Bank Lending Cycle and Expected Stock Returns*

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Abstract

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We examine the roles played by bank lending cycle in predicting U.S. stock returns. Using a cycle component of U.S. commercial and industrial (C&I) loans (*Lending Gap*), we find that the cycle component is a strong predictor of U.S. stock returns. *Lending Gap* performs well both in-sample and out-of-sample and is robust to a small sample analysis. Moreover, we find that the aggregate stock returns respond more strongly to the cycle components during credit tightening periods and the stock returns of firms that primarily relied on banks for capital is more sensitive to the cycle components. The predictability of *Lending Gap* is consistent with capturing neglected risk with bank loan expansion.

Keywords: Return predictability, financial markets, bank loans

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1 Introduction

Bank lending has been strongly pro-cyclical across the business cycle. A large theoretical literature including Bernanke and Gertler (1989) and Kiyotaki and Moore (1997) suggests that the bank lending is important in explaining the evolution of the business cycle. Also, many empirical papers show the pro-cyclicality of the bank lending with different measures of the bank lending. Asea and Blomberg (1998) examine the relationship between the cyclical component of aggregate unemployment and bank lending standards. They find that cycles in bank lending standards are important in explaining aggregate economic activity. Lown and Morgan (2006) find that shocks to lending standards are significantly correlated with innovations in commercial loans at banks and in real output, using the bank credit standards in the Federal Reserve's Senior Loan Officer Opinion Survey. Also, den Haan et al. (2007) document that commercial and industrial (C&I) loans display a sharp decrease during a non-monetary downturn in the business cycle. A recent paper of Bassett et al. (2014) uses bank-level responses on changes in bank lending standards with an econometric model to control for the effect of loan demand. They find that tightening shocks to their credit supply indicator is significantly related to a decline in output and a widening of corporate credit spreads.

However, recent empirical studies show that unusually strong bank lending growth tends to precede recessions. In particular, Chari et al. (2008), Gourinchas and Obstfeld (2012), and Jordà et al. (2013) provide empirical evidence showing that bank lending expansion predicts subsequent banking crises. The counter-cyclicality of the bank lending affects the banking crisis risk in asset pricing. In this paper, we examine how the bank lending cycle is related to the business cycle through stock prices.

Our work joins a growing literature that uses credit condition variables to explain asset returns. Gorton and He (2008) find that the relative performance of commercial and industrial loans leads to endogenous credit cycles and is an autonomous source of various asset prices. Longstaff and Wang (2012) show that aggregate credit forecasts the equity premium with a heterogenous agent framework. Gilchrist and Zakrajšek (2012) construct a credit spread index from micro-level corporate bond data and show that this index provides robust predictive power for real activity. Chava et al. (2015) examine impact of credit standards on expected aggregate stock returns and find that credit standards strongly predicts aggregate stock market returns. We use a cycle component of bank lending (*Lending Gap*) from the Hodrick-Prescott filter as a measure of credit conditions, and examine whether *Lending Gap* predicts stock returns.

Also, our work is motivated by papers that study how cycle components impact the asset prices. In particular, Cooper and Priestley (2009) construct a measure of the output 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. They show that the output gap has predictive power for excess stock returns in G7 countries and US excess government bond returns. Instead of analyzing the state of the macroeconomy through the output gap, we examine whether the cycle components of the bank lending are related to future stock returns.

Overall, we find that our measure of *Lending Gap* 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 debated relationship between bank lending and business cycle, we provide a direct link to the predictability of stock returns and *Lending Gap*. Since this measure is not linked to the level of asset prices, its ability to predict is unlikely to be driven by stock mispricing. *Lending Gap* performs well both in-sample and out-of-sample. It is also robust to a small sample bias analysis. Moreover, we find that the aggregate stock returns respond more strongly to *Lending Gap* during credit tightening periods and the stock returns of firms that primarily relied on banks for capital is more sensitive to the cycle components.

The predictive power of *Lending Gap* might be consistent with capturing neglected risk with the bank loan expansion. Recent work on credit cycles, such as Greenwood and Hanson

(2013), Chernenko et al. (2015), Baron and Xiong (2016), and Park and Sohn (2016), has explored neglected risk with different asset returns. In particular, Greenwood and Hanson (2013) find that the credit quality of corporate debt issuance deteriorates and this deterioration forecasts lower corporate bond returns. Baron and Xiong (2016) show that bank credit expansion predicts lower future bank equity returns. However, past work has not directly considered the influence of the neglected risk with the bank loan expansion on overall stock market returns. In particular, it is unclear whether the bank lending can be related to either pro-cyclical or counter-cyclical channel with time-varying risk premium of stock returns. In this paper, we address this issue by examining whether the cycle components of the bank lending predict stock returns.

The rest of the paper is organized as follows. Section 2 describes the data used in the paper and presents detailed information about the *Lending Gap* in the paper. Section 3 presents evidence on stock return predictability. In Section 4, the channel of the predictability is discussed. Section 5 concludes.

2 Data

We use aggregate level of commercial and industrial (C&I) loans as a measure of bank lending. The aggregate level of the C&I loans is taken form the Federal Reserve (H8.Assets and Liabilities of Commercial Banks in the United States) and given at a monthly frequency from January 1947. Previous studies usually include total bank loans for the bank lending analysis, and do not focus on each component of the total bank loans. However, den Haan et al. (2007) show that the analysis with the total bank loans are not robust and are not significant, because each bank loan component has heterogeneous function and response for macro economy changes. In particular, den Haan et al. (2007) find that the C&I loans increase after a money tightening and the C&I loans display a sharp decrease during a non-monetary downturn while real estate loans and consumer loans display either a moderate decrease or no decrease. This paper examines relationship between bank lending and business cycle with asset prices and the C&I loans are the best measure to analyze the relationship.

In addition, several recent studies including Lown and Morgan (2006), Bassett et al. (2014), and Chava et al. (2015), employ a measure of credit conditions, bank lending standards (*Standards*) from the Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices and they find that *Standards* are closely related to the business cycle. The survey question of *Standards* deals with the tightening condition of C&I loans in a supply side and using the connection with *Standards* and the C&I loans, we analyze whether the bank loans affect stock prices with a different angle.

To compute the cycle components of the C&I loans, we apply the filter developed by Hodrick and Prescott (1997) to the log of the C&I loans. The Hodrick-Prescott (HP) filter differentiate between the short-term ups and downs and the long-term trend. Specifically, the series x_t is made up a trend component, denoted by τ_t and a cycle component, denoted by c_t such that $x_t = \tau_t + c_t + \epsilon_t$ and this filter extracts the trend component, τ_t, of the log of a series solving the following problem:

$$\min_{\{\tau_t\}} \sum_{t=1}^{T}(x_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1}[(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2, \tag{1}$$

where x_t is the log of the C&I loans and the parameter λ denotes the smoothness of the trend. λ is set at 14,400 for monthly series and at 1,600 for quarterly series. Using the HP filter, we measure *Lending Gap* as the cycle components of the C&I loans and examine *Lending Gap* predicts excess stock returns.

Figure 1 plots the *Lending Gap* across time with the shaded regions representing the NBER recession periods. In most cases of the NBER dated recessions, it appears that *Lending Gap* has increased entering a recession. Equally important, banks appear to reduce their C&I lending exiting a recession. It implies that the bank lending expansion predicts the subsequent recession, which is consistent with findings of Chari et al. (2008), Gourinchas and Obstfeld (2012), and Jordà et al. (2013). From the figure, it appears that *Lending Gap* is a counter-cyclical leading indicator of a business cycle. At least at a univariate level, it seems plausible that *Lending Gap* is a contender for predicting stock returns.

To study stock return predictability, we analyze stock returns on the CRSP value-weighted index (CRSP-VW), which are sampled from January 1947 to December 2014.[1] 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.

To compare the forecasting power of *Lending Gap*, we consider some of the standard predictor variables used in the literature. Following previous research on stock return predictability, we use the dividend-price ratio (dp), the 30 day T-bill rate (RF), the term spread ($TERM$), and the default yield spread (DEF). 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 *Lending Gap* to a measure of corporate issuing activity *ntis* from Goyal and Welch (2008) and the aggregate consumption-wealth ratio measure *cay* from Lettau and Ludvigson (2001). 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 and *cay* from Lettau and Ludvigson (2009) is the residual obtained from estimating a cointegrating relation between aggregate consumption, wealth, and labor income. We use the Goyal-Welch measure of *ntis* and *cay* for our predictability test.[2]

Moreover, we use a measure of the output gap from Cooper and Priestley (2009). As a business cycle indicator to predict stock and bond returns, Cooper and Priestley (2009)

[1] We also check the predictability for the log excess returns on the CRSP equally-weighted index and the S&P 500 index. The results for the CRSP equally-weighted returns and the S&P 500 returns are nearly identical to those for the CRSP value-weighted returns.

[2] The Goyal-Welch measure of *ntis* and *cay* is available at Amit Goyal's web site: http://www.hec.unil.ch/agoyal/.

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:

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

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.

Descriptive statistics (number of observations, mean, min, max, standard deviation, and autocorrelation) of the various predictor variables and asset returns with their monthly frequencies are presented in Panel A of Table 1. The descriptive statistics of the standard predictor variables as well as the stock returns are in line with the results reported in previous work (for example, Goyal and Welch (2008)), so we skip the discussion of these results in the interest of space. The key variable of interest in the analysis, *Lending Gap*, has an autocorrelation of 0.975 at the monthly frequency. The autocorrelation is high, even if *Lending Gap* represents a cyclical components from the HP filter. Controlling for the small sample bias from the high autocorrelation, we do conduct the Campbell and Yogo (2006) test, Bootstrapping Test, and Monte Carlo test in a robust check.

Panel B in Table 1 present the correlations across various predictor variables. *Lending Gap* (*Lgap*) is not highly correlated with other predictor variables. Surprisingly, the correlation between *Lgap* and a business cycle component, output gap (*gap*), is not significantly high (17%). In general, the correlations across other predictor variables are consistent with the earlier literature.

Table 2 shows the descriptive statistics of the various predictors and stock returns with their quarterly frequencies. Not surprisingly, autocorrelation of quarterly *Lending Gap* is lower than monthly series and volatility of quarterly *Lending Gap* is higher than monthly series. The correlation structure of the quarterly series are almost identical to that of the monthly series.

3 Stock Return Predictability

We first explore ability of *Lending Gap* to predict stock market 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.

3.1 In-Sample Evidence

Following much of the existing stock return predictability literature, we first assess the in-sample predictive ability of *Lending Gap* for the log excess returns on the CRSP value weighted index. We estimate the following regression:

$$ret_t = \alpha + \beta Lgap_{t-1} + \gamma X_{t-1} + \epsilon_t, \tag{3}$$

where ret_t is the log excess returns on the CRSP value weighted index, $Lgap_{t-1}$ is the cycle components of the C&I loans from the HP filter, X_{t-1} corresponds to a particular forecasting variable and ϵ_t is an error term. The in-sample predictive ability of *Lgap* is assessed via the t-statistic of the β estimate and the adjusted R^2 from the predictability regression. Under the null hypothesis that *Lgap* does not predict stock return, β=0. We report Newey and West (1987) standard errors that correct for serial correlation and heteroscedasticity.[3]

Table 3 reports in-sample forecasting regressions with *Lending Gap*, for the monthly log excess returns on the CRSP-VW index.[4] The CRSP-VW excess returns are strongly predictable with negative coefficients on the *Lgap* variable at traditional significance levels. The negative sign implies that the expansion of the C&I loans results in a subsequent drop in stock returns. As demonstrated in Section 4, this negative sign is consistent with neglected risk with the loan expansion.

[3]We also compute Hansen and Hodrick (1980) and Hodrick (1992) standard errors. These results are similar and are available from the authors.

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

Also, Table 3 reports estimates from predictability regressions that include a variety of variables used in past predictability studies. 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. In the second column of Table 3, we include these financial market variables, DEF, TRM, RF, and dp, in our predictive regressions on the CRSP-VW excess return. Note that *Lending Gap* still retains its forecasting power with roughly the same coefficient size and the same level of statistical significance when compared to the financial market-based variables.

Recent studies find evidence that corporate issuing activity forecasts stock returns. Boudoukh et al. (2007), Larrain and Yogo (2008), and Robertson and Wright (2006) document that payout yields derived from dividends, repurchases, and issuances, as opposed to the simple dividend yields, are robust predictors of excess returns. Moreover, Goyal and Welch (2008) find that $ntis$ which measures equity issuing and repurchasing (plus dividends) relative to the price level, has good in-sample performance, but a negative out-of-sample adjusted R^2. We add $ntis$ in our predictability regression to determine its in-sample performance relative to *Lending Gap*. The third column of Table 3 shows that $ntis$ is not statistically significant, but *Lending Gap* is.

More importantly, 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. During our sample period, gap still seem to have forecasting power for excess stock returns, while its predictability is less than the predictability of *Lending Gap*. It implies that cycle components of both bank lending and business cycle predict stock market returns and both components are not closely related in prediction of the stock market returns.

In the last column of Table 3, we present the in-sample forecasting regression with all the variables included. Interestingly, *Lending Gap* has the most statistically significant coefficient among all the predictor variables. This suggests that *Lending Gap* is capturing future excess stock returns at a monthly frequency, while other predictor variables except *dp* have little predictive power of excess stock returns at this horizon.

Additionally, we analyze in-sample predictability with *Lending Gap*, for the quarterly log excess returns on the CRSP-VW index. Table 4 shows results of the in-sample forecasting. For the quarterly analysis, we add the ratio of consumption to wealth, *cay* in our multivariate regressions. Lettau and Ludvigson (2001) find that the ratio of consumption to wealth, *cay*, predicts stock returns at a quarterly frequency.

According to Table 3, *Lending Gap* is a strongest predictor for the excess stock returns in our all specifications. The adjusted R^2 of *Lending Gpa* is 3% in univariate forecasting. Unlike the case of the monthly prediction, RF shows statistically significant coefficients in all specifications, which implies quarterly excess returns are sensitive to RF, compared as the monthly excess returns. Also, *cay* has statically significant coefficient with *Lending Gap*. The last column of Table 4 presents the in-sample forecasting regression with all the variables included and we find that *Lending Gap*, RF, and *dp* has strong predictability for excess stock returns.

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 *Lending Gap* in out-of-sample tests.[5]

To perform the out-of-sample tests, we compute four test statistics designed to determine

[5] We analyze the out-of-sample forecasting tests with other predictor variables which we use in the in-sample regression. From our unreported results, *Lending Gap* shows the best forecasting ability, compared as other predictor variables.

whether the *Lending Gap* forecasting model has superior forecasting performance relative to the historical mean model of the stock returns. We conduct out-of-sample R^2, $\Delta RMSE$, $MSE - F$, and $ENC - NEW$.

$$R^2_{oos} = 1 - \frac{MSE_A}{MSE_N}, \tag{4}$$

$$\Delta RMSE = \sqrt{MSE_N} - \sqrt{MSE_A}, \tag{5}$$

$$MSE - F = (T - h + 1) \cdot \frac{MSE_N - MSE_A}{MSE_A}, \tag{6}$$

$$ENC - NEW = \frac{T - h + 1}{T} \cdot \frac{\sum_{t=1}^{T}(\epsilon_t^2 - \epsilon_t \cdot e_t)}{MSE_A}, \tag{7}$$

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 of the stock returns. T is the number of observations and h is the degree of overlap (h=1 for no overlap). ϵ_t is the vector of out-of-sample errors from the historical mean model of the stock returns and e_t is the vector of out-of-sample errors from the forecasting model with a predictor. 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 different starting points of estimation windows to check whether our results are robust to choice of estimation periods. We conduct the out-of-sample tests in a recursive regression which assumes that the model is estimated with more data as the forecasting date moves forward in time.[6]

Table 5 compares forecasts based on the historic mean model to those based on *Lending Gap*, using the CRSP-VW excess returns. We conduct four out-of-sample tests — adjusted R^2, ΔRMSE, MSE-F, and ENC-NEW — in recursive regressions. For the tests, we consider the first initial estimation period of January 1947 to December 1956 and we change our

[6]We also use a rolling window approach to check the out-of-sample tests. If we set over 30 years as the moving window, the results of the out-of-sample predictability are very similar to those with the recursive approach.

initial estimation period. The last initial estimation period is January 1947 to December 1996.

Table 5 shows that the forecasting model with *Lending Gap* has superior forecasting performance relative to the historic mean model in both the monthly and the quarterly frequencies. In particular, across all specification of the initial estimation window, *Lending Gap* is better for prediction of excess stock returns than historical mean model. For example, we take the first estimation period of Q1:1947 to Q4:1986 for quarterly excess stock returns and we forecast the excess stock returns from Q1:1987 with the estimated parameters. The out-of-sample R^2 is 4% in the recursive regression. The ΔRMSE is 0.002 in the recursive regression, which implies that the forecast errors with *Lending Gap* are lower than those with the historic average returns. The MSE-F test rejects the null hypothesis that the MSEs from the forecasts that use *Lending Gap* 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 *Lending Gap* forecasting model. These results suggest that *Lending Gap* plays a strong role as a predictor of excess stock returns. 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.

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. In this section, we investigate whether *Lending Gap* tracks longer-term tendencies in stock markets rather than provides shorter-term forecasts. Table 6 reports long-horizon forecasting regressions of quarterly excess returns on the CRSP-VW index.[7] 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.

[7] We also conduct the long-horizon analysis for the monthly excess stock returns and the results are nearly identical to those for the quarterly excess stock returns.

From the top panel of Table 6, we document the forecasting power of *Lending Gap* for future excess returns at horizons ranging from 1 to 12 quarters. The coefficient for *Lending Gap* is hump-shaped and peaks around 4 quarters in the sample. At an 4 quarter horizon, the coefficient estimate for *Lending Gap* is significant and the adjusted R^2 is approximately 4%, so the predictive power decreases at a horizon greater after 4 quarters. Here, *Lending Gap* seems to better forecast future excess returns at a business cycle frequency as the informational content of *Lending Gap* decreases at longer horizons.

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

In the last panel of Table 6, we add cay, $ntis$, and gap to the previous regression. The hump-shaped forecasting pattern of *Lending Gap* is robust, and the predictive power of *Lending Gap* is insignificant at a 8 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 *Lending Gap* predictive power occurs at a shorter horizon than most of the predictive variables explored in the literature.

3.4 Small Sample Robustness of Stock Return Predictability

To examine the robustness of *Lending Gap* as a stock return predictor, we perform a small sample analysis. 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 *Lending Gap* is a persistent variable, its degree of persistence is not as strong as measures such as the dividend price ratio (see Table 1 and Table 2). Additionally, it is not a priced-based variable and it is a cycle components. However, given the high auto-correlation of the *Lending Gap* data series, we explore whether the in-sample results of *Lending Gap* could be driven by small sample biases.[8]

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 7. Following Campbell and Yogo (2006), we report the confidence interval for $\tilde{\beta}=(\sigma_e/\sigma_u)\beta$ instead of β.[9] In the fourth (fifth) column of the table, we report the 90% Bonferroni confidence intervals for β using the t-test (Q-test), whose the null hypothesis is β=0. Both the Bonferroni t-test and the Q-test reject the null of no predictability for *Lending Gap*. For example, the confidence intervals for *Lending Gap* 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:

$$r_t = \gamma + e_t, \tag{8}$$

[8]We analyze the tests for the small sample biases with other predictor variables which we use in the in-sample regression. From our unreported results, *Lending Gap* shows the best forecasting ability, compared as other predictor variables.

[9]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.

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

$$Lgap_t = \mu + \phi Lgap_{t-1} + \nu_t, \tag{9}$$

where the values of μ and ϕ are those estimated from the actual data for *Lending Gap*. Then, we generate artificial sequences of excess returns and *Lending Gap* 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 *Lending Gap* data series. Using these samples created under either a bootstrap or Monte Carlo simulation, we then estimate in-sample univariate forecasting regression which yields a distribution of our test statistics.

Panel B of Table 7 reports the results of the bootstrap procedure for the Newey-West t-statistics and adjusted R^2 coefficients of the predictive regression with *Lending Gap*. For both the monthly and quarterly excess returns, the estimated t-statistics of *Lending Gap* lies outside of the 95% confidence interval based on the empirical distribution from the bootstrap procedure. This implies we can reject the hypothesis that *Lending Gap* 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 *Lending Gap* is robust to correcting for small sample biases. Panel C of Table 7 presents the results of the Monte Carlo simulation and the results are nearly identical to those of the bootstrap procedures.

4 Channel of Predictability

In Section 3, we find that the CRSP-VW excess returns are strongly predictable with negative coefficients on *Lending Gap*. The negative sign implies that the expansion of the C&I loans results in a subsequent drop in stock returns. To interpret the negative coefficients on the *Lending Gap*, the relationship between *Lending Gap* and business cycle should be analyzed.

An active debate has arisen over whether bank lending is pro-cyclical or counter-cyclical across the business cycle. In particular, recent empirical studies, such as Chari et al. (2008), Gourinchas and Obstfeld (2012), and Jordà et al. (2013), find that bank lending expansion predicts economic recessions, while a large body of literature shows the pro-cyclicality of the bank lending. According to the debates, our empirical findings of the negative sign between *Lending Gap* and future stock returns can be interpreted differently. On one hand, the negative sign can be interpreted with time-varying risk premium, which implies that investors require higher expected returns in bad times. If *Lending Gap* is positively correlated with the business cycle, a decline of *Lending Gap* leads to a negative shock in real economy and investors could demand a higher risk premium and earn higher future stock returns, which implies a negative sensitivity between *Lending Gap* and future stock returns. On the other hand, Figure 1 in Section 2 shows *Lending Gap* has increased with entering a recession and decreased exiting a recession in most cases of the NBER dated recessions. If *Lending Gap* is negatively related with the macro economic conditions like Figure 1, a rise in *Lending Gap* can predict a recession and a positive sign between between *Lending Gap* and future stock returns can be suggested in predictive regressions, because of the time-varying risk premium. Thus, it might seem inconsistent with our empirical findings. However, recent work on credit cycles, including Greenwood and Hanson (2013), Chernenko et al. (2015), Baron and Xiong (2016), and Park and Sohn (2016), has studied neglected downside risk with credit expansion. They argue that investors believe that serious adverse outcomes during credit expansion are highly unlikely, making credit related assets appear attractive even in bad times. Thus, our negative sensitivity between *Lending Gap* and future stock returns might be interpreted with the neglected risk. The channel of the predictability of *Lending Gap* is now explored to better understand the negative sensitivity between *Lending Gap* and future stock returns.

4.1 Stock Return Volatility Predictability

As a first step, we examine whether *Lending Gap* predict stock market risks positively or negatively. We use the realized volatility and the log realized volatility of the aggregate stock returns as the measure of the stock market risk and estimate the predictive regression model of Equation 3. Table 8 presents the results for the predictive regressions of the realized volatility ($rvol$) and the log realized volatility ($lrvol$). In univariate analysis, both $rvol$ and $lrvol$ are strongly predictable with positive coefficients on the *Lending Gap* and $lrvol$ has stronger effect than $rvol$. The positive sign implies that an increase of *Lending Gap* leads to a subsequent rise in stock return volatility. Thus, the bank lending expansion predicts the increase of the stock market risk, which might be consistent with the counter-cyclicality of the bank lending. Additionally, the adjusted R^2 of $rvol$ ($lrvol$) is 11% (9%). Also, the results of multivariate tests support those of univariate setup. *Lending Gap* has significantly positive coefficients and the coefficients of *Lending Gap* are more similar than those of other predictors in all specifications; in $rvol$, 0.15 - 0.21 and in $lrvol$, 1.47 - 2.21. In the "Kitchen Sink" regression of both $rvol$ and $lrvol$, *Lending Gap*, DEF, and dp are significant at traditional significant level.

Given our work presents evidence that *Lending Gap* predicts stock return volatility with positive coefficients, our results seem more inclined to the counter-cyclicality of the bank lending. Moreover, through the counter-cyclicality of the bank lending, our previous findings of the negative sensitivity between *Lending Gap* and future stock returns might be somewhat interpreted with the story of the neglected risk.

4.2 Stock Return Predictability in Tightening Periods

Next, we examine whether predictability of *Lending Gap* for excess stock returns is asymmetric across credit market conditions.[10] For the analysis, we use a dummy variable, tightening

[10]We also examine whether effect of *Lending Gap* on excess stock returns is asymmetric in recessions versus expansions. To capture the asymmetric predictability, we use a dummy variable, $LowGDP$, which equals one if the prior quarter's GDP growth is below its time series median. We find that *Lending Gap*

bank lending standards (*Standards*) from the Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices. The survey question on the bank lending standards deals with supply conditions of Commercial and Industrial (C&I) Loans. For the question, bank senior loan officers answer using 5 ratings on the current C&I loans conditions from considerably tightening to considerably easing. Lown and Morgan (2006) measure the bank lending standards as the number of bank tightening minus the number of bank easing divided by total number of banks and the range of the bank lending standards value is from -1 to 1. The positive values mean that the number of bank tightening is above the number of bank easing. In many recent studies, *Standards* is employed as a measure of aggregate 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. Chava et al. (2015) examines impact of *Standards* on expected aggregate stock returns and they find *Standards* has a strong forecasting power of the aggregate stock market returns.

We generate a dummy variable of $Tightening$ and $Tightening$ equals one if the prior quarter's $Standards$ is greater than 0. We include $Tightening$ and an interaction of $Tightening$ with *Lending Gap* as predictive variables to forecast excess stock returns in Equation 3. Table 9 shows the results of the predictability of *Lending Gap* for stock excess returns. The sample period is Q2:1990 to Q4:2014, because of the availability of $Standards$. We find that the coefficients on the interaction terms have the consistent signs with our main results and they show statistically significance to forecast excess stock returns. Specifically, the coefficient for predicting excess stock returns on *Lending Gap* is 0.22 and that on the interaction of *Lending Gap* with $Tightening$ is -0.74 without control variables. In other words, in periods of tightening credit conditions, the impact of *Lending Gap* on future excess stock returns is -0.52, which is about twice the coefficient on *Lending Gap* compared to our previous results. Thus, expected returns are much more sensitive to *Lending Gap* in period of

predicts the excess stock returns in recessions better than in expansions.

tightening credit conditions. Furthermore, the results provide evidence of neglected risk that investors tend to overlook subsequent market-wide credit risk during the loan expansion and they hardly require higher expected returns in credit tightening periods.

4.3 Bank Dependent Stock Return Predictability

In this section, we explore predictability of *Lending Gap* with bank dependent stocks. Following Chava and Purnanandam (2011), we use the absence of public debt rating as the proxy for bank-dependence. To construct the proxy, we assume that firms without credit rating information in Compustat do not have access to to the public debt market and they are assigned as the bank dependent firms. We exclude financial firms with SIC codes between 6000 and 6999 and utility firms with SIC codes between 4910 and 4940. We also remove firms with less than a $1 stock price as of the end of the prior fiscal year. Last, we drop firms with zero debt in the prior fiscal year. Then, we calculate the value weighted excess stock returns of the bank dependent firms and we estimate the predictive regression model of Equation 3 over the periods 1985-2013. The sample period is limited by the availability of Compustat data on bond ratings.

Table 10 shows the results of forecasting the excess stock returns for the CRSP value weighted index and the value weighted portfolio of the bank dependent stocks. The results in Table 10 indicate that *Lending Gap* causes an economically significant difference between the CRSP value weighted returns and the bank dependent stock returns. The coefficients with the bank dependent portfolios are more than doubled than those with the market index portfolios. Moreover, they are more statistically significant than those with the market index portfolios. According to the results, future stock returns of firms that primarily relied on banks for capital is more sensitive to the cycle components. More importantly, these findings might be related to neglected risk story. In particular, Greenwood and Hanson (2013) find that the credit quality of corporate debt issuance deteriorates and this deterioration forecasts lower corporate bond returns. Baron and Xiong (2016) show that bank credit expansion predicts lower future bank equity returns. With the bank dependent portfolios, we add evidence of the neglected risk with the loan expansion.

4.4 Control for Future Macroeconomic Activity

Last, we examine the predictability of *Lending Gap* controlling for macroeconomic expectation variables. One might be concerned that the forecasting power of *Lending Gap* is not due to the neglected risk but due to expectation about future macroeconomic activity. Our findings of negative sensitivity between *Lending Gap* and future stock returns can be argued with pro-cyclicality of bank lending. To address the issue, 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 from the Survey of Professional Forecasters as control variables in Equation 3. The sample period is Q3:1981 to Q4:2013, because the survey variables are available over the periods. Table 11 reports the in-sample predictive regressions for the excess stock returns. The *Lending Gap* is still statistically significant with the negative coefficients in all specifications. It implies that the predictability of *Lending Gap* still exists with the negative signs to control for the expectations of the future macroeconomic activity.

5 Conclusion

This work provides evidence that a cycle component of U.S. commercial and industrial loans (*Lending Gap*) from the HP filter is a strong predictor of U.S. stock returns. Given this variable has been shown to predict aggregate macroeconomic variables, our results provide a direct link of a macroeconomic supply variable to the predictability of stock returns. Given the *Lending Gap* measure is not derived from financial market prices, it seems unlikely that the source of its predictive power is from capturing mispricing in financial markets. Moreover, the aggregate stock returns respond more strongly to the cycle components during credit tightening periods and the stock returns of firms that primarily relied on banks for capital is more sensitive to the cycle components. Additionally, since *Lending Gap* predicts stock market returns negatively, its predictive power is more consistent with capturing neglected risk.

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Figure 1: **Change in Cycle Components of Commercial and Industrial Loans 1947-2014**

This figure plots the changes in the cycle components of commercial and industrial loans. The sample period is January 1947 to December 2014. The shaded regions represent NBER-dated recessions.

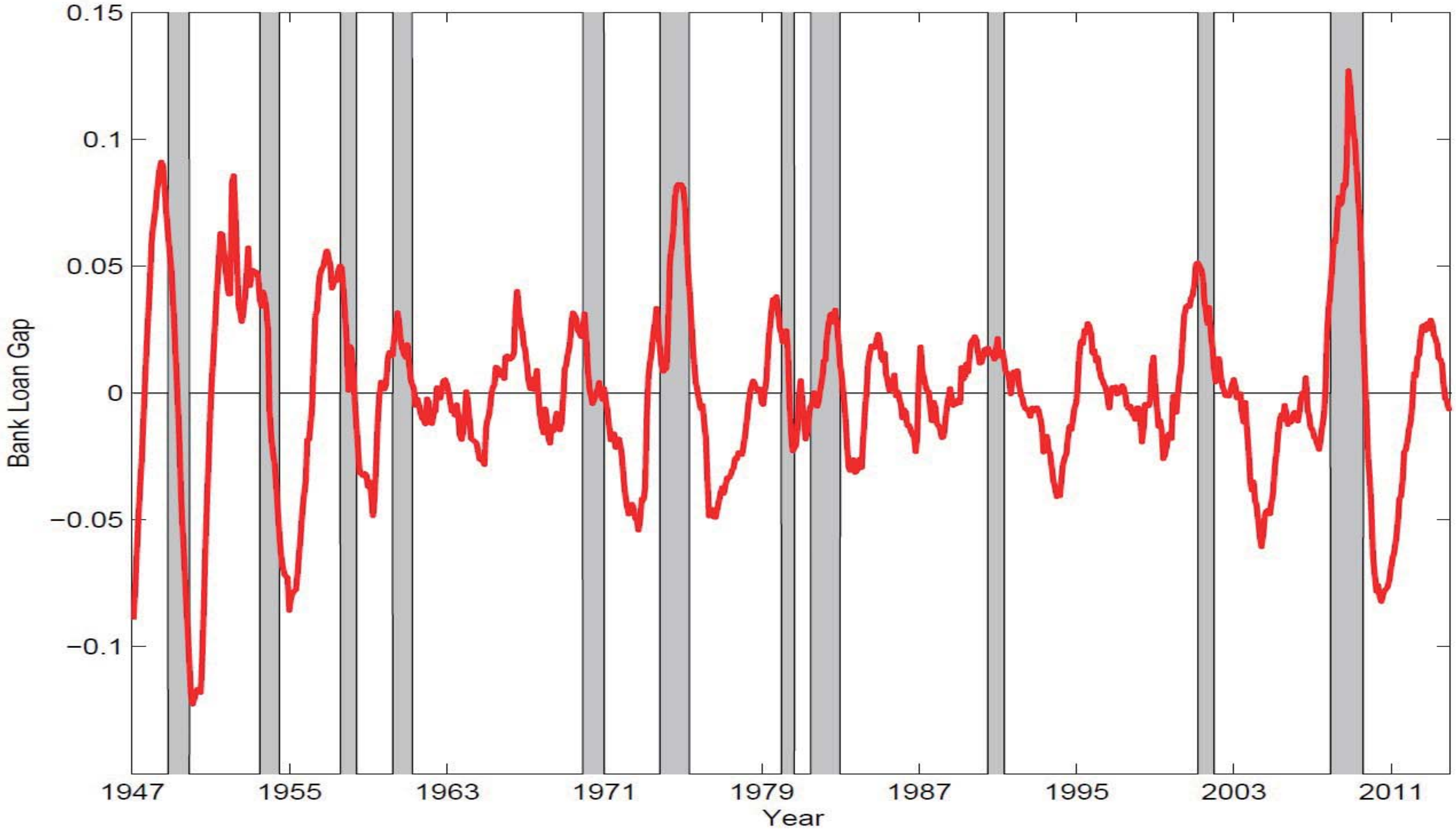

Table 1: **Descriptive Statistics (Monthly Level)**

The table reports descriptive statistics and correlations for the stock return predictive variables. *Excess Ret* is the log excess return on the CRSP-VW index. *Lgap* is the cycle components of C&I loan from the HP filter. *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 *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 January 1947 to December 2014.

Panel A: Descriptive Statistics of Predictive Variables						
Variable	*Obs*	*Mean*	*StdDev*	*Min*	*Max*	*Autocorr*
Excess Ret	816	.005	.043	-.261	.148	.087
Lgap	816	0	.035	-.123	.127	.975
DEF	816	.009	.004	.003	.034	.971
TERM	816	.01	.011	-.031	.034	.971
RF	816	.003	.003	0	.014	.971
dp	816	-3.502	.419	-4.558	-2.629	.993
ntis	816	.015	.018	-.058	.051	.978
gap	816	0	.066	-.156	.124	.989

Panel B: Correlations of Stock Return Predictive Variables							
	Lending Gap	*DEF*	*TERM*	*RF*	*dp*	*ntis*	*gap*
Lgap	1.000						
DEF	0.188	1.000					
TERM	-0.238	0.173	1.000				
RF	0.142	0.368	-0.551	1.000			
dp	0.098	0.101	-0.232	0.181	1.000		
ntis	-0.274	-0.406	-0.091	-0.084	0.207	1.000	
gap	0.168	-0.342	-0.467	0.074	-0.295	0.105	1.000

Table 2: **Descriptive Statistics (Quarterly Level)**

The table reports descriptive statistics and correlations for the stock return predictive variables. *Excess Ret* is the log excess return on the CRSP-VW index. *Lgap* is the cycle components of C&I loan from the HP filter. *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 Q1:1947 to Q4:2014.

Panel A: Descriptive Statistics of Predictive Variables						
Variable	*Obs*	*Mean*	*StdDev*	*Min*	*Max*	*Autocorr*
Excess Ret	272	.016	.082	-.302	.205	.081
Lgap	272	0	.058	-.155	.195	.937
DEF	272	.009	.004	.003	.034	.88
TERM	272	.01	.011	-.031	.033	.863
RF	272	.003	.003	0	.015	.934
dp	272	-3.501	.422	-4.512	-2.629	.977
ntis	272	.015	.018	-.053	.048	.928
cay	272	0	.022	-.051	.04	.954
gap	272	0	.066	-.145	.124	.955

Panel B: Correlations of Stock Return Predictive Variables								
	Lending Gap	*DEF*	*TERM*	*RF*	*dp*	*ntis*	*cay*	*gap*
Lgap	1.000							
DEF	0.252	1.000						
TERM	-0.301	0.164	1.000					
RF	0.190	0.350	-0.589	1.000				
dp	0.115	0.212	-0.275	0.366	1.000			
ntis	-0.354	-0.378	-0.089	-0.031	0.154	1.000		
cay	-0.072	-0.010	0.195	0.108	0.129	-0.110	1.000	
gap	0.181	-0.324	-0.485	0.072	-0.291	0.085	-0.621	1.000

Table 3: **Forecasting Monthly Stock Excess Returns**

The table reports estimates of OLS regressions of stock returns on one-month lagged predictive variables: $r_t = \alpha + \beta \cdot Lgap_{t-1} + \gamma \cdot Z_{t-1} + \epsilon_t$, where r_t is the log excess return on the CRSP-VW index. Newey-West corrected t-statistics appear in parentheses below the coefficient estimates and adjusted R^2 statistics in square brackets. The sample period is January 1947 to December 2014.

	Excess returns on CRSP				
$Lgap$	-0.14	-0.15	-0.16	-0.13	-0.15
	(-2.44)	(-2.63)	(-3.08)	(-2.45)	(-2.91)
DEF		0.70	0.48	0.55	0.37
		(1.09)	(0.78)	(0.86)	(0.61)
$TERM$		0.07	0.08	-0.12	-0.10
		(0.37)	(0.42)	(-0.57)	(-0.48)
RF		-1.64	-1.57	-1.79	-1.72
		(-1.54)	(-1.51)	(-1.72)	(-1.70)
dp		0.01	0.01	0.01	0.01
		(2.98)	(3.22)	(1.86)	(2.13)
$ntis$			-0.13		-0.11
			(-1.11)		(-0.93)
gap				-0.05	-0.05
				(-1.97)	(-1.80)
Constant	0.01	0.04	0.05	0.03	0.04
	(3.36)	(3.20)	(3.42)	(2.49)	(2.70)
$\bar{R}^2$	[0.01]	[0.03]	[0.03]	[0.03]	[0.03]

Table 4: **Forecasting Quarterly Stock Excess Returns**

The table reports estimates of OLS regressions of stock returns on one-quarter lagged predictive variables: $r_t = \alpha + \beta \cdot Lgap_{t-1} + \gamma \cdot Z_{t-1} + \epsilon_t$, where r_t is the log excess return on the CRSP-VW index. Newey-West corrected t-statistics appear in parentheses below the coefficient estimates and adjusted R^2 statistics in square brackets. The sample period is Q1:1947 to Q4:2014.

	Excess returns on CRSP					
$Lgap$	-0.24	-0.26	-0.30	-0.29	-0.23	-0.32
	(-2.45)	(-2.70)	(-2.62)	(-3.17)	(-2.56)	(-3.13)
DEF		2.70	4.01	2.09	2.24	3.62
		(1.72)	(2.29)	(1.33)	(1.43)	(1.57)
$TERM$		-0.19	-1.24	-0.18	-0.89	-1.20
		(-0.32)	(-1.65)	(-0.33)	(-1.36)	(-1.69)
RF		-6.06	-10.31	-5.86	-6.76	-10.05
		(-2.26)	(-3.33)	(-2.31)	(-2.55)	(-3.11)
dp		0.03	0.03	0.04	0.02	0.03
		(2.69)	(2.12)	(2.79)	(1.63)	(2.12)
cay			0.80			0.76
			(3.19)			(1.74)
$ntis$				-0.38		-0.21
				(-1.09)		(-0.63)
gap					-0.19	-0.00
					(-2.22)	(-0.02)
Constant	0.02	0.13	0.13	0.15	0.10	0.15
	(3.40)	(3.12)	(2.61)	(3.12)	(2.42)	(2.58)
$\bar{R}^2$	[0.03]	[0.06]	[0.09]	[0.07]	[0.07]	[0.08]

Table 5: **Forecasting Stock Excess 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-month (1-quarter) lagged lending gap (conditional forecast). 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 January 1947 to December 2014.

	Monthly Excess Returns				Quarterly Excess Returns			
	$\bar{R}^2_{oos}$	$\Delta RMSE$	$MSE-F$	$ENC-NEW$	$\bar{R}^2_{oos}$	$\Delta RMSE$	$MSE-F$	$ENC-NEW$
From 1957	0.0083	0.0002	5.8398	5.0970	0.0099	0.0004	2.3177	3.7348
From 1967	0.0057	0.0001	3.2769	2.9638	0.0135	0.0006	2.6263	4.0320
From 1977	0.0055	0.0001	2.5399	1.7184	0.0251	0.0011	3.9164	4.5202
From 1987	0.0138	0.0003	4.6945	1.6202	0.0405	0.0018	4.7261	4.5807
From 1997	0.0233	0.0006	5.1473	1.0517	0.0468	0.0021	3.5378	3.4162

Table 6: **Long Horizon Regression: Quarterly Stock Excess Returns**

The table reports results from long-horizon regressions of quarterly log returns on lagged variables: $r_{t+1}+...+r_{t+H} = \alpha+\beta\cdot Lgap_t+\gamma\cdot Z_t+\epsilon_{t+1}$, where H denotes the return horizon in quarters and the dependent variable is the sum of H log returns on the CRSP Value-weighted stock market index, $r_{t+1} + ... + r_{t+H}$. Newey-West corrected t-statistics appear in parentheses below the coefficient estimate and adjusted R^2 statistics in square brackets. The sample period is Q1:1947 to Q4:2014.

	Forecast Horizon H				
Regressors	1	2	4	8	12
$Lgap$	-0.24	-0.42	-0.61	-0.41	-0.16
	(-2.45)	(-2.25)	(-1.95)	(-0.90)	(-0.31)
$\bar{R}^2$	[0.03]	[0.04]	[0.04]	[0.01]	[-0.00]
$Lgap$	-0.26	-0.48	-0.64	-0.15	0.48
	(-2.70)	(-2.57)	(-2.25)	(-0.42)	(1.20)
DEF	2.70	5.95	7.87	0.69	-8.72
	(1.72)	(2.74)	(2.37)	(0.11)	(-1.23)
$TERM$	-0.19	-0.64	0.09	5.33	11.47
	(-0.32)	(-0.61)	(0.05)	(2.15)	(4.28)
RF	-6.06	-12.25	-19.11	-13.64	-5.88
	(-2.26)	(-2.68)	(-2.67)	(-1.23)	(-0.49)
dp	0.03	0.07	0.13	0.24	0.34
	(2.69)	(2.91)	(3.21)	(3.79)	(5.72)
$\bar{R}^2$	[0.06]	[0.12]	[0.19]	[0.24]	[0.38]
$Lgap$	-0.32	-0.59	-0.85	-0.40	0.23
	(-3.13)	(-3.09)	(-2.88)	(-0.98)	(0.45)
DEF	3.62	9.20	15.41	14.28	7.05
	(1.57)	(3.09)	(3.87)	(2.93)	(1.37)
$TERM$	-1.20	-2.79	-3.59	-0.18	4.47
	(-1.69)	(-2.05)	(-1.65)	(-0.07)	(1.61)
RF	-10.05	-21.41	-36.83	-40.67	-32.04
	(-3.11)	(-4.37)	(-5.05)	(-3.59)	(-2.97)
dp	0.03	0.07	0.14	0.26	0.32
	(2.12)	(2.18)	(2.75)	(3.36)	(3.93)
cay	0.76	1.85	3.89	6.47	7.15
	(1.74)	(2.48)	(3.18)	(3.52)	(3.14)
$ntis$	-0.21	-0.04	0.02	0.66	1.56
	(-0.63)	(-0.07)	(0.02)	(0.51)	(1.29)
gap	-0.00	0.08	0.42	0.91	0.74
	(-0.02)	(0.31)	(1.05)	(1.70)	(1.14)
$\bar{R}^2$	[0.08]	[0.18]	[0.29]	[0.38]	[0.48]

Table 7: **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 monthly and quarterly log excess CRSP-VW return on a constant and on a one-quarter lagged lending gap. 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 and Panel C describes confidence intervals from a Monte Carlo simulation. 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 $r_t = \gamma + e_t$, $Lgap_t = \mu + \phi \cdot Lgap_{t-1} + \nu_t$ where r_t is the log excess return on the monthly and quarterly CRSP-VW index. The parameters in the data-generating process are set to the sample estimates for the bootstrap and the Monte Carlo. We then compute OLS regressions with a Newey-West standard error correction: $r_t = \alpha + \beta \cdot Lgap_{t-1} + \epsilon_t$ 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 January 1947 to December 2014.

Panel A: Campbell and Yogo (2006) Test				
Variable	t-stat($\hat{\beta}$)	$\hat{\beta}$	90% CI: β	
			t-test	Q-test
Monthly CRSP	-3.473	-0.020	[-0.030,-0.011]	[-0.032,-0.013]
Qurterly CRSP	-2.860	-0.037	[-0.059,-0.016]	[-0.067,-0.023]

Panel B: Bootstrap Stock Return Test						
Variable	t-stat($\hat{\beta}$)	95% CI	99% CI	$\bar{R}^2$	95% CI	99% CI
Monthly CRSP	2.44	(-2.01 2.00)	(-2.68 2.65)	0.01	(-0.00 0.00)	(-0.01 0.01)
Qurterly CRSP	2.45	(-2.09 2.09)	(-2.79 2.80)	0.03	(-0.00 0.01)	(-0.01 0.03)

Panel C: Monte Carlo Stock Return Test						
Variable	t-stat($\hat{\beta}$)	95% CI	99% CI	$\bar{R}^2$	95% CI	99% CI
Monthly CRSP	2.44	(-2.01 2.02)	(-2.66 2.68)	0.01	(-0.00 0.01)	(-0.00 0.01)
Quarterly CRSP	2.45	(-2.08 2.09)	(-2.79 2.81)	0.03	(-0.00 0.01)	(-0.00 0.03)

Table 8: **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: $vol_t = \alpha + \beta \cdot Lgap_{t-1} + \gamma \cdot X_{t-1} + \epsilon_t$, where vol_t are $rvol$ and $lrvol$. Newey-West corrected t-statistics appear in parentheses below the coefficient estimates and adjusted R^2 statistics in square brackets. The sample period is Q1:1947 to Q4:2014.

			Panel A: *Realized Volatility*			
$Lgap$	0.20	0.16	0.21	0.15	0.15	0.18
	(1.99)	(2.44)	(2.96)	(2.56)	(2.27)	(3.06)
DEF		3.10	2.95	2.91	3.28	3.30
		(4.70)	(4.37)	(4.95)	(4.93)	(4.81)
$TERM$		-0.26	-0.06	-0.26	0.02	0.13
		(-0.87)	(-0.19)	(-0.85)	(0.07)	(0.42)
RF		-2.42	-1.06	-2.35	-2.14	-1.41
		(-1.76)	(-0.73)	(-1.73)	(-1.62)	(-1.02)
dp		-0.03	-0.03	-0.03	-0.02	-0.03
		(-4.53)	(-6.33)	(-4.05)	(-3.56)	(-4.04)
cay			-0.04			0.12
			(-0.35)			(0.74)
$ntis$				-0.12		-0.08
				(-0.64)		(-0.49)
gap					0.08	0.11
					(2.26)	(1.80)
Constant	0.06	-0.05	-0.08	-0.04	-0.04	-0.06
	(18.56)	(-2.13)	(-3.78)	(-1.57)	(-1.61)	(-2.32)
$\bar{R}^2$	[0.11]	[0.29]	[0.34]	[0.29]	[0.30]	[0.34]
			Panel B: *Log Realized Volatility*			
$Lgap$	2.19	1.66	2.21	1.62	1.47	2.00
	(2.19)	(2.30)	(3.12)	(2.22)	(2.00)	(2.83)
DEF		39.76	37.27	38.93	42.57	41.47
		(5.88)	(5.57)	(5.23)	(6.18)	(5.08)
$TERM$		-3.00	0.80	-2.99	1.34	2.51
		(-0.77)	(0.19)	(-0.76)	(0.33)	(0.63)
RF		-17.62	8.64	-17.34	-13.28	4.77
		(-1.16)	(0.53)	(-1.13)	(-0.91)	(0.29)
dp		-0.35	-0.48	-0.35	-0.28	-0.43
		(-4.15)	(-6.71)	(-3.80)	(-3.02)	(-4.65)
cay			-1.61			0.04
			(-1.05)			(0.02)
$ntis$				-0.52		-0.32
				(-0.27)		(-0.19)
gap					1.21	1.03
					(2.28)	(1.48)
Constant	-2.86	-4.37	-4.97	-4.34	-4.20	-4.80
	(-62.03)	(-13.35)	(-16.58)	(-11.66)	(-12.40)	(-13.23)
$\bar{R}^2$	[0.09]	[0.30]	[0.38]	[0.30]	[0.32]	[0.38]

Table 9: **Forecasting Quarterly Stock Excess Returns in Tightening Credit Conditions**

The table reports estimates of OLS regressions of stock returns on one-quarter lagged predictive variables: $r_t = \alpha + \beta \cdot Lgap_{t-1} + \delta \cdot Tightening_{t-1} + \lambda \cdot lgap_{t-1} \cdot Tightening_{t-1} + \gamma \cdot Z_{t-1} + \epsilon_t$, where r_t is the log excess return on the CRSP-VW index. Tightening is a dummy variable when credit standards is greater than 0. 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 Q4:2014.

	Excess returns on CRSP					
$Lgap$	0.22	0.19	0.21	0.20	0.19	0.22
	(1.99)	(1.22)	(1.29)	(1.25)	(1.21)	(1.28)
$Tightening$	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
	(-1.67)	(-1.12)	(-1.11)	(-1.08)	(-1.07)	(-1.06)
$Lgap{\cdot}Tightening$	-0.74	-1.00	-0.99	-0.97	-0.99	-0.98
	(-3.31)	(-3.61)	(-3.53)	(-3.32)	(-3.61)	(-3.39)
DEF		5.16	4.76	5.20	5.17	4.76
		(1.54)	(1.36)	(1.53)	(1.53)	(1.32)
$TERM$		-0.78	-1.23	-1.05	-0.81	-1.27
		(-0.53)	(-0.77)	(-0.61)	(-0.45)	(-0.69)
RF		0.18	-4.92	-1.44	0.13	-5.55
		(0.02)	(-0.44)	(-0.16)	(0.02)	(-0.47)
dp		0.04	0.04	0.05	0.04	0.05
		(0.98)	(0.82)	(1.05)	(0.75)	(0.77)
cay			0.35			0.34
			(0.68)			(0.59)
$ntis$				0.18		0.10
				(0.30)		(0.16)
gap					-0.01	0.03
					(-0.04)	(0.10)
Constant	0.04	0.18	0.18	0.20	0.18	0.21
	(6.25)	(0.81)	(0.79)	(0.88)	(0.70)	(0.78)
$\bar{R}^2$	[0.10]	[0.13]	[0.12]	[0.12]	[0.12]	[0.10]

Table 10: **Forecasting Quarterly Stock Excess Returns on Portfolios of Bank Dependent Firms**

The table reports estimates of OLS regressions of stock returns on one-quarter lagged predictive variables: $r_t = \alpha + \beta \cdot Lgap_{t-1} + \gamma \cdot Z_{t-1} + \epsilon_t$, where r_t is the log excess return on the CRSP-VW index and value weighted (VW) portfolios of band dependent firms. Newey-West corrected t-statistics appear in parentheses below the coefficient estimates and adjusted R^2 statistics in square brackets. The sample period is Q1:1985 to Q4:2013.

	Excess returns on CRSP					
$Lgap$	-0.29	-0.38	-0.37	-0.33	-0.38	-0.35
	(-1.84)	(-1.97)	(-1.92)	(-1.93)	(-2.02)	(-1.98)
DEF		1.17	1.71	2.27	1.41	2.20
		(0.48)	(0.64)	(0.81)	(0.55)	(0.77)
$TERM$		-1.78	-2.42	-2.31	-1.96	-2.53
		(-1.94)	(-2.10)	(-1.98)	(-1.77)	(-2.03)
RF		-6.15	-11.94	-7.77	-5.92	-11.37
		(-0.87)	(-1.27)	(-1.04)	(-0.83)	(-1.08)
dp		0.06	0.05	0.07	0.05	0.06
		(1.91)	(1.31)	(2.13)	(0.95)	(1.25)
cay			0.68			0.48
			(1.08)			(0.57)
$ntis$				0.53		0.35
				(1.11)		(0.59)
gap					-0.08	0.02
					(-0.32)	(0.08)
Constant	0.02	0.29	0.25	0.33	0.24	0.30
	(2.19)	(1.73)	(1.39)	(1.87)	(1.04)	(1.35)
$\bar{R}^2$	[0.04]	[0.05]	[0.05]	[0.05]	[0.05]	[0.04]
	Excess returns on Bank Dependent Stocks					
$Lgap$	-0.72	-0.86	-0.85	-0.80	-0.87	-0.82
	(-2.48)	(-2.81)	(-2.74)	(-2.89)	(-2.76)	(-2.81)
DEF		4.24	5.13	5.80	3.86	5.25
		(1.16)	(1.30)	(1.35)	(0.95)	(1.14)
$TERM$		-3.04	-4.11	-3.80	-2.75	-3.86
		(-2.51)	(-2.71)	(-2.52)	(-1.83)	(-2.49)
RF		-20.44	-30.03	-22.74	-20.79	-31.81
		(-1.84)	(-2.09)	(-2.15)	(-1.82)	(-1.86)
dp		0.18	0.16	0.19	0.20	0.23
		(2.67)	(2.24)	(3.00)	(1.98)	(2.56)
cay			1.13			1.03
			(1.17)			(0.74)
$ntis$				0.75		0.57
				(1.05)		(0.59)
gap					0.13	0.34
					(0.33)	(0.77)
Constant	-0.03	0.73	0.66	0.78	0.81	0.93
	(-2.26)	(2.28)	(2.01)	(2.54)	(1.82)	(2.37)
$\bar{R}^2$	[0.09]	[0.22]	[0.22]	[0.21]	[0.21]	[0.21]

Table 11: **Forecasting Quarterly Excess Stock Returns with Macroeconomic Expectation Variables**

This table reports estimates of OLS regressions of excess stock returns on one-quarter lagged predictive variables: $r_t = \alpha + \beta \cdot Lgap_{t-1} + \gamma \cdot Z_{t-1} + \epsilon_t$, where r_t is the log excess stock return on the CRSP-VW index. The variable $GDP4Qavg$ is the average expected growth rate of GDP over the next four quarters from the Survey of Professional Forecasters. The variable $CPI4Qavg$ is the average expected CPI inflation rate over the next four quarters from the Survey of Professional Forecasters. Newey-West corrected t-statistics appear in parentheses below the coefficient estimates and adjusted R^2 statistics are in square brackets. The sample period is Q3:1981 to Q4:2013.

	Excess stock returns on the CRSP-VW index					
$Lgap$	-0.39	-0.59	-0.38	-0.48	-0.33	-0.55
	(-2.39)	(-3.29)	(-2.30)	(-2.95)	(-1.97)	(-2.92)
$GDP4Qavg$	-0.02	-0.03	-0.02	-0.03	-0.02	-0.03
	(-2.55)	(-3.78)	(-2.36)	(-2.58)	(-2.53)	(-2.68)
$CPI4Qavg$	0.03	-0.02	0.02	0.03	0.02	-0.02
	(2.57)	(-1.08)	(2.10)	(2.64)	(1.82)	(-1.20)
DEF		2.27				2.04
		(1.01)				(0.65)
$TERM$		-0.79				-0.75
		(-0.86)				(-0.47)
RF		13.33				12.84
		(1.60)				(1.07)
dp		0.11				0.16
		(2.63)				(2.04)
cay			0.20			-0.04
			(0.57)			(-0.06)
$ntis$				-0.45		0.43
				(-1.25)		(0.92)
gap					-0.19	0.19
					(-1.52)	(0.60)
Constant	0.07	0.59	0.07	0.07	0.07	0.80
	(2.24)	(2.91)	(2.23)	(2.27)	(2.93)	(2.27)
$\bar{R}^2$	0.05	0.12	0.04	0.05	0.06	0.10