Credit Expansion and Aggregate Stock Returns

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Abstract

We provide empirical evidence that credit expansions have a strong prediction power for aggregate stock returns, and suggest possible explanations for the predictability of credit expansions. Credit expansion predicts lower aggregate market returns in subsequent three-month to three-year. We find that credit expansion outperforms popular return predictors both in and out of sample. The information content of credit expansions is economically important and credit expansion can generate utility gains for a mean-variance investor. Moreover, we investigate three potential sources that explain the predictive power of credit expansion: investment-based explanations, misevaluation exploitation explanations and health of financial intermediary explanations. We show that each of the three potential sources plays a distinct role in explaining the return predictability of credit expansions.

Classification codes: G10, G12, G14, G21

Keywords: credit expansion, equity risk premium, investment-based explanation, misevaluation, financial intermediary, return predictability

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1. Introduction

Recent empirical research in finance and economics has dealt with the close link between credit expansions and subsequent instability reflected by banking crisis, housing market crashes, and economic recessions, (e.g., Borio and Lowe 2002, Mian and Sufi 2009, Schularick and Taylor 2012, and Lopez-Salido, Stein, and Zakrajsek 2016). A traditional view on the cause of credit expansion considers overoptimism as an important driver, which is put forward by Minsky (1977) and Kindleberger (1978). However, the cause of credit expansion remains inconclusive because it is still challenging to find definite evidence of overoptimism. According to this view, prolonged periods of economic booms tend to breed optimism, which in turn leads to credit expansions that can eventually destabilize the financial system and the economy. Baron and Xiong (2017) empower this perspective by presenting the evidence of overoptimism and neglect of crash risk by bank equity investors during credit expansions. Including this traditional perspective, we suggest two additional perspectives that potentially explain the underlying sources of the effect of credit expansion on stock returns to identify what drives the effect of credit expansion on stock returns, which is our main goal in this article.

From the perspective of rational explanation, we wonder if countercyclical risk premia are reflected in credit expansion. To examine this possibility, we consider the external habit model of Campbell and Cochrane (1999), which shows that that prolonged consumption growth raises the “surplus consumption ratio”, a measure of how far current consumption is from the habit level. According to their model, a high consumption surplus decreases risk aversion, leading to lower risk premia. We find that that high credit expansion follows periods of rising consumption and that credit expansion forecasts low future returns, which suggests a rational risk-premia explanation. Even though Campbell and Cochrane (1999)’s model does not tell about investment behavior, the decrease in risk premia would plausibly imply a decrease in cost of capital and an increase in investment in a general equilibrium setting with production. This result provides a background of rational rather than behavioral explanations for the return predictability of credit expansion, the investment-based approach which is discussed in section 4.

Before discussing the underlying sources of the return predictability of credit expansion, we need to examine specifically how credit expansion affects the stock market returns. By investigating bank equity returns predicted by credit expansion, Baron and Xiong (2017) examine whether bank shareholders anticipate the risk that large credit expansions often lead to financial distress and whether shareholders demand a risk premium as compensation. They find that although credit expansion predicts an increased equity crash risk in subsequent quarters, credit expansion predicts lower mean bank equity returns in subsequent one to three years, implying that the increased equity crash risk is not compensated by higher equity returns on average. Their analysis demonstrates the clear presence of overoptimism by bank shareholders during bank credit expansions.

Our analysis focus on the effect of credit expansion on market returns. We compare the predictive power of credit expansion with that of well-known predictor variables in the previous literatures. Moreover, we examine the information content of credit expansion, the economic value of the predictive ability from the perspective of mean-variance investors, and at last we suggest the underlying sources for the predictive power of credit expansion.

While Baron and Xiong (2017) focus on in-sample predictability of credit expansion on bank equity returns and nonfinancial equity returns, we extend their analysis to examine the market return predictability of credit expansion in both in-sample and out-of-sample from the short-term to the long-term period. We find a significantly negative return predictability of credit expansion not just in in-sample but in out-of-sample as well.[1] We find positive out-of-sample R^2 statistics (Campbell and Thompson, 2008) of 1.87%, 3.45%, 8.95%, 18.37%, and 23.44% at horizons of three-month, six-month, one-, two-, and three-year, respectively, which are statistically significant and substantially larger than those for all of the well-known predictors in the literature. Credit expansion outperforms a host of well-known existing return predictors in both in-sample and out-of-sample tests over subsequent three months to three years.

We also show that forecasts based on credit expansion have superior information content relative to forecasts based on existing predictors. Moreover, we measure the economic value of predictability of credit expansion from an asset allocation perspective. Our analysis focuses on information content regarding credit expansion from the perspective of a mean-variance investor. Baron and Xiong (2017) are concerned about the relatively modest R^2, which implies that constructing a high Sharpe ratio trading strategy based on credit expansion may be challenging even though credit expansion has return predictability. Our results will ease the concern. We find that traders are able to obtain substantial CER (certainty equivalent return) gains or to construct a high Sharpe ratio trading strategy based on the return forecasts of credit expansion. Credit expansion generates stunning CER gains and striking Sharpe ratios for the 2007:01-2015:12 period encompassing the Global Financial Crisis. The sparkling results of credit expansion during the period of 2007:01-2015:12 is consistent with the recent finding of Rapach, Strauss, and Zhou (2010), Henkel, Martin, and Nardari (2011), Rapach and Zhou (2013), and Neely, Rapach, Tu, and Zhou (2014), who show that aggregate stock return predictability and the associated utility gains tend to be particularly sizable around periods of severe economic recessions.

Now, we return to our main research question why credit expansion predicts future market returns. In this article, we address three potential sources of return predictability of credit expansion: (1) investment-based explanations, (2) misevaluation exploitation explanations, and (3) health of financial intermediary explanations. In attempting to discriminate between these sources, we recognize that it is impossible to fully exclude one explanation or another. Furthermore, there is little reason to believe that there is just one channel to work for the predictability.

First, we consider whether the results might be explained by investment-based models in which q-theory of investment and real options theory imply a negative relation between real investment and expected returns. Cochrane (1991) and Zhang (2005) derive the negative relation between real

[1] Goyal and Welch (2008) show that, despite significant evidence of in-sample predictive ability, well-known predictor variables in the literature fail to predict the equity risk premium in the context of out-of-sample tests.

investment and expected returns. We explore empirically the investment-based hypothesis for the explanation of the negative return predictability of credit expansion.

Under the investment-based theory, firms raising capital are likely to invest more and earn lower expected returns, and firms distributing capital are likely to invest less and earn higher expected returns. Lyandres, Sun and Zhang (2008) document that equity issuers and debt issuers invest more than matching nonissuers at the firm level. We extend the mechanism of investment-based model to the market-level, which infers that credit expansion induces higher investment at the aggregate level and earns lower expected market returns and that credit contraction induces lower investment at the aggregate level and earns higher expected market returns. Thus, we expect negative expected returns following credit expansions when investment level is high or when the greater growth of investment is observed. In this paper, we empirically find that the predictive power of credit expansion is particularly strong when investment level is high or the growth of investment is high, implying that the negative return predictability of credit expansion is related to the information regarding the future low cost of capital. Thus, credit expansion and investment interact to give credit expansion even stronger predictive power.

Second, we suggest misevaluation exploitation explanations in which firms exploit misevaluations of securities by issuing securities when they are overvalued and by repurchasing securities when they are undervalued. Although the investment-based explanation explains large part of the predictive power of credit expansion, the investment effect does not fully explain the predictive power. The reason is that the negative return predictability of credit expansion might be derived from investors' irrational market valuation, such as overpricing in the bond or stock markets. Bradshaw, Richardson and Sloan (2006) find that a negative relation between external financing (equity financing or debt financing) and both future stock returns and future profitability, and show that their measure of external financing is positively related to overoptimism in analysts' forecasts, supporting the misevaluation as explanations for the negative relation between external financing and future stock returns at the firm-level.

We use the market-wide disagreement measure to capture the extent that stock markets reflect investors' overoptimism based on Miller(1977)'s model in which stock prices reflect only the beliefs of optimists in the presence of both divergence of opinion among investors and short-sale constraints. We find that market-wide disagreement increases with credit expansions and thus overoptimism during credit expansion becomes readily reflected in stock markets, which results in overvaluation in stock markets. We also find deeper negative expected returns following credit expansion when market-wide disagreement is high, which implies that the sentiment associated with credit expansion and the extent of market-wide disagreement amplify each other in predicting market returns.

To directly examine the mispricing effect on the predictability of credit expansion, we use the investor sentiment measures defined by Baker and Wurgler (2006). We find that overoptimism is maintained for three months following the high-sentiment period, and then the more deeply negative returns are realized following higher sentiment period for the long term.

Lastly, we consider the balance sheet healthiness of financial intermediary as a potential explanation for the predictability of credit expansion because it is known that expected returns fluctuate depending on the health of financial institutions. Following the view that intermediary sector's net worth is the key determinant of its marginal value of wealth, we use the equity capital ratio of financial intermediary to examine the risk tolerance due to financial intermediary-related explanations as the potential source of return predictability of credit expansion.

A growing body of literature argues that fluctuations in intermediary equity capital or balance sheet health may drive in risk premia. Following the tradition of Bernanke and Gertler (1989) and Holmstrom and Tirole (1997), the recent intermediary asset pricing models of He and Krishnamurthy (2012, 2013) and Brunnermeier and Sannikov (2014) show that the intermediary sector's net worth (or, equivalently, its equity capital ratio) is the key determinant of its marginal value of wealth.

To explore the balance sheet healthiness of financial intermediary as explanation for CE's predictability, we use two equity capital ratios. One is the aggregate bank equity to total bank assets (E/A) and the other is the primary dealers' market equity capital ratio (PDE) defined by He, Kelly and Manela (2017). There are two big differences between the two measures. He, Kelly and Manela (2017) include the selected group of financial intermediaries that serve as trading counterparties to the Federal Reserve Bank of New York in its implementation of monetary policy, whereas the E/A measure includes banks as financial intermediary. The other difference is that the E/A measure uses book values of equity while He, Kelly and Manela (2017) use market values of equity.

We find that both the primary dealers' market equity capital ratio (PDE) and the aggregate bank equity to total bank assets (E/A) help to explain the return predictability of credit expansion, but E/A explains more strongly than PDE. The time varying risk premium predicted by credit expansions is associated with the state of the intermediary capital ratio. When the intermediary capital ratio is low, credit expansion predicts lower expected future returns.

We have examined three potential channels for predictive power of credit expansion one by one. Are those channels subsumed by one another? We investigate whether one effect is absorbed by another. The answer is no. Investment-based effect, mispricing effect, and the effect of the healthiness of financial intermediary distinctly and separately still contribute to explain the return predictability of credit expansion. Baron and Xiong (2017) demonstrate the clear presence of overoptimism by bank shareholders during bank credit expansions. Our result does not refute the presence of overoptimism during credit expansions, but rather explains given the presence of overoptimism how the optimism associated with credit expansions is related to equity market by incorporating the investment-based model. The credit boom fuels investment, and consequently markets earn lower expected returns. Thus, the investment-based approach is able to explain the predictive power of credit expansion.

The article is constructed as follows. Section 2 describes the data and measures used in our analysis. Section 3 examines the predictability of credit expansion, the information content and economic value of the predictive ability. Section 4 provides the three potential sources of predictive power of credit expansion. Section 5 concludes.

2. Data

To examine the information content of aggregate credit growth, we construct a credit expansion measure that captures the credit accumulation from 1963 to 2015. To evaluate potential explanations of the underlying variation in expected returns caused by credit expansion, we construct aggregate equity issuance, investment, aggregate disagreement measure, and the capital ratio of intermediary sector.

2.1 Data Construction

1) Credit Expansions

We construct the credit expansion measure using "bank credit" from the Bank for International Settlements (BIS) long series on credit to private non-financial sectors. The term "bank credit" in the BIS data set refers broadly to credit in various forms such as loans, leases and securities extended from banks to domestic households and private non-financial corporations. The dataset excludes interbank lending and lending to governments and related entities. Schularick and Taylor (2012) provide bank loans data that extend back over a century, but the dataset is provided at an annual frequency. Thus, we use the BIS data since it is provided at a quarterly frequency.

Credit expansion is considered as the key explanatory variable (i.e. predictor) in our analysis and is defined by the past five-year percentage point change in bank credit to GDP.

$$\mathrm{CE_t} = \Delta log\left(\frac{bank\ credit}{GDP}\right)_t = log\left(\frac{bank\ credit}{GDP}\right)_t - log\left(\frac{bank\ credit}{GDP}\right)_{t-60} \quad (1)$$

To standardize the magnitude of credit expansion across long time horizon, we divide bank credit by GDP. It is reasonable that bank credit is high when GDP is high, and so we control the GDP growth effect by constructing the measure for credit expansion dividing by GDP growth.

We use the change in bank credit per GDP rather than the level of the ratio for the following reason. The change in bank credit is the measure that captures credit expansions and contractions while the level of credit exhibits a long-term trend. The increase in bank credit represents the increase in the amount of new lending to private non-financial sector. Moreover, according to Baron and Xiong (2017) credit expansions cause the crash risk of stock prices, and Schularick and Tylor (2012) show that credit growth eventually leads to a financial crisis. Thus, we expect that the change in bank credit per GDP rather than the level has the prediction power on aggregate stock returns. We use the 5-year change in bank credit per GDP for the main analysis. We add the results of out-of-sample test by using the 1-year and 3-year change as a predictor for robustness checks in section 3.1, and the results are consistent with the results of using the 5-year change.

2) Other Predicting Variables

To relate our findings to the voluminous literature on market return predictability, we compare the predictive ability of aggregate credit expansion to that of 14 popular predictor variables from Goyal and Welch (2008). Rapach, Ringgenberg, and Zhou (2016) compare their main variable, short interest, with 14 popular predictors to give concrete evidence that short interest has a strong return predictability. We follow their comparison framework to relate the predictability of credit expansion to the literature on market return predictability. The included predictors are described in detail in Table 1. We first compare the forecasting power of individual predictor with credit expansion. To isolate effects associated with bank credit expansion, we extract the first three principal components from the entire set of Goyal and Welch (2008) variables, and use the three principals as controls for the popular predictors. Because credit expansion measure is provided at a quarterly frequency, the 14 predictors are used at quarterly frequency in our predictive regression analysis even though they are provided at monthly frequency.

[Table1]

3) Market excess return

Following the existing literature on predicting aggregate returns, we focus on predicting the excess return on a value-weighted portfolio. We measure the market excess return as the log return on the S&P 500 index minus the log return on a one-month Treasury bill. Because our main explanatory variable is provided at a quarterly frequency, we use quarterly excess return as the main dependent variable.

4) Equity financing measure

To explore investment-based approach when suggesting a potential source for the return predictability of credit expansion, we include equity financing in our analysis because equity financing is alternative to debt financing for external financing. We construct a stock-level equity issuance measure by using the shares outstanding and the cumulative factor to adjust shares outstanding from the CRSP database. We then aggregate this stock-level equity issuance measure and construct the aggregate equity issuance. Daniel and Titman (2006) construct a composite share issuance measure that takes into account share-issues, repurchases, and equivalent actions. The share issuance measure is the part of a firm's growth in market value that is not attributable to stock returns. We follow their construction method, but do not take log for the measure.

5) Investment

We construct the real investment per GDP and the growth of real investment per GDP by using the real investment data from the database of Federal Reserve Bank of St. Louis. We use the seasonally adjusted investment measure and remove a linear trend from the investment measure during our sample period. We use the 5-year growth of real investment per GDP because the main explanatory variable is the 5-year growth of bank credit per GDP. We also employ the investment to capital ratio proposed in Cochrane (1991), which is defined by the ratio of aggregated (private nonresidential fixed) investment to aggregate capital for the whole economy.

6) Disagreement

Following Hong and Sraer (2016), we establish a market-wide aggregate disagreement measure. We first calculated the stock-level disagreement measure as the dispersion in analyst forecasts of the

EPS LTG from the I/B/E/S dataset. We then aggregate this stock-level disagreement measure, weighting by its preranking β. We have high-β stocks to play major role in the aggregate disagreement measure because disagreement about a low-β stock has to come mostly from idiosyncratic disagreement. Thus, we weight each stock's disagreement by the stock's prerankiung β, following Hong and Sraer(2016). The aggregate disagreement measure reflects divergence about market valuation.

7) Sentiment

We measure investor sentiment using the monthly market-based sentiment series constructed by Baker and Wurgler (2006). The BW sentiment index spans over 42 years, from July 1965 to December 2007. Baker and Wurgler form their composite index by taking the first principal component of six measures of investor sentiment, since the first component captures much of the common variation (49%). The principal component analysis filters out idiosyncratic noise in the six measures and captures their common component. The six measures are the closed-end fund discount, the number and the first-day returns of IPOs, NYSE turnover, the equity share in total new issues, and the dividend premium. Baker and Wurgler construct orthogonalized investor sentiment measure by using the residual from the regression of each of the six raw proxies on growth in the industrial production index, growth in consumer durables, nondurables, and services, and a dummy variable for NBER recessions. We use the original investor sentiment measure as well as the orthogonalized investor sentiment measure.

8) Capital ratio of intermediary sector

To obtain the capital ratio of the intermediary sector, we need to define financial intermediary sector. Our first definition of the financial intermediary sector is commercial banks in the United States. We use aggregate bank equity to total bank assets (E/A) as the capital ratio of the intermediary sector. Bank asset and equity data are obtained from the database of Federal Reserve Bank of St. Louis. We use the detrended bank equity to total bank assets.

We next consider the set of primary dealers as the intermediary sector, following the definition of He, Kelly and Manela (2017). We obtain the aggregate primary dealer capital ratio from Zhiguo He's website. The set of primary dealers includes the selected group of financial intermediaries that serve as trading counterparties to the Federal Reserve Bank of New York in its implementation of monetary policy. This selected group includes the likes of Goldman Sachs, JP Morgan, and Deutsche Bank.

2.2 Summary Statistics

Table 2(a) shows summary statistics for credit expansion (i.e., the annualized past five-year change in bank credit per GDP), aggregate equity issuance, real investment per GDP, investment growth, aggregate disagreement, aggregate bank equity to total bank assets, the capital ratio of primary dealers.

Credit expansion is on average 2.96% a year. Because Baron and Xiong (2017) use the annualized past three-year change in bank credit per GDP, their measure has the mean of 1.3% a year. In terms of variability, credit expansion grows as rapidly as 22 percentage points of GDP a year (in the 95th percentile) and contracts as rapidly as -23 percentage points of GDP a year (in the 5th percentile).

We examines time-series correlations for credit expansion and other variables. Because each variable is sampled over different time periods due to the data availability, the time-series correlations are not calculated using the same time-series data for every variable. Table 2(b) presents Pearson correlation coefficients between credit expansion and the seven aggregate variables: aggregate equity issuance (EQT), investment (INV), investment growth (ΔINV), market-wide disagreement (DIS), aggregate bank equity to total bank assets (E/A), the primary dealer capital ratio (PDE) constructed by He, Kelly and Manela (2017), and the investment to capital ratio (IK) proposed in Cochrane (1991) . Credit expansion has a correlation of 0.28 with investment level, 0.32 with investment to capital ratio and 0.23 with market-wide disagreement measure. The correlation between credit expansion and E/A is 0.08 and the correlation between credit expansion and PDE is 0.04.

[Table2]

We examine Pearson correlation coefficients between credit expansion and the 14 popular predictors from Goyal and Welch (2008), which we add the correlation matrix in the appendix. Credit expansion appears largely unrelated to most of the 14 predictors. The strongest correlation (in magnitude) between credit expansion and one of the popular predictors occurs with term spread (TMS), which has a correlation of -0.41. The correlation between credit expansion and default return spread (DFR) is also negative (-0.07). The both negative correlations and the positive correlation between credit expansion and investment indicate that credit expansion is procyclical. However, the all of the correlations are below 0.41 in absolute value, implying that the credit expansion measure appears to contain substantially different information from many of the stock return predictors used in the existing literature.

3. Empirical Results

In this chapter, we focus on examining the predictive power of credit expansion and its information content. We examine whether credit expansion has the predictive power before and after controlling for the 14 popular predictor variables. For the controls, we extract the first three principal components from the entire set of Goyal and Welch (2008) variables. We then implement out-of-sample tests according to Goyal and Welch (2008), who show that the in-sample predictive ability of a variety of plausible return predictors generally does not hold up in out-of-sample tests. In addition, we compare the information content from credit expansion to that from other predictors by using forecast encompassing tests. Lastly, we measure the economic value of CE (credit expansion)'s predictive ability from asset allocation perspective.

3.1 Theory-implied risk premia

Before implementing a standard predictive regression approach, we discuss whether countercyclical risk premia are reflected in credit expansion. Based on the correlation evidence that credit expansion is procyclical in section 2.2, we wonder if credit expansion reflects countercyclical risk premia. To examine this possibility, we consider the recent asset pricing literature that suggests a number of possible underlying mechanisms for countercyclical risk premia. The external habit model of Campbell and Cochrane (1999) shows that prolonged consumption growth raises the "surplus consumption ratio", a measure of how far current consumption is from the habit level. According to Campbell and Cochrane (2001), a high consumption surplus decreases risk aversion, leading to lower risk premia. Therefore, the result that credit expansion follows the increase in surplus consumption ratio and forecasts low future returns infers that credit expansion reflects countercyclical risk premia and thus suggests a rational risk-premia explanation.

We implement the regression tests in which the dependent variable is $ln(bank\ loan_{t+1}/bank\ loan_{\ t})$, and explanatory variables include the surplus consumption ratio computed using the model of Campbell and Cochrane (1999) and an S&P 500 volatility computed from daily index returns. Following Jones and Tuzel (2013), we compute the consumption surplus by applying the Campbell-Cochrane habit model to the per capita consumption series using the parameter values reported in their paper. The volatility of theS&P500 Index, an alternative measure of economic uncertainty, is computed as the standard deviation of the most recent 12 months of daily returns.

The result in Table 3 clearly shows that credit expansion has a significant relation to the consumption surplus and to sock return volatility. The strongly significantly positive relation between the surplus consumption and credit expansion indicates that external habit is a driver of variation in credit expansion. Although the stock return volatility shows significantly negative effect on credit expansion, the effect is absorbed by the surplus of consumption.

In sum, credit expansion is significantly related to the well-known variables that drive risk premia under standard asset pricing models. The finding that high credit expansion follows periods of rising consumption and forecasts low future returns suggests a rational risk-premia explanation. When the surplus consumption ratio is high, aggregate risk aversion falls, leading to a decline in market-wide risk premia. Although Campbell and Cochrane (2001)'s model is silent about investment behavior, the decrease in risk premia would plausibly imply an increase in investment in a general equilibrium setting with production. This result provides a background of rational rather than behavioral explanations for the return predictability of credit expansion, which will be discussed in section 4.1. In the next section, we examine directly the relation between credit expansion and risk premia by using a standard predictive regression approach.

3.2 Predictive regression analysis

In this section, we begin with applying a predictive regression model, which is the standard framework for analyzing stock return predictability. We conduct in-sample and out-of-sample tests.

3.2.1 In-sample test

A standard predictive regression model is

$$r_{t:t+h} = \alpha + \beta x_t + \epsilon_{t:t+h} \ \ for \ \ t = 1, \dots, T-h, \tag{2}$$

where $r_{t:t+h} = (1/h)(r_{t+1} + \cdots + r_{t+h}), r_t$ is the S&P 500 log excess return for month t, and x_t is a predictor variable. Consistent with the existing literature on predicting aggregate returns, we focus on predicting the excess return on a value-weighted market portfolio. Because the key predictor variable in our analysis is provided at a quarterly frequency, quarterly excess return is the main dependent variable.

Baron and Xiong (2017) show the significantly negative sign of β for predicting one-, two-, and three-year-ahead excess returns, when using three-year change in bank credit per GDP. We find that when we use five-year change in bank credit per GDP, credit expansion shows strong predictability even for three-, and six-month-ahead excess returns. Table 4 presents the in-sample predictive regression results associated with predicting three-month, six-month, one-, two-, and three-year-ahead excess returns. A one standard deviation increase in credit expansion predicts 8.3%, 16.7%, and 36.8% of decreases in the subsequent three-month, six-month, and one-year-ahead excess returns, respectively, all significant at the 5% level. Coefficients are roughly proportional to the forecasting horizon, meaning that the predictability is persistent and roughly constant per year up to three years.

We test the predictive power of credit expansion after controlling for the popular predictors taken together by including the first three principal components extracted from the entire set of Goyal and Welch (2008) variables. Ludvigson and Ng(2007) show that principal components provide an effective strategy for incorporating the information from a large number of economic variables in predictive regression models for stock returns. The last two rows of Table 4(a) show the coefficient of CE without and with the first three principal components. When the first three principal components are included for the controls, the coefficients are slightly smaller but still significant at the 5% level. The result implies that controlling for the popular predictors from literature does not affect the predictive ability of credit expansion.

Table 4(b) shows the coefficients on the first three principal components with and without CE. The size of the coefficient on the first principal component (PC1) becomes smaller and the significance becomes weaker when we include CE as an additional explanatory variable. PC1 is correlated with term spread by 0.88, correlated with default yield spread by 0.42 and correlated with long-term yield by 0.34. On the other hand, the second principal component (PC2) is correlated with long-term return by 0.98[2], and the size and the significance of the coefficient on PC2 does not change much when we include CE. The result that including CE affects only on PC1, but not on PC2, is consistent with the fact that CE is highly correlated with the term spread by -0.41 and is correlated with the long-term return only by 0.03.[3]

In the analysis we implement in section 4, we employ the principal components for controls, but the result does not change the analysis without the principal components, consistent with the result in this section. Thus, we report the result implemented without the principal components in section 4.

2 PC3 has strongest correlations with Treasury bill rate by 0.99, and long-term yield by 0.94, and its coefficient is significant at the 10% level at three- and six-month horizons.

3 The correlation between PC1 and CE is -0.43, the correlation between PC2 and CE is -0.04, and the correlation between PC3 and CE is 0.03.

Regarding the controls, table reports the result of using each of 14 predictors as an explanatory variable. For consistency, we use quarterly excess return as the dependent variable, and the latest value of each predictor as the explanatory variable. The signs of these coefficients are in line with prior work on equity premium predictability. RVOL and LTR show significant coefficients for predicting three-, and six-month-ahead excess returns, and LTR, TMS, INFL show significant coefficients for predicting one-, two-, and three-year-ahead excess returns. Nevertheless, the coefficient for credit expansion retains rather bigger coefficient and significant when the controls are added.

[Table4]

Table 4 also reports R^2 statistic. In the univariate framework with just credit expansion as the predictor, the R^2 is 1.51%, 2.85%, 7.05%, 16.1% and 26.07% for three-month, six-month, one-, two-, three-year-ahead market excess return, respectively. Adding the first three principal components for controls increases the R^2 to 3.74%, 6.81%, 11.71%, 21.73% and 32.83% for the same horizons. Baron and Xiong (2017) remark that the relatively modest R^2 implies that it may be challenging for policy makers to adopt a sharp, real-time policy to avoid the severe consequences of credit expansion and for traders to construct a high Sharpe ratio trading strategy based on credit expansion. We will examine and discuss the performance of the trading strategy based on credit expansion by measuring CER (certainty equivalent return) gains and Sharpe ratios in section 3.3. Overall, the return predictability of credit expansion is strong compared to other predictors examined in the previous literature.

Baron and Xiong (2017) show that despite the increased crash risk associated with bank credit expansion, the predicted excess return is lower rather than higher. We suggest potential explanations for the underlying variation in the predicted excess return in section 4.

3.2.2 Out-of-sample test

To examine the robustness of the in-sample results, we conduct out-of-sample tests of return predictability. Goyal and Welch (2008) emphasize the importance of out-of-sample tests to assert the return predictability of variables, showing that in-sample predictability of many plausible return predictors generally does not stand in out-of-sample tests. For each predictor, we compute a predictive regression forecast as

$$\hat{r}_{t:t+h} = \hat{\alpha}_t + \hat{\beta}_t x_t, \tag{3}$$

where $\hat{\alpha}_t$ and $\hat{\beta}_t$ are the OLS estimates of α and β, respectively, based on data from the beginning of the sample through *t*. The average excess return from the beginning of the sample through *t* (i.e. the prevailing mean forecast) serves as a benchmark in computing out-of-sample R^2. This prevailing mean forecast corresponds to the constant expected excess return model in our predictive regression model with $\beta = 0$, and implies that returns are not predictable.

Table5A reports the out-of-sample R^2 statistic (R^2_{os}), the proportional reduction in mean squared forecast error (MSFE) at the h –month horizon for a predictive regression forecast of the S&P 500 log excess return based on the predictor variable from MSFE for the prevailing mean benchmark forecast, consistent with Campbell and Thompson (2008). We evaluate the excess-return forecasts in two forecast evaluation periods, 1983:01-2015:12 and 2007:01-2015:12 surrounding the recent crisis. We use the Clark and West (2007) statistic to examine whether the predictive regression forecast delivers a statistically significant improvement in MSFE. The null hypothesis that the prevailing mean MSFE is less than or equal to the predictive regression MSFE is defined against the alternative hypothesis that the prevailing mean MSFE is greater than the predictive regression MSFE (corresponding to $H_0: R_{os}^2 \leq 0, H_A: R_{os}^2 > 0$)

[Table 5]

As indicated by the negative R_{os}^2 statistics in Table5A, all popular predictors fail to outperform the prevailing mean benchmark except TMS and INFL for longer horizons, confirming the findings of Goyal and Welch (2008). In contrast, the R_{os}^2 statistic of credit expansion is 1.87%, 3.45%, 8.95%, 18.37%, and 23.44% for three-month, six-month, one-, two-, three-year-ahead market excess return, respectively, and significant at the 1% level according to the Clark and West (2007) statistic. Thus, unlike the 14 popular predictors, credit expansion outperforms the prevailing mean benchmark for all horizons.

The out-of-sample performance of credit expansion becomes stronger during the period surrounding the recent global financial crisis (2007:01-2015:12). The R_{os}^2 statistics become larger at every horizons in that period: 4.83%, 7.17%, 16.46%, 26.79%, and 31.03%, which is consistent with the finding of Rapach, Strauss, and Zhou (2010)[4] , Henkel, Martin, and Nardari (2011)[5] , Rapach, Ringgenberg, and Zhou (2016)[6] , and Neely, Rapach, Tu, and Zhou (2014)[7], who show that aggregate stock return predictability is particularly sizable around periods of severe economic recessions.

Considering other predictors, INFL outperform the benchmark for the semi-annual, annual, and two-year horizons, but its R_{os}^2 statistics (2.02%, 7.07%, 3.28%) are still well below that of CE (3.45%, 8.95%,18.37%). TMS also outperforms the benchmark but its performance is still well below that of CE, and moreover the R_{os}^2 statistics at three-month and six-month horizons are negative. In sum, CE is the only predictor with a meaningfully lower MSFE than the benchmark at every horizon. The R_{os}^2 statistic for CE is sizable and significant at every horizon for both forecast evaluation periods.To check robustness of the credit expansion measure, we use two alternative credit expansion measures instead of the 5-year credit expansion; the 1-year and 3-year credit expansions.

Table5B shows the results of out-of-sample tests when we use 1-year, 3-year change in bank credit

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4 Rapach, Strauss, and Zhou (2010) recommend combining individual forecasts, such as the forecast based on the dividend yield and that on the term spread, examine the return predictability during periods of "good", "normal", and "bad" economic growth, and show that out-of-sample predictability are concentrated in bad periods.

5 Henkel, Martin, and Nardari (2011) provides the evidence that the short-horizon performance of aggregate return predictors such as the dividend yield and the short rate appears non-existent during Expansions but sizable during contractions.

6 Rapach, Ringgenberg, and Zhou (2016) present sizable out-of-sample CER gains during the period of 2007:01-2014:12, which we explore in the section 3.3, when they use short interest as the main explanatory variable.

7 Neely, Rapach, Tu, and Zhou (2014) use technical indicators as the main explanatory variables and find that only during the recession periods the R_{os}^2 statistics are significantly positive.

to GDP as the main explanatory variable during the 1983:01-2015:12 period. The table reports out-of-sample R^2 statistics and the statistical significance based on the Clark and West (2007). R^2_{OS} of the 3-year credit expansion measure are all significantly positive for predicting three-month, six-month, one-, two-, and three-year returns. R^2_{OS} of the 1-year credit expansion measure are also significantly positive for predicting one-, two-, and three-year returns, relatively longer horizons. From the results, we find that the 5-year credit expansion measure shows the strongest predictability and the 3-year credit expansion measure shows the next strongest predictability. This finding implies that the longer-period credit expansion measure has more information than shorter-period measures when we consider credit expansion as an explanatory variable for predicting stock returns.

3.3 Forecast encompassing tests

To directly compare the information content of the predictive regression forecasts, we conduct forecast encompassing tests. We define an optimal combination forecast as a weighted average of individual forecasts, and estimate the weight that should satisfy the condition that the combined forecast maximize out-of-sample R^2. Because our main predictor is credit expansion, we find the optimal weight for the combination of a predictive regression forecast based on one of the popular predictors and based on credit expansion. The combined forecast is

$$\hat{r}^{*}_{t:t+h} = (1-\lambda)\hat{r}^{i}_{t:t+h} + \lambda\hat{r}^{CE}_{t:t+h}, \tag{4}$$

where $\hat{r}^{i}_{t:t+h}(\hat{r}^{CE}_{t:t+h})$ is the predictive regression forecast based on one of the popular predictors (credit expansion) and $0 \leq \lambda \leq 1$. If $\lambda = 0$, the optimal combined forecast does not include any information of the predictive regression forecast based on credit expansion so that predictive regression forecast based on one of the popular predictor encompasses the predictive regression forecast based on credit expansion. If $0 < \lambda < 1$, then the optimal combined forecast includes both information from one of the popular predictors and credit expansion. If $\lambda = 1$, the optimal combined forecast only incorporates information from credit expansion, and the predictive regression forecast based on credit expansion encompasses a predictive regression forecast based on one of the popular predictors.

[Table6]

Table6 reports the results of encompassing test in the forecast evaluation period of 1983:01-2015:12. The second through sixth columns report the estimate of λ corresponding to each popular predictor and indicate the significance of the estimate using the procedure of Harvey, Leybourne and Newbold (1998). Most $\hat{\lambda}$ estimates equal one meaning that the optimal forecast only incorporates information from CE. In the case of that the $\hat{\lambda}$ estimates do not equal one, the $\hat{\lambda}$ estimates are sizable and close to one meaning that optimal forecast mainly incorporates information from CE. Based on the forecast encompassing test, the predictive regression forecast based on credit expansion always or almost encompasses a predictive regression forecast based on one of the popular predictors.

In sum, we have strong evidence that $\lambda = 1$ or $\lambda \cong 1$ regardless of the popular predictor included in the previous literature, which infers that credit expansion has the superior information content relative to numerous popular predictors with respect to out-of-sample forecasting.

3.4 Asset allocation

In this section, we measure the economic value of CE's predictability from an asset allocation perspective. We examine whether traders are able to obtain bigger CER (certainty equivalent return) gains or to construct a high Sharpe ratio trading strategy based on the return forecasts of credit expansion. Baron and Xiong (2017) are concerned about the relatively modest R^2, which implies that constructing a high Sharpe ratio trading strategy based on credit expansion may be challenging even though credit expansion has return predictability. Our results will ease the concern.

3.4.1 Out-of-sample CER gains

As in Campbell and Thompson (2008), Rapach, Strauss, and Zhou (2010) and Ferreira and Santa-Clara (2011), we consider an investor with mean-variance preferences who allocates between equities and risk-free bills using a predictive regression forecast of excess stock returns. At the end of month, the investor chooses an optimal portfolio weight by

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

where γ is the investor's coefficient on relative risk aversion, $\hat{r}_{t+1}$ is a predictive regression excess-return forecast, and $\hat{\sigma}^2_{t+1}$ is a forecast of the excess return variance. The predictive regression excess-return forecast that we use for the asset allocation analysis is a simple excess return, not the log excess return. Similarly to Campbell and Thompson (2008), we construct the volatility forecast using a ten-year moving window of past returns. The same volatility forecast is used in calculating the optimal weight for the various excess return forecasts and thus the difference in weights derives from the difference in excess return forecasts. We restrict w_t to lie between -0.5 and 1.5.

The average utility or the certainty equivalent return (CER) of the investor is

$$CER = \bar{R}_p - 0.5\gamma\sigma_p^2$$

where $\bar{R}_p$ and σ_p^2 are the mean and variance of the portfolio return over the forecast evaluation period. The certainty equivalent return is the guaranteed return that an investor would be willing to accept rather than holding the risky portfolio. We also compute the CER for the investor who uses the prevailing mean excess return forecast (i.e. simple mean return) instead of the predictive regression forecast when choosing the optimal portfolio weight. Then, CER gain is obtained by subtracting the CER for the investor who uses the prevailing mean excess return forecast from the CER for the investor who uses the predictive regression excess-return forecast. We annualize the CER gain so that it can be interpreted as the annual portfolio management fee that the investor would be willing to pay to have access to the predictive regression forecast in place of the prevailing mean forecast. In this way, we measure the direct economic value of return predictability.

Table7A reports the CER gains accruing to predictive regression forecasts based on each of the 14 popular predictor variables from Goyal and Welch (2008) and CE for the two evaluation periods:

1983:01-2015:12 and 2007:01-2015:12. We assume a relative risk aversion coefficient on three[8]. The performance of CE clearly stands out among the 14 popular predictors for shorter and longer horizons. The CER gain of CE is 2.28% per annum and the CER of no other predictors shows even greater than 1% at 3 or 6 months. Among the 14 popular predictors, only LTR, TMS, DFR, and INFL generate positive CER gains (0.76, 0.93, 0.31, and 0.54 %s, respectively) and gains are well below those of CE. CE continues to generate sizable CER gains of 2.28, 2.13, 2.47, 2.77 and 2.83% per annum at three-month, six-month, one-, two-, and three-year horizons, respectively.

Although the performance of CE clearly stands out among popular predictors, a buy-and-hold portfolio that passively holds the market portfolio also produces sizable CER gains and slightly outperforms CE during the period of 1983:01-2015:12. However, CE generate stunning CER gains of 5.67, 5.39, 5.63, 4.18, and 4.90% per annum at the quarterly, semi-annual, annual, two-year and three-year, respectively, for the 2007:01-2015:12 period corresponding to the Global Financial Crisis. A buy-and-hold portfolio produces CER gains well below those of CE during the period for the Global Financial Crisis, and CE easily outperforms a buy-and-hold strategy that shows the better performance than the strategies based on predictive variables other than CE.

3.4.2 Sharpe ratios

Besides analyzing CER gains, we compute Sharpe ratios for the portfolios to compare portfolio performance independently of the investor's relative risk aversion. Table7B reports the Sharpe ratios of the portfolios for the entire forecast evaluation period of 1983:01-2015:12 and the recent period of 2007:01-2015:12. The ratios for the portfolio based on the prevailing mean benchmark forecast range from 0.32 to 0.40 at the various horizons. While the 14 popular predictors from the literature rarely outperform the prevailing mean in terms of the Sharpe ratio, CE produces higher Sharpe ratios than those of prevailing mean. The Sharpe ratios for CE are always greater than those for the popular predictors and the buy-and-hold strategy.

The Sharpe ratios for the portfolio based on the prevailing mean benchmark forecast does not change much in the period of 2007:01-2015:12 compared to the result in the whole evaluation period. The performance of the buy-and-hold strategy gets worse by 0.1 in the recent period. However, similar to the pattern in CER gains, the performance of CE is striking for the 2007:01-2015:12 encompassing the Global Financial Crisis. CE generates substantial Sharpe ratios ranging from 0.75 to 0.86.

The sparkling results of credit expansion during the recent period is consistent with the recent finding of Rapach, Ringgenberg, and Zhou (2016) who find sizable out-of-sample CER gains and Sharpe ratios during the period of 2007:01-2014:12 when they use short interest as the main explanatory variable. The 2007:01–2015:12 period surrounding the Global Financial Crisis contains the Great Recession, which is by most measures the most severe recession since the Great Depression. In sum,

[8]We choose this value consistent with the estimates of relative risk aversion from the literature, such as Bliss and Panigirtzoglou (2004). The results are qualitatively similar for other reasonable relative aversion coefficient values.

credit expansion offers gains as much as a buy-and-hold strategy during the normal times, and striking gains during the period that include macroeconomic stress.

The results in this section indicate that the information in credit expansion has substantial economic value for a risk-averse investor. This is especially true around the Global Financial Crisis. Reiterating the results of encompassing tests in section 3.2, the information contained in credit expansion appears considerably more valuable than that found in popular predictors from the literature, and there exists the economic value of CE's predictive ability.

4. Potential Explanations

In section 3, we show that credit expansion is a statistically and economically significant predictor of future market excess returns, and the predictive ability of credit expansion contains the economic value when we examine the value from the asset allocation perspective. This section evaluates potential explanations on the underlying sources of the CE's return predictability.

4.1 Investment-based explanations

4.1.1 Credit expansion and real investment

In section 3.1, we show that the finding that high credit expansion follows periods of rising consumption and forecasts low future returns suggests a rational risk-premia explanation. According to Campbell and Cochrane (1999), a high consumption surplus decreases risk aversion, leading to lower risk premia. Although the external habit model of Campbell and Cochrane (1999) does not tell about investment behavior, the decrease in risk premia would plausibly imply the decrease in cost of capital and an increase in investment in a general equilibrium setting. Thus, in this section, we consider the investment-based theory to explain the predictive power of credit expansion.

We first examine how credit expansion is linked to investment-based theory. If future discount rate becomes lower or if overall risk of investment becomes smaller, investors experience an expansion in their investment opportunity set, which tends to lead the increase in bank loans and credit expansion occurs as a consequence. Thus, we expect lower expected returns following credit expansion, and it is plausible that investment-based theory explains the observed return predictability of credit expansion. To examine this hypothesis, we examine whether credit expansion has a positive relation with investment, which implies that the obtained capital from credit expansion is used to finance investment.

Following Abel and Blanchard (1986), a countercyclical cost of capital creates an additional incentive to increase investment during booms, at both the corporate and household levels, and thus we expect that both investment and credit expansion increase during booms. Lyandres, Sun and Zhang (2008) present equity issuers and debt issuers invest more than matching non issuers at the firm level. Specifically, they show that the investment-to-assets spread between issuers and matching nonissuers is the highest in the IPO sample, followed by the SEO and convertible debt samples, and is the lowest in the straight debt sample. We explore the relationship between credit expansion and investment at the aggregate level.

We examine whether the proceeds from credit expansions are used to finance investment and at the same time credit contraction is related to decrease in investment at the aggregate level. We find that the correlation between credit expansion and investment is 28%. The fact that credit expansion is positively correlated with investment implies that the proceeds from credit expansions are used for investment, and at the same time credit contraction occurs when investors experience a contraction in their investment opportunity set. It is possible that all proceeds from credit expansion are not used for investment, but still credit expansion has the positive relation with investment level. We can conclude that cash flow obtained from credit expansion is used to finance investment, and thus credit expansion reflects the investment level.

4.1.2 Investment-based explanations

In this section, we further relate the return predictability of credit expansion to investment-based models, and examine whether credit expansion and investment interact to give credit expansion the strong predictive power on market returns.

Under the investment-based theory, firms raising capital are likely to invest more and earn lower expected returns, and firms distributing capital are likely to invest less and earn higher expected returns. We extend the mechanism of investment-based models to the market-level, which infers that credit expansion induces higher investment at the aggregate level and earns lower expected market returns and that credit contraction induces lower investment at the aggregate level and earns higher expected market returns.

First, we examine whether the coefficient on credit expansion is attenuated once we control for investment.

$$r_{t:t+h} = \alpha + \beta CE_t + \gamma X_t + \epsilon_{t:t+h} \ \ for \ \ t = 1, \dots, T-h. \tag{6}$$

where CE_t is credit expansion, and X_t is real investment per GDP (INV_t) that is seasonally adjusted and detrended, the growth of real investment per GDP (ΔINV_t) or the investment to capital ratio (IK) from Cochrane (1991). If the information of credit expansion is subsumed by investment, β_1 becomes insignificant or the absolute value of β_1 shrinks significantly, less than that of β_1 in the original predictive regression when we add an investment as an explanatory variable.

Model 3 in Table 8 reports the result of the coefficients of the regression analysis. For all horizons, the absolute value of CE's coefficient and the t-statistics decrease, still significant at the 5% level, when we compare the coefficient and t-statistics with the result of the univariate predictive regression. This result implies that some predictive power of credit expansion stems from the investment effect, which can be considered as the information regarding the future discount rate.

We expect the coefficient on investment variable to be negative according to the investment-based approach in which q-theory of investment and real options theory imply a negative relation between real investment and expected returns. Model 2 in Table 8 reports that the coefficient on investment is significantly negative for all horizons at the 10% level, which supports the investment-based theory.

Second, if the predictive power of credit expansion is related to the information about the future cost of capital, we expect deeper negative expected returns following credit expansions when the greater growth of investment is observed under the investment-based model. We consider the level of investment or the growth of investment as a state variable and analyze the following predictive regressions:

$$r_{t:t+h} = \alpha + (\beta_0 + \beta_1 X_t)CE_t + \gamma X_t + \epsilon_{t:t+h} \; for \; t = 1, \dots, T-h. \quad (7)$$

where X_t is real investment per GDP (INV_t) that is seasonally adjusted and detrended, the growth of real investment per GDP (ΔINV_t), median dummy for investment per GDP ($INVD_t$), or median dummy for real investment per GDP ($\Delta INVD_t$). β_1 captures the interaction effect of investment and credit expansions on expected market returns. We expect β_1 to be negative because the more proceeds from credit expansion are used to finance real investment, the lower expected returns by investment-based models.

We find a strong predictive power of credit expansion when investment level is high, when there exists the growth of investment, or when the investment to capital ratio is high. β_1 is significantly negative at the 5% level, -6.619, -16.473, -41.41, -66.176, and -63.543, respectively for predicting three-month, six-month, one-, two-, and three-year excess returns, implying that expected stock returns become lower following credit expansions when investment level is high.

[Table8]

The results become stronger when we use the growth of investment instead of investment level as a state variable. β_1 is significantly negative at the 1% level, -0.688, -1.724, -3.872, -7.745, and -8.820 respectively for predicting three-month, six-month, one-, two-, and three-year excess returns. This result indicates that expected stock returns become strongly negative following credit expansions when there exists the growth of investment.

For the simplicity, we define only two states that consist of high and low investment levels or investment growth, and analyze the same regression. In the case of using $INVD_t$, we obtain significantly negative $\hat{\beta}_1$s at the 10% level, -0.195, -0.349, -0.969, -1.115, -1.004 for predicting three-month, six-month, one-, two-, and three-year excess returns, respectively. The result becomes stronger in the case of using $\Delta INVD_t$ as the state variable. The obtained β_1's are -0.172, -0.392, -0.699, -1.382, and -1.621 and significant at the 5% level. When we define two states as high and low credit expansion, the obtained β_1's are -0.280, -0.572, -1.186, and -1.164 for six-month, one-, two-, and three-year horizons, respectively, and significant at the 1% level.

The result shows that the predictive power of credit expansion is particularly strong when the investment level is high or the growth of investment is high: the regression coefficient is significantly negative. To interpret the magnitudes, take the coefficient of -0.172 for three-month horizon. A one standard deviation increase in credit expansion predicts an additional lower mean return of 17.2% when the growth of investment in its higher level than its median. The magnitude is considerably larger at longer horizons.

4.1.3. Implications of the predictability

Credit expansion and investment interact with each other to give credit expansion even stronger predictive power. The finding of deeper negative expected returns following credit expansions when the greater growth of investment is observed implies that the negative return predictability of credit expansion is related to the information regarding the future low cost of capital. This empirical result supports the investment-based approach that lower cost of capital increases investment and consequently credit expansion occurs. Abel and Blanchard (1986)'s finding that cost of capital is countercyclical and the countercyclical cost of capital increases an additional incentive to increase investment during booms is consistent with the implication of our empirical result. Thus, the investment-based theory is able to explain the predictive power of credit expansion.

However, an alternative explanation is still possible that it is mispricing rather than risk premia that drives investment behavior. During the period of credit expansion investors become more optimistic and increase investment, implying that the credit boom fuels investment and consequently markets earn lower expected returns. We provide evidence that is inconsistent with this behavioral explanations. The evidence is that high credit expansion predicts low returns not only on stocks, but also on bonds, in particular U.S. Treasury bonds. While stock returns could be low as the result of overoptimism on cash flows from investment, Treasury bond returns should be immune to overoptimism on cash flows from investment. Because cash flows of Treasury bonds are fixed, Treasury bond returns are not affected by the overoptimism on cash flows. Moreover, investors would like to participate in stock markets rather than Treasury bond markets when overoptimism spreads, consequently resulting in stock markets to earn low returns and Treasury bond markets to earn high returns. Thus, Treasury bond returns should not be low as the result of mispricing arising from overoptimism on cash flow.

[Table 8B]

Table 8B shows the significantly negative coefficients on credit expansion predicting the excess returns of long-term Treasury bonds, which is inconsistent with the mispricing from overoptimism. The coefficients here are smaller than the coefficients for equities, but still significant at the 5% level in the univariate regression. In contrasts to predicting stock returns, including the first three principal components extracted from the 14 predictors of Goyal and Welch (2008) eliminate the significance of CE except the 3-year horizon. Including three PCs easily overwhelms the predictive power of CE because the first principal component (PC1) is correlated with term spread by 0.88, correlated with default yield spread by 0.42 and correlated with long-term yield by 0.34, and because the third principal component (PC3) is correlated with Treasury bill rate by 0.99, and correlated with long-term yield by 0.94.

The result does not completely rule out the presence of overoptimism during credit expansions, but rather explains given the presence of overoptimism how the return predictability of credit expansion is incorporated by the investment-based model, so that risk premia drive investment behavior.

4.2 Misevaluation exploitation explanations

Although the investment-based explanation explains large part of the predictive power of credit expansion, the investment effect does not fully explain the predictive power. The reason is that the negative return predictability of credit expansion might be derived from investors' irrational market valuation, such as overpricing in the bond or stock markets. Bradshaw, Richardson and Sloan (2006) find that a negative relation between external financing (equity financing or debt financing) and both future stock returns and future profitability, and show that their measure of external financing is positively related to overoptimism in analysts' forecasts, supporting the misevaluation as explanations for the negative relation between external financing and future stock returns.

There is some evidence that the investor sentiment affects financing decisions or actual investment decisions (Baker and Wurgler 2002; Baker, Stein, and Wurgler 2003; and Gilchrist, Himmelberg, and Huberman 2005). Stein(1996) shows that the manager, who issue more equity when a firm's stock price is too high, should not channel the fresh capital into any actual new investment, but instead keep it in cash or in another fairly priced capital market security. After issuing equity, the overpricing may disappear in the future even though the manager does not finance new investment with the capital. Thus, it is possible that negative return predictability credit expansion does not stem from investment-based approach, and that the predictive power of credit expansion comes from misevaluation in the stock market.

In the corporate bond market, Greenwood and Hanson (2013) provide evidence that the credit quality of corporate debt issuers deteriorates during credit booms and this deterioration forecasts lower corporate bond excess returns. This finding supports the argument that debt holders are overly optimistic at the time of credit booms. Then, are shareholders also overly optimistic during credit booms? If shareholders recognize the financial instability associated with credit expansion at the time of an expansion and anticipate the equity crash risk, they should demand a risk premium as compensation. Baron and Xiong (2017) address this linkage by systematically examining the expectations of bank shareholders.[9] However, Baron and Xiong (2017) find that there clearly exists overoptimism by bank shareholders during credit expansions. If we push Baron and Xiong's conclusion further, it may be possible that shareholders and managers in general are overoptimistic and seek for credits and external financing, which result in credit expansion. From this perspective, in this section we explore how the optimism by shareholders is linked to credit expansion, and how the optimism by shareholders affects the return predictability of credit expansion.

4.2.1 Disagreement measure and overvaluation

Although we accept that both debt holders and shareholders are overly optimistic during credit

[9] Baron and Xiong (2017) deliberately choose to examine bank shareholders because bank shareholders often suffer large losses during financial crises, and should have strong incentives to forecast the possibility of financial crisis. Thus, while overoptimism might have caused debt holders to neglect credit risk during credit expansions, this might not be true of equity holders, especially bank shareholders. Moreover, bank shareholders are originally the main decision makers who determine the capacity of bank loans investors are able to borrow.

expansions, we are still wondering how the optimism associated with credit expansions is related to equity market valuation. We expect that the negative return predictability of credit expansion is amplified when the stock market is readily able to reflect the overoptimism during credit expansions.

Credit valuation is particularly sensitive to the belief held by the market about the lower tail risk, while equity valuation is primarily determined by the belief about the mean or upper end of the distribution of future economic fundamentals, which is consistent with the limit-to-arbitrage framework. According to Miller (1977)'s model, stock prices reflect only the beliefs of optimists in the presence of both divergence of opinion among investors and short-sale constraints. Gilchrist, Himmelberg, and Huberman (2005) build a model in which an increase in the dispersion of investor beliefs under short-selling constraints predicts a rise in a stock's price above its fundamental value. Using different proxies for disagreement, both Diether, Malloy, and Scherbina (2002) and Chen, Hong, and Stein (2002) provide cross-sectional evidence that supports the prediction of Miller's model.

The mechanism in Miller (1977) can be extended to markets: greater disagreement about market valuation is associated with subsequent market returns. This prediction is explored by Park (2005) who finds supportive evidence that the dispersion in analyst forecasts of Standard & Poor's(S&P) 500 index annual earnings-per-share (EPS) has strong predictive power for future aggregate stock returns. Based on the literatures, we use the market disagreement measure to capture the extent that stock markets reflect investors' overoptimism.

When credit expansion occurs together with asset market boom, it is easy for managers to exploit the overvaluation. The model of Gilchrist, Himmelberg, and Huberman (2005) predicts that managers respond to bubbles by issuing new equity and increasing capital expenditures[10]. According to Simsek (2013), a credit boom arise in equilibrium only when both creditors and borrower share similar beliefs about downside states, and this credit boom is then able to fuel the optimism of the borrowers about the overall distribution and lead to an asset market boom. Thus, when credit expansion occurs together with asset market boom, it is easy for managers to exploit the overvaluation. Consequently, the following returns predicted by credit boom are strongly negative.

The correlation between credit expansion and market-wide disagreement is significantly positive (0.234), implying that credit expansion might lead to overvaluation of stocks. The correlation between credit expansion at t-1 and disagreement at t is also significantly positive. The significantly positive correlation infers that the market-wide disagreement increase with credit expansions and thus overoptimism during credit expansion becomes readily reflected in stock markets, which results in overvaluation in stock markets. Thus, we expect deeper negative expected returns following credit expansion when market-wide disagreement is high.

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[10] Investment can be caused by managers exploiting irrational market valuation, so a positive correlation of external financing with investment does not preclude a behavioral explanation. Baker and Wurgler (2002) document capital structure is the cumulative outcome of past attempts of "equity market timing", which refers to the practice of issuing shares at high prices and repurchasing at low prices. Baker, Stein, and Wurgler (2003) suggest a model that outlines the conditions under which corporate investment is sensitive to nonfundamental movements in stock prices.

4.2.2 Misevaluation exploitation explanations

Because overvalued firms tend to have both overpriced equity and risky debt, overvalued firms should issue risky debts as well as stocks to exploit mispricing and their equity subsequently underperforms. Bradshaw, Richardson and Sloan (2006) find that a negative relation between external financing and both future stock returns and future profitability. They document that future stock returns decrease following debt financing or equity financing and they show that this negative relation is associated with misevaluation. We find this negative relation is still valid at the market level: future aggregate stock returns decrease following the increase in the market-level external financing, i.e., credit expansions or the aggregate equity issuance.

First, we examine whether the coefficient on credit expansion is attenuated once we control for misevaluation.

$$r_{t:t+h} = \alpha + \beta CE_t + \gamma DIS_t + \epsilon_{t:t+h} \ for \ t = 1, \ldots, T-h. \quad (8)$$

Model 3 in Table 9 report the result of the bivariate predictive regressions. The size of the coefficient on credit expansion becomes small, and the significance becomes weaker. This result implies that some predictive power of credit expansion stems from misevaluation, which can be considered as the information regarding the future discount rate.

Second, when a credit boom occurs together with optimistic beliefs of the borrowers (usually managers of firms) and creditors about the upper states of the distribution of future economic fundamentals, the borrowers are able to use leverage to bid up asset prices. In this case, it is easy for borrowers to exploit the overvaluation. Consequently, the following returns predicted by credit boom are strongly negative. To examine whether this negative relation of credit expansions or the aggregate equity issuance with stock returns is associated with misevaluation, we analyze the following analysis:

$$r_{t:t+h} = \alpha + (\beta_0 + \beta_1 DIS_t) CE_t + \gamma DIS_t + \epsilon_{t:t+h} \ for \ t = 1, \ldots, T-h. \quad (9)$$

where DIS_t is market-wide aggregate disagreement measure that reflect divergence about market valuation. We use the aggregate equity issuance, EQT_t, as another explanatory variable instead of credit expansion in the equation(9).

The significantly negative β_1 indicates that the impact of credit expansion or equity issuance on aggregate stock returns become strong when aggregate dispersion is high and thus misevaluation is severe. $\hat{\beta}_1$ is negatively significant at the 1% level, -0.125, -0.206, -0.415, -0.690, and -0.693, respectively for predicting three-month, six-month, one-, two-, and three-year excess returns. This result implies that credit expansion or equity issuance predicts lower expected returns more severely when there exists greater disagreement and thus greater overpricing. Therefore, negatively significant $\hat{\beta}_1$ indicates that managers exploit overpricing by external financing, and stocks subsequently underperform more when the market-wide disagreement is greater.

It is interesting that $\hat{\beta}_1$ estimates are significant for both credit expansions and aggregate equity issuance of equation (9). This result indicates that both bond and stock markets are used to exploit misevaluation. Overvaluation should cause greater issuance in total, and cause a substitution from debt to equity issuance because equity is more sensitive to changes in firm value. Baker and Wurgler (2000) test a hypothesis about the substitution based on market timing of the relative mispricing of equity versus debt. However, debt and equity issuance are imperfect substitutes because of agency and tax considerations. Thus, despite the substitution effect, the increase in total financing is not absorbed entirely by new equity issuance, and both debt financing and equity financing are used to exploit misevaluation, which is consistent with our result.

In sum, we observe that the sentiment associated with credit expansion and the extent of market-wide disagreement amplify each other to give credit expansion even stronger predictive power when market-wide disagreement is high. We conclude that explanations involving misevaluation exploitation appear to explain the strong predictive power of credit expansion.

4.2.3 Investor sentiment and the predictability of credit expansion

We find that credit expansion and the equity market sentiment captured by disagreement amplify each other in predicting market returns. In this section, we directly examine the mispricing effect on the predictability of credit expansion by using the investor sentiment measures defined by Baker and Wurgler(2006). We implement the regression analysis including the interaction term of the investor sentiment and credit expansion instead of the market aggregate dispersion measure.

$$r_{t:t+h} = \alpha + (\beta_0 + \beta_1 SENT_t)CE_t + \gamma DIS_t + \epsilon_{t:t+h} \;\; for \;\; t = 1, \ldots, T-h. \qquad (10)$$

where $SENT_t$ is the investor sentiment measure from Baker and Wurgler(2006). We use both $SENT_t$ and $SENT_t^{\perp}$ that is orthogonalized sentiment measure from Baker and Wurgler(2006).

Table 10 reports the result. We obtain the opposite results between short-term and long-term analysis, the positive β_1 for predicting 3-month returns, but the negative β_1 for predicting 2-year and 3-year returns. In the high sentiment-period, subsequent 3-month returns are high when credit expansion is high, and then finally the subsequent 2-year and 3-year returns becomes low. This result implies that the overoptimism is maintained for 3 months following the high-sentiment period, and then the more deeply negative returns are expected following the higher sentiment period for the long term.

4.2.4 Investment-based explanation vs Misevaluation exploitation explanation

Until now, we discuss investment-based explanations and misevaluation exploitation explanations one by one. However, the two approaches are not completely separated. Gilchrist, Himmelberg, and Huberman (2005) find that increase in dispersion causes increase in new equity issuance, Tobin's Q, and real investment. Because firms exploit overpricing by issuing new securities, the cost of capital becomes lower and real investment increases. Applying their finding, our result of the strongly significant $\hat{\beta}_1$ in this section can be related to the investment-based approach as well as misevaluation exploitation approach.

We show that both investment and mispricing exploitation explain the predictability of credit expansions. To explore whether one perspective is absorbed entirely by the other, we implement the following regression analysis:

$$r_{t:t+h} = \alpha + (\beta_0 + \beta_1 INV_t + \beta_2 DIS_t)CE_t + \gamma_1 INV_t + \gamma_2 DIS_t + \epsilon_{t:t+h} \quad for \;\; t = 1, \dots, T-h. \quad (11)$$

where β_1 captures investment effect, and β_2 captures mispricing effect.

Table 11 reports the estimates of the regression analysis. $\hat{\beta}_1$ is negatively significant for predicting six-month, one-, two-, and three-year returns, and $\hat{\beta}_2$ is negatively significant for predicting three-month, six-month, one-, two-, and three-year returns. While mispricing effect remains strong for all horizons, investment effect becomes stronger for longer horizons (one-, two-, three-year). When we use ΔINV_t instead of INV_t, the investment effect become even stronger: β_1 becomes significant in predicting three-month, six-month, one-, two-, and three-year returns. The result implies that any of investment or mispricing effect is not subsumed by the other.

4.3 financial intermediary explanations

We next consider financial intermediary explanations in which expected returns could fluctuate due to the health of financial intermediary balance sheets as one of potential explanations for return predictability of credit expansion.

4.3.1 Health of financial intermediary balance sheets and risk premia

A growing body of literature argues that fluctuations in intermediary equity capital or balance sheet health may drive in risk premia. Following the tradition of Bernanke and Gertler (1989) and Holmstrom and Tirole (1997), the recent intermediary asset pricing models of He and Krishnamurthy (2012, 2013) and Brunnermeier and Sannikov (2014) show that the intermediary sector's net worth (or, equivalently, its equity capital ratio) is the key determinant of its marginal value of wealth. More recently, He, Kelly and Manela (2017) find that shocks to the equity capital ratio of financial intermediaries possess significant explanatory power for cross-sectional variation in expected returns. They also find that intermediary capital ratio predicts future returns on equities, foreign sovereign bonds, options, CDS, currencies.

This view implies that intermediaries become more risk averse following negative shocks to their capital. Intermediaries' risk bearing capacity is inhibited, and they have high marginal value of wealth when they experience a negative shock to its equity capital. This perspective predicts in the time series that a positive shock to equity capital drives down the marginal value of wealth, and hence investors require higher expected equilibrium return.

A second approach to intermediary asset pricing emphasizes the role of leverage, not equity capital ratio. Brunnermeier and Pedersen (2009) propose a model where shocks to the pricing kernel are proportional to the financial intermediary's leverage multiplier on its leverage constraint in addition to the market factor. Adrian, Etula, and Muir (2014) construct a leverage factor and find that the leverage factor is powerful for describing the cross section of stock and bond returns. Extending Adrian, Etula, and Muir (2014), Adrian, Moench, and Shin (2014) demonstrate that broker-dealer leverage has significant time-series forecasting power for returns on stocks and bonds. This view predicts that high intermediary leverage is associated with a low price of risk.

4.3.2 Intermediary equity capital and risk premia

Following the view that intermediary sector's net worth is the key determinant of its marginal value of wealth, we use the equity capital ratio of financial intermediary to examine the risk tolerance due to financial intermediary-related explanations as the potential source of return predictability of credit expansion. According to He and Krishnamurthy (2012), the risk price can be described in a simplified version as

$$\lambda_{\eta,\mathrm{t}} = \gamma Var_t\left[\frac{d\eta_t}{\eta}\right] = \gamma\sigma_{\eta,t}^2 \propto \left(\frac{1}{\eta}\right)^2, \tag{12}$$

where η is the capital ratio of the intermediary sector, γ is the constant relative risk aversion. The risk premium is linear in the squared reciprocal of the capital ratio of the intermediary sector, implying that low intermediary capital ratio is associated with a high price of risk. By using $1/\eta^2$ as an explanatory variable, He, Kelly and Manela (2017) perform time-series predictive regressions to evaluate lagged primary dealer capital ratio predict time-varying expected asset returns, and find that the intermediary capital ratio predicts future returns on equities, foreign sovereign bonds, options, CDS, currencies.

4.3.3 Analysis

First, we examine whether the coefficient on credit expansion is attenuated once we control for intermediary balance sheet strength.

$$r_{t:t+h} = \alpha + \beta CE_t + \gamma\frac{1}{\eta_t^2} + \epsilon_{t:t+h} \;\; for \;\; t = 1, \dots, T-h. \tag{13}$$

Second, based on the result of He, Kelly and Manela (2017), we use $1/\eta^2$ as a state variable to examine whether the predictability of credit expansions on time-varying risk premia is associated with the degree of financial sector distress. We regress h-month holding period excess returns of S&P 500 on credit expansion, $1/\eta^2$ (the capital ratio of the intermediary sector) and the product of credit expansion and $1/\eta^2$:

$$r_{t:t+h} = \alpha + (\beta_0 + \beta_1\frac{1}{\eta_t^2})CE_t + \gamma\frac{1}{\eta_t^2} + \epsilon_{t:t+h} \;\; for \;\; t = 1, \dots, T-h. \tag{14}$$

where η is the capital ratio of the intermediary sector and captures the financial soundness of intermediary. These regressions allow us to assess the impact of credit expansion on market returns is related to financial distress of intermediary sector. We expect that the influence of credit expansions on returns is strong in the state when the intermediary's equity capital is high.

We define the capital ratio of the intermediary sector by two ways. One is the primary dealers' market equity capital ratio (PDE) defined by He, Kelly and Manela (2017). The other is the aggregate bank equity to total bank assets (E/A) of commercial banks based on the balance sheet data and book values of equity. The big differences in the two measures are the definition of financial intermediary groups and the values used in the measure. He, Kelly and Manela (2017) include the selected group of financial intermediaries that serve as trading counterparties to the Federal Reserve Bank of New York in its implementation of monetary policy, whereas the E/A measure includes banks as financial intermediary. The other difference is that the E/A measure uses book values of equity while He, Kelly and Manela (2017) use market values of equity.

4.3.4 Results

Table 12 shows the effect of the capital ratio of the intermediary sector. The primary dealers' market equity capital ratio (PDE) defined by He, Kelly and Manela (2017) has the predictive power on market returns in the univariate predictive regression, which is consistent with the result of He, Kelly and Manela (2017). The coefficient is significantly positive at the 10% level for predicting three-month, six-month, one-, two-, three-year returns.

The interesting result is that PDE still has the predictive power on the market return when we control for credit expansion. Model3 in Table 12 indicates that both credit expansion and PDE have effect on predicting returns, implying that the information in PDE is not overlapping the information in credit expansion. The significantly positive coefficient on PDE implies that low intermediary capital ratio (high leverage) states are associated with low expected future returns, because intermediary capital ratio is highly persistent (the autocorrelation coefficient is 0.94).

Although PDE has the predictive power in the bivariate predictive regressions, adding PDE hardly impacts the coefficient on credit expansion in our predictive regressions. The size of the coefficient on credit expansion becomes even bigger when we add PDE, and the coefficient on credit expansion is significant at the 1% level.

Next, in the regression that we consider PDE as a state variable, the coefficient on the cross term of credit expansion and PDE is significantly positive for predicting two-, and three-year returns. The cross term is not significant for predicting short-term returns, but becomes significant at the 5% level for predicting long-term returns.

When we use the aggregate bank equity to total bank assets (E/A) as a state variable, the coefficient on the product term of credit expansion and E/A is significantly positive at the 1% level for predicting three-month, six-month, one-, two-, and three-year returns. This result implies that the time varying risk premium predicted by credit expansions is associated with the state of the intermediary capital ratio. When the intermediary capital ratio is low, credit expansion predicts lower expected future returns.

In sum, the explanations involving limited intermediary capital seem go in the right direction but do not appear to fully explain the predictive power of credit expansion.

4.3.5 Investment-based, Misevaluation vs Health of financial intermediary

We suggest three possible explanations for the negative predictability of credit expansion on the aggregate stock returns. In section 4.3, we find that any of the investment-based or the misevaluation approach does not absorb the other. In this section, we explore whether the financial intermediary explanation is entirely subsumed by the investment-based or the misevaluation approach by implementing the following regression analysis:

$$r_{t:t+h} = \alpha + (\beta_0 + \beta_1 \frac{1}{\eta_t^2} + \beta_2 INV_t)CE_t + \gamma_1 \frac{1}{\eta_t^2} + \gamma_2 INV_t + \epsilon_{t:t+h} \ \ for \ \ t = 1, \ldots, T-h. \quad (15)$$

$$r_{t:t+h} = \alpha + (\beta_0 + \beta_1 \frac{1}{\eta_t^2} + \beta_2 DIS_t)CE_t + \gamma_1 \frac{1}{\eta_t^2} + \gamma_2 DIS_t + \epsilon_{t:t+h} \ \ for \ \ t = 1, \ldots, T-h. \quad (16)$$

where β_1 the captures investment effect or misevaluation effect, and β_2 captures the financial intermediary effect.

Table 13 reports the estimates of the regression analysis. First, we compare the investment-based effect and the balance sheet healthiness effect of financial intermediary. When we use the aggregate bank equity to total bank assets (E/A) as a state variable, $\hat{\beta}_1$ is positively significant for every horizon and $\hat{\beta}_2$ is negatively significant for every horizon, implying that the two effects separately contribute to explain the predictive power of credit expansion.

Second, we compare the mispricing explanation and the balance sheet healthiness explanation of financial intermediary. When we use the aggregate bank equity to total bank assets (E/A) as a state variable, $\hat{\beta}_1$ is positively significant for 6-month, 1-year, 2-year and 3-year horizons and $\hat{\beta}_2$ is negatively significant for 3-month, 6-month, 1-year and 2-year horizons. Moreover, the significance of $\hat{\beta}_1$ becomes stronger as predictive horizon becomes longer while the significance of $\hat{\beta}_2$ becomes stronger as predictive horizon becomes shorter. This result implies that the effect of the healthiness of financial intermediary is distinct from the effect of mispricing.

4.4 Equity financing

From the perspective of external financing, credit expansion is not the only source of external financing. Firms can finance new investment by issuing equity when the firms need external financing. Thus, aggregate equity issuance might be another measure that reflects investment level as well as credit expansion.

We compare the result of credit expansion with that of equity issuance. We find that the aggregate equity issuance does not show predictive power in in-sample or in out-of-sample whereas credit expansion shows the strong predictive power both in in-sample and out-of-sample. Table 14 shows the results of in-sample betas and out-of-sample R^2 statistics for predicting three-month, six-month, one-, two- and three-year returns. All betas except the two-year beta are not significant, and all out-of-sample R^2 statistics are negative, implying that the aggregate equity issuance measure does not predict better than the prevailing mean benchmark forecast.

Then, why does the aggregate equity issuance not have predictive power on the market excess-returns? Bradshaw, Richardson and Sloan (2006) find that a negative relation between external financing (equity financing or debt financing) and both future stock returns and future profitability, but their result does not hold for equity financing at the aggregate level. Lyandres, Sun, and Zhang (2007) show that at the firm level equity issuers invest more than nonissuers. However, it is hard to conclude that the high aggregate equity issuance implies high investment at the aggregate level. We examine whether the proceeds from equity issuance are used to finance investment at the aggregate level and, at the same time, aggregate equity repurchases are related to decrease in investment. We find that the correlation between aggregate equity issuance and investment level is 56% when investment remains at higher level than the mean, and is -24% when investment remains at lower level than the mean. The relation between aggregate equity issuance and investment is U-shaped.

The fact that aggregate equity issuance increases rapidly at the high level of investment implies that firms use equity financing at the high level of investment for financing extra investment after using debt financing first, which is consistent with the pecking order theory. The fact that aggregate equity issuance increases when investment decreases at the low level implies that at the market-level we cannot conclude that firms use stock repurchase when they experiences a contraction in their investment opportunity set, whereas Grullon and Michaely (2004) shows that at the firm level repurchasing firms do not invest more than the matching firms. Thus, equity issuance does not reflect the investment level while credit expansion always moves in the same direction as investment does. We conclude that the equity financing has little information about future discount rate at the aggregate level.

5. Conclusion

We provide empirical evidence on the relationship between credit expansion and aggregate stock returns. We find that credit expansion, when aggregated across financial institutions, is a statistically and economically significant predictor of future market excess returns over our 1963:01-2015:12 sample period. Indeed, our credit expansion measure is the strongest predictor of equity risk premium comparing with the 14 popular predictors from Goyal and Welch (2008). Credit expansion consistently exhibits stronger both in-sample and out-of-sample predictive power than the 14 popular predictor variables. In out-of-sample tests for the 1983:01–2014:12 forecast evaluation period, a predictive regression forecast based on credit expansion is the only explanatory variable that outperforms the constant expected excess return benchmark forecast by a statistically and economically significant margin at all horizons. The predictability of CE becomes stronger for the 2007:01-2015:12 period corresponding to the Global Financial Crisis.

Furthermore, the information contained in the CE-based forecast dominates the information found in forecasts based on popular predictors. CE also generates substantial utility gains for a mean-variance investor with a relative risk aversion coefficient of three, and the gains are especially large during the recent Global Financial Crisis. Moreover, the CE-based forecast allows to generate a high Sharpe ratio trading strategy, and the Sharpe ratio during the recent Global Financial Crisis is strikingly high.

In this article, we suggest three potential sources of return predictability of credit expansion: investment-based explanations, misevaluation exploitation explanations, and health of financial intermediary explanations. These three channels are not subsumed by one another, and moreover each of the three possible explanations distinctly and separately contributes to explain the return predictability of credit expansion.

First, the investment-based approach indicates that the negative return predictability of credit expansion is related to the information regarding the future low cost of capital. Second, we find that the sentiment associated with credit expansion and the extent of market-wide disagreement amplify each other to give credit expansion even stronger predictive power when market-wide disagreement is high. Third, we find that the balance sheet healthiness of financial intermediary, such as the primary dealers' market equity capital ratio (PDE) and the aggregate bank equity to total bank assets (E/A), helps to explain the return predictability of credit expansion. Therefore, we can conclude that all the three explanations appear to explain the strong predictive power of credit expansion.

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Table 1

14 predictor variables from Goyal and Welch (2008).

The table describes 14 popular predictor variables from Goyal and Welch (2008). We include the 14 predictors in our analysis to compare the predictive ability of aggregate credit expansion to that of 14 predictor variables from Goyal and Welch (2008), which constitute a set of popular predictors from the literature. The table describes the predictors.

	Predictors	Descriptions
1.	Log dividend-price ratio (DP)	Log of a 12-month moving sum of dividends paid on the S&P 500 index minus the log of stock prices (S&P 500 index).
2.	Log dividend yield (DY)	Log of a 12-month moving sum of dividends minus the log of lagged stock prices.
3.	Log earnings-price ratio (EP)	Log of a 12-month moving sum of earnings on the S&P 500 index mi- nus the log of stock prices.
4.	Log dividend-payout ratio (DE)	Log of a 12-month moving sum of dividends minus the log of a 12-month moving sum of earnings.
5.	Excess stock return volatility (RVOL)	Computed using a 12-month moving standard deviation estimator, as in Mele (2007) .
6.	Book-to-market ratio (BM)	Book-to-market value ratio for the Dow Jones Industrial Average.
7.	Net equity expansion (NTIS)	Ratio of a 12-month moving sum of net equity issues by NYSE-listed stocks to the total end-of-year market capitalization of NYSE stocks.
8.	Treasury bill rate (TBL)	Interest rate on a three- month Treasury bill (secondary market).
9.	Long-term yield (LTY)	Long-term government bond yield.
10.	Long-term return (LTR)	Return on long-term government bonds.
11.	Term spread (TMS)	Long-term yield minus the Treasury bill rate.
12.	Default yield spread (DFY)	Difference between Moody’s BAA- and AAA-rated corporate bond yields.
13.	Default return spread (DFR)	Long-term corporate bond return minus the long-term government bond return.
14.	Inflation (INFL)	Calculated from the Consumer Price Index (CPI) for all urban consumers

Table2

Summary statistics, 1963:01-2015:12, and correlations.

Our dataset contains 212 quarterly observations for January 1963 to December 2015. Table(a) displays summary statistics for 10 aggregate-level variables used in analysis. Table(b) shows the time-series correlations between the 10 variables. CE is credit expansion variable constructed by using the Bank for International Settlements (BIS) data set, defied by $\mathrm{CE_t} = \Delta log\left(\frac{bank\ credit}{GDP}\right)_t = \frac{log\left(\frac{bank\ credit}{GDP}\right)_t - log\left(\frac{bank\ credit}{GDP}\right)_{t-60}}{60}$. EQT is the aggregate equity issuance measure, INV is investment per GDP obtained from the database of Federal Reserve Bank of St. Louis, ΔINV is the 5-year growth of bank credit per GDP, DIS is a market-wide aggregate disagreement measure, PDE is the squared reciprocal of the aggregate primary dealer capital ratio constructed by He, Kelly and Manela (2017), and E/A is the squared reciprocal of the aggregate bank equity to total bank assets obtained from the database of Federal Reserve Bank of St. Louis. The aggregate bank equity to total bank assets is detrended and not seasonally adjusted.

Table2(a) summary statistics

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	N	Mean	P5	P10	Median	P90	P95	STD
CE	212	0.030	-0.229	-0.150	0.057	0.160	0.221	0.120
EQT	212	1.023	0.997	1.000	1.022	1.044	1.054	0.018
INV	212	0.000	-0.024	-0.019	-0.001	0.018	0.023	0.014
ΔINV	192	0.026	-0.237	-0.128	0.036	0.217	0.238	0.135
E/A	112	135.735	80.148	80.580	122.640	241.117	249.570	53.580
PDE	184	383.341	76.912	113.592	318.571	775.360	876.874	271.125
DIS	137	4.762	3.645	3.751	4.399	6.103	6.942	1.063
IK	212	0.036	0.030	0.032	0.036	0.041	0.043	0.004

Table2(b) correlations

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CE	EQT	INV	ΔINV	E/A	PDE	DIS
CE	1.000						
EQT	-0.093	1.000					
INV	0.280	0.309	1.000				
ΔINV	0.039	0.256	0.720	1.000			
E/A	-0.066	0.124	-0.127	-0.009	1.000		
PDE	0.083	-0.328	-0.404	-0.285	0.069	1.000	
DIS	0.234	0.397	0.188	0.029	-0.446	-0.148	1.000
IK	0.324	0.412	0.767	0.715	0.078	-0.184	0.224

Table3

CE and theory-implied risk premia determinants.

This table shows the result of quarterly regressions in which the dependent variable is $ln(bank\ loan_{t+1}/bank\ loan_{t})$, and explanatory variables include the surplus consumption ratio computed using the model of Campbell and Cochrane (1999) and an S&P 500 volatility computed from daily index returns. Newey-West t - statistics in parentheses use four lags.

(1)	(2)	(3)	(4)	(5)
Model	Intercept	Surplus Consumption$_t$	S&P500 Volatility$_t$	Adjusted R^2(%)
1	-0.015	0.278		17.19
	(-4.46)	(5.56)		
2	0.006		-0.526	3.63
	(2.73)		(-2.72)	
3	-0.012	0.261	-0.220	17.45
	(-2.57)	(4.77)	(-1.36)	

Table4

In-sample predictive regression estimation results, 1963:01-2015:12.

The table reports the β estimate, the t -statistics of the ordinary least squares estimate of β and R^2 statistic for the predictive regression model, $r_{t:t+h} = \alpha + \beta x_t + \epsilon_{t:t+h}$ for $t=1,\dots,T\text{-}h$ where $r_{t:t+h} = (1/h)(r_{t+1} + \cdots + r_{t+h})$, r_t is the S&P 500 log excess return for month t, x_t is the predictor variable in the first column. See the notes to Table4 for the variable definitions and sample description. The "CE|PC" row corresponds to a multiple predictive regression that includes an intercept, CE, and the first three principal components extracted from the non-CE predictors in the first column. We report heteroskedasticity- and autocorrelation-robust t -statistics for testing β_0: $\beta = 0$ against β_A : $\beta > 0$; ∗, ∗∗, and ∗∗∗ indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 4(a)

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	h=3		h=6		h=12		h=24		h=36	
Predictor	β	R^2(%)	β	R^2(%)	β	R^2(%)	β	R^2(%)	β	R^2(%)
DP	0.014	0.50	0.032	1.19	0.060	2.15	0.107	3.60	0.137	4.27
DY	0.015	0.56	0.033	1.22	0.060	2.10	0.106	3.46	0.129	3.76
EP	0.006	0.10	0.010	0.15	0.026	0.49	0.030	0.35	0.038	0.42
DE	0.011	0.20	0.030	0.67	0.043	0.73	0.107	2.34	0.135	2.74
RVOL	0.200**	1.65	0.357**	2.42	0.539**	2.83	0.695	2.46	0.413	0.64
BM	0.004	0.02	0.017	0.15	0.032	0.26	0.017	0.04	-0.014	0.02
NTIS	-0.180	0.18	-0.215	0.12	-0.490	0.31	-0.926	0.59	-1.089	0.60
TBL	-0.002	0.70	-0.004	0.88	-0.006	1.25	-0.009	1.32	-0.009	1.03
LTY	-0.001	0.12	-0.001	0.06	0.000	0.01	0.006	0.38	0.013	1.55
LTR	0.004**	1.73	0.008**	3.11	0.009***	2.12	0.011**	1.53	0.011*	1.05
TMS	0.006*	1.34	0.012	2.38	0.027**	6.01	0.051***	11.44	0.073***	16.91
DFY	0.011	0.40	0.029	1.28	0.047	1.68	0.070	1.95	0.097*	2.78
DFR	0.005	0.81	0.005	0.36	-0.003	0.10	-0.005	0.15	0.000	0.00
INFL	-0.021	0.71	-0.048*	1.72	-0.116***	5.07	-0.139***	3.76	-0.133**	2.52
CE	-0.083**	1.51	-0.167***	2.85	-0.368***	7.05	-0.776***	16.10	-1.178***	26.07
CE|PC	-0.058*	3.74	-0.124*	6.81	-0.283**	11.71	-0.618***	21.73	-0.932***	32.83

Table 4(b)

	Without CE					With CE				
Predictor	h=3	h=6	h=12	h=24	h=36	h=3	h=6	h=12	h=24	h=36
PC1	0.006***	0.012***	0.023***	0.046***	0.067***	0.004*	0.008*	0.015**	0.027**	0.039**
PC2	0.003***	0.007**	0.009***	0.010**	0.009*	0.003***	0.007**	0.009***	0.011**	0.010**
PC3	-0.001*	-0.002**	-0.003	-0.003	-0.002	-0.001*	-0.002*	-0.003	-0.004	-0.004

Table5A

Out-of-sample test results, 1983:01-2015:12, 2007:01-2015:12.

The table reports out-of-sample R^2 statistics and the statistical significance based on the Clark and West(2007). The out-of-sample R^2, which Campbell and Thompson (2008) label, reports the proportional reduction in mean squared forecast error (MSFE) at the h -month horizon for a predictive regression forecast of the S&P 500 log excess return based on the predictor variable in the first column vis-á-vis the prevailing mean benchmark forecast. Statistical significance is based on the Clark and West (2007) statistic for testing the null hypothesis that the prevailing mean MSFE is less than or equal to the predictive regression MSFE against the alternative hypothesis that the prevailing mean MSFE is greater than the predictive regression MSFE. See the notes to Table4 for the variable definitions and sample description. The second through sixth columns reports the out-of-sample R^2 statistics during the period of 1983:01-2015:12. The seventh through eleventh columns reports the out-of-sample R^2 statistics during the period of 2007:01-2015:12. $*$, $**$, and $***$ indicate significance of the out-of-sample R^2 statistics at the 10%, 5%, and 1% levels, respectively.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	1983:01-2015:12					2007:01-2015:12				
	Out-of-sample R^2 statistics (%)					Out-of-sample R^2 statistics (%)				
	h=3	h=6	h=12	h=24	h=36	h=3	h=6	h=12	h=24	h=36
DP	-2.38	-5.84	-16.32	-32.33	-31.07	-0.20	0.22	-0.38	-3.22	-15.56
DY	-2.27	-5.44	-15.62	-32.18	-31.60	0.20	0.87	0.06	-2.64	-13.88
EP	-1.97	-5.26	-8.39	-13.41	-15.43	-4.73	-11.66	-13.57	-14.70	-25.59
DE	-3.86	-6.59	-5.69	-9.04	-9.72	-5.93	-7.39	0.16	-3.93	-16.95
RVOL	-1.45	-2.96	-6.19	-8.49	-7.96	3.22	4.29*	7.56**	4.65**	-15.25
BM	-1.92	-4.35	-10.41	-18.33	-22.29	-0.29	-0.56	-1.47	-2.55	-3.50
NTIS	-2.96	-8.95	-22.35	-9.15	-5.60	-10.60	-20.05	-34.66	-14.43	-5.00
TBL	-0.86	-1.30	-0.78	-3.50	-9.09	-0.84	-1.24	0.62	-1.67	-17.63
LTY	-0.58	-1.36	-3.17	-6.63	-8.49	-0.46	-1.77	-6.08	-21.14	-58.00
LTR	0.33	-0.42	2.24**	1.14*	0.46	-1.23	2.06	2.23	2.26	0.27
TMS	-1.96	-1.56	4.18***	13.08***	13.76***	-1.00	-0.54	8.04***	23.10***	39.40***
DFY	-1.55	-1.52	-1.19	-1.78	-5.10	-3.21	-0.28	3.10	4.87**	9.34***
DFR	-1.31	-5.34	-3.27	-4.39	-1.85	-3.40	-10.54	-9.27	-9.44	-5.91
INFL	0.24	2.02**	7.07***	3.28***	-1.28	-2.52	4.02	11.60***	10.40***	8.76***
CE	1.87***	3.45***	8.95***	18.37***	23.44***	4.83**	7.17***	16.46***	26.79***	31.03***

Table5B

Out-of-sample test results: 1-year, 3-year change in (bank credit/GDP), 1983:01-2015:12

The table reports out-of-sample R^2 statistics and the statistical significance based on the Clark and West(2007). The out-of-sample R^2, which Campbell and Thompson (2008) label, reports the proportional reduction in mean squared forecast error (MSFE) at the h -month horizon for a predictive regression forecast of the S&P 500 log excess return based on the predictor variable in the first column vis-á-vis the prevailing mean benchmark forecast. Statistical significance is based on the Clark and West (2007) statistic for testing the null hypothesis that the prevailing mean MSFE is less than or equal to the predictive regression MSFE against the alternative hypothesis that the prevailing mean MSFE is greater than the predictive regression MSFE. The second through sixth columns reports the out-of-sample R^2 statistics during the period of 1983:01-2015:12. $*$, $**$, and $***$ indicate significance of the out-of-sample R^2 statistics at the 10%, 5%, and 1% levels, respectively.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
		h = 3	h = 6	h = 12	h = 24	h = 36
3-year credit	OOS R^2 statistics (%)	0.98	1.92	5.11	11.16	16.82
expansion	*t-stat.*	1.49*	2.23**	4.09***	5.50***	5.76***
1-year credit	OOS R^2 statistics (%)	-0.25	0.30	1.88	5.04	11.08
expansion	*t-stat.*	0.18	0.79	2.16**	3.49***	5.46***

Table6

Out-of-sample test results, 1983:01-2015:12.

The table reports the results of forecast encompassing tests during the period of 1983:01-2015:12. The second through sixth columns reports the estimated weight on the predictive regression forecast based on CE in a combination forecast that takes the form of a convex combination of a predictive regression forecast based on CE and a predictive regression forecast based on one of the non-CE predictor variables in the first column, where statistical significance is based on the Harvey, Leybourne, and Newbold (1998) statistic for testing the null hypothesis that the weight on the CE-based forecast is equal to zero against the alternative hypothesis that the weight on the CE-based forecast is greater than zero; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

(1)	(2)	(3)	(4)	(5)	(6)
	Encompassing test				
	h=3	h=6	h=12	h=24	h=36
DP	1.00**	1.00***	1.00***	1.00***	1.00***
DY	1.00**	1.00***	1.00***	1.00***	1.00***
EP	1.00*	1.00**	1.00***	1.00***	1.00***
DE	1.00*	1.00**	1.00***	1.00***	1.00***
RVOL	0.88**	0.95***	1.00***	1.00***	1.00***
BM	1.00*	1.00**	1.00***	1.00***	1.00***
NTIS	0.84***	0.91***	0.91***	0.96***	1.00***
TBL	1.00	1.00*	1.00**	1.00***	1.00***
LTY	1.00	1.00*	1.00***	1.00***	1.00***
LTR	0.73*	0.80***	1.00***	1.00***	1.00***
TMS	1.00**	1.00***	0.84***	0.85***	0.91***
DFY	1.00**	1.00**	1.00***	1.00***	1.00***
DFR	1.00*	1.00*	1.00***	1.00***	1.00***
INFL	1.00*	0.90*	0.71**	1.00***	1.00***
CE	-	-	-	-	-

Table7A

Out-of-sample CER gains, 1983:01-2015:12, 2007:01-2015:12.

The table reports the annualized certainty equivalent return (CER) gain (in percent) for a mean-variance investor with relative risk aversion coefficient of three who allocates between equities and risk-free bills using a predictive regression excess return forecast based on the predictor variable in the first column relative to the prevailing mean benchmark forecast. See the notes to Table4 for the variable definitions and sample description. The equity weight is constrained to lie between −0.5 and 1.5. Buy and hold corresponds to the investor passively holding the market portfolio. The forecast horizon and rebalancing frequency coincide and are given by *h*.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	1983:01-2015:12					2007:01-2015:12				
	h=3	h=6	h=12	h=24	h=36	h=3	h=6	h=12	h=24	h=36
DP	-2.24	-2.55	-3.11	-3.42	-3.26	-0.52	-0.74	-0.05	0.63	-0.62
DY	-2.24	-2.34	-2.82	-3.64	-2.83	-0.14	-0.60	0.02	0.67	-0.57
EP	-0.35	-0.36	-1.04	-1.93	-0.66	0.31	-0.20	-1.55	-3.46	-0.25
DE	-1.95	-3.12	-1.56	-1.11	-1.10	-2.09	-4.23	-0.67	0.76	-0.61
RVOL	-1.58	-2.35	-1.19	-0.95	-0.52	1.01	0.36	1.50	0.34	-1.97
BM	-1.69	-2.01	-2.59	-2.66	-1.94	-0.17	-0.25	-0.60	-0.33	-0.28
NTIS	-0.76	-0.96	-1.45	-1.18	-0.17	-5.57	-6.20	-4.69	-1.61	-0.87
TBL	-0.18	-0.40	-0.17	-0.43	-0.45	-0.28	0.32	0.73	-0.14	-0.76
LTY	-0.37	-0.42	-0.82	-0.81	-0.51	0.07	-0.38	-1.96	-3.84	-3.31
LTR	0.76	-0.51	0.67	0.23	-0.11	-0.61	-3.70	-1.47	0.49	-1.23
TMS	0.93	0.98	2.22	3.45	1.99	-1.41	0.67	3.32	5.25	3.62
DFY	-1.54	-0.83	-0.39	-0.08	-0.84	-3.93	-1.60	0.46	1.16	0.06
DFR	0.31	-0.30	-0.13	-1.49	0.08	1.44	-0.24	-2.92	-5.44	-0.88
INFL	0.54	1.12	0.77	0.83	-0.04	-1.64	2.76	3.13	3.54	1.43
CE	2.28	2.13	2.47	2.77	2.83	5.67	5.39	5.63	4.18	4.90
buy and hold	2.46	2.35	2.53	2.96	2.82	1.10	0.94	1.08	0.95	0.73

Table7B

Out-of-sample Sharpe ratios, 1983:01-2015:12, 2007:01-2015:12.

The table reports the annualized Sharpe ratio for a mean-variance investor who allocates between equities and risk-free bills using a predictive regression excess return forecast based on the predictor variable in the first column or the prevailing mean benchmark forecast. See the notes to Table4 for the variable definitions and sample description. The equity weight is constrained to lie between -0.5 and 1.5. Buy and hold corresponds to the investor passively holding the market portfolio. The forecast horizon and rebalancing frequency coincide and are given by h .

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	1983:01-2015:12					2007:01-2015:12				
	h=3	h=6	h=12	h=24	h=36	h=3	h=6	h=12	h=24	h=36
Prevailing mean	0.37	0.38	0.36	0.32	0.34	0.36	0.37	0.36	0.36	0.40
DP	0.10	0.07	-0.04	-0.05	-0.02	0.33	0.34	0.42	0.44	0.57
DY	0.11	0.11	0.02	-0.05	0.02	0.41	0.37	0.44	0.44	0.53
EP	0.35	0.39	0.26	0.08	0.27	0.42	0.37	0.18	0.00	0.39
DE	0.21	0.13	0.23	0.23	0.22	0.12	-0.13	0.30	0.42	0.44
RVOL	0.27	0.23	0.28	0.23	0.28	0.43	0.39	0.47	0.39	0.20
BM	0.20	0.18	0.10	0.08	0.16	0.36	0.38	0.31	0.33	0.37
NTIS	0.33	0.32	0.29	0.28	0.33	-0.01	-0.03	0.09	0.26	0.30
TBL	0.36	0.34	0.34	0.28	0.29	0.35	0.39	0.41	0.35	0.33
LTY	0.33	0.34	0.28	0.23	0.32	0.36	0.34	0.10	-0.14	-0.33
LTR	0.42	0.34	0.42	0.34	0.33	0.32	0.12	0.24	0.40	0.27
TMS	0.44	0.45	0.52	0.65	0.57	0.29	0.42	0.58	0.74	0.68
DFY	0.22	0.30	0.32	0.31	0.24	0.08	0.25	0.39	0.45	0.42
DFR	0.39	0.35	0.36	0.15	0.35	0.46	0.34	0.00	-0.19	0.31
INFL	0.41	0.45	0.42	0.39	0.33	0.26	0.56	0.56	0.60	0.56
CE	0.58	0.57	0.59	0.59	0.59	0.84	0.83	0.86	0.75	0.86
buy and hold	0.54	0.54	0.54	0.54	0.54	0.43	0.43	0.43	0.43	0.43

Table 8

Investment-based approach: In-sample predictive regression estimation results, 1963:01-2015:12.

The table reports the β estimate and the t -statistics of the ordinary least squares estimate of β for the predictive regression model, $r_{t:t+h} = \alpha + \beta x_t + \epsilon_{t:t+h}$ for $t=1,...,T-h$ where $r_{t:t+h} = (1/h)(r_{t+1} + \cdots + r_{t+h}), r_t$ is the S&P 500 log excess return for month t. x_t is the predictor variable in the second column. CE is the credit expansion measure, INV is the real investment per GDP that is seasonally adjusted and detrended, ΔINV is the growth of real investment per GDP that is seasonally adjusted and detrended. $INVD_t$ is median dummy for investment per GDP, and $\Delta INVD_t$ is median dummy for real investment per GDP. We report heteroskedasticity- and autocorrelation-robust t -statistics for testing β_0: $\beta = 0$ against β_A : $\beta > 0$; $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

Investment and CE

(1)	(2)	(3)	(4)	(5)	(6)	(7)
		h=3	h=6	h=12	h=24	h=36
	Predictor					
Model 1	CE	-0.083**	-0.167***	-0.368***	-0.776***	-1.178***
Model 2	INV	-0.790**	-1.575***	-2.884***	-5.520***	-9.031***
Model 3	CE	-0.062**	-0.126**	-0.296**	-0.642***	-0.944***
	INV	-0.640*	-1.270**	-2.164**	-3.984**	-6.859***
Model 4	CE	-0.100**	-0.221**	-0.539***	-1.042***	-1.341***
	INV	-0.350	-0.546	-0.330	-1.036	-4.013**
	CE×INV	-6.619**	-16.473***	-41.410***	-66.176***	-63.543**
Model 5	CE	-0.013	-0.046	-0.084	-0.430***	-0.805***
	INVD	-0.010	-0.015	0.000	-0.014	-0.068
	CE×INVD	-0.195**	-0.349*	-0.969***	-1.115**	-1.004*
Model 6	CED	-0.014	-0.039*	-0.104***	-0.195***	-0.200***
	INV	-0.621	-0.135	0.546	0.197	-5.355**
	CED×INV	-0.073	-1.962**	-4.494***	-7.166***	-3.459
Model 7	CED	-0.005	-0.012	-0.031	-0.129***	-0.214***
	INVD	-0.010	-0.003	0.030	0.001	-0.126**
	CED×INVD	-0.021	-0.058	-0.153***	-0.153**	-0.031
Model	ΔINV	-0.036	-0.095	-0.219	-0.493*	-0.719**
	CE	-0.108***	-0.222***	-0.475***	-0.920***	-1.309***
	ΔINV	-0.033	-0.086	-0.195*	-0.405*	-0.585**
	CE	-0.100**	-0.201***	-0.436***	-0.910***	-1.324***
	ΔINV	-0.032	-0.083	-0.178*	-0.283*	-0.435**
	CE× ΔINV	-0.688***	-1.724***	-3.872***	-7.745***	-8.820***
	CE	-0.034	-0.078	-0.178	-0.372**	-0.704***

ΔINVD	-0.007	-0.020	-0.035	-0.071*	-0.071
CE× ΔINVD	-0.172**	-0.329**	-0.699***	-1.382***	-1.621***
CED	-0.026***	-0.050***	-0.109***	-0.213***	-0.255***
ΔINV	-0.010	0.021	0.032	0.111	-0.098
CED× ΔINV	-0.058	-0.280***	-0.572***	-1.186***	-1.164***
CED	-0.017	-0.031	-0.070**	-0.105***	-0.175***
ΔINVD	0.000	0.000	0.006	0.041	-0.001
CED× ΔINVD	-0.021	-0.055	-0.111*	-0.284***	-0.236*
IK	-3.579***	-6.898***	-12.765***	-21.987***	-34.174***
CE	-0.054*	-0.114*	-0.276**	-0.636***	-0.964***
IK	-2.982**	-5.651**	-9.787**	-15.454**	-25.217***
CE	0.991**	2.176**	4.267**	5.244*	4.238
IK	-1.684	-2.805	-4.129	-8.095	-18.526**
CE×IK	-29.943**	-65.620**	-130.186**	-168.404*	-148.574

Table 8B

Predictability in excess long-term Treasury bond returns

The table reports the β estimate and the t -statistics of the ordinary least squares estimate of β for the predictive regression model, $r_{t:t+h} = \alpha + \beta x_t + \epsilon_{t:t+h}$ for $t=1,...,T-h$ where $r_{t:t+h} = (1/h)(r_{t+1} + \cdots + r_{t+h}), r_t$ is the excess returns of long-term Treasury bonds for month t. x_t is the predictor variable in the first column. CE is the credit expansion measure, PC1 is the first principal component extracted from the 14 predictors of Goyal and Welch (2008), PC2 is the second principal component, and PC3 is the third principal component. We report heteroskedasticity- and autocorrelation-robust t -statistics for testing $\beta_0: \beta = 0$ against $\beta_A : \beta > 0$; $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

(a) Univariate predictive regression

(1)	(2)	(3)	(4)	(5)	(6)
Predictor	h=3	h=6	h=12	h=24	h=36
Intercept	0.020***	0.041***	0.085***	0.177***	0.279***
CE	-0.037**	-0.082**	-0.179**	-0.363**	-0.611**
R^2(%)	0.60	1.60	3.60	6.70	11.70

(b) Controlling for the PCs

(1)	(2)	(3)	(4)	(5)	(6)
Predictor	h=3	h=6	h=12	h=24	h=36
Intercept	0.019***	0.038***	0.078***	0.163***	0.255***
CE	0.003	0.007	-0.003	-0.113	-0.265**
PC1	0.007***	0.015***	0.028***	0.035***	0.040***
PC2	-0.001	-0.002	-0.004	-0.007**	-0.004**
PC3	0.002***	0.003***	0.007***	0.018***	0.028***
R^2(%)	6.2	13.4	25.4	35.7	46.5

Table 9

Misevaluation exploitation approach: In-sample predictive regression estimation results, 1982:01-2015:12.

The table reports the β estimate and the t -statistics of the ordinary least squares estimate of β for the predictive regression model, $r_{t:t+h} = \alpha + \beta x_t + \epsilon_{t:t+h}$ for $t=1,\ldots,T-h$ where $r_{t:t+h} = (1/h)(r_{t+1} + \cdots + r_{t+h})$, r_t is the S&P 500 log excess return for month t, x_t is the predictor variable in the second column. CE is the credit expansion measure, DIS is a market-wide disagreement measure, and DISD is median dummy for the disagreement measure. EQT is the aggregate equity issuance measure, and EQTD is median dummy for the disagreement measure. We report heteroskedasticity- and autocorrelation-robust t -statistics for testing $\beta_0: \beta = 0$ against $\beta_A : \beta > 0$; $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
		h=3	h=6	h=12	h=24	h=36
	Predictor			β		
Model1	CE	-0.091**	-0.184**	-0.398***	-0.853***	-1.306***
Model2	DIS	-0.010*	-0.027**	-0.059***	-0.095**	-0.095*
Model3	CE	-0.074*	-0.135	-0.291*	-0.686***	-1.161***
	DIS	-0.008	-0.024**	-0.051**	-0.075*	-0.062
Model4	CE	0.459***	0.741***	1.466***	2.216***	1.724**
	DIS	-0.006	-0.019**	-0.041***	-0.059**	-0.044*
	CE× DIS	-0.125***	-0.206***	-0.415***	-0.690***	-0.693***
Model5	CE	-0.028	-0.066	-0.205	-0.650**	-1.162***
	DISD	-0.005	-0.018	-0.037	-0.051	-0.008
	CE×DISD	-0.179***	-0.312***	-0.496**	-0.499	-0.518
Model6	CED	0.086**	0.066	0.089	0.155	0.018
	DIS	0.007*	-0.006	-0.021	-0.015	-0.004
	CED×DIS	-0.022***	-0.023**	-0.038	-0.078*	-0.073*
Model1	EQT	-0.298	-0.592	-1.459	-3.584**	-3.310
Model3	EQT	-0.131	-0.064	-0.090	-2.035	-2.845
	DIS	-0.009	-0.027*	-0.058**	-0.077**	-0.070
Model4	EQT	2.133**	4.621**	9.300***	18.136***	17.135**
	DIS	0.410**	0.841***	1.689***	3.665***	3.611**
	EQT × DIS	-0.403**	-0.833***	-1.677***	-3.592***	-3.535**
Model6	EQTD	0.074*	0.168***	0.459***	1.011***	1.348***
	DIS	0.005	0.002	0.019	0.081**	0.129**
	EQTD ×DIS	-0.018**	-0.037***	-0.097***	-0.218***	-0.281***

Table 10

In-sample predictive regression estimation results, 1965:07-2015:12.

The table reports the β estimate and the t -statistics of the ordinary least squares estimate of β and for the predictive regression model, $r_{t:t+h} = \alpha + \beta x_t + \epsilon_{t:t+h}$ for $t=1,\dots,T\text{-}h$ where $r_{t:t+h} = (1/h)(r_{t+1} + \cdots + r_{t+h})$, r_t is the S&P 500 log excess return for month t. x_t is the predictor variable in the second column. Model1 uses the credit expansion as an explanatory variable, Model2 uses the sentiment measure from Baker and Wurgler (2006) as an explanatory variable. Model 3 uses the credit expansion and the sentiment measure as explanary variables, and Model 4 uses the credit expansion, the sentiment measure and the product of the credit expansion and the sentiment measure as explanatory variables. For model 5, 6, and 7, we use the orthogonal sentiment measure form Baker and Wurgler (2006) instead of the original investor sentiment measure of Baker and Wurgler (2006). We report heteroskedasticity- and autocorrelation-robust t -statistics for testing β_0: $\beta = 0$ against β_A : $\beta \neq 0$; $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
		h=3	h=6	h=12	h=24	h=36
	Predictor					
Model 1	CE	-0.083**	-0.167***	-0.368***	-0.776***	-1.178***
Model 2	SENT	-0.005	-0.009	-0.015	-0.002	0.034
Model 3	CE	-0.133***	-0.263***	-0.539***	-0.981***	-1.374***
	SENT	-0.009**	-0.017**	-0.033**	-0.034	-0.011
Model 4	CE	-0.141***	-0.265***	-0.517***	-0.908 ***	-1.256***
	SENT	-0.014***	-0.018**	-0.021	0.001	0.036
	CE× SENT	0.067*	0.016	-0.175	-0.514*	-0.683**
Model 5	$\text{SENT}^{\perp}$	-0.005	-0.009	-0.014	0.001	0.036
Model 6	CE	-0.135***	-0.268***	-0.543***	-0.982***	-1.375***
	$\text{SENT}^{\perp}$	-0.010**	-0.018**	-0.032**	-0.032	-0.011
Model 7	CE	-0.158***	-0.284***	-0.516***	-0.846***	-1.173***
	$\text{SENT}^{\perp}$	-0.018***	-0.024**	-0.023	0.012	0.050
	CE× $\text{SENT}^{\perp}$	0.108**	0.073	-0.127	-0.578*	-0.784**

Table 11

Investment-based vs misevaluation exploitation: In-sample predictive regression estimation results, 1982:01-2015:12.

The table reports the β estimate and the t -statistics of the ordinary least squares estimate of β for the predictive regression model, $r_{t:t+h} = \alpha + \beta x_t + \epsilon_{t:t+h}$ for $t=1,\ldots,T\text{-}h$ where $r_{t:t+h} = (1/h)(r_{t+1} + \cdots + r_{t+h}), r_t$ is the is the S&P 500 log excess return for month t, x_t is the predictor variable in the second column. CE is the credit expansion measure, INV is the real investment per GDP that is seasonally adjusted and detrended, and ΔINV is the growth of real investment per GDP that is seasonally adjusted and detrended. DIS is a market-wide disagreement measure. We report heteroskedasticity- and autocorrelation-robust t -statistics for testing $\beta_0: \beta = 0$ against $\beta_A : \beta > 0$; $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
		h=3	h=6	h=12	h=24	h=36
	Predictor			β		
Model1	CE	-0.070*	-0.141**	-0.322**	-0.650***	-0.918***
	INV	-0.420*	-0.868*	-1.511*	-4.024**	-7.491***
Model2	CE	-0.057	-0.103	-0.237	-0.521**	-0.818***
	INV	-0.359	-0.695	-1.149	-3.515**	-7.130***
	DIS	-0.008	-0.022**	-0.049**	-0.070**	-0.051**
Model3	CE	0.397***	0.575***	1.151***	1.509***	0.582
	INV	0.027	0.210	1.094	0.996	-1.914*
	DIS	-0.005	-0.018***	-0.036***	-0.045**	-0.024*
	CE× INV	-5.625	-16.397**	-42.221***	-89.954***	-109.81***
	CE× DIS	-0.117***	-0.188***	-0.402***	-0.645***	-0.543***
Model4	CE	-0.093**	-0.189**	-0.407**	-0.860***	-1.299***
	ΔINV	-0.024	-0.056	-0.120	-0.282	-0.631**
Model5	CE	-0.073*	-0.134	-0.286*	-0.654**	-1.083***
	ΔINV	-0.024	-0.054	-0.096*	-0.293	-0.603**
	DIS	-0.008	-0.023	-0.051	-0.076**	-0.064**
Model6	CE	0.475***	0.775***	1.609***	3.192***	3.105***
	ΔINV	-0.017	-0.043	-0.054	-0.050	-0.266**
	DIS	-0.005	-0.017**	-0.035**	-0.033*	-0.005
	CE× ΔINV	-0.562**	-1.333**	-2.711**	-8.270***	-11.776***
	CE× DIS	-0.128***	-0.213***	-0.446***	-0.931***	-1.042***

Table 12

Health of financial intermediary explanations: In-sample predictive regression estimation results, 1963:01-2015:12.

The table reports the β estimate and the t -statistics of the ordinary least squares estimate of β for the predictive regression model, $r_{t:t+h} = \alpha + \beta x_t + \epsilon_{t:t+h}$ for $t=1,\ldots,T\text{-}h$ where $r_{t:t+h} = (1/h)(r_{t+1} + \cdots + r_{t+h})$, r_t is the is the S&P 500 log excess return for month t, x_t is the predictor variable in the second column. CE is the credit expansion measure, PDE is the squared reciprocal of the aggregate primary dealer capital ratio constructed by He, Kelly and Manela (2017), and E/A is the squared reciprocal of the aggregate bank equity to total bank assets obtained from the database of Federal Reserve Bank of St. Louis. The aggregate bank equity to total bank assets is detrended and not seasonally adjusted. For PDE and E/A, we use the squared reciprocal of PDE or E/A as the explanatory variable of the capital ratio of the intermediary sector. We report heteroskedasticity- and autocorrelation-robust t -statistics for testing β_0: $\beta = 0$ against β_A : $\beta > 0$; $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
		h=3	h=6	h=12	h=24	h=36
	Predictor			β		
Model1	CE	-0.083**	-0.167***	-0.368***	-0.776***	-1.178***
	PDE	0.32*	0.82**	1.31**	2.18*	2.93**
Model3	CE	-0.117***	-0.235***	-0.489***	-0.972***	-1.438***
	PDE	0.36**	0.90**	1.47**	2.46**	3.31**
	CE	-0.066	-0.286*	-0.664**	-1.583***	-2.108***
	PDE	0.43**	0.83**	1.22**	1.62	2.38**
	CE×PDE	-1.60	1.61	5.52	19.14**	21.18**
Model2	E/A	0.137	0.476	1.212	0.860	3.703
	CE	-0.092**	-0.190**	-0.404***	-0.886***	-1.314***
	E/A	-0.011	0.159	0.422	-1.643	-1.984
Model4	CE	-0.286***	-0.568***	-1.265***	-2.329***	-3.590***
	E/A	-0.1	-0.091	-0.3	-3.5*	-6.9*
	CE×(E/A)	13.34***	26.02***	39.13***	97.54***	148.16***

Table 13

Investment-based, misevaluation exploitation vs Health of financial intermediary explanations: In-sample predictive regression estimation results, 1963:01-2015:12 for Model 1,2,4 and 5, 1982:01-2015:12 for the Model 3 and 6.

The table reports the β estimate and the t -statistics of the ordinary least squares estimate of β for the predictive regression model, $r_{t:t+h} = \alpha + \beta x_t + \epsilon_{t:t+h}$ for $t=1,\ldots,T\text{-}h$ where $r_{t:t+h} = (1/h)(r_{t+1} + \cdots + r_{t+h})$, r_t is the is the S&P 500 log excess return for month t, x_t is the predictor variable in the second column. CE is the credit expansion measure, PDE is the squared reciprocal of the aggregate primary dealer capital ratio constructed by He, Kelly and Manela (2017), and E/A is the squared reciprocal of the aggregate bank equity to total bank assets obtained from the database of Federal Reserve Bank of St. Louis. The aggregate bank equity to total bank assets is detrended and not seasonally adjusted. For PDE and E/A, we use the squared reciprocal of PDE or E/A as the explanatory variable of the capital ratio of the intermediary sector. INV is the real investment per GDP that is seasonally adjusted and detrended, ΔINV is the growth of real investment per GDP that is seasonally adjusted and detrended, and DIS is a market-wide disagreement measure. We report heteroskedasticity- and autocorrelation-robust t -statistics for testing $\beta_0: \beta = 0$ against $\beta_A : \beta > 0$; $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
		h=3	h=6	h=12	h=24	h=36
	Predictor			β		
Model1	CE	-0.244***	-0.468***	-1.071***	-1.917***	-2.932***
	E/A	-0.058	0.13	0.037	-3.7*	-7.8***
	INV	-0.065	-0.007	0.022	-1.249	-4.070**
	CE× E/A	8.6**	13.66*	33.26**	46.75*	85.44***
	CE× INV	-6.703*	-17.802**	-39.106***	-81.600***	-96.395***
Model2	CE	-0.294***	-0.592***	-1.326***	-2.683***	-4.364***
	E/A	0.23	0.82	1.4	-0. 3	-3.4*
	ΔINV	-0.031	-0.084	-0.170	-0.359**	-0.568***
	CE× E/A	14.19***	28.32***	64.4***	122.23***	199.04***
	CE× ΔINV	-0.619**	-1.541***	-2.930**	-8.345***	-11.704***
Model3	CE	0.424**	0.250	0.497	-0.098	-4.097**
	E/A	-0.5	-2.0*	-3.7*	-10.3**	-17.8***
	DIS	-0.009*	-0.026***	-0.049***	-0.085***	-0.104***
	CE× E/A	2.77	17.22**	38.91*	79.22*	189.14***
	CE× DIS	-0.124***	-0.146***	-0.314***	-0.412*	0.028
Model4	CE	-0.054	-0.281*	-0.695***	-1.621***	-1.954***
	PDE	0.32**	0.65*	0.83*	0.86	1.09

	INV	-0.099	0.083	0.710	0.674	-2.087
	CE× PDE	-3.1*	-1.1	-1.4	8.03	7.76
	CE× INV	-8.122*	-16.835**	-45.225***	-71.890***	-70.800**
Model5	CE	0.010	-0.142	-0.363*	-1.088***	-1.553***
	PDE	0.48***	0.89**	1.29**	1.69*	2.31**
	ΔINV	-0.009	-0.036	-0.102	-0.180	-0.306
	CE× PDE	-3.7*	-2.2	-2.5	5.11	5.29
	CE× ΔINV	-0.930***	-1.761***	-3.784***	-6.846***	-7.941**
Model6	CE	0.347**	0.454*	0.991*	1.746*	0.928
	PDE	0.36	0.91**	1.46*	1.61	2.65***
	DIS	-0.007*	-0.019**	-0.038**	-0.040*	-0.018
	CE× PDE	-2.7**	-2.8	0.093	17.3**	23.24***
	CE× DIS	-0.080**	-0.121*	-0.309**	-0.718***	-0.693***

Table 14

In-sample predictive regression estimation results, 1963:01-2015:12, and Out-of-sample test results, 1983:01-2015:12

The table reports the β estimate, the t -statistics of the ordinary least squares estimate of β and out-of-sample R^2 statistic for the predictive regression model, $r_{t:t+h} = \alpha + \beta x_t + \epsilon_{t:t+h}$ for $t=1,\ldots,T\text{-}h$ where $r_{t:t+h} = (1/h)(r_{t+1} + \cdots + r_{t+h})$, r_t is the is the S&P 500 log excess return for month *t*, x_t is the predictor variable in the second column. EQT is the aggregate equity issuance measure. We report heteroskedasticity- and autocorrelation-robust t -statistics for testing β_0: $\beta = 0$ against β_A : $\beta > 0$; $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

(1)	(2)	(3)	(4)	(5)	(6)
Predictor	h=3	h=6	h=12	h=24	h=36
			In-sample β		
EQT	-0.298	-0.592	-1.459	-3.584*	-3.310
			OOS R^2 statistics (%)		
EQT	-1.16	-3.49	-8.94	-18.06**	-34.61***

Appendix

Correlation matrix of credit expansion and 14 predictors form Goyal and Welch (2008), 1963:01-2015:12.

The table displays Pearson correlation coefficients for 14 predictor variables from Goyal and Welch (2008) and the credit expansion variable (CE). See the notes to Table4 for the variable definitions and sample description. 0.00 indicates less than 0.005 in absolute value.

	DP	DY	EP	DE	RVOL	BM	NTIS	TBL	LTY	LTR	TMS	DFY	DFR	INFL	CE
DP	1.00														
DY	1.00	1.00													
EP	0.71	0.71	1.00												
DE	0.27	0.27	-0.49	1.00											
RVOL	0.01	0.02	-0.20	0.30	1.00										
BM	0.90	0.90	0.80	0.02	0.06	1.00									
NTIS	0.10	0.11	0.10	-0.01	-0.08	0.19	1.00								
TBL	0.65	0.65	0.65	-0.07	0.00	0.67	0.12	1.00							
LTY	0.67	0.67	0.59	0.02	0.11	0.64	0.10	0.88	1.00						
LTR	0.08	0.09	-0.09	0.22	0.10	0.01	-0.09	0.01	0.01	1.00					
TMS	-0.21	-0.21	-0.33	0.20	0.20	-0.30	-0.08	-0.57	-0.11	0.00	1.00				
DFY	0.39	0.39	0.12	0.32	0.47	0.40	-0.32	0.24	0.40	0.21	0.20	1.00			
DFR	-0.07	-0.06	-0.01	-0.08	0.06	-0.03	0.14	-0.05	-0.01	-0.43	0.10	0.03	1.00		
INFL	0.41	0.39	0.45	-0.12	0.07	0.52	0.13	0.52	0.41	-0.18	-0.39	0.02	-0.03	1.00	
CE	0.04	0.04	-0.02	0.08	0.15	0.15	-0.20	0.09	-0.12	0.03	-0.41	0.01	-0.07	0.16	1.00