Margin Credit and Stock Return Predictability

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Abstract

Margin credit, the excess debt capacity of investors buying securities on the margin, is a very strong predictor of aggregate stock returns, outperforming other forecasting variables proposed in the literature. Its out-of-sample R^2 of 7.5% at the monthly horizon is more than twice that of the next best predictor. A margin-credit-strategy generates a Sharpe ratio of 0.95 and 1.28 in expansions and recessions, respectively. Margin credit predicts lower future cash flows and higher future discount rates. It anticipates higher future risk – measured by VIX, average equity correlation, macro and financial uncertainty –, lower intermediary equity ratio, and tighter borrowing conditions.

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1 Introduction

Formal equity premium prediction is older than sliced bread.[1] Yet, generating even a small forecasting advantage is still no "piece of cake." Investors move billions of dollars worth of shares daily on formal and informal predictions of future returns. We find that a signal based on the behavior of a subset of potentially informed and sophisticated investors is a powerful, actionable, and economically meaningful predictor that is substantially better than others previously suggested.

Over time, the academic literature has proposed a host of signals for future returns. These variables include various price and accounting ratios such as dividend-price ratio, earnings-price ratio, book-to-market ratio, dividend-payout ratio, and macroeconomic variables such as interest rate spreads, consumption-wealth ratio, labor income-to-consumption ratio, housing collateral ratio and corporate issuing activity, among others.[2] In a seminal paper, Welch and Goyal (2008) conduct a comprehensive investigation of the most popular predictors and find that none outperform the simple historical average equity premium. Recent work by Huang, Jiang, Tu, and Zhou (2015) and Rapach, Ringgenberg, and Zhou (2016) takes a different approach towards predictability. They extract informative signals from subset of investors and develop actionable predictors. Our paper extends this new approach, by extracting a signal from investors who establish leveraged long positions using margin debt.

Margin investors are likely to have strong beliefs since they are willing to be more aggressive by levering up. We construct a measure from the *excess debt capacity* of investors that use margin debt to establish long positions. We call this measure *margin credit*, details in Section 2. The excess debt capacity of margin investors results when they *choose not to borrow against their gains* to reinvest further. This decision, *not to reinvest*, is a pessimistic signal coming from the margin long investors. These investors are also likely to be informed since they have made gains from their past bets. Investor level studies of short sellers, like the work of Chague and Giovannetti (2016), find that only a subset of short sellers are informed, yet when this subset can be identified, a stronger signal of future returns can be generated; similarly, using accounting rules, margin credit identifies a subset of margin traders that are likely to be informed. Rule 4521(d) by the Financial Industry Regulatory Agency (FINRA) requires brokers to report monthly aggregate debt and credit balances for margin accounts used to take only long positions. The rule specifically requires that the brokers *not consider short positions* for the purpose of this reporting. Thus, the information contained in margin credit is different from that in short positions.

Given the pessimistic nature of the signal, we hypothesize *an inverse relationship between*

[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.

[2] Some of the papers that predict returns from financial ratios include Campbell and Shiller (1988a), Campbell and Shiller (1988b), Fama and French (1988), Fama and French (1989), Kothari and Shanken (1997), Pontiff and Schall (1998), Cochrane (2008), Lettau and Van Nieuwerburgh (2008), Pástor and Stambaugh (2009), Kelly and Pruitt (2013). For term-structure variables, see Fama and Schwert (1977) and Campbell (1987). Lettau and Ludvigson (2001), Menzly and Santos (2004), and Lustig and Van Nieuwerburgh (2005) examine predictability through macroeconomic variables. Baker and Wurgler (2000) and Boudoukh, Michaely, Richardson, and Roberts (2007) examine predictability with corporate issuing activity. See Koijen and Van Nieuwerburgh (2011) and Rapach and Zhou (2013) for excellent surveys.

margin credit and future returns. We test this hypothesis of using the monthly series of the aggregate margin credit published by the New York Stock Exchange (NYSE). We scale these monthly values by the GDP to generate a number proportional to the size of the economy and comparable across time. The ratio displays a strong and statistically significant upward trend from 1984 to 2014, most likely due to the expansion of the equity market, deregulation of margin purchasing and easing of access to credit. We remove this uninformative increase by detrending the monthly ratio of margin credit to GDP. Our new predictor MC is formed by standardizing the detreded ratio, details in Section 3.1.

Consistent with our hypothesis, we find an inverse relationship between margin credit and future returns. A one standard deviation increase in MC is associated with a 1.12% lower market return for the next month. MC generates an in-sample R^2 of 6.31% for next month's returns which increases to 26.79% at the annual horizon, numbers typically at least twice the next best predictor. MC performs strongly out-of-sample as well, generating an R^2 of 7.51% at the monthly frequency, which rises to more than 36% at annual frequency, again producing substantially better performance than other predictors. At most horizons not only is MC the best predictor, it encompasses all information contained in the other predictors. We also examine margin credit without scaling, scaled by market capitalization, and scaled by consumer price index (CPI). All show strong predictability with out-of-sample monthly R^2 ranging from 3.21% to 6.37%. Interestingly, aggregate margin debt, quite popular among the practitioners and the financial press, is a much weaker predictor compared to margin credit.

In line with this strong predictive performance, an asset allocation strategy based on MC produces large gains. It has a substantially larger Sharpe ratio at 0.98 than that of strategies based on previous predictors. Over the out-of-sample period of 21 years from 1994 to 2014, it produces an annualized certainty equivalent return (CER) gain of 9.3% compared to a strategy based on the historical average return. Figure 4 shows the cumulative log returns of this strategy and a simple S&P 500 buy-and-hold strategy. We can clearly see that the allocation strategy based on MC outperforms the buy-and-hold strategy by a large margin. Figure 5 shows the returns of MC-based strategy during the 12 worst and 12 best months of S&P 500. MC not only captures 8 of the 12 best S&P 500 months but generates substantial positive returns in 7 of the 12 worst months by shorting the market.

MC's superior performance compared to other predictors comes about partly by being substantially better during NBER contractions. But even during NBER expansions, it is, at least, modestly better than other predictors. Its asymmetric performance is not surprising as margin credit is an asymmetric signal, since *excess* debt capacity cannot be negative. Thus, while margin credit for an investor can take large positive values in case of her pessimism, it cannot take negative values to accurately capture her optimism. Still, economic gains to following MC are substantial both in contractions and expansions. A MC-based asset allocation strategy generates a Sharpe ratio of 1.28 and 0.95 during recessions and expansions respectively. Moreover, in both expansions and contractions, no other predictors contain useful information for return prediction over and above what MC provides.

Two questions arise. Who are margin long investors and why would MC predict future returns? The use of margin itself allows us to draw a comparison to another group. Margin debt is one of the important ways in which hedge funds can obtain leverage, as Fung and Hsieh (1999) and Ang, Gorovyy, and van Inwegen (2011) report. Thus, we can gain some insight into the behavior of margin investors by looking at hedge funds.[3] Chen and Liang (2007) find evidence that market timing hedge funds do anticipate bear and volatile markets.[4] 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 2008 crisis due to redemptions and pressure from their lenders. Similar behavior by margin investors in response to information on greater risk would result in accumulation of margin credit.

In addition to changes in the risk environment, margin investors may have better information about future cash flows. Chague and Giovannetti (2016) show that informed short sellers trade prior to the announcement of negative cash flow news. Rapach, Ringgenberg, and Zhou (2016) find that aggregate short interest contains cash flow news. Hedge funds being sophisticated investors are thought to 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. Dai and Sundaresan (2010) theoretically show that hedge funds optimally cut back leverage if their estimate of the Sharpe ratio declines either due to increase in the estimate of risk i.e. discount rate or a decrease in the estimate of return i.e. cash flows.

Using the return identity in Campbell and Shiller (1988b) and following the approach in Huang, Jiang, Tu, and Zhou (2015), we find that MC's predictive power flows through both the cash flow and discount rate channels. Specifically, we find that high margin credit anticipates lower cash flow growth as measured by lower future dividend growth, earnings growth and GDP growth. Margin credit also predicts a higher dividend/price ratio, a proxy for discount rate. These results are consistent with the information encompassing tests, which show that MC encompasses predictors that have been shown to operate through each channel.

The above evidence supports our hypothesis that informed margin investors do not borrow further against accumulated margin credit in anticipation of adverse future market conditions. But there are two alternate explanations for our findings. One possibility is that investors accumulate

[3]This is not to say that a majority of margin investors are hedge funds. Not much is known about composition of margin long investors. There are no significant regulatory hurdles to open a margin account and the data provided by the NYSE and FINRA is aggregate for all investors with long positions in margin accounts. Reported margin debt is the result of all long positions taken by any investor.

[4]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.

higher margin credit *in response to* higher observed risk, rather than *in anticipation of* higher future risk and uncertainty. We examine this possibility and do not find evidence in its support. Using specific proxies of risk and uncertainity, such as VIX, average equity correlation, macro and financial uncertainty, we find that MC predicts higher risk.[5] Higher observed risk does not predict MC.

A second possibility is that MC accumulates in response to tighter borrowing conditions for the margin investors, i.e. high MC indicates that the margin investors *are forced to* rather than *choose to* borrow less due to higher cost or lower supply of funds. Tests using bank and broker interest rates, credit standards used by banks (Chava, Gallmeyer, and Park (2015)) bank credit growth (Gandhi (2016)) and intermediary capital ratio (He, Kelly, and Manela (2016)), do not support this mechanism. On the other hand, we find that high MC precedes the tightening of credit standards by banks, contraction of bank credit and lower intermediary capital ratio. Thus, evidence suggests that investors, not brokers, determine changes in margin credit which precede shifts in lending conditions.

Given the strong predictive ability of margin credit, a question arises: why do the margin investors continue holding long positions even after receiving a pessimistic signal? In the theoretical model in Abreu and Brunnermeier (2003), a synchronization problem among the investors along with their incentive to sell just before the price falls, means that they stay invested in the overvalued asset for some time even after receiving the pessimistic signal. Behavior of margin investors can be interpreted in the light of this model. We do find some evidence consistent with this interpretation which we discuss in Section 6.5.

Our paper contributes to the long literature on return predictability, see footnote 2. 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. Rapach, Ringgenberg, and Zhou (2016) show that an index based on the positions of short investors is a strong negative predictor of S&P 500 returns through forecasts of lower future cash flows. Similar to the above studies, we find that conservative behavior by a subset of investors, potentially informed levered investors in our case, indicates lower future market returns, in the process 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 borrowing conditions and intermediary constraints on asset prices.[6] While this literature focuses on the impact of margin

[5]See Pollet and Wilson (2010) for average correlation as a measure of risk, Jurado, Ludvigson, and Ng (2015) and Ludvigson, Ma, and Ng (2015) for macro and financial uncertainty.

[6]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. Adrian, Moench, and Shin (2013) and Adrian, Etula, and Muir (2014) find that a measure of intermediary constraints based on broker-dealer leverage has significant explanatory power for the cross-section and time-series of asset prices. Rytchkov (2014) presents an analysis of risk-free rate, risk-premium and volatilities in a general equilibrium model with endogenously changing margin constraints. Kruttli, Patton, and Ramadorai (2015) show that aggregate illiq-

requirements or capital constraints, we empirically show that *voluntary* reduction in leverage by margin investors has information about future returns. Further, we find that higher MC is a signal preceding tighter credit standards by banks, lower bank credit growth and lower intermediary capital ratio – states where the intermediaries are likely to be capital constrained.

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

Federal Reserve Board Regulation T (Reg T) establishes certain baseline requirements for investors that wish to open margin trading accounts. In general, an investor can only borrow up to a certain percentage of the value of the securities, Reg T allows 50% but her brokerage house may set a lower limit. The amount of her own funds she must deposit is called margin. At the time of establishing the position, the investor has to satisfy the "initial margin" requirement which is 1 minus the maximum borrowing limit. The fraction financed by the brokerage house is her margin debt.

2.1. How does margin credit arise?

While the investor's margin debt will not move directly with the market, her equity in the margin position will. If due to favorable price movements the investors' equity becomes higher than the initial margin required, the investor gets credit in her margin account which she can withdraw without closing the position. We call this credit "margin credit". Specifically,

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.*

To clarify the accounting and the statutory rules regarding margin debt and credit, we work through an extended example in Appendix A.1 (also see Fortune (2000)). Can we extract any information about future returns from margin debt and margin credit balances?

2.2. 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 - implying a positive relationship between margin debt and future returns. But Allen

uidity of hedge fund portfolios is a significant predictor of a large number of international equity indices including the U.S. index. He, Kelly, and Manela (2016) find that capital ratio of primary dealers is a cross-sectionally priced factor for many assets. Chen, Joslin, and Ni (2016) show that a measure of intermediary constraints based on willingness of option traders to sell deep out-of-the-money options can explain risk premia in a wide range of financial assets. Chava, Gallmeyer, and Park (2015) show that tightening credit standards by banks predict lower aggregate stock returns. Gandhi (2016) finds that bank credit expansion predicts lower equity returns.

and Gale (2000) show that that risk shifting associated with investing borrowed money results in inflated prices for the risky assets. Further, if a long position supported by margin debt loses value and the investor fails to pay the margin call, the position is closed and margin debt becomes zero. 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. Indeed, Burger and Curtis (2016) find that the ratio of aggregate margin debt to price is negatively related to future returns. Likewise, Jiang (2015) finds that stocks held by highly levered hedge funds have more negatively skewed future returns.[7] Further, margin debt balances, aggregated across investors, cannot distinguish between investors with superior and inferior information about future returns.

Larger margin credit balances signal that investors have chosen *not to borrow to the fullest extent* to invest in risky assets, indicating a lukewarm belief about future returns. However, if investors choose to withdraw margin credit, margin credit balance drops without a corresponding improvement in the belief about future returns. Thus, high margin credit is a proxy, albeit noisy, of investors' pessimistic beliefs. We expect a negative relationship between margin credit and future returns. Margin credit typically results from the appreciation in value of the 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 more sophisticated and more informed investors, circumventing the problem of margin debt.

To continue accumulating margin credit an investor must keep the long position open. Why would an investor who is pessimistic about the asset continue to hold a long position? One possibility is that her private signal is not the strongest pessimistic signal. So, margin credit might not be the strongest signal of investor pessimism. But short positions may not reflect negative beliefs perfectly either. Short sale constraints prevent sophisticated investors from fully expressing their pessimism. Still, as Rapach, Ringgenberg, and Zhou (2016) find, short interest aggregated across investors and stocks, is a powerful signal. Likewise, while margin credit at a disggregated level may be noisy, when aggregated, it has the potential to be an informative signal.

Another possibility is based on synchronization risk. As Abreu and Brunnermeier (2003) theoretically show, if investors observing a pessimistic signal privately cannot synchronize their selling activity, they may stay invested in the overvalued asset for some time even after receiving the signal. We discuss this possibility further along with some supportive evidence in section 6.5. Overall, it is matter of empirical investigation as to how well the marketwide margin credit balance works as a predictive signal about stock index returns.

[7]Supply of credit by optimistic lenders may also play a role in this negative relationship. Baron and Xiong (2016) find that expansion of credit by banks predicts negative future bank equity returns due to neglected crash risk.

3 Data

We use monthly data for aggregate margin debt and margin credit for all investors with NYSE member organizations.[8] 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. Specifically, FINRA rule 4521(d)(3)(A) states that,

"Only free credit balances in cash and securities margin accounts shall be included in the member's report. Balances in short accounts and in special memorandum accounts (see Regulation T of the Board of Governors of the Federal Reserve System) shall not be considered as free credit balances."

FINRA further clarifies that "Balances in short accounts" refers to balances derived from the proceeds of short sales. In other words, margin credit numbers represent different information than what is contained in the monthly short positions.

3.1. Variable construction

The data are available at the NYSE website with a two month delay.[9] 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 at the end of August 1995 to predict return for September 1995. NYSE margin statistics are available from January 1959. However revisions to Reg T make pre and post June 1983 margin statistics incomparable.[10] To insure comparability of data across time we begin our predictions in 1984, using the margin statistics available as of December 1983.

The raw margin statistics numbers are reported in millions of dollars. We scale these values by nominal GDP so that they are relative to the size of the economy. We pull the history of all GDP announcements from the Federal Reserve Bank of Philadelphia website.[11] This provides the numbers announced in each 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 up to Q4 1995 and the numbers for Q4 1994 would be in their 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 the time of making a prediction are used to avoid

[8] 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.

[9] 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 also makes available the same numbers at http://www.finra.org/investors/margin-statistics. From February 2010 onwards, FINRA also makes available combined margin debit and credit of both NYSE and National Association Of Securities Dealers (NASD) members.

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

[11] https://www.philadelphiafed.org/

any look-ahead bias. So for making a prediction at the end of 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.

3.1.1. Stationarity and detrending

The ratio of margin credit to GDP is highly persistent with an auto-correlation above 0.95. As Stambaugh (1999) demonstrates, highly persistent regressors generate biased estimates that distort inferences. Further, we do not see evidence of stationarity in margin credit to GDP. We fail to reject the null of a unit root using the Ng and Perron (2001), Kwiatkowski, Phillips, Schmidt, and Shin (1992) (KPSS) and augmented Dickey-Fuller tests.

We find that margin credit to GDP shows a deterministic trend at the 1% level in the Perron and Yabu (2009) test with a t-statistic of 3.36.[12] Indeed, the statistical tests reject the null of unit root in margin credit to GDP against the alternative of trend stationarity as summarized in the table below:

Test	Statistic	Critical Value	Inference Null: Unit root Alternative: Trend stationarity
Ng-Perron	-2.58	-2.57	Unit root rejected at 10%
KPSS	0.1614	0.146	Unit root rejected at 5%
Augmented Dickey-Fuller			Unit root rejected at 1%

This secular trend is both a statistical and theoretical problem. It distorts the economic meaning of the changes in margin credit to GDP. We suspect the presence of a deterministic trend in margin credit for the same reasons as cited in Rapach, Ringgenberg, and Zhou (2016) for a trend in short interest. They highlight the expansion of equity lending along with an 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. Thus, detrending the time series better identifies the information contained in the margin credit balance that would be relevant for predicting returns. Further, even statistically, detrending the series is the best approach. Boucher and Maillet (2011) show that detrending, when the data show a trend, is an efficient means of correcting the bias of a highly persistent regressor and restoring power to the inference.

We detrend the ratio of margin credit to GDP using the full sample for the in-sample tests. For the out-of-sample tests, we detrend only over the trailing period, to avoid any look-ahead bias. Using the same approach as Rapach, Ringgenberg, and Zhou (2016), we run the following

[12] Statistical tests for the presence of a significant deterministic trend 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 of 372 months, and given the naive estimate of the auto-correlation which, for example, is above 0.95 for margin credit.

regressions,

$$\frac{Margin\ Credit_t}{GDP_t} = \alpha_c + \beta ct + u_t$$

The residual from this regression, u_t, is our main predictor – we call it MC. For robustness, we test MC for non-stationarity which is rejected by the augmented Dickey-Fuller, Ng-Perron, and the KPSS tests. Removing the uninformative increases from the margin credit to GDP ratio leaves us with MC, an economically relevant measures of the excess debt capacity held by margin long investors.

Again to emphasize, for out-of-sample tests, we detrend using only the information available at the time of making the forecast and compute MC recursively to avoid any look-ahead bias.

3.1.2. Alternate versions

In addition to the GDP scaled version of margin credit, MC, we also consider alternative constructions – unscaled margin credit, margin credit scaled by consumer price index (CPI) to convert the reported margin credit number into real 1984 dollars, and margin credit scaled by total market capitalization.[13] These three alternatives also show a statistically significant trend using the Perron and Yabu (2009) test. We use the same methodology as for MC to construct detrended versions of these variables. We also find a significant trend in margin debt to GDP and detrend it to produce another predictor that captures the level of debt taken on by margin investors. To summarize, the four versions of margin credit, along with margin debt, are defined as:

- Margin Credit to GDP (MC): the detrended ratio of aggregate margin credit to reported GDP.
- Margin Credit (MC_{NOM}): the detrended aggregated amount of credit in margin accounts as reported by the NYSE.
- Real Margin Credit (MC_{REAL}): the detrended aggregated amount of credit in margin accounts deflated by publicly available CPI to real 1984 dollars.
- Margin Credit to Market Cap (MC_{MCAP}): the detrended ratio of aggregate margin credit to total market capitalization.
- Margin Debt to GDP (MD): the detrended ratio of aggregate margin debt, money borrowed from brokers to take leveraged long positions, to reported GDP.

We note that scaling by market capitalization may weaken the predictive ability of margin credit. The aggregate market capitalization may reflect over or undervaluation on which margin investors may have information. Dividing by market capitalization takes away the valuation effect

[13] We use the same vintage reporting method for CPI numbers as used with GDP to insure there is no look ahead bias from using later revised reports.

by hiding unusually large (small) accumulations of margin credit in the numerator with inflated (deflated) capitalization numbers in the denominator.

3.1.3. Other predictors

We compare the predictive ability of margin credit and margin debt to the 14 monthly predictors of Welch and Goyal (2008), including log dividend-price ratio (DP).[14] The other predictors we examine are the short interest index measure of Rapach, Ringgenberg, and Zhou (2016), the investor sentiment aligned measure of Huang, Jiang, Tu, and Zhou (2015), and market capitalization to GDP, the so called "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. We construct this measure as:

- Market Capitalization to GDP ($MCAP/GDP$): 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.[15] These numbers are available through the end of 2014. Because EWSI ends in 2014, we end our data in December of 2014. 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), lagged by one month.

Huang, Jiang, Tu, and Zhou (2015) construct a sentiment index from the six proxies from Baker and Wurgler (2006) based on the partial least square approach. The data for this variable is available from Zhou's webpage.[16] We call this variable S^{PLS}. The data provided by Huang, Jiang, Tu, and Zhou (2015) defines:

- Sentiment Index from Partial Least Squares (S^{PLS}): partial least squares measure of investor sentiment extracted from the cross-section of six Baker and Wurgler sentiment proxies.

Our focus is on the prediction of excess returns to a value-weighted market portfolio. Consistent with existing literature, we measure this excess return as the log of the return to the S&P 500, including dividends, minus the log of the return to a one month Treasury bill.

3.2. 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 margin debt to GDP ratio of 1.36%. Margin credit has a mean

[14] The data on 14 Welch and Goyal (2008) predictors is available on Amit Goyal's website: http://www.hec.unil.ch/agoyal/. The details of these predictors are in Appendix A.2. The descriptive statistics and predictability results for these variables are in Tables A.1 to A.7.

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

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

level of \$73.10 billion and a mean margin credit to GDP ratio of 0.57%. All of the highest ten values of the margin credit to GDP ratio 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. It shows a large increase in late 2000 before the dotcom bust of 2001 and again before the 2008 financial crisis. SII and S^{PLS} show similar behavior. The large increase in margin credit during financial crisis raises a question: to what extent is this period driving our predictability results? We will explicitly examine this issue in Section 4.3.2 as part of our robustness tests.

Table 2 displays Pearson correlation statistics for DP, $MCAP/GDP$, SII, S^{PLS}, MD and the four versions of margin credit. Indeed MC and SII are correlated with coefficient of 0.57 indicating that margin long investors hold cash buffers at the same time that heavy short trading occurs. MC is positively correlated with S^{PLS} with coefficient of 0.34. So margin investors are also being conservative when investor sentiment is high. The correlation of MC with MD is only 0.24 giving some early indication that the changes in MC are not simply mechanical movements related to changes in margin debt. Additionally, MC is far less correlated with the $MCAP/GDP$, only 0.11, meaning that MC does not simply reflect market valuations. MC also shows the strongest negative correlation, -0.25, with next month's return, an early indication of predictive power of MC. Indeed, of all of the variables, the various versions of margin credit are the most correlated with next month's return.

4 Return predictability tests

While simple correlations between MC and aggregate future returns is useful, it does not give us enough information to determine how strong a predictor MC is, particularly compared to other signals. To assess that, we now examine the in-sample and out-of-sample predictive ability of different variables including margin credit.

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 is the value of predictor variable 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 LHS 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 finite sample properties compared to the use of heteroskedasticity and autocorrelation-adjusted robust t-statistics correction for overlapping observations. However, the R^2 of the transformed regression is not the same as the R^2 of the original regression in Equation (1). So we take the R^2 from the original regression.

Table 3 reports the coefficients, t-statistics and R^2 for four versions of MC and other predictors for the sample period 1984 to 2014. We correct the bias in estimated βs using the Stambaugh correction procedure in Amihud and Hurvich (2004). 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. For ease of comparison across different regressors, we scale all predictors so that they all have zero mean and unit standard deviation.

Table 3 shows that dividend-price ratio, DP, has significant in-sample βs at all horizons and R^2 of 0.71% 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), S^{PLS} and SII are even more impressive with larger beta coefficients and higher R^2 at all horizons. The β for MD has the same negative sign found in Burger and Curtis (2016). 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 26% compared to around 17% for SII.

The variable that stands out in Table 3 is MC. MC has the largest R^2, often more than double the corresponding numbers for the next best non-margin credit predictors, SII, S^{PLS} or MD. Campbell and Thompson (2008) suggest that a monthly R^2 as low as 0.5% in a predictive regression is economically significant. Thus, the monthly R^2 of 6% for MC is highly significant. Its β of around 1.1 is also large. That is, a one standard deviation higher value of MC predicts a market return lower by 1.1%, or 25% of standard deviation in monthly return. The other predictors constructed from margin credit, MC_{MCAP}, MC_{NOM} and MC_{REAL} also perform quite well.

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. Out-of-sample prediction makes use of only information available to investors at the time of prediction and thus avoids the look-ahead bias.

4.2 Out-of-sample tests

To examine the predictive relationship out-of-sample, we follow 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 $\{x_s\}_{s=1}^{t-1}$. 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 $\{x_s\}_{s=1}^{t}$. We follow this process for all subsequent months. Wherever the predictor is a detrended residual, we first detrend only over the training window and then estimate regression (2) to avoid any look-ahead bias.

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 an equally-weighted combination of 14 individual forecasts from Goyal and Welch variables. We call this forecast, *GW MEAN*. In a related work, Campbell and Thompson (2008) recommend economically motivated sign restrictions on $\hat{\beta}_t$ and $\hat{r}_{t+1}$ to improve forecasts. Following them, we set $\hat{r}_{t+1} = 0$, if $\hat{r}_{t+1}$ turns out to be negative. 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) into an initial training period (q months) and the remaining period $(q+1, q+2, .., T)$ 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 $(q+1)$. 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.[17]

R^2_{OS} measures proportional reduction in $MSFE$ when variable x is used to forecast returns relative to use of the historical average equity premium. 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 tests the null hypothesis that $H_0 : R^2_{OS} \leq 0$ against the alternative $H_A : R^2_{OS} > 0$.

Table 4 presents the out-of-sample results. At the monthly horizon of H=1, R^2_{OS} is negative for *DP*, *GW MEAN* and *GW MEAN CT*.[18] While *MD* displays significant in-sample performance,

[17]Specifically, we define $MSFE_x = \frac{1}{T-q}\sum_{t=q}^{T-1}(r_{t+1} - \hat{r}_{t+1})^2$ and $MSFE_h = \frac{1}{T-q}\sum_{t=q}^{T-1}(r_{t+1} - \bar{r}_{t+1})^2$. $\bar{r}_{t+1}$ is the historical mean of log excess returns defined as $\bar{r}_{t+1} = \frac{1}{t}\sum_{s=1}^{t} r_s$.

[18]All the 14 variables in Welch and Goyal (2008) perform poorly. See Table A.4.

as we observed earlier, it does poorly out-of-sample with a negative R^2_{OS}. Consistent with Rapach, Ringgenberg, and Zhou (2016), we find that short interest (SII) generates positive and statistically significant R^2_{OS} of 1.16%. S^{PLS} also has large and significant R^2_{OS} in our sample period at 2.77%. While SII and S^{PLS} outperform the historical benchmark in MSFE terms, it is MC which exhibits the highest R^2_{OS} of 7.51% and statistically significant at 1% level. MC also generates highest R^2_{OS} at the quarterly, semi-annual and annual horizons. Other versions of MC also do quite well at all horizons with monthly R^2_{OS} ranging between 3.21%-6.37%.

4.3 Robustness

The strong out-of-sample predictive ability of MC in our prediction window is clear. We next examine predictability over different subsamples to understand the dynamics and consistency of the relationship between MC and future returns. We also perform additional tests using alternative detrending methods and training windows.

4.3.1 Subsamples

Table 5 presents out-of-sample results for the two halves of our sample, NBER contractions, and expansions. The broad observation is that MC has a positive and larger R^2_{OS} than non-MC predictors in all subsamples. We also find that the other versions of MC generally perform well, but don't always outperform S^{PLS}. MC and its other versions do well during recessions with monthly R^2_{OS} in the range of 11%-20% against 4.3% for S^{PLS}, the next best predictor. In expansions, MC produces a R^2_{OS} of 2.73%, which is marginally higher than that of S^{PLS} and SII. The better performance of MC during recessions is expected, as we note in the introduction, because margin credit is a censored variable, unable to take negative values. So it cannot reflect optimism of margin investors as well as it reflects pessimism. Further, as we show in Section 5, MC generates substantial portfolio gains even during expansions. More crucially, Section 6.1 shows that during expansions as well as contractions, no other predictor provides useful information for return prediction over and above what MC contains.[19]

4.3.2 Financial crisis

Given the strong performance of MC during recessions and the sharp rise in MC in 2008, a question may arise if the results are driven entirely by the financial crisis. The results discussed in the previous subsection indicate that even during expansions MC is a strong predictor. Still, in this subsection, we specifically examine the robustness of our results to excluding financial crisis. A useful tool to assess the time-variation in predictability is a plot showing the cumulative difference in squared forecast error ($CDSFE$) over time as in Welch and Goyal (2008), Rapach, Strauss, and Zhou (2010), and Rapach and Zhou (2013). $CDSFE$ is obtained over the out-of-sample period

[19]Subsample analysis for the in-sample tests also show that MC does relatively better during contractions, but still outperforms other predictors even during expansions. These results are in the Table A.8.

starting from $t = q$ to $t = \tau$ as

$$CDSFE_{\tau+1} = \sum_{t=q}^{\tau}(r_{t+1} - \bar{r}_{t+1})^2 - \sum_{t=q}^{\tau}(r_{t+1} - \hat{r}_{t+1})^2 \quad (4)$$

An increase in $CDSFE$ indicates improvement in performance of the predictor relative to the historical mean return. First we plot $CDSFE$ over the full sample for MC, SII and S^{PLS}. This is the left-most panel in Figure 2. For the most part, MC outperforms the historical mean, SII and S^{PLS} during the out-of-sample period. We see that performance of all three predictors jumps up substantially during one month of the financial crisis, October 2008, and this jump is substantially bigger for MC. So in the middle panel of Figure 2, we plot $CDSFE$ excluding October 2008. It shows that the performance of MC is still quite impressive. The columns under x2008:10 in Table 5 show the R^2_{OS} and t-stats for all the predictors for a period excluding October 2008. Just like the whole sample, MC is the best predictor during this subsample, with R^2_{OS} of 6.33%, a number not too different from the full sample R^2_{OS} for MC of 7.51%. This provides evidence that one outlier month is not driving the performance of MC. We also exclude the entire financial crisis period, 2008:01 to 2009:06. The right-most panel of Figure 2 plots $CDSFE$ for this subsample. It shows that performance of MC even when we exclude the entire financial crisis is at least marginally better than other predictors. Columns x2008:01-2009:06 in Table 5 confirms the visual evidence by providing R^2_{OS} numbers for this subsample of 2.09% for MC and 1.64% for S^{PLS}, the next best non-MC predictor.

Thus, compared to other predictors, MC does at least marginally better outside of financial crisis and substantially better during the crisis and it also encompasses information contained in other predictors (Section 6.1). As noted before, this asymmetric behavior is in line with the asymmetric nature of the variable which is unable to fully capture optimistic beliefs of margin investors.

4.3.3 Detrending

As we discus in Section 3.1.1, there is economic justification for detrending the margin credit variables. The statistical tests presented there support linear detrending and hence our tests use that specification. However, as a robustness, here we present results based on different ways to detrend. We consider four alternative ways of detrending: quadratic, cubic, logarithmic and stochastic. In Table A.9, we present in-sample and out-of-sample return predictability results based on differently detrended versions of margin credit. We find that the in-sample coefficients, t-stats and R^2 are broadly of similar magnitude as those for linear detrending. The R^2_{OS} is also positive and statiscally significant for 15 out of 16 versions presented in Table A.9. R^2_{OS} for stocahstic detrending is in the range of 4.59% to 6.44%, a magnitude similar to R^2_{OS} for linear detrending. R^2_{OS} for quadratic and cubic detrending, while statistically significant, is smaller ranging from 0.39% to 3.83%. One possible reason for worse relative performance with quadratic and cubic detrending is that these models with higher number of parameters result in overfitting in the training period and hence worse out-of-sample performance.

4.3.4 Different training windows

As a further robustness check, we examine the effect of different initial training windows of 5, 10, 15 and 20 years, on the out-of-sample predictability. The results in Table A.10 in the Appendix show large and statistically significant monthly out-of-sample R^2 of 6.28% or more for MC. We conclude that MC generates robust out-of-sample performance over the full sample, over various subsamples, and also with different initial training windows.

5 Asset allocation

While superior out-of-sample predictability usually translates into higher returns for investors by allowing them to time the market, it is important to make adjustments for riskiness of such a strategy. To quantify the risk-adjusted performance of various asset allocation strategies, we consider a mean-variance investor, as in Kandel and Stambaugh (1996), Campbell and Thompson (2008), Ferreira and Santa-Clara (2011), and Rapach, Ringgenberg, and Zhou (2016), among others. This investor allocates money optimally, at the end of month t, between the S&P 500 index, and a risk-free asset, based on out-of-sample prediction of excess return. The investor re-balances her portfolio at the monthly frequency. Specifically, at the end of month t, the investor optimally allocates the following weight to equities during the month $t+1$:

$$w_{x,t} = \frac{1}{\gamma}\frac{\hat{r}_{x,t+1}}{\hat{\sigma}^2_{t+1}} \tag{5}$$

where γ is the risk-aversion coefficient, $\hat{r}_{x,t+1}$ is the out-of-sample forecast of the simple excess return using predictor x, 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. If the investor uses the historical mean of excess returns at time t as the only predictor then the optimal weight is $w_{h,t}$, calculated the same way. As in Rapach, Ringgenberg, and Zhou (2016), we restrict $w_{x,t}$ and $w_{h,t}$ to lie between -0.5 and 1.5 and consider $\gamma = 3$. Figure 3 plots the time series of $w_{h,t}$ and $w_{MC,t}$, weight in equities based on MC. $w_{MC,t}$ shows substantial variation over time, much more than $w_{h,t}$. It shows some quick changes between the maximum of 1.5 and the minimum of -0.5 around recessions, indicating strong responsiveness to the signal.

We compute the certainty equivalent return (CER) gain and Sharpe ratio of different strategies to assess their risk-adjusted performance. Using a strategy based on predictor x, an investor realizes an average utility gain, or CER gain, of

$$CER = \left(\hat{\mu}_x - \frac{1}{2}\gamma\hat{\sigma}^2_x\right) - \left(\hat{\mu}_h - \frac{1}{2}\gamma\hat{\sigma}^2_h\right) \tag{6}$$

where $\hat{\mu}_x$, $\hat{\mu}_h$, $\hat{\sigma}^2_x$, and $\hat{\sigma}^2_h$ are the means and variances, over the out-of-sample period, of the return on a portfolio that invests w_t in the market index based on predictor x and the historical mean respectively. We multiply the CER by 12 to annualize it. The annualized CER can be interpreted as the management fee that an investor would be willing to pay to invest in a fund using x to forecast the equity premium rather than investing on her own using the historical mean.

Table 6 presents returns, standard deviation and the risk-adjusted performance of various strategies over the out-of-sample period of 1994-2014. Similar to their strong predictive ability, SII, S^{PLS}, and all the versions of margin credit generate strong CER gains. Out of these predictors MC generates the highest annualized CER gain of 9.3%. MC_{NOM} and MC_{REAL} generate CER gains of around 6%-8% comparable to 7.4% of S^{PLS}. MC_{MCAP} is again the weakest version but still it produces CER gain of nearly 5%. All margin credit strategies also produce high Sharpe ratios, from 0.72 to 0.98, as opposed to 0.51 of the buy-and-hold strategy.

Table 6 also shows results over different subsamples as well as over the NBER recessions and expansion periods. The broad observation is that over all sample splits, 1994:01 to 2004:12, 2005:01 to 2014:12, NBER recessions and expansions, MC outperforms other predictors both in terms of Sharpe ratio as well as CER gains. During recessions, all four versions of MC have better Sharpe ratios than all other predictors, including S^{PLS}, the only non-MC predictor to have positive Sharpe ratio during recessions. All MC strategies also produce large CER gains in the range of 35%-50%. MC does better in recessions than in expansions, in line with its out-of-sample predictive ability and consistent with its nature as a censored variable. Still, the Sharpe ratio of the MC strategy during expansions is 0.95, comparable to 0.93 of S^{PLS} and higher than the other predictors.

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. The strategy invests either 100% in the equity market or 100% in the risk-free asset. This binary investment constraint also serves to highlight the importance of avoiding large negative returns. Strategies that fail to avoid negative months here are not able to use leverage to recover returns later. 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. Table A.11 and Figure A.1 in the Appendix provide details of the performance of this strategy. This strategy also outperforms buy-and-hold strategy by a large margin robustly across subsamples. Thus, MC is a robust predictor of future returns and a valuable signal for the investors.

6 Economic channels

Despite not being the most pessimistic signal possible, MC is a strikingly good and valuable predictor. The first step in understanding the channels through which MC operates is to compare the information it has with that in the other predictors.

6.1 Information encompassing tests

We use forecast encompassing tests to compare the information content of MC, to that of other predictors relevant for making return forecasts (Rapach, Strauss, and Zhou (2010), Rapach and Zhou (2013), Rapach, Ringgenberg, and Zhou (2016)). Forecast encompassing tests come from the literature on optimal forecast combination (Chong and Hendry (1986), Fair and Shiller (1990)). An optimal forecast as a convex combination of two forecasts for month $t+1$ is

$$\hat{r}^{*}_{t+1} = (1-\lambda)\hat{r}_{1,t+1} + \lambda\hat{r}_{2,t+1}, \tag{7}$$

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 λ such that $0 \leq \lambda \leq 1$ is chosen to minimize $MSFE$ of $\hat{r}^{*}_{t+1}$. $\lambda = 0$ 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 relevant to predict excess market returns beyond the information contained in the first variable. However, if $\lambda > 0$, it suggests that that the forecast $\hat{r}^{*}_{t+1}$ does not encompasses $\hat{r}_{2,t+1}$ and both variable 1 and 2 have information 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.

Table 7 shows the λ's, the weight in MD, SII, S^{PLS}, and one of the margin credit variables in combination with each other and other predictors, for monthly horizon ($H = 1$). Predictor 1, generating $r_{1,\hat{t}+1}$ with weight $1-\lambda$ is listed in column 1. Predictor 2, generating $r_{2,\hat{t}+1}$ with weight λ are listed as headings of the remaining columns. We find that 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, MC encompasses the predictions based on all other variables. These include DP, MD, $MCAP/GDP$, SII, S^{PLS}, and even other margin credit variables. Focusing on the last row, we find that none of the predictions based on other variables have λ's significantly different from 0. MC_{REAL}, MC_{NOM}, and MC_{MCAP}, while not being as informative as MC, still encompass the information in all other non-margin credit variables. In unreported results, we find similar evidence for longer horizon predictions. Thus, none of the other variables seem to provide additional information not already contained in margin credit.

Results in Sections 4 and 5 indicate that while MC is a good predictor both in expansions and recessions, it does better during recessions. Table 8 investigates incremental information in MC during different subsamples. During neither contractions nor expansions, do other predictors provide any additional information compared to that in MC. For the optimal forecast combination, the weight in MC-based forecast is always 1 against all other forecasts both during contractions and expansions.

Evidence in Huang, Jiang, Tu, and Zhou (2015) and Rapach, Ringgenberg, and Zhou (2016) suggests that S^{PLS} and SII predict returns because they contain information about future growth in cash flows. Since MC encompasses all the information in S^{PLS} and SII, we would expect it to have information relevant for future cash flows.

6.2 Cash flow or discount rate?

A fundamental relationship in finance is that the value of a stock is the discounted present value of the future expected cash flows. Thus, return for any period can result from change in the discount rate or change in the expectations of the cash flows or both. Thus, a variable that predicts lower stock market return must either predict an increase in the discount rate, 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. While investor level demographics are not available for margin investors, we can examine the investing behavior of hedge funds, as hedge funds routinely use leverage, part of which comes from margin debt. Ang, Gorovyy, and van Inwegen (2011) find that hedge fund leverage decreased in mid-2007 prior to the financial crisis. They show that hedge funds reduced their leverage in response to increased riskiness of assets, a strategy consistent with hedge funds targeting a particular risk profile. 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.

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 the 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 2008 crisis was primarily due to redemptions and pressure from their lenders. Margin investors may face the same trade-offs while managing their own investments against their liquidity needs and more directly if managing the investments of others. When anticipating greater redemption risk, they accumulate margin credit rather than reinvesting it. All the above possibilities of conservatism in anticipation of higher risk point to margin credit predicting higher discount rate.

On the other hand, the 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. The theoretical model in Dai and Sundaresan (2010) shows that a hedge funds' optimal leverage depends upon Sharpe ratio of their assets. If the Sharpe ratio goes down, either due to lower expected return, the cash flow channel, or higher standard deviation, the discount rate channel, the hedge fund lowers their leverage. 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 the ability of SII to predict aggregate returns comes because short investors have better information on future cash flows. As we argue in Section 2, margin credit, as opposed to margin debt, allows us to focus on informed investors who are correct about their past beliefs. These investors pull back from reinvesting their gains when they expect the future cash flows to be low or when cash flows become uncertain. Thus, 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 (1988b) log-linearize the stock return and give the following approximate identity:

$$R_{t+1} = k + DG_{t+1} - \rho D/P_{t+1} + D/P_t. \tag{8}$$

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/P_{t+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 (8) 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,

$$Y_{t+1} = \alpha + \beta MC_t + \psi DP_t + \eta_{t+1}, \qquad Y = Ret, DP, DG, EG, GDPG. \tag{9}$$

Here, Ret is the log excess return on the S&P 500 index (including dividends). DP is 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.[20] 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 (9) at quarterly and annual frequencies. Quarterly observations allow us to use the information available at a higher frequency. However, to avoid influence of strong seasonal patterns, particularly in DG and EG, we run the regressions also at annual frequency. We also run regressions, except $Y = GDPG$, at the monthly frequency with returns and growth rates measured as monthly averages over annual overlapping periods.[21] These use the information available monthly and yet retain the annual growth rates to avoid the seasonality issue. 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, where X is the matrix containing the values of MC and DP.

Table 9 presents the results. For all frequencies, we correct the coefficients for the Stambaugh (1999) bias, calculate Newey-West t-statistics, and report the statistical significance based on wild boot-strapped p-values. The first row in each panel reports univariate regression of Ret_{t+1} on

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

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

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 adds DP as a control. We see that the coefficient β in row 2 is very similar in magnitude and significance to 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 Section 6.1 on forecast encompassing tests. Rows 3 onward in the panels in Table 9 present results of our investigations of the economic channels. In all the panels, Coefficient for MC when $Y = DP$ 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 almost all panels, the coefficients for MC when $Y = DG$, EG or $GDPG$ 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) and Rapach, Ringgenberg, and Zhou (2016) that S^{PLS} and SII predict future return via the cash flow channel. From the forecast encompassing tests we know that MC contains all the information in SII and S^{PLS} that is relevant for forecasting returns. Thus, it is reasonable that, just like SII and S^{PLS}, it contains information about future cash flows. Overall, both the discount rate and cash flow channels contribute to MC's very strong ability to predict future returns.

6.3 Changing risk and uncertainty

Rather than act on better private information, margin investors may decrease leverage in response to an observed increase in risk and uncertainty. Indeed, Moreira and Muir (2017) demonstrate that moving money from the market portfolio to the risk-free asset in response to increased realized volatility can improve the Sharpe ratio. To see if MC anticipates or reacts to observed risk and uncertainty, we investigate the predictive relationship between MC and various proxies of risk and uncertainty using bivariate Vector Autoregressions (VAR). Specifically, we run the VAR:

$$V_{t+1} = A + BV_t + \zeta_{t+1}, \qquad V_t = [Risk_t; MC_t]. \tag{10}$$

As discussed in Section 3, for predicting returns, we use margin credit numbers that are two months old to account for the reporting delay, to make sure that we are only using information available to the investor at the time of making a prediction. However, for bivariate VAR, we use MC without the two-month lag, to align the timing of $Risk_t$ and MC_t and draw correct inferences about two-way predictability.

We consider stock market based as well as macroeconomic proxies of risk and uncertainty. We measure stock market volatility using standard deviation of daily market returns during month t, $MVOL_t$, as well as using VIX, the Chicago Board Options Exchange (CBOE) volatility index based on S&P 500 index options.

We also use average correlation between stocks as a proxy of risk. Pollet and Wilson (2010) show theoretically and empirically that average correlation between stocks is a good proxy for aggregate risk. Following them, we calculate AC_t as the market-cap-weighted average correlation of daily returns within month t of the 500 stocks with the largest market capitalization.

Further, we examine if MC is related to macroeconomic and financial uncertainty using measures constructed by Jurado, Ludvigson, and Ng (2015) and Ludvigson, Ma, and Ng (2015). Jurado, Ludvigson, and Ng (2015) construct macroeconomic uncertainty as an aggregated conditional volatility of surprise in hundreds of macroeconomic variables. Financial uncertainty is similarly constructed using hundreds of financial indicators. We obtain the data for macroeconomic and financial uncertainty from Sydney Ludvigson's website.[22] We use estimates of one-month ahead uncertainty (H=1).

The results of bivariate Granger causality tests based Equation (10) for the period from 1984 to 2014 are in Panel A of Table 10. They indicate that MC strongly predicts rise in all the proxies of risk and uncertainty, statistically significant at least at 5%. These results are consistent with the evidence presented in Section 6.2 that MC predicts a rise in the discount rate. Thus, higher values of margin credit, anticipate times of greater risk and uncertainty.

We also examine predictability in the other direction, from the proxies of risk and uncertainty to MC. If investors accumulate margin credit *in response to* rather than *in anticipation of* higher risk, we should find that higher values of the risk proxies predict higher MC. As we see in Table 10, $MVOL$, VIX and AC have no ability to predict MC. We do find that the uncertainty variables predict MC, macroeconomic with a statistical significance of 10% and financial with that of 5%. However, this relationship is negative i.e. higher uncertainty predicts *lower* margin credit. These results are not consistent with the interpretation that margin investors are acting conservatively in response to observed increase in risk and uncertainty.

Next, we investigate if these risk proxies themselves have any ability to predict returns and if they do, whether they contain information in addition to that contained in MC. Here we use MC with two month lag, to be consistent with the out-of-sample results in Section 4.2 and forecast encompassing tests in Section 6.1. For each of the above risk proxies, we calculate out-of-sample R^2 (R^2_{OS}) and its statistical significance for prediction of next month's S&P 500 return, see Section 4.2. We also conduct forecast encompassing tests as in section 6.1, to choose the optimal weights for a convex combination of a forecast based on MC and a forecast based on the risk proxy, λ_{MC} and $1-\lambda_{MC}$ respectively. These results are in Panel B of Table 10. We see that $MVOL$, VIX and AC do not have statistically significant ability to predict returns at monthly horizon. Macroeconomic and financial uncertainty show large and statistically significant R^2_{OS} of 2.6% and 3%, respectively. But even they do not contain any information over and above that in MC, as indicated by λ_{MC} of 1 or almost 1 in all cases.

Thus, margin credit accumulates in anticipation of the times of higher risk and uncertainty, and not as a reaction to the higher values of observed risk proxies. Moreover, the proxies of risk and uncertainty themselves cannot improve on the forecasting ability of MC. However, the "decision"

[22]https://www.sydneyludvigson.com/data-and-appendixes/.

by margin investors not to borrow more may not be a decision at all if their brokers won't lend more.

6.4 Changing borrowing conditions and intermediary constraints

Since the use of margin requires borrowing from brokers, the decisions and financial conditions of the brokers could also drive MC. Brokers could tighten lending conditions or themselves be capital constrained and as a result margin investors could be unwilling or unable to borrow more. For example, the brokers may increase the margin requirements or the interest rates charged on the loans or otherwise tighten the borrowing conditions. Under this scenario, margin investors accumulate credit not because *they* are pessimistic but *their brokers* make borrowing more difficult or unprofitable. This line of argument is consistent with the rise in interest rates on margin loans before the 1929 crash as examined in Rappoport and White (1994). Further, Chava, Gallmeyer, and Park (2015) show that tightening credit standards by banks predicts lower aggregate stock returns at quarterly frequency. Thus, it is important to investigate if predictability of margin credit is simply a reflection of tightening borrowing conditions.

Accumulation of margin credit by investors cannot result from a formal increase in margin requirements by the brokers. An increase in margin requirements means that the investor is *required* to put in more equity and borrow less. Thus her debt capacity and hence excess debt capacity goes down. As per the FINRA rule, brokers can only treat equity over and above the margin requirements as margin credit.[23] Thus, margin credit will *decrease, not increase* if the brokers increase margin requirements.

However, we do examine if margin credit increases as a consequence of tightening borrowing conditions in other ways. Similar to the examination of risk and uncertainty, we investigate predictive relationship between MC and various proxies of borrowing conditions using bivariate VAR. We use several interest rates as well as bank credit growth and intermediary capital ratio as our proxies of borrowing conditions.

We use data on broker call money rates from 1988 to 2014 from Bloomberg ($Broker_{Call}$), average bank call money rates for 1984-2005 from Datastream ($Bank_{Call}$), and bank prime lending rates for 1984-2014 from Datastream ($Bank_{Prime}$).[24] TBL is the treasury-bill rate used by Welch and Goyal (2008).

In addition to the interest rate variables, we use bank credit growth, $Credit_{CHG}$, as another proxy of borrowing conditions. Following Gandhi (2016), we construct this variable as year-on-year growth rate in nominal monthly bank credit from 1984 to 2014.[25] Presumably capital available to brokers for lending is positively correlated with growth in bank credit. Then, if margin credit

[23] FINRA regulatory notice 10-08 clarifies that for the purpose of rule 4521, credit balances in securities margin accounts are considered free (withdrawable) when the firm has no lien or claim against them, nor has imposed any other encumbrance, irrespective of whether the same customer has offsetting debits in another account.

[24] Call money is the money loaned by a bank or other institution which is repayable on demand.

[25] Nominal monthly bank credit is available in statistical release H.8 (Assets and Liabilities of Commercial Banks in the U.S.) of the Board of Governors of the Federal Reserve System.

accumulation happens due to tighter borrowing conditions, we would expect bank credit growth to predict lower MC.

We also examine intermediary capital risk factor ($ICRF$) and intermediary leverage factor (LF_{AEM}) as other proxies of capital available to brokers. $ICRF$ is constructed by He, Kelly, and Manela (2016) as shocks to the intermediary capital ratio of primary dealer counterparties of the New York Federal Reserve.[26] We use $ICRF$ from 1984 to 2012, available from Asaf Manela's website. It is reasonable to suppose that when this factor is low, i.e. when prime dealer's equity capital is low, brokers are likely to be constrained and possibly unwilling to lend easily to the margin investors. Indeed, He, Kelly, and Manela (2016) find that lower $ICRF$ indicates tighter financial conditions as measured by the Chicago Fed's National Financial Conditions Index. Again, if margin credit accumulation is in response to tighter borrowing conditions, $ICRF$ should predict lower MC. LF_{AEM} is constructed as the shocks to broker-dealer leverage ratio of Adrian, Etula, and Muir (2014), also available from Asaf Manela's website.[27] Adrian, Etula, and Muir (2014) argue that lower leverage, as measured by them, is a proxy of tighter financial funding liquidity.[28] So, if margin credit accumulates due to tighter funding conditions, LF_{AEM} should predict lower MC.

Panel A of Table 11 shows the results for the bivariate Granger causality tests between MC and the proxies of borrowing conditions. Just as in Section 6.3, for bivariate VAR, we use MC without the two-month lag, to align the timing of borrowing conditions and MC_t and draw correct inferences about two-way predictability. We see that MC predicts each of these lending rates at least at the 5% level and most at the 1% level. Only the bank prime lending rate shows some evidence of predicting MC with a p-value of 0.099. No other lending rate shows even weak evidence of being able to predict MC. The inability of lending interest rates to predict MC is inconsistent with the argument that the higher interest rates charged by brokers restrain reinvestment causing the unusual rise in margin credit. We also find that MC predicts lower bank credit growth. $MC's$ ability to predict risk as well as bank credit growth is consistent with the conclusion in Gandhi (2016) that bank credit responds to rather than causes changes in future macroeconomic risk.

Further, higher MC predicts lower intermediary capital ratio. This finding is consistent with the interpretation in Section 6.3 that high MC predicts higher future risk, since He, Kelly, and Manela (2016) argue that states with low $ICRF$ have high risk.

In the other direction, as with the various lending rates, neither $ICRF$ nor LF_{AEM} have any ability to predict MC. Growth in bank credit predicts MC but positively. This result is inconsistent with the interpretation that MC accumulates in response to tighter borrowing conditions or intermediary constraints.

Next, we examine if any of these proxies for borrowing conditions and intermediary constraints

[26] He, Kelly, and Manela (2016) define the intermediary capital ratio as the aggregate value of market equity divided by aggregate market equity plus aggregate book debt of the primary dealers.

[27] Adrian, Etula, and Muir (2014) calculate the broker-dealer leverage ratio as the book value of total assets divided by book value of total equity of broker-dealers using the Federal Reserve Flow of Funds.

[28] See Section 4 of He, Kelly, and Manela (2016) for a comparison of their approach with that of Adrian, Etula, and Muir (2014).

can predict returns or have information over and above MC at monthly horizon. For these tests, as in Panel B for Table 10, we use MC with two month lag, to be consistent with the out-of-sample results in Section 4.2 and forecast encompassing tests in Section 6.1. Panel B of Table 11 shows out-of-sample R^2 and forecasting encompassing tests. While $Bank_{Call}$ and $Credit_{CHG}$ show statistically significant out-of-sample R^2, neither they nor any other proxy for funding conditions improve the forecasts made by MC. The weight on MC in the optimal forecast combination (λ_{MC}) is always 1.

We also investigate the variable $Credit_{STD}$ used by Chava, Gallmeyer, and Park (2015). This variable reflects "Net Percentage of Domestic Banks Tightening Standards for Commercial and Industrial Loans to Large and Middle-Market Firms". The variable, available from FRED[29], is based on responses to a quarterly survey, conducted by the Federal Reserve, of up to eighty large domestic banks and twenty-four U.S. branches and agencies of foreign banks. Thus, higher $Credit_{STD}$ captures tighter borrowing conditions. Since $Credit_{STD}$ is available only quarterly, monthly analysis as in Table 11 is not possible. But we do conduct an exercise similar to that in Table 11 at quarterly frequency. First, there is no evidence that $Credit_{STD}$ can predict MC for the next quarter (p-value = 0.254). On the other hand, high MC predicts significantly higher $Credit_{STD}$ in the next quarter (p-value < 0.001). We also examine return predictability using $Credit_{STD}$. As documented by Chava, Gallmeyer, and Park (2015), we find that $Credit_{STD}$ is a good predictor of returns at the quarterly horizon, with an R^2_{OS} of 5.56%. Note from Table 4 that R^2_{OS} for MC at quarterly horizon is 19.85%. Forecast encompassing tests put weight of 0.45 in $Credit_{STD}$ and 0.55 in MC, both statistically significant. Thus, MC has information over and above that contained in $Credit_{STD}$. This evidence reinforces the results presented in Table 11 that i) lending conditions do not predict MC, ii) MC predicts future lending conditions and intermediary constraints, and iii) MC has independent information relevant for return predictability not contained in the lending variables.

Overall, the data do not support the interpretation that margin credit predicts returns because it is a result of higher interest rates or otherwise tighter borrowing conditions. Nor does the evidence support the notion that higher MC results from intermediary or other lending constraints.

6.5 Why is margin credit such a powerful predictor?

So far we have seen that margin credit subsumes information of other predictors. It forecasts lower future cash flows and higher future risk. Further, the predictive ability of margin credit does not flow from tighter borrowing conditions. We now discuss why margin credit might be such a powerful signal.

The two periods when margin credit does really well as a predictor are internet crash in the early 2000s and the financial crisis. Accumulation of margin credit prior to a market crash is consistent with the theoretical model in Abreu and Brunnermeier (2003). In this model, rational arbitrageurs

[29] Board of Governors of the Federal Reserve System (US), Net Percentage of Domestic Banks Tightening Standards for Commercial and Industrial Loans to Large and Middle-Market Firms [DRTSCILM], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/DRTSCILM.

know about the existence of the bubble, but they do not know how many other arbitrageurs have this knowledge. Price only falls when sufficient number of arbitrageurs sell the asset. Decision to sell depends on a personal signal as well as an estimate of how many other investors have received a pessimistic signal. Any signal that sufficient number of arbitrageurs are pessimistic accelerates the fall in prices. Brunnermeier and Nagel (2004) and Griffin, Harris, Shu, and Topaloglu (2011) find evidence from the 1999-2000 period supporting this model.

We can view each margin investor's decision to accumulate margin credit as a reaction to an individual signal about overvaluation or upcoming market crash. Note that margin credit is high when investors do not borrow against their gains i.e. when they are being cautious. Only when sufficient number of investors decide to pull back, i.e. when aggregate margin credit accumulates, the time is ripe for prices to fall. Further, only when investors know that margin credit has accumulated, they will act on this aggregate signal and prices will fall further. Some evidence about the lag with which margin credit predicts returns also indirectly supports this interpretation. As explained in Section 3, the return predictability and asset allocation tests use margin credit numbers that are two months old to account for the two month reporting lag – at the end of month t the margin credit numbers we use to predict return for the month $t+1$, are in fact for margin credit accumulated by the investors at the end of month $t-2$, but reported by NYSE during month t. We do this to make sure that the aggregate margin credit numbers are part of investors' information set at the time of prediction. But we can examine how well MC based on numbers accumulated at time t predict the return for month $t+1$. This variable at t – call it MC_{NoLag} – is the aggregate of individual signals but the aggregate signal itself is not yet observed by investors. Thus while MC accumulated at $t-2$ and reported at time t can act as synchronization device, MC_{NoLag} cannot. We find that MC_{NoLag} is a strong predictor of returns at $t+1$, better than all other non-margin-credit predictors. But it is not as strong as MC. Its in-sample R^2 is 3.31% compared to MC's 6.31%. Its out-of-sample R^2 is 2.81% compared to MC's 7.51%.

Thus, while aggregated margin credit is a powerful signal in itself – monthly R^2_{OS} of 2.81% is no mean feat – it becomes more powerful when the signal becomes public, possibly because it acts as a synchronizing device indicating that many investors have individually received the pessimistic signal.

Abreu and Brunnermeier (2003) also show that the synchronization problem along with the incentive of arbitrageurs to time the crash means that the arbitrageurs stay invested in the overvalued asset for some time even after they find out that the price is inflated. This aspect of the model also helps us resolve the conundrum: why do investors accumulating margin credit still continue to hold a long positions if they have a pessimistic signal? In the light of Abreu and Brunnermeier (2003) model, they do so since they don't know if enough other investors have received a pessimistic signal for prices to fall.

7 Conclusion

Our study finds that margin credit, the excess debt capacity of investors buying securities on the margin, is a powerful predictor of future excess market returns. A one standard deviation higher margin credit predicts that next month's return will be lower by 72 to 112 basis points per month. Out-of-sample tests show that from 1994 to 2014, MC outperforms other predictive variables by large margins. A trading strategy based on MC generates 9.3% annualized CER gains, relative to a strategy based on the historical equity premium. A MC-based strategy delivers superior risk-adjusted performance during recessions as well as expansions. Moreover, once we consider the information in MC, the other predictors don't provide any additional information relevant for forecasting.

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 that MC predicts both lower future cash flows and higher future discount rate. Further, MC anticipates higher VIX, higher average equity correlation, higher macroeconomic and financial uncertainty all states associated with greater risk. We do not find evidence that accumulation of MC is due to margin investors *reacting* to higher risk or tighter borrowing conditions, but rather that MC precedes changes in lending conditions and intermediary constraints.

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 is a powerful predictor of future returns carrying substantial information about future cash flows as well as risk. The paper contributes to the asset pricing literature on borrowing conditions and intermediary constraints by establishing that voluntary changes in leverage by a set of potentially sophisticated investors has implications for asset prices.

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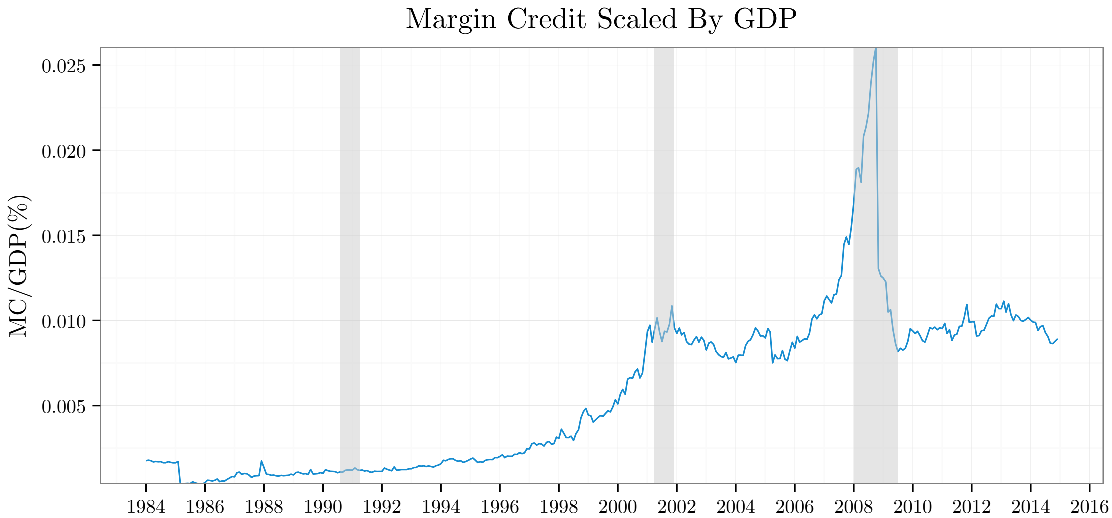
Figure 1: **Margin credit**

This figure plots growth of (a) the margin credit to GDP ratio, and (b) the detrended margin credit to GDP ratio. The shaded vertical regions show NBER dates recessions.



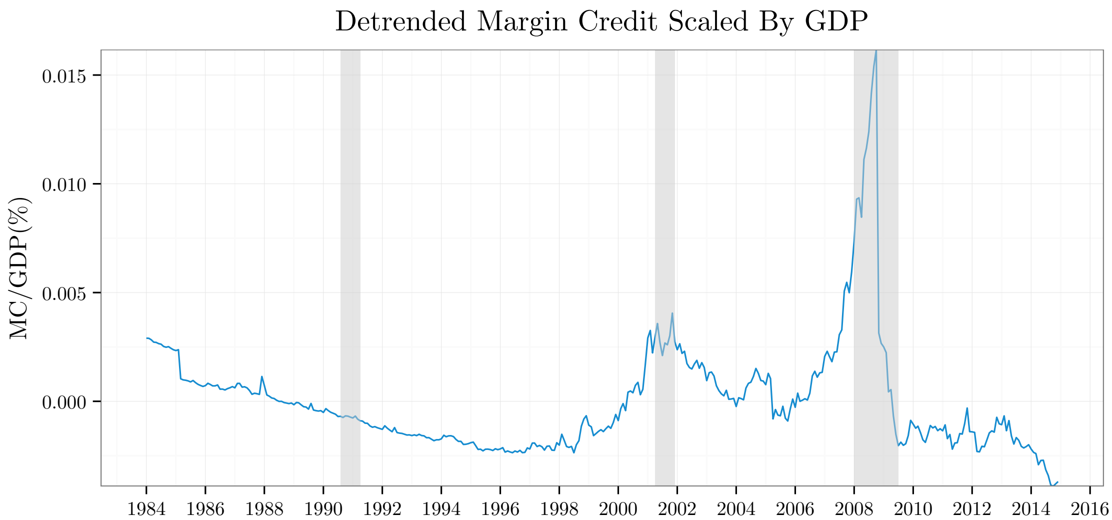


Figure 2: **Cumulative difference in squared forecast error**

This figure plots cumulative difference in squared forecast errors (CDSFE)for the historical average benchmark and out-of-sample forecasts based on individual predictors, see Section 4.3.2 for the definition of CDSFE. A positive value indicates that the predictor is better than the historical average. A rise in this difference indicates improvement in the predictive ability of a particular variable compared to historical mean. The individual predictors are short interest index in Rapach, Ringgenberg, and Zhou (2016) (SII), investor sentiment aligned in Huang, Jiang, Tu, and Zhou (2015) (S^{PLS}), and detrended margin credit to GDP ratio (MC). The shaded regions correspond to NBER recessions. The first graph covers the whole out-of-sample prediction period from January 1994 to December 2014. The middle figure excludes October of 2008 the prediction which contributes most to the cummulative accuracy of MC. The third figure excludes the financial crisis recession from January 2008 to June 2009.

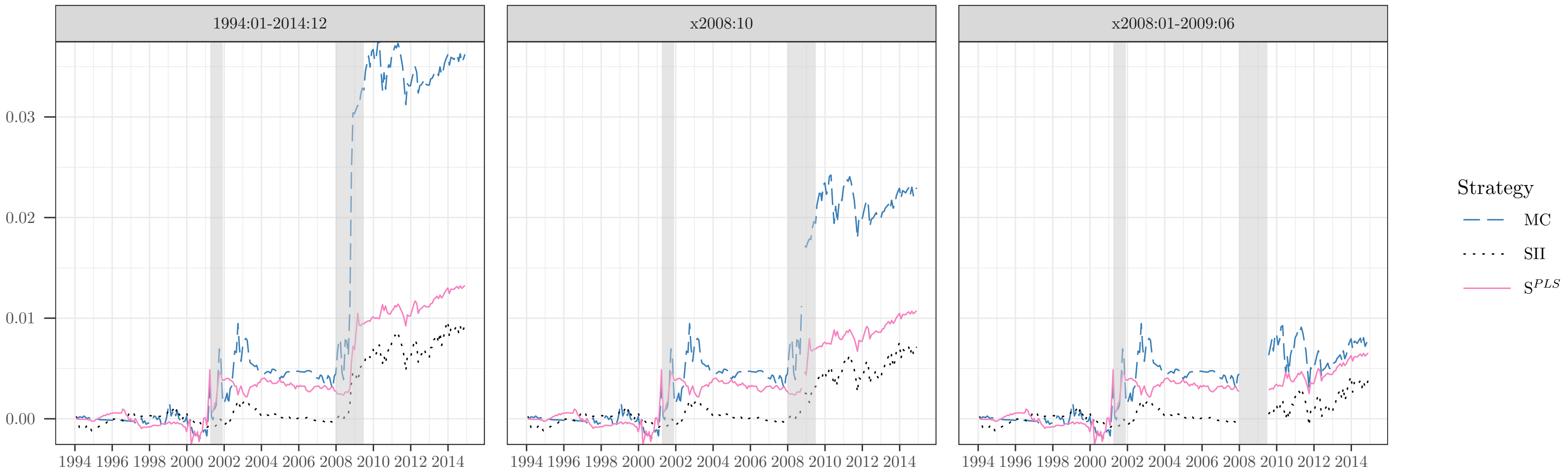


Figure 3: **Mean-variance investment weight**

This figure plots the weight in the S&P 500 each month for the out-of-sample strategy of a mean-variance investor with relative risk aversion coefficient of three who allocates between equities and risk-free T-bills using S&P 500 excess return forecast based on the historical mean or detrended margin credit to GDP ratio (MC). The equity weight is constrained to lie between -0.5 and 1.5. See Section 3 for the detailed variable definitions and Section 5 for the details of asset allocation.

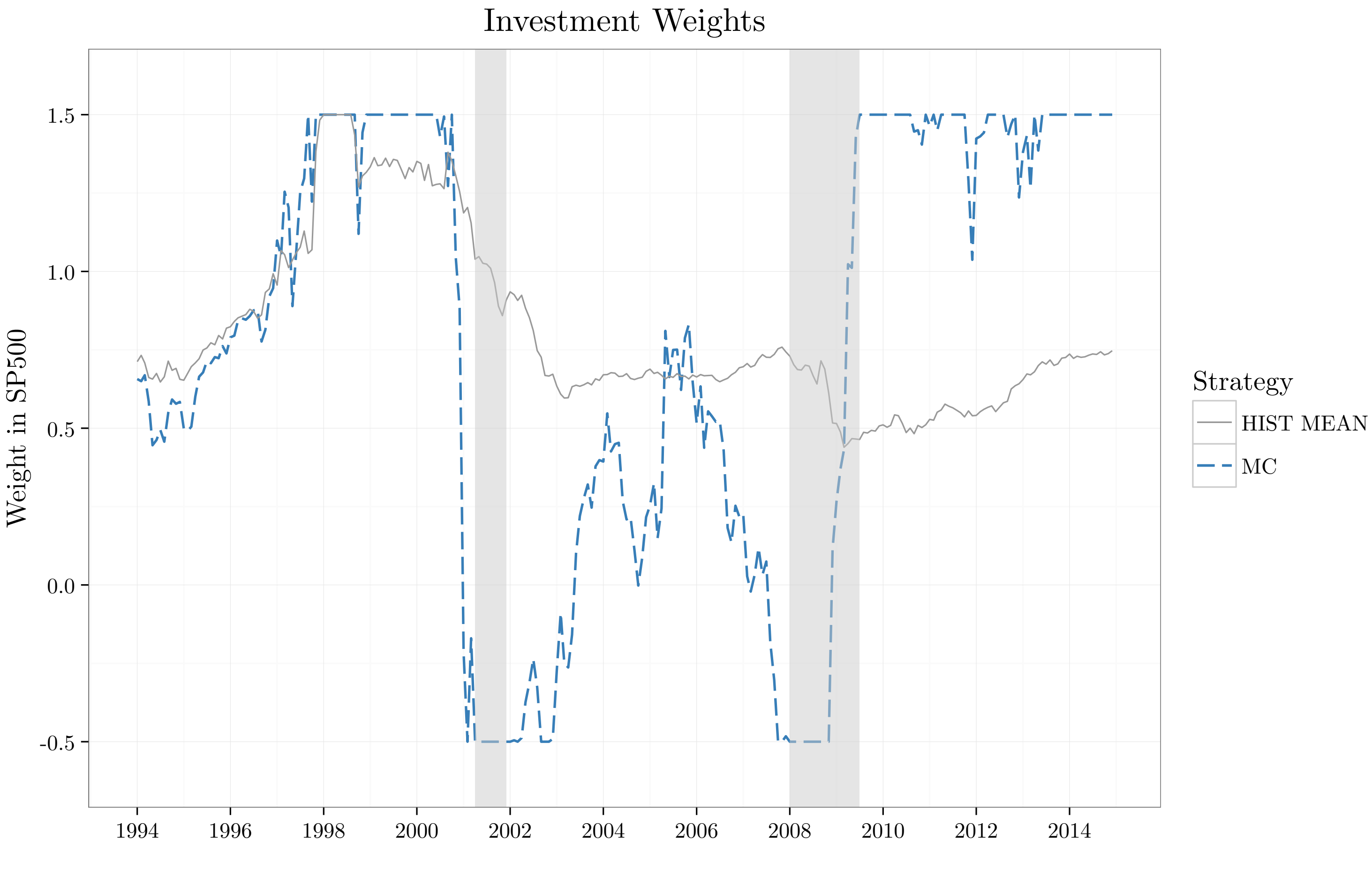


Figure 4: **Cumulative returns to $1: mean-variance investor**
This figure plots cumulative returns (sum of logs) for the out-of-sample strategy of a mean-variance investor with relative risk aversion coefficient of three who allocates between equities and risk-free T-bills using S&P 500 excess return forecast based on the historical mean or a predictor. 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. The predictors are margin credit variously scaled and de-trended (MC_{NOM}, MC_{REAL}, MC_{MCAP}, and MC). See Section 3 for the detailed variable definitions and Section 5 for the details of asset allocation.

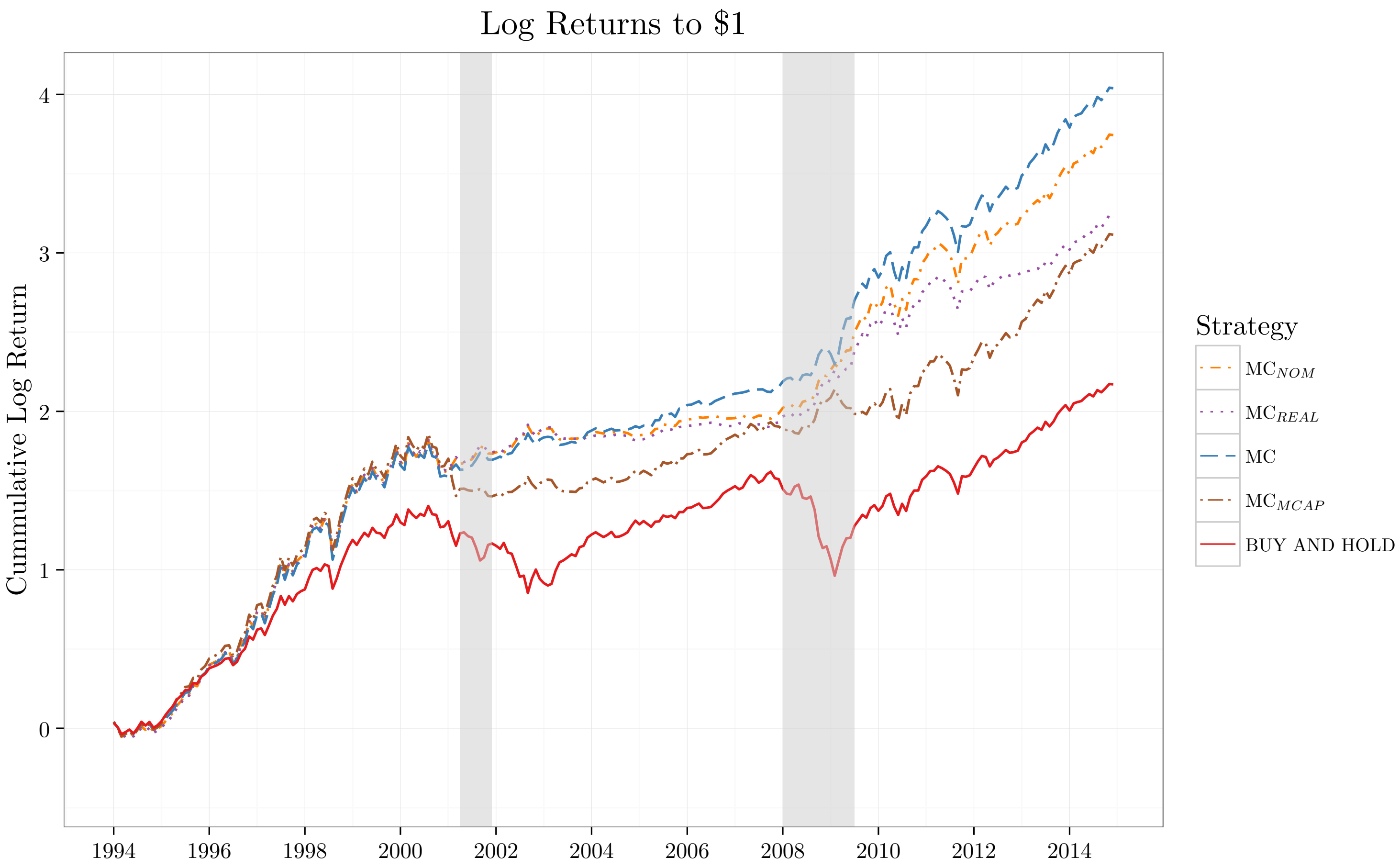
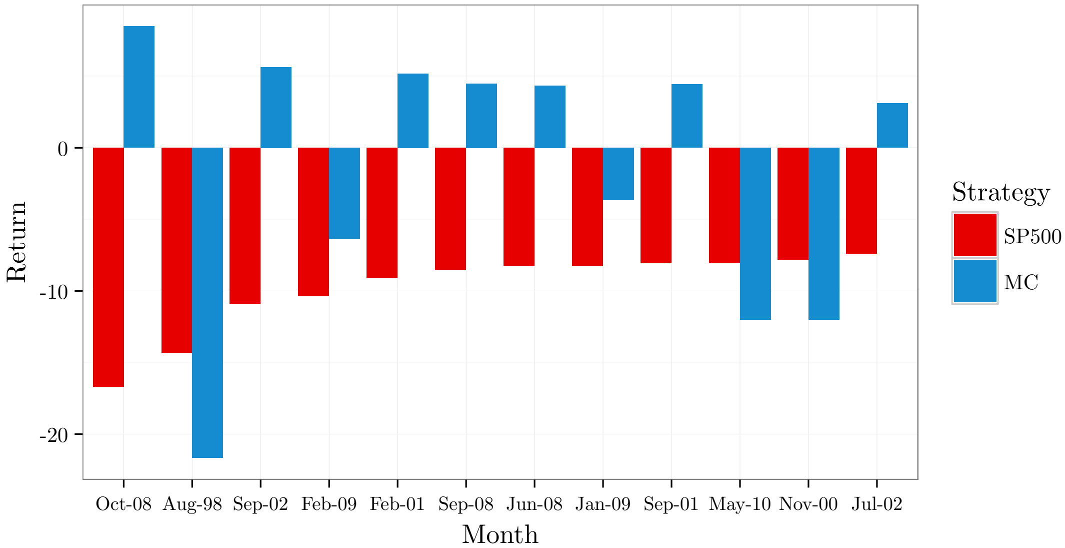
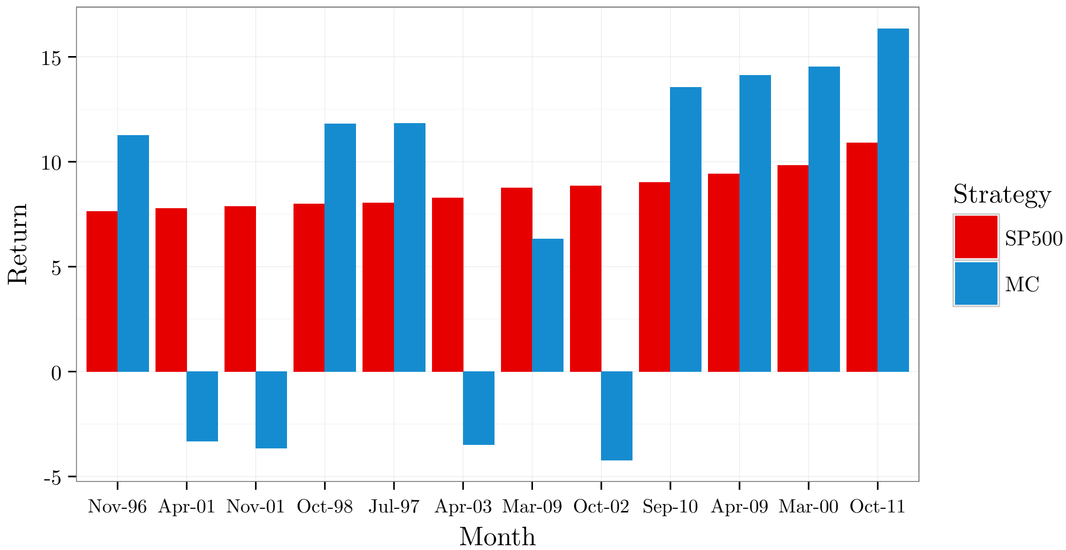


Figure 5: **Worst and best months: mean-variance investor**
This figure shows, for the worst and best months of S&P 500, returns for the index and for the out-of-sample strategy of a mean-variance investor with relative risk aversion coefficient of three who allocates between equities and risk-free T-bills using S&P 500 excess return forecast based detrended margin credit to GDP ratio (MC). The equity weight is constrained to lie between -0.5 and 1.5. See Section 3 for the detailed variable definitions and Section 5 for the details of the asset allocation.



(a) Lowest S&P 500 return months



(b) Highest S&P 500 return months

TABLE 1: Summary statistics

The table displays summary statistics for dividend price ratio from the predictor variables of Welch and Goyal (2008), aggregate short interest, investor sentiment, the valuation indicator and the margin statistics. DP is the log dividend-price ratio. 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. S^{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
EWSI	372	2.79	1.93	0.45	8.92
S^{PLS}	372	−0.24	0.77	−1.18	3.03
Margin Debt ($B)	372	153.08	117.86	21.79	465.72
Margin Credit ($B)	372	73.10	74.05	1.67	385.85
Margin Debt (1984 $B)	372	81.74	50.11	20.92	202.60
Margin Credit (1984 $B)	372	37.22	34.39	1.62	181.13
MCAP/GDP (%)	372	98.92	37.56	40.18	181.09
MC/MCAP (%)	372	0.51	0.35	0.09	2.15
MD/GDP (%)	372	1.33	0.64	0.45	2.81
MC/GDP (%)	372	0.57	0.48	0.04	2.60

TABLE 2: **Correlations**

The table displays Pearson correlation coefficients for log dividend price ratio (DP), the short interest index (SII), the sentiment index based on a partial least squares approach (S^{PLS}), CRSP total market capitalization to GDP ratio ($MCAP/GDP$), de-trended margin debt to GDP (MD), and margin credit variously scaled and de-trended (MC_{MCAP}, MC_{NOM}, MC_{REAL}, and MC). RET_{t+1} is the one-month-ahead log excess return on the S&P 500. See Section 3 and the caption for Table 1 for the detailed variable definitions and sample description.

	DP	SII	S^{PLS}	$^{MCAP}/_{GDP}$	MD	MC_{MCAP}	MC_{NOM}	MC_{REAL}	MC	RET_{t+1}
DP	1.000									
SII	-0.005	1.000								
S^{PLS}	-0.125	-0.154	1.000							
$^{MCAP}/_{GDP}$	-0.888	-0.016	0.164	1.000						
MD	-0.387	-0.152	0.490	0.501	1.000					
MC_{MCAP}	0.248	0.536	0.223	-0.131	-0.133	1.000				
MC_{NOM}	0.254	0.488	0.209	-0.012	0.186	0.851	1.000			
MC_{REAL}	0.164	0.540	0.290	0.039	0.193	0.857	0.938	1.000		
MC	0.053	0.571	0.337	0.108	0.240	0.878	0.944	0.944	1.000	
RET_{t+1}	0.084	-0.130	-0.163	-0.087	-0.122	-0.160	-0.226	-0.214	-0.251	1.000

TABLE 3: In-sample predictive regressions

This table reports the ordinary least squares estimate of β and R^2 statistic for the model predicting log excess return on the S&P 500, measured as percentages (1=1%), for the sample 1984 to 2014. The predictors are log dividend price ratio (DP), the short interest index (SII), the sentiment index based on a partial least squares approach (S^{PLS}), CRSP total market capitalization to GDP ratio ($MCAP/GDP$), de-trended margin debt to GDP (MD), and margin credit variously scaled and de-trended (MC_{MCAP}, MC_{NOM}, MC_{REAL}, and MC). See Section 3 and the caption for Table 1 for the detailed variable definitions and sample description. Each predictor variable is standardized to have mean 0 and standard deviation of one. The sign (+/-) following the variable in column 1 indicates the expected sign of the coefficient. Reported betas are corrected for bias in Stambaugh (1999). 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. H=1, 3, 6 or 12 indicates the horizon in months for which average monthly return is predicted.

	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(+)	0.018**	0.279**	0.364**	0.413**	1.614	1.913	2.14	2.275	0.713	2.352	5.166	10.909
SII(-)	-0.586***	-0.65***	-0.678***	-0.581**	-2.38	-2.471	-2.297	-1.811	1.689	6.013	12.24	16.63
S^{PLS}(-)	-0.747***	-0.642***	-0.506**	-0.394*	-2.923	-3.02	-2.624	-2.084	2.649	5.612	6.686	8.207
MCAP/GDP(-)	-0.384*	-0.416**	-0.444**	-0.491***	-1.684	-1.862	-2.014	-2.109	0.76	2.38	5.245	12.297
MD(-)	-0.536***	-0.605***	-0.653***	-0.701***	-2.306	-2.921	-3.334	-3.515	1.477	5.232	11.824	25.826
MC_{MCAP}(-)	-0.724***	-0.683***	-0.67***	-0.376	-1.962	-1.888	-1.686	-0.935	2.578	6.592	11.807	6.97
MC_{NOM}(-)	-1.001***	-0.93***	-0.884***	-0.568**	-3.095	-3.431	-3.24	-1.738	5.126	12.518	21.546	17.262
MC_{REAL}(-)	-0.966***	-1.041***	-0.906***	-0.597**	-2.902	-4.489	-3.213	-1.756	4.596	15.629	22.338	18.757
MC(-)	-1.12***	-1.062***	-1.032***	-0.717***	-3.611	-4.264	-4.333	-2.371	6.314	16.121	28.904	26.791

TABLE 4: Out-of-sample predictability

This table shows out-of-sample R^2 (R^2_{OS}) for predicting log excess return on the S&P 500. The predictors are log dividend price ratio (DP), equally-weighted mean of 14 individual forecasts from Welch and Goyal (2008) variables ($GW\,MEAN$), equally-weighted mean of the 14 individual forecasts with Campbell and Thompson (2008) restrictions ($GW\ MEAN\ CT$), the short interest index (SII), the sentiment index based on a partial least squares approach (S^{PLS}), CRSP total market capitalization to GDP ratio ($MCAP/GDP$), de-trended margin debt to GDP (MD), and margin credit variously scaled and de-trended (MC_{MCAP}, MC_{NOM}, MC_{REAL}, and MC). See Sections 3 and 4.2 and the caption for Table 1 for the detailed variable definitions and sample description. Statistical significance is based on the Clark and West (2007) t-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 initial training window is 1984 to 1993. The out-of-sample period is 1994 to 2014. H=1, 3, 6 or 12 indicates the horizon in months for which average monthly return is predicted.

	$R^2_{OS}(\%)$				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
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
S^{PLS}	2.768***	6.169***	5.424***	-5.418	2.300	2.992	2.925	-0.486
MCAP/GDP	-2.172	-3.42	-7.111	-22.534	-0.412	0.180	0.139	-1.452
MD	-0.447	2.054**	5.155***	5.76***	0.515	1.805	2.567	2.885
MC_{MCAP}	3.208*	6.564**	8.966***	1.965*	1.518	1.868	2.186	1.602
MC_{NOM}	6.367***	16.637***	30.182***	31.291***	2.279	3.060	3.562	4.369
MC_{REAL}	5.173***	13.485***	24.321***	24.426***	2.105	2.869	3.404	4.288
MC	7.51***	19.854***	35.872***	36.04***	2.501	3.310	3.823	4.647

TABLE 5: Out-of-sample predictability: Subsamples

This table shows out-of-sample R^2 (R^2_{OS}) for predicting log excess return on the S&P 500 at monthly horizon for different subsamples and over NBER contractions and expansions. The predictors are log dividend price ratio (DP), equally-weighted mean of 14 individual forecasts from Welch and Goyal (2008) variables ($GW\ MEAN$), equally-weighted mean of the 14 individual forecasts with Campbell and Thompson (2008) restrictions ($GW\ MEAN\ CT$), the short interest index (SII), the sentiment index based on a partial least squares approach (S^{PLS}), CRSP total market capitalization to GDP ratio ($MCAP/GDP$), de-trended margin debt to GDP (MD), and margin credit variously scaled and de-trended (MC_{MCAP}, MC_{NOM}, MC_{REAL}, and MC). See Sections 3 and 4.2 and the caption for Table 1 for the detailed variable definitions and sample description. Statistical significance is based on the Clark and West (2007) t-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.

	1994:01-2004:12		2005:01-2014:12		Contractions		Expansions		x2008:10		x2008:01-2009:06	
	R^2_{OS}(%)	t-stat	R^2_{OS}(%)	t-stat	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	-1.245	-0.292	-1.661	-0.398
GW MEAN	-0.497	-0.708	-0.381	-0.141	-0.072	0.071	-0.585	-1.223	-0.558	-0.552	-0.422	-0.870
GW MEAN CT	-0.486	-0.926	-0.018	-0.005	0.415	0.653	-0.531	-1.418	-0.336	-0.926	-0.431	-1.121
SII	-0.487	0.154	3.09***	2.651	2.213	1.264	0.761**	1.940	1.672***	2.631	0.848**	2.133
S^{PLS}	1.51	1.184	4.242**	2.194	4.352	1.240	2.167**	1.850	2.457**	2.205	1.638**	1.707
MCAP/GDP	-4.135	-0.909	0.13	0.692	3.123**	1.829	-4.179	-1.279	-4.422	-0.770	-4.13	-0.324
MD	-2.18	-0.897	1.585	1.266	1.007	0.494	-0.998	0.274	-0.436	0.528	-1.304	0.005
MC_{MCAP}	0.336	0.817	6.573*	1.305	11.371	1.243	0.113	1.126	2.625*	1.451	0.364	1.257
MC_{NOM}	0.776*	1.291	12.919**	1.901	17.857**	1.774	2.01**	1.875	5.192**	2.29	1.421**	1.79
MC_{REAL}	0.289*	1.302	10.897**	1.675	16.835**	1.729	0.751*	1.515	5.956***	2.493	2.033**	2.057
MC	1.551	1.250	14.493**	2.214	20.112**	1.830	2.731***	2.340	6.329***	2.55	2.087**	2.174

TABLE 6: **Performance statistics for a mean-variance investor**

The table reports the annualized returns, standard deviations, Sharpe ratios and certainty equivalent return (CER) gains (in percent) for a mean-variance investor with relative risk aversion coefficient of three who allocates between equities and risk-free T-bills using a predictive regression to forecast S&P 500 excess return based on the predictor variable in the first column. CER gains are relative to the historical mean as the benchmark forecast ($HIST\ MEAN$). 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. The predictors are log dividend price ratio (DP), equally-weighted mean of 14 individual forecasts from Welch and Goyal (2008) variables ($GW\ MEAN$), equally-weighted mean of the 14 individual forecasts with Campbell and Thompson (2008) restrictions ($GW\ MEAN\ CT$), the short interest index (SII), the sentiment index based on a partial least squares approach (S^{PLS}), CRSP total market capitalization to GDP ratio ($MCAP/GDP$), de-trended margin debt to GDP (MD), and margin credit variously scaled and de-trended (MC_{MCAP}, MC_{NOM}, MC_{REAL}, and MC). See Sections 3 and 4.2 and the caption for Table 1 for the detailed variable definitions and sample description.

	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
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
S^{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
MD	7.808	18.726	0.417	-0.427	0.362	-1.711	0.481	0.957	-0.597	3.652	0.630	-0.971
MCAP/GDP	2.875	14.027	0.205	-3.053	0.146	-4.929	0.336	-0.996	-0.492	18.975	0.323	-5.714
MC_{MCAP}	12.128	16.838	0.720	4.891	0.592	2.698	0.901	7.283	0.332	35.749	0.754	1.214
MC_{NOM}	15.120	16.438	0.920	8.095	0.739	5.224	1.150	11.236	1.702	50.324	0.870	3.097
MC_{REAL}	12.701	15.391	0.825	6.161	0.723	4.945	0.999	7.487	1.444	47.589	0.782	1.255
MC	16.529	16.849	0.981	9.302	0.777	5.852	1.219	13.087	1.278	50.043	0.949	4.468
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 7: 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 variables along the rows, while the $\hat{r}_{2,t+1}$ prediction is based on the prediction by the variable in the columns. 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 column 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. *HIST MEAN* refers to historical mean as the forecast. The other predictors are log dividend price ratio (*DP*), equally-weighted mean of 14 individual forecasts from Welch and Goyal (2008) variables (*GW MEAN*), equally-weighted mean of the 14 individual forecasts with Campbell and Thompson (2008) restrictions (*GW MEAN CT*), the short interest index (*SII*), the sentiment index based on a partial least squares approach (S^{PLS}), CRSP total market capitalization to GDP ratio (*MCAP/GDP*), de-trended margin debt to GDP (*MD*), and margin credit variously scaled and de-trended (MC_{MCAP}, MC_{NOM}, MC_{REAL}, and MC). See Sections 3 and 4.2 and the caption for Table 1 for the detailed variable definitions and sample description.

λ values for $\hat{r}^{*}_{t+1} = (1-\lambda)\hat{r}_{1,t+1} + \lambda\hat{r}_{2,t+1}$							
	$\hat{r}_{2,t+1}$						
$\hat{r}_{1,t+1}$	SII	S^{PLS}	MD	MC_{MCAP}	MC_{NOM}	MC_{REAL}	MC
HIST MEAN	0.845^{***}	1^{***}	0.309	0.933^{**}	1^{***}	0.901^{***}	1^{***}
DP	0.914^{***}	1^{***}	0.783^{**}	1^{***}	1^{***}	1^{***}	1^{***}
GW MEAN	0.917^{***}	1^{***}	0.499	1^{***}	1^{***}	0.984^{***}	1^{***}
GW MEAN CT	0.904^{***}	1^{***}	0.427	1^{**}	1^{***}	0.958^{***}	1^{***}
SII		0.846^{**}	0.256	0.875^{*}	1^{***}	0.823^{***}	1^{***}
S^{PLS}	0.154		0	0.558	0.791^{***}	0.676^{***}	0.906^{***}
MD	0.744^{***}	1^{***}		0.8^{***}	0.973^{***}	0.866^{***}	1^{***}
MC_{MCAP}	0.125	0.442	0.2		1^{***}	0.825^{***}	1^{***}
MC_{NOM}	0	0.209	0.027	0		0	0.987^{**}
MC_{REAL}	0.177	0.324	0.134	0.175	1^{***}		0.951^{***}
MC	0	0.094	0	0	0.013	0.049	

TABLE 8: **Forecast encompassing tests: Subsamples**

This table shows estimated weights for a convex combination $\hat{r}^*_{t+1} = (1 - \lambda_{MC})\hat{r}_{1,t+1} + \lambda_{MC}\hat{r}_{2,t+1}$. $\hat{r}_{1,t+1}$ prediction is based on the variables along the rows, while the $\hat{r}_{2,t+1}$ prediction is based on MC. The statistical significance of $1 - \lambda_{MC}$ and λ_{MC} is based on the Harvey, Leybourne, and Newbold (1998) statistic. *, **, and *** indicate significance levels at 10%, 5%, and 1%, respectively. We report combinations over monthly horizon ($H = 1$). Different columns show the results for different subsamples and NBER contractions and expansions. *HIST MEAN* refers to historical mean as the forecast. The other predictors are log dividend price ratio (DP), equally-weighted mean of 14 individual forecasts from Welch and Goyal (2008) variables ($GW\,MEAN$), equally-weighted mean of the 14 individual forecasts with Campbell and Thompson (2008) restrictions ($GW\ MEAN\ CT$), the short interest index (SII), the sentiment index based on a partial least squares approach (S^{PLS}), CRSP total market capitalization to GDP ratio ($MCAP/GDP$), de-trended margin debt to GDP (MD), and margin credit variously scaled and de-trended (MC_{NOM}, MC_{REAL}, MC_{MCAP}, and MC). See Sections 3 and 4.2 and the caption for Table 1 for the detailed variable definitions and sample description.

	1994:01-2004:12		2005:01-2014:12		Contractions		Expansions	
	λ_{MC}	$1-\lambda_{MC}$	λ_{MC}	$1-\lambda_{MC}$	λ_{MC}	$1-\lambda_{MC}$	λ_{MC}	$1-\lambda_{MC}$
HIST MEAN	0.712	0.288	1***	0	1**	0	1**	0
DP	1**	0	1***	0	1**	0	1**	0
GW MEAN	0.837*	0.163	1***	0	1**	0	1**	0
GW MEAN CT	0.828*	0.172	1***	0	1**	0	1**	0
SII	0.878*	0.122	1**	0	1**	0	1**	0
S^{PLS}	0.506	0.494	1***	0	1**	0	1**	0
MD	0.869**	0.131	1***	0	1**	0	1**	0
MC_{MCAP}	1	0	1***	0	1**	0	1**	0
MC_{NOM}	1	0	0.883*	0.117	1	0	1	0
MC_{REAL}	1*	0	0.886**	0.114	1	0	1	0

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

This table reports in-sample estimation results for the predictive regressions of economic channels proxies. *Ret* is log excess return on the S&P 500. *DP* is the log ratio to total 12 month dividends paid to S&P 500 price; *DG* is the log of the 12 month dividend growth rate; *EG* is the log of the 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 Robert Shiller. *MC* is margin credit scaled by GDP and de-trended. Returns and growth rates are measured as fractions (1=0.01). Explanatory variables are standardized to have mean 0 and standard deviation of one. We report bias and sample size corrected regression slopes, Newey-West t-statistics, as well as R^2. * ,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, based on one-sided wild bootstrapped p -values. The sample period is over 1984:01-2014:12.

Panel A : Non-overlapping Quarterly Regressions

	MC		DP		
	β	t-stat	ψ	t-stat	R^2(%)
Ret_{t+1}	-0.032***	-10.061			21.480
Ret_{t+1}	-0.027***	-10.555	0.011***	3.828	24.479
DP_{t+1}	0.007***	4.839	0.99***	171.223	98.778
DG_{t+1}	-0.109*	-1.640	-0.007	-0.213	0.761
EG_{t+1}	-0.26***	-6.657	0.009	0.327	10.764
GDPG_{t+1}	-0.106***	-2.666	0.060	1.260	2.167

Panel B : Non-overlapping Annual Regressions

	MC		DP		
	β	t-stat	ψ	t-stat	R^2(%)
Ret_{t+1}	-0.126***	-15.422			38.370
Ret_{t+1}	-0.135***	-18.513	0.058***	9.877	50.934
DP_{t+1}	0.017***	2.890	0.989***	142.428	98.210
DG_{t+1}	-0.079	-1.198	-0.002	-0.301	0.436
EG_{t+1}	-0.11***	-2.393	0.044	1.276	1.710
GDPG_{t+1}	-0.045	-0.913	0.025	0.571	0.270

Panel C : Overlapping Annual Regressions

	MC		DP		
	β	t-stat	ψ	t-stat	R^2(%)
Ret_{t+1}†	-0.007**	-2.371			26.791
Ret_{t+1}†	-0.007***	-3.380	-0.002	-0.440	41.970
DP_{t+1}	0.286***	24.931	1.029***	99.443	96.548
DG_{t+1}	-0.257***	-2.951	0.025	0.091	2.766
EG_{t+1}	-0.564***	-13.163	-0.042	-0.587	34.977

† Average monthly return over a 12-month holding period as in the H=12 in-sample in Table 3.

TABLE 10: Margin credit and changing risk and uncertainty

This table reports Granger causality results based on bivariate VAR and comparison of return predictability, of MC, the detrended margin credit to GDP ratio, and risk proxies. $MVOL$ is the standard deviation of daily market returns within a month; VIX is the Chicago Board Options Exchange volatility index; AC is the market-cap-weighted average correlation of daily returns within a month of the 500 largest stocks as in Pollet and Wilson (2010); $MACRO_U$ and $FINANCIAL_U$ are the measures of macroeconomic and financial uncertainty as constructed in Jurado, Ludvigson, and Ng (2015) and Ludvigson, Ma, and Ng (2015) taken from Ludvigson's website. The sample period is from 1984 to 2014, except in case of VIX where it is from 1990 to 2014. For the bivariate VARs in Panel A, we use MC without the two-month lag, to align the timing of other variables and MC and draw correct inferences about two-way predictability. $\rightarrow MC_{t+1}$ columns present the coefficient and p-values for the null hypothesis that the risk proxy does not predict MC. $MC_{t-1} \rightarrow$ columns present the coefficient and p-values for the null hypothesis that MC does not predict the corresponding risk proxy. For the return predictability results in Panel B, we use MC with two month lag, to be consistent with the rest of the out-of-sample results and forecast encompassing tests. Panel B shows the out-of-sample R^2 (R^2_{OS}), Clark and West (2007) t-statistic and forecast encompassing tests for predicting log excess return on the S&P 500 at monthly horizon. The out-of-sample period starts in 1994, with the period before that acting as the initial training window. The last two columns show weights for a convex combination $\hat{r}^*_{t+1} = (1-\lambda_{MC})\hat{r}_{1,t+1} + \lambda_{MC}\hat{r}_{2,t+1}$. $\hat{r}_{1,t+1}$ prediction is based on the the variables along the rows, while the $\hat{r}_{2,t+1}$ prediction is based on MC. Both the predictions use the same out-of-sample and training periods. The statistical significance of $1-\lambda_{MC}$ and λ_{MC} is based on the Harvey, Leybourne, and Newbold (1998) statistic. *, **, and *** indicate significance levels at 10%, 5%, and 1%, respectively.

Panel A: Bivariate Granger Causality				
	$\rightarrow MC_{t+1}$		$MC_{t-1} \rightarrow$	
	β	P-val	β	P-val
$MVOL$	-0.594	0.314	0.004***	0.000
VIX	-0.002	0.416	0.604**	0.012
AC	-0.064	0.712	0.008**	0.037
$MACRO_U$	-0.432*	0.055	0.007***	0.000
$FINANCIAL_U$	-0.384**	0.032	0.013***	0.000
Panel B: Return Predictability				
	$R^2_{OS}(\%)$	t-stat	$1-\lambda_{MC}$	λ_{MC}
$MVOL$	1.450	1.275	0.000	1***
VIX	-0.063	0.478	0.000	1***
AC	0.333	0.957	0.000	1***
$MACRO_U$	2.630*	1.348	0.000	1***
$FINANCIAL_U$	2.996**	1.798	0.010	0.990***

TABLE 11: Margin credit and changing borrowing conditions

This table reports Granger causality results based on bivariate VAR and comparison of return predictability, MC, the detrended margin credit to GDP ratio, and proxies of borrowing conditions. $Broker_{Call}$ is the broker call money lending rate from Bloomberg from 1988 to 2014; $Bank_{Call}$ is the bank call money rate from Datastream from 1984 to 2005; $Bank_{Prime}$ is the bank prime borrower lending rate from Datastream from 1984 to 2014; TBL is the treasury-bill rate used by Welch and Goyal (2008) from 1984 to 2014; $Credit_{CHG}$ is the year-on-year growth rate in monthly nominal bank credit as in Gandhi (2016) from 1984 to 2014. $ICRF$ is the intermediary capital risk factor of He, Kelly, and Manela (2016) from 1984 to 2012 taken from Asaf Manela's website; LF_{AEM} is the intermediary leverage factor of Adrian, Etula, and Muir (2014) from 1984 to 2012 also from Manela's website. For the bivariate VARs in Panel A, we use MC without the two-month lag, to align the timing of other variables and MC and draw correct inferences about two-way predictability. $\rightarrow MC_{t+1}$ columns present the coefficient and p-values for the null hypothesis that the borrowing condition proxy does not predict MC. $MC_{t-1} \rightarrow$ columns present the coefficient and p-values for the null hypothesis that MC does not predict the corresponding borrowing condition proxy. For the return predictability results in Panel B, we use MC with two month lag, to be consistent with the rest of the out-of-sample results and forecast encompassing tests. Panel B shows the out-of-sample R^2 (R^2_{OS}), Clark and West (2007) t-statistic and forecast encompassing tests for predicting log excess return on the S&P 500 at monthly horizon. The out-of-sample period starts in 1994, with the period before that acting as the initial training window. The last two columns show weights for a convex combination $\hat{r}^*_{t+1} = (1-\lambda_{MC})\hat{r}_{1,t+1} + \lambda_{MC}\hat{r}_{2,t+1}$. $\hat{r}_{1,t+1}$ prediction is based on the the variables along the rows, while the $\hat{r}_{2,t+1}$ prediction is based on MC. Both the predictions use the same out-of-sample and training periods. The statistical significance of $1-\lambda_{MC}$ and λ_{MC} is based on the Harvey, Leybourne, and Newbold (1998) statistic. *, **, and *** indicate significance levels at 10%, 5%, and 1%, respectively.

Panel A: Bivariate Granger Causality

	$\rightarrow MC_{t+1}$		$MC_{t-1} \rightarrow$	
	β	P-val	β	P-val
$Broker_{Call}$	0.012	0.118	-0.051***	0.000
$Bank_{Call}$	0.001	0.68	-0.073**	0.018
$Bank_{Prime}$	0.01*	0.099	-0.049***	0.000
TBL	0.008	0.174	-0.05***	0.000
$ICRF$	-0.185	0.458	-0.009**	0.019
LF_{AEM}	0.489	0.233	0.001	0.616
$Credit_{CHG}$	0.014***	0.006	-0.135***	0.000

Panel B: Return Predictability

	$R^2_{OS}(\%)$	t-stat	$1-\lambda_{MC}$	λ_{MC}
$Broker_{Call}$	-0.004	0.562	0.000	1***
$Bank_{Call}$	1.301*	1.346	0.000	1***
$Bank_{Prime}$	0.253	0.792	0.000	1***
TBL	-0.856	-0.597	0.000	1***
$ICRF$	0.579	1.243	0.000	1***
LF_{AEM}	-0.297	0.303	0.000	1***
$Credit_{CHG}$	0.466*	1.286	0.000	1***

Internet Appendix

A.1 Margin accounting

Here, we illustrate with an example how actions of investors lead to changes in margin debt and how margin credit is generated.

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. Reg T specifies maximum debt as fraction the collateral that can be obtained against different types of securities. In general, an investor can borrow up to 50% of the value of the stock. But different brokerages can specify their own tighter borrowing limits. 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". We work through an extended example below to clarify the 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.

A.2 Predictors in Welch and Goyal (2008)

In the section, we provide details of the 14 predictors considered by Welch and Goyal (2008).

Data on the 14 monthly variables of Welch and Goyal (2008) is available from Amit Goyal's website. The variables are:

- 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.

- 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

Descriptive statistics and prediction results for these fourteen variables are in Tables A.1 to A.7.

Figure A.1: **Cumulative Returns to $1: long only investor**
This figure plots cumulative returns (sum of logs) for the out-of-sample strategy of a long only investor that invests 100% in S&P 500 or 100% in T-bills based on the sign of the predicted log excess return on the S&P 500. The predictors are margin credit variously scaled and de-trended (MC_{MCAP}, MC_{NOM}, MC_{REAL}, and MC). Buy and hold corresponds to the investor passively holding the market portfolio. Section 3 for the detailed variable definitions and Section 5 for the details of asset allocation.

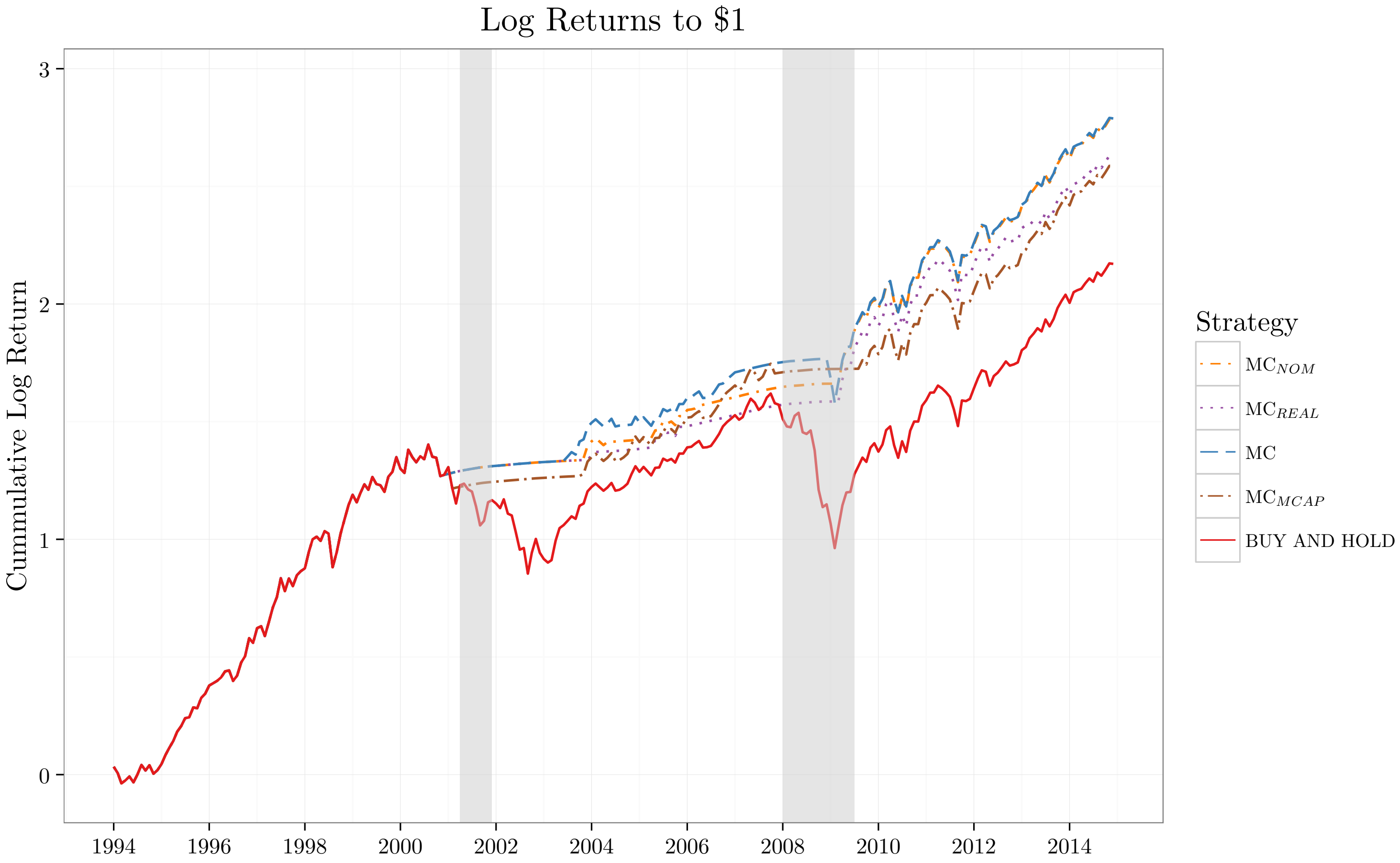


TABLE A.1: Summary statistics

The table displays summary statistics for all the 14 variables of Welch and Goyal (2008).

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

TABLE A.2: Correlations

The table displays Pearson correlation coefficients for the 14 variables of Welch and Goyal (2008), detrended margin credit scaled by GDP (MC) and the one-month-ahead log excess return on the S&P 500 (RET_{t+1}).

	DP	DY	EP	DE	RVOL	B/M	NTIS	TBL	LTY	LTR	TMS	DFY	DFR	INFL	MC	RET$_{t+1}$
DP	1.00															
DY	0.99	1.00														
EP	0.47	0.46	1.00													
DE	0.43	0.42	-0.60	1.00												
RVOL	-0.10	-0.10	-0.50	0.42	1.00											
B/M	0.87	0.86	0.62	0.15	-0.14	1.00										
NTIS	-0.22	-0.21	-0.11	-0.08	-0.10	-0.24	1.00									
TBL	0.47	0.47	0.45	-0.04	-0.18	0.46	-0.10	1.00								
LTY	0.67	0.67	0.43	0.17	-0.09	0.65	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	-0.17	0.40	0.21	0.23	0.25	-0.49	-0.02	-0.13	1.00					
DFY	0.40	0.39	-0.24	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	-0.06	0.01	-0.52	0.13	0.10	1.00			
INFL	0.11	0.11	0.22	-0.12	-0.11	0.13	0.00	0.26	0.25	-0.04	-0.10	-0.22	-0.12	1.00		
MC	0.05	0.02	-0.07	0.12	0.02	0.09	-0.56	0.07	0.08	-0.02	0.01	0.44	-0.16	0.07	1.00	
RET$_{t+1}$	0.08	0.09	0.07	0.00	0.04	0.06	0.03	-0.01	-0.01	0.04	-0.01	-0.04	0.09	0.05	-0.25	1.00

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

This table reports the ordinary least squares estimate of β and R^2 statistic for the model predicting log excess return on the S& 500 for the sample 1984 to 2014. The predictors are the 14 Welch and Goyal (2008) variables. Each predictor variable is standardized to have a standard deviation of one. The sign (+/-) following the variable in column 1 indicates the expected sign of the coefficient. Reported betas are corrected for bias in Stambaugh (1999). 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. H=1, 3, 6 or 12 indicates the horizon in months for which average monthly return is predicted.

	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(+)	0.018**	0.279**	0.364**	0.413**	1.614	1.913	2.14	2.275	0.713	2.352	5.166	10.909
DY(+)	0.385**	0.407**	0.43**	0.446**	1.806	1.964	2.153	2.269	0.838	2.438	5.224	11.09
EP(+)	0.203	0.241	0.224	0.245	0.988	0.81	0.72	0.924	0.521	1.03	1.587	3.53
DE(+)	-0.025	0.065	0.13	0.136	0.033	0.323	0.593	0.842	0.001	0.12	0.583	1.124
RVOL(+)	0.168	0.136	0.092	0.043	0.854	0.695	0.482	0.273	0.159	0.255	0.228	0.094
B/M(+)	0.07*	0.253**	0.338**	0.377**	1.213	1.614	1.91	2.023	0.366	1.563	4.115	8.572
NTIS(-)	0.125	0.218	0.258	0.249	0.442	0.763	0.765	0.795	0.088	0.815	1.969	3.448
TBL(-)	-0.018	-0.006	-0.001	-0.028	-0.151	-0.036	-0.005	-0.07	0.007	0.002	0.005	0.092
LTY(+)	-0.078	-0.026	0.014	0.088	-0.273	-0.069	0.141	0.573	0.022	0.006	0.01	0.435
LTR(+)	0.191	0.065	0.149**	0.09*	0.814	0.377	1.532	2.009	0.184	0.057	0.626	0.427
TMS(+)	-0.063	-0.021	0.051	0.237*	-0.203	-0.047	0.262	1.267	0.01	0.001	0.108	3.328
DFY(+)	-0.192	-0.095	0.078	0.144	-0.442	-0.217	0.296	0.752	0.139	0.098	0.205	1.207
DFR(+)	0.4**	0.167*	0.131*	0.077	1.026	0.843	1.037	0.696	0.815	0.394	0.48	0.335
INFL(-)	0.205	-0.038	-0.184**	-0.212**	0.697	-0.156	-1.404	-1.716	0.219	0.026	0.959	2.478

TABLE A.4: Out-of-sample predictability

This table shows out-of-sample R^2 (R^2_{OS}) for predicting log excess return on the S& 500. The predictors are the 14 Welch and Goyal (2008) variables. Statistical significance is based on the Clark and West (2007) t-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 initial training window is 1984 to 1993. The out-of-sample period is 1994 to 2014. H=1, 3, 6 or 12 indicates the horizon in months for which average monthly return is predicted.

	$R^2_{OS}(\%)$				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

TABLE A.5: **Out-of-sample predictability: Subsamples**
This table shows out-of-sample R^2 (R^2_{OS}) for predicting log excess return on the S& 500 at monthly horizon for different subsamples and over NBER contractions and expansions. The predictors are the 14 Welch and Goyal (2008) variables. Statistical significance is based on the Clark and West (2007) t-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.

	1994:01-2004:12		2005:01-2014:12		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

TABLE A.6: **Performance statistics for a mean-variance investor**

The table reports the annualized returns, standard deviations, Sharpe ratios and certainty equivalent return (CER) gains (in percent) for a mean-variance investor with relative risk aversion coefficient of three who allocates between equities and risk-free T-bills using a predictive regression to forecast S&P 500 excess return based on the predictor variable in the first column. CER gains are relative to the historical mean as the benchmark forecast ($HIST\ MEAN$). 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. The predictors are the 14 Welch and Goyal (2008) variables.

	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
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
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 A.7: 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 variables along the rows, while the $\hat{r}_{2,t+1}$ prediction is based on the prediction by the variable in the columns. 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 column 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. $HIST\,MEAN$ refers to historical mean as the forecast. The other predictors are the 14 Welch and Goyal (2008) variables, the short interest index (SII), the sentiment index based on a partial least squares approach (S^{PLS}), de-trended margin debt to GDP (MD), and margin credit variously scaled and de-trended (MC_{MCAP}, MC_{NOM}, MC_{REAL}, and MC). See Section 3 and the caption for Table 1 for the detailed definitions of SII, S^{PLS}, MD and the margin credit variables.

λ values for $\hat{r}^*_{t+1} = (1-\lambda)\hat{r}_{1,t+1} + \lambda\hat{r}_{2,t+1}$							
	$\hat{r}_{2,t+1}$						
$\hat{r}_{1,t+1}$	SII	S^{PLS}	MD	MC_{MCAP}	MC_{NOM}	MC_{REAL}	MC
HIST MEAN	0.845***	1***	0.309	0.933**	1***	0.901***	1***
DP	0.914***	1***	0.783**	1***	1***	1***	1***
DY	0.889***	1***	0.743*	1***	1***	1***	1***
EP	0.795*	1**	0.564	1***	1***	0.974***	1***
DE	1**	1***	0.745	1***	1***	1***	1***
RVOL	0.898***	1***	0.387	0.948**	1***	0.939***	1***
B/M	0.884***	1***	0.498	1**	1***	0.979***	1***
NTIS	0.96***	1***	0.72	1***	1***	0.939***	1***
TBL	0.983***	1***	0.6	1***	1***	1***	1***
LTY	1***	1***	0.588	1***	1***	1***	1***
LTR	0.896***	1***	0.473	0.968**	1***	0.916***	1***
TMS	0.992***	1***	0.527	1***	1***	0.966***	1***
DFY	0.912***	1***	0.725	1***	1***	1***	1***
DFR	1**	1***	0.853	1***	1***	0.972***	1***
INFL	0.976***	1***	0.61	0.985**	1***	0.952***	1***
GW MEAN	0.917***	1***	0.499	1***	1***	0.984***	1***
GW MEAN CT	0.904***	1***	0.427	1**	1***	0.958***	1***

TABLE A.8: In-sample predictive regressions: Subsamples

This table reports the ordinary least squares estimate of β and R^2 statistic for the model predicting next month's log excess return on the S&P 500 for different subsample windows and over NBER business cycle contraction and expansion months. The predictors are log dividend price ratio (DP), the short interest index (SII), the sentiment index based on a partial least squares approach (S^{PLS}), CRSP total market capitalization to GDP ratio ($MCAP/GDP$), de-trended margin debt to GDP (MD), and margin credit variously scaled and de-trended (MC_{MCAP}, MC_{NOM}, MC_{REAL}, and MC). See Section 3 and the caption for Table 1 for the detailed variable definitions and sample description. Each predictor variable is standardized to have a standard deviation of one. The sign (+/-) following the variable in column 1 indicates the expected sign of the coefficient. Reported betas are corrected for bias in Stambaugh (1999). 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.

	1984:01-1999:12			2000:01-2014:12			Contractions			Expansions		
	β	t-stat	R^2	β	t-stat	R^2	β	t-stat	R^2	β	t-stat	R^2
DP(+)	0.314	-0.044	0.001	0.387**	1.322	2.311	0.655**	1.253	3.769	-0.036	1.412	0.589
SII(-)	-0.609	-0.871	0.512	-0.532**	-1.913	2.069	-0.983*	-1.186	5.647	-0.375*	-1.77	0.599
S^{PLS}(-)	-0.347	-1.353	0.557	-0.915***	-2.494	4.931	-1.853***	-2.514	13.073	-0.479*	-1.877	1.058
MCAP/GDP(-)	0.517	0.616	0.222	-1.542***	-2.863	4.006	-2.182**	-2.514	13.923	-0.163	-0.804	0.189
MD(-)	0.079	-0.185	0.021	-0.642***	-2.442	3.508	-1.987***	-2.249	15.403	-0.366**	-1.703	0.789
MC_{MCAP}(-)	-0.306	-0.649	0.181	-0.782***	-1.702	4.226	-1.337**	-1.775	11.291	-0.357	-0.979	0.232
MC_{NOM}(-)	-0.336	-0.755	0.291	-1.157***	-3.03	10.146	-1.341***	-2.799	23.04	-0.591*	-1.616	0.749
MC_{REAL}(-)	-0.195	-0.875	0.353	-1.069***	-2.621	8.241	-1.305**	-2.079	15.786	-0.762**	-2.113	1.156
MC(-)	-0.312	-0.652	0.188	-1.249***	-3.512	12.198	-1.493***	-3.066	25.43	-0.855**	-2.411	1.549

TABLE A.9: Alternate Detrending Methods

This table reports the in-sample and out-of-sample results for forecasting returns over one month horizon (H=1) where margin credit is detrended using four alternative methods. Margin credit is variously scaled (MC_{MCAP}, MC_{NOM}, MC_{REAL}, and MC). See Sections 3 and 4.2 and the caption for Table 1 for the detailed variable definitions and sample description. Scaled margin credit is detrended using quadratic (QUAD), cubic (CUB), logarithmic (LOG), or stochastic (STOC) methods and used as return predictor.

	In-Sample			Out-of-Sample	
	β	t-stat	R^2	R^2_{OS}	t-stat
MC_{NOM} QUAD	-1.103***	-3.435	6.245	3.829***	2.719
MC_{NOM} CUB	-1.058***	-3.317	5.705	0.391**	2.108
MC_{NOM} LOG	-0.724**	-2.202	2.663	1.423*	1.495
MC_{NOM} STOC	-1.081***	-3.38	6.024	5.572**	2.223
MC_{REAL} QUAD	-1.100***	-3.453	6.217	2.507***	2.644
MC_{REAL} CUB	-1.083***	-3.425	5.981	0.639**	2.043
MC_{REAL} LOG	-0.805**	-2.491	3.266	2.594*	1.615
MC_{REAL} STOC	-1.076***	-3.377	5.985	5.927**	2.275
MC_{MCAP} QUAD	-0.817**	-2.095	3.415	2.178**	1.94
MC_{MCAP} CUB	-0.743	-1.865	2.824	3.470**	1.892
MC_{MCAP} LOG	-0.657*	-1.715	2.21	1.487	1.099
MC_{MCAP} STOC	-0.932**	-2.584	4.484	4.585**	1.707
MC QUAD	-1.116***	-3.559	6.398	1.993***	2.52
MC CUB	-1.118***	-3.634	6.402	1.727**	1.974
MC LOG	-0.865***	-2.691	3.749	3.564**	1.692
MC STOC	-1.091***	-3.442	6.152	6.443**	2.257

TABLE A.10: Out-of-sample predictability: Different training windows

This table shows out-of-sample R^2 (R^2_{OS}) for predicting log excess return on the S& 500 at monthly horizon using different initial training windows as indicated in the column headings. The predictor is margin credit variously scaled and de-trended (MC_{MCAP}, MC_{NOM}, MC_{REAL}, and MC). See Section 3 and the caption for Table 1 for the detailed variable definitions and sample description. Statistical significance is based on the Clark and West (2007) t-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.

Training Window	1984-1988		1984-1993		1984-1998		1984-2004	
Out-of-sample Period	1989-2014		1994-2014		1999-2014		2005-2014	
	R^2_{OS}(%)	t-stat	R^2_{OS}(%)	t-stat	R^2_{OS}(%)	t-stat	R^2_{OS}(%)	t-stat
MC_{MCAP}	2.577*	1.475	3.208*	1.518	4.074*	1.497	6.573*	1.305
MC_{NOM}	5.311***	2.244	6.367***	2.279	8.328***	2.191	12.919**	1.901
MC_{REAL}	4.269***	2.066	5.173***	2.105	6.811***	1.984	10.897**	1.675
MC	6.277***	2.462	7.51***	2.501	9.809***	2.482	14.493***	2.214

TABLE A.11: **Performance statistics for a long-only investor**

This table reports the annualized excess returns, standard deviation of returns, Sharpe ratios and certainty equivalent return (CER) gains for a long only investor who invests fully in either equities or risk-free T-bills. The investments weights are determined by the prediction of one month ahead excess log return on the S&P 500. The investment weight is 1 in S&P 500, when the prediction is positive and 0 otherwise. CER gains are relative to the historical mean as the benchmark forecast ($HIST\,MEAN$). Buy and hold corresponds to the investor passively holding the market portfolio. The predictors are log dividend price ratio (DP), equally-weighted mean of 14 individual forecasts from Welch and Goyal (2008) variables ($GW\,MEAN$), equally-weighted mean of the 14 individual forecasts with Campbell and Thompson (2008) restrictions ($GW\ MEAN\ CT$), the short interest index (SII), the sentiment index based on a partial least squares approach (S^{PLS}), CRSP total market capitalization to GDP ratio ($MCAP/GDP$), de-trended margin debt to GDP (MD), and margin credit variously scaled and de-trended (MC_{MCAP}, MC_{NOM}, MC_{REAL}, and MC). See Sections 3 and 4.2 and the caption for Table 1 for the detailed variable definitions and sample description.

	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
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
S^{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
MD	6.494	14.643	0.444	-0.940	0.510	-0.222	0.367	-1.715	-0.809	0.000	0.714	-1.064
MCAP/GDP	5.145	14.426	0.357	-2.120	0.339	-2.595	0.374	-1.602	-0.809	0.000	0.611	-2.398
MC_{MCAP}	9.604	11.409	0.842	4.274	0.751	3.174	0.962	5.493	†	31.999	0.892	0.969
MC_{NOM}	10.544	11.149	0.946	5.374	0.773	3.353	1.158	7.607	0.961	37.698	0.951	1.511
MC_{REAL}	9.812	11.075	0.886	4.679	0.749	3.046	1.052	6.485	0.961	37.698	0.886	0.735
MC	10.575	11.890	0.889	4.973	0.837	4.150	0.944	5.884	0.180	29.975	0.983	1.956
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

† MC_{MCAP} invests in the risk-free rate in all contraction months thus there is no excess return or standard deviation of excess returns from which to calculate a Sharpe ratio.