Credit Conditions and Expected Stock Returns*

Sudheer Chava†
College of Management
Georgia Institute of Technology

Michael Gallmeyer‡
McIntire School of Commerce
University of Virginia

Heungju Park§
Mays Business School
Texas A&M University

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Abstract

We analyze the predictability of U.S. stock returns using a measure of credit standards (*Standards*) derived from the Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices. We find that *Standards* is a strong predictor of stock returns at a business cycle frequency, especially in the post-1990 data period. Empirically we find that a tightening of *Standards* predicts lower future stock returns at horizons up to one year. *Standards* performs well both in-sample and out-of-sample and is robust to a host of consistency checks including a small sample analysis and a Canadian stock market analysis.

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†Sudheer.Chava@mgt.gatech.edu

‡mgallmeyer@virginia.edu

§hpark@mays.tamu.edu

1 Introduction

Recently, an active academic debate has arisen over whether any economic variables predict future excess stock returns better than historical average excess returns. Goyal and Welch (2008) argue that many predictive variables used in the literature perform poorly both in-sample and out-of-sample, especially over the last 30 years. In contrast, Campbell and Thompson (2008) show that many predictive regressions beat the historical average return, once weak restrictions are imposed on the signs of coefficients and return forecasts. We contribute to this literature by providing evidence that an economically-motivated predictive variable that measures credit conditions has robust in-sample and out-of-sample predictive power in forecasting future stock excess returns. Further, the predictive power is strongest in the post-1990 time period and is quantitatively significant.

Our work is motivated by several papers that study how supply-based measures of credit could impact the overall economy. Some of this work was prompted by papers that have studied the impact of the Federal Reserve's monetary policy on macroeconomic quantities such as real output (Romer and Romer (1989), Bernanke and Blinder (1992), Christiano, Eichenbaum, and Evans (1996, 1999)) as well as stock returns (Thorbecke (1997), Bernanke and Kuttner (2005), Patelis (1997), Jensen, Johnson, and Mercer (1996)). A possible explanation of the predictive power of monetary indicators relates to the credit channel of monetary policy transmission (Bernanke and Gertler (1995)). In particular, a tighter monetary policy can lead to a reduced and costlier bank loan supply that in turn impacts future stock returns. However, past work has not considered the direct influence of bank loan supply changes on stock returns. In particular, it is unclear whether the credit channel either through a monetary policy transmission mechanism or some other economic channel has predictive power for stock returns. In this paper, we address this issue and examine whether shocks to the aggregate supply of bank loans predicts future stock returns.

Besides the credit channel transmission mechanism, fluctuations in the supply of bank loans can be caused by frictions in the credit creation process through the bank's view of future market conditions.[1] In particular, if agency costs time-vary as in the financial propagation mechanism described in Fazzari, Hubbard, and Petersen (1988) and Bernanke and Gertler (1989), banks naturally can change their supply of credit based on their views of the balance sheets of borrowers. In a recent speech, Bernanke (2007) argues that this view of the role of bank loan supply is tightly linked to the credit channel of monetary policy.

Bank lending standards, or the terms in which loans are offered, have been used as a measure of bank loan supply in several papers to study whether banks change their loan supply systematically over the business cycle and if there is an important loan supply effect in macroeconomic fluctuations. Asea and Blomberg (1998) examine the relationship between the cyclical component of aggregate unemployment and bank lending standards using a bank-level panel data set constructed from the terms of individual loan contracts obtained from the Federal Reserve Survey of Terms of Bank Lending. They find that cycles in bank lending standards are important in explaining aggregate economic activity. Our work uses survey data on bank lending standards obtained from the Federal Reserve's Senior Loan Officer Opinion Survey. An earlier study using this data is Lown and Morgan (2006) who find that shocks to lending standards are significantly correlated with innovations in commercial loans at banks and in real output. In particular, they find that "bank lending standards are far more informative about future lending than are loan rates." Gorton and He (2008) show that the relative performance of commercial and industrial loans leads to endogenous credit cycles and is an autonomous source of macroeconomic fluctuations.

Despite this pro-cyclical feature of bank lending to macroeconomic variables, limited evidence exists whether changes in bank loan supply predict stock returns which is our contribution. Keim and Stambaugh (1986), Campbell (1987), Fama and French (1988), Fama and French (1989), and Schwert (1990) provide evidence that business condition proxies such as aggregate dividend yield, default spreads, term spreads, and the level of short-term interest rates explain significant variation in expected stock returns. Given these variables are all

[1] See Berlin (2009) for a recent survey of models that explain bank lending cycles.

functions of market bond and stock prices, it is difficult to discern if their predictive power is driven by rational time-varying opportunity sets or simply mispricing. We examine whether bank lending standards, a variable that captures aggregate supply-side credit conditions that is not a direct function of market prices, serves as a leading indicator of future stock returns. In particular, this links a quantity-based variable shown to predict macroeconomic variables to the stock predictability literature.

Our work joins a growing literature that uses survey data to explain stock returns and macroeconomic variables. Campbell and Diebold (2009) find that expected business cycle conditions obtained from the Livingston survey data has forecasting ability for stock returns. Ang, Bekaert, and Wei (2007) use the Livingston survey, the Survey of Professional Forecasters, and the Michigan survey to build inflation expectations. They show that the survey-based measures of inflation outperform other forecasting methods out-of-sample. For predictions of various macroeconomic variables, Engel, Mark, and West (2007), Engel and Rogers (2006), Engel and Rogers (2009), and Ghysels and Wright (2009) use the Consensus Forecasts survey data. Lown and Morgan (2006) document the predictive power of the Federal Reserve Board's Senior Loan Officer Opinion Survey on loan growth, GDP growth, and various other measures of business activity. We use the Senior Loan Officer Opinion Survey to provide direct evidence on the relationship between credit conditions through a bank loan supply measure and future excess stock returns.

Overall, we find that our measure of credit conditions derived from the Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices is a strong predictor of U.S. stock returns at a frequencies up to and including a year. In particular, a tightening of credit standards predicts lower expected stock returns. This measure contains additional information beyond the variables shown to have predictive power from the past predictability literature. Given this measure has been shown to predict macroeconomic variables in Lown and Morgan (2006), we provide a direct link to the predictability of stock returns and an aggregate macroeconomic supply variable. This credit condition measure performs well both in-sample and out-of-sample. It is also robust to a host of consistency checks that we consider including a small sample bias analysis as well as a Canadian stock return analysis.

The rest of the paper is organized as follows. Section 2 describes the data used in the paper and presents detailed information about the Senior Lending Officer Survey used in the paper. We describe the empirical methodology used in the paper in Section 3. Section 4 presents evidence on stock return predictability, while Section 5 concludes.

2 Data

2.1 Senior Loan Officer Survey Data

Our measure of aggregate supply-side credit conditions through bank lending standards is derived from a quarterly survey of bank senior loan officers published by the Federal Reserve Board. The survey, titled the *Senior Loan Officer Opinion Survey on Bank Lending Practices*, polls major U.S. banks around the country about credit conditions. The survey was first publicly available starting in the first quarter of 1967 with approximately 120 banks participating. As of the fourth quarter of 2008, 55 banks participated capturing the general trend of the number of U.S. banks shrinking over time. The participating banks capture a sizeable portion of lending by U.S. banks. From Lown and Morgan (2006), survey banks account for "about 60% of all loans by U.S. banks and about 70% of all U.S. bank business loans." Recent survey results are available at http://www.federalreserve.gov/boarddocs/surveys.

The survey's questions can be classified as measures of supply and demand for commercial and industrial loans, commercial real estate loans, residential mortgage loans, and consumer loans. Our focus is on the question that pertains to credit standards for approving commercial and industrial (C&I) loans. The question in the survey is currently (as of the fourth quarter 2008 survey) asked as follows:

> *For applications for C&I loans or credit lines – other than those to be used to finance mergers and acquisitions – from large and middle-market firms [annual*

sales of $50 *million or more] that your bank currently is willing to approve, how have the terms of those loans changed over the past three months? 1) tightened considerably, 2) tightened somewhat, 3) remained basically unchanged, 4) eased somewhat, 5) eased considerably.*

To convert the survey data into a quantifiable time-series variable, we follow Lown, Morgan, and Rohatgi (2000) and Lown and Morgan (2002, 2006) by creating a credit standards index (*Standards*) as a net percentage of banks tightening credit. Specifically, *Standards* is computed as the number of banks reporting tightening standards less the number of banks reporting easing standards divided by the total number reporting. The quarterly data is constructed by using the surveys conducted in January (Q1), April (Q2), July (Q3), and October (Q4) of each year. The Federal Reserve makes the results of these surveys public in the month following when the survey was taken. For example in 2007, the Q1 through Q4 surveys were released on February 5, May 17, August 13, and November 5 respectively. Hence, the *Standards* number pertaining to a specific quarter is publicly known well before the end of that quarter.

Lown and Morgan (2006) find that changes in *Standards* are strongly correlated with real output and bank loan changes. In particular, they show that *Standards* strongly dominates loan interest rates in explaining variation in the supply of business loans and aggregate output. They also show that *Standards* remains significant when proxies for loan demand are included which suggests *Standards* can be used as a proxy for loan supply as we do in our work.

Other recent studies also employ *Standards* as a measure of bank loan supply. Gorton and He (2008) analyze the relationship between their Performance Difference Index (PDI) and *Standards* to explain the time-series behavior of the Credit Standard Survey responses. Leary (2009) uses *Standards* as an alternate proxy for changes in bank loan supply to show the role of credit supply in capital structure choice. Our work differs in that we use *Standards* as a measure of aggregate supply-based credit conditions to examine the link between stock return predictability and supply-side credit conditions.

We use the *Standards* series from Q2:1990 to Q4:2008. Though the Senior Loan Officer Opinion Survey was made public starting in 1967, the data from the commercial and industrial (C&I) loan standards question pre-1990 faces several issues.[2] First, the wording of the C&I loan standards question was not consistent across the pre-1990 time period. From 1978 through 1983, the C&I loan standards question was split into two separate questions. The first question asked how standards changed for prime rate loans, while the second question asked how standards changed for above prime rate loans. However, as documented in Brady (1985), the link between market loan rates and the prime rate weakened during this time. Banks largely began pricing loans to large borrowers at market rates. Prime-based rate loans were largely reserved for smaller and low credit quality borrowers. Hence, the C&I loans standards questions was no longer a reflection of changing credit supply for large borrowers. Second, the C&I loan standards question was even suspended for a time as it was not asked from Q1:1984 until Q2:1990. Finally, Schreft and Owens (1991) note that from 1967 through 1983 survey respondents almost never report a net easing of standards on business loans suggesting a possible bias in the early years of the survey. They hypothesize that the incentive to always report tightening standards might exist "if respondent banks perceive a risk of closer regulatory scrutiny if they admit to having eased standards."

Given these issues with the pre-1990 C&I loans standards question, the focus of our study is on the post-1990 data. However, as a robustness check, we do construct a *Standards* series from Q1:1967 to Q4:2008 by splicing together the Q1:1967 to Q4:1983 data with the Q2:1990 to Q4:2008 data.[3] To fill in the missing data from Q1:1984 to Q1:1990, we use one question that has remained relative constant through the entire lifetime of the Senior Loan Officer Opinion Survey — a question concerning a bank's willingness to make consumer installment loans. Using a similarly constructed variable for this consumer willingness question, we

[2]See Schreft and Owens (1991) for a discussion of how the Senior Loan Officer Opinion Survey evolved pre-1990.

[3]The *Standards* series, including updates for the most recent survey, is available at Donald Morgan's web site: http://www.newyorkfed.org/research/economists/morgan/index.html.

regress the *Standards* variable from Q1:1967 to Q4:1983 on it. We then extrapolate from Q1:1984 to Q1:1990 using the consumer willingness variable with the regression model to construct the missing *Standards* data.

Figure 1 plots the *Standards* measure across time with the shaded regions representing the NBER recession periods. In our main analysis period, Q2:1990-Q4:2008, there are three NBER-dated recessions. In all cases, it appears that *Standards* has tightened entering a recession. Equally important, banks appear to relax lending standards exiting a recession. From the figure, it appears that *Standards* is a leading indicator of a business cycle. At least at a univariate level, it seems plausible that *Standards* is a contender for predicting stock returns.

2.2 Stock Returns

To study stock return predictability, we analyze stock returns on the CRSP value-weighted index (CRSP-VW) and the S&P500 index. All stock returns are expressed as continuously compounded returns with dividends included. To calculate excess stock returns, we use the continuously-compounded 30 day T-bill rate as the risk-free rate.

2.3 Other Stock Return Predictor Variables Used

To compare the forecasting power of *Standards* in the predictability regressions, we also consider some of the standard price-based predictor variables used in the literature: the dividend-price ratio (dp), the 30-day T-bill rate (RF), the term spread ($TERM$), and the default yield spread (DEF). The dividend-price ratio, dp, is the difference between the log of dividends and the log of the CRSP-VW index price. The dividends are 12 month moving sums of dividends paid on the CRSP-VW index. $TERM$ is computed as the difference between the yield on a 10-year and a 1-year government bond. DEF is computed as the difference between the BAA-rated and AAA-rated corporate bond yield. Data on bond yields are collected from the FRED database at the Federal Reserve Bank of St. Louis.

We also compare the forecasting power of *Standards* to the aggregate consumption-wealth ratio measure *cay* from Lettau and Ludvigson (2001), a measure of corporate issuing activity *ntis* from Goyal and Welch (2008), and a measure of the output gap from Cooper and Priestley (2009). As a measure of the aggregate consumption-wealth ratio, Lettau and Ludvigson (2001) estimate:

$$c_t = \alpha + \beta_a \cdot y_t + \sum_{i=-k}^{k} b_{a,i} \cdot \Delta a_{t-i} + \sum_{i=-k}^{k} b_{y,i} \cdot \Delta y_{t-i} + \epsilon_t, \tag{1}$$

where $t = k+1, \ldots, T-k$, c is aggregate consumption, a is aggregate wealth, y is aggregate income, and ϵ is an error term. Using estimated coefficient from the above equation provides $cay \equiv \widehat{cay}_t = c_t - \hat{\beta}_a \cdot a_t - \hat{\beta}_y \cdot y_t$, $t = 1, \ldots, T$. Goyal and Welch (2008) also estimate a *cay* measure that excludes advance information from the estimation equation. We use the Goyal-Welch measure of *cay* for our predictability test.[4]

Goyal and Welch (2008) use *Net Equity Expansion* (*ntis*) as a measure of corporate issuing activity. The variable *ntis* is computed as the ratio of the 12 month moving sum of net issues by NYSE listed stocks divided by their total end-of-year market capitalization. This dollar amount of net equity issuing activity (IPOs, SEOs, stock repurchases, less dividends) for NYSE listed stocks is computed from CRSP data as

$$NetIssue_t = Mcap_t - Mcap_{t-1} \cdot (1 + vwretx_t), \tag{2}$$

where *Mcap* is the total market capitalization and *vwret* is the value-weighted return (excluding dividends) on the NYSE index. Goyal and Welch document that *ntis* is closely related to a payout variable proposed in Boudoukh et al. (2007).

To predict stock returns, Cooper and Priestley (2009) construct a measure of the output gap, *gap*, which is measured as the deviation of the log of industrial production from a trend

[4] The Goyal-Welch measure of *cay* is available at Amit Goyal's web site: http://www.bus.emory.edu/AGoyal.

that incorporates both a linear and a quadratic component:

$$p_t = a + b \cdot t + c \cdot t^2 + \epsilon_t, \tag{3}$$

where p is the log of industrial production, t is a time trend, and ϵ is an error term. We estimate the *gap* variable using our sample period data.

2.4 Descriptive Statistics

Descriptive statistics (number of observations, mean, min, max, standard deviation, and autocorrelation) of the various predictor variables and stock returns are presented in Panel A of Table 1. The descriptive statistics of the standard predictor variables as well as the stock returns are in line with the results reported in previous work (for example, Goyal and Welch (2008)), so we skip the discussion of these results in the interest of space. The key variable of interest in the analysis, *Standards*, has an autocorrelation of 0.81 at a quarterly frequency. This autocorrelation while high, is the second lowest of all the predictor variables considered in the analysis (only DEF has a lower autocorrelation coefficient than *Standards*).

Panel B and C in Table 1 present the correlations across various predictor variables. *Standards* is most positively correlated with the default spread DEF (65%) and next with the output gap, *gap* (24%). Not surprisingly, *Standards* is negatively correlated with net stock issuances *ntis* (-44%). The correlations across other predictor variables are consistent with the earlier literature.

3 Empirical Methods

Following much of the existing predictability literature, we first assess the in-sample predictive ability of *Standards* for stock excess returns. We estimate the following univariate regression:

$$r_t = \alpha + \beta \cdot Standards_{t-1} + \epsilon_t, \tag{4}$$

where r_t is the excess stock return, $Standards$ is the net percent tightening of the C&I loan supply, and ϵ is an error term. The in-sample predictive ability of $Standards$ is assessed via the t-statistic of the β estimate and the adjusted R^2 from the excess return regression. Under the null hypothesis that $Standards$ does not predict excess returns, β=0. We report Newey and West (1987) standard errors that correct for serial correlation and heteroscedasticity.[5]

For robustness tests of the predictability of stock returns using $Standards$, we also consider the following predictor variables: DEF, $TERM$, RF, dp, cay, $ntis$, and gap, defined by the vector Z added to the regression that includes $Standards$ and estimate

$$r_t = \alpha + \beta \cdot Standards_{t-1} + \gamma \cdot Z_{t-1} + \epsilon_t, \tag{5}$$

where γ is a vector of coefficient estimates on the variables in Z_{t-1}, and ϵ is an error term. After controlling for these predictor variables, we assess the in-sample predictive ability of $Standards$.

To generate out-of-sample predictions, we compute four test statistics designed to determine whether the $Standards$ forecasting model has superior forecasting performance relative to a model of historical average returns. We first calculate the out-of-sample R^2 (R^2_{oos}), which following Fama and French (1989) is defined as

$$R^2_{oos} = 1 - \frac{MSE_A}{MSE_N}, \tag{6}$$

where MSE_A is the mean-squared error from the forecasting model with $Standards$, and MSE_N is the mean-squared error from the historical mean model. If the R^2_{oos} is positive, then the predictive regression has a lower average mean-squared prediction error than the historical mean return model.

The second out-of-sample test statistic computed is the difference between the root-mean-

[5] We have also computed our results using Hodrick (1992) standard errors with similar results. We later perform a small sample analysis of the significance of our results.

squared prediction error using the historical average return model and the root-mean-squared prediction error using the predictive regression model, denoted ΔRMSE:

$$\Delta RMSE = \sqrt{MSE_N} - \sqrt{MSE_A}. \tag{7}$$

The third test statistic is an out-of-sample MSE-F test developed by McCracken (2007). It tests whether the historical mean model has a mean-squared forecasting error that is equal to that of the *Standards* forecasting model:

$$MSE - F = (T - h + 1) \cdot \frac{MSE_N - MSE_A}{MSE_A}, \tag{8}$$

where T is the number of observations and h is the degree of overlap (h=1 for no overlap).

The last out-of sample test is the ENC-NEW test proposed by Clark and McCracken (2001). We use the ENC-NEW test to examine whether the forecasts from the historical mean model encompass those from the *Standards* forecasting model:

$$ENC - NEW = \frac{T - h + 1}{T} \cdot \frac{\sum_{t=1}^{T}(\epsilon_t^2 - \epsilon_t \cdot e_t)}{MSE_A}, \tag{9}$$

where ϵ_t is the vector of out-of-sample errors from the historical mean model and e_t is the vector of out-of-sample errors from the *Standards* forecasting model. For both the MSE-F and ENC-NEW tests, we follow the methodology in Clark and McCracken (2005), which provides bootstrapped critical values for these tests.

For the out-of-sample tests, we use 10 years (40 quarters) of data as an initial estimation window. We conduct the out-of-sample tests in two ways, as a recursive regression and a rolling regression. The recursive approach assumes the model is estimated with more data as the forecasting date moves forward in time. The rolling approach assumes the model is estimated with a moving window of the most recent 40 observations as the forecasting moves forward in time.

4 Stock Return Predictability

We now explore the ability of *Standards* to predict stock returns. We start by exploring in-sample evidence, followed by out-of-sample evidence. Lastly, we consider several robustness checks of the stock return predictability regressions including a small-sample analysis.

4.1 In-Sample Evidence

Table 2 reports in-sample forecasting regressions with *Standards*, for the quarterly log excess returns on the CRSP-VW index and the S&P 500 index.[6] In all of the regressions in Table 2, the t-statistics are reported using a Newey and West (1987) correction to account for serial correlation in the residuals.

Panel A of Table 2 reports results from a univariate regression of the CRSP-VW and S&P500 quarterly excess returns on one lag of the *Standards* variable. Both the CRSP-VW and the S&P500 excess returns are strongly predictable with negative coefficients on the *Standards* variable at traditional significance levels. Also, the adjusted R^2 coefficients are 13% and 14% respectively.

The negative sign implies that a tightening loan supply results in a subsequent drop in stock returns. Here our *Standards* measure leads stock market performance which itself tends to lead the business cycle. See for example Backus, Routledge, and Zin (2010) for an analysis of lead-lag relationships between asset returns and economic growth. This negative sign is also consistent with the results in Patelis (1997) where the impact of tightening monetary policy leads to short-term lower expected stock returns.

Panel B of Table 2 reports estimates from predictability regressions that include a variety of variables used in past predictability studies. Unreported results using the log excess returns on the S&P500 index are very similar to those on the CRSP-VW index. Shiller (1981), Campbell and Shiller (1988), and Fama and French (1988) find that the dividend-

[6] The results reported for the log excess returns are nearly identical to log actual returns, raw actual returns, and raw excess returns.

price ratio has predictive power for excess returns. Bekaert and Hodrick (1992) find that the T-bill rate predicts returns, while Fama and French (1989) study the forecasting power of the term and the default spreads. Henkel, Martin, and Nardari (2010) present evidence that the dividend yield and term structure variables are effective predictors almost exclusively during recessions. We include these financial market variables, DEF, TRM, RF, and dp, in our predictive regressions on the CRSP-VW excess return.

The first column of Panel B in Table 2 shows that these financial variables together have less forecasting power at the quarterly frequency than $Standards$ alone and are individually statistically insignificant. The default spread (DEF) is the only predictor that could be considered marginally significant with a t-statistic of -1.94. In the second column, $Standards$ is included in the regression; this leads to DEF's coefficient flipping signs and becoming strongly insignificant.[7] Note that $Standards$ still retains its forecasting power with roughly the same coefficient size and same level of statistical significance when compared to the financial market-based variables. Moreover, the addition of $Standards$ approximately doubles the adjusted R^2 in our forecasting regression.

Lettau and Ludvigson (2001) find that the ratio of consumption to wealth, cay, predicts stock returns at a quarterly frequency. We are able to replicate the findings of Lettau and Ludvigson (2001) for their sample period. During our sample period, including cay by itself in the predictability regression in the third column leads to a statistically insignificant positive coefficient with an adjusted R^2 coefficient of roughly 2%. In the fourth column of Panel B, including both cay and $Standards$ jointly leads to a significantly higher R^2 of 16% as both coefficients are statistically significant. The incorporation of $Standards$ into the regression provides additional information above and beyond cay generating the higher adjusted R^2 coefficient.

Recent studies find evidence that corporate issuing activity meant to capture total firm payouts forecasts stock returns. Boudoukh, Michaely, Richardson, and Roberts (2007), Lar-

[7]We also analyzed the predictive power of $Standards$ on DEF. DEF is strongly predictable with a positive coefficient on $Standards$ at traditional significance levels.

rain and Yogo (2008), Robertson and Wright (2006), and Bansal and Yaron (2006) document that payout yields derived from dividends, repurchases, and issuances, as opposed to the simple dividend yields, are robust predictors of excess returns. Moreover, Goyal and Welch (2008) find that *ntis* which measures equity issuing and repurchasing (plus dividends) relative to the price level, has good in-sample performance, but a negative out-of-sample adjusted R^2. We add *ntis* in our predictability regression to determine its in-sample performance relative to *Standards*. The fifth column of Panel B, shows that *ntis* is statistically significant with an adjusted R^2 of 7%. However, the next column of Panel B reports a regression of returns on both *ntis* and *Standards*. It shows that *ntis* is not statistically significant, but *Standards* is. Also, the inclusion of *Standards* in the previous regression doubles the adjusted R^2.

More recently, Cooper and Priestley (2009) show that the output gap, *gap*, as measured by the deviation of the log of industrial production from a trend that incorporates both a linear and a quadratic component, predicts excess returns on stock indices and Treasury bonds. We are able to replicate the results of Cooper and Priestley (2009) for their sample period. However, during our sample period, *gap* does not seem to have forecasting power for excess stock returns. The difference can be attributed to the differences in the sample periods of the two studies. After controlling for *gap* in our regression, *Standards* still has a significant negative coefficient and a higher adjusted R^2 coefficient.

In the last column of Panel B, we present the in-sample forecasting regression with all the variables included. Interestingly, only *Standards* has a significant coefficient among all the predictor variables and the adjusted R^2 is very similar to that in the univariate regression with *Standards*. This suggests that *Standards* is capturing future excess stock returns at a quarterly frequency, while other predictor variables have little predictive power of excess stock returns at this horizon. Goyal and Welch (2008) show that most predictor variables lose their in-sample forecasting power after the oil price crisis in the 1970s. Though our sample is limited to the period after the 1990s, the in-sample predictability of *Standards* is noteworthy in view of the findings in Goyal and Welch (2008).

4.2 Out-of-Sample Evidence

Two recent papers, Goyal and Welch (2008) and Campbell and Thompson (2008), examine the out-of-sample forecasting ability of predictor variables that can predict in-sample. Goyal and Welch (2008) find little evidence that most predictor variables can predict out-of-sample better than a constant, while Campbell and Thompson (2008) find that the predictors have out-of-sample predictive power with sensible restrictions on the forecasting models. We now examine the forecasting ability of *Standards* in out-of-sample tests and compare it to other predictor variables.[8]

Table 3 compares forecasts based on the historic mean model to those based on each predictor variable, using the CRSP-VW excess returns. We conduct four out-of-sample tests — adjusted R^2, ΔRMSE, MSE-F, and ENC-NEW — in recursive and rolling regressions. For the tests, we consider the initial estimation period of Q2:1990 to Q1:2000.

The first row of Table 3 shows that the forecasting model with *Standards* has superior forecasting performance relative to the historic mean model in both the recursive and the rolling regressions. The out-of-sample R^2 is 17% in the recursive regression and 9.3% in the rolling regression. The ΔRMSE is 0.009 in the recursive regression and 0.005 in the rolling regression, which implies that the forecast errors with *Standards* are lower than those with the historic average return. The MSE-F test rejects the null hypothesis that the MSEs from the forecasts that use *Standards* is equal to those based on the historical average return. The ENC-NEW test also rejects the null hypothesis that the forecasts from the historical mean model encompass those from the *Standards* forecasting model. These results suggest that *Standards* plays a strong role as a predictor of excess stock returns since the 1990s. These results contrast with Goyal and Welch (2008) who find that in general variables typically

[8]We analyze the out-of-sample forecasting tests with other predictor variables which we use in the in-sample regression, but we do not report the out-of-sample results of *cay* and *gap*. The reason is that the estimation periods of both variables in the out-of-sample test are relatively short. From our unreported results, *cay* shows better forecasting ability than the historical average return in the recursive regression.

used in predictability regressions have been unsuccessful out-of-sample over the last few decades. Interestingly, we do not impose any economic restrictions on the forecasting model as Campbell and Thompson (2008) employ.

The remaining rows of Table 3 report the out-of-sample test results with the other predictor variables. The variables DEF and $ntis$ show better forecasting ability than the historical average return in both the recursive and the rolling regression. However, the adjusted R^2 and ΔRMSE for *Standards* are twice as large as that of DEF, implying *Standards* has a higher forecasting power than DEF.

4.3 Long-Horizon Forecasts

Much of the existing predictability literature finds that some of the predictor variables, such as dp and cay, forecast excess stock returns in sample at longer horizons better than at shorter horizons. With the exception of gap, most of these variables seem to predict stock returns at horizons larger than for example the length of a typical recession.[9] In this section, we investigate whether *Standards* tracks longer-term tendencies in stock markets rather than providing shorter-term forecasts. Table 4 reports long-horizon forecasting regressions of quarterly excess returns on the CRSP-VW index. The dependent variable is the H-quarter log excess return on the CRSP-VW index, equal to $r_{t+1} + ... + r_{t+H}$. We use the horizons of $H = 1$, 2, 4, 8, and 12 quarters.

From the top panel of Table 4, we document the forecasting power of *Standards* for future excess returns at horizons ranging from 1 to 12 quarters. The coefficient for *Standards* is hump-shaped and peaks around 8 quarters in the sample. At an 8 quarter horizon, the coefficient estimate for *Standards* is insignificant and the adjusted R^2 is approximately 11%, so the predictive power decreases at a horizon greater than 4 quarters. Here, *Standards* seems to better forecast future excess returns at a business cycle frequency as the informational content of *Standards* decreases at longer horizons.

[9] Cooper and Priestley (2009) document "the average length of NBER contractions in the 1945-2001 period is 10 months."

After including the price-based variables DEF, TRM, RF, and dp, *Standards* still exhibits a hump-shaped forecasting pattern. The forecasting significance peaks at 4 quarters, declining at longer horizons. Regarding the adjusted R^2 coefficient, it increases with the horizon and is not hump-shaped. This is driven by the increased predictive power of the dividend-price rate dp with the horizon and is consistent with the findings in the predictability literature summarized for example in Campbell et al. (1997) and Cochrane (2001) for example.

In the last panel of Table 4, we add cay, $ntis$, and gap to the previous regression. The hump-shaped forecasting pattern of *Standards* is robust, and the predictive power of *Standards* is insignificant at a 12 quarter horizon. The predictive power of cay and the adjusted R^2 increase with the horizon, which supports the findings of Lettau and Ludvigson (2001). Here *Standards* predictive power occurs at a shorter horizon than most of the predictive variables explored in the literature.

5 Robustness

To examine the robustness of loan supply as captured by *Standards* as a stock return predictor, we consider several robustness tests including performing a small sample analysis, using other Senior Loan Officer Opinion Survey variables as well as a measure of broker-dealer leverage growth considered by Adrian, Moench, and Shin (2010), extending the *Standards* data series to use earlier data, and studying stock return predictability in the Canadian stock market.[10]

5.1 Small Sample Robustness of Stock Return Predictability

Many predictability studies find that regression coefficients and standard errors, obtained from predictive regressions with a highly persistent predictor, exhibit small sample biases

[10]Several other robustness checks are available from the authors including using monthly returns. In these checks, we find that *Standards* still retains its predictive power.

(Mankiw and Shapiro (1986), Nelson and Kim (1993), Elliott and Stock (1994), and Stambaugh (1999)). These biases have the potential to be severe, especially when the predictor variables are scaled by price. Though *Standards* is a persistent variable, its degree of persistence is not as strong as measures such as the dividend price ratio (see Table 1). Additionally, it is not a priced-based variable. However, given the length of the *Standards* data series, we explore whether the in-sample results of *Standards* could be driven by small sample biases.

To address these small sample bias problems, we perform two robustness checks. First, we compute the small-sample tests of Campbell and Yogo (2006). Campbell and Yogo employ local-to-unity asymptotics to achieve a better approximation of the finite sample distribution when the predictor variable is persistent. Their construction of the confidence interval uses the Bonferroni method to combine a confidence interval for the largest autoregressive root of the predictor variable with confidence intervals for the predictive coefficient conditional on the largest autoregressive root. These results are presented in Panel A of Table 5. Following Campbell and Yogo, we report the confidence interval for $\tilde{\beta}=(\sigma_e/\sigma_u)\beta$ instead of β.[11] In the fourth (fifth) column of the table, we report the 90% Bonferroni confidence intervals for β using the t-test (Q-test), whose the null hypothesis is $\beta=0$. Both the Bonferroni t-test and the Q-test reject the null of no predictability for *Standards*, *DEF*, and *ntis*. For example, the confidence intervals for the *Standards* coefficient using both the t-test and the Q-test do not include zero, which implies we reject the null of no predictability using both tests.

Our second method for addressing small sample bias problems is to use both a bootstrap and a Monte Carlo simulation of the predictive regression. The data for both simulations are generated under the null hypothesis of no predictability:

$$r_t = \gamma + e_t, \tag{10}$$

where γ is a constant. Also, we use an AR(1) specification for our predictive variable

[11]The standard deviations σ_e and σ_u are computed from the residuals of the following regression model: $r_t = \alpha + \beta x_{t-1} + u_t$, $x_t = \gamma + \rho x_{t-1} + e_t$ where r_t denotes the excess stock return in period t and x_t denotes the predictor variable in period t.

Standards:

$$Standards_t = \mu + \phi Standards_{t-1} + \nu_t, \tag{11}$$

where the values of μ and ϕ are those estimated from the actual data for *Standards*. Then, we generate artificial sequences of excess returns and *Standards* by drawing randomly from the sample residuals for the bootstrap procedure or a normal distribution for the Monte Carlo simulation under the null of no predictability. We generate $100,000$ samples equal to the length of the *Standards* data series. Using these samples created under either a bootstrap or Monte Carlo simulation, we then estimate equation (4) which yields a distribution of our test statistics.

Panel B of Table 5 reports the results of the bootstrap procedure for the Newey-West t-statistics and adjusted R^2 coefficients of the predictive regression with *Standards*.[12] For both the CRSP-VW and S&P500 excess returns, the estimated t-statistics of *Standards* lies outside of the 95% confidence interval based on the empirical distribution from the bootstrap procedure. This implies we can reject the hypothesis that *Standards* has no predictive power for excess stock returns. In addition, the results show that the estimated adjusted R^2 coefficient is outside of the 99% confidence intervals for the bootstrap adjusted R^2 coefficients. Therefore, we conclude that the predictability of *Standards* is robust to correcting for small sample biases.

5.2 Other Survey Variables and Alternative Measures of Credit

In addition to the information used to construct *Standards*, the Senior Loan Officer Opinion Survey contains other questions relating to the supply and demand of commercial and industrial (C&I) loans, commercial real estate loans, residential mortgage loans, and consumer loans. To measure *Standards*, we use the question of supply for C&I loans and find that *Standards* has strong forecasting power for stock excess returns.

As a robustness test, we examine whether other variables in the Survey also have fore-

[12]The results of Monte Carlo simulation are nearly identical to those of the bootstrap procedure.

casting power. We focus on two other questions in the survey to construct measures of the demand for C&I loans (*Demands*) and the supply of consumer loans (*Consumer*). *Demands* measures the net percentage of banks reporting stronger demand for C&I loans. *Consumer* measures the net percentage of banks reporting stronger willingness to grant consumer installment loans. The *Demands* series is from Q1:1991 to Q4:2008. The *Consumer* series is from Q3:1966 to Q4:2008. The variables *Standards* and *Consumer* represent information about the supply side of lending. Given *Standards* captures net tightening, while *Consumer* captures net willingness to lend, they should naturally be negatively correlated. Indeed, this is the case as the correlation between *Standards* and *Consumer* is -71%. Additionally, the correlation between *Standards* and *Demands* is -67%. Because of these high correlations between *Standards* and other survey variables, we orthogonalize *Demands* and *Consumer* by regressing them on *Standards* and use the orthogonalized components of *Demands* and *Consumer*.

Table 6 report results for the predictive regressions of excess returns of the CRSP-VW and S&P500 indices on the Survey variables: *Standards*, *Demands*, and *Consumer*. *Standards* is significant with a negative coefficient after controlling for *Demands* and *Consumer*. In addition, *Demands* is significant with a negative coefficient in the CRSP-VW index regression. The result is consistent with a substitution effect in the financial market. If the stock market is expected perform poorly in the future, firms intend to rely on bank loans for financing, so the demand for C&I loan increases. Thus, *Demands* should be negatively related to future stock returns. However, compared to Table 2, the increase in the adjusted R^2 is relatively low by adding *Demands* and *Consumer*, providing evidence that *Standards* is the best predictor of future excess stock returns.

In contemporaneous work to our own, Adrian, Moench, and Shin (2010) argue that financial intermediary balance sheet aggregates, in particular a measure of security broker-dealer leverage growth $ySBRDLR : levg$, predicts excess stock returns. Table 7 reports in-sample predictive regressions of stock returns on one-quarter lagged predictive variables where both $Standards$ and $ySBRDLR : levg$ are considered. The first regression in the table reports univariate results using $Standards$, while the second regression reports univariate results using $ySBRDLR : levg$. The final regression includes both predictive variables. From the regressions, neither credit measure subsumes the other and both measures are statistically significant at standard significance levels. In particular, when $Standards$ is added to the $ySBRDLR : levg$ regression, the adjusted R^2 jumps from 0.08 to 0.19.

5.3 Extended Sample Period

Our main results use the $Standards$ series from Q2:1990 to Q4:2008.[13] This is the longest time-series available after the C&I loan supply question was re-established in the Senior Loan Officer Opinion Survey. For robustness, we build a $Standards$ measure from Q1:1967 to Q4:2008 by constructing an estimate of the missing $Standards$ data. We accomplish this by using the $Standards$ series before the question's suspension (Q1:1967-Q4:1983) to build an estimate of the missing $Standards$ data from Q1:1984 to Q1:1990. This is possible by using the $Consumer$ series, a measure of the supply of consumer loans, which is available over the entire history of the Senior Loan Officer Opinion Survey. Given $Standards$ captures net tightening, while $Consumer$ captures the net willingness to lend, they should naturally be negatively correlated. Indeed, this is the case as the correlation between $Standards$ and $Consumer$ is -71%.

Given $Standards$ and $Consumer$ are highly correlated and both provide loan supply side information, we regress $Standards$ on lagged $Standards$ and current $Consumer$ over Q1:1967 to Q4:1983:

$$Standards_t = \alpha + \beta\, Standards_{t-1} + \gamma\, Consumer_t + \epsilon_t, \tag{12}$$

Estimating this regression gives an adjusted R^2 of 53% with significant coefficients. This

[13] We also examined the in-sample predictability of $Standards$ from Q2:1990 to Q2:2007 to eliminate the financial crisis from the data. Our results were still robust. Details are available from the authors.

regression model is then used to extrapolate an estimate of the *Standards* variable from Q1:1984 to Q1:1990. Splicing this estimated data into the earlier and later *Standards* data computed from the survey gives an unbroken *Standards* variable from Q1:1967 to Q4:2008. This new series has a mean of 0.09 and a standard deviation of 0.19.

Panel A and B of Table 8 show results for return predictability regressions using various predictor variables over Q1:1967 to Q4:1983. During this period, *Standards* is insignificant in both the univariate and the multivariate regressions. Additionally, the adjusted R^2 with *Standards* included is close to zero. On the other hand, most predictor variables except *ntis* have strong predictive powers in multivariate regression of stock excess returns, which is consistent with the finding of Goyal and Welch (2008) that most predictability results from the periods before the oil crises. Based on problems with the C&I loan standards question before 1990, the insignificance of *Standards* is not necessarily surprising. As discussed earlier, the C&I loan question before 1990 was re-worded several times and from 1978 through 1983 was framed in terms of the prime rate. Additionally, Schreft and Owens (1991) document a reporting bias in the early years of the survey.

Panel C of Table 8 reports results from a univariate regression across the sample period from Q1:1967 to Q4:2008. The univariate regression shows a significant negative *Standards* coefficients with an adjusted R^2 coefficient of roughly 4%. These results are weaker evidence of forecasting ability of *Standards* than the main sample period (Q2:1990-Q4:2008). In Panel D of Table 8, we find *Standards* is significant in most of the multivariate regressions. In addition, *cay* also has forecasting ability which is consistent with the findings in Lettau and Ludvigson (2001).

5.4 Canadian Stock Return Predictability

In order to control for possible data-snooping issues, we examine the in-sample predictability of Canadian stock returns using the Canadian equivalent of our *Standards* measure.[14]

[14]The Bank of England, the European Central Bank, and the Bank of Japan also conduct credit condition surveys similar to the Senior Loan Officer Survey in the US. Unfortunately, these surveys have only been

Since 1999, the Bank of Canada has conducted a quarterly Senior Loan Officer Survey of the business-lending practices of major Canadian financial institutions.[15] The survey gathers information on changes to both the price and non-price terms of business lending over the current quarter and surveys the views of financial institutions on how changing economic or financial conditions are affecting business lending. Overall business-lending conditions are calculated as a simple average of the pricing and non-pricing dimensions. We use overall business-lending conditions as the measure of *Standards* and investigate whether these lending conditions help predict Canadian stock market returns.

Table 9 presents results of the in-sample predictive regression on log excess returns of the S&P/TSX Composite index. The sample period is from Q2:1999 to Q4:2008. The excess returns are strongly predictable with negative coefficients on the *Standards* variable and the adjusted R^2 is 12% providing evidence that *Standards* has predictive power in the Canadian stock market. For a small sample robustness test of the Canadian stock market return predictability results, we construct confidence intervals of the Newey-West t-statistics and adjusted R^2 coefficients using the same bootstrap and Monte Carlo simulation procedure from before. In both the bootstrap and the Monte Carlo simulation procedures, the estimated t-statistics and adjusted R^2 lies outside of the 95% confidence level implying that we can reject the hypothesis that *Standards* has no predictive power in the Canadian stock market.

6 Conclusion

We provide evidence that a measure of aggregate supply-based credit conditions *Standards* as derived from the Federal Reserve Board's Senior Loan Office Opinion Survey on Banking Lending Practices is a strong predictor of U.S. stock returns. Given that *Standards* has been shown to predict aggregate macroeconomic variables, our results provide a direct link between a macroeconomic supply variable and the predictability of asset returns. Addition-

recently adopted leading to too short of a sample period.

[15] The survey data is available at http://www.bankofcanada.ca/en/slos/. We thank Greg Bauer for making us aware of the Canadian survey.

ally, *Standards* is not derived from financial market prices making it is less likely that the source of its predictive power is from capturing mispricing in financial markets. *Standards* captures predictability at a business cycle frequency, indicating that its predictive power is more consistent with either capturing time-varying risk aversion or time-varying risk.

Figure 1: **Change in *Standards* from the Senior Loan Officer Survey 1967-2008**

The figure plots the changes in the *Standards* variable constructed from the Senior Loan Officer Survey. The sample period is Q1:1967 to Q4:2008. The shaded regions represent NBER-dated recessions. The *Standards* variable is not available from Q1:1983 to Q1:1990 due to the survey dropping the C&I loans standards question during this time period.

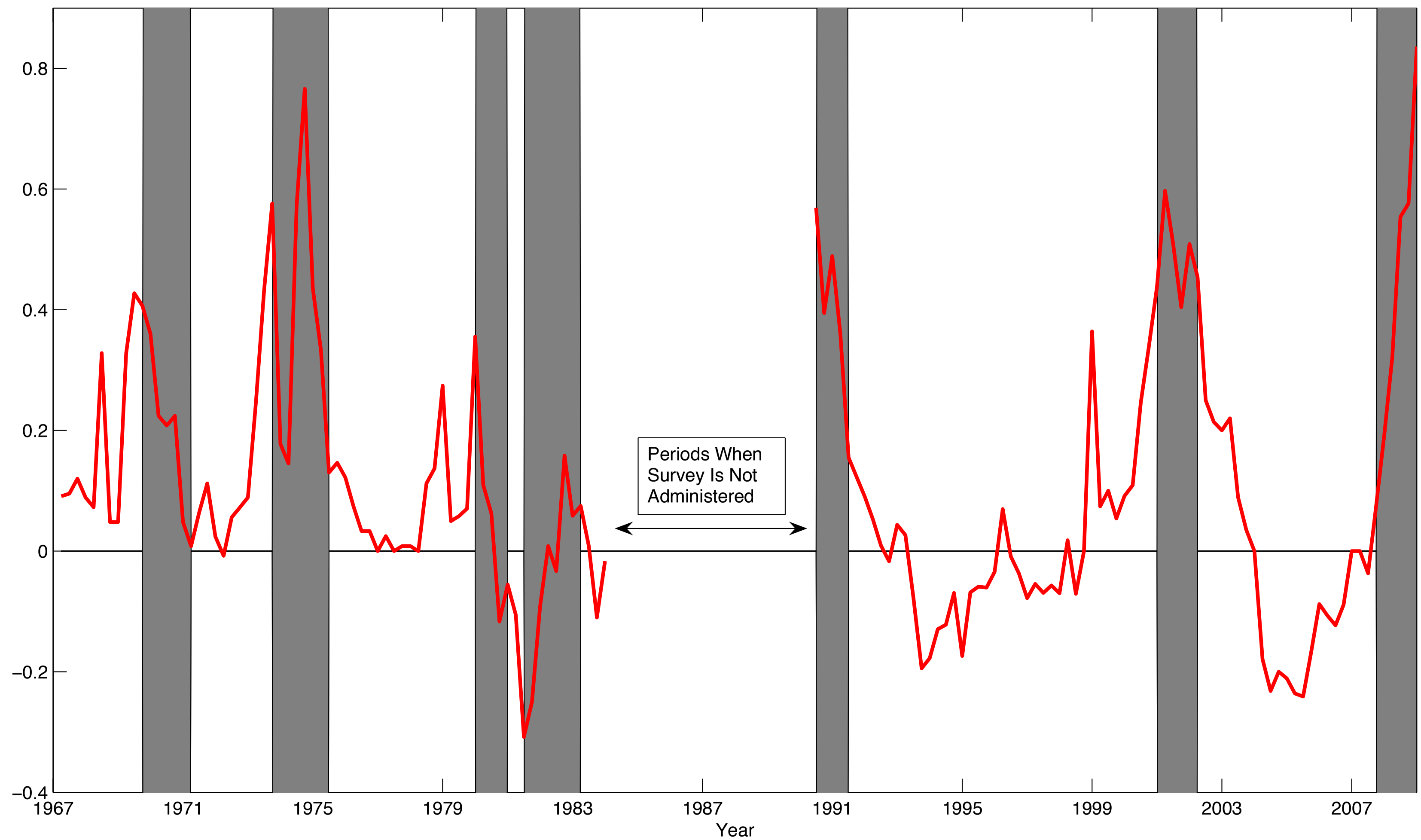

Table 1: **Descriptive Statistics**

The table reports descriptive statistics and correlations for the stock return predictive variables. *Ret* is the log return and *Excess Ret* is the log excess return on the CRSP-VW index. *Standards* is the tightening standards measure. *DEF* is the BAA bond yield minus the AAA bond yield. *TERM* is the difference between the 10 year Treasury yield and the 1 year Treasury yield. *RF* is the 1 month T-bill rate. The log dividend-price ratio is denoted *dp*. The variable *cay* is the Lettau and Ludvigson (2001) consumption-wealth ratio variable. The variable *ntis* is the ratio of the 12 month moving sum of net issues by NYSE listed stocks divided by the total end-of-year market capitalization. The variable *gap* is the deviation of the log of industrial production from a trend that incorporates both a linear and a quadratic component. The sample period is Q2:1990 to Q4:2008.

Panel A: Descriptive Statistics of Stock Return Predictive Variables

Variable	*Obs*	*Mean*	*StdDev*	*Min*	*Max*	*Autocorr*
Ret	75	0.018	0.086	-0.272	0.193	0.021
Excess Ret	75	0.009	0.085	-0.273	0.183	0.010
Standards	75	0.089	0.242	-0.241	0.836	0.815
DEF	75	0.009	0.004	0.006	0.034	0.507
TERM	75	0.013	0.011	-0.004	0.032	0.922
RF	75	0.003	0.001	0.000	0.006	0.864
dp	75	-3.966	0.308	-4.513	-3.235	0.922
cay	75	0.004	0.024	-0.037	0.043	0.928
ntis	75	0.012	0.021	-0.053	0.046	0.903
gap	75	0.000	0.032	-0.059	0.086	0.847

Panel B: Correlations of Stock Return Predictive Variables

	Standards	*DEF*	*TERM*	*RF*	*dp*	*cay*	*ntis*	*gap*
Standards	1.000							
DEF	0.655	1.000						
TERM	0.078	0.243	1.000					
RF	-0.007	-0.433	-0.677	1.000				
dp	0.031	0.227	0.362	0.097	1.000			
cay	0.065	-0.145	0.283	0.343	0.646	1.000		
ntis	-0.441	-0.470	0.358	0.019	0.088	0.460	1.000	
gap	0.238	-0.172	-0.648	0.630	-0.307	-0.238	-0.300	1.000

Table 2: **Forecasting Quarterly Excess Stock Returns**

The table reports estimates of OLS regressions of stock returns on one-quarter lagged predictive variables: $r_t = \alpha + \beta \cdot Standards_{t-1} + \gamma \cdot Z_{t-1} + \epsilon_t$, where r_t is the log excess return on the CRSP-VW index and the S&P500 index. The predictive variables are all defined in Table 1. Newey-West corrected t-statistics appear in parentheses below the coefficient estimates and adjusted R^2 statistics in square brackets. The sample period is Q2:1990 to Q4:2008.

Panel A: Excess returns on CRSP and S&P

	CRSP	S&P
$Standards$	-0.14	-0.14
	(-2.86)	(-3.02)
Constant	0.02	0.01
	(2.57)	(1.82)
$\bar{R}^2$	[0.13]	[0.14]

Panel B: Additional controls; Excess returns on CRSP

$Standards$		-0.20		-0.15		-0.12		-0.15	-0.23
		(-2.37)		(-3.18)		(-2.87)		(-2.61)	(-2.27)
DEF	-11.36	4.40							9.42
	(-1.94)	(0.52)							(0.88)
$TERM$	-0.03	2.52							1.01
	(-0.02)	(1.21)							(0.37)
RF	-2.55	27.64							14.90
	(-0.19)	(1.32)							(0.55)
dp	0.05	-0.03							-0.05
	(0.99)	(-0.48)							(-0.84)
cay			0.63	0.72					0.96
			(1.91)	(2.18)					(1.03)
$ntis$					1.15	0.63			0.23
					(2.10)	(1.42)			(0.32)
gap							-0.29	0.08	0.23
							(-0.86)	(0.23)	(0.45)
Constant	0.31	-0.24	0.01	0.02	-0.01	0.01	0.01	0.02	-0.32
	(1.29)	(-0.69)	(0.55)	(2.26)	(-0.41)	(1.20)	(0.81)	(2.59)	(-0.85)
$\bar{R}^2$	[0.06]	[0.13]	[0.02]	[0.16]	[0.07]	[0.14]	[-0.00]	[0.12]	[0.11]

Table 3: **Forecasting Quarterly Excess Stock Returns Out-Of-Sample**

The table reports the results of an out-of-sample forecast comparison of the log excess return on the CRSP-VW index. The comparisons are of forecasts of excess returns based on a constant (unconditional forecast) and forecasts based on a constant and a 1-quarter lagged predictive variable (conditional forecast). The predictive variables are all defined in Table 1. We conduct the out-of-sample test in two ways. The recursive approach assumes the model is estimated with more data as the forecasting date moves forward in time. The rolling approach assumes the model is estimated with a moving window of the most recent 40 observations as the forecasting moves forward in time. The column $\bar{R}^2_{oos}$ is the out-of-sample R^2. $\Delta RMSE$ is the RMSE difference between the unconditional forecast and the conditional forecast. $MSE-F$ gives the F-test of McCracken (2007), which tests for an equal MSE of the unconditional forecast and the conditional forecast. $ENC-NEW$ provides the Clark and McCracken (2001) encompassing test statistic. Significance levels of $MSE-F$ and $ENC-NEW$ at the 90%, the 95%, and the 99% level are denoted by one, two, and three stars, respectively. The sample period is Q2:1990 to Q4:2008.

	Recursive approach				Rolling approach			
	$\bar{R}^2_{oos}$	$\Delta RMSE$	$MSE-F$	$ENC-NEW$	$\bar{R}^2_{oos}$	$\Delta RMSE$	$MSE-F$	$ENC-NEW$
$Standards$	0.170	0.009	7.146***	2.518**	0.093	0.005	3.596**	2.220**
DEF	0.070	0.004	2.618**	0.787	0.036	0.002	1.288*	0.879
$TERM$	-0.033	-0.002	-1.101	-0.242	-0.079	-0.004	-2.547	-0.540
RF	-0.036	-0.002	-1.214	-0.187	-0.118	-0.006	-3.688	-0.652
dp	0.001	0.000	0.042	0.062	-0.124	-0.006	-3.849	-0.337
$ntis$	0.064	0.003	2.372**	0.671	0.022	0.001	0.802*	0.432

Table 4: **Long Horizon Regression: Quarterly Excess Stock Returns**

The table reports results from long-horizon regressions of quarterly log returns on lagged variables. H denotes the return horizon in quarters. The dependent variable is the sum of H log returns on the CRSP Value-weighted stock market index, $r_{t+1} + ... + r_{t+H}$. The regressors are all defined in Table 1. Newey-West corrected t-statistics appear in parentheses below the coefficient estimate and adjusted R^2 statistics in square brackets. The sample period is Q2:1990 to Q4:2008.

	Forecast Horizon H				
Regressors	1	2	4	8	12
Standards	-0.14	-0.23	-0.28	-0.39	-0.32
	(-2.86)	(-2.67)	(-2.05)	(-1.91)	(-1.59)
$\bar{R}^2$	[0.13]	[0.18]	[0.11]	[0.11]	[0.04]
Standards	-0.20	-0.33	-0.41	-0.34	0.06
	(-2.37)	(-2.86)	(-3.52)	(-1.61)	(0.24)
DEF	4.40	8.07	16.28	4.44	-30.38
	(0.52)	(0.78)	(1.40)	(0.21)	(-1.21)
$TERM$	2.52	3.96	3.87	1.76	1.21
	(1.21)	(1.21)	(0.81)	(0.24)	(0.11)
RF	27.64	45.47	41.72	-19.88	-68.73
	(1.32)	(1.40)	(0.92)	(-0.34)	(-0.79)
dp	-0.03	-0.01	0.10	0.38	0.64
	(-0.48)	(-0.10)	(0.82)	(2.10)	(2.48)
$\bar{R}^2$	[0.13]	[0.24]	[0.21]	[0.36]	[0.41]
Standards	-0.23	-0.39	-0.54	-0.73	-0.36
	(-2.27)	(-2.98)	(-3.46)	(-3.34)	(-1.67)
DEF	9.42	21.79	48.04	56.82	21.54
	(0.88)	(1.51)	(3.50)	(3.50)	(1.19)
$TERM$	1.01	-0.61	-6.37	-7.43	-2.51
	(0.37)	(-0.16)	(-1.12)	(-1.30)	(-0.40)
RF	14.90	14.86	-14.93	-88.49	-79.98
	(0.55)	(0.39)	(-0.30)	(-1.65)	(-1.27)
dp	-0.05	-0.06	-0.04	-0.07	0.01
	(-0.84)	(-0.77)	(-0.31)	(-0.34)	(0.03)
cay	0.96	2.31	4.92	11.20	12.57
	(1.03)	(1.79)	(2.45)	(4.17)	(4.04)
$ntis$	0.23	0.80	2.26	-3.03	-8.44
	(0.32)	(0.63)	(0.63)	(-1.24)	(-3.49)
gap	0.23	0.22	0.06	-0.54	-3.58
	(0.45)	(0.33)	(0.05)	(-0.31)	(-1.86)
$\bar{R}^2$	[0.11]	[0.28]	[0.36]	[0.60]	[0.75]

Table 5: **Robustness: Test of Small Sample Bias**

This table reports tests of small sample bias. Panel A shows OLS estimates along with 90% Bonferroni confidence intervals following Campbell and Yogo (2006). The second and third columns report the t-statistics and the point estimate $\hat{\beta}$ from regressions of the log excess CRSP-VW return on a constant and on a one-quarter lagged predictive variable. The predictive variables are all defined in Table 1. The next two columns report the 90% Bonferroni confidence intervals for β using the t-test and Q-test, respectively. Panel B reports confidence intervals from a bootstrap procedure. We generate 100,000 artificial time series of the size of our data set under the null hypothesis of no predictability. The data generating process is $r_t = \gamma + e_t$, $Standards_t = \mu + \phi \cdot Standards_{t-1} + \nu_t$ where r_t is the log excess return on the CRSP-VW index and the S&P500 index. The parameters in the data-generating process are set to the sample estimates for the bootstrap. We then compute OLS regressions with a Newey-West standard error correction: $r_t = \alpha + \beta \cdot Standards_{t-1} + \epsilon_t$ to compute the empirical distributions of the t-statistic of $\hat{\beta}$ and the $\bar{R}^2$ coefficient. We draw from the residuals of the system estimated under the null hypothesis. The sample period is from Q2:1990 to Q4:2008.

Panel A: Campbell and Yogo (2006) Test

Variable	t-stat($\hat{\beta}$)	$\hat{\beta}$	90% CI: β	
			t-test	Q-test
$Standards$	-3.446	-0.187	[-0.282,-0.100]	[-0.279,-0.099]
DEF	-2.517	-0.281	[-0.516,-0.115]	[-0.380,-0.025]
$TERM$	-0.301	-0.012	[-0.075,0.053]	[-0.075,0.053]
RF	1.394	0.067	[-0.009,0.153]	[-0.002,0.156]
dp	1.069	0.034	[-0.059,0.062]	[-0.049,0.074]
cay	1.512	0.062	[-0.039,0.115]	[-0.027,0.136]
$ntis$	2.476	0.113	[0.031,0.186]	[0.036,0.191]
gap	-0.211	-0.010	[-0.083,0.068]	[-0.077,0.072]

Panel B: Bootstrap Stock Return Test

Variable	t-stat($\hat{\beta}$)	95% CI	99% CI	$\bar{R}^2$	95% CI	99% CI
CRSP	-2.86	(-2.29 2.29)	(-3.10 3.14)	0.13	(-0.01 0.05)	(-0.01 0.09)
S&P	-3.02	(-2.28 2.29)	(-3.12 3.13)	0.14	(-0.01 0.05)	(-0.01 0.09)

Table 6: **Robustness: Other Survey Variables**

The table reports estimates from OLS regressions of stock returns on one-quarter lagged predictive variables with other survey variables: $r_t = \alpha + \beta \cdot Standards_{t-1} + \gamma \cdot Z_{t-1} + \epsilon_t$, where r_t is the log excess return on the CRSP-VW index and the S&P500 index. *Standards* is the tightening standards for C&I loans from the Senior Loan Officer Survey. *Demands* is the net percentage of banks reporting a stronger demand for C&I Loans. *Consumer* is the net percentage of banks reporting a stronger willingness to grant consumer installment loans. Newey-West corrected t-statistics appear in parentheses below the coefficient estimates. Adjusted R^2 statistics are given in the square brackets. The sample period is Q2:1990 to Q4:2008.

	CRSP	S&P
Standards	-0.18	-0.17
	(-4.29)	(-4.18)
Demands	-0.09	-0.07
	(-2.08)	(-1.64)
Consumer	0.13	0.10
	(1.13)	(0.92)
Constant	0.01	0.00
	(0.71)	(0.35)
$\bar{R}^2$	[0.20]	[0.19]

Table 7: **Robustness: Controlling for a Measure of Broker-Dealer Leverage**

The table reports estimates from OLS regressions of stock returns on one-quarter lagged predictive variables with a measure of broker-dealer leverage $ySBRDLR : levg$ as defined in Adrian et al. (2010): $r_t = \alpha + \beta \cdot Standards_{t-1} + \gamma \cdot ySBRDLR : levg_{t-1} + \epsilon_t$, where r_t is the log excess return on the CRSP-VW index. $Standards$ is the tightening standards for C&I loans from the Senior Loan Officer Survey. Newey-West corrected t-statistics appear in parentheses below the coefficient estimates. Adjusted R^2 statistics are given in the square brackets. The sample period is Q2:1990 to Q4:2008.

$Standards$	-0.14		-0.13
	(-2.86)		(-3.04)
$ySBRDLR : levg$		-0.10	-0.08
		(-2.38)	(-2.62)
Constant	0.02	0.02	0.03
	(2.57)	(2.28)	(4.06)
$\bar{R}^2$	[0.13]	[0.08]	[0.19]

Table 8: **Robustness: Extension of the Sample Period**

The table reports estimates from OLS regressions of stock returns on one-quarter lagged predictive variables with different sample periods: $r_t = \alpha + \beta \cdot Standards_{t-1} + \gamma \cdot Z_{t-1} + \epsilon_t$, where r_t is the log excess return on the CRSP-VW index or the S&P500 index. The regressors are all defined in Table 1. Newey-West corrected t-statistics appear in parentheses below the coefficient estimate and adjusted R^2 statistics in square brackets.

Panel A: Excess returns on CRSP and S&P (1967:Q1-1983:Q4)		
	CRSP	S&P
$Standards$	-0.03	-0.02
	(-0.36)	(-0.27)
Constant	0.01	-0.01
	(0.49)	(-0.54)
$\bar{R}^2$	[-0.01]	[-0.01]

Panel B: Additional controls; Excess returns on CRSP (1967:Q1-1983:Q4)									
$Standards$		-0.07		0.00		-0.02		-0.00	-0.09
		(-1.09)		(0.03)		(-0.31)		(-0.08)	(-1.37)
DEF	6.74	7.47							5.95
	(2.39)	(2.50)							(1.42)
$TERM$	-1.69	-2.87							-4.69
	(-1.24)	(-2.03)							(-3.49)
RF	-22.09	-27.22							-28.87
	(-5.24)	(-4.81)							(-4.44)
dp	0.18	0.19							0.17
	(4.50)	(4.51)							(2.03)
cay			2.24	2.25					1.38
			(2.22)	(2.19)					(0.90)
$ntis$					-1.38	-1.36			0.43
					(-1.43)	(-1.40)			(0.41)
gap							-0.69	-0.68	-0.43
							(-2.76)	(-2.78)	(-1.02)
Constant	0.65	0.73	0.03	0.03	0.03	0.04	0.00	0.00	0.68
	(4.32)	(4.54)	(1.59)	(1.47)	(1.24)	(1.52)	(0.25)	(0.26)	(2.57)
$\bar{R}^2$	[0.18]	[0.18]	[0.07]	[0.05]	[0.01]	[0.00]	[0.10]	[0.09]	[0.17]

Panel C: Excess returns on CRSP and S&P (1967:Q1-2008:Q4)		
	CRSP	S&P
Standards	-0.10	-0.10
	(-2.29)	(-2.35)
Constant	0.02	0.01
	(2.69)	(1.35)
$\bar{R}^2$	[0.04]	[0.04]

Panel D: Additional controls; Excess returns on CRSP (1967:Q1-2008:Q4)									
Standards		-0.11		-0.09		-0.10		-0.09	-0.14
		(-2.73)		(-2.24)		(-2.43)		(-1.90)	(-3.61)
DEF	0.49	1.74							7.79
	(0.15)	(0.65)							(2.57)
TERM	0.51	-0.31							-2.87
	(0.53)	(-0.39)							(-2.43)
RF	-3.88	-8.12							-23.33
	(-0.59)	(-1.40)							(-3.70)
dp	0.04	0.04							0.05
	(1.53)	(1.95)							(2.49)
cay			0.86	0.80					1.66
			(2.96)	(3.04)					(3.82)
ntis					0.05	-0.09			0.04
					(0.11)	(-0.22)			(0.08)
gap							-0.25	-0.19	0.28
							(-1.31)	(-1.02)	(1.35)
Constant	0.15	0.19	0.01	0.02	0.01	0.02	0.01	0.02	0.26
	(1.37)	(1.93)	(1.16)	(2.58)	(0.62)	(2.23)	(1.13)	(2.50)	(2.76)
$\bar{R}^2$	[0.01]	[0.05]	[0.03]	[0.07]	[-0.01]	[0.03]	[0.01]	[0.04]	[0.10]

Table 9: **Robustness: Canadian Stock Return Predictability**

The table reports estimates of OLS regressions of Canadian stock market returns on a one-quarter lagged Canadian *Standards* variable: $r_t = \alpha + \beta \cdot Standards_{t-1} + \epsilon_t$, where r_t is the log excess return on the S&P/TSX Composite index. To calculate excess stock returns, we use the continuously compounded 30 day Canadian T-bill rate as the risk-free rate. We use the overall business-lending conditions of the Canadian Senior Loan Officer Survey as the measure of *Standards*. Newey-West corrected t-statistics appear in parentheses below the coefficient estimates. Adjusted R^2 statistics are given in the square brackets. The values 95% (90%) CI (Bootstrap) are confidence intervals from a bootstrap procedure and the values 95% (90%) CI (MC) are confidence intervals from a Monte Carlo simulation. The sample period is Q2:1999 to Q4:2008.

	Excess returns on S&P/TSX Composite Index		
Standards	-0.07		
t-statistics	(-2.63)		
95% CI (Bootstrap)	(-2.57 2.60)	95% CI (MC)	(-2.59 2.59)
Constant	0.00		
t-statistics	(0.15)		
$\bar{R}^2$	[0.12]		
95% CI (Bootstrap)	(-0.03 0.11)	95% CI (MC)	(-0.03 0.11)

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