situation	Shares	Price	Position Value	Margin Debt	Equity	Margin Credit
1	10	50	500	400	100	0

In this case, P's equity (Position Value - Margin Debt) is only 20% of the position value, a fraction lower than the maintenance margin. So P will receive a margin call for USD 25 and will have to deposit additional money in the margin account.

Now, consider a different situation where price increases to 250 instead of dropping to

50. This will result in margin credit.

Situation	Shares	Price	Position Value	Margin Debt	Equity	Margin Credit
2	10	250	2500	400	2100	600

With the position value of 2500 and margin debt only 400, the equity is 84% of the value of the position, higher than the margin requirement of 60%. This excess 24% of the position value i.e. 600 is reflected as margin credit. The formula for margin credit is thus

Margin Credit = (Position Value) * (1 - Margin Requirement) - Margin Debt.

(1 - Margin Requirement) is the maximum debt the investor can take as a fraction of the position value. Hence, (Position Value) * (1 - Margin Requirement) gives the total debt capacity of the investor. Once we subtract the debt already taken, we get margin credit which is nothing but *excess debt capacity*.

The investor can choose to withdraw the balance of margin credit, or use it to increase the position value or keep it as margin credit balance. If withdrawn, the margin account numbers will look as follows:

Situation	Shares	Price	Position Value	Margin Debt	Equity	Margin Credit
3	10	250	2500	1000	1500	0

Note that margin credit is part of equity. So if margin credit is withdrawn, equity drops by the amount of margin credit is withdrawn and since position value doesn't change, margin debt goes up. In the above example, after margin credit is withdrawn, margin credit drops to 0 and margin debt increases by 600.

P can choose to use the margin credit to take additional position in Apple. The margin credit of 600 will act as 60% equity for the additional position and P can supplement it with additional loan of 400 to support a position of 1000 or 4 additional shares.

Situation	Shares	Price	Position Value	Margin Debt	Equity	Margin Credit
4	14	250	3500	1400	2100	0

Now the margin debt stands at 1400, an initial loan of 400, withdrawn margin credit of 600 and the additional loan of 400 to buy 4 more shares.

Can we extract any information about future performance of Apple stock from margin debt and margin credit balances? We next turn to this question.

2.3. Information in margin debt and margin credit

An investor would want to lever up a long position using margin debt when she is bullish about the stock. So higher values of margin debt would indicate more positive beliefs about future returns. However, margin debt levels are imperfect proxy of the investor's belief. For example, notice that from Situation 2 to 3, margin debt increased on withdrawal of margin credit even though P did not take additional long position in Apple. Further, there are additional reasons why margin debt may be a noisy signal.

Consider Situation 1 above. In this case, P's position lost value and P received a margin call. If P cannot pay the margin call, the position will have to be closed and margin debt and position value become 0. In case of such forced deleveraging, margin debt balance drops *after* the fall in price, and hence is not useful as a predictive signal for future price movements. Moreover, forced selling to close the long positions may lead to even more price drops and potentially, a spiral of margin calls, forced deleveraging, forced selling and further price drops. In fact, many market participants believe that that high levels of margin debt predict *fall, not rise,* in the market index. For example, an article on a popular blog site $http://www.zerohedge.com/$ asserts[4]

"What is important to remember is that margin debt fuels major market reversions as

[4] $http://www.zerohedge.com/news/2016-03-15/margin-debt-flashes-red-fed-cometh.$

margin calls lead to increased selling pressure to meet required settlements. Unfortunately, since margin debt is a function of portfolio collateral, when the collateral is reduced it requires more forced selling to meet margin requirements. If the market declines further, the problem becomes quickly exacerbated.... The danger of high levels of margin debt, as we have currently, is that the right catalyst could ignite a selling panic.... The issue is not whether margin debt will matter, it is just when. ”

Further, margin debt balances, aggregated across investors, cannot distinguish between investors with superior and inferior information about future returns. Thus, if the population buying on the margin is dominated by investors with incorrect beliefs, high levels of margin debt, would indicate lower future returns. As we discuss below, margin credit is less susceptible to this particular drawback of margin debt because it focuses on winning investors who were correct about their past beliefs.

While margin debt could be a “buy” or “sell” signal (although quite noisy), margin credit appears to be “hold” signal. Greater the margin credit balance, greater is the signal that investors have chosen *not to reinvest*, indicating a lukewarm belief about future returns. Thus we would expect a negative relationship between margin credit and future returns. Moreover, margin credit only results from appreciation of value of long positions indicating that the investors with margin credit have been correct in the past. This focus on winning investors potentially allows margin credit to extract beliefs of relatively sophisticated investors.

However, margin credit is not a perfect signal either. If investors choose to withdraw margin credit as in Situation 3, margin credit balance drops without corresponding improvement in the belief about future returns. Further, margin credit is not the strongest signal of investor pessimism. If investors strongly believe that the market will drop, they would close their leveraged long position and take a short position. This is consistent with Rapach, Ringgenberg, and Zhou (2016) who find that aggregate short interest is a “sell” signal. Thus, it is matter of empirical investigation how well margin debt and margin credit balances work as predictive signals about aggregate stock returns.

3 Data

We construct scaled margin debt and scaled margin credit from monthly data on the value borrowed by all investors with NYSE member organizations and the amount held by the same investors which could be withdrawn.[5] The data are end of month values and FINRA rule 4521 requires that these numbers be reported for only investor accounts used to take long positions on margin. That is, these numbers represent different information than is contained in the monthly reporting on short trading.[6] The data is available at the NYSE and FINRA websites with a two month delay.[7] To account for the two month reporting delay, we use margin debt and credit numbers that are two months old to avoid look-ahead bias. For example, we use the June 1995 numbers for August 1995.

The raw margin statistics numbers are reported in millions of dollars. We scale these values so they are relative to the size of the economy by dividing by nominal GDP. We pull the history of all GDP announcements from the Federal Reserve Bank of Philadelphia website (https://www.philadelphiafed.org/). This provides the numbers announced in each

[5]NYSE Rules Chapter 1.2.1.17 rule 2 defines ”member organization” as a registered broker or dealer that is a member of the Financial Industry Regulatory Authority, Inc. (”FINRA”) or another registered securities exchange.

[6]Rule 4521(d) requires that a member must only include free credit balances in cash and securities margin accounts in the report. Balances in short accounts and in special memorandum accounts (see Regulation T of the Board of Governors of the Federal Reserve System) are not considered free credit balances.

[7]Updated margin debt and credit numbers are available from the NYSE at http://www.nyxdata.com/nysedata/asp/factbook/viewer_edition.asp?mode=tables&key=50&category=8. FINRA makes available the same numbers at http://www.finra.org/investors/margin-statistics.

quarter since 1965 which includes numbers for every quarter since 1947. So, for example the announcement in Q1 1995 would include numbers for each quarter since 1947 up to the first announced numbers for Q4 1994 while the announcement in Q1 1996 would include numbers from 1947 upto Q4 1995 and the numbers for Q4 1994 would be in the fourth revision.

For the purposes of in-sample testing we take the values announced in Q4 2015 which have the fourth, usually final, revisions for the numbers through Q4 2014. For out of sample testing, the GDP numbers that are available to investors at that time of making a prediction are used to avoid any look-ahead bias. So for making a prediction in August 1997, we use the numbers available in the Q2 1997 announcement. The GDP numbers used are further lagged by taking the Q1 1997 GDP value from Q2 1997 announcement. This last adjustment is done because there seems to be the largest change in value from the first to second revision in GDP announcements.

The GDP numbers provided are in real 2009 dollars. To eliminate the look ahead bias that would be introduced by dividing MC, a nominal value, by real 2009 GDP dollars, we convert the numbers to the nominal values before dividing. This gives us the ratio that investors would have had seen when dividing nominal MC by nominal GDP in a given month.

Margin statistics are available from January 1959. However revisions to Reg T in June 1983 make post-1983 margin credit incomparable to pre-1983 margin credit.[8] To insure comparability of data across time we begin our sample in 1984, using the margin statistics available as of December 1983.[9]

Our focus is on the prediction of excess returns to a value-weighted portfolio. Consistent with existing literature we measure this excess return as the log of the return to the S&P 500

[8]See the NYSE margin statistics website for details.

[9]Due to reporting lag the margin statistics are the value reported for October 1983 which are made available in December 1983.

minus the log of the return to a one month Treasury bill.[10] We compare the predictive ability of margin credit and margin debt to the 14 monthly predictors of Welch and Goyal (2008), the mean prediction of those 14 variables (Rapach, Strauss, and Zhou (2010)), the modified mean prediction using the strictest modification proposed by Campbell and Thompson (2008), market capitalization to GDP, the so called "Buffett Valuation Indicator", and the short interest index measure of Rapach, Ringgenberg, and Zhou (2016).[11] Data on the 14 monthly variables of Welch and Goyal (2008) is available from Amit Goyal's website this includes:

- Log dividend-price ratio (DP): log of the ratio of the 12-month moving sum of dividends paid on the S&P500 index and the S&P 500 index.
- Log dividend yield (DY): log of the ration of the 12-month moving sum of dividends paid and the previous month's S&P 500 index.
- Log earnings-price ratio (EP): log of the ratio of the 12-month moving sum of earnings on the S&P 500 index and the S&P 500 index.
- Log dividend-payout ratio (DE): log of the ratio of the 12-month moving sum of dividends and the 12-month moving sum of earnings.
- Excess stock return volatility (RVOL): computed using the 12-month moving standard deviation estimator.
- Book-to-market ratio (BM): book-to-market value ratio for the Dow Jones Industrial Average.

[10] These data are available from Amit Goyal's website: http://www.hec.unil.ch/agoyal/

[11] In addition to the popularity of Buffett Valuation Indicator, we include this measure to demonstrate that the performance of margin credit scaled by GDP is not induced by a valuation effect coming from the ratio of market capitalization to GDP.

- Net equity expansion (NTIS): ratio of the 12-month moving sum of net equity issues by NYSE-listed stocks to the total end-of-year market capitalization of NYSE stocks.
- Treasury bill rate (TBL): interest rate on a three-month Treasury bill traded on the secondary market.
- Long-term yield (LTY): long-term government bond yield.
- Long-term return (LTR): return on long-term government bonds.
- Term spread (TMS): long-term yield minus the Treasury bill rate.
- Default yield spread (DFY): difference between Moodys BAA- and AAA-rated corporate bond yields.
- Default return spread (DFR): long-term corporate bond return minus the long-term government bond return.
- Inflation (INFL): calculated from one month lagged Consumer Price Index (CPI) for all urban consumers

We scale market capitalization numbers from the Center for Research in Security Prices (CRSP) by GDP. This is available monthly through the end of 2015 and from this we construct:

- Market Capitalization to GDP (CAP/GDP): the ratio of the monthly CRSP total market capitalization to quarterly GDP number.

Rapach makes available the monthly equally-weighted short interest (EWSI) data on his website.[12] These numbers are available through the end of 2014. Because EWSI ends in

[12]http://sites.slu.edu/rapachde/home/research

2014, we end our data in December of 2014.[13] From EWSI we calculate:

- Short Interest Index (SII): the residual values from the detrending of the log of the monthly equally-weighted short interest (EWSI).

Huang, Jiang, Tu, and Zhou (2015) construct a sentiment index from the 6 proxies from Baker and Wurgler (2006) based on the partial least square approach. The data for this variable is available from Zhou's webpage.[14] We call this variable SI_PLS.[15]

Rapach, Ringgenberg, and Zhou (2016) detrend the log of EWSI by regressing it against a time variable, due to evidence of a significant linear trend. We suspect the presence of a deterministic trend in our primary variable of interest, the ratio of margin credit to GDP, for the same reason which Rapach, Ringgenberg, and Zhou (2016) cite for the rising trend in equally-weighted short interest. They highlight the expansion of the equity lending market along with the increase in the number of hedge funds and size of assets managed by hedge funds. This expands the portfolios against which margin debt can be raised and by which margin credit is generated, but is uninformative in regards to the expectations of margin long investors. Statistical tests for the presence of a significant deterministic trend, tests of the significance of β_c and β_d, are subject to size and power distortions depending on the sample size and the estimated auto-correlation in the sample. (See Harvey, Leybourne, and Taylor (2007) and Perron and Yabu (2009).) Perron and Yabu (2009) show that their trend test is at least as efficient and powerful as any other in our sample size, 373 months, and given the naive estimate of the auto-correlation which, for example, is above 0.95 for margin credit. We find that margin credit to GDP shows a deterministic trend at the 1% level in

[13] Due to the substantial performance of SII shown in Rapach, Ringgenberg, and Zhou (2016), we also extend back from 1983 to 1973 the monthly data available for EWSI and construct SII 1973 using all of the data made available on Rapach's website.

[14] $http://apps.olin.wustl.edu/faculty/zhou/SentimentIndices_Dec2014.xls$

[15] Similar to SII 1973, we also use SI_PLS 1965 where we use all of the data available for SI_PLS.

the Perron-Yabu test with a t-statistic of 3.36. Indeed, Ng and Perron (2001) unit root test rejects unit root in Margin Credit to GDP against the alternative of trend stationary at 10% (statistic: -2.58, critical value: -2.57). Kwiatkowski, Phillips, Schmidt, and Shin (1992) (KPSS) unit root test rejects the unit root against the alternative of trend stationarity at 5% (statistic: 0.1614, critical value: 0.146). We thus detrend the ratios of margin credit and margin debt to GDP by the same regression method as Rapach, Ringgenberg, and Zhou (2016). We run the following regressions,

$$\frac{MarginCredit_t}{GDP_t} = \alpha_c + \beta ct + u_t$$
$$\frac{MarginDebt_t}{GDP_t} = \alpha_d + \beta_d t + v_t$$

The residuals from these regressions u_t and v_t are our predictors, MC and MD, respectively. For robustness, we test MC and MD for non-stationarity which is rejected by the augmented Dickey-Fuller, Ng-Perron, and the KPSS tests.

Removing the uninformative increases from MC and MD leaves us with economically relevant measures of the debt level and excess debt capacity held by margin long investors. As with SII, these measures are standardized with mean zero and standard deviation 1 as are all other predictors for comparability. For out-of-sample tests, MC and MD are computed recursively using only the data available up to time t to avoid look-ahead bias.

3.1. Summary statistics

Over the period January 1984 to December 2014, as shown in Table 1, margin debt has a mean value of \$153.08 billion and a mean MD/GDP ratio of 1.36%. Margin credit has a mean level of \$73.10 billion and a mean MC/GDP ratio of 0.58%. All of the highest 10 values of the ratio of margin credit to GDP occur in 2008 with the peak, 2.6%, occurring in October of 2008. Figure 1 shows that margin credit to GDP remains low through the 1980s and 1990s with the exception of a spike in 1987. It shows a large increase in late 2000 before the "Dotcom Bubble" burst of 2001 and again before the 2008 financial crisis. This behavior is similar to that for SII and as such we expect margin credit to GDP and SII to be correlated.

Table 2 displays Pearson correlation statistics for the 14 Goyal and Welch variables, the Buffett Valuation Indicator, SII, SI_PLS, MC and MD. Indeed MC and SII are correlated with coefficient of 0.58 indicating that margin long investors are holding cash buffers at the same time that heavy short trading occurs. This coefficient is even higher than the correlation of MC with MD giving some early indication that the changes in MC are not simply mechanical movements related to changes in margin debt. Additionally, MC is largely unrelated to the Buffett Valuation Indicator which in turn is not highly related to next month returns. MC is positively correlated with SI_PLS with coefficient of 0.34. So margin investors are also being conservative when investor sentiment is high. MC also shows the largest magnitude of correlation – -0.25 –with next months returns, an early indication of predictive power of MC.

4 Return predictability tests

4.1 In-sample tests

Following the literature, we estimate a predictive regression of the following form:

$$r_{t:t+H} = \alpha + \beta x_t + \epsilon_{t:t+H}, \tag{1}$$

where $r_{t:t+H}$ is the average monthly S&P 500 log excess return for month $t+1$ to month $t+H$, and x_t the predictor variable which part of investors' information set at time t. We test for return predictability at monthly, quarterly, semi-annual and annual frequency by setting value of H to 1, 3, 6 and 12. For $H > 1$, returns on the RHS of Equation (1) overlap and OLS t-statistics are overstated. To deal with this problem we follow the approach in Britten-Jones, Neuberger, and Nolte (2011)). They show that regression of overlapping observations of N-period return on a set of X variables can, instead, be estimated using a transformed, equivalent representation of regression of one-period return on aggregation of N lags of the X variables. They also show that their methodology retains the asymptotic validity of conventional inference procedure and has better properties in finite sample compared to the use of standard heteroskedasticity and autocorrelation-adjusted robust t-statistics correct for overlapping observations.

Table 3 reports the coefficients, t-statistics and R^2 for 14 popular predictors examined by Welch and Goyal (2008), the Buffett indicator, SII, SII_PLS, and our variables MD and MC for the sample period 1984 to 2014. Following Inoue and Kilian (2005), we use a one-sided test for the statistical significance of β based on its theoretically expected sign. Following Huang, Jiang, Tu, and Zhou (2015) and Rapach, Ringgenberg, and Zhou (2016), we base our inference on empirical p-values calculated using a wild bootstrap procedure to address the issues of regressor persistence and correlation between regressor innovations and excess returns (see Stambaugh (1999)).[16] For ease of comparison across different regressors, we scale all RHS variables so that they all have a unit standard deviation.

Table 3 shows that out of the 14 Goyal and Welch variables, DP and DY have the best performance, with significant in-sample βs at all horizons and R^2 higher than the rest, 0.70%-0.80% at monthly horizons, rising to more than 10% at annual frequency. Consistent with evidence in Huang, Jiang, Tu, and Zhou (2015) and Rapach, Ringgenberg, and Zhou (2016), SI_PLS and SII are even more impressive with larger beta coefficients and higher R^2 at all horizons. β for MD has the expected negative sign, as argued in Section 2. The ability of MD to predict returns in-sample matches that of SII in terms of magnitude of β and R^2, even surpassing it occasionally, as it generates significantly larger R^2 at annual frequency of around 25% compared to around 17% for SII.

The variable that stands out in Table 3 is MC. At all horizons, the β for MC substantially bigger. MC also has the largest R^2, often more than double the corresponding numbers for the next best predictors, SII and MD. Standards of predictive return regressions established in Campbell and Thompson (2008) suggest that a monthly R^2 as low as 0.5% in a predictive regression is economically significant. The monthly R^2 of MC is over 6%. The economic significance of β for MC of around 1.1 is also large. A one standard deviation higher value of MC predicts a market return lower by 1.1%, or 25% of standard deviation in monthly return.

[16]The p-values based on the wild bootstrap procedure accounts for the issues raised in Stambaugh (1999). However, we also explicitly correct the bias in estimated β using a procedure in Stambaugh (1999). The results are very similar as those reported in Table 3. The bias-corrected coefficients are available from the authors upon request.

Even though in-sample performance of MC is quite impressive, Bossaerts and Hillion (1999), Goyal and Welch (2003), and Welch and Goyal (2008) show that in-sample performance does not always translate into out-of-sample return predictability. So next, we examine out-of-sample performance of MC.

4.2 Out-of-sample tests

Our results so far suggest robust in-sample predictability of aggregate stock returns by margin credit. However, as Bossaerts and Hillion (1999) and Goyal and Welch (2003, 2008) show that many robust in-sample predictors do no exhibit out-of-sample predictability. In this section, we first show that margin credit is a robust out-of-sample return predictor. We then use forecast encompassing tests to compare the information content of return prediction by margin credit with that of other predictors.

Following Welch and Goyal (2008), we generate an equity premium prediction for $t+1$ by a predictor x at time t,

$$\hat{r}_{t+1} = \hat{\alpha}_t + \hat{\beta}_t x_t \tag{2}$$

where $\hat{\alpha}_t$ and $\hat{\beta}_t$ are estimated with information available only until time t. That is, we estimate $\hat{\alpha}_t$ and $\hat{\beta}_t$ by regressing $\{r_{s+1}\}_{s=1}^{t-1}$ on a constant and $\{x\}_{s=1}^{t-1}$. We follow an expanding window approach so that for the next period $t+2$, $\hat{r}_{t+2}$ is estimated as $\hat{\alpha}_{t+1} + \hat{\beta}_{t+1} x_{t+1}$, where $\hat{\alpha}_{t+1}$ and $\hat{\beta}_{t+1}$ by regressing $\{r_{s+1}\}_{s=1}^{t}$ on a constant and $\{x\}_{s=1}^{t}$. We follow this process for all subsequent months.

We consider all the predictors covered in the in-sample tests and two new combinations of the Goyal and Welch variables. Timmermann (2006) and Rapach, Strauss, and Zhou (2010) show that a simple combination of individual forecasts significantly improves predictability.

Thus, we also consider a equally-weighted combination of 14 individual forecasts from Goyal and Welch variables. We call this forecast, $GW\ MEAN$. In a related work to improve forecasts, Campbell and Thompson (2008) recommend economically motivated sign restrictions on $\hat{\beta}_t$ and $\hat{r}_{t+1}$. Specifically, the strictest recommend setting $\hat{r}_{t+1} = 0$, if $\hat{r}_{t+1}$ turns out to be negative is used. We call the equally-weighted combination of individual forecasts with Campbell and Thompson (2008) restriction $GW\ MEAN\ CT$.

As in Welch and Goyal (2008), Rapach, Strauss, and Zhou (2010), Rapach and Zhou (2013), Kelly and Pruitt (2013), Huang, Jiang, Tu, and Zhou (2015), Rapach, Ringgenberg, and Zhou (2016) among others, we divide the total sample (1984:01 - 2014:12) in to initial training period ($t = q$ months) and the remaining period ($t = q+1, q+2, .., T$) for out-of-sample forecast evaluation. We use the data for the first 10 years from January 1984 through December 1993 for the first out-of-sample prediction for January 1994 ($t = q + 1$). We then generate the subsequent periods' predictions as outlined above.

We use the R^2_{OS} statistic (Campbell and Thompson (2008)) to evaluate out-of-sample predictions. R^2_{OS} is defined as

$$R^2_{OS} = 1 - \frac{MSFE_x}{MSFE_h} \tag{3}$$

where $MSFE_x$ is the mean squared forecast error when the variable x is used to generate out-of-sample predictions. $MSFE_h$ is mean squared forecast error when the historical mean, $\bar{r}$, is used to generate out-of-sample predictions. Specifically, we define $MSFE_x$ as

$$MSFE_x = \frac{1}{T-q} \sum_{t=q}^{T-1} (r_{t+1} - \hat{r}_{t+1})^2 \tag{4}$$

Similarly, $MSFE_h$ is defined as,

$$MSFE_h = \frac{1}{T-q}\sum_{t=q}^{T-1}(r_{t+1} - \bar{r}_{t+1})^2 \tag{5}$$

where $\bar{r}$ is the historical mean of log excess returns. We obtain $\bar{r}$ as

$$\bar{r}_{t+1} = \frac{1}{t}\sum_{s=1}^{t} r_t \tag{6}$$

R^2_{OS} measures proportional reduction in $MSFE$ when variable x is used to forecast equity premium relative to historical average. An $R^2_{OS} > 0$ suggests that $MSFE$ based on variable x is less than that based on historical mean. As in Rapach, Strauss, and Zhou (2010) and Rapach, Ringgenberg, and Zhou (2016), among others, we evaluate the statistical significance of R^2_{OS} using Clark and West (2007) statistic. This statistic is also known as the $MSFE-adjusted$ statistic and it follows the standard normal distribution.[17] $MSFE-adjusted$ statistic tests the null hypothesis that $H_0 : R^2_{OS} \leq 0$ against $H_A : R^2_{OS} > 0$.

Table 4 presents the out-of-sample results. At the monthly horizon of H=1, none of the 14 macroeconomic predictors considered in Welch and Goyal (2008) produce positive R^2_{OS}. $GW\,MEAN$ and $GW\,MEAN\,CT$ are also negative. Consistent with Rapach, Ringgenberg, and Zhou (2016), we find that short interest (SII) generates positive and statistically significant R^2_{OS} of 1.16%. Short interest generates an even higher R^2_{OS} of 2.17% when we start the training period in 1973 (SII 1973). SI_PLS also has large and significant R^2_{OS} in our sample period at 2.5%-3.0%. MD does poorly with a negative R^2_{OS}. While SII and SI_PLS beat the historical benchmark in MSFE terms, it is MC which exhibits the highest R^2_{OS} of

[17] The Diebold and Mariano (1995) and West (1996) statistic has a nonstandard distribution for forecast comparison across nested models. The historical benchmark model is a nested model that corresponds to $\hat{\beta}_t = 0$.

7.45% statistically significant at 1% level. MC also generates highest R^2_{OS} at the quarterly, semi-annual and annual horizons.

Table 5 examines the out-of-sample performance of the two halves of our sample as well as during NBER contractions and expansions. MC has positive R^2_{OS} and beats almost all predictors in all four subsamples. Only EP and SI_PLS 1965 have larger R^2_{OS} than MC during 1994-2004, and only SI_PLS 1965 during NBER expansions.

We further assess the cumulative difference in squared forecast error ($CDSFE$) graphically (see, for instance, Welch and Goyal (2008), Rapach, Strauss, and Zhou (2010), Rapach and Zhou (2013)). $CDSFE$ is obtained over the out-of-sample period starting from $t = q+1$ to $t = \tau$ as

$$CDSFE_\tau = \sum_{t=q}^{\tau}(r_{t+1} - \bar{r}_{t+1})^2 - \sum_{t=q}^{\tau}(r_{t+1} - \hat{r}_{t+1})^2 \tag{7}$$

Recall that the initial training period is from $t = 1$ to $t = q$, so that the first out-of-sample prediction starts at $t = q + 1$. Figure 2 shows the time-series plot of $CDSFE$ over January 1994 to December 2014 for six variables: MC, MD, SII, SI_PLS, $GW\ MEAN$, and $GW\ MEAN\ CT$. A positive $CDSFE$ indicates that the predictive model based on a variable outperforms historical benchmark in terms of $MSFE$. For large part of the out-of-sample period MC outperforms the historical mean. MC especially bests the historical mean during and around recessions. During uncertainty high risk-version, margin credit is very useful in asset allocation decisions. This is consistent with the evidence in other studies, such as Huang, Jiang, Tu, and Zhou (2015) that out-of-sample predictability is more significant around recessions. Performance of SII and SI_PLS also improves during recessions. The GW combination forecasts and MD do not outperform the historical mean. Overall, based on R^2_{OS} and $CDSFE$, MC exhibits robust out-of-sample predictability.

4.3 Forecast encompassing tests

Our in-sample and out-of-sample results suggest that MC predicts stock returns better than all predictors used in the literature. We now examine statistically the explanation for these results based on forecast encompassing tests (Chong and Hendry (1986) and Fair and Shiller (1990)). Forecast encompassing tests compare the information content of return forecasts of a common dependent variable across predictive regressions of different independent variables (see for instance, Rapach, Strauss, and Zhou (2010), Rapach and Zhou (2013), and Rapach, Ringgenberg, and Zhou (2016)).

We form an optimal forecast as a convex combination of two forecasts for month $t+1$ as

$$\hat{r}^*_{t+1} = (1-\lambda)\hat{r}_{1,t+1} + \lambda\hat{r}_{2,t+1}, \tag{8}$$

where $\hat{r}_{1,t+1}$ is the forecast based on the first variable, $\hat{r}_{2,t+1}$ is the forecast based on the second variable, and $0 \leq \lambda \leq 1$. If $\lambda = 0$, it suggests that the forecast $\hat{r}_{1,t+1}$ encompasses $\hat{r}_{2,t+1}$. In other words, the second variable does not have any information beyond the information contained in the first variable to predict excess market returns. However, if $\lambda > 0$, it suggests that the forecast $\hat{r}_{1,t+1}$ does not encompasses $\hat{r}_{2,t+1}$ and both variable 1 and 2 have some information not contained in the other that is useful to predict excess returns. We test the null hypothesis that $H_0 : \lambda = 0$ against the alternative that it is greater than zero $H_A : \lambda > 0$. The statistical significance is based on the Harvey, Leybourne, and Newbold (1998) statistic. We report combinations over monthly ($H = 1$), quarterly ($H = 3$), semi-annual ($H = 6$) and annual horizons ($H = 12$).

The values in 6 represent the λ's for the predictors in the columns against the predictors along the rows. The first predictor variable, generating $r_{1,\hat{t}+1}$ is in column 1, while the second predictor variable changes across the remaining columns. Focusing on monthly prediction combinations ($H = 1$), the column under MC has large positive and statistically significant λ's with values of either 1 or very close to 1. In other words, predictions based on MC encompass the predictions based on all other variables. These include MD, $GW\ MEAN$, SII, SII 1973, SI_PLS, and SI_PLS 1965. Focusing on the last row, we find that none of the predictions based on other variables have λ's significantly different from 0. Thus, none of the other variables seem to provide additional information not already contained in MC. We find similar evidence at longer horizon predictions.[18] Margin credit has superior information in comparison to other predictors for future excess market returns.

5 Asset allocation

Our out-of-sample results based R^2_{OS} show that margin credit is a robust predictor of stock returns which encompasses the information available in all other predictors with power. This should allow an investor to profit more from a strategy based on MC than based on any other predictor. As in Kandel and Stambaugh (1996), Campbell and Thompson (2008), Ferreira and Santa-Clara (2011), and Rapach, Ringgenberg, and Zhou (2016), among others, we consider a mean-variance investor who allocates money optimally, at the end of month t, between a risky asset , the S&P500 index, and a risk-free asset based on out-of-sample prediction of excess return. The investor re-balances portfolio at the monthly frequency. We compute the certainty equivalent return (CER) gain and Sharpe Ratio for strategies using each predictor. Specifically, at the end of month t, the investor optimally allocates the

[18] λ's for quarterly ($H = 3$), semi-annual ($H = 6$) and annual horizons ($H = 12$) are not reported but are available from the authors upon request.

following weight to equities during the month $t + 1$:

$$w_t = \frac{1}{\gamma} \frac{\hat{r}_{t+1}}{\hat{\sigma}^2_{t+1}} \tag{9}$$

where γ is the risk-aversion coefficient, $\hat{r}_{t+1}$ is the out-of-sample forecast of the simple excess return, and $\hat{\sigma}^2_{t+1}$ is the variance forecast. We follow Campbell and Thompson (2008) and estimate $\hat{\sigma}^2_{t+1}$ using monthly returns over a 10 year moving window. As in Rapach, Ringgenberg, and Zhou (2016), we restrict w_t to lie between -0.5 and 1.5 and consider $\gamma = 3$. This investor realizes an average utility of

$$\hat{\nu}_x = \hat{\mu}_x - \frac{1}{2}\gamma\hat{\sigma}^2_x \tag{10}$$

where $\hat{\nu}_x$ and $\hat{\sigma}^2_x$ are the mean and variance over the out-of-sample period for the return of the portfolio formed using $\hat{r}_{t+1}$ and $\hat{\sigma}^2_{t+1}$. If however, the investor allocates money based on the historical mean, she optimally allocates

$$w_t = \frac{1}{\gamma} \frac{\bar{r}_{t+1}}{\hat{\sigma}^2_{t+1}} \tag{11}$$

to equities during the month $t + 1$ and realizes an average utility of

$$\hat{\nu}_h = \hat{\mu}_h - \frac{1}{2}\gamma\hat{\sigma}^2_h \tag{12}$$

where $\hat{\mu}_h$ and $\hat{\sigma}^2_h$ are the mean and variance over the out-of-sample period for the return of the portfolio formed using $\bar{r}_{t+1}$ and $\hat{\sigma}^2_{t+1}$. The CER gain is given by the difference between ν_x and ν_h. We multiply it by 12 to annualize the CER. The annualized CER can be interpreted as the management fee that an investor will be willing to pay to have access to the equity premium forecasts based on the predictor x instead of historical mean.

Table 7 shows that, consistent with out-of-sample predictability, SII, SI_PLS, MC generate strong CER gains. Out of these predictors, margin credit generates highest annualized CER gains of 9.55%. The second highest CER gain is generated by SI_PLS around 7%-7.5%. Thus margin credit outperforms the next best predictor by more than 2 percentage points p.a. Margin credit also outperforms all other strategies in terms of Sharpe ratio. It generates the highest Sharpe ratio of 1.0 nearly doubling the Sharpe ratio of the buy and hold market return.

Table 7 shows results over different subsamples as well as over NBER recessions and expansion periods. During both the subsamples, 1994:01 to 2004:12 and 2005:01 to 2014:12, margin credit outperforms other predictors both in terms of Sharpe ratio as well as CER gains. We find similar results over NBER business cycles. The performance is particularly spectacular during recessions. Out of the very few predictors that generate positive Sharpe ratio, MC is the best with Sharpe ratio of 1.42, more than 6 times the Sharpe ratio for the next best predictor. MC also performs the best with the highest CER gain, 50% more that of SI_PLS, the next best predictor. This is consistent with the earlier evidence in Figure 2 that shows that margin credit outperforms historical mean dramatically during recessions.

While the strategy for the mean-variance investor, that allows for shorting the S&P 500 can be easily implemented using S&P 500 futures, we also consider a long only strategy that even retail investors can implement. Table 8 shows out-of-sample performance statistics for a long only investor that invests either 100% in the equity market or 100% in the risk-free asset. The investments weights are determined by the prediction of one month ahead excess log return to the S&P 500. The investment weight is 1 in S&P 500, when the prediction is positive and 0 otherwise. Buy and hold corresponds to the investor passively holding the market portfolio.

We find that using this very simple switching strategy between the equities and risk-free asset, a long only investor realizes the highest Sharpe Ratio utilizing the predictions based on margin credit. Over the full out-of-sample from 1994:01 to 2014:12, the investor realizes a Sharpe Ratio of 0.92. SI_PLS 1965 does almost as well with 0.90. Both have CER gains of around 5% p.a. Over the subsamples and as well as NBER business cycles, MC and SI_PLS 1965 continues to be the two best predictors, consistently generating higher Sharpe ratios and CER gains than the other predictors.

6 Economic channels

A fundamental relationship in finance is that the value of a stock is the discounted present value of the future expected cash flows. Thus, stock return for any period can result from change in the discount rate or change in the expectations of the cash flows or both. Then a variable that predicts lower stock market return must either predict an increase in the discount rate or a decrease in cash flow expectations or both.

We have seen so far that MC predicts aggregate stock market return with a negative sign. If its predictive ability comes from the discount rate channel, MC must predict an increase in the discount rate. This is plausible. A higher value of MC means the investors are choosing not to reinvest in the stock market and holding cash instead - a reduction in the effective leverage. Ang, Gorovyy, and van Inwegen (2011) find that hedge funds' leverage decreased in mid-2007 prior to the financial crisis. They show that hedge fund reduce their leverage in response to increased riskiness of the assets - a strategy consistent with hedge funds targeting a particular risk profile. They reduce their exposure if the risk goes up. The evidence in Agarwal, Ruenzi, and Weigert (2016) shows that before the 2008 crisis, hedge funds reduced their exposure to tail risk. Margin investors could also be following a similar strategy. This withdrawal from risky assets by investors who are usually willing to bear risk means the overall risk-bearing capacity of the market goes down, pushing up the risk premium and the discount rate.

Liu and Mello (2011) also report that, just prior to the 2008 market crash, hedge funds reduced their risky investments and increased their allocation to cash. To explain such a phenomenon, they present a model where hedge funds act conservatively when faced with a risk of run by their investors. Consistent with this notion, Ben-David, Franzoni, and Moussawi (2012) find that reduction in hedge funds' stock holdings during the 2007-8 crisis was primarily due to redemptions and pressure from their lenders. If the margin long investors are managing money on behalf of others, they may face trade-offs similar to the hedge funds. They may, thus, act conservatively when anticipating greater redemption risk and hold more money as margin credit rather than reinvesting it. This conservative behavior when faced with greater risk also results in higher risk premium and consequently a higher discount rate.

Note that for the above arguments to hold, the margin investors do not need to be the *marginal* investors. They simply need to act on the basis of anticipated behavior of the *marginal* investors for their actions to predict the discount rate.

On the other hand, predictive power of MC could also come from the cash flow channel. Brunnermeier and Nagel (2004) find supportive evidence by showing that hedge funds successfully timed price movements of technology stocks during the Nasdaq bubble. Theoretical model in Dai and Sundaresan (2010) shows that hedge funds' optimal leverage depends upon Sharpe ratio of the assets. If Sharpe ratio goes down, either due to lower expected return – cash flow channel – or higher standard deviation – discount rate channel. Thus, conservativeness on the part of margin investors could also reflect superior information about future cash flows that has not been incorporated in the prices. The argument here is similar as in the case of aggregate short interest. Rapach, Ringgenberg, and Zhou (2016) provide evidence that that ability of SII to predict aggregate returns comes about because short investors are better informed about future cash flows. As we argue in Section 2, margin credit, as opposed to margin debt, allows us to focus on winning investors which are likely to be sophisticated investors. So it is possible that they pull back from reinvesting their gains when they expect the future cash flows to be low. Then, the ability of MC to predict future returns would come via the cash flow channel.

We use the approach in Huang, Jiang, Tu, and Zhou (2015) to investigate whether the discount rate channel or the cash flow channel or both play a role in the predictive ability of MC.

Campbell and Shiller (1988) log-linearize the stock return and give the following approximate identity:

$$R_{t+1} = k + DG_{t+1} - \rho D/P_{t+1} + D/P_t. \tag{13}$$

Here R_{t+1} is the aggregate stock market return from t to $t+1$. DG_{t+1} is the log aggregate dividend-growth rate from from t to $t+1$. D/P_t is the log aggregate dividend price ratio at time t. k and ρ are constants.

Based on the above equation, controlling for information already available in D/P_t, MC

predicting R_{t+1} means it must forecast either $D/Pt+1$ or DG_{t+1} or both. Arguments in Cochrane (2008) and Cochrane (2011) suggest that the variation in dividend-price ratio is mainly due to changes in the discount rate. Dividend growth captures the changes in cash flows. Thus, Equation 13 formalizes the cash flow channel and discount rate channel dichotomy. MC's ability to predict the aggregate dividend-price ratio, our proxy of the discount rate, would point to the discount rate channel. If it predicts aggregate dividend growth rate, the channel would be cash flow predictability.

Following Huang, Jiang, Tu, and Zhou (2015), we run the following regressions,

$$Y_{t+1} = \alpha + \beta MC_t + \psi DP_t + \eta_{t+1}, \qquad Y = Ret, DP, DG, EG, GDPG. \tag{14}$$

Here, Ret is the log excess return on the S&P 500 index (including dividends). DP is the the log of 12-month dividend to price ratio for the S&P 500. DG and EG are the growth rates of log aggregate dividends and log aggregate earnings respectively. GDPG is the growth rate of log real GDP. DP, DG and EG are constructed from the data provided by Robert Shiller on his website.[19] In addition to the dividend growth, we use aggregate earnings growth rate and real GDP growth rate as alternative measures of changes in cash flows. We run the regressions in (14) at quarterly and annual frequency. Quarterly observations allow us to use the information available at finer frequency. However, to avoid influence of strong seasonal patterns, particularly in DG and EG, we run the regressions also at annual frequency.

Further, to use the information available monthly and yet retain the annual growth rates to avoid the seasonality issue, we also run the regressions (except $Y = GDPG$)[20] at monthly frequency, with returns and growth rates measured as monthly averages over annual

[19]http://www.econ.yale.edu/ shiller/data.htm

[20]GDP numbers only change quarterly preventing a monthly calculation of GDP growth.

overlapping periods. These specifications are similar to the ones in our in-sample analysis with $H = 12$ We again follow the methodology suggested in Britten-Jones, Neuberger, and Nolte (2011) to transform the regression of overlapping observations of Y on X to a regression of monthly, non-overlapping observations of Y on the aggregation of lags of the X.[21]

Table 9 presents the results. For all frequencies, calculate Newey-West t-statistics, and report the statistical significance based on wild boot-strapped p-values. First row in each panel reports univariate regression of Ret_{t+1} on MC_t. Consistent with our in-sample results discussed in Section 2, MC has predictive power at all frequencies. The second row in each panel shows results for Equation (14) for $Y = Ret$ - specification in Row 1 with DP added as a control. We see that the coefficient β in Row 2 has magnitude and significance very similar that in Row 1. Thus MC retains its ability to predict return even after controlling for DP. This is not surprising given the results in Table 6 on forecast encompassing tests. There we find that for quarterly, semi-annual and annual frequencies, forecasts based on DP do not provide any additional information over and above the forecasts based on MC.

Rows 3 onward in the panels in Table 9 present results of our investigations of the economic channels. In all the panels, β for DP is positive and statistically significant. This result is consistent with MC predicting the returns via the discount rate channel. It predicts a lower return because it predicts a higher value of DP i.e. a higher discount rate.

We also find support for the cash flow channel. In all the panels, the coefficients for DG, EG and $GDPG$ are negative and statistically significant. Thus, MC also captures information about future cash flows. It predicts a lower return partly because it predicts lower cash flow growth. This result is similar to those of Huang, Jiang, Tu, and Zhou (2015)

[21]Differences arise from allowing more observations in the tests here. While the in-sample transformed regressions are restricted to drop end of sample observations as the overlapping in-sample specifications do.

and Rapach, Ringgenberg, and Zhou (2016) that SI_PLS and SII predict return via the cash flow channel. From the forecast encompassing tests (Section 4.3), we know that at quarterly, semi-annual and annual frequencies, MC contains all the information in SII and SI_PLS that is relevant for forecasting returns. Thus, it is reasonable that, just like SII and SI_PLS, it contains the information about future cash flows. Overall, both the discount rate channel and cash flow channel information contribute to MC's very strong ability to predict future returns.

7 Conclusion

Our study finds that margin credit, excess debt capacity of investors buying on the margin, is a powerful predictor of future excess market returns. After taking out a statistically significant trend, a one standard deviation higher margin credit predicts that future return would be lower by 70 to 110 basis points per month. Over a period from 1984 to 2014, MC produces R^2 for an in-sample predictive regression ranging from 6% at monthly horizons to 27% at annual horizons. These numbers are often more than twice as large as the R^2 of the best predictors, old and new, previously suggested in the literature. In the out-of-sample tests over a period from 1994 to 2014, MC again outperforms other predictive variables by large margins. Moreover, once we consider the information in MC, the other predictors don't provide any additional information relevant for forecasting. A trading strategy based on MC generates 9.5% annualized CER gains, relative to a strategy based on the historical equity premium.

Substantial predictive power of MC is partly due to its ability to successfully predict and hence avoid substantial parts of the market downturns of the early 2000s and 2008. Out of the 12 worst months for S&P 500 in our sample, an MC-based strategy generated positive returns during 7 months by shorting the market.

Large values of MC result from the levered long investors' decision not to reinvest their gains. This conservatism may be a sign that they expect risk and hence discount rate to be higher or future cash flows to be lower. We find the ability of MC to predict future returns comes via both discount rate and cash flow channels.

Our study extends a recent strand of return predictability literature that strives to extract information from the beliefs and actions of a subset of investors. We show that the information extracted from the actions of winning, levered long investors has substantial information about future cash flows as well as discount rates. Timing the market based on this information produces large gains for the investors.

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Figure 1: **Margin credit: 1983-2014**
This figure plots growth of (a) margin credit/GDP, and (b) detrended margin credit/GDP. The shaded vertical regions show NBER dates recessions.

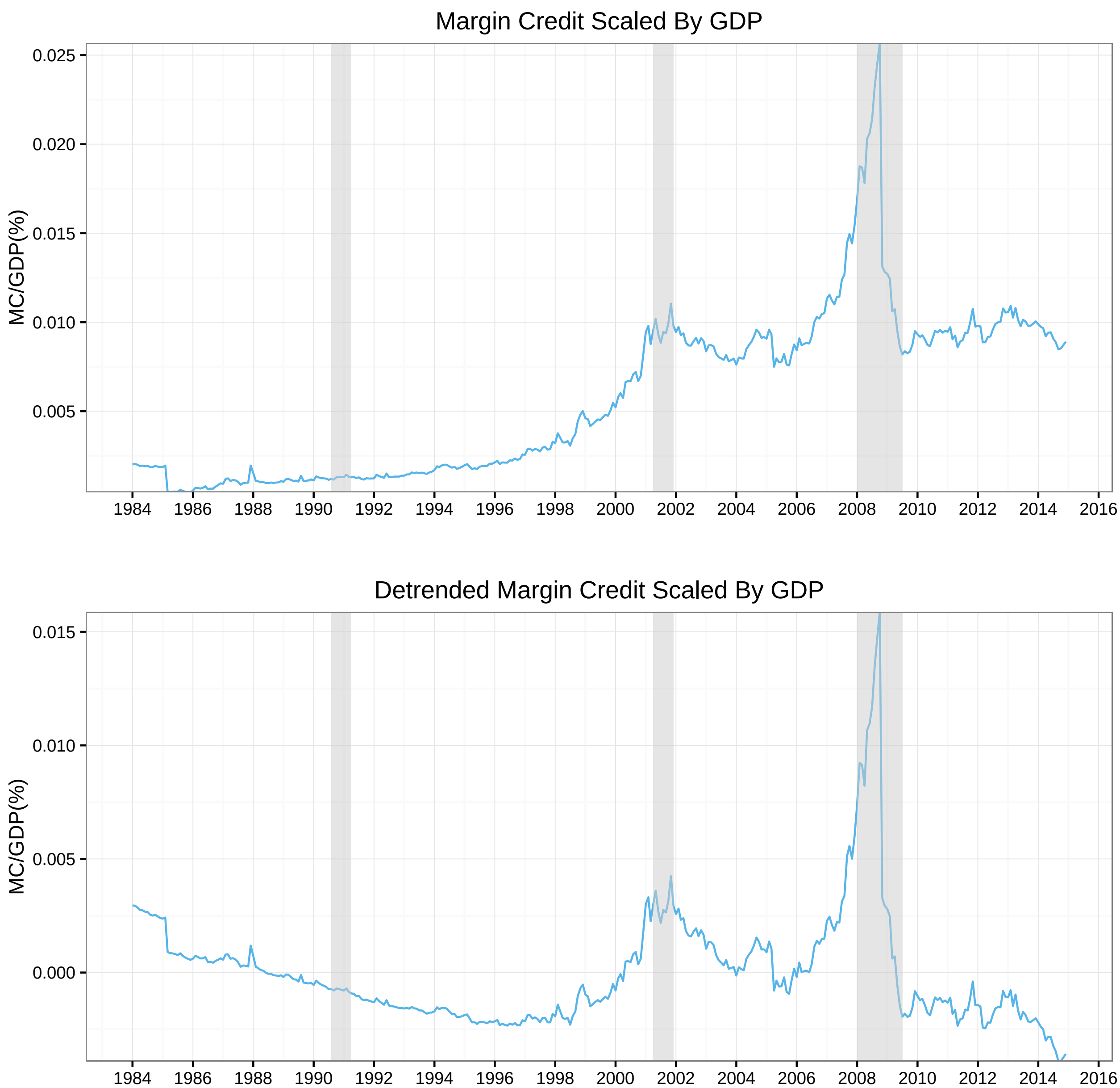


Figure 2: **Cumulative difference in squared forecast error: 1994-01 to 2014-12**

This figure plots cumulative difference in squared forecast errors for the historical average benchmark and out-of-sample forecasts based on individual predictors. The individual predictors are margin credit (MC), margin debt (MD), short interest index in Rapach, Ringgenberg, and Zhou (2016) (SII), investor sentiment aligned in Huang, Jiang, Tu, and Zhou (2015) (SI_PLS), an equally-weighted combination of forecasts based on Goyal and Welch 14 predictors ($GW\ MEAN$), and modified mean as suggested in Campbell and Thompson (2008) ($GW\ MEAN\ CT$). The shaded regions correspond to NBER recessions.

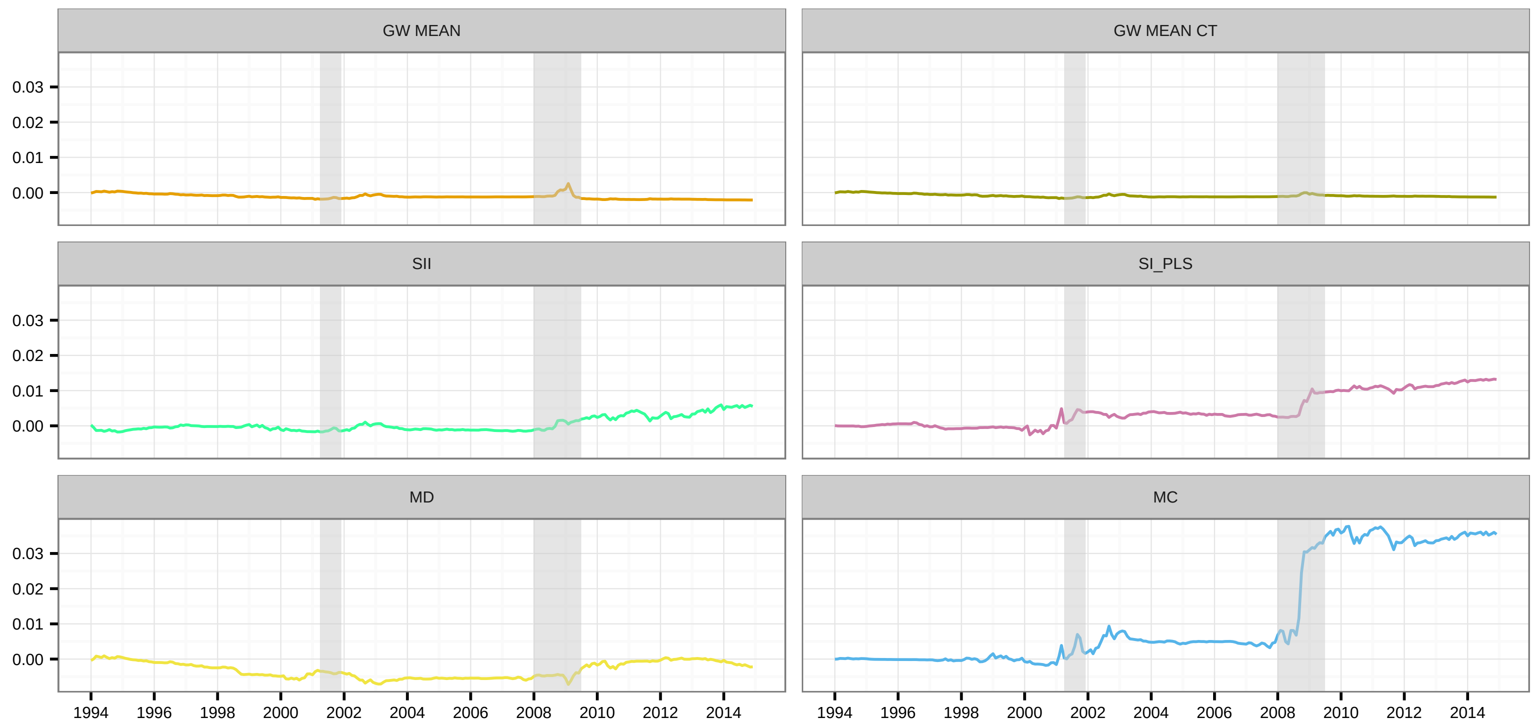


Figure 3: **Cumulative returns to $1: mean-variance investor**
This figure plots cumulative returns (sum of logs) for an out-of-sample strategy for a mean-variance investor that invests in S&P500 and T-bills with weights that lie in the interval [-0.5,1.5].

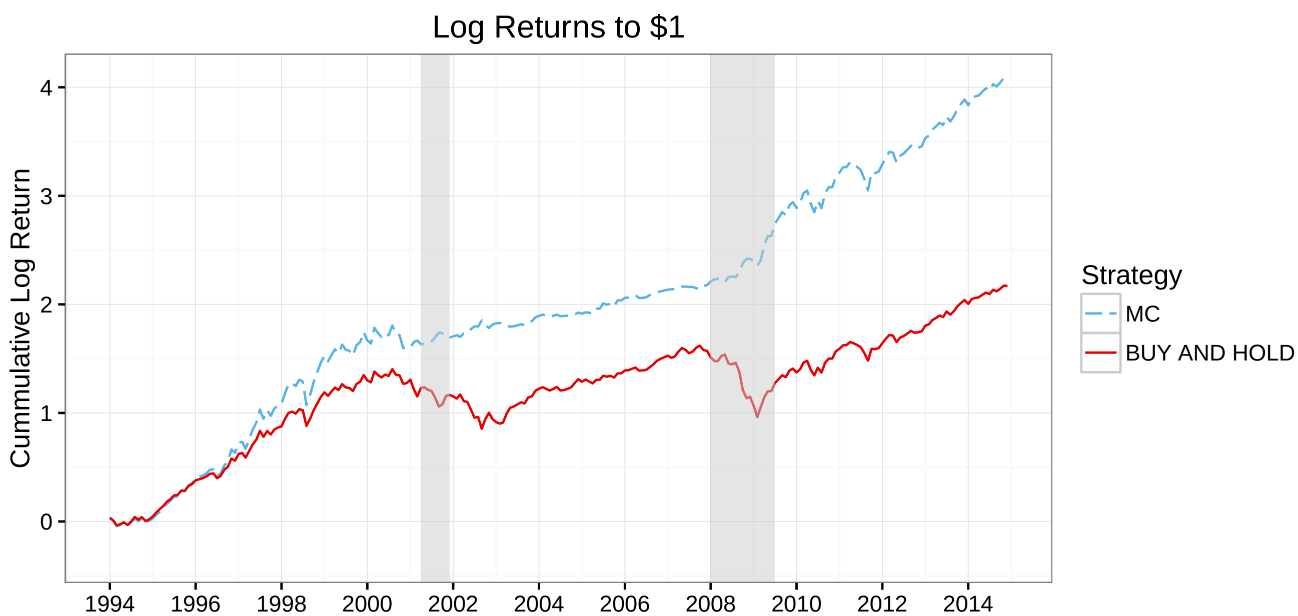
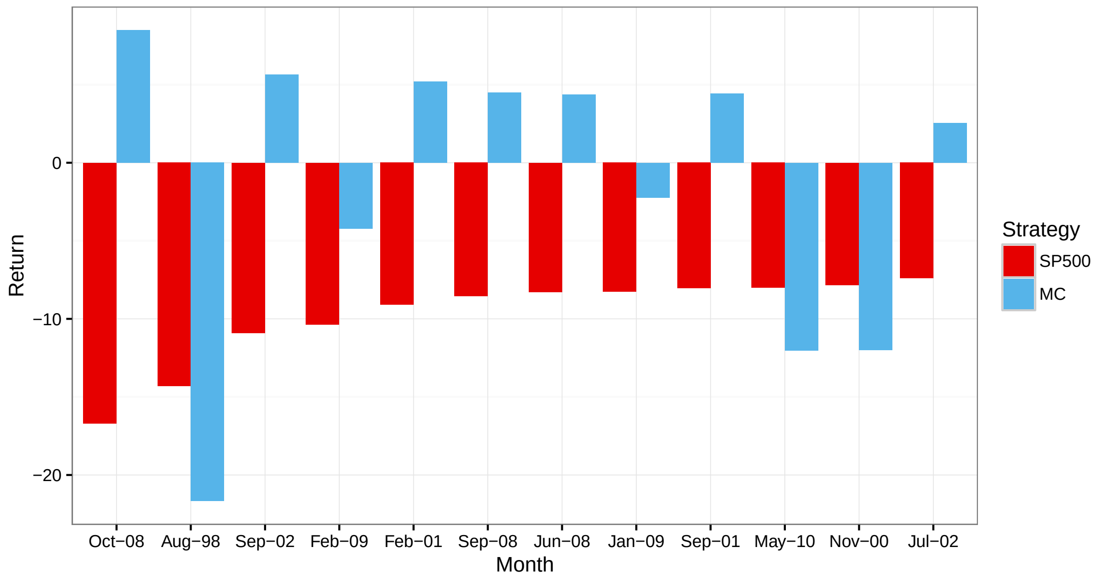
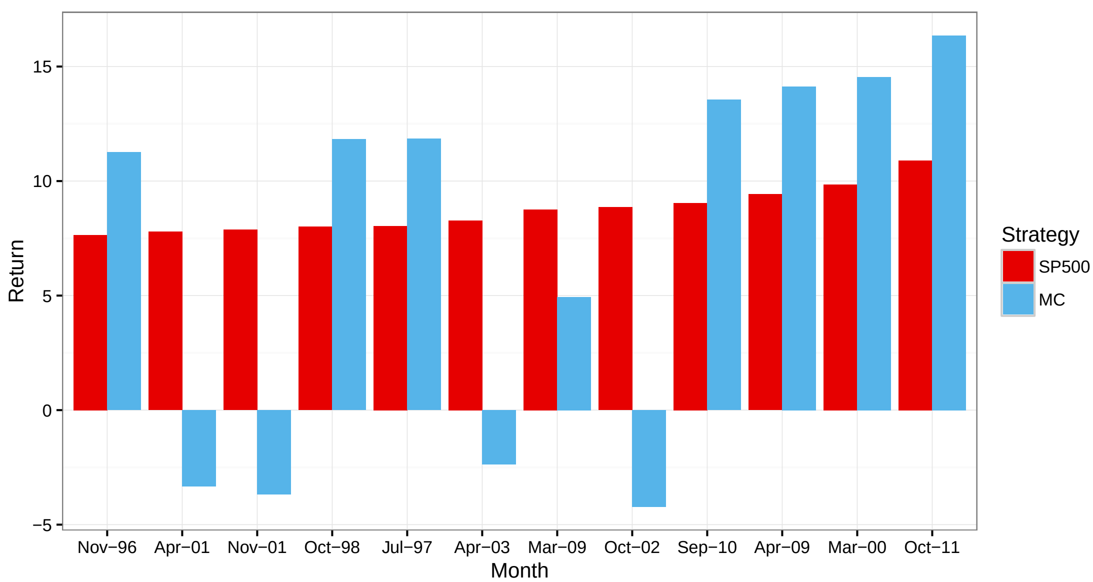


Figure 4: **Worst and best months: mean-variance investor**
This figure shows returns in worst and best months for an out-of-sample strategy for a mean-variance investor that invests in S&P500 and T-bills with weights that lie in the interval [-0.5,1.5].



(a) Lowest S&P500 return months



(b) Highest S&P500 return months

Figure 5: **Cumulative Returns to $1: long only investor**
This figure plots cumulative returns (sum of logs) for an out-of-sample strategy for a long only investor that invests in S&P500 or T-bills.

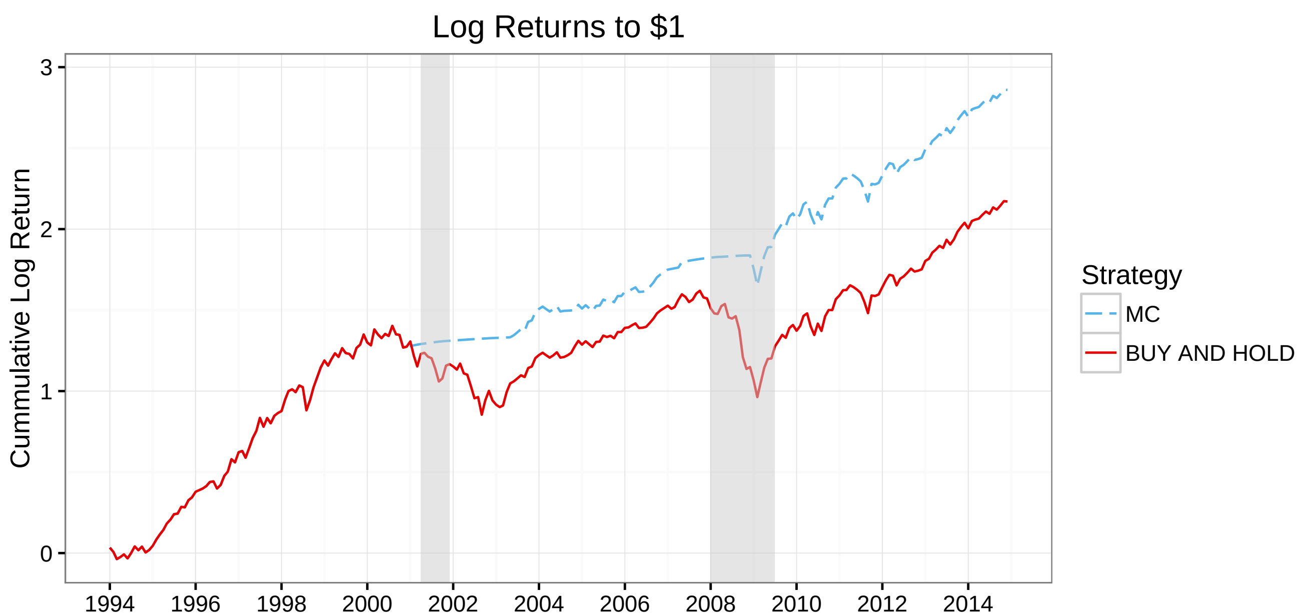
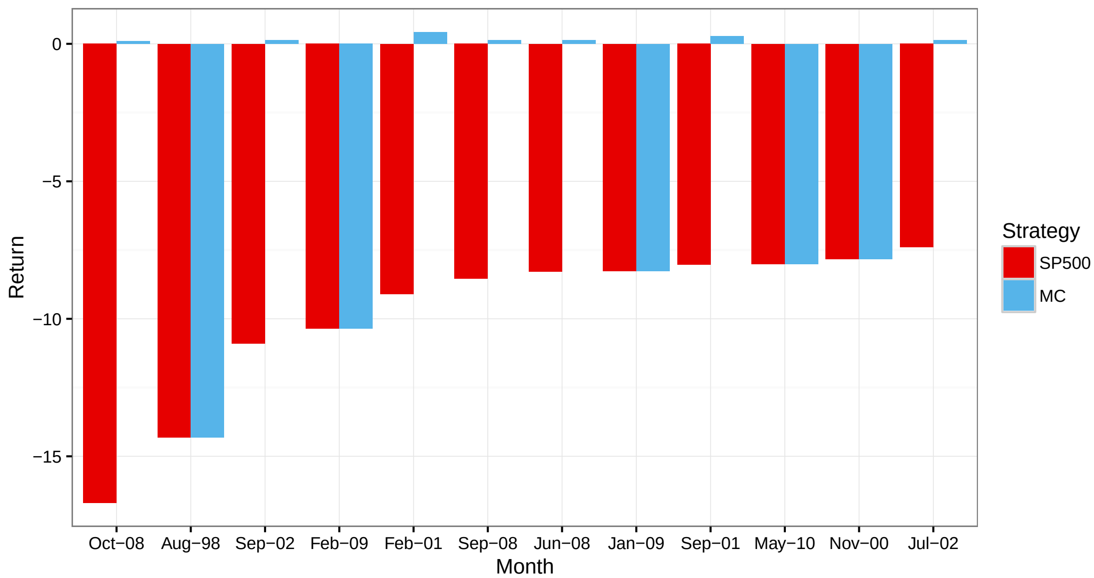
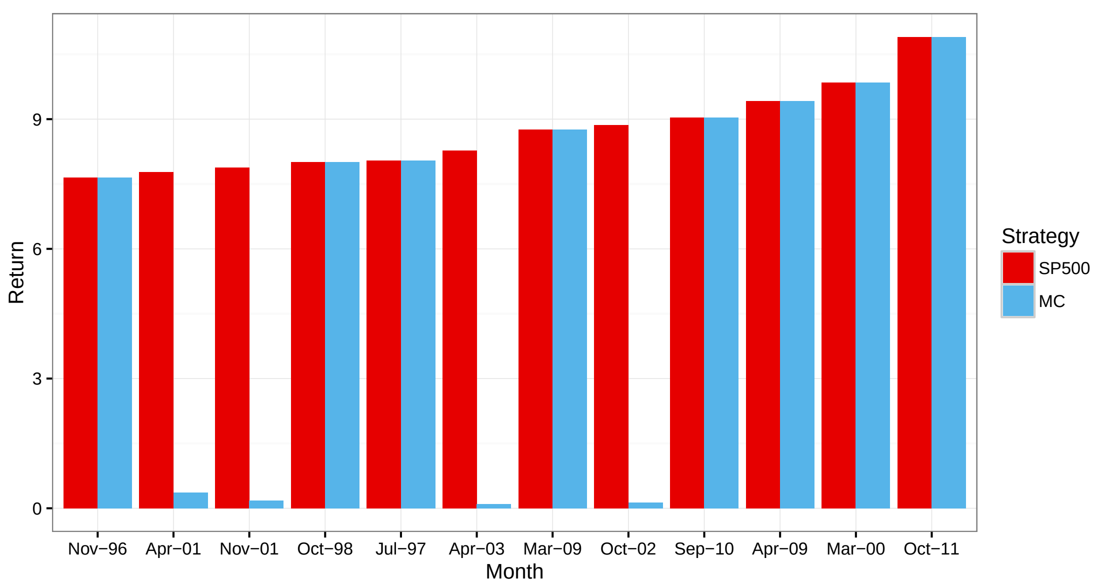


Figure 6: **Worst and best months: long only investor**
This figure shows returns in worst and best months for an out-of-sample strategy for a long only investor that invests in S&P500 or T-bills.



(a) Lowest S&P500 return months



(b) Highest S&P500 return months

TABLE 1: **Summary statistics**

The table displays summary statistics for 14 predictor variables from Goyal and Welch (2008) and aggregate short interest. DP is the log dividend-price ratio, DY is the log dividend yield, EP is the log earnings-price ratio, DE is the log dividend-payout ratio, RVOL is the volatility of excess stock returns, BM is the book-to-market value ratio for the Dow Jones Industrial Average, NTIS is net equity expansion, TBL is the interest rate on a three-month Treasury bill, LTY is the long-term government bond yield, LTR is the return on long-term government bonds, TMS is the long-term government bond yield minus the Treasury bill rate, DFY is the difference between Moody's BAA- and AAA-rated corporate bond yields, DFR is the long-term corporate bond return minus the long-term government bond return, and INFL is inflation calculated from the CPI for all urban consumers. EWSI, constructed by Rapach, Ringgenberg, and Zhou (2016), is the equal-weighted mean across all firms of the number of shares held short in a given firm normalized by each firm's shares outstanding. The data for raw short interest and shares outstanding are from Compustat and CRSP, respectively. EWSI includes all publicly listed stocks on U.S. exchanges, ADRs, ETFs, and REITs, after excluding assets with a stock price below $5 per share and assets that are below the fifth percentile breakpoint of NYSE market capitalization. SII is the detrended log of EWSI, constructed by removing a linear trend from the log of EWSI; SII is standardized to have a standard deviation of one. SI_PLS is the sentiment index created by Huang, Jiang, Tu, and Zhou (2015) based on the partial least square approach from the 6 sentiment proxies from Baker and Wurgler (2006). MCAP/GDP is the ratio of the CRSP total market capitalization to GDP. Margin Debit is the total amount borrowed by investors with margin accounts at NYSE member organizations used to take margin long positions, in millions of dollars. Margin credit is the total amount available for withdrawal held by investors in margin accounts at NYSE member organizations, in millions of dollars. MD/GDP and MC/GDP are the ratios of margin debt and margin credit to GDP respectively. The sample period is from 1984:01 to 2014:12.

Statistic	N	Mean	St. Dev.	Min	Max
DP	372	−3.80	0.36	−4.52	−3.02
DY	372	−3.79	0.36	−4.53	−3.02
EP	372	−3.01	0.41	−4.84	−2.22
DE	372	−0.79	0.40	−1.24	1.38
RVOL	372	0.15	0.05	0.05	0.32
B/M	372	0.34	0.14	0.12	0.80
NTIS	372	0.01	0.02	−0.06	0.05
TBL	372	3.85	2.70	0.01	10.47
LTY	372	6.30	2.35	2.06	13.81
LTR	372	0.83	3.01	−11.24	14.43
TMS	372	2.45	1.27	−0.41	4.55
DFY	372	1.01	0.40	0.55	3.38
DFR	372	−0.02	1.57	−9.75	7.37
INFL	372	0.23	0.26	−1.77	1.38
EWSI	372	2.79	1.93	0.45	8.92
SI_PLS	372	−0.24	0.77	−1.18	3.03
MCAP/GDP	372	101.75	35.54	45.61	184.90
Margin Debt ($M)	372	153,078.60	117,861.30	21,790	465,720
Margin Credit ($M)	372	73,103.74	74,052.88	1,670	385,850
MD/GDP (%)	372	1.36	0.61	0.49	2.84
MC/GDP (%)	372	0.58	0.47	0.04	2.57

TABLE 2: **Correlations**

The table displays Pearson correlation coefficients for 14 predictor variables from Goyal and Welch (2008), the short interest index (SII), the sentiment index based on a partial least squares approach (SI_PLS), and the de-trended ratios of margin debt and margin credit to GDP. See the notes to Table 1 for the variable definitions and sample description.

	DP	DY	EP	DE	RVOL	B/M	NTIS	TBL	LTY	LTR	TMS	DFY	DFR	INFL	SII	SI_PLS	MCAP /GDP	MD	MC	RET_{t+1}
DP	1.00																			
DY	0.99	1.00																		
EP	0.46	0.46	1.00																	
DE	0.43	0.42	-0.60	1.00																
RVOL	-0.10	-0.09	-0.50	0.42	1.00															
B/M	0.87	0.86	0.62	0.15	-0.14	1.00														
NTIS	-0.22	-0.22	-0.12	-0.08	-0.10	-0.25	1.00													
TBL	0.46	0.47	0.45	-0.04	-0.17	0.45	-0.10	1.00												
LTY	0.67	0.67	0.42	0.17	-0.08	0.64	0.02	0.88	1.00											
LTR	0.08	0.08	0.08	-0.01	-0.02	0.10	-0.05	0.07	0.01	1.00										
TMS	0.25	0.24	-0.18	0.40	0.21	0.23	0.25	-0.49	-0.03	-0.13	1.00									
DFY	0.40	0.39	-0.25	0.61	0.41	0.39	-0.54	-0.10	0.04	0.04	0.29	1.00								
DFR	0.00	0.03	-0.14	0.14	0.14	-0.01	0.03	-0.05	0.01	-0.52	0.13	0.10	1.00							
INFL	0.11	0.11	0.22	-0.12	-0.10	0.13	0.00	0.27	0.25	-0.04	-0.10	-0.22	-0.11	1.00						
SII	-0.01	-0.02	-0.12	0.11	-0.06	-0.10	-0.36	0.06	-0.01	-0.02	-0.16	0.16	-0.07	0.15	1.00					
SI_PLS	-0.14	-0.16	-0.19	0.07	0.15	-0.07	0.00	0.24	0.23	0.03	-0.07	0.16	-0.04	-0.07	-0.15	1.00				
MCAP/GDP	-0.90	-0.90	-0.37	-0.42	0.00	-0.72	0.03	-0.50	-0.72	-0.04	-0.27	-0.24	-0.06	-0.15	-0.02	0.20	1.00			
MD	-0.40	-0.41	0.05	-0.40	-0.04	-0.21	-0.11	0.25	0.04	0.04	-0.45	-0.24	-0.15	0.04	-0.16	0.49	0.54	1.00		
MC	0.04	0.01	-0.10	0.13	0.03	0.07	-0.56	0.07	0.08	-0.02	0.01	0.45	-0.15	0.06	0.58	0.34	0.11	0.22	1.00	
RET_{t+1}	0.09	0.09	0.07	0.00	0.04	0.06	0.03	0.00	-0.01	0.04	-0.01	-0.04	0.09	0.05	-0.13	-0.16	-0.09	-0.12	-0.25	1.00

TABLE 3: **In-sample predictive regressions**

In-sample predictive regression estimation results, 1984:01-2014:12. The table reports the ordinary least squares estimate of β and R^2 statistic for the predictive regression model (-) indicates that we take the negative of the predictor variable. See the notes for Table 1 for the variable definitions and sample description. Each predictor variable is standardized to have a standard deviation of one. Variables with expected negative betas are denoted with (-) all other variables are expected to have positive beta. Reported t-statistics are heteroskedasticity and auto-correlation robust for testing $H_0 : b = 0$ against $H_A : b > 0$ for variables with positive expected beta and $H_A : b < 0$ for variables with negative expected beta;*, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively, according to wild bootstrapped p -values.

	β				t-stat				$R^2(\%)$			
	H=1	H=3	H=6	H=12	H=1	H=3	H=6	H=12	H=1	H=3	H=6	H=12
DP(+)	0.372**	0.401**	0.426***	0.441**	1.614	1.913	2.14	2.275	0.713	2.352	5.166	10.909
DY(+)	0.404**	0.408**	0.428***	0.445***	1.806	1.964	2.153	2.269	0.838	2.438	5.224	11.09
EP(+)	0.318*	0.265*	0.236	0.251	0.988	0.81	0.72	0.924	0.521	1.03	1.587	3.53
DE(+)	0.011	0.091	0.143	0.142	0.033	0.323	0.593	0.842	0.001	0.12	0.583	1.124
RVOL(+)	0.176	0.132	0.09	0.041	0.854	0.695	0.482	0.273	0.159	0.255	0.228	0.094
B/M(+)	0.267	0.326**	0.38**	0.39**	1.213	1.614	1.91	2.023	0.366	1.563	4.115	8.572
NTIS(-)	0.131	0.236	0.263	0.248	0.442	0.763	0.765	0.795	0.088	0.815	1.969	3.448
TBL(-)	-0.036	-0.013	-0.013	-0.042	-0.151	-0.036	-0.005	-0.07	0.007	0.002	0.005	0.092
LTY(+)	-0.066	-0.02	0.019	0.091	-0.273	-0.069	0.141	0.573	0.022	0.006	0.01	0.435
LTR(+)	0.189	0.062	0.149**	0.088**	0.814	0.377	1.532	2.009	0.184	0.057	0.626	0.427
TMS(+)	-0.045	-0.01	0.062	0.244*	-0.203	-0.047	0.262	1.267	0.01	0.001	0.108	3.328
DFY(+)	-0.164	-0.082	0.085	0.148	-0.442	-0.217	0.296	0.752	0.139	0.098	0.205	1.207
DFR(+)	0.398**	0.164**	0.13**	0.078*	1.026	0.843	1.037	0.696	0.815	0.394	0.48	0.335
INFL(-)	0.207	-0.042	-0.184*	-0.211**	0.697	-0.156	-1.404	-1.716	0.219	0.026	0.959	2.478
SII(-)	-0.577***	-0.65***	-0.674***	-0.577**	-2.38	-2.471	-2.297	-1.811	1.689	6.013	12.24	16.63
SI_PLS(-)	-0.718***	-0.619***	-0.485**	-0.385**	-2.923	-3.02	-2.624	-2.084	2.649	5.612	6.686	8.207
MCAP/GDP(-)	-0.39**	-0.413***	-0.448***	-0.504***	-1.72	-1.928	-2.116	-2.228	0.775	2.443	5.485	13.285
MD(-)	-0.513**	-0.572**	-0.624***	-0.683***	-2.215	-2.79	-3.239	-3.477	1.347	4.744	10.849	24.908
MC(-)	-1.106***	-1.047***	-1.015***	-0.715***	-3.608	-4.147	-4.178	-2.392	6.25	15.808	28.447	27.288

TABLE 4: **Out-of-sample predictability**

This table shows out-of-sample R^2 (R^2_{OS}) at monthly, quarterly, half-yearly and annual horizons in second through fifth columns. Statistical significance is based on the Clark and West (2007) statistic for testing the null hypothesis that $H_0 : R^2_{OS} \leq 0$ against $H_A : R^2_{OS} > 0$. *, **, and *** indicate significance levels at 10%, 5%, and 1%, respectively. The out-of-sample period is 1994-01 to 2014-12.

	$R^2_{OS}(\%)$				t-stat			
	H=1	H=3	H=6	H=12	H=1	H=3	H=6	H=12
DP	-1.33	-3.189	-5.07	-15.847	-0.384	-0.169	-0.225	-1.917
DY	-1.197	-2.236	-3.887	-13.768	-0.232	0.030	-0.041	-1.732
EP	-1.022	-6.387	-14.074	-16.838	0.351	0.023	-0.330	-0.259
DE	-2.001	-7.832	-12.347	-11.558	-0.268	-1.072	-1.988	-1.045
RVOL	-0.229	-1.129	-2.521	-6.192	-0.394	-1.607	-2.063	-2.246
B/M	-0.441	-0.601	-0.784	-7.095	-0.320	0.214	0.401	-1.566
NTIS	-1.078	-2.667	-5.645	-5.595	-0.944	-1.279	-2.607	-2.736
TBL	-0.856	-3.197	-6.595	-9.707	-0.597	-1.040	-1.893	-4.030
LTY	-0.779	-2.419	-5.119	-13.409	-0.719	-1.222	-1.790	-3.206
LTR	-0.374	-1.312	-0.879	-1.767	-0.437	-0.360	0.304	-0.760
TMS	-0.53	-2.018	-4.022	-3.074	-0.828	-1.643	-2.489	-0.536
DFY	-1.725	-7.465	-13.257	-8.726	-0.127	-0.776	-2.381	-4.393
DFR	-2.302	-2.431	-1.914	-3.261	-0.117	-1.116	-0.655	-1.971
INFL	-0.754	-2.301	-0.272	-0.721	-0.885	-1.389	0.027	0.086
GW MEAN	-0.444	-1.886	-3.386	-5.058	-0.396	-1.150	-2.022	-4.368
GW MEAN CT	-0.271	-0.523	-1.274	-3.911	-0.686	-0.486	-0.814	-1.731
SII	1.16***	4.552***	6.58***	3.924***	2.280	3.684	4.479	3.763
SII 1973	2.17***	7.725***	13.202***	17.371***	2.820	4.111	4.944	5.736
SI_PLS	2.768***	6.169***	5.424***	-5.418	2.300	2.992	2.925	-0.486
SI_PLS 1965	2.953***	6.673***	8.907***	10.629***	3.034	3.900	4.400	4.483
MCAP/GDP	-2.096	-3.274	-6.55	-20.7	-0.456	0.136	0.143	-1.384
MD	-0.461	1.607*	4.392***	5.293***	0.420	1.619	2.390	2.772
MC	7.447***	19.316***	35.006***	35.676***	2.515	3.322	3.862	4.670

TABLE 5: Out-of-sample predictability: Subsamples

This table shows out-of-sample R^2 (R^2_{OS}) at monthly horizon for different subsamples and over NBER contractions and expansions. Statistical significance is based on the Clark and West (2007) statistic for testing the null hypothesis that $H_0 : R^2_{OS} \leq 0$ against $H_A : R^2_{OS} > 0$. *, **, and *** indicate significance levels at 10%, 5%, and 1%, respectively.

	1994-2004		2005-2014		Contractions		Expansions	
	R^2_{OS}(%)	t-stat	R^2_{OS}(%)	t-stat	R^2_{OS}(%)	t-stat	R^2_{OS}(%)	t-stat
DP	-2.522	-0.580	0.067	0.316	0.359	0.300	-1.97	-0.632
DY	-2.648	-0.620	0.505	0.742	1.235	0.747	-2.119	-0.708
EP	1.786	1.232	-4.312	-0.171	-3.57	0.114	-0.055	0.570
DE	-0.547	0.072	-3.704	-0.297	-5.019	-0.193	-0.856	-0.302
RVOL	-0.472	-0.893	0.056	0.332	-0.518	-1.381	-0.12	0.044
B/M	-1.08	-0.704	0.308	0.746	0.886	1.011	-0.944	-0.967
NTIS	-0.746	-0.467	-1.468	-0.827	-1.017	-0.323	-1.102	-1.085
TBL	-0.778	-0.775	-0.949	-0.292	0.838	0.398	-1.499	-1.637
LTY	-0.924	-0.634	-0.61	-0.385	0.552	0.374	-1.284	-1.247
LTR	-0.504	-0.699	-0.223	-0.023	-0.312	-0.213	-0.398	-0.382
TMS	-0.707	-0.632	-0.321	-0.598	0.075	0.149	-0.759	-0.948
DFY	-1.406	-1.523	-2.098	0.070	-2.061	0.206	-1.597	-2.195
DFR	-2.474	-0.723	-2.1	0.130	-4.586	-0.123	-1.436	-0.011
INFL	-0.583	-0.567	-0.954	-0.680	-1.371	-0.683	-0.519	-0.579
GW MEAN	-0.497	-0.708	-0.381	-0.141	-0.072	0.071	-0.585	-1.223
GW MEAN CT	-0.486	-0.926	-0.018	-0.005	0.415	0.653	-0.531	-1.418
SII	-0.487	0.154	3.09***	2.651	2.213	1.264	0.761**	1.940
SII 1973	-0.007	0.512	4.725***	2.936	3.9*	1.520	1.529***	2.439
SI_PLS	1.51	1.184	4.242***	2.194	4.352	1.240	2.167**	1.850
SI_PLS 1965	2.312**	1.708	3.705***	2.845	2.611	1.101	3.079***	2.764
MCAP/GDP	-4.034	-0.940	0.175	0.715	2.777**	1.751	-3.944	-1.263
MD	-2.058	-0.938	1.411	1.218	0.735	0.421	-0.914	0.216
MC	1.654	1.260	14.235***	2.228	20.218**	1.843	2.605***	2.344

TABLE 6: **Forecast encompassing tests**

This table shows estimated weights (λ) on a convex combination of two forecasts $\hat{r}_{1,t+1}$ and $\hat{r}_{2,t+1}$ for month $t+1$. $\hat{r}_{1,t+1}$ prediction is based on the prediction by the variable in column 1, while the $\hat{r}_{2,t+1}$ prediction is based on the prediction by the variable in rows. The convex combination is formed by $\hat{r}^*_{t+1} = (1-\lambda)\hat{r}_{1,t+1} + \lambda\hat{r}_{2,t+1}$. The statistical significance is based on the Harvey, Leybourne, and Newbold (1998) statistic for testing the null hypothesis that the weight on the row predictor based forecast is equal to zero ($H_0 : \lambda = 0$) against the alternative that it is greater than zero ($H_A : \lambda > 0$); * , **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. We report combination over monthly horizon ($H = 1$). The sample period for forecast combination is 1994:01 to 2014:12.

λ values for $\hat{r}^*_{t+1} = (1-\lambda)\hat{r}_{1,t+1} + \lambda\hat{r}_{2,t+1}$					
	$\hat{r}_{2,t+1}$				
	H=1				
$\hat{r}_{1,t+1}$	MC	MD	SII	SI_PLS	GW MEAN
HIST MEAN	1***	0.269	0.845***	1***	0
DP	1***	0.795**	0.914***	1***	1*
DY	1***	0.752*	0.889***	1***	1
EP	1***	0.567	0.795*	1**	0.682
DE	1***	0.763	1**	1***	1
RVOL	1***	0.359	0.898***	1***	0
B/M	1***	0.49	0.884***	1***	0.492
NTIS	1***	0.742	0.96***	1***	1*
TBL	1***	0.607	0.983***	1***	1
LTY	1***	0.595	1***	1***	1
LTR	1***	0.464	0.896***	1***	0.388
TMS	1***	0.525	0.992***	1***	0.751
DFY	1***	0.74	0.912***	1***	1
DFR	1***	0.867	1**	1***	0.996
INFL	1***	0.619	0.976***	1***	1
GW MEAN	1***	0.493	0.917***	1***	
GW MEAN CT	1***	0.408	0.904***	1***	0
SII	1***	0.237		0.846**	0.083
SII 1973	1***	0	0	0.63*	0
SI_PLS	0.912***	0	0.154		0
SI_PLS 1965	0.883***	0	0.144	0.134	0
MCAP/GDP	1***	1***	0.884***	1***	1***
MD	1***		0.763***	1***	0.507
MC		0	0	0.088	0

TABLE 7: **Performance statistics for a mean-variance investor**

The table reports the annualized certainty equivalent return (CER) gain (in percent) for a mean-variance investor with relative risk aversion coefficient of three who allocates between equities and risk-free bills using a predictive regression to forecast excess return based on the predictor variable in the first column relative to the prevailing mean benchmark forecast. The equity weight is constrained to lie between -0.5 and 1.5. Buy and hold corresponds to the investor passively holding the market portfolio.

	1994:01 - 2014:12				1994:01 - 2004:12		2005:01 - 2014:12		NBER Contraction		NBER Expansion	
	Ex Ret	SD	Sharpe	CER	Sharpe	CER	Sharpe	CER	Sharpe	CER	Sharpe	CER
HIST MEAN	8.109	18.465	0.439	0.000	0.466	0.000	0.413	0.000	-0.921	0.000	0.686	0.000
DP	8.396	18.873	0.445	0.055	0.491	0.453	0.389	-0.377	-1.038	-1.982	0.700	0.320
DY	4.535	15.552	0.292	-2.067	0.230	-3.343	0.367	-0.678	-0.760	2.965	0.545	-2.715
EP	7.134	17.924	0.398	-0.686	0.450	-0.328	0.333	-1.065	-1.169	-1.812	0.659	-0.520
DE	8.639	18.004	0.480	0.778	0.520	1.169	0.440	0.360	-0.974	5.972	0.695	0.169
RVOL	6.675	18.179	0.367	-1.278	0.416	-0.985	0.304	-1.597	-1.254	-5.992	0.649	-0.669
B/M	8.430	19.061	0.442	-0.017	0.496	0.533	0.374	-0.614	-0.957	-3.203	0.704	0.372
NTIS	5.894	17.850	0.330	-1.880	0.428	-0.414	0.204	-3.482	-1.296	-12.811	0.669	-0.513
TBL	5.822	16.369	0.356	-1.207	0.409	-1.030	0.297	-1.379	-0.963	8.088	0.558	-2.322
LTY	8.121	18.839	0.431	-0.203	0.493	0.438	0.350	-0.891	-1.122	-2.297	0.686	0.081
LTR	6.737	17.542	0.384	-0.863	0.263	-3.295	0.528	1.790	-0.749	3.125	0.614	-1.374
TMS	7.759	16.247	0.478	0.792	0.547	1.852	0.389	-0.346	-1.221	3.019	0.746	0.557
DFY	5.883	17.360	0.339	-1.625	0.325	-2.772	0.385	-0.374	-0.853	7.584	0.527	-2.741
DFR	7.187	17.750	0.405	-0.538	0.446	-0.207	0.353	-0.900	-0.759	7.841	0.597	-1.561
INFL	7.888	18.793	0.420	-0.408	0.462	-0.033	0.366	-0.823	-0.856	-4.178	0.690	0.025
GW MEAN	8.054	17.399	0.463	0.513	0.485	0.452	0.463	0.589	-1.203	2.588	0.710	0.299
GW MEAN CT	7.875	18.145	0.434	-0.064	0.482	0.365	0.376	-0.526	-1.060	-1.785	0.699	0.162
SII	10.471	18.790	0.557	2.193	0.477	0.393	0.663	4.143	-0.854	7.371	0.765	1.582
SII 1973	11.271	16.866	0.668	4.033	0.464	0.380	0.933	8.040	0.155	32.078	0.729	0.669
SI_PLS	14.606	16.829	0.868	7.380	0.753	5.709	1.038	9.198	0.220	34.099	0.932	4.185
SI_PLS 1965	13.814	15.657	0.882	7.159	0.766	5.574	1.041	8.887	0.198	34.113	0.947	3.940
MCAP/GDP	3.006	14.420	0.208	-3.088	0.148	-4.934	0.327	-1.067	-0.548	16.268	0.344	-5.436
MD	7.936	19.026	0.417	-0.470	0.381	-1.390	0.458	0.513	-0.626	1.408	0.642	-0.750
MC	16.739	16.783	0.997	9.546	0.787	6.020	1.246	13.416	1.422	51.405	0.956	4.586
BUY AND HOLD	7.632	14.913	0.512	1.312	0.529	1.481	0.490	1.119	-0.809	7.245	0.791	0.583

TABLE 8: **Performance statistics for a long-only investor**

This table reports the annualized Sharpe ratio for a long only investor who allocates between equities and risk-free bills. The investments weights are determined by the prediction of one month ahead excess log return to the SP500. The investment weight is 1 in SP500, when the prediction is positive and 0 otherwise. Buy and hold corresponds to the investor passively holding the market portfolio. Panel A shows the values for the full out-of-sample period 1994:01 to 2014:12 and two sub-periods. Panel B shows reports results for the NBER contraction and expansion periods covered by the out-of-sample period.

	1994:01 - 2014:12				1994:01 - 2004:12		2005:01 - 2014:12		NBER Contraction		NBER Expansion	
	Ex Ret	SD	Sharpe	CER	Sharpe	CER	Sharpe	CER	Sharpe	CER	Sharpe	CER
HIST MEAN	7.632	14.913	0.512	0.000	0.529	0.000	0.490	0.000	-0.809	0.000	0.791	0.000
DP	5.998	14.561	0.412	-1.354	0.339	-2.595	0.490	0.000	-0.809	0.000	0.676	-1.533
DY	5.916	14.559	0.406	-1.436	0.329	-2.750	0.490	0.000	-0.847	-0.695	0.676	-1.533
EP	7.928	12.549	0.632	1.909	0.740	3.103	0.508	0.633	-0.736	15.217	0.835	0.317
DE	7.327	14.133	0.518	0.258	0.529	0.000	0.506	0.552	-1.003	5.559	0.767	-0.343
RVOL	7.632	14.913	0.512	0.000	0.529	0.000	0.490	0.000	-0.809	0.000	0.791	0.000
B/M	7.211	14.745	0.489	-0.291	0.487	-0.559	0.490	0.000	-0.809	0.000	0.768	-0.330
NTIS	7.791	14.106	0.552	0.745	0.548	0.331	0.558	1.206	-0.996	5.658	0.807	0.194
TBL	5.726	13.741	0.417	-1.083	0.462	-0.921	0.360	-1.241	-1.003	5.559	0.655	-1.860
LTY	7.599	14.356	0.529	0.375	0.529	0.000	0.529	0.792	-0.991	3.814	0.791	0.000
LTR	7.543	14.849	0.508	-0.042	0.529	0.000	0.482	-0.086	-0.939	-1.960	0.808	0.218
TMS	7.632	14.913	0.512	0.000	0.529	0.000	0.490	0.000	-0.809	0.000	0.791	0.000
DFY	6.936	13.959	0.497	-0.004	0.490	-0.505	0.506	0.552	-1.003	5.559	0.745	-0.641
DFR	5.943	13.614	0.437	-0.762	0.411	-1.660	0.474	0.231	-1.148	3.959	0.698	-1.284
INFL	7.566	14.668	0.516	0.117	0.529	0.000	0.498	0.249	-0.785	3.201	0.772	-0.255
GW MEAN	6.946	14.448	0.481	-0.351	0.529	0.000	0.421	-0.722	-1.331	-2.418	0.791	0.000
GW MEAN CT	7.632	14.913	0.512	0.000	0.529	0.000	0.490	0.000	-0.809	0.000	0.791	0.000
SII	7.632	14.913	0.512	0.000	0.529	0.000	0.490	0.000	-0.809	0.000	0.791	0.000
SII 1973	8.626	13.893	0.621	1.740	0.511	-0.285	0.775	3.963	-0.071	22.751	0.730	-0.823
SI_PLS	10.003	12.799	0.781	3.851	0.681	2.385	0.911	5.464	0.118	28.850	0.866	0.833
SI_PLS 1965	11.263	12.570	0.896	5.243	0.882	4.976	0.910	5.548	0.118	28.850	0.998	2.393
MCAP/GDP	5.162	14.485	0.356	-2.145	0.339	-2.595	0.374	-1.656	-0.809	0.000	0.609	-2.426
MD	6.676	14.708	0.454	-0.806	0.515	-0.164	0.383	-1.499	-0.809	0.000	0.725	-0.912
MC	10.912	11.903	0.917	5.301	0.846	4.261	0.991	6.450	0.180	29.975	1.014	2.324
BUY AND HOLD	7.632	14.913	0.512	0.000	0.529	0.000	0.490	0.000	-0.809	0.000	0.791	0.000

TABLE 9: **Forecasting discount rates and cash flows with margin credit**

This table reports in-sample estimation results for the bivariate predictive regressions where DP is the log of the 12 month dividend paid to SP500 price ratio DG log 12 month dividend growth rate, EG log 12 month earnings growth rate and GDPG is the annual log real GDP growth rate. DP, EG, and DG are constructed from the data provide by Schiller. We report the regression slopes, Newey-West t -statistics, as well as R^2's. * ,*, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, based on one-sided wild bootstrapped p -values. The sample period is over 19842014.

Panel A : Non-overlapping Quarterly Regressions (1984-2014)

	MC		DP		
	β	t-stat	ψ	t-stat	R^2(%)
Ret_{t+1}	-0.031***	-5.699			0.210
Ret_{t+1}	-0.032***	-5.928	0.012***	2.103	0.238
DP	0.079***	5.065	0.962***	59.509	0.968
DG	-0.18**	-2.076	-0.025	-0.279	0.036
EG	-0.55***	-7.564	0.019	0.257	0.323
GDPG	-0.455***	-5.857	0.093	1.165	0.225

Panel B : Non-overlapping Annual Regressions (1984-2014)

	MC		DP		
	β	t-stat	ψ	t-stat	R^2(%)
Ret_{t+1}	-0.115***	-4.277			0.379
Ret_{t+1}	-0.131***	-4.957	0.047**	2.590	0.495
DP	0.285**	3.326	0.827***	11.580	0.848
DG	-0.358**	-1.690	-0.075	-0.426	0.104
EG	-0.493**	-2.436	0.206	1.255	0.198
GDPG	-0.612**	-3.229	0.170	1.008	0.279

Panel C : Overlapping Annual Regressions (1984-2014)

	MC		DP		
	β	t-stat	ψ	t-stat	R^2(%)
Ret_{t+1}	-0.007***	-2.392	NA		0.273
Ret_{t+1}	-0.009***	-3.426	-0.001	-0.498	0.033
DP	0.27***	25.583	1.043***	98.889	0.965
DG	-0.176***	-3.139	0.003	0.036	0.031
EG	-0.598***	-12.905	-0.037	-0.815	0.342