CREDIT CONDITIONS AND STOCK RETURN PREDICTABILITY

A Dissertation

by

HEUNGJU PARK

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

August 2011

Major Subject: Finance

CREDIT CONDITIONS AND STOCK RETURN PREDICTABILITY

A Dissertation

by

HEUNGJU PARK

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Approved by:

Co-Chairs of Committee,	Shane A. Johnson
	Michael F. Gallmeyer
Committee Members,	Hwagyun Kim
	Sudheer Chava
	Ryo Jinnai
Head of Department,	Sorin M. Sorescu

August 2011

Major Subject: Finance

ABSTRACT

Credit Conditions and Stock Return Predictability. (August 2011)

Heungju Park, B.A., Korea University;

M.S., Korea University

Co-Chairs of Advisory Committee: Dr. Shane A. Johnson
Dr. Michael F. Gallmeyer

This dissertation examines stock return predictability with aggregate credit conditions. The aggregate credit conditions are empirically measured by credit standards (*Standards*) derived from the Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices. Using *Standards*, this study investigates whether the aggregate credit conditions predict the expected returns and volatility of the stock market.

The first essay, "Credit Conditions and Expected Stock Returns," analyzes the predictability of U.S. aggregate stock returns using a measure of credit conditions, *Standards*. The analysis reveals that *Standards* is a strong predictor of stock returns at a business cycle frequency, especially in the post-1990 data period. Empirically the essay demonstrates that a tightening of *Standards* predicts lower future stock returns. *Standards* performs well both in-sample and out-of-sample and is robust to a host of consistency checks including a small sample analysis.

The second essay, "Credit Conditions and Stock Return Volatility," examines the role played by credit conditions in predicting aggregate stock market return volatility. The essay employs a measure of credit conditions, *Standards* in the stock return volatility prediction. Using the level and the log of realized volatility as the estimator of the stock return volatility, this study finds that *Standards* is a strong predictor of U.S. stock return volatility. Overall, the forecasting power of *Standards* is strongest during tightening credit periods.

ACKNOWLEDGMENTS

I gratefully acknowledge the advice and support of my dissertation committee, Shane A. Johnson, Michael F. Gallmeyer, Hwagyun Kim, Sudheer Chava, and Ryo Jinnai. Their guidance, assistance, support, and encouragement were imperative for this work. I am very thankful to the faculty members in the Finance Department as well as my colleagues in the Ph.D. program for all of their help and support. I also thank the Finance Department and the Dean's Office at Mays Business School for their financial support.

I would like to express great gratitude to Dong-Hyun Ahn in the Seoul National University and Inmoo Lee in the Korea Advanced Institute of Science and Technology (KAIST) for their constant encouragement and support. I would also like to thank Bumjean Sohn in Georgetown University for the various fruitful discussions I had with him.

Finally, I am extremely grateful to my family, including my wife, Sae Ah, my children, Seonwoo and Eunseo, and my mother, for their enduring patience and support as I completed this work.

TABLE OF CONTENTS

Page

LIST OF TABLES

LIST OF FIGURES

1. INTRODUCTION

This dissertation contains two essays, as presented in Sections 2 and 3, which are parts of larger research efforts of Chava, Gallmeyer, and Park (2011a) and Chava, Gallmeyer, and Park (2011b), respectively. They focus on stock return predictability using an aggregate credit condition variable. We use credit standards (*Standards*) as the aggregate credit condition variable. *Standards* is derived from the Fed's senior loan officer opinion survey on bank lending practice. The Fed conducts a quarterly survey of bank senior loan officers on the supply and the demand credit conditions. The survey question on *Standards* deals with supply of Commercial and Investment Loans. For the question, bank senior loan officers answer using 5 ratings on current loan conditions from considerably tightening to considerably easing. Lown and Morgan (2006) measure *Standards* as the number of bank tightening minus the number of bank easing divided by total number of banks. So, *Standards* includes both quantitative and qualitative conditions of bank loan supply. Due to the information advantages, we apply *Standards* to aggregate stock return and volatility predictability.

In the first essay, "Credit Conditions and Expected Stock Returns,"[1] we study the predictability of *Standards* for the excess stock returns. According to previous research, such as Lown and Morgan (2006), *Standards* predicts macroeconomic variables and this predictability of *Standards* could be consistent with economic models, like the credit channel of monetary policy transmission and the borrowers' balance sheet effects. For example, a tighter monetary policy leads to a reduced and costly

---

This dissertation follows the style of *Journal of Finance*.

[1]We would like to thank Dong-Hyun Ahn, Greg Bauer, Frederico Belo, Zhanhui Chen, Burton Hollifield, Shane Johnson, Nishad Kapadia, Hagen Kim, Inmoo Lee, J. Spencer Martin, and participants at the 2010 European Finance Association Meeting, the McGill Risk Management Conference, and the UBC Summer Finance Conferences for helpful input. All errors are our own.

bank loan supply and it has impacts on future economic activity. Also, if banks have bad prospects on future economic conditions, they increase their *Standards*. It affects the risk structure of the economy and also the risk characteristics of stock market. While previous studies focus on the impact of *Standards* on macroeconomic variables, they have not considered the direct influences of *Standards* on the stock market. We examine whether *Standards* predicts variations of expected stock returns.

From our empirical findings, *Standards* is a strong predictor of U.S. aggregate stock returns. That is, a tightening of *Standards* predicts lower future stock returns and it is consistent with economic intuition. This result is confirmed both through in-sample and out-of sample tests. In long horizon tests, we find that the predictive power of *Standards* is sustained at a horizon of 1 year and less (business cycle frequency) because the informational content of *Standards* decreases at longer horizons. The predictive power of *Standards* is robust to many consistency checks, like an analysis of small sample bias, an extension of sample periods, and an exclusion of financial crisis data.

The predictability of *Standards* is particularly interesting in light of the findings of Goyal and Welch (2008). Goyal and Welch (2008) show that most predictive variables used in the literature have performed poorly both in-sample and out-of-sample, especially over the last 30 years. On the other hand, we find that the relationship between *Standards* and expected stock returns is especially strong in the post-1990 time period. In a multivariate analysis, we use many predictors in previous studies as control variables and find that only *Standards* is statistically significant. Other predictors have their insignificant coefficients, which is consistent with Goyal and Welch (2008)'s results. Though our sample is limited to the period after the 1990s, the predictability of *Standards* is noteworthy according to the findings in Goyal and Welch (2008).

Using $Standards$, we also examine predictability of different moment of aggregate stock returns distribution. The second essay, "Credit Conditions and Stock Return

Volatility,"[2] deals with the predictability of stock return volatility. Many predictability literature about stock return volatility, including Schwert (1989) and Paye (2009), argues that predictive powers of macro and financial variables are weak. This weak evidence of the predictability of stock return volatility shows that the macroeconomic variables fail to capture the asymmetric time-varying pattern of stock return volatility. A recent paper of Chava, Gallmeyer, and Park (2011a) finds that *Standards* has the strong forecasting power in tightening periods and *Standards* might shed light on the economic channel that drives the counter-cyclical and asymmetric pattern of aggregate stock market return volatility given its micro foundations are not well understood. Therefore, we examine whether *Standards* is related to the asymmetric time-varying pattern of aggregate stock return volatility.

We find that *Standards* is a strong predictor of U.S. stock return volatility at frequencies up to and including a year. This is not surprising, since *Standards* has strong forecasting power of for both stock returns (Chava, Gallmeyer, and Park (2011a)) and macroeconomic variables (Lown and Morgan (2006)). The ability of *Standards* to track time-varying expected returns could help forecast future volatility. The relation between stock volatility and *Standards* is positive, which implies that tighter credit conditions predict higher future stock volatility. We also perform out-of-sample forecasting tests and find that the forecasts of volatility with *Standards* are more accurate than those with the historical mean and an AR(1) model of volatility. The ability of *Standards* to predict stock return volatility is also robust to a host of consistency checks including a bootstrap procedure, other model specifications of volatility, and extended the sample period.

This empirical findings are related to the role played by financial intermediaries in stabilizing economic volatility. Larrain (2006) examines the contemporaneous

[2]We would like to thank Bumjean Sohn for helpful input. All errors are our own.

relationship between bank loan supply and output volatility and finds that on average bank loan supply increases reduce industrial output volatility. Correa and Suarez (2009) also find that firm-level employment, production, sales and cash flows are less volatile after wider access to bank loans. However, past work has not considered the effect of bank loan supply changes on the stock market volatility. In this paper, we find that the aggregate bank loan supply, *Standards* affects variations of aggregate stock return volatility.

2. CREDIT CONDITIONS AND EXPECTED STOCK RETURNS

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 stock returns (Thorbecke (1997), Bernanke and Kuttner (2005), Patelis (1997) among others) as well as the behavior of business condition proxies such as term premia, default premia, and dividend yields (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 leads 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 bank loan supply affect 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.[3] 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.

---

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

Despite this pro-cyclical feature of bank lending to macroeconomic variables, limited evidence exists whether changes in bank loan supply affect 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 also driven by market 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 equity market prices, serves as a leading indicator of future stock returns.

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 macro 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.

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. Subsection 2.1 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 Subsection 2.2. Subsection 2.3 presents evidence on stock return predictability, while Subsection 2.4 addresses results from an extensive set of robustness checks. Subsection 2.5 investigates the predictability of *Standards* and Subsection 2.6 concludes.

2.1 Data

2.1.1 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 (2006, 2002) 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.[4] 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)

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

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.[5] 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 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 2.1 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.

[5]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.

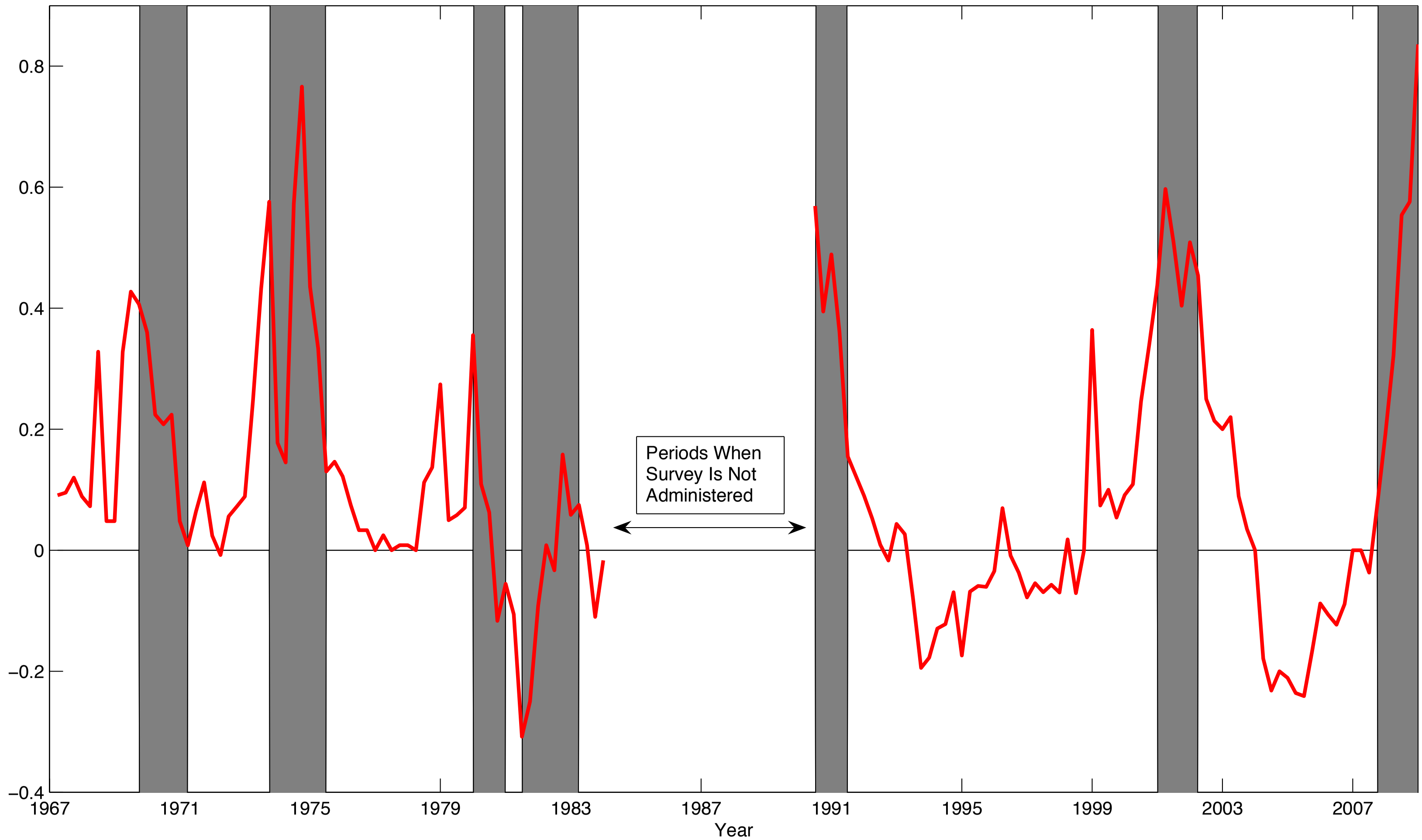


Fig. 2.1. Change in *Standards* from the Senior Loan Officer Survey 1967-2008

2.1.2 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.

2.1.3 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:

$$c_t = \alpha + \beta_a \cdot y_t + \sum_{i=-k}^{k} b_{a,i} \cdot \Delta a_{t-i} + \sum_{i=-k}^{k} b_{y,i} \cdot \Delta y_{t-i} + \epsilon_t, \tag{2.1}$$

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.[6]

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

$$NetIssue_t = Mcap_t - Mcap_{t-1} \cdot (1 + vwretx_t), \tag{2.2}$$

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, Michaely, Richardson, and Roberts (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 that incorporates both a linear and a quadratic component:

$$p_t = a + b \cdot t + c \cdot t^2 + \epsilon_t, \tag{2.3}$$

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.

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

Table 2.1
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

2.1.4 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 2.1. 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 2.1 present the correlations across various predictor variables. *Standards* is highly positively correlated with default spread DEF (65%) and next with output gap, *gap* (24%). Not surprisingly, *Standards* is significantly negatively correlated with net stock issuances *ntis* (-44%). The correlations across other predictor variables are consistent with the earlier literature.

2.2 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:

$$r_t = \alpha + \beta \cdot Standards_{t-1} + \epsilon_t, \tag{2.4}$$

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.

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 (CP and gap), defined by the vector Z added to the regression that includes $Standards$ and estimate

$$r_t = \alpha + \beta \cdot Standards_{t-1} + \gamma \cdot Z_{t-1} + \epsilon_t, \tag{2.5}$$

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

$$R^2_{oos} = 1 - \frac{MSE_A}{MSE_N}, \tag{2.6}$$

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

$$\Delta RMSE = \sqrt{MSE_N} - \sqrt{MSE_A}. \tag{2.7}$$

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:

$$MSE - F = (T - h + 1) \cdot \frac{MSE_N - MSE_A}{MSE_A}, \tag{2.8}$$

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:

$$ENC - NEW = \frac{T - h + 1}{T} \cdot \frac{\sum_{t=1}^{T}(\epsilon_t^2 - \epsilon_t \cdot e_t)}{MSE_A}, \tag{2.9}$$

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.

2.3 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.

2.3.1 In-Sample Evidence

Table 2.2 reports in-sample forecasting regressions with *Standards*, for the quarterly log excess returns on the CRSP-VW index and the S&P 500 index.[7] In all of the regressions in Table 2.2, the t-statistics are reported using a Newey and West (1987) correction to account for serial correlation in the residuals.

Panel A of Table 2.2 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 which is consistent with economic intuition.

Panel B of Table 2.2 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-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 (2011) 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.

---

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

Table 2.2

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 2.1. 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]

The first column of Panel B in Table 2.2 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.[8] 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 forecasts stock returns. Boudoukh, Michaely, Richardson, and Roberts (2007), Larrain 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

---

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

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).

2.3.2 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.[9]

Table 2.3 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 2.3 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

[9]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.

Table 2.3

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 2.1. 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

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 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 2.3 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*.

2.3.3 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.[10] In this subsection, we investigate whether *Standards* tracks longer-term tendencies in stock markets rather than providing shorter-term forecasts. Table 2.4 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 2.4, we document the forecasting power of *Standards* for future excess returns at horizons ranging from 1 to 12 quarters. The coefficient

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

Table 2.4

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 2.1. 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]

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.

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, Lo, and MacKinlay (1997) and Cochrane (2001) for example.

In the last panel of Table 2.4, 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.

2.4 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, extending the *Standards* data series to use earlier data, and studying stock return predictability in the Canadian stock market.[11]

2.4.1 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 (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 2.1). 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 2.5. Following Campbell and Yogo, we report the confidence interval for $\tilde{\beta}$=$(\sigma_e/\sigma_u)\beta$ instead of β.[12] In the fourth (fifth)

---

[11]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.

[12]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.

Table 2.5
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 2.1. 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)

column of the table, we report the 90% Bonferroni confidence intervals for β using the t-test (Q-test), whose the null hypothesis is β=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:

$$r_t = \gamma + e_t, \tag{2.10}$$

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

$$Standards_t = \mu + \phi Standards_{t-1} + \nu_t, \tag{2.11}$$

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 (2.4) which yields a distribution of our test statistics.

Panel B of Table 2.5 reports the results of the bootstrap procedure for the Newey-West t-statistics and adjusted R^2 coefficients of the predictive regression with *Standards*.[13] 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

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

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.

2.4.2 Other Survey Variables

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 forecasting 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

Table 2.6

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]

Demands and *Consumer* by regressing them on *Standards* and use the orthogonalized components of *Demands* and *Consumer*.

Table 2.6 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 2.2, 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.

2.4.3 Extended Sample Period

Our main results use the *Standards* series from Q2:1990 to Q4:2008.[14] 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:

$$Standards_t = \alpha + \beta\, Standards_{t-1} + \gamma\, Consumer_t + \epsilon_t, \tag{2.12}$$

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

[14] 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.

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 2.7 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 2.7 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 2.7, 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).

Table 2.7
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 2.1. 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]

Table 2.7 continued

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]

2.4.4 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.[15] Since 1999, the Bank of Canada has conducted a quarterly Senior Loan Officer Survey of the business-lending practices of major Canadian financial institutions.[16] 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 2.8 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.

---

[15]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 recently adopted leading to too short of a sample period.

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

Table 2.8

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)

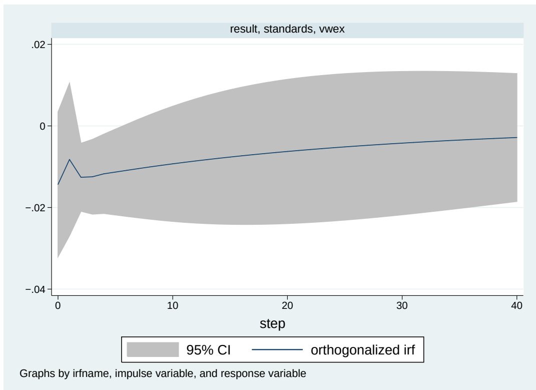
2.5 Discussion

In the previous subsection, we show that the excess stock returns are strongly predictable with negative coefficients on *Standards* and the predictive power declines across time horizon. After 2 years, the size of the coefficient declines and the predictive power also decreases at a horizon greater than 4 quarters. In multivariate cases with traditional predictors for stock returns, the results are very similar as those in the univariate case. The negative coefficients suggest that tightening *Standards* predicts the subsequent drop in stock returns and it seems to be somewhat inconsistent with an asset pricing model with time-varying risk, which implies that investors usually require high expected returns in bad time. We now explore the predictability of *Standards* in depth.

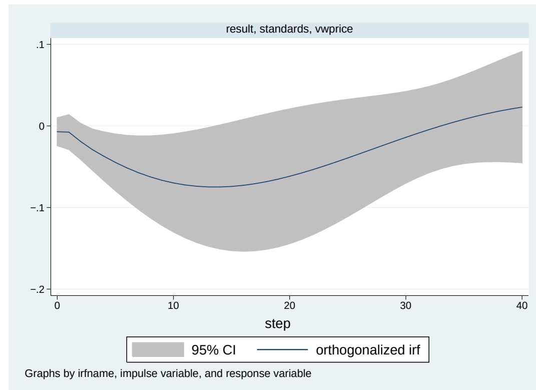
2.5.1 Channel of Predictability

The first empirical approach to study the predictability is the estimation of vector autoregression (VAR). We use two lags in the VAR specification following optimal lag length selection criteria. To examine the formation of stock return expectations, we order the excess stock returns last. Figure 2.2 shows the response of the excess stock returns to *Standards*. To both the excess stock return and the log stock price, *Standards* shock moves very slowly.[17] It implies that the information content of *Standards* slowly gets incorporated into the stock price and is consistent with our findings in the long-horizon regression analysis.

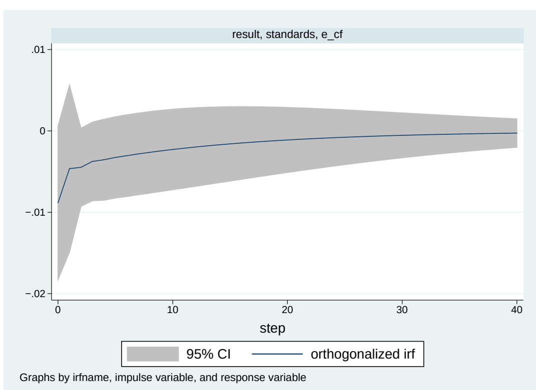
[17] We check whether the *Standards* shock is a persistent predictor for excess stock returns. We decompose the *Standards* shock into the trend component and the cyclical component using a band pass filter of Christiano and Fitzgerald (2003) and the Hodrick and Prescott (1997) filter and find that the most predictability for excess stock returns results from the trend component of *Standards*.



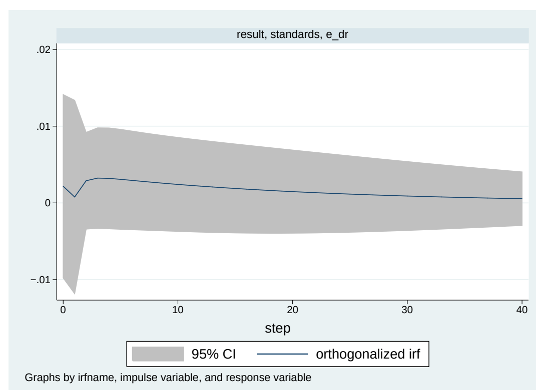
(a) IRF plot of excess stock returns



(b) IRF plot of log price



(c) IRF plot of cash flow components



(d) IRF plot of discount rate components

Fig. 2.2. Impulse Response Functions for CRSP-VW Index

From the columns (3) and (4) of Figure 2.2, we show the impulse-response relationship between *Standards* and the decomposition components of the unexpected excess stock returns, cash flow news and discount rate news, from Campbell and Vuolteenaho (2004).[18] The decomposition can be written as,

$$e_{y,t+1} = \tilde{e}_{CF,t+1} - \tilde{e}_{DR,t+1} \tag{2.13}$$

where

$$\begin{aligned} \tilde{e}_{CF,t+1} &= (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j}, \\ \tilde{e}_{DR,t+1} &= (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j y_{t+1+j}. \end{aligned} \tag{2.14}$$

The empirical implementation assumes that a vector of state variables evolves according to a first order VAR. The VAR includes a six variable one-lag system that has the excess equity return, the real interest rate, the relative bill rate (defined as the 1 month bill rate minus its 12 month lagged moving average), the change in the 1 month bill rate, the smoothed dividend price ratio, and the spread between 10 year and 1 month treasury bills. Then DR news and CF news follows,

$$\begin{aligned} \tilde{e}_{DR,t+1} &= e1'\rho A(I - \rho A)^{-1} w_{t+1}, \\ \tilde{e}_{CF,t+1} &= (e1' + e1'\rho A(I - \rho A)^{-1}) w_{t+1}. \end{aligned} \tag{2.15}$$

This approach enables us to analyze the sources of the predictability of *Standards*. The negative cash flow news and the positive discount rate news of the unexpected excess stock returns can result in the drop in stock returns and have negative coefficients of our predictive regression. The columns (3) and (4) of Figure 2.2 show the responses of the decompositions of the cash flow and discount rate news to *Standards*.

[18] We also conduct the Campbell and Ammer (1993) decomposition. The results are similar as those in Campbell and Vuolteenaho (2004). For the simplicity, we report the Campbell and Vuolteenaho (2004) decomposition.

The initial response of the cash flow news appears negative and moves slowly, while the discount rate news has the positive shocks of *Standards*. To compare the sizes of the shocks, *Standards* has more impact on the cash flow news than the discount rate news. Table 2.9 reports in-sample forecasting regressions with *Standards* for the cash flow news and the discount rate news of the unexpected excess stock returns. The cash flow news is strongly predictable with negative coefficients on *Standards*, while the forecasting power for the discount rate news is statistically insignificant. The results of this in-sample regression correspond with the magnitude of the initial shocks in the impulse-response function.

Table 2.9

Forecasting Decomposition Components for Quarterly Unexpected Excess Stock Returns

The table reports estimates of OLS regressions of decomposition components for unexpected excess 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 unexpected components of the log excess return on the CRSP-VW index. To decompose the unexpected excess stock returns, we follow the Campbell and Vuolteenaho (2004) approach using a first order VAR. The VAR includes a six variable one-lag system that include the excess equity return, the real interest rate, the relative bill rate (defined as the 1 month bill rate minus its 12 month lagged moving average), the change in the 1 month bill rate, the smoothed dividend price ratio, and the spread between 10 year and 1 month treasury bills. e_{CF} is the cash flow components and e_{DR} is the discount rate components. 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.

	e_{CF}	e_{CF}	e_{DR}	e_{DR}
Standards	-0.05	-0.05	0.04	0.02
	(-2.44)	(-2.26)	(1.22)	(0.66)
e_{CF}		-0.10		
		(-0.91)		
e_{DR}				0.03
				(0.27)
constant	0.00	0.00	-0.00	-0.00
	(0.82)	(0.85)	(-0.42)	(-0.48)
$\bar{R}^2$	[0.06]	[0.04]	[0.01]	[-0.02]

However, the VAR approach to estimate the cash flow and discount rate news can have a potential problem in case of the model misspecification, since it is based on the comparison between the specified model (the discount rate news) and the residual (the cash flow news). Chen and Zhao (2009) argue that the VAR approach has a potential limitation because of the small predictive power in the model specification. Therefore, we now examine the robustness of the relationship between *Standards* and the decomposition components of the unexpected excess stock returns, the cash flow and discount rate news.

As a robustness test, we examine the predictability of *Standards* controlling for other expectation variables. From the Survey of Professional Forecasters, we use the average expected growth rate of GDP over the next four quarters and the average expected CPI inflation rate over the next four quarters. Also, we employ the quarterly growth rate of analysts earnings forecasts over the next year for the S&P500 index from I/B/E/S. Table 2.10 reports the in-sample predictive regressions for the excess stock returns. The expectation variables are statistically insignificant in all specifications, while the significance of *Standards* still remains. Moreover, the addition of *Standards* rapidly increases the adjusted R^2 in the forecasting regression. It implies that the predictability of *Standards* shows time variations in discount rate news to control for the expectations of the future macroeconomic activity and the future earnings growth.

Table 2.11 shows the predictability of *Standards* for the proxies of the future cash flows. We use the quarterly growth rate of real earnings for the S&P500 index and the quarterly growth rate of real dividends as the proxies. The earnings and dividends data is obtained for Robert Shiller's website. For the predictive regression, we also add the lagged proxies as the explanatory variables. Except for the specification with the lagged real dividend growth, *Standards* has the significantly negative coefficients. It implies that tightening *Standards* affects the subsequent decrease in the real dividend growth and the real earnings growth, which accords with the findings of the

Table 2.10

Forecasting Quarterly Excess Stock Returns with Cash Flow Expectation Variables

The table reports estimates of OLS regressions of excess 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.$GDP4Qavg$ is the average expected growth rate of GDP over the next four quarters from the Survey of Professional Forecasters. $CPI4Qavg$ is the average expected CPI inflation rate over the next four quarters from the Survey of Professional Forecasters. $expearn1qg$ is the quarterly growth rate of analysts earnings forecasts over the next year for the S&P500 index from I/B/E/S. 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.

MKT	0.28	0.30	0.10	0.37	0.35	-0.02	0.02
	(0.93)	(0.91)	(0.37)	(1.12)	(1.08)	(-0.05)	(0.04)
$GDP4Qavg$	0.01	0.00	-0.00	-0.00	0.01	-0.02	-0.00
	(0.15)	(0.06)	(-0.07)	(-0.08)	(0.45)	(-0.99)	(-0.03)
$CPI4Qavg$	0.01	0.02	0.01	-0.00	-0.02	0.03	-0.05
	(0.41)	(1.03)	(0.55)	(-0.06)	(-0.60)	(1.33)	(-0.61)
$expearn1qg$	0.07	0.08	0.03	0.08	0.08	-0.03	-0.02
	(0.67)	(0.69)	(0.30)	(0.78)	(0.83)	(-0.27)	(-0.19)
RF	2.26						31.73
	(0.14)						(1.54)
$TERM$		0.14					1.97
		(0.11)					(0.78)
DEF			-8.79				6.87
			(-1.46)				(0.65)
dp				0.05			0.00
				(0.59)			(0.01)
cay					1.09		0.99
					(1.51)		(0.92)
$Standards$						-0.17	-0.22
						(-3.33)	(-2.38)
Constant	-0.06	-0.05	0.06	0.23	0.00	0.05	-0.02
	(-0.42)	(-0.42)	(0.61)	(0.42)	(0.03)	(0.56)	(-0.03)
$\bar{R}^2$	[-0.03]	[-0.03]	[0.02]	[-0.02]	[0.00]	[0.12]	[0.09]

Table 2.11

Forecasting Future Cash Flows

The table reports estimates of OLS regressions of the quarterly growth rates of real earnings and the quarterly growth rates of real dividends on the S&P500 index on one-quarter lagged predictive variables: $r_t = \alpha + \beta \cdot Standards_{t-1} + \gamma \cdot Z_{t-1} + \epsilon_t$. 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.

	realearnings	*realearnings*	*realdividends*	*realdividends*
realearnings		0.62		
		(6.63)		
realdividends				0.22
				(1.91)
Standards	-0.25	-0.13	-0.03	-0.02
	(-2.78)	(-1.67)	(-2.88)	(-2.37)
Constant	0.02	0.00	0.01	0.01
	(1.48)	(0.53)	(3.33)	(2.72)
$\bar{R}^2$	[0.24]	[0.37]	[0.15]	[0.18]

previous VAR approach. These results confirm that the predictability of *Standards* for the excess stock returns result from both the cash flow and discount rate news.

2.5.2 Source of Risk

In this subsection, we examine whether the predictability of *Standards* for the excess stock returns is related to the time-varying risk model. Patelis (1997) examines whether tightening monetary policy predicts the excess stock returns and finds that following the initial negative response of stock prices to monetary policy shocks, the size of the coefficient of the monetary policy variables declines across time. He interprets the decreasing coefficient as the evidence of the time-varying risk premia and argues that the expected stock returns increase to compensate for the deterioration in the financial health of the firms caused by the monetary policy shocks. To reconcile the predictability of *Standards* with the time-varying risk model,we apply this argument to our empirical findings that the predictability of *Standards* declines across time horizon and examine whether *Standards* affects the variations of expected stock returns across the financial constraints of the firms.

Following the previous literature[19], we use four measures of financial constraints, payout ratio, asset size, debt rating, and paper rating.[20] Firms with low payout ratio, small asset size, unrated debt, or unrated commercial papers are financially more constrained than firms with high payout ratios, big asset size, rated debt, or rated commercial papers.

---

[19]See Almeida, Campello, and Weisbach (2004), Faulkender and Wang (2006), Almeida and Campello (2007), Denis and Sibilkov (2010), and Li and Zhang (2010).

[20]We perform our analysis using several alternative approaches for sorting firms into financially constrained and financially unconstrained groups like the Kaplan and Zingales (1997) index, the Whited and Wu (2006) index, and the Hadlock and Pierce (2010) index. They show the similar conclusions as the four measures.

Payout ratio: We assign firms in the bottom (top) three deciles of the annual cash payout ratio distribution to the financially constrained (unconstrained) group. Payout ratio is defined as the ratio of dividends and common stock repurchases to operating income. Observations with a positive payout and zero or negative cash flow are assigned the highest payout ratio.

Asset size[21]: We measure asset size as book value of total assets. We rank firms based on the asset size and assign those firms in the bottom (top) three deciles of the firm size distribution to the financially constrained (unconstrained) group.

Debt rating[22]: We classify firms as financially unconstrained if they have had their long term debt rated by Standard & Poor's and their debt is not in default. We also classify firms as constrained if they have debt outstanding that year, but have never had their public debt rated before. Firms with no debt outstanding are classified as unconstrained.

Paper rating: We assign firms that never had their commercial paper rated to the financially constrained group when they report positive commercial paper. The financially unconstrained group contains firms whose commercial paper has been rated and firms without commercial paper outstanding.

[21] Asset size can be used as the measure of the size effect. We also find *Standards* strongly predicts SMB in the long horizon regression.

[22] The existence of debt rating is related to the degree of bank dependence. Chava and Purnanandam (2011) use the absence of public debt rating as the proxy for the bank-dependence. Following their measure, we check the predictability of *Standards* for the excess stock returns of the bank dependent firms and *Standards* for the bank dependent firms shows the similar predictability as *Standards* for the financially constrained firms

Table 2.12
Long Horizon Regression: Excess Stock Returns by Financially Constrained Groups

The table reports results from long-horizon regressions of quarterly log excess stock returns by financially constrained groups on lagged *Standards*. H denotes the return horizon in quarters. The dependent variable is the sum of H log excess stock returns by the financially constrained groups, $r_{t+1} + ... + r_{t+H}$. We employ four measures of financial constraints, (1) payout ratio, (2) asset size, (3) debt rating, and (4) paper rating and sort firms into financially constrained and financially unconstrained groups. 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.

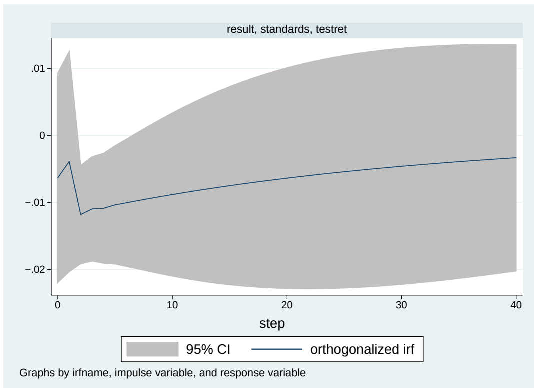
	Forecast Horizon H				
Regressors	1	2	4	8	12
Unconstrained 1: Payout					
Standards	-0.13	-0.22	-0.31	-0.50	-0.53
	(-3.16)	(-2.85)	(-2.37)	(-2.57)	(-2.64)
$\bar{R}^2$	[0.14]	[0.21]	[0.16]	[0.20]	[0.12]
Unconstrained 2: Size					
Standards	-0.15	-0.25	-0.32	-0.50	-0.49
	(-3.05)	(-2.84)	(-2.32)	(-2.40)	(-2.38)
$\bar{R}^2$	[0.15]	[0.21]	[0.14]	[0.17]	[0.09]
Unconstrained 3: Bond ratings					
Standards	-0.15	-0.25	-0.32	-0.49	-0.47
	(-3.02)	(-2.80)	(-2.26)	(-2.33)	(-2.27)
$\bar{R}^2$	[0.14]	[0.20]	[0.14]	[0.16]	[0.08]
Unconstrained 4: Paper ratings					
Standards	-0.14	-0.23	-0.31	-0.49	-0.49
	(-3.05)	(-2.76)	(-2.23)	(-2.37)	(-2.37)
$\bar{R}^2$	[0.14]	[0.20]	[0.14]	[0.17]	[0.09]
Constrained 1: Payout					
Standards	-0.24	-0.38	-0.39	-0.56	-0.38
	(-2.47)	(-2.30)	(-1.53)	(-1.58)	(-1.17)
$\bar{R}^2$	[0.10]	[0.12]	[0.05]	[0.07]	[0.01]
Constrained 2: Size					
Standards	-0.15	-0.22	-0.15	-0.10	0.29
	(-2.09)	(-1.75)	(-0.69)	(-0.31)	(1.37)
$\bar{R}^2$	[0.04]	[0.04]	[-0.00]	[-0.01]	[0.01]

Table 2.12 continued

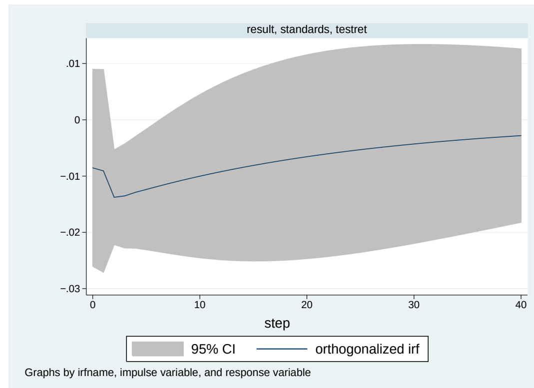
Constrained 3: Bond ratings					
Standards	-0.17	-0.27	-0.27	-0.36	-0.15
	(-2.56)	(-2.34)	(-1.49)	(-1.37)	(-0.75)
$\bar{R}^2$	[0.09]	[0.12]	[0.05]	[0.06]	[-0.01]
Constrained 4: Paper ratings					
Standards	-0.19	-0.31	-0.33	-0.45	-0.29
	(-2.74)	(-2.65)	(-1.91)	(-1.74)	(-1.32)
$\bar{R}^2$	[0.11]	[0.16]	[0.08]	[0.09]	[0.02]

Table 2.12 and Figure 2.3 show the long-horizon predictability of *Standards* for the excess stock returns across the financial health of firms.[23] Using four measures of the financial constraints, we assign firms to the financially constrained and unconstrained groups and compare the pattern of the predictability of *Standards*. The long-horizon predictability pattern of two groups is distinct from each other, while both of them have the significantly negative coefficients for predictability of *Standards* in the initial horizon. The financially unconstrained group shows stronger initial negative response of excess stock returns to *Standards* than the financially constrained group, since the magnitude of the *Standards* impulse on the excess stock returns are much high in the financially constrained group. Figure 2.3 shows the magnitude of the impulse in the financially constrained group are twice as much as those in the unconstrained groups. For the financially constrained group, the coefficients of *Standards* and the significance level peak around 2 quarters. On the other hand, in the financially unconstrained group, the predictability of *Standards* decreases at a horizon greater than 2 years. The pattern to decline the size of the co-

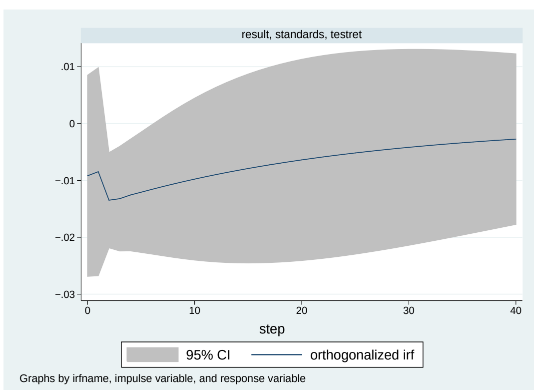
[23]We conduct the multivariate long-horizon regressions with traditional predictors and the results are very similar as those in the univariate case.



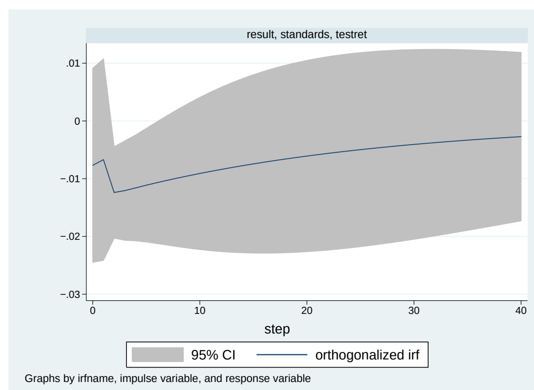
(a) IRF plot of Unconstrained 1



(b) IRF plot of Unconstrained 2

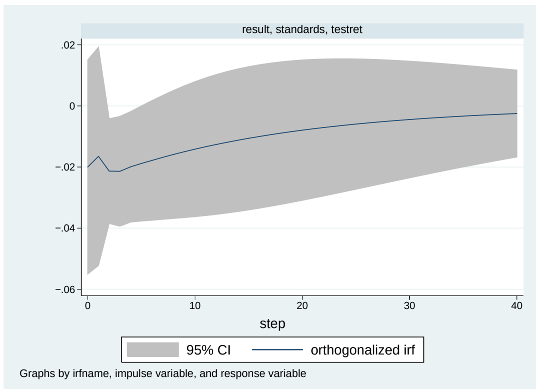


(c) IRF plot of Unconstrained 3

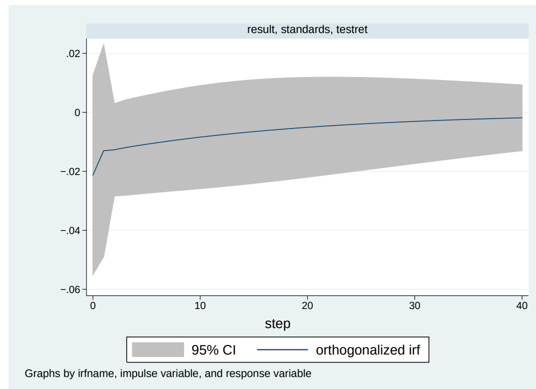


(d) IRF plot of Unconstrained 4

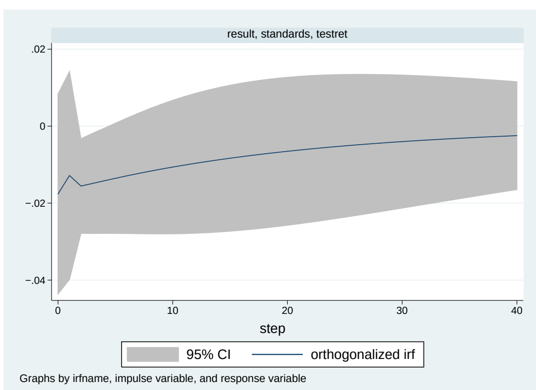
Fig. 2.3. Impulse Response Functions for Excess Stock Returns by Financially Unconstrained Groups



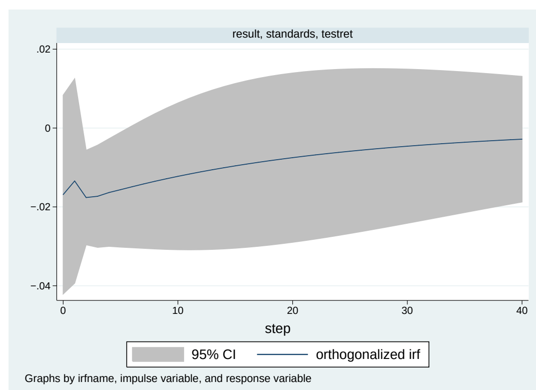
(e) IRF plot of Constrained 1



(f) IRF plot of Constrained 2



(g) IRF plot of Constrained 3



(h) IRF plot of Constrained 4

Fig. 2.3. continued

efficients across time implies that the expected stock returns increase to compensate for the deterioration in the financial constraint resulted from tightening *Standards*. We find that following the tightening *Standards* shock, the financially constrained group has the higher expected long-horizon returns than the unconstrained group, which is consistent with the financial constraint risk literature.[24] The results of four measures confirm that *Standards* predicts the high long-horizon excess stock returns in the financially constrained group compared to the unconstrained group.

2.6 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. Additionally, *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.

[24]Lamont, Polk, and Saa-Requejo (2001) and Whited and Wu (2006) show the different results of the financial constraint risk. Lamont, Polk, and Saa-Requejo (2001) report that more constrained firms earn lower average returns than less constrained firms, while Whited and Wu (2006) find that more constrained firms earn higher average returns than less constrained firms. Our results with conditioning on *Standards* support the financial constraint risk.

3. CREDIT CONDITIONS AND STOCK RETURN VOLATILITY

Empirically, stock market volatility is strongly counter-cyclical across the business cycle as shown in a number of studies. For example, Schwert (1989) and Brandt and Kang (2004) empirically find that the volatility of stock returns is higher during recessions than at other times. In theoretical work, Campbell and Cochrane (1999) show that counter-cyclical risk aversion from external habit formation leads to a counter-cyclical equity volatility. Mele (2007) shows that equity return volatility is counter-cyclical because risk premia change asymmetrically in response to variations in economic conditions.

This counter-cyclical volatility led to several studies that examine the predictability of aggregate stock market return volatility with measures of macroeconomic activity meant to capture the business cycle. Schwert (1989) examines the link of stock return volatility with real and nominal macroeconomic volatility and economic activity using monthly data from 1857 to 1987. He finds weak evidence that macroeconomic volatility can help predict stock return volatility. Beltratti and Morana (2006) also study the relationship between macroeconomic and stock market volatility with a common long memory factor model. They find that the break process in stock returns is associated with the break process in the volatility of the Federal funds rate and M1 growth, while two common long memory factors are associated with output and inflation volatilities. Paye (2009) tests the forecasting ability of the level of macroeconomic and financial variables on aggregate stock return volatility. He finds that the predictive ability of most macroeconomic and financial variables is weak. This weak evidence of the predictability of stock return volatility shows that the macroeconomic variables fail to capture the asymmetric time-varying pattern of stock return volatility. Also, the evidence supports the arguments of Christoffersen and Diebold (2000) and Campbell (2003) that stock return volatility is not strongly predictable at frequencies as low as a quarter.

Recently, several papers have argued that aggregate credit conditions could covary with time-varying risk in the equity market. Longstaff and Wang (2008) show that variation in the size of the credit market is connected with variation in expected stock returns. Gomes and Schmid (2009) show that movements in credit spreads forecast recessions by predicting movements in corporate investment. They argue that corporate investment is the common link between credit markets, equity markets, and macroeconomic aggregates. Gilchrist, Yankov, and Zakrajsek (2009), using a broad array of credit spread measures, find that credit market shocks have contributed significantly to US economic fluctuations. Adrian, Moench, and Shin (2010) investigate whether financial intermediary balance sheets contain strong predictive power for future excess returns on equity, corporate, and Treasury bond portfolios. They find that the intermediary variables predict real economic activity as well as excess returns. Chava, Gallmeyer, and Park (2011a) examine the impact of a measure of credit conditions, credit standards (*Standards*), on expected aggregate stock returns. They find that *Standards* has a counter-cyclical and asymmetric time-varying pattern and strong predicts aggregate stock market returns.

These previous studies however have only focused on the return itself. Little attention has been paid to the prediction of stock return volatility using credit condition variables. We analyze the predictability of US aggregate stock market return volatility using a measure of credit conditions, credit standards (*Standards*), from the Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices. Since Chava, Gallmeyer, and Park (2011a) find that *Standards* has the strongest forecasting power in tightening periods, *Standards* might shed light on the economic channel that drives the counter-cyclical and asymmetric pattern of aggregate stock market return volatility given its micro foundations are not well understood.

Our work is also motivated by how financial intermediaries could impact economic volatility. Larrain (2006) examines the contemporaneous relationship between bank loan supply and output volatility finding that on average bank loan supply increases reduce industrial output volatility. The reduction in volatility comes mainly from a reduction in idiosyncratic volatility. Correa and Suarez (2009) find that firm-level employment, production, sales and cash flows are less volatile after wider access to bank loans. However, past work has not considered the effect of bank loan supply changes on the stock market volatility. In this paper, we examine whether shocks to the aggregate bank loan supply affect aggregate stock market return volatility.

Overall, we find that credit standards (*Standards*) is a strong predictor of US stock return volatility at frequencies up to and including a year. This is not surprising, since *Standards* has strong forecasting power of for both stock returns (Chava, Gallmeyer, and Park (2011a)) and macroeconomic variables (Lown and Morgan (2006)). The ability of *Standards* to track time-varying expected returns could help forecast future volatility. The relation between stock volatility and *Standards* is positive, which implies that tighter credit conditions predict higher future stock volatility. We also perform out-of-sample forecasting tests and find that the forecasts of volatility with *Standards* are more accurate than those with the historical mean and an AR(1) model of volatility. The ability of *Standards* to predict stock return volatility is also robust to a host of consistency checks including a bootstrap procedure, other model specifications of volatility, and extended the sample period.

The rest of the paper is organized as follows. Subsection 3.1 describes the data. Subsection 3.2 presents results from forecasting stock volatility using *Standards*. Subsection 3.3 addresses results from an extensive set of robustness checks. Subsection 3.4 concludes.

3.1 Data

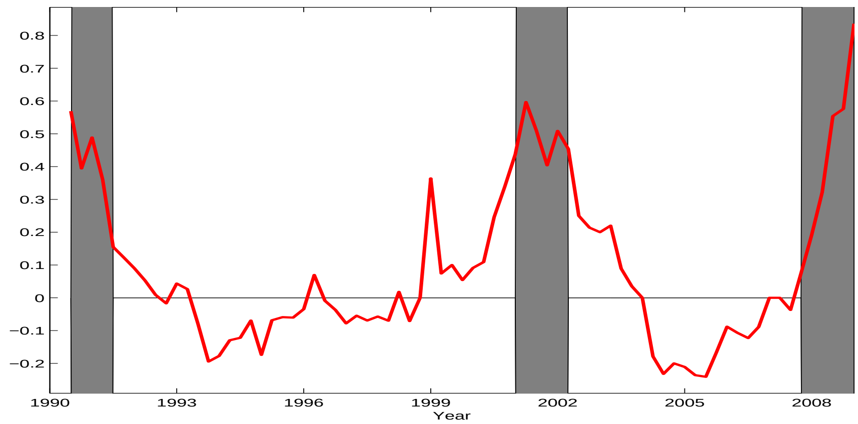
3.1.1 Senior Loan Officer Survey Data

We use a measure of credit conditions, bank lending standards (*Standards*), from the Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices.[32] Recently, *Standards* has been employed as a measure of aggregate supply-side credit conditions. 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. Chava, Gallmeyer, and Park (2011a) examines the impact of *Standards* on expected aggregate stock returns. They find that *Standards* strongly forecasts aggregate stock market returns. Our work differs from this earlier work as we examine the link between stock return volatility and bank loan supply.

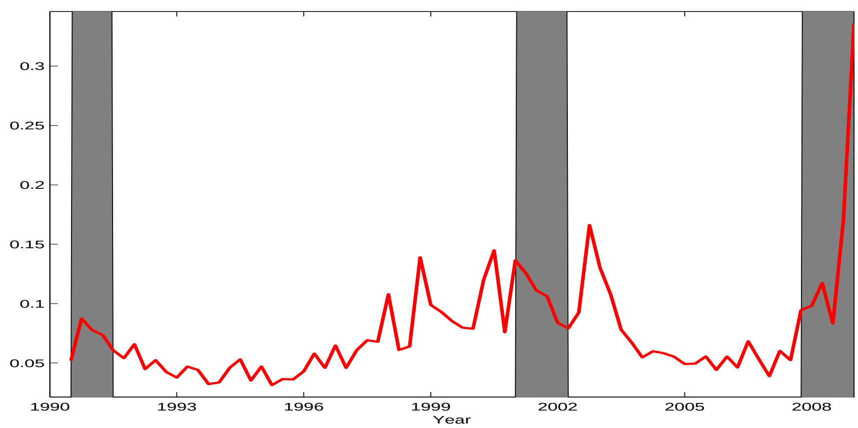
To analyze the predictive power of *Standards* on aggregate stock return volatility, we use the *Standards* series from Q2:1990 to Q4:2008. Panel (a) of Figure 3.1 plots the *Standards* measure across time with the shaded regions representing NBER recession periods. In our main analysis period, Q2:1990-Q4:2008, 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. As a robustness check, we do construct a *Standards* series from Q1:1967

---

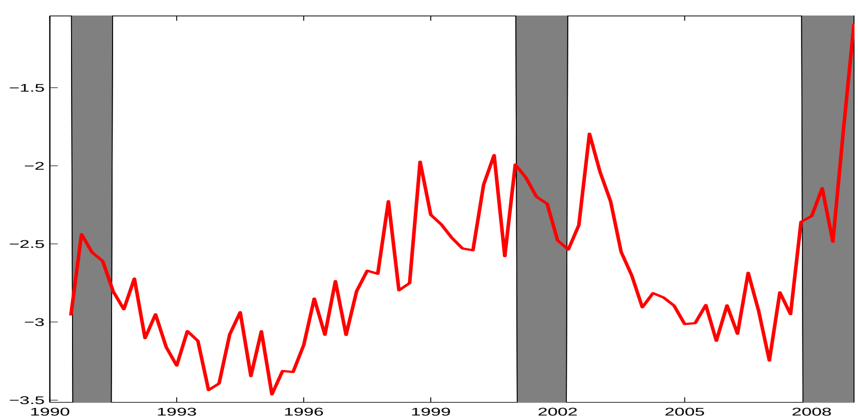
[32] See Chava, Gallmeyer, and Park (2011a) for more details of *Standards*.



(a) Time series plot for *Standards*



(b) Time series plot for realized volatility



(c) Time series plot for log realized volatility

Fig. 3.1. Time Series of *Standards*, Realized Volatility, and Log Realized Volatility

to Q4:2008 by filling in the missing the *Standards* series from Q1:1984 to Q4:1983 and examine the predictability of the stock return volatility with *Standards*.[33]

3.1.2 Stock Return Volatility

To study stock return volatility predictability, we focus on realized volatility as our measure of the volatility of stock returns. Following the approach of French, Schwert, and Stambaugh (1987), Schwert (1989), Ludvigson and Ng (2007), Lettau and Ludvigson (2009), and Paye (2009), we sum the squared daily returns on the CRSP-VW index to obtain quarterly realized volatility,[34]

$$vol_t = \sqrt{\sum_{k \in t} (r_{sk} - \bar{r}_s)^2}, \tag{3.1}$$

where vol_t is the realized volatility of the CRSP-VW return in period t, r_{sk} is the daily return, $\bar{r}_s$ is the mean of r_{sk} over the whole sample, k represents a day, and t is a quarter. Barndorf-Nielsen and Shephard (2002) and Andersen, Bollerslev, Diebold, and Labys (2003) show that the realized volatility is a consistent and theoretically error-free estimator of the integrated volatility of a frictionless, arbitrage-free asset price process and performs better than parametric GARCH or stochastic volatility models at capturing volatility. Moreover, the realized volatility allows us to employ traditional time-series procedures for forecasting based on predetermined conditioning variables.[35]

---

[33]Our sample period choice of Q2:1990-Q4:2008 stems from biases, lack of reporting, and survey question inconsistencies in the earlier data. See Chava, Gallmeyer, and Park (2011a) for a discussion.

[34]As a robustness check, we use excess returns computed from the daily 1 month T-bill rate. Also, we use daily returns and daily excess returns on the S&P500 index. These results are nearly identical to those of the CRSP-VW daily returns.

[35]Engle and Rangel (2008) propose a spline-GARCH model to isolate low-frequency volatility to explore the links between macroeconomic fundamentals and low-frequency volatility. Engle, Ghysels, and Sohn (2008) develops a GARCH-MIDAS modeling framework where macroeconomic variables

Following Lettau and Ludvigson (2009) and Paye (2009), we use the logarithm of realized volatility instead of the level of realized volatility. One reason for the logarithmic transformation is that realized volatility cannot be negative. Another reason is that the distribution of log realized volatility is approximately Gaussian, while realized volatility gives weight to high volatility periods (Engle and Patton (2000) and Andersen, Bollerslev, Diebold, and Labys (2003)).

Panel (b) and (c) of Figure 3.1 show time series plots of quarterly realized volatility and the logarithm of quarterly realized volatility for the CRSP-VW index over the period Q2:1990-Q4:2008. Stock return volatility is high at the begin of a recession and decreases at the end of a recession. The pattern is similar as that of $Standards$ and at least at a univariate level, it seems plausible that $Standards$ is a contender for predicting stock return volatility. As compared to the realized volatility, the log realized volatility lessens the effect of high volatility observations.

3.1.3 Other Stock Return Volatility Predictor Variables Used

To compare the forecasting power of *Standards*, we consider some of the standard predictor variables used in the literature. Following Lettau and Ludvigson (2009), we use the dividend-price ratio (dp), the default spread (DEF), the commercial paper spread (CP), the one-year treasury bill yield ($TB1Y$), and the consumption to aggregate wealth ratio (cay). The quantity 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. DEF is computed as the difference between the BAA-rated and AAA-rated corporate bond yield. CP is the difference between the yield on six-month commercial paper and the three-

are incorporated with a MIDAS polynomial. However, we focus primarily on the information content of the conditioning variables rather than more sophisticated modeling frameworks.

month treasury bill yield. DEF, CP, and $TB1Y$ are those used by Whitelaw (1994) to forecast volatility at monthly and quarterly horizons. The variable *cay* from Lettau and Ludvigson (2009) is the residual obtained from estimating a cointegrating relation between aggregate consumption, wealth, and labor income.

We also compare the predictive power of *Standards* to the investment to capital ratio (*ik*). The quantity *ik* proposed by Cochrane (1991) is the ratio of aggregate investment to aggregate capital for the whole economy. Paye (2009) shows that *ik* is the most successful predictor of stock return volatility.

3.1.4 Descriptive Statistics

Descriptive statistics (number of observations, mean, standard deviation, skewness, kurtosis, and autocorrelation) of the various predictor variables and stock return volatility are presented in Panel A of Table 3.1. Consistent with features of the time series plot, the log realized volatility reduces the heavily skewed and leptokurtotic features of realized volatility. As Panel A of Table 3.1 and Figure 3.2 show, both realized volatility and log realized volatility are persistent, so we include lagged realized volatility in the predictive regressions.

Panel B in Table 3.1 presents the correlations across the various predictor variables. *Standards* is highly positively correlated with the default spread DEF (65%), because *Standards* and DEF represent credit market condition.[36] The correlations across the other predictor variables are consistent with the earlier literature.

[36]The high correlation can affect the regression results, so we orthogonalize DEF by regressing DEF on *Standards* and regress the stock volatility with *Standards* and the orthogonalized component of DEF. *Standards* still shows strong predictive powers in the regression.

Table 3.1
Descriptive Statistics

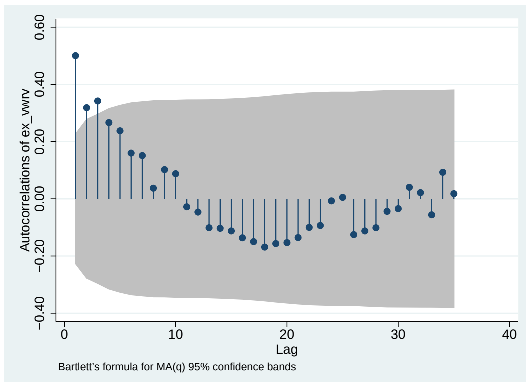
The table reports descriptive statistics and correlations for realized volatility, excess stock returns, and predictive variables used in the realized volatility predictability regressions. Th variable *rvol* is the realized volatility for the CRSP-VW index, while *lrvol* is the log realized volatility for the CRSP-VW index. The variable *exret* is the log excess return on the CRSP-VW index and *rsharpe* is the realized Sharpe ratio. The tightening credit condition measure is *standards*. The log dividend-price ratio is denoted *dp*. DEF is the BAA bond yield minus the AAA bond yield. CP is the difference between the yield on six-month commercial paper and the three-month Treasury yield. $TB1Y$ is the one-year Treasury yield. The variable *cay* is the Lettau and Ludvigson (2001) consumption-wealth ratio variable. The variable *ik* is the investment-capital ratio. The table presents the mean, the standard deviation, the skewness, the kurtosis, and the first order autocorrelation (ρ_1) for each series as well as the correlations of the predictive variables used in the realized volatility predictability regressions. The sample period is Q2:1990 to Q4:2008.

Panel A: Descriptive Statistics of Predictive Variables

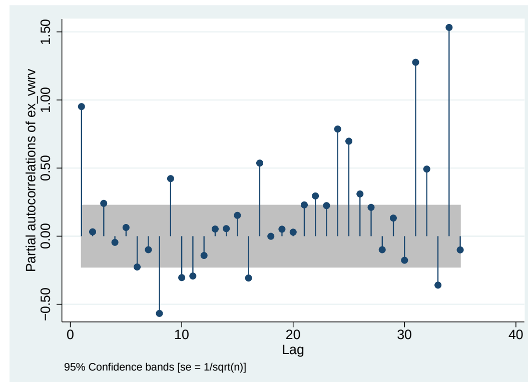
Variable	*Obs*	*Mean*	*StdDev*	*Skew*	*Kurt*	ρ_1
rvol	75	0.076	0.044	3.075	17.296	0.500
lrvol	75	-2.696	0.454	0.750	3.758	0.685
exret	75	0.013	0.085	-0.519	3.674	-0.010
rsharpe	75	0.416	1.042	0.145	2.383	-0.019
standards	75	0.089	0.242	0.930	3.152	0.815
dp	75	-3.966	0.308	0.280	2.349	0.922
DEF	75	0.009	0.004	4.043	26.308	0.508
CP	75	0.004	0.005	2.998	15.124	0.664
$TB1Y$	75	0.043	0.018	-0.296	2.328	0.881
cay	75	0.004	0.024	-0.021	1.627	0.928
ik	75	0.036	0.004	0.577	2.215	0.973

Panel B: Correlations of Stock Return Predictive Variables

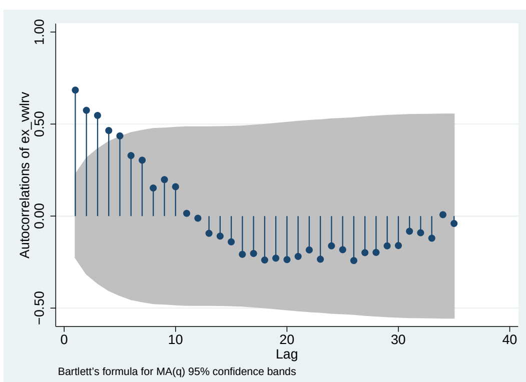
	standards	*dp*	DEF	CP	$TB1Y$	*cay*	*ik*
standards	1.000						
dp	0.031	1.000					
DEF	0.655	0.227	1.000				
CP	0.247	0.185	0.471	1.000			
$TB1Y$	-0.094	0.150	-0.468	-0.127	1.000		
cay	0.065	0.646	-0.145	-0.078	0.397	1.000	
ik	0.088	-0.733	-0.293	0.011	0.379	-0.203	1.000



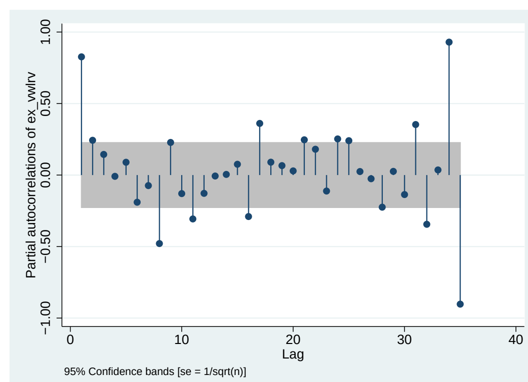
(a) ACF plot of rvol



(b) PACF plot of rvol



(c) ACF plot of lrvol



(d) PACF plot of lrvol

Fig. 3.2. ACF and PACF Plots

3.1.5 Univariate Model Selection for Stock Return Volatility

To investigate the dynamic structure of stock return volatility, we compare the fit of several standard univariate ARMA time series models over the sample period,

$$(1 - \phi_1 L - \phi_2 L^2 - \phi_3 L^3)(vol_t - \mu_{vol}) = (1 - \theta L)\epsilon_t, \tag{3.2}$$

where vol_t is realized volatility ($rvol$) or log realized volatility ($lrvol$) and ϵ_t is an error term. Table 3.2 presents results of a univariate model selection for the realized volatility and the log realized volatility. In each case, the results are reported for an intercept-only model, AR models of order one through three, and an ARMA (1,1) model.

Panel A of Table 3.2 shows that the dynamics of the realized volatility follow an AR(1) process the best as additional lags are insignificant and the Akaike information criterion (AIC) and Bayesian information criterion (BIC) prefer the AR(1) process among other model specifications. Additionally, Panel (a) and (b) of Figure 3.2 show that the patterns of the autocorrelation function (ACF) and the partial autocorrelation function (PACF) suggest AR processes for the realized volatility.

In Panel B of Table 3.2, the dynamics of the log realized volatility follow an AR(1) or an ARMA(1,1) process as the AIC prefers the ARMA(1,1) process and the BIC prefers the AR(1) process among other model specification. Panel (c) and (d) of Figure 3.2 show that the patterns of the ACF and the PACF suggest an AR process for the log realized volatility. Thus, we use the AR(1) model for the log realized volatility in our main test and the AR(2) and ARMA(1,1) models in our robustness checks.

Table 3.2
Univariate Model Selection

The table reports estimation results for univariate ARMA time series models of the realized volatility ($rvol$) and the log realized volatility ($lrvol$) for the CRSP-VW index:

$$(1-\phi_1 L-\phi_2 L^2-\phi_3 L^3)(Y_t-\mu_Y)=(1-\theta L)\epsilon_t. \tag{3.3}$$

The t-statistics of the coefficient estimates appear in parentheses below the coefficient estimates and AIC is Akaike information criterion and BIC is Bayesian information criterion. The sample period is Q2:1990 to Q4:2008.

Panel A: ARMA time series of $rvol$					
μ_Y	0.08	0.10	0.10	0.10	0.10
	(9.66)	(2.11)	(2.14)	(1.85)	(2.16)
ϕ_1		-0.89	0.90	0.84	0.88
		(8.62)	(8.32)	(7.23)	(5.15)
ϕ_2			-0.01	-0.13	
			(-0.07)	(-0.69)	
ϕ_3				0.20	
				(0.94)	
θ					0.02
					(0.12)
σ	0.04	0.03	0.03	0.03	0.03
	(22.65)	(16.94)	(15.95)	(14.20)	(15.90)
AIC	-251.7	-296.5	-294.5	-294.0	-294.5
BIC	-247.1	-289.6	-285.3	-282.4	-285.3
Panel B: ARMA time series of $lrvol$					
μ_Y	-2.70	-2.63	-2.57	-2.55	-2.55
	(-46.22)	(-12.83)	(-8.74)	(-7.55)	(-7.30)
ϕ_1		0.81	0.64	0.59	0.93
		(9.46)	(6.06)	(5.23)	(11.63)
ϕ_2			0.23	0.16	
			(1.90)	(1.14)	
ϕ_3				0.14	
				(1.04)	
θ					-0.33
					(-2.28)
σ	0.45	0.30	0.29	0.29	0.29
	(12.83)	(11.25)	(11.46)	(10.51)	(11.28)
AIC	97.27	37.42	35.90	36.82	35.12
BIC	101.9	44.37	45.17	48.41	44.39

3.2 Empirical Results

3.2.1 In-Sample Evidence

Following much of the existing stock volatility predictability literature, we first assess the in-sample predictive ability of *Standards* for the realized volatility and the log realized volatility. We estimate the following regression:

$$vol_t = \alpha + \phi\, vol_{t-1} + \beta\, Standards_{t-1} + \gamma\, X_{t-1} + \epsilon_t, \tag{3.4}$$

where vol_t is the realized volatility ($rvol$) or the log realized volatility ($lrvol$), X_{t-1} corresponds to a particular forecasting variable, and ϵ_t 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 volatility regression. Under the null hypothesis that *Standards* does not predict stock return volatility, β=0. We report Newey and West (1987) standard errors that correct for serial correlation and heteroscedasticity.

Table 3.3 presents in-sample results for predictive regressions of the realized volatility ($rvol$) and the log realized volatility ($lrvol$). In the univariate analysis in the table, both $rvol$ and $lrvol$ are strongly predictable with positive coefficients on *Standards* where $lrvol$ has a stronger effect than $rvol$. The positive sign implies that a tightening loan supply results in a subsequent rise in stock return volatility. Also, the adjusted R^2 of $rvol$ ($lrvol$) is 34% (42%) and is much higher than those of cay or ik.

The results of the multivariate regressions support those of the univariate regressions. *Standards* has significant positive coefficients in all regressions. Additionally, the *Standards* coefficients are relatively stable across specifications. For $rvol$ ($lrvol$), the estimates range from 0.08 to 0.12 (0.94 to 1.36). Also, the addition of *Standards* largely increases the adjusted R^2 of all specifications. In the last regression that includes all variables, *Standards* and CP are significant at traditional significant levels for both $rvol$ and $lrvol$.

Table 3.3
Forecasting Quarterly Stock Return Volatility

The table reports estimation results of forecasting the realized volatility ($rvol$) and the log realized volatility ($lrvol$) for the CRSP-VW index with one-quarter lagged predictive variables: $vol_t = \alpha + \phi vol_{t-1} + \beta Standards_{t-1} + \gamma X_{t-1} + \epsilon_t$, where vol_t are $rvol$ and $lrvol$. The predictive variables are all defined in Table 2.1. 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: $rvol$ with no dynamics									
$standards$	0.12		0.09		0.12		0.11		0.08
	(3.13)		(4.80)		(3.49)		(2.82)		(2.98)
dp		-0.06	-0.05					-0.05	-0.04
		(-5.83)	(-6.14)					(-1.14)	(-0.91)
DEF		8.89	1.16					10.17	2.57
		(5.01)	(0.51)					(5.63)	(0.74)
CP		4.15	4.71					3.76	4.43
		(2.26)	(2.89)					(2.12)	(2.46)
$TB1Y$		0.40	-0.13					-0.10	-0.26
		(1.88)	(-0.77)					(-0.25)	(-0.76)
cay				-0.44	-0.51			0.41	0.10
				(-1.76)	(-3.73)			(1.63)	(0.36)
ik						3.48	2.62	3.30	1.43
						(3.54)	(2.66)	(1.07)	(0.45)
Constant	0.07	-0.29	-0.14	0.08	0.07	-0.05	-0.03	-0.34	-0.17
	(15.83)	(-5.61)	(-3.70)	(9.94)	(18.32)	(-1.30)	(-0.77)	(-3.44)	(-1.61)
$\bar{R}^2$	[0.34]	[0.55]	[0.64]	[0.04]	[0.41]	[0.08]	[0.38]	[0.59]	[0.64]

Table 3.3 continued

				Panel B: *rvol* with AR(1)					
$rvol_{t-1}$	0.73	0.56	0.36	0.92	0.64	0.93	0.68	0.46	0.36
	(3.71)	(4.56)	(2.33)	(3.62)	(3.03)	(3.14)	(2.71)	(3.28)	(2.18)
$standards$	0.05		0.07		0.06		0.05		0.06
	(2.26)		(2.66)		(2.96)		(2.52)		(2.30)
dp		-0.03	-0.03					-0.04	-0.04
		(-2.93)	(-3.25)					(-1.31)	(-1.06)
DEF		4.72	0.69					6.09	0.85
		(3.13)	(0.35)					(3.22)	(0.31)
CP		3.63	4.21					3.69	4.24
		(2.47)	(2.82)					(2.38)	(2.62)
$TB1Y$		0.24	-0.08					0.11	-0.07
		(1.48)	(-0.44)					(0.32)	(-0.20)
cay				-0.16	-0.29			0.25	0.03
				(-1.59)	(-2.85)			(1.37)	(0.16)
ik						0.59	0.94	0.84	-0.13
						(0.48)	(0.81)	(0.32)	(-0.05)
Constant	0.02	-0.16	-0.10	0.01	0.03	-0.01	-0.01	-0.23	-0.11
	(1.52)	(-3.40)	(-2.62)	(0.61)	(1.90)	(-0.41)	(-0.36)	(-2.91)	(-1.32)
$\bar{R}^2$	[0.51]	[0.63]	[0.67]	[0.47]	[0.52]	[0.47]	[0.51]	[0.63]	[0.66]

Table 3.3 continued

Panel C: *lrvol* with no dynamics									
standards	1.31		0.99		1.36		1.22		0.94
	(5.03)		(4.98)		(6.42)		(4.54)		(3.34)
dp		-0.89	-0.72					-0.53	-0.42
		(-8.37)	(-8.10)					(-1.40)	(-1.15)
DEF		112.66	29.29					124.22	34.78
		(6.05)	(1.23)					(6.94)	(0.98)
CP		22.43	28.45					15.57	23.43
		(1.93)	(3.14)					(1.38)	(2.13)
$TB1Y$		7.02	1.30					0.91	-0.97
		(3.20)	(0.72)					(0.24)	(-0.31)
cay				-6.17	-7.02			2.76	-0.96
				(-1.91)	(-4.36)			(1.12)	(-0.38)
ik						48.98	39.38	45.86	23.83
						(4.06)	(3.94)	(1.62)	(0.85)
Constant	-2.80	-7.60	-6.06	-2.67	-2.77	-4.48	-4.22	-7.67	-5.66
	(-44.99)	(-16.22)	(-13.32)	(-30.55)	(-54.44)	(-9.36)	(-11.21)	(-9.12)	(-5.84)
$\bar{R}^2$	[0.42]	[0.57]	[0.68]	[0.09]	[0.55]	[0.16]	[0.52]	[0.61]	[0.67]

Table 3.3 continued

					Panel D: *lrvol* with AR(1)				
$lrvol_{t-1}$	0.63	0.48	0.30	0.79	0.49	0.77	0.52	0.40	0.30
	(9.02)	(5.66)	(2.26)	(8.64)	(6.57)	(6.52)	(5.26)	(4.26)	(2.39)
$standards$	0.58		0.73		0.76		0.65		0.77
	(2.98)		(2.70)		(3.86)		(3.45)		(2.46)
dp		-0.52	-0.53					-0.39	-0.34
		(-4.91)	(-5.03)					(-1.41)	(-1.19)
DEF		61.94	19.62					75.29	14.71
		(3.73)	(1.03)					(4.04)	(0.53)
CP		18.87	24.66					16.02	22.35
		(2.07)	(2.80)					(1.70)	(2.32)
$TB1Y$		4.76	1.40					2.19	0.32
		(2.85)	(0.82)					(0.69)	(0.11)
cay				-2.44	-4.31			1.17	-1.46
				(-1.93)	(-3.68)			(0.65)	(-0.70)
ik						16.40	21.74	22.32	10.39
						(2.05)	(2.53)	(0.94)	(0.49)
Constant	-1.04	-4.27	-4.40	-0.54	-1.40	-1.21	-2.12	-4.80	-3.90
	(-5.40)	(-6.04)	(-6.07)	(-2.11)	(-6.38)	(-2.05)	(-3.94)	(-5.40)	(-4.21)
$\bar{R}^2$	[0.61]	[0.66]	[0.70]	[0.57]	[0.65]	[0.57]	[0.63]	[0.65]	[0.69]

Panel B and D of Table 3.3 report results from a regression of (log) realized volatility on lagged (log) realized volatility plus other variables. In the regressions with *Standards* plus lagged volatility, *rvol* and *lrvol* are strongly predictable with positive coefficients on *Standards*. The adjusted R^2 of *rvol* (*lrvol*) is 51% (61%). The multivariate regressions with additional predictors show that *Standards* has significant positive coefficients throughout. The addition of *Standards* increases the adjusted R^2 of all specifications.

3.2.2 Out-of-Sample Evidence

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 the historical mean model of realized volatility and the AR(1) dynamics of realized volatility.[37] We conduct out-of-sample R^2, $\Delta RMSE$, $MSE-F$, and $ENC-NEW$ as commonly computed:

$$R^2_{oos} = 1 - \frac{MSE_A}{MSE_N}, \tag{3.5}$$

$$\Delta RMSE = \sqrt{MSE_N} - \sqrt{MSE_A}, \tag{3.6}$$

$$MSE-F = (T-h+1)\cdot\frac{MSE_N - MSE_A}{MSE_A}, \tag{3.7}$$

$$ENC-NEW = \frac{T-h+1}{T}\cdot\frac{\sum_{t=1}^{T}(\epsilon_t^2 - \epsilon_t\cdot e_t)}{MSE_A}, \tag{3.8}$$

where MSE_A is the mean squared error from the forecasting model with a predictor and MSE_N is the mean-squared error from the historical mean model (AR(1) dynamics) of realized volatility. The number of observations is T and h is the degree of overlap (h=1 for no overlap). The error ϵ_t is the vector of out-of-sample errors from the historical mean model (AR(1) dynamics) of realized volatility and e_t is

[37] The results for log realized volatility are nearly identical to those for realized volatility.

Table 3.4

Forecasting Quarterly Stock Return Volatility Out-Of-Sample

The table reports results of an out-of-sample forecast comparison of realized volatility. Panel A documents a comparison of forecasts based on a constant (unconditional forecast) and forecasts based on a constant plus a 1-quarter lagged predictive variable (conditional forecast). Panel B includes AR(1) dynamics and compares forecasts of realized volatility based on anAR(1) process with forecasts of realized volatility based on an AR(1) process plus a 1-quarter lagged predictive variable. The predictive variables are all defined in Table 2.1. 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. 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 (2005) 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			
	$\bar{R}^2_{oos}$	$\Delta RMSE$	$MSE-F$	$ENC-NEW$	$\bar{R}^2_{oos}$	$\Delta RMSE$	$MSE-F$	$ENC-NEW$
Panel A: *rvol* with no dynamics								
Standards	0.3604	0.0118	19.7188***	6.1862***	0.3915	0.0128	22.5217***	8.1514***
dp	0.0283	0.0008	1.0177	0.7086	-0.0013	-0.0000	-0.0459	0.9197
DEF	0.2360	0.0074	10.8125***	2.9635***	0.1824	0.0056	7.8068***	2.5236**
CP	0.0858	0.0026	3.2842**	0.9589*	0.0443	0.0013	1.6228*	0.6509
TB1Y	-0.0151	-0.0004	-0.5193	-0.0231	-0.0991	-0.0028	-3.1551	-0.4794
ik	0.0277	0.0008	0.9953*	0.6359	-0.0050	-0.0001	-0.1726	0.6127
Panel B: *rvol* with AR(1)								
standards	0.0764	0.0017	2.8935**	0.8325	0.0675	0.0015	2.5343**	0.9049
dp	-0.1000	-0.0021	-3.1813	-0.4709	-0.1481	-0.0031	-4.5147	-0.1295
DEF	0.0407	0.0009	1.4855*	0.3795	0.0409	0.0009	1.4917	0.4632
CP	0.1230	0.0028	4.9108***	1.2672*	0.1137	0.0026	4.4893***	1.2015*
TB1Y	-0.0314	-0.0007	-1.0659	-0.1738	-0.0617	-0.0013	-2.0327	-0.3741
ik	-0.0751	-0.0016	-2.4438	-0.3483	-0.0958	-0.0021	-3.0593	-0.2828

the vector of out-of-sample errors from the forecasting model with a predictor. For both the MSE-F and the ENC-NEW tests, we follow the methodology of 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 forecast moves forward in time.

Panel A of Table 3.4 reports results of out-of-sample forecasts of realized volatility and compares forecasts based on the historical mean model to those based on each predictor variable. The forecasting model with *Standards* has superior forecasting performance relative to the historical mean model of the realized volatility in both the recursive and the rolling regression. Additionally, the variables DEF and CP show better forecasting ability than the historical average of the realized volatility. Panel B in Table 3.4 presents results of out-of-sample forecasts of realized volatility with lagged realized volatility and it compares forecasts based on the AR(1) model to those based on each predictor variable plus lagged realized volatility. *Standards* has good forecasting performance for the R^2, the $\Delta RMSE$ and the $MSE - F$ measures, although the predictive power of *Standards* is insignificant for the $ENC - NEW$ measure. CP has better forecasting performance than *Standards* in both the recursive and the rolling regression.

3.2.3 Long-Horizon Forecasts

In this subsection, we investigate whether *Standards* has long-horizon predictive power for realized volatility. Table 3.5 reports long-horizon forecasting regressions of quarterly realized volatility on the CRSP-VW index.[38] The dependent variable is the H-quarter realized volatility on the CRSP-VW index,

$$vol_{t+1,t+H} = \sqrt{\sum_{s \in t+1,\ldots,t+H} (r_s - \bar{r})^2}, \tag{3.9}$$

where the horizon is $H = 1, 2, 4, 8$, and 12 quarters.

Panel A of Table 3.5 reports results of the long horizon forecast of realized volatility without the lagged realized volatility and the dependent variable is the H-step ahead volatility. In the univariate regressions, the coefficient and adjusted R^2 of *Standards* shows a humped pattern with the horizon. The significance of the coefficient is highest for the 4 quarter horizon, while the adjusted R^2 is highest for the 2 quarter horizon. In the multivariate regressions, the significance of *Standards* decreases with the horizon. The significance of the coefficients for dp, DEF, and ik increase with the horizon, while the significance of the coefficients for CP, $TB1Y$, and cay decrease with the horizon like *Standards*.

Panel B in Table 3.5 shows results of long horizon forecasts of realized volatility when lagged realized volatility is also included. Both the univariate and multivariate regressions show the forecasting power of *Standards* decreases with horizon. In the multivariate regressions, the significance of the coefficients for dp and DEF increases with the horizon, while the significance of the coefficient for CP, $TB1Y$, ik, and cay decrease with the horizon like *Standards*.

[38]The results for log realized volatility are almost similar as those for the realized volatility.

Table 3.5

Forecasting Long Horizon Quarterly Stock Return Volatility

The table reports results from long-horizon forecasting regressions of quarterly realized volatility (*rvol*) for the CRSP-VW index on lagged variables. H denotes the realized volatility horizon in quarters. The dependent variable is the H-step ahead volatility, equal to $v_{t+1,t+H} = \sqrt{\sum_{s \in t+1,\ldots,t+H} (r_s - \bar{r})^2}$. The regressors are all defined in Table 2.1. 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
Panel A: *rvol* with no dynamics					
standards	0.12	0.14	0.15	0.15	0.09
	(3.13)	(3.41)	(3.64)	(2.46)	(1.26)
$\bar{R}^2$	[0.34]	[0.35]	[0.23]	[0.15]	[0.03]
standards	0.09	0.13	0.13	0.03	-0.05
	(4.80)	(3.16)	(3.46)	(0.59)	(-1.07)
dp	-0.05	-0.08	-0.13	-0.22	-0.27
	(-6.14)	(-6.39)	(-10.20)	(-11.90)	(-13.81)
DEF	1.16	2.49	3.86	7.71	8.72
	(0.51)	(0.81)	(1.07)	(1.75)	(1.74)
CP	4.71	5.13	8.05	-5.63	-3.38
	(2.89)	(2.71)	(2.04)	(-1.81)	(-1.88)
TB1Y	-0.13	-0.07	0.29	2.47	3.20
	(-0.77)	(-0.20)	(0.68)	(4.15)	(6.19)
$\bar{R}^2$	[0.64]	[0.62]	[0.73]	[0.81]	[0.86]
standards	0.08	0.12	0.12	0.03	-0.05
	(2.98)	(2.67)	(2.97)	(0.97)	(-1.35)
dp	-0.04	0.02	-0.07	-0.15	-0.13
	(-0.91)	(0.27)	(-1.20)	(-3.22)	(-3.24)
DEF	2.57	2.79	4.95	8.03	9.96
	(0.74)	(0.59)	(1.14)	(2.52)	(2.73)
CP	4.43	3.52	7.59	-5.70	-3.22
	(2.46)	(2.73)	(2.06)	(-1.92)	(-2.50)
TB1Y	-0.26	-0.72	-0.21	1.83	1.88
	(-0.76)	(-1.17)	(-0.32)	(2.00)	(2.45)
cay	0.10	-0.46	-0.17	-0.31	-0.42
	(0.36)	(-0.98)	(-0.35)	(-0.61)	(-0.82)
ik	1.43	6.76	4.55	5.27	10.35
	(0.45)	(1.60)	(1.06)	(1.43)	(3.07)
$\bar{R}^2$	[0.64]	[0.64]	[0.73]	[0.81]	[0.87]

Table 3.5 continued

	Forecast Horizon H				
Regressors	1	2	4	8	12
Panel B: *rvol* with AR(1)					
$rvol_{t-1}$	0.73	0.54	0.49	0.06	-0.19
	(3.71)	(2.71)	(1.59)	(0.26)	(-0.99)
standards	0.05	0.08	0.08	0.21	0.21
	(2.26)	(1.32)	(1.10)	(4.05)	(4.53)
$\bar{R}^2$	[0.51]	[0.45]	[0.37]	[0.30]	[0.18]
$rvol_{t-1}$	0.36	0.02	-0.07	-0.26	-0.29
	(2.33)	(0.09)	(-0.40)	(-1.17)	(-1.77)
standards	0.07	0.12	0.14	0.07	-0.02
	(2.66)	(2.03)	(2.61)	(2.28)	(-0.31)
dp	-0.03	-0.08	-0.14	-0.25	-0.29
	(-3.25)	(-5.75)	(-6.31)	(-7.47)	(-7.38)
DEF	0.69	2.45	4.55	9.62	12.82
	(0.35)	(0.81)	(1.09)	(1.98)	(1.97)
CP	4.21	5.12	7.97	-5.38	-2.80
	(2.82)	(2.60)	(2.02)	(-1.80)	(-1.12)
$TB1Y$	-0.08	-0.06	0.29	2.06	2.57
	(-0.44)	(-0.17)	(0.66)	(3.84)	(2.87)
$\bar{R}^2$	[0.67]	[0.62]	[0.73]	[0.81]	[0.83]
$rvol_{t-1}$	0.36	-0.06	-0.14	-0.24	-0.48
	(2.18)	(-0.30)	(-0.73)	(-1.18)	(-1.71)
standards	0.06	0.13	0.14	0.08	0.08
	(2.30)	(1.97)	(2.27)	(1.62)	(1.05)
dp	-0.04	0.02	-0.06	-0.16	-0.10
	(-1.06)	(0.27)	(-0.77)	(-3.09)	(-1.76)
DEF	0.85	2.98	7.20	9.88	10.52
	(0.31)	(0.62)	(1.36)	(3.15)	(2.54)
CP	4.24	3.50	7.33	-5.19	-1.85
	(2.62)	(2.70)	(2.13)	(-1.86)	(-0.82)
$TB1Y$	-0.07	-0.75	-0.39	1.52	1.05
	(-0.20)	(-1.10)	(-0.48)	(1.75)	(1.07)
cay	0.03	-0.46	-0.19	-0.37	-1.59
	(0.16)	(-0.94)	(-0.36)	(-0.62)	(-1.65)
ik	-0.13	6.99	6.46	5.02	9.95
	(-0.05)	(1.48)	(1.08)	(1.22)	(2.26)
$\bar{R}^2$	[0.66]	[0.63]	[0.73]	[0.81]	[0.86]

3.3 Robustness

3.3.1 Bootstrap Procedure of Forecasting Stock Return Volatility

Many predictability studies find that the coefficients and the standard errors obtained from predictive regressions with a highly persistent predictor exhibit small sample biases (Mankiw and Shapiro (1986), Nelson and Kim (1993), Elliott and Stock (1994), and Stambaugh (1999)). Regarding the volatility prediction, Paye (2009) shows that the high persistence in both realized volatility and macroeconomic and financial predictors creates the potential of a spurious regression bias. As *Standards* is a persistent variable, we explore whether the in-sample results of *Standards* could be driven by small sample biases.

Following the approach of Lettau and Ludvigson (2009), we use a bootstrap procedure to address these small sample bias problems. In the bootstrap procedure, $Standards_t$ is generated from an AR(1) specification:

$$Standards_t = \mu + \gamma Standards_{t-1} + \nu_t, \tag{3.10}$$

where the values of μ and γ are those estimated from the actual data for *Standards*. Dependent variables ($rvol_t$) are generated in two ways — an unrestricted model and a restricted model under the null hypothesis of no predictability. In the unrestricted model, the realized volatility follows

$$vol_t = \alpha + \beta Standards_{t-1} + \epsilon_t, \tag{3.11}$$

where the values of α and β are those estimated from the realized volatility regression with *Standards*. In the restricted model under the null hypothesis ($\beta = 0$), the realized volatility follows

$$vol_t = \lambda + e_t \tag{3.12}$$

where λ is a constant. Then, we generate artificial sequences of realized volatility and *Standards* by drawing randomly from the sample residuals for the bootstrap

Table 3.6

Robustness: Bootstrap Procedure of Forecasting Quarterly Stock Return Volatility

This table reports confidence intervals of forecasting realized volatility for CRSP-VW index from bootstrap procedures. We generate 100,000 artificial time series using quarterly data from Q2:1990 to Q4:2008. *Standards* are generated form first-order autocorrelation model: $X_t = \mu + \gamma X_{t-1} + \nu_t$. Bootstrap sample of $rvol$ are obtained in two ways by imposing the null hypothesis of no predictability: $rvol_t = \lambda + e_t$ and without imposing the null by resampling the residual of $rvol_t = \alpha + \beta X_{t-1} + \epsilon_t$. We then compute OLS regressions with a Newey-West standard error correction to compute the empirical distributions of the coefficient of *Standards* and the $\bar{R}^2$ coefficient.

		Unrestricted model		Under the null	
	$\hat{\beta}$	95% CI	90% CI	95% CI	90% CI
		Panel A: $rvol$ with no dynamics			
Standards	0.12	(0.08 0.16)	(0.08 0.15)	(-0.05 0.05)	(-0.04 0.04)
$\bar{R}^2$	0.34	(0.08 0.70)	(0.11 0.65)	(-0.01 0.05)	(-0.01 0.04)
		Panel B: $rvol$ with AR(1)			
$rvol_{t-1}$	0.73	(0.61 0.84)	(0.64 0.82)	(-0.17 0.17)	(-0.13 0.13)
Standards	0.05	(0.02 0.09)	(0.02 0.08)	(-0.05 0.05)	(-0.04 0.04)
$\bar{R}^2$	0.51	(0.43 0.95)	(0.49 0.93)	(-0.03 0.07)	(-0.03 0.05)

procedure. We generate $100,000$ samples equal to the length of the *Standards* data series. Using these samples created under the bootstrap procedure, we then estimate the predictive regressions which yields a distribution of our test statistics.

Table 3.6 reports confidence intervals of forecasting realized volatility from the bootstrap procedure.[39] In generating the process for vol_t, we have two specifications — no dynamics and AR(1) specification. In the restricted model under the null hypothesis of no predictability, the coefficient on *Standards* and the adjusted R^2 are statistically different from zero at the 95% level and are outside the 95% confidence interval. The unrestricted model shows that the coefficient on *Standards* and the adjusted R^2 are inside the 95% confidence interval, which implies that lagged *Standards*

[39] The results for log realized volatility are nearly identical to those for realized volatility.

affects the generated vol_t series. In sum, the statistical relation of *Standards* to stock return volatility is strong, even accounting for the small-sample distribution of t statistics.

3.3.2 Other Model Specification for the Log Realized Volatility

Paye (2009) shows that the spurious predictability bias can be reduced by the inclusion of a sufficiently rich dynamic structure in the prediction model. Our quarterly volatility sample appears to have AR(1) dynamics in the univariate model, so we use AR(1) model for realized volatility and log realized volatility. However, according to the score of the Akaike information criterion (AIC) for log realized volatility, the volatility appears to have ARMA(1,1) dynamics. In this subsection, we investigate whether *Standards* shows predictive power for the log realized volatility in other model specification than the AR(1) model.

Table 3.7 reports estimation results for an AR(2) and an ARMA(1,1) time series models of log realized volatility with lagged predictive variables:

$$AR(2)\ Dynamics: vol_t = c + \phi_1 vol_{t-1} + \phi_2 vol_{t-2} + \beta X_{t-1} + \epsilon_t \tag{3.13}$$

$$ARMA(1,1)\ Dynamics: vol_t = c + \phi_1 vol_{t-1} + \beta X_{t-1} + (1 - \theta L)\epsilon_t, \tag{3.14}$$

where vol_t is log realized volatility and X_{t-1} corresponds to a particular forecasting variable. For the AR(2) dynamics, *Standards* has significant positive coefficients in the multivariate regressions, while it has slightly insignificant coefficients at the 5% significance level. The AR(2) coefficient (ϕ_2) is insignificant in all specifications, which implies that the AR(2) model does not fit log realized volatility well. The control variables of the multivariate analysis have the same sign of the coefficients as those of no dynamics and the AR(1) dynamics in Table 3.3. In the regression with all predictive variables, *Standards* and *CP* are significant at traditional significant levels.

Table 3.7

Robustness: Other model specifications

The table reports estimation results for ARMA time series models of log realized volatility ($lrvol$) with one-quarter lagged predictive variables:

$$AR(2)\ Dynamics : vol = c + \phi_1 vol_{t-1} + \phi_2 vol_{t-2} + \beta X_{t-1} + \epsilon_t$$

$$ARMA(1,1)\ Dynamics : vol = c + \phi_1 vol_{t-1} + \beta X_{t-1} + (1 - \theta L)\epsilon_t,$$

where vol_t is the log realized volatility and X_{t-1} corresponds to a particular forecasting variable. The estimation applies maximum likelihood estimation. The sample period is Q2:1990 to Q4:2008.

Panel A: $lrvol$ with AR(2)									
$standards$	0.68		0.99		1.13		0.95		0.91
	(1.91)		(4.04)		(4.71)		(2.92)		(2.65)
dp		-0.80	-0.74					-0.54	-0.45
		(-4.35)	(-5.94)					(-1.44)	(-1.23)
DEF		83.91	31.49					129.38	40.62
		(3.11)	(1.06)					(6.78)	(0.93)
CP		22.95	27.55					13.43	22.15
		(3.00)	(3.93)					(1.28)	(2.04)
$TB1Y$		5.47	1.39					0.89	-0.92
		(1.36)	(0.39)					(0.25)	(-0.24)
cay				-1.48	-6.07			2.88	-0.67
				(-0.29)	(-1.89)			(1.34)	(-0.27)
ik						21.27	36.58	46.97	24.58
						(0.58)	(1.99)	(1.66)	(0.85)
ϕ_1	0.56	0.38	0.16	0.65	0.43	0.64	0.47	0.14	0.14
	(4.30)	(2.65)	(1.45)	(4.53)	(2.58)	(6.17)	(3.34)	(1.03)	(1.18)
ϕ_2	0.20	0.01	-0.19	0.22	0.06	0.22	0.09	-0.20	-0.20
	(1.31)	(0.06)	(-1.47)	(1.45)	(0.39)	(1.76)	(0.49)	(-1.58)	(-1.56)
$\bar{R}^2$	[0.60]	[0.60]	[0.69]	[0.60]	[0.61]	[0.59]	[0.60]	[0.62]	[0.68]

Table 3.7 continued

Panel B: *lrvol* with ARMA(1,1)									
standards	0.79		1.04		0.98		0.84		1.06
	(2.72)		(4.02)		(3.32)		(2.84)		(2.99)
dp		-0.42	-0.70					-0.51	-0.29
		(-1.32)	(-5.18)					(-1.35)	(-0.77)
DEF		42.15	19.73					117.12	14.64
		(1.26)	(0.68)					(5.57)	(0.36)
CP		24.34	28.05					15.10	23.04
		(2.69)	(3.74)					(1.42)	(2.15)
TB1Y		2.74	0.57					0.80	-2.51
		(0.53)	(0.16)					(0.22)	(-0.63)
cay				-0.55	-4.54			2.36	-1.98
				(-0.10)	(-1.08)			(0.90)	(-0.61)
ik						21.29	25.05	45.20	27.22
						(0.58)	(1.17)	(1.61)	(1.03)
ϕ_1	0.91	0.86	-0.67	0.92	0.81	0.92	0.88	-0.38	-0.72
	(9.08)	(6.65)	(-3.40)	(10.85)	(4.52)	(9.59)	(5.66)	(-0.77)	(-4.15)
θ	-0.50	-0.46	0.85	-0.30	-0.43	-0.31	-0.50	0.58	0.91
	(-2.74)	(-2.24)	(6.33)	(-1.56)	(-1.60)	(-2.06)	(-2.30)	(1.31)	(7.77)
$\bar{R}^2$	[0.61]	[0.60]	[0.69]	[0.59]	[0.61]	[0.59]	[0.61]	[0.61]	[0.69]

Panel B of Table 3.7 shows that *Standards* has significantly positive coefficients in ARMA(1,1) models for log realized volatility. The coefficient of the MA(1) component (θ) is significant in some specifications. The control variables of the multivariate setups have the same sign as the coefficients as those of no dynamics and the AR(1) dynamics in Table 3.3. In the regression with all predictors, *Standards*, CP, the AR(1) component (ϕ_2), and the MA(1) component (θ) are all significant at traditional significant levels.

3.3.3 Extended Sample Period

Our main results use the *Standards* series from Q2:1990 to Q4:2008. 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:

$$Standards_t = \alpha + \beta\, Standards_{t-1} + \gamma\, Consumer_t + \epsilon_t \tag{3.15}$$

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

Table 3.8
Robustness: Extension of the Sample Period

The table reports estimation results of forecasting realized volatility ($rvol$) and log realized volatility ($lrvol$) with one-quarter lagged predictive variables: $vol_t = \alpha + \phi vol_{t-1} + \beta Standards_{t-1} + \gamma X_{t-1} + \epsilon_t$, where vol_t are $rvol$ and $lrvol$. The regressors are all defined in Table 2.1. Newey-West corrected t-statistics appear in parentheses below the coefficient estimate and adjusted R^2 statistics in square brackets. The sample period is Q1:1967 to Q4:2008.

Panel A: *rvol* with no dynamics									
standards	0.09		0.09		0.08		0.08		0.08
	(3.49)		(4.13)		(3.48)		(3.12)		(4.40)
dp		-0.04	-0.04					-0.03	-0.04
		(-4.02)	(-6.51)					(-1.77)	(-4.03)
DEF		3.12	2.79					4.17	3.05
		(2.23)	(2.71)					(2.34)	(2.25)
TB1Y		0.09	0.18					-0.25	0.10
		(0.37)	(1.11)					(-0.69)	(0.37)
cay				-0.19	-0.14			0.15	0.06
				(-1.32)	(-1.12)			(0.86)	(0.45)
ik						2.06	1.08	3.58	0.76
						(1.99)	(0.98)	(1.84)	(0.54)
Constant	0.06	-0.12	-0.14	0.07	0.06	-0.01	0.02	-0.18	-0.16
	(19.04)	(-2.64)	(-4.88)	(16.59)	(19.29)	(-0.20)	(0.52)	(-4.07)	(-4.34)
$\bar{R}^2$	[0.20]	[0.14]	[0.34]	[0.00]	[0.20]	[0.03]	[0.20]	[0.18]	[0.34]
Panel B: *rvol* with AR(1)									
$rvol_{t-1}$	0.55	0.58	0.40	0.68	0.55	0.66	0.54	0.55	0.39
	(3.43)	(3.08)	(2.96)	(3.51)	(3.45)	(3.32)	(3.35)	(3.31)	(3.10)
standards	0.05		0.06		0.05		0.05		0.06
	(3.00)		(3.92)		(3.00)		(2.73)		(3.91)
dp		-0.02	-0.03					-0.02	-0.03
		(-2.21)	(-3.67)					(-1.22)	(-2.53)
DEF		1.47	1.77					2.01	1.84
		(1.70)	(2.42)					(1.76)	(1.90)
TB1Y		0.06	0.13					-0.10	0.11
		(0.35)	(0.87)					(-0.36)	(0.45)
cay				-0.15	-0.13			0.01	-0.01
				(-2.23)	(-1.81)			(0.12)	(-0.13)
ik						1.11	0.73	1.73	0.27
						(1.77)	(0.98)	(1.41)	(0.24)
Constant	0.03	-0.07	-0.10	0.02	0.03	-0.02	0.00	-0.10	-0.11
	(2.68)	(-2.00)	(-3.33)	(1.93)	(2.69)	(-0.95)	(0.05)	(-3.13)	(-3.58)
$\bar{R}^2$	[0.36]	[0.34]	[0.41]	[0.31]	[0.36]	[0.32]	[0.36]	[0.34]	[0.41]

Table 3.8 continued

					Panel C: *lrvol* with no dynamics				
standards	1.01		1.04		1.00		0.95		1.03
	(5.12)		(6.21)		(5.25)		(4.58)		(6.15)
dp		-0.60	-0.64					-0.42	-0.63
		(-4.72)	(-7.88)					(-2.71)	(-5.77)
DEF		38.04	34.06					48.07	34.05
		(2.93)	(3.94)					(3.29)	(3.31)
TB1Y		3.00	4.10					-0.41	4.01
		(1.47)	(3.38)					(-0.14)	(2.04)
cay				-2.90	-2.27			0.83	-0.32
				(-1.40)	(-1.42)			(0.42)	(-0.23)
ik						30.16	18.82	36.27	0.99
						(2.27)	(1.43)	(2.14)	(0.08)
Constant	-2.87	-5.53	-5.80	-2.78	-2.87	-3.89	-3.56	-6.12	-5.80
	(-64.43)	(-9.69)	(-16.28)	(-55.93)	(-66.01)	(-7.90)	(-7.55)	(-11.86)	(-13.67)
$\bar{R}^2$	[0.23]	[0.21]	[0.46]	[0.01]	[0.24]	[0.05]	[0.25]	[0.24]	[0.45]
					Panel D: *lrvol* with AR(1)				
$lrvol_{t-1}$	0.58	0.60	0.40	0.69	0.58	0.67	0.57	0.58	0.40
	(9.89)	(7.49)	(7.59)	(9.84)	(9.73)	(8.87)	(9.48)	(8.19)	(7.68)
standards	0.49		0.68		0.48		0.45		0.67
	(3.72)		(4.94)		(3.70)		(3.37)		(5.01)
dp		-0.31	-0.43					-0.24	-0.43
		(-3.53)	(-6.25)					(-2.21)	(-4.69)
DEF		13.06	18.70					17.08	17.17
		(1.71)	(2.93)					(1.90)	(2.22)
TB1Y		2.04	3.07					0.71	3.26
		(1.49)	(2.96)					(0.35)	(1.93)
cay				-2.06	-1.89			-0.62	-0.94
				(-2.27)	(-2.17)			(-0.57)	(-0.94)
ik						16.90	13.49	14.79	-1.86
						(2.91)	(2.01)	(1.38)	(-0.18)
Constant	-1.20	-2.50	-3.68	-0.86	-1.21	-1.52	-1.72	-2.79	-3.57
	(-7.03)	(-4.25)	(-9.46)	(-4.25)	(-7.10)	(-4.08)	(-5.00)	(-5.58)	(-8.77)
$\bar{R}^2$	[0.47]	[0.47]	[0.54]	[0.44]	[0.48]	[0.45]	[0.48]	[0.47]	[0.54]

Table 3.8 shows results from regressions of realized volatility and log realized volatility. In Panel A and C of Table 3.8, both level and log realized volatility

are strongly predictable with positive coefficients on $Standards$ as with our main results. In the univariate analysis of $Standards$, the adjusted R^2 of (log) realized volatility is 20% (23%) and is much higher than those of cay or ik. The multivariate regressions show $Standards$ still has significant positive coefficients. The addition of $Standards$ largely increases the adjusted R^2 of all specifications. In the regression with all predictor variables, $Standards$, DEF, and dp are significant in the realized volatility prediction and $Standards$, DEF, dp, and $TB1Y$ are significant in the log realized volatility prediction.

Panels B and D of Table 3.8 include the first lag of realized volatility. Like the case without lagged realized volatility, both level and log realized volatility are strongly predictable with positive coefficients on $Standards$. The significance levels are smaller than those of the specifications without the lagged realized volatility. Univariate regressions show that the adjusted R^2 of the (log) realized volatility is 36% (47%) and is much higher than those of cay or ik. In the multivariate regressions, $Standards$ still has significant positive coefficients. The addition of $Standards$ increases the adjusted R^2 of all specifications. As before, $Standards$, dp, and DEF are significant at traditional significant levels in the regressions with all predictive variables.

3.4 Conclusion

We analyze the predictability of aggregate stock return volatility using a measure of credit standards (*Standards*) from the Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices. Using level and log realized volatility as the estimator of stock return volatility, we find that *Standards* is a strong predictor of stock return volatility in both in-sample and out-of-sample tests. In particular, a tightening *Standards* predicts higher future stock volatility. The positive relationship between *Standards* and future stock return volatility suggests a negative correlation between the conditional mean and conditional volatility of stock returns using aggregate credit conditions, because our previous research (Chava, Gallmeyer, and Park (2011a)) shows that *Standards* is negatively related to future expected stock returns in the same sample period as this study. It is consistent with Brandt and Kang (2004) and Lettau and Ludvigson (2009) who show a negative conditional correlation between risk and return.

4. CONCLUSIONS

My dissertation focuses on stock return predictability with aggregate credit conditions. The aggregate credit conditions are empirically measured by credit standards (*Standards*) derived from the Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices. Using the information advantages of *Standards*, we examine whether the aggregate credit conditions predict the expected returns and volatility of the stock market.

From the findings presented in the first essay, "Credit Conditions and Expected Stock Returns," we provide evidence that *Standards* is a strong predictor of U.S. aggregate 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. Additionally, *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.

From the second essay, "Credit Conditions and Stock Return Volatility," we analyze the predictability of *Standards* for aggregate stock return volatility. Using level and log realized volatility as the estimator of stock return volatility, we find that *Standards* is a strong predictor of stock return volatility in both in-sample and out-of-sample tests. In particular, a tightening *Standards* predicts higher future stock volatility. The positive relationship between *Standards* and future stock return volatility suggests a negative correlation between the conditional mean and conditional volatility of stock returns using aggregate credit conditions, because our previous research (Chava, Gallmeyer, and Park (2011a)) shows that *Standards* is negatively related to future expected stock returns in the same sample period as this study. It is consistent with Brandt and Kang (2004) and Lettau and Ludvigson (2009) who show a negative conditional correlation between risk and return.

Our empirical findings contribute to stock return and volatility predictability literature by providing evidence that an economically-motivated predictive variable to measure the aggregate credit conditions has robust in-sample and out-of-sample predictive power in forecasting future stock returns and volatility. Goyal and Welch (2008) argue that many predictive variables used in the literature have performed poorly both in-sample and out-of-sample, especially over the last 30 years. Paye (2009) tests the forecasting ability of the level of macroeconomic and financial variables on the aggregate stock return volatility and finds that the predictive ability of most macroeconomic and financial variables is weak. Though our sample is limited to the period after the 1990s, the predictability of *Standards* is noteworthy in light of the findings in Goyal and Welch (2008) and Paye (2009).

REFERENCES

Adrian, Tobias, Emanuel Moench, and Hyun Song Shin, 2010, Financial intermediation, asset prices, and macroeconomic dynamics, *Federal Reserve Bank of New York Staff Reports* 422, 1–40.

Almeida, Heitor, and Murillo Campello, 2007, Financial constraints, asset tangibility, and corporate investment, *Review of Financial Studies* 20, 1429–1460.

Almeida, Heitor, Murillo Campello, and Michael S. Weisbach, 2004, The cashflow sensitivity of cash, *Journal of Finance* 59, 1777–1804.

Andersen, Torben G., Tim Bollerslev, Francis X. Diebold, and Paul Labys, 2003, Modeling and forecasting realized volatility, *Econometrica* 71, 579–626.

Ang, Andrew, Geert Bekaert, and Min Wei, 2007, Do macro variables, asset markets, or surveys forecast inflation better? *Journal of Monetary Economics* 54, 1163–1212.

Asea, Patrick K., and Brock Blomberg, 1998, Lending cycles, *Journal of Econometrics* 83, 89–128.

Bansal, Ravi, and Amir Yaron, 2006, The asset pricing-macro nexus and return-cash flow predictability, Working paper, Duke University.

Barndorf-Nielsen, Ole E., and Neil Shephard, 2002, Econometric analysis of realized volatility and its use in estimating stochastic volatility models, *Journal of the Royal Statistical Society* 64, 253–280.

Bekaert, Geert, and Robert J. Hodrick, 1992, Characterizing predictable components in excess returns on equity and foreign exchange markets, *Journal of Finance* 47, 467–509.

Beltratti, Andrea, and Claudio Morana, 2006, Breaks and persistency: Macroeconomic causes of stock market volatility, *Journal of Econometrics* 131, 151–177.

Berlin, Mitchell, 2009, Bank credit standards, *Business Review* 2, 1–10.

Bernanke, Ben S., 2007, The financial accelerator and the credit channel, Speech at The Credit Channel of Monetary Policy in the Twenty-First Century Conference, Federal Reserve Bank of Atlanta, Atlanta, GA.

Bernanke, Ben S., and Mark Gertler, 1989, Agency costs, net worth, and business fluctuations, *American Economic Review* 79, 14–31.

Bernanke, Ben S., and Mark Gertler, 1995, Inside the black box: The credit channel of monetary policy transmission, *Journal of Economic Perspectives* 9, 27–48.

Bernanke, Ben S., and Kenneth N. Kuttner, 2005, What explains the stock market's reaction to federal reserve policy? *Journal of Finance* 60, 1221–1257.

Boudoukh, Jacob, Roni Michaely, Matthew Richardson, and Michael R. Roberts, 2007, On the importance of measuring payout yield: Implications for empirical asset pricing, *Journal of Finance* 62, 877–915.

Brady, Thomas F., 1985, The role of the prime rate in pricing of business loans by commercial banks, 1977-84, *Federal Reserve Bulletin* 71, 862–863.

Brandt, Michael W., and Qiang Kang, 2004, On the relation between the conditional mean and volatility of stock returns: A latent var approach, *Journal of Financial Economics* 72, 217–257.

Campbell, John Y., 1987, Stock returns and the term structure, *Journal of Financial Economics* 18, 373–399.

Campbell, John Y., 2003, Consumption-based asset pricing, in George M. Constantinides, Milton Harris, and Rene Stulz, ed.: *Handbook of the Economics of Finance*, vol. 1B, pp. 801–885 (Elsevier: Amsterdam).

Campbell, John Y., and John Ammer, 1993, What moves the stock and bond markets? A variance decomposition for long-term asset returns, *Journal of Finance* 48, 3–37.

Campbell, John Y., and John H. Cochrane, 1999, By force of habit: A consumption-based explanation of aggregate stock market behavior, *Journal of Political Economy* 107, 205–251.

Campbell, John Y., Andrew W. Lo, and Craig A. MacKinlay, 1997, *The Econometrics of Financial Markets* (Princeton University Press, Princeton, NJ).

Campbell, John Y., and Robert J. Shiller, 1988, The dividend-price ratio and expectations of future dividends and discount factors, *Review of Financial Studies* 1, 195–228.

Campbell, John Y., and Samuel B. Thompson, 2008, Predicting excess stock returns out of sample: Can anything beat the historical average? *Review of Financial Studies* 21, 1509–1531.

Campbell, John Y., and Tuomo Vuolteenaho, 2004, Bad beta, good beta, *American Economic Review* 94, 1249–1275.

Campbell, John Y., and Motohiro Yogo, 2006, Efficient tests of stock return predictability, *Journal of Financial Economics* 81, 27–60.

Campbell, Sean D., and Francis X. Diebold, 2009, Stock returns and expected business conditions: Half a century of direct evidence, *Journal of Business and Economics Statistics* 27, 266–278.

Chava, Sudheer, Michael F. Gallmeyer, and Heungju Park, 2011a, Credit conditions and expected stock returns, Working paper, Texas A&M University.

Chava, Sudheer, Michael F. Gallmeyer, and Heungju Park, 2011b, Credit conditions and stock return volatility, Working paper, Texas A&M University.

Chava, Sudheer, and Amiyatosh Purnanandam, 2011, The effect of banking crisis on bank-dependent borrowers, *Journal of Financial Economics* 99, 116–135.

Chen, Long, and Xinlei Zhao, 2009, Return decomposition, *Review of Financial Studies* 22, 5213–5249.

Christiano, Lawrence J., and Terry J. Fitzgerald, 2003, The band pass filter, *International Economic Review* 44, 435–465.

Christoffersen, Peter F., and Francis X. Diebold, 2000, How relevant is volatility forecasting for financial risk management? *Review of Economics and Statistics* 82, 12–23.

Clark, Todd E., and Michael W. McCracken, 2001, Tests of equal forecast accuracy and encompassing for nested models, *Journal of Econometrics* 105, 85–110.

Clark, Todd E., and Michael W. McCracken, 2005, Evaluating direct multistep forecasts, *Econometric Reviews* 24, 369–404.

Cochrane, John H., 1991, Production-based asset pricing and the link between stock returns and economic fluctuations, *Journal of Finance* 46, 207–234.

Cochrane, John H., 2001, *Asset Pricing* (Princeton University Press, Princeton, NJ).

Cooper, Ilan, and Richard Priestley, 2009, Time-varying risk premiums and the output gap, *Review of Financial Studies* 22, 2601–2633.

Correa, Ricardo, and Gustavo A. Suarez, 2009, Firm volatility and banks: Evidence from U.S. banking deregulation, Finance and Economics Discussion Series 2009-46, Federal Reserve Board., Washington, D.C.

Denis, David J., and Valeriy Sibilkov, 2010, Financial constraints, investment, and the value of cash holdings, *Review of Financial Studies* 23, 247–269.

Elliott, Graham, and James H. Stock, 1994, Inference in time series regression when the order of integration of a regressor is unknown, *Econometric Theory* 10, 672–700.

Engel, Charles, Nelson C. Mark, and Kenneth D. West, 2007, Exchange rate models are not as bad as you think, in Daron Acemoglu, Kenneth Rogoff, and Michael Woodford, ed.: *NBER Macroeconomics Annual 2007*, pp. 381–441 (University of Chicago Press, Chicago).

Engel, Charles, and John H. Rogers, 2006, The U.S. current account deficit and the expected share of world output, *Journal of Monetary Economics* 53, 1063–1093.

Engel, Charles, and John H. Rogers, 2009, Expected consumption growth from cross-country surveys: Implications for assessing international capital markets, *IMF Staff Papers* 56, 543–573.

Engle, Robert F., Eric Ghysels, and Bumjean Sohn, 2008, On the economic sources of stock market volatility, Working paper, New York University and University of North Carolina.

Engle, Robert F., and Andrew J. Patton, 2000, What good is a volatility model? Working paper, NewYork University.

Engle, Robert F., and Jose Gonzalo Rangel, 2008, The spline-garch model for low-frequency volatility and its global macroeconomic causes, *Review of Financial Studies* 21, 1187–1222.

Fama, Eugene F., and Kenneth R. French, 1988, Dividend yields and expected stock returns, *Journal of Financial Economics* 22, 3–25.

Fama, Eugene F., and Kenneth R. French, 1989, Business conditions and expected returns on stocks and bonds, *Journal of Financial Economics* 25, 23–49.

Faulkender, Michael, and Rong Wang, 2006, Corporate financial policy and the value of cash, *Journal of Finance* 61, 1957–90.

Fazzari, Steven M., R. Glenn Hubbard, and Bruce C. Petersen, 1988, Financing constraints and corporate investment, *Brookings Papers on Economic Activity* 19, 141–206.

French, Kenneth R., G. William Schwert, and Robert F. Stambaugh, 1987, Expected stock returns and volatility, *Journal of Financial Economics* 19, 3–29.

Ghysels, Eric, and Jonathan H. Wright, 2009, Forecasting professional forecasters, *Journal of Business and Economics Statistics* 27, 504-516.

Gilchrist, Simon, Vladimir Yankov, and Egon Zakrajsek, 2009, Credit market shocks and economic fluctuations: Evidence from corporate bond and stock markets, *Journal of Monetary Economics* 56, 471-493.

Gomes, Joao F., and Lukas Schmid, 2009, Equilibrium credit spreads and the macroeconomy, Working paper, Duke University and University of Pennsylvania.

Gorton, Gary, and Ping He, 2008, Bank credit cycles, *Review of Economic Studies* 75, 1181–1214.

Goyal, Amit, and Ivo Welch, 2008, A comprehensive look at the empirical performance of equity premium prediction, *Review of Financial Studies* 21, 1455–1508.

Hadlock, Charles J., and J. Pierce, 2010, New evidence on measuring financial constraints: Moving beyond the kz index, *Review of Financial Studies* 23, 1909–1940.

Henkel, Samuel J., J. Spencer Martin, and Federico Nardari, 2011, Time-varying short-horizon predictability, *Journal of Financial Economics* 99, 560–580.

Hodrick, Robert, and Edward C. Prescott, 1997, Postwar U.S. business cycles: An empirical investigation, *Journal of Money, Credit, and Banking* 29, 1–16.

Jensen, Gerald R., Robert R. Johnson, and Jeffrey M. Mercer, 1996, Business conditions, monetary policy, and expected security returns, *Journal of Financial Economics* 40, 213–237.

Kaplan, Steven N., and Luigi Zingales, 1997, Do financing constraints explain why investment is correlated with cash flow? *Quarterly Journal of Economics* 112, 169–215.

Keim, Donald B., and Robert F. Stambaugh, 1986, Predicting returns in the stock and bond markets, *Journal of Financial Economics* 17, 357–390.

Lamont, Owen A., Christopher K. Polk, and Jesus Saa-Requejo, 2001, Financial constraints and stock returns, *Review of Financial Studies* 14, 529–554.

Larrain, Borja, 2006, Do banks affect the level and composition of industrial volatility? *Journal of Finance* 61, 1897–1925.

Larrain, Borja, and Motohiro Yogo, 2008, Does firm value move too much to be justified by subsequent changes in cash flow? *Journal of Financial Economics* 87, 200–226.

Leary, Mark T., 2009, Bank loan supply, lender choice, and corporate capital structure, *Journal of Finance* 64, 1143–1185.

Lettau, Martin, and Sydney Ludvigson, 2001, Consumption, aggregate wealth, and expected stock returns, *Journal of Finance* 56, 815–849.

Lettau, Martin, and Sydney Ludvigson, 2009, Measuring and modeling variation in the risk-return tradeoff, in Yacine Ait-Sahalia, and Lars Hansen, ed.: *Handbook of Financial Econometrics*, vol. 1, pp. 617–690 (Elsevier: Amsterdam).

Li, Dongmei, and Lu Zhang, 2010, Does q-theory with investment frictions explain anomalies in the cross-section of returns? *Journal of Financial Economics* 98, 297–314.

Longstaff, Francis A., and Jiang Wang, 2008, Asset pricing and the credit market, Working paper, UCLA and MIT.

Lown, Cara, and Donald P. Morgan, 2006, The credit cycle and the business cycle: New findings using the loan officer opinion survey, *Journal of Money, Credit and Banking* 38, 1575–1597.

Lown, Cara S., and Donald P. Morgan, 2002, Credit effects in the monetary mechanism, *Federal Reserve Bank of New York Economic Policy Review* 8, 217–235.

Lown, Cara S., Donald P. Morgan, and Sonali Rohatgi, 2000, Listening to loan officers: the impact of commercial credit standards on lending and output, *Federal Reserve Bank of New York Economic Policy Review* 6, 1–16.

Ludvigson, Sydeny C., and Serena Ng, 2007, The empirical risk-return relation: A factor analysis approach, *Journal of Financial Economics* 83, 171–222.

Mankiw, N. Gregory, and Matthew D. Shapiro, 1986, Do we reject too often?: Small sample properties of tests of rational expectations models, *Economics Letters* 20, 139–145.

McCracken, Michael W., 2007, Asymptotics for out of sample tests of granger causality, *Journal of Econometrics* 140, 719–752.

Mele, Antonio, 2007, Asymmetric stock market volatility and the cyclical behavior of expected returns, *Journal of Financial Economics* 86, 446–478.

Nelson, Charles R., and Myung J. Kim, 1993, Predictable stock returns: The role of small sample bias, *Journal of Finance* 48, 641–661.

Newey, Whitney K., and Kenneth D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–08.

Patelis, Alex D., 1997, Stock return predictability and the role of monetary policy, *Journal of Finance* 52, 1951–1972.

Paye, Bradley S., 2009, Which variables forecast aggregate stock market volatility? Working paper, Rice University.

Robertson, Donald, and Stephen Wright, 2006, Dividends, total cash flow to shareholders, and predictive return regressions, *The Review of Economics and Statistics* 88, 91–99.

Schreft, Stacey L., and Raymond E. Owens, 1991, Survey evidence of tighter credit conditions: What does it mean? *Federal Reserve Bank of Richmond Economic Review* 77, 29–34.

Schwert, G. William, 1989, Why does stock market volatility change over time? *Journal of Finance* 44, 1115–1153.

Schwert, G. William, 1990, Stock returns and real activity: A century of evidence, *Journal of Finance* 45, 1237–1257.

Shiller, Robert J., 1981, Do stock prices move too much to be justified by subsequent changes in dividends? *American Economic Review* 71, 421–36.

Stambaugh, Robert F., 1999, Predictive regressions, *Journal of Financial Economics* 54, 375–421.

Thorbecke, Willem, 1997, On stock market returns and monetary policy, *Journal of Finance* 52, 635–654.

Whited, Toni M., and Guojun Wu, 2006, Financial constraints risk, *Review of Financial Studies* 19, 531–59.

Whitelaw, Robert F., 1994, Time variations and covariations in the expectation and volatility of stock market returns, *Journal of Finance* 49, 515–541.

VITA

Heungju Park

Department of Finance	Office:	+1.979.450.5509
Texas A&M University	Fax:	+1.979.845.3884
360 Wehner Building, 4218 TAMU	E-Mail:	hpark@mays.tamu.edu
College Station, TX 77843-4218, USA	WWW:	http://people.tamu.edu/ parkhj/

- Education
  - Texas A&M University: 2011 Ph.D.
  - Korea University: 2002 M.S.; 2000 B.A.
- Awards and Honors
  - Regents' Graduate Fellowship, Texas A&M University, 2007-2011
  - PhD program Merit-Based Summer Funding, 2008-2010
  - Travel Grants to the AFA (2010, 2011), MFA (2010), EFA (2010), and FMA (2010) Annual Meetings
  - Graduate School Scholarship, Korea University, 2000-2001
  - First Class Honors, Korea University, 1999
- Invited Academic Seminars
  - European Finance Association Annual Meeting, Frankfurt, Germany, August 2010
  - Midwest Finance Association Annual Meeting, Las Vegas, February 2010
- Teaching and Service
  - Instructor, Managerial Finance I, 2009